Essays on the Migration of Heterogeneous Individuals

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Preface

This doctoral thesis was written while I was working as a research and teaching staff member at the Chair of International Economics at the University of Tübingen. I would like to use the opportunity to thank all people who have supported me in writing this thesis over the past three and a half years.

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CHAPTER 1

Introduction

Although individuals have migrated during most phases of history, systematic empirical analyses of the characteristics, causes, and consequences of migration have only become possible in the last century due to the emerging availability of rich data (see Bodvarsson and Van den Berg, 2009, 69, and Heckman, 2001, 675). The conducted empirical analyses relying on aggregate migration data provide interesting insights concerning, e.g., the scale of migration, its major determinants, and its macroeconomic implications. As ever more detailed data on migration are becoming available, these insights are gradually complemented by findings from empirical studies analyzing individuals' motives for migration, the composition of aggregate migration flows, or the implications of different types of migration for the sending and receiving countries. Thus, the availability of disaggregated data increasingly allows for an analysis of the heterogeneity inherent in the phenomenon migration. The more differentiated insights obtained from these analyses are key to a better understanding of the nature and the determinants of migration, and they allow for a better assessment of the macroeconomic implications of migration in terms of production, trade, and welfare. This thesis contributes to the literature on the migration of heterogeneous individuals by providing some new answers to the following questions: *What determines migration? Who migrates? How does migration impact on the sending countries?*

Unless specified differently, the term *migrant* is used in a general sense and refers to an individual who changes his place of residence for a certain period of time. This definition embraces individuals moving across national borders (international migrants), as well as individuals moving within national borders (internal migrants). The terms *developing countries* and *developed countries* are used as synonyms for low-income countries and high-income countries, respectively.

In the following, some of the central answers to the above questions provided in the established literature are summarized. This summary is by no means intended to be exhaustive, but, rather, it is meant to put the research presented in this thesis into a broader perspective. Following this summary, an outlook is provided on the answers that this thesis will add to the literature concerned with the above questions.

What Determines Migration?

> "Despite the obstacles inherent within highly regulated national migration systems, people continue to move for many of the same reasons that have driven migrants throughout history: to seek new opportunities and to escape economic and political distress. Many factors related to family, wages, security, values, and opportunities influence migration decisions. Migration confounds simplistic analysis, as the decision to migrate is nested within relationships, networks, and structures." (Goldin et al., 2011, 4)

The statement by Goldin and his co-authors alludes to the multifaceted nature of the determinants of individual decisions to migrate. The classical determinant emphasized by economic theories of migration is based on considerations about inter-regional income differences. In various types of models, it is argued that workers migrate in order to earn higher incomes. An early and influential contribution to this strand of literature is the two-sector model on rural-to-urban migration in the presence of urban unemployment by Harris and Todaro (1970). While their model abstracts from any costs of migration, many other theoretical studies explicitly account for the fact that the incentives to move are in general curbed by the monetary and non-monetary costs of migration or by restrictive migration policies. In his seminal article on the costs and returns associated with migration, Sjaastad (1962) characterizes migration as an individual's investment into his human capital. Assuming that migration costs are a decreasing function of past migration (due to, e.g., the assistance with the search for jobs that is provided by settled migrants), Carrington et al. (1996) and Chau (1997) formalize the idea that current migration is determined by the magnitude of past migration. The former study shows that under certain conditions, migration flows may increase despite a narrowing wage gap. The research compiled in Stark (1991) complements these investigations related to absolute (expected) income by highlighting the importance of individuals' considerations about relative income or relative deprivation, the influence of asymmetric information, as well as the role of the family on the decision to migrate. Recently, Fan and Stark (2011) have presented a model of migration in which migration serves as a means to increase a worker's "distance" to his familiar social environment. This migration is motivated by its reductive effect on disutility resulting from work in a stigmatized sector.

While theoretical models of migration typically focus on a single rationale for migration at a time, empirical models have to account for the simultaneity and intertwined nature of the multiple factors determining migration. These determinants include economic, political, social, and ecological factors. They may be classified into the categories of "push", "pull", "stay", and "stay away" factors (see Bodvarsson and Van den Berg, 2009, 6-7). Empirical analyses relying on aggregate data often explore the determinants of migration by using cross-country information on immigration to OECD countries; see, e.g., Greenwood and McDowell (1991), Hatton (1995), Clark et al. (2007), Pedersen et al. (2008), Lewer and Van den Berg (2008), Mayda (2010), and Ortega and Peri (2013). Amongst others, these studies show that absolute and relative incomes, employment conditions in sending and receiving countries, as well as immigration policies are important determinants of migration. Furthermore, migration is found to be negatively related to bilateral distance, while it is positively related to the existence of a common language or common colonial history of the sending and receiving countries, as well as to the number of established migrants at destination. The latter effect is commonly referred to as the "network effect" in migration.

With the recent availability of survey data, empirical analyses of individual decisions to migrate have become possible. Migration from Mexico, specifically in the Mexican-U.S. corridor, is particularly well-researched. The evidence reported in Stark (1991, chapters 9 and 10) confirms the relevance of Mexican households' relative deprivation for their decision to migrate abroad. Mckenzie and Rapoport (2007) find that the propensity of Mexicans to migrate to the United States is increasing in wealth at low levels of household resources and decreasing at high levels of resources, and that it is higher in communities with large migrant networks in the United States. The interaction between the effects of wealth and networks is found to be negative. Exploiting data from surveys conducted in

Ecuador, Spain, and the United States, Bertoli, Fernández-Huertas Moraga, and Ortega (2013) find that cross-country wage differences are important factors determining migration from Ecuador to the United States and to Spain, although in the considered period most migrants preferred the lower income destination Spain. Accordingly, the migration costs inferred by Bertoli, Fernández-Huertas Moraga, and Ortega (2013) from their estimates are much higher for migration to the United States than for migration to Spain. Using survey data from Germany, Jäger et al. (2010) provide evidence on a positive relationship between an individual's propensity to take risks and the probability of migrating to another German region.

Who Migrates?

> "Because the act of moving from one country to another generally involves risk, temporary hardship, and difficult changes in culture, language, and lifestyle, immigrants tend to be especially ambitious, more willing to take risks, harder working, more open to new ideas, and energetic. Evidence suggests that this romantic view of immigrants as exceptional people may be a bit of an exaggeration, but immigrants are seldom 'average' relative to the population they left behind or the ones they join." (Bodvarsson and Van den Berg, 2009, 8)

Similar to most studies that analyze the composition of migrant populations, the statement by Bodvarsson and Van den Berg is concerned with the characteristics of international migrants. The pioneering work on the self-selection behavior of migrants is Borjas (1987). In his model, migrants are positively selected in terms of the income distributions of both the sending and receiving country if the income distribution is more unequal in the receiving country than in the sending country and if skills are valued in a similar way in both countries. Chiswick (1999) proposes a framework in which the probability that migrants are positively selected from the population in the sending country in terms of their skills is a positive function of the costs of migration, of the extent to which these costs are decreasing in ability, as well as of the relative skill differentials in the destination relative to the origin.

Comprehensive descriptive evidence on the selection of different migrant populations in terms of education has first become available from the cross-country datasets compiled by Carrington and Detragiache (1998) and by Adams (2003). These datasets were the first to provide estimates on absolute as well as relative numbers of immigrants in OECD countries by country of origin and educational attainment. A later compilation of data that has been frequently cited and used in empirical analyses is the one by Docquier and Marfouk (2006). Their data reveal that the share of skilled (tertiary-educated) migrants in the total stock of migrants in the OECD in the year 2000 was highest for low-income sending countries (45.1%). The same share amounted to 38.3% for high-income countries, to 35.4% for lower-middle income countries, and to 25.2% for upper-middle income countries (see Docquier and Marfouk, 2006, 170). For each of these groups of countries, the reported share of skilled workers in the origin population was considerably lower (see Docquier and Marfouk, 2006, 170), suggesting positive selection of migrants. The extent of this positive selection was highest for the group of low-income countries. Regarding migrants' occupations, the focus is often on the occupation-specific incidence of migration rather than on the selection in terms of occupations. Thereby, the most comprehensive evidence is available for health professionals. According to figures reported in Docquier and Bhargava (2007, 9), the number of physicians working abroad relative to the total number of physicians educated in the source countries amounted to 7.2% for low-income countries, to 3.5% for high-income countries, and to 1.6% (3.7%) for lower- (upper-) middle income countries in 2004. A look at the age structure of the foreign-born and of the native population in the OECD around the year 2000 reveals that the share of the immigrant population aged 25-64 exceeded the respective share of the native population, while the shares of those aged 15-24 as well as of those aged 65 and more were lower in the immigrant population compared to the native population (see OECD, 2008, 69).

How Does Migration Impact on the Sending Countries?

> "The effects of migration on the sending countries depend critically upon the magnitudes, composition and nature of the migration streams, as well upon the specific context from which migrants are drawn. In particular four key aspects of migrations may be distinguished: the effects of unskilled labour flows; the consequences of a brain drain and the potential for gain routed through a highly educated diaspora; the importance of return migration; and, the contributions of remittances." (Katseli et al., 2006, 30)

In addition to the four repercussions mentioned by Katseli and her co-authors, migration may impact on the sending countries through several other channels, including the effects on trade and capital flowing to or from these countries. The effects of high-skilled migration (or "brain drain") and of remittances on developing migrant-sending countries have received the most attention in the economic literature. Through these channels, migration may have important effects on growth and development in the sending countries. The focus of the following paragraph is on the brain drain literature.

The theoretical literature on the effects of the emigration of high-skilled workers on the sending economies can be divided into three phases: A phase dominated by a neutral view starting in the late 1960s, another phase dominated by a negative view (1970s-1990s), and a third more optimistic phase starting in the late 1990s; see the literature overview provided in Docquier and Rapoport (2012, 682-683). Concerns about the brain drain generally evolve from both the emigration of human capital and the associated loss of funds that have been spent for the education of the emigrants. In the 1970s, Bhagwati has proposed a tax on high-skilled emigrants as an instrument to mitigate the negative effects of the brain drain on the sending countries, see, e.g., Bhagwati (1972). Starting with Stark et al. (1997, 1998) and Mountford (1997), the theoretical literature on the brain drain has recognized the possibility that a brain drain may as well have a positive effect on human capital in the sending countries. The essential argument is that the prospect of migration to a high-income country may increase the investments in human capital in low-income countries (in the following referred to as "brain gain" hypothesis). The available empirical tests of this hypothesis provide mixed results. Some studies also try to gauge the effect of the brain drain on the *ex post* level of human capital in the sending countries, trading the potential brain gain off against the final outflow of human capital. According to the results of Beine, Docquier, and Oden-Defoort (2011), many low-income countries are likely to benefit from the brain drain in terms of their *ex post* levels of human capital, while middle- and high-income countries do not seem to experience a brain gain that might compensate their outflows of human capital. Bhargava et al. (2011) provide evidence on a medical brain gain effect, which was too small, however, to yield a positive effect on the *ex post* stock of physicians in the developing migrant-sending countries.

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This thesis contributes to the literature on the migration of heterogeneous individuals by providing some new answers to the three questions outlined above. The thesis consists of seven self-contained essays that are intended for separate publication. These essays are included in Chapters 2 to 8 and deal with three different subjects. The following overview provides a summary of each chapter and elaborates on the research questions addressed.

The Relationship between Occupational Status and Migration

Chapters 2 and 3 are concerned with the relationship between occupational status and migration. These chapters address the questions of who migrates and of what determines an individual's decision to migrate.

Chapter 2 is theoretical in nature and studies the desire to avoid disutility from occupational stigma as a possible motive for migration. As a first contribution, this chapter presents a consolidated version of the two-country, two-sector model by Fan and Stark (2011), in which one sector of production carries a stigma that confers disutility to its workers. Unlike in the original version of this model, the costs of migration are modeled such as to leave the relative price of the goods in the open economy setting unaffected. This entails the advantage that some of the model's major implications can be derived graphically. The second contribution of this chapter is a modification of the reference model regarding the heterogeneity of individuals. It is assumed that individuals have different abilities, but that – contrary to Fan and Stark (2011) – they do not differ with respect to their aversions to occupational stigma. This modification is motivated by the abundant evidence of positive selection of migrants from the populations in the origin countries in terms of their education. In the model, differences in individual ability translate into differences in wages and determine the selection of individuals into the two sectors of production. If migration to an identical foreign country is possible, all individuals working in the stigmatized sector have an incentive to migrate because it is assumed that changing one's social environment reduces disutility from occupational stigma. However, given that migration is costly, only the workers with the highest ability levels of those working in the stigmatized sector will be capable of migrating. While preserving the motive for migration proposed by Fan and Stark (2011), the modified model thus proposes a case for migrants' positive selection on skills that is unrelated to international differences in the distribution of wages. In addition, it is shown that the main results of the reference model concerning the effects of opening the countries to migration are robust to the modification of individuals' heterogeneity.

Chapter 3 is empirical in nature and uses data on internal migration in Germany in order to assess the hypothesis that migration may be driven by discontent with occupational status. Based on rich individual-level data from the German Socio-Economic Panel, it is tested whether – other things held constant – individuals working in occupations with low prestige relative to the prestige of their vocational training have a higher probability of moving to another destination in Germany compared to individuals working in occupations with relatively high prestige. In line with the theoretical model considered in Chapter 2, the intuition underlying this hypothesis is that an individual can lower the disutility associated with being employed in a low-prestige occupation by increasing the “distance” to his familiar social environment. In order to rule out the possibility that changes in utility derive from changes in the occupational status itself, the focus in the empirical analysis is exclusively on workers who do not improve upon their occupational status. A distinctive feature of the analysis relative to the existing literature is its explicit distinction between a pecuniary dimension and a prestige dimension of relative occupational status. The conducted estimations control for a rich set of individual and household characteristics related to education, employment, dwelling, and attachment to one’s place of residence. The results robustly reject the hypothesis that discontent with occupational status may lead to a higher propensity to migrate, pointing to a negative relationship between the probability of migration and the incidence of relatively low occupational prestige for the considered sample. Possible explanations of this finding include the existence of particularly high migration costs or of a strong occupational culture for individuals in low-prestige occupations. The negative relationship is found along with a positive relationship between the absolute level of income and migration. By contrast, there appears to be no relationship between the absolute prestige level or the relative income level and migration.

Networks Effects in Migration

Chapters 4 to 6 study network effects in migration. They address the questions of who migrates and of what determines migration at the aggregate level. Chapters 4 and 5 are based on joint works with Marcel Smolka; Chapter 6 is based on a joint work with Marcel Smolka and Anne Steinbacher.

Chapter 4 introduces the Spanish migration data that is used in the econometric analyses of the two subsequent chapters. It describes the policy setting relevant for immigration to Spain in the period 1997-2009, and it documents a number of stylized facts on this immigration. This chapter serves to motivate the Spanish immigration experience from the end of the 1990s until the beginning of the global financial and economic crisis in 2007 as a unique case for the empirical study of network effects in migration.

Chapter 5 contributes to the literature on network effects in migration by expanding the definition of migrant networks to a broader population basis. A large literature documents that migrants are attracted to destinations that already host migrants of their same nationality (*co-national pull*). The hypothesis in Chapter 5 is that – whatever the precise support channel – the migrants who promote follow-up migration include not only past co-national migrants but also past migrants from other nationalities. This hypothesis is motivated by the increasing interactions among individuals from different nationalities, which are facilitated by the economic globalization of the recent decades, and has not been considered in the related empirical literature so far. Exploiting the Spanish data described in Chapter 4 with respect to migrants' countries of origin and provinces of destination in the period 1996-2006, it is analyzed whether migrants are also attracted to destinations that already host migrants from nationalities that are adjacent to their own (*cross-national pull*). To this end, a migration function that can be estimated empirically is derived from a multinomial logit model à la McFadden (1984). In the estimations, the influence of the cross-national pull is captured by a generic network term that weights each settled migrant by the inverse distance between his country of origin and the country of origin of a potential follow-up migrant. The underlying intuition is that cross-national interactions are more likely to arise the smaller the geographical and cultural distance between the nationalities concerned. The estimation results reveal that follow-up migrants move to destinations with large representations of other migrants when these migrants are from adjacent nationalities; in addition, they confirm the well-known pull effect due to co-national migrants. Ignoring the cross-national pull effect leads to a small omitted variable bias in the estimate of the co-national pull effect.

Chapter 6 builds on the same dataset as Chapter 5 and studies further types of heterogeneity inherent in the effects of migrant networks on follow-up migration. In order to allow also for an analysis of the impact of migrant networks on the skill composition of migration flows, the dataset is complemented with aggregate information on migrants' educational attainment compiled from a unique immigrant survey conducted in Spain. Unlike Chapter 5, Chapter 6 relies on a generalized version of the multinomial logit model described in McFadden (1984) in order to derive an estimable migration function that is based on less restrictive assumptions than the function derived from the standard model. Firstly, the generalized model provides for the fact that destinations in the same territorial entity (e.g., country or region) are similar in many respects (legal and political framework, economic activities, cultural background) and should therefore be treated as close substitutes. Secondly, the model accounts for cross-regional differences in the substitutability across alternative migration destinations. These differences are likely to exist in the Spanish case because regional authorities in Spain differ in the extent of their legislative autonomy, and because some regions in Spain have a second official language. Migrants are likely to consider destinations in regions with a pronounced autonomy as close substitutes, relative to destinations in other regions. These aspects challenge previous identification strategies, but they can be appropriately addressed with the generalized model. The estimation results reveal substantial heterogeneity in the network effect of co-national migrants across Spanish regions, rejecting a constant degree of cross-alternative substitutability as implied by the standard model. Another finding is that established migrant networks exerted a strong negative effect on the ratio of high-to-low-skilled migrants coming to Spain.

Occupation-Specific South-North Migration

Chapters 7 and 8 deal with occupation-specific migration from developing countries to developed countries ("south-north migration"). While Chapter 7 is concerned with the question of who migrates, Chapter 8 primarily studies the question of how migration of different types of human capital impacts on human capital in the sending countries.

The major contribution of Chapter 7 is the presentation of two new datasets with south-north migration rates by occupational category at different levels of disaggregation for a large number of developing countries around the year 2000. These migration rates have been constructed using occupation-specific employment data from ILO and OECD and following the methodology of Docquier and Marfouk (2006). Chapter 7 exploits the two datasets as well as data on the populations in the sending countries and receiving countries. Stylized facts on the occupational composition of south-north migrants in conjunction with the composition of human capital in the sending and receiving countries are presented. As the focus is put on high-skilled migration, this chapter complements the available evidence on the occupation-specific brain drain. The evidence presented in Chapter 7 suggests the existence of substantial "overeducation" or "brain waste" from the perspective of the developing migrant-sending countries, since south-north migrants with a university degree worked more often in occupational categories requiring less than tertiary education compared to OECD natives. The average incidence of migration appears to be largest for occupations requiring the highest education levels. South-north migrants working as professionals exhibited a higher probability of working in several science or health professions and a lower probability of working in teaching professions compared to native professionals in the OECD. Also, the emigration rates of science, health, and other professionals are significantly larger than those of teaching professionals. These findings likely suggest that the degree of international transferability of skills is largest for the former types of professionals. These stylized facts have to be seen in the context of comparatively low employment shares of professionals and other highly educated workers in developing sending countries in general. When used to study the overall incidence of the brain drain, the employment-based data give smaller estimates than the conventionally used population-based data. The reason for this is that some highly educated migrants worked in occupations requiring low education levels – an observation that is most likely related to the imperfect international transferability of skills.

Chapter 8 combines the data considered in Chapter 7 with detailed information on enrollment in tertiary education from UNESCO in order to analyze the effect of occupation-specific brain drain on the accumulation of different types of human capital in the sending countries. It contributes to the empirical literature on the brain drain by providing the first conjoint test of the brain gain hypothesis for four different types of human capital and a sample of almost forty developing countries. In addition to allowing for a distinction between the effects of different types of brain drain, the use of the occupation-specific data allows for an application of estimation techniques that purge the estimates of unobservable heterogeneity at the country level. This is an advantage relative to existing empirical studies, which either rely on data for one aggregated type of human capital or on data for a single more specific type of human capital. The estimations reveal a negative average effect of the incidence of occupation-specific brain drain on tertiary enrollment. This result is in line with the results from studies that use aggregate enrollment data. It reflects a reduction in the investments in human capital in the sending countries that is induced by the prospect of migration. This reduction may coincide with an increase in the investments in human capital undertaken abroad by individuals from these countries. The negative effect is weaker for the fields *Science & Engineering* and *Health & Agriculture* than for the fields *Education* and *Humanities & Social Sciences*. Given that the fields *Science & Engineering* and *Health & Agriculture* are likely to involve skills with a considerably high degree of international transferability, it is not surprising that the negative effect on enrollment is weakest for these fields.

CHAPTER 2

Occupational Stigma and the Decision to Migrate

2.1 Introduction

In the economic migration literature, income differences are generally considered as the most important force driving interregional or international migration. Whereas this pecuniary focus is clearly justified regarding, e.g., the migration flows observed from poor countries to rich countries, the desire to take advantage of income differences certainly does not constitute the only motive underlying the movement of individuals. The recent migration literature increasingly incorporates other motives for migration, accounting even for migration between regions or countries that are identical in all respects.[1] In Berninghaus and Seifert-Vogt (1991), two-way migration between identical countries is driven by individuals' incomplete information concerning future wages and the quality of life in the destination country. In Kreickemeier and Wrona (2011), firms choose workers of similar ability for production, and two-way migration of high-skilled individuals is motivated by their desire to get separated from low-skilled individuals and to be employed together with another high-skilled individual in the same firm. Fan and Stark (2011) propose the desire of individuals to reduce their disutility from occupational stigma as an explanation for two-way migration between identical countries. The underlying intuition is that migrants generally suffer less from working in the stigmatized sector of the foreign country than

[1] The presentation of these motives in a setup with identical regions or countries actually emphasizes the arguments of interest.

they suffer from working in the stigmatized sector of their native country because they are surrounded by a non-familiar reference group abroad. In the presence of positive migration costs, those individuals in the stigmatized sector who suffer most from the stigma attached to their work have an incentive to migrate.

This chapter focuses on the motive for migration put forward by Fan and Stark (2011). Contrasting the latter, it assumes that individuals are heterogeneous with respect to their ability, rather than with respect to their aversion to occupational stigma. Even though selection into sectors of production and migration based on differences in stigma aversion seems intuitive, it can hardly be assessed empirically. However, there is substantial evidence that migrants are positively selected from the populations in the origin countries in terms of their skills or education, see, e.g., Grogger and Hanson (2011).[2] This chapter shows that the main results of Fan and Stark (2011) are preserved if individuals differ in terms of their innate ability, but not in terms of their aversion to occupational stigma. Given that differences in ability (or productivity) translate into differences in wages, the presented model variant predicts that the workers with the highest ability levels choose to work in the domestic high-skilled sector, while the workers with the lowest ability levels have a comparative advantage to work in the domestic stigmatized, low-skilled sector. If migration to an identical foreign economy is possible at some cost, the individuals with the highest ability levels (and wages) of those individuals working in the stigmatized sector will find it optimal to migrate in order to reduce their disutility from occupational stigma. Thus, while preserving the motive for migration proposed by Fan and Stark (2011), the considered model variant links the individual rationale for migration to individual ability rather than to individual aversion to occupational stigma. It thereby proposes an alternative case for migrants' positive selection on skills that is unrelated to international differences in the distribution of wages.

The remainder of this chapter is organized as follows: In Section 2.2, we present a consolidated version of the general framework, the main mechanisms, as well as the most important results of the model by Fan and Stark (2011), choosing a form of representation that serves best for a comparison with the modified model variant that is introduced thereafter. Most importantly, this comprises two graphical illustrations, one for the joint determination of the sectoral labor allocation and the relative price in equilibrium and

[2] The classical explanation for this observation is based on differences in wages across countries and skill types as well as on the existence and characteristics of migration costs, see Borjas (1987) and Chiswick (1999).

another one for the production pattern. We argue that the main results of the model can be derived more easily if the costs of migration are modeled such as to leave the relative price unaffected. In Section 2.3, we show that the main results of the reference model are robust to the modification that individuals differ with respect to their productivity while the stigma effect provides the same disutility for any individual working in the stigmatized sector. Furthermore, we argue that modeling migration costs in a way that reduces a migrant's output even reinforces the result that more individuals will work in the stigmatized sector in the presence of the possibility of migration. At the same time, this modification renders the effect on the relative price ambiguous. Section 2.4 concludes.

2.2 A Model of Migration with Heterogeneous Stigma: Fan and Stark (2011)

In this section we revisit the model of migration between identical countries or regions that is motivated by a desire to reduce occupational stigma as proposed by Fan and Stark (2011). Contrasting the original model, however, we model migration costs in a way so as to leave the equilibrium relative price unaffected. Due to this modification, all effects introduced by the possibility of migration in the open economy setting can be derived graphically.

2.2.1 General Equilibrium in the Closed Economy Setting

Let us follow Fan and Stark (2011) and consider an economy that is populated by a large number of individuals with size measure 1. Individuals derive utility from both consumption and social status, which is associated with the sector in which they work. They produce one of two possible goods but consume both goods, x and y, which are produced in sectors X and Y, respectively. Work in sector Y is characterized by a certain stigma, i.e., working in this sector reduces an individual's utility. Before individuals choose either of the two possible occupations/sectors, they only differ with respect to their "idiosyncratic taste for working in the 'humiliation' sector" (Fan and Stark, 2011, 552), or, in other words, they differ with respect to the degree of aversion that they attribute to work in the stigmatized sector Y. This degree of aversion, denoted by the random variable ϵ_i, is distributed over the interval $[0, \infty)$. Its probability function is denoted by $f(\epsilon)$, and its distribution function $F(\epsilon)$ is assumed to be continuous and differentiable, with $f(\epsilon) = F^{'}(\epsilon) > 0 \quad \forall \epsilon_i \in [0, \infty)$. The utility of an individual i working in one of the two sectors j is given by:

$$u_{i,j} = \alpha \ln(x) + (1-\alpha)\ln(y) - \kappa(j)\epsilon_i \tag{2.1}$$

where x and y denote consumption of the two goods, respectively, $\alpha \in (0,1)$, $j = X, Y$, $\kappa(X) = 0$, and $\kappa(Y) = 1$.

Each individual produces one unit of output, regardless of the sector in which he works. Thus, the aggregate production functions are given as:

$$X = L_X \quad \text{and} \quad Y = L_Y, \tag{2.2}$$

where L_X and L_Y denote the size of the labor inputs in sectors X and Y, respectively. Good x is taken as the numéraire and its price is normalized to 1. The price of good y is denoted by p.

Since the economy is assumed to be perfectly competitive, workers in either sector are paid their value marginal product:

$$w_X = 1 \quad \text{and} \quad w_Y = p \tag{2.3}$$

With the budget constraint of an individual working in sector $j = X, Y$ being

$$x + yp = w_j, \tag{2.4}$$

the utility maximization problem of an individual i in sector j can be expressed as:

$$\max_{x,y} \mathscr{L} = \alpha \ln(x) + (1-\alpha)\ln(y) - \kappa(j)\epsilon_i - \lambda\,(x + yp - w_j) \tag{2.5}$$

Solving for x and y yields the Marshallian demand functions:

$$x = \alpha w_j \quad \text{and} \quad y = \frac{(1-\alpha)}{p} w_j \quad \text{with} \quad j = X, Y \tag{2.6}$$

Hence, the utility of an individual working in sector X can be rewritten as:

$$u_{i,X} = \alpha \ln(\alpha w_X) + (1-\alpha)\ln\left(\frac{1-\alpha}{p} w_X\right) = \alpha \ln(\alpha) + (1-\alpha)\ln(1-\alpha) - (1-\alpha)\ln(p) \tag{2.7}$$

Similarly, the utility of an individual working in sector Y can be expressed as:

$$u_{i,Y} = \alpha \ln(\alpha w_Y) + (1-\alpha)\ln\left(\frac{1-\alpha}{p} w_Y\right) - \epsilon_i = \alpha \ln(\alpha) + \alpha \ln(p) + (1-\alpha)\ln(1-\alpha) - \epsilon_i \tag{2.8}$$

Occupational Choice

An individual will prefer to work in sector Y over working in sector X if:

$$u_{i,Y} > u_{i,X} \tag{2.9}$$

$$\ln(\alpha) + (1-\alpha)\ln(1-\alpha) + \alpha\ln(p) - \epsilon_i > \alpha\ln(\alpha) + (1-\alpha)\ln(1-\alpha) - (1-\alpha)\ln(p)$$

$$\epsilon_i < \epsilon^* = \ln(p) \tag{2.10}$$

$$p = e^{\epsilon^*} \tag{2.11}$$

Thus, all individuals with a rather low degree of aversion to working in the stigmatized sector (i.e., for whom $\epsilon_i < \ln(p)$) will work in sector Y, while all individuals for whom working in the stigmatized sector is particularly humiliating (i.e., for whom $\epsilon_i \geq \ln(p)$) will work in sector X (see Fan and Stark, 2011, Proposition 1 c). This implies that the "marginal" individual who is indifferent between working in either sector is assumed to opt for the non-stigmatized sector.

Goods Market Equilibrium

Since the production technology in either sector is characterized by constant returns to scale, aggregate sectoral output is given by the total sum of the produced quantities over all individuals working in the relevant sector. Hence, the total quantity supplied of good y is given by:

$$y^s = L_Y = \int_0^{\epsilon^*} f(\epsilon)d\epsilon = F(\epsilon^*) \tag{2.12}$$

The total quantity demanded of good y can be calculated as the expenditure share attributed to good y multiplied by the total wage income of all individuals working in the two sectors:

$$y^d = \frac{(1-\alpha)}{p}\left[\int_0^{\epsilon^*} w_Y f(\epsilon)d\epsilon + \int_{\epsilon^*}^{\infty} w_X f(\epsilon)d\epsilon\right]$$

$$y^d = (1-\alpha)F(\epsilon^*) + \frac{(1-\alpha)}{p}\left[1 - F(\epsilon^*)\right] \tag{2.13}$$

Equilibrium in the market for good y requires that supply equals demand, $y^s = y^d$:

$$F(\epsilon^*) = (1-\alpha)F(\epsilon^*) + \frac{(1-\alpha)}{p}\left[1 - F(\epsilon^*)\right] \tag{2.14}$$

$$p = \frac{(1-\alpha)\left[1 - F(\epsilon^*)\right]}{\alpha F(\epsilon^*)} = \frac{(1-\alpha)\left[1 - F(\ln p)\right]}{\alpha F(\ln p)} = \frac{(1-\alpha)x}{\alpha y} \tag{2.15}$$

With perfectly competitive markets for goods and for labor, the market for good x will be simultaneously cleared if both the market for good y and the labor market are cleared (Walras' law).

Figure 2.1 serves to illustrate the joint determination of the cut-off disutility level ϵ^{*c} of the individual who is just indifferent between work in either sector in equilibrium and the equilibrium relative price for good y, p^c, in the closed economy setting. The upward sloping locus represents the condition of indifference between the two occupations (2.11), and the downward-sloping curve illustrates the goods market equilibrium condition (2.15). Since in general equilibrium both conditions must hold, ϵ^{*c} and p^c can be read off at the intersection of the two loci.

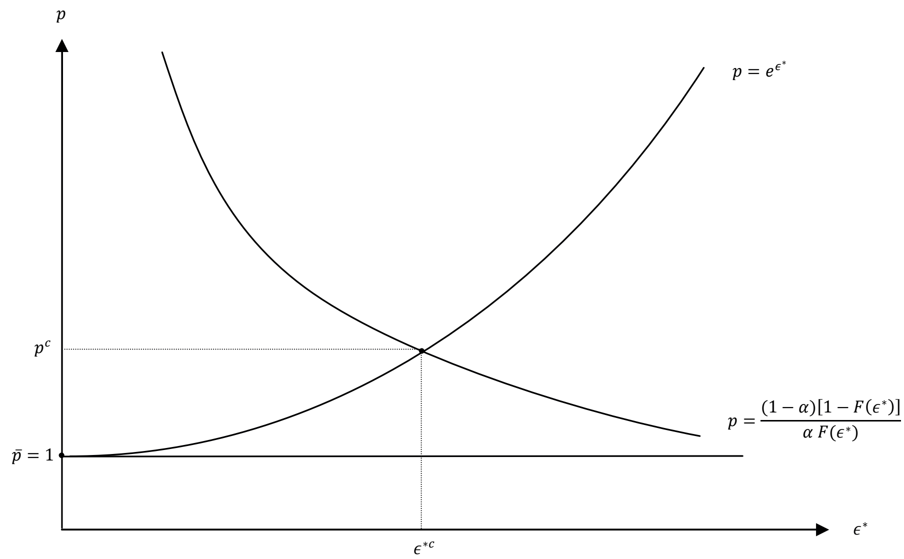

Figure 2.1: Joint Determination of the Cut-off Stigma Aversion Level and the Relative Price in the Closed Economy Setting

Own illustration based on the Fan and Stark (2011) model.

Figure 2.2 illustrates the general equilibrium in the closed economy setting with the help of the concept of the production possibilities frontier (PPF), which indicates all possible combinations of output of the two goods that the economy is able to produce using all its available resources. If all individuals worked in sector Y, they would produce

$y^{max} = \int_0^\infty f(\epsilon)d\epsilon = 1$ units of good y, while the output of good x would be zero. Similarly, if all individuals worked in sector X, the output of good x would amount to $x^{max} = \int_0^\infty f(\epsilon)d\epsilon = 1$, while the output of good y would be zero. The slope of the PPF (the marginal rate of transformation, MRT) is constant and equal to 1, because all individuals are equally productive in both sectors and the production technologies are characterized by constant returns to scale. In equilibrium, both the occupational indifference condition (2.11) and the goods market clearing condition (2.15) must be fulfilled. In the diagram, this is given at the intersection point of the PPF[3] with the indifference curve whose slope in this point in absolute terms (the marginal rate of substitution (MRS), which corresponds to (2.15)) is such that (2.11) is fulfilled:

$$p^c = \frac{(1-\alpha)x^c}{\alpha y^c} = e^{\epsilon^{*c}} \tag{2.16}$$

This intersection point determines the equilibrium quantities of the two goods, x^c and y^c, which can be read off at the axes.

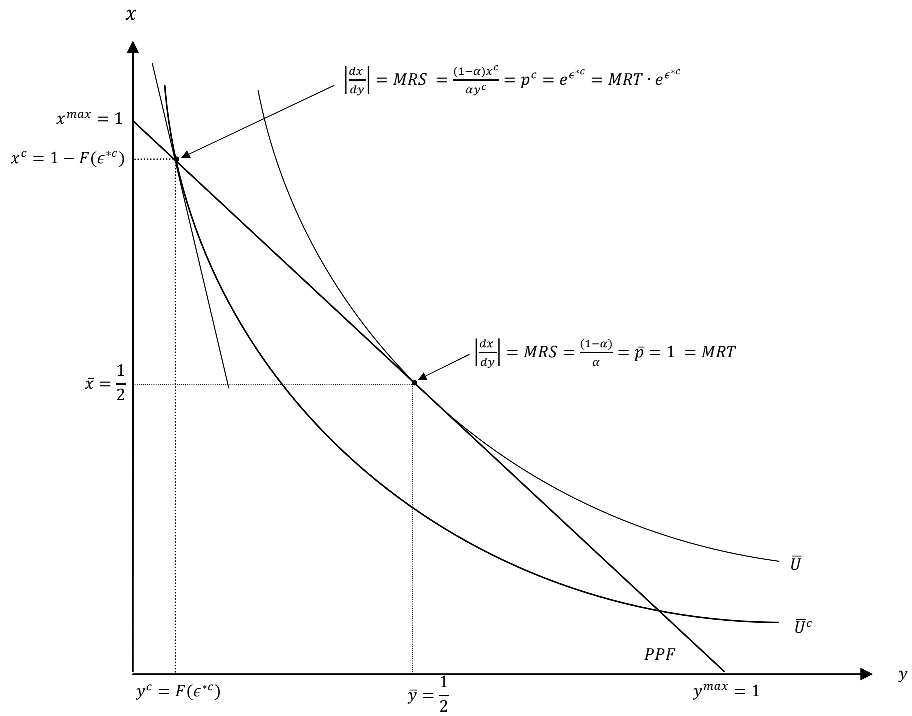

Figure 2.2: General Equilibrium in the Closed Economy Setting ($\alpha = 0.5$)

Own illustration based on the Fan and Stark (2011) model.

For any $\epsilon^{*c} > 0$, we can easily infer that $p^c > 1$. This implies that $w_Y > w_X$, reflecting a “compensating wage differential” (Fan and Stark, 2011, 554). By contrast, in

[3] Note that the production point in the presence of occupational stigma lies on the PPF because the labor market is assumed to be perfectly competitive, implying that wages will adjust to clear the labor market.

the absence of occupational stigma associated with work in sector Y (i.e., for $\epsilon^{*c} = 0$) the relative price would be $\bar{p} = 1$ in equilibrium, implying that real wages would be equalized across sectors. Thus, the relative price would be more favorable to production in sector Y compared to the situation with occupational stigma. In the diagram, the equilibrium in the situation without stigma can be discerned at the point where the higher indifference curve $\bar{U}$ is just tangent to the PPF. At this point, more (less) individuals work in sector Y (X), and output of good y (x) is larger (smaller) compared to the situation in which occupational stigma is associated with work in sector Y. Since the diagram is drawn for $\alpha = 0.5$, the output levels of both goods, $\bar{x}$ and $\bar{y}$, each amount to 0.5 in this scenario.

2.2.2 General Equilibrium in the Open Economy Setting

Let us further follow Fan and Stark (2011) and consider the case in which individuals of the described economy (Home) can migrate to another economy (Foreign), which is identical to Home in all respects. Due to the symmetry of the two economies and the assumption of constant returns to scale production, there will be no trade. Migration incurs a fixed cost of c. Furthermore, working in sector Y in Foreign is assumed to generate disutility of $\gamma\epsilon_i$ with $\gamma \in (0, 1)$ for a worker i from Home. This reflects an attenuation of the perceived humiliation from occupational stigma if a worker is surrounded by a non-familiar reference group. Hence, individuals who choose to work in sector Y have an incentive to work in Foreign if the reduction in the disutility due to occupational stigma compensates for the reduction in utility that is caused by migration costs.[4] By contrast, individuals who choose to work in sector X have no incentive to migrate because wages are identical across the two economies and migration does not provide them with any utility gain (or reduction in disutility) that could exceed the reduction in utility caused by migration costs.

Let us initially assume that some migration of individuals working in sector Y takes place. Then, denoting the wage in sector Y in Foreign with w_Y^f and noting that there is wage equalization across the two economies, $w_Y^f = w_Y = p$, the utility of a worker in sector Y who has emigrated to Foreign can be expressed as:

$$\begin{aligned} u_{i,Y}^f =& \alpha \ln(x) + (1-\alpha)\ln(y) - \gamma\epsilon_i = \alpha \ln[\alpha(w_Y^f - c)] + (1-\alpha)\ln\left[\frac{1-\alpha}{p}\left(w_Y^f - c\right)\right] - \gamma\epsilon_i \\ =& \alpha\ln(\alpha) + (1-\alpha)\ln(1-\alpha) + \ln(p-c) - (1-\alpha)\ln(p) - \gamma\epsilon_i \qquad (2.17) \end{aligned}$$

[4] Note that due to the symmetry assumption for the two economies, the same argument holds true for individuals in Foreign. In the following, however, the focus is on Home and country indices are omitted where possible.

Occupational Choice

An individual will prefer to work in sector Y in Foreign over working in sector X in Home if:

$$u_{i,Y}^{f} > u_{i,X} \tag{2.18}$$

$$\begin{aligned}&\alpha \ln(\alpha) + (1-\alpha)\ln(1-\alpha) + \ln(p-c) - (1-\alpha)\ln(p) - \gamma\epsilon_i > \\ &\alpha \ln(\alpha) + (1-\alpha)\ln(1-\alpha) - (1-\alpha)\ln(p)\end{aligned} \tag{2.19}$$

$$\begin{aligned}\gamma\epsilon_i &< \ln(p-c) \\ \epsilon_i &< \epsilon^* = \frac{\ln(p-c)}{\gamma} && (2.20) \\ p &= e^{\gamma\epsilon^*} + c && (2.21)\end{aligned}$$

An individual will prefer to work in sector Y in Foreign over working in sector Y in Home if:

$$u_{i,Y}^{f} > u_{i,Y} \tag{2.22}$$

$$\begin{aligned}&\alpha \ln(\alpha) + (1-\alpha)\ln(1-\alpha) + \ln(p-c) - (1-\alpha)\ln(p) - \gamma\epsilon_i > \\ &\alpha \ln(\alpha) + (1-\alpha)\ln(1-\alpha) + \alpha\ln(p) - \epsilon_i\end{aligned}$$

$$\begin{aligned}\epsilon_i\,(1-\gamma) &> \ln(p) - \ln(p-c) && (2.23) \\ \epsilon_i > \epsilon^{**} &= \frac{\ln(p) - \ln(p-c)}{1-\gamma} && (2.24)\end{aligned}$$

We can infer from inequality (2.20) that individuals with a very high sense for humiliation derived from work in the stigmatized sector, $\epsilon_i \geq \epsilon^*$, will find it optimal to work in sector X in Home also in the open economy setting, thereby totally avoiding occupational stigma.[5] Furthermore, inequality (2.24) reveals that individuals with a very low aversion to stigma (i.e., for whom $0 \leq \epsilon_i < \epsilon^{**}$ holds true) will choose to work in sector Y in Home even though they are confronted with the possibility of migration in the open economy setting. Under the assumption that migration takes place – i.e., that $\epsilon^{**} < \epsilon^*$ (the condition for which is derived below), all individuals with intermediate stigma aversion levels, i.e., with $\epsilon^{**} \leq \epsilon_i < \epsilon^*$, will choose to migrate to Foreign and work in sector Y.

The result that the individuals with the largest aversion to occupational stigma of the group of individuals working in sector Y will migrate to Foreign is intuitive: The higher

[5] We assume that the individual who is indifferent between working in sector X in Home or in sector Y in Foreign will choose to work in sector X, and that the individual who is indifferent between working in sector Y in Foreign or in Home will migrate to Foreign.

the degree of aversion ϵ_i, the higher are the gains from migration in terms of decreased humiliation from occupational stigma, $\epsilon_\mathrm{i}\,(1-\gamma)$, and thus the more likely it is that these gains outweigh the reduction in utility due to migration costs, $\ln(p) - \ln(p-c)$.

Following Fan and Stark (2011), we derive the condition for migration to take place, starting from the initial situation in which $p = p^c$. In order for an individual with a preference for migration to exist, inequalities (2.20) and (2.24) need to specify a non-empty interval for ϵ_i, i.e., $\epsilon^* >^! \epsilon^{**}$:

$$\begin{aligned}\frac{\ln(p^c-c)}{\gamma} &> \frac{\ln(p^c) - \ln(p^c-c)}{1-\gamma} \\ (1-\gamma)\ln(p^c-c) &> \gamma\ln(p^c) - \gamma\ln(p^c-c) \\ \gamma &< \frac{\ln(p^c-c)}{\ln(p^c)} \qquad (2.25)\end{aligned}$$

Thus, if γ is sufficiently small (implying that the reduction in humiliation from occupational stigma due to migration is sufficiently high) there will exist some individuals with intermediate degrees of aversion to stigma who will find it optimal to work in sector Y in Foreign (see Fan and Stark, 2011, Proposition 2). In this situation, $p = p^o \neq p^c$. Inequality (2.25) reveals that the lower the cost of migration c, the more likely it is that there exist some individuals with a preference for migration.

In the following, p^o denotes the equilibrium relative price of good y and ϵ^{*o} refers to the degree of stigma aversion of the individual who is just indifferent between work in either sector in the open economy equilibrium. The range of aversion to occupational stigma of the individuals choosing to migrate can then be expressed as:

$$[\epsilon^{**}, \epsilon^{*o}) = \left[\frac{\ln(p^o) - \ln(p^o-c)}{1-\gamma}, \frac{\ln(p^o-c)}{\gamma}\right) \qquad (2.26)$$

Since Home and Foreign are identical in all respects, in the open economy setting the equilibrium "range of individuals" (in terms of aversion to occupational stigma) from Foreign working in sector Y in Home is equal to the "range of individuals" from Home working in sector Y in Foreign.

Goods Market Equilibrium

Departing from the reference model, we assume that migration costs reduce the supply of both goods that is available for consumption in the same proportion in which individuals demand the two goods. This is the case if one considers a government (or social planner) that has the same preference structure as the workers and that can spend the revenue from the migration costs. Then, the supply of good y that is available for consumption in the open economy setting can be expressed as:

$$\begin{aligned} y^{s,o} &= \int_0^{\epsilon^{**}} f(\epsilon)d\epsilon + \int_{\epsilon^{**}}^{\epsilon^*} f(\epsilon)d\epsilon - \frac{(1-\alpha)}{p} c[F(\epsilon^*) - F(\epsilon^{**})] \\ y^{s,o} &= F(\epsilon^*) - \frac{(1-\alpha)}{p} c[F(\epsilon^*) - F(\epsilon^{**})] \end{aligned} \tag{2.27}$$

Aggregating the demand for good y of the three groups of individuals in the open economy setting, the total demand for good y in Home can be expressed as:

$$\begin{aligned} y^{d,o} &= \frac{(1-\alpha)}{p} \left[\int_0^{\epsilon^{**}} w_Y f(\epsilon)d\epsilon + \int_{\epsilon^{**}}^{\epsilon^*} \left(w_Y^f - c \right) f(\epsilon)d\epsilon + \int_{\epsilon^*}^{\infty} w_X f(\epsilon)d\epsilon \right] \\ y^{d,o} &= (1-\alpha)F(\epsilon^{**}) + \frac{(1-\alpha)}{p} (p-c) \left[F(\epsilon^*) - F(\epsilon^{**}) \right] + \frac{(1-\alpha)}{p} [1 - F(\epsilon^*)] \\ y^{d,o} &= (1-\alpha)F(\epsilon^*) + \frac{(1-\alpha)}{p} \left\{ [1 - F(\epsilon^*)] - c \left[F(\epsilon^*) - F(\epsilon^{**}) \right] \right\} \end{aligned} \tag{2.28}$$

Equating total demand for good y with the available supply of good y (total supply net of the usage that is due to migration costs), it is straightforward to see that the goods market equilibrium condition in the open economy setting takes the same form as the one in the closed economy setting (2.15):

$$p = \frac{(1-\alpha)[1 - F(\epsilon^*)]}{\alpha F(\epsilon^*)} = \frac{(1-\alpha)[1 - F(\ln p)]}{\alpha F(\ln p)} = \frac{(1-\alpha)x}{\alpha y}$$

From equation (2.21) we can infer that for any cut-off aversion level $\epsilon^* > 0$, it must be true that the equilibrium relative price in the open economy setting fulfills $p^o > 1 + c$ (see Fan and Stark, 2011, Proposition 3b).

In the original model variant migration costs exclusively reduce the supply of good x that is available for consumption in the open economy setting. Fan and Stark (2011, 567-568) analytically prove that $p^o < p^c$ if condition (2.25) holds.

Figure 2.3 illustrates the joint determination of the cut-off stigma aversion level ϵ^{*o} and the equilibrium (relative) price p^o for good y in the open economy setting and in the closed economy setting. The comparison of the two conditions for occupational indifference, (2.21) and (2.11), reveals that the intercept of the occupational indifference locus is higher but that its shape is generally less convex in the open economy setting (discontinuous locus) than in the closed economy setting (continuous locus). Due to the above introduced modification concerning the nature of migration costs, the goods market equilibrium locus in the open economy situation is the same as in the closed economy situation. On this account and contrasting Fan and Stark (2011), Figure 2.3 can be used to unambiguously show that the cut-off stigma aversion level is higher and that the relative price is lower in the open economy equilibrium than in the closed economy equilibrium. The necessary condition for these results to obtain is given by condition (2.25): By ensuring that $\epsilon^{*c}|_{p=p^c} < \epsilon^{*o}|_{p=p^c}$, the condition that ensures the existence of migration implies that the occupational indifference locus in the open economy setting lies below the occupational indifference locus in the closed economy setting at $\epsilon^* = \epsilon^{*c}$.

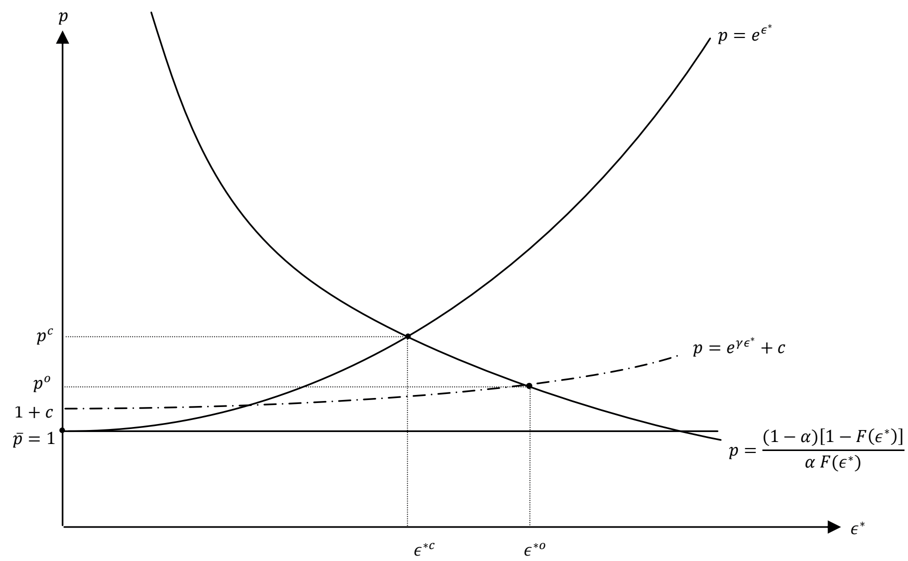

Figure 2.3: Joint Determination of the Cut-off Stigma Aversion Level and the Relative Price in the Open Economy Setting Compared to the Closed Economy Setting

Own illustration based on a slightly adapted variant of the Fan and Stark (2011) model.

Figure 2.4 illustrates the lower equilibrium relative price as well as the production levels in the open economy setting in comparison to the closed economy setting. In the migration equilibrium, the occupational indifference condition (2.21) and the goods market clearing condition (2.15) must simultaneously hold. Thus, we have:

$$p^o = \frac{(1-\alpha)x^o}{\alpha y^o} = e^{\gamma\epsilon^{*o}} + c \tag{2.29}$$

Since at the intersection of the PPF with the highest possible indifference curve (drawn discontinuously), the slope of the indifference curve, $\left|\frac{dx}{dy}\right| = p^o$, must be flatter than it was in the closed economy setting, a higher utility level can be reached ($\bar{U^o} > \bar{U^c}$).

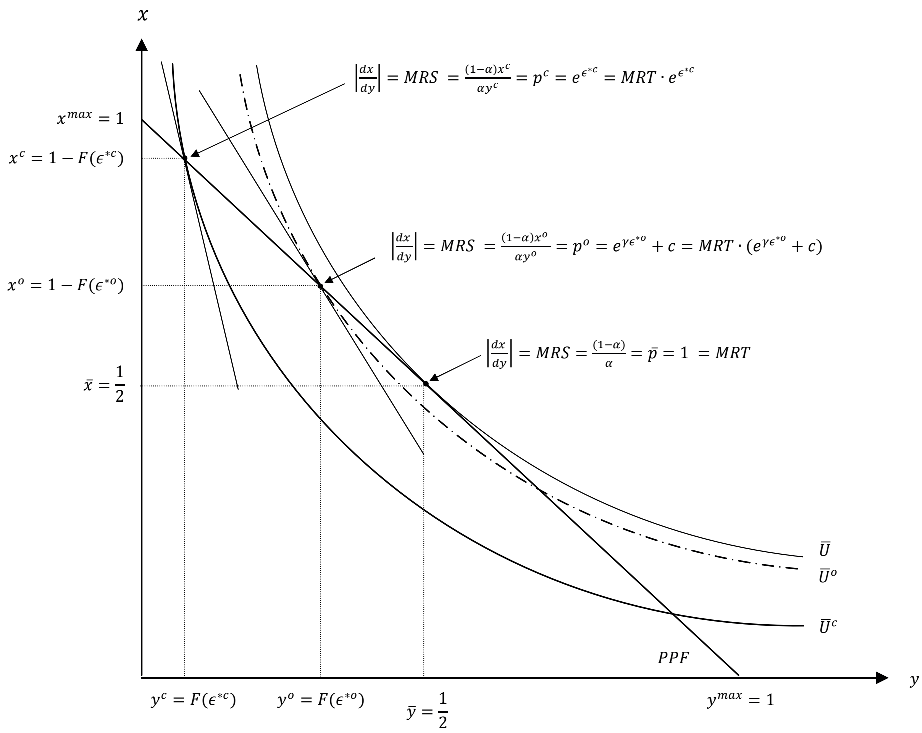

Figure 2.4: General Equilibrium in the Open Economy Setting Compared to the Closed Economy Setting ($\alpha = 0.5$)

Own illustration based on a slightly adapted variant of the Fan and Stark (2011) model.

Figure 2.4 furthermore reveals that the equilibrium quantity of good y (x) in the open economy setting is larger (smaller) compared to the closed economy setting. This, however, is only possible because more (less) individuals (natives plus migrants) work in sector Y (X) when migration is an option – i.e., because the cut-off stigma aversion level that defines the range of individuals working in either sector is higher in the open economy setting compared to the closed economy setting: $\epsilon^{*o} > \epsilon^{*c}$. Thus, the possibility of migration to Foreign for individuals employed in sector Y partly corrects for the suboptimal labor allocation and production pattern resulting from occupational stigma in the closed economy setting. However, since there are positive migration costs and since migration does not drive the disutility from occupational stigma to zero, some individuals working in sector Y will stay in Home. As a consequence, the optimal labor allocation and the optimal production pattern as illustrated in Figure 2.2 cannot be obtained in the open economy setting.

2.2.3 Welfare Analysis

Individuals who work in sector X in Home in both the closed economy setting and the open economy setting are better off in the latter situation because the lower equilibrium price of good y increases the purchasing power of their income in terms of good y while the purchasing power in terms of good x stays constant.

By contrast, individuals who work in sector Y in Home in both settings are worse off in the open economy setting because the purchasing power of their income in terms of good x has decreased while it has remained constant in terms of good y.

Furthermore, Fan and Stark (2011, 570) formally prove that all individuals who work in sector X in the closed economy setting but decide to work in sector Y in Foreign in the open economy setting are better off when migration is possible.[6]

Of the individuals who work in sector Y in Home in the closed economy setting but emigrate to Foreign in the open economy setting only those with a very high degree of aversion to stigma will be better off, namely those with:

$$\epsilon_i > \frac{\alpha \ln(p^c) - \ln(p^o - c) + (1-\alpha)\ln(p^o)}{1-\gamma} \tag{2.30}$$

(Fan and Stark, 2011, 560). Rearranging inequality (2.30) yields:

$$\epsilon_i(1-\gamma) > \ln(p^o) - \ln(p^o - c) + \alpha\left[\ln(p^c) - \ln(p^o)\right] \tag{2.31}$$

Thus, only those individuals working in sector Y for whom the gains from migration in terms of decreased humiliation from occupational stigma, $\epsilon_{\mathrm{i}}(1-\gamma)$, compensate for both the reduction in utility that is due to migration costs, $\ln(p^o) - \ln(p^o - c)$, and the reduction in utility that is due to the decreased purchasing power in terms of good x, $\alpha\left[\ln(p^c) - \ln(p^o)\right]$, will be better off when migrating to Foreign in the open economy setting as compared to the closed economy setting.

2.3 A Model Variant with Heterogeneous Workers and Homogeneous Stigma

In this section we allow individuals to differ with respect to their innate ability, while we assume that occupational stigma generates the same disutility for all individuals working

6 The intuition for this result can be summarized under the concept of “revealed preferences”.

in the stigmatized sector. We show that the main results of the reference model are robust to this modification and derive some additional results. We also explain how the main results of the model change if migration costs reduce a migrant's productivity due to the imperfect transferability of skills.

2.3.1 General Equilibrium in the Closed Economy Setting

We now consider a variant of the Fan and Stark (2011) model in which individuals differ with respect to their ability level $a_i \in [0, 1]$, which is assumed to be uniformly distributed with $f(a) = 1$, and in which the disutility associated with the stigmatized sector Y is the same for any individual i who works in this sector: $\epsilon_i \equiv \epsilon > 0 \quad \forall i$. We furthermore assume that the work of any individual in sector Y yields relatively less output than the work of the same individual would yield in sector X. The individual production functions are assumed to take the following forms:

$$x_i = 1 + \beta a_i \quad \text{and} \quad y_i = 1 + a_i \tag{2.32}$$

where $\beta > 1$. This modeling approach is similar to the one in Meckl (2006), except that education is not explicitly modeled. Nevertheless, one possible interpretation of the differing sectoral productivities consists in considering sector X as the skill-intensive sector that requires education that can be obtained instantaneously at zero costs. Similar to Meckl (2006, 1926), β can be considered to measure the "efficiency of the educational system".

Following Fan and Stark (2011), the price of good y is denoted by p and good x is taken as the numéraire with its price being normalized to 1. With a perfectly competitive labor market, workers in either sector are paid the values of their marginal product. Since individuals are assumed to be unequally productive, wages in both sectors vary with workers' ability a_i:

$$w_{i,X} = 1 + \beta a_i \quad \text{and} \quad w_{i,Y} = (1 + a_i)p \tag{2.33}$$

Since the modifications to the Fan and Stark (2011) model that have been introduced above do not affect the general form of the demand functions, the utility of an individual i working in sector X can be written as:

$$u_{i,X} = \alpha \ln (\alpha w_{i,X}) + (1 - \alpha) \ln \left[\frac{(1 - \alpha)}{p} w_{i,X} \right]$$

$$=\alpha\ln(\alpha)+\ln\left(1+\beta a_i\right)+(1-\alpha)\ln(1-\alpha)-(1-\alpha)\ln(p) \tag{2.34}$$

Similarly, the utility of an individual i working in sector Y can be expressed as:

$$\begin{aligned} u_{i,Y} =&\alpha\ln\left(\alpha w_{i,Y}\right)+(1-\alpha)\ln\left[\frac{(1-\alpha)}{p}w_{i,Y}\right]-\epsilon \\ =&\alpha\ln(\alpha)+\ln\left(1+a_i\right)+\alpha\ln(p)+(1-\alpha)\ln(1-\alpha)-\epsilon \end{aligned} \tag{2.35}$$

Occupational Choice

An individual will prefer to work in sector Y over working in sector X if:

$$u_{i,Y} > u_{i,X} \tag{2.36}$$

$$\begin{aligned} &\alpha\ln(\alpha)+\ln\left(1+a_i\right)+\alpha\ln(p)+(1-\alpha)\ln(1-\alpha)-\epsilon \\ &> \alpha\ln(\alpha)+\ln\left(1+\beta a_i\right)+(1-\alpha)\ln(1-\alpha)-(1-\alpha)\ln(p) \\ &\ln(p) > \ln\left(\frac{1+\beta a_i}{1+a_i}\right)+\epsilon \end{aligned}$$

$$a_i < a^* = \frac{e^\epsilon - p}{p-\beta e^\epsilon} = \frac{p-e^\epsilon}{\beta e^\epsilon - p} \tag{2.37}$$

$$p = \frac{1+\beta a^*}{1+a^*}\cdot e^\epsilon \tag{2.38}$$

With $\beta > 1$ and $a \in [0,1]$, it must be true that the (relative) price for good y in the closed economy setting fulfills: $p^c \in \left(e^\epsilon, \frac{(1+\beta)}{2}e^\epsilon\right)$. From this we can easily infer that $(p^c - \beta e^\epsilon) < 0$. Assuming that the indifferent individual will work in sector X, we obtain:

Proposition 1. *In the closed economy all individuals with ability $a_i < a^* = \frac{p-e^\epsilon}{\beta e^\epsilon - p}$ will work in sector Y. By contrast, all individuals with ability $a_i \geq a^* = \frac{p-e^\epsilon}{\beta e^\epsilon - p}$ will work in sector X. The equilibrium relative price for good y, p^c, will lie in the interval $\left(e^\epsilon, \frac{(1+\beta)}{2}e^\epsilon\right)$.*

Compared to the closed economy setting without occupational stigma associated with work in sector Y ($\epsilon = 0$), a^* is smaller implying that less individuals work in sector Y for $\epsilon > 0$.

The derivative of a^* with respect to p reveals that the higher the relative price of good y, the higher a^*, implying that more individuals will choose to work in the stigmatized sector Y, ceteris paribus:

$$\frac{\partial a^*}{\partial p} = \frac{\beta e^\epsilon - p + p - e^\epsilon}{\left(\beta e^\epsilon - p\right)^2} = \frac{(\beta-1)\,e^\epsilon}{\left(\beta e^\epsilon - p\right)^2} > 0 \tag{2.39}$$

Goods Market Equilibrium

As in Fan and Stark (2011), we assume that the production technology in either sector is characterized by constant returns to scale. The total quantity supplied of good y is then given by:

$$y^s = \int_0^{a^*} (1+a) f(a)\, da = a^* + \frac{(a^*)^2}{2} \tag{2.40}$$

The total quantity demanded of good y can be written as:

$$\begin{aligned} y^d =& \frac{(1-\alpha)}{p} \left[\int_0^{a^*} w_{i,Y} f(a)\, da + \int_{a^*}^{1} w_{i,X} f(a)\, da \right] \\ y^d =& \int_0^{a^*} (1-\alpha)(1+a)\, da + \int_{a^*}^{1} \frac{1-\alpha}{p} (1+\beta a)\, da \\ y^d =& (1-\alpha)\left[a^* + \frac{(a^*)^2}{2} \right] + \frac{(1-\alpha)}{p} \left[1 + \frac{\beta}{2} - a^* - \frac{\beta (a^*)^2}{2} \right] \end{aligned} \tag{2.41}$$

Equilibrium in the market for good y requires that supply equals demand, $y^s = y^d$:

$$a^* + \frac{(a^*)^2}{2} = (1-\alpha)\left[a^* + \frac{(a^*)^2}{2} \right] + \frac{(1-\alpha)}{p} \left[1 + \frac{\beta}{2} - a^* - \frac{\beta (a^*)^2}{2} \right] \tag{2.42}$$

$$p = \frac{(1-\alpha)\left[1 + \frac{\beta}{2} - a^* - \frac{\beta (a^*)^2}{2}\right]}{\alpha \left[a^* + \frac{(a^*)^2}{2} \right]} = \frac{(1-\alpha)x}{\alpha y} \tag{2.43}$$

Figure 2.5 illustrates the joint determination of the cut-off ability level a^{*c} and the equilibrium price p^c in the closed economy equilibrium of the considered model variant. The upward sloping locus represents the condition of indifference between the two occupations (2.38), and the downward-sloping curve illustrates the goods market equilibrium condition (2.43). The equilibrium values of a^{*c} and p^c can be read off at the intersection of the two loci.

The following Proposition summarizes the effect of a change in the productivity parameter β on the equilibrium values in the closed economy setting:

Proposition 2. *The higher the productivity parameter β, the higher the equilibrium price p^c of good y in the closed economy setting. The effect of an increase in β on the cut-off ability level a^{*c} is ambiguous.*

Proof. See Section 2.5.1 in the appendix.

The first part of Proposition 2 is intuitive, since more productive individuals in sector X produce more output, thereby exerting an upward pressure on the relative price for good y, ceteris paribus. However, since this price effect may incentivize some workers to switch to sector Y, it depends on the size of the change in β as well as on the other model parameters to what extent the sectoral labor allocation will change.

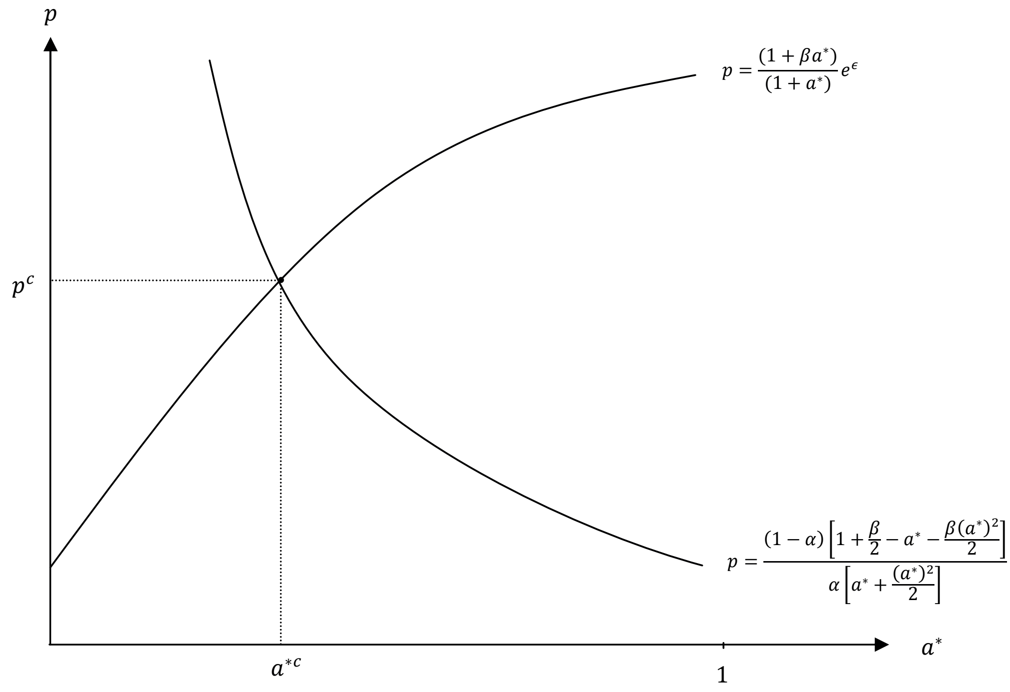

Figure 2.5: Joint Determination of the Cut-off Ability Level and the Relative Price in the Closed Economy Setting

Own illustration based on a variant of the Fan and Stark (2011) model.

Figure 2.6 illustrates the general equilibrium in the closed economy setting for the model variant in which individuals differ with respect to their ability and in which the work in sector Y generates a constant disutility for all workers in this sector.[7] If all individuals worked in sector Y, they would produce $y^{max} = \int_0^1 (1+a)\,da = \frac{3}{2}$ units of good y, while the output of good x would be zero. By contrast, if all individuals worked in sector X, the output of good x would amount to $x^{max} = \int_0^1 (1+\beta a)\,da = 1 + \frac{\beta}{2}$, while the output of good y would be zero. The slope of the PPF (the marginal rate of transformation, MRT) is given by:

$$\left|\frac{dx}{dy}\right| = \frac{1+\beta a'}{1+a'} \tag{2.44}$$

where $a^{'}$ refers to the ability of the "marginal individual" (i.e., of the individual who is

[7] See Bougheas and Riezman (2007) for an illustration of a similar model without occupational stigma.

just indifferent between working in either sector). At the intersection of the PPF with the vertical axis its slope (in absolute value) is equal to 1, because the individual who is indifferent between the two sectors at this stage – i.e., the one who would be the first to switch from sector X to sector Y – is the individual with the smallest ability level ($a_i = 0$). As more of good y is being produced, the MRT gets steeper, because the ability level of the "marginal worker" increases. The slope of the PPF (in absolute value) at its intersection with the horizontal axis is $\frac{1+\beta}{2}$, because the individual who is indifferent between the two sectors at this stage is the one with the largest ability level ($a_i = 1$).

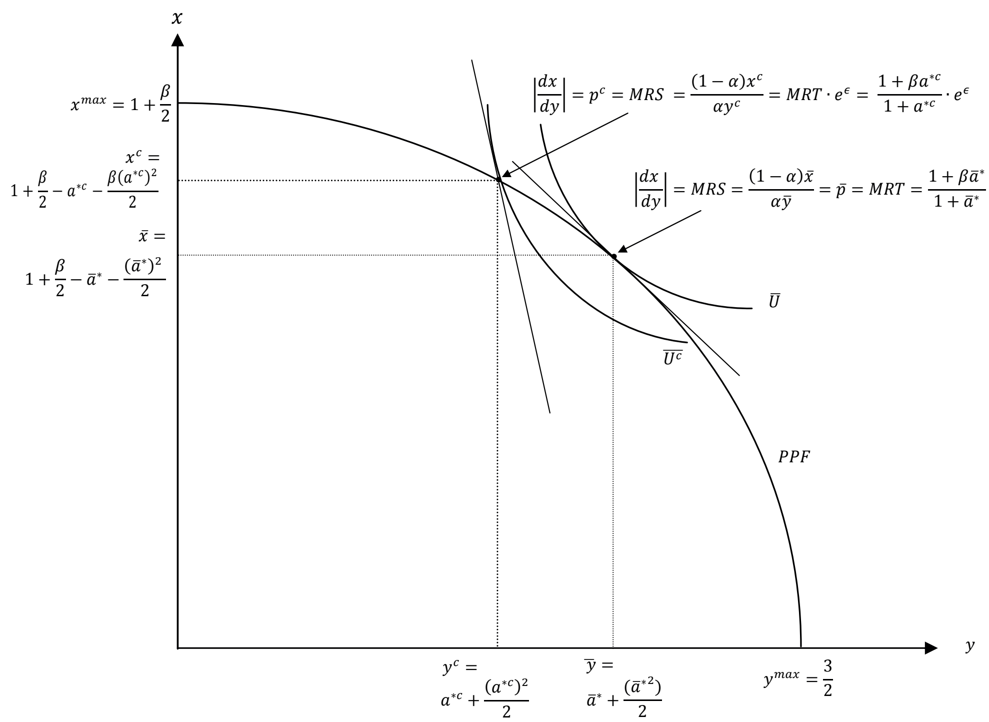

Figure 2.6: General Equilibrium in the Closed Economy Setting ($\alpha = 0.5$)

Own illustration based on a variant of the Fan and Stark (2011) model.

In equilibrium both the occupational indifference condition (2.38) and the goods market clearing condition (2.43) must be fulfilled. In the diagram, this is given at the intersection point of the PPF with the indifference curve whose slope (in absolute value) in this point (the MRS which corresponds to (2.43)) is such that (2.38) is fulfilled:

$$p^c = \frac{(1-\alpha)x^c}{\alpha y^c} = \frac{(1+\beta a^{*c})}{1+a^{*c}} e^{\epsilon} \tag{2.45}$$

Since in the absence of occupational stigma associated with work in sector Y the cut-off ability level would be larger than a^{*c}, more (less) individuals would work in sector $Y(X)$

and output of good $y(x)$ would be larger (smaller) compared to the situation in which occupational stigma is associated with work in sector Y. This benchmark equilibrium can be discerned at the point where the higher indifference curve $\bar{U}$ is just tangent to the PPF.

2.3.2 General Equilibrium in the Open Economy Setting

Let us now again consider the possibility that individuals of Home can migrate to Foreign, which is identical to Home in all respects. Following Fan and Stark (2011), we assume that migration lowers the strength of the stigma effect associated with work in sector Y, such that work in this sector decreases a migrant's utility by only $\gamma\epsilon$ where $\gamma \in (0, 1)$. Furthermore, every worker who decides to migrate has to incur a fixed cost of c, which lowers his income that is available for consumption. Contrasting the reference model in which these costs exert a downward pressure on the relative price of good y, we model the costs of migration again in a manner that leaves the relative price unaffected. To this end, we assume that the costs of migration are wasteful and reduce the supply of the two goods that are available for consumption in the same proportion in which individuals demand the goods. This modification allows us to concentrate on the effect on the relative price that is related to changes in the sectoral labor allocation due to migration. We show that the main results of the Fan and Stark (2011) model are preserved in the considered model variant and that the different modeling of migration costs simplifies their derivation.

With w_Y^f referring to the wage in sector Y in Foreign and noting that $w_Y^f = w_Y = (1 + a_i)p$, the utility of worker i in sector Y who has emigrated to Foreign can be written as:

$$\begin{aligned} u_{i,Y}^f =& \alpha \ln (x) + (1-\alpha) \ln (y) - \gamma\epsilon = \alpha \ln[\alpha(w_{i,Y}^f - c)] + (1-\alpha) \ln \left[\frac{1-\alpha}{p} \left(w_{i,Y}^f - c \right) \right] - \gamma\epsilon \\ =& \alpha \ln\{\alpha[(1+a_i)\,p - c]\} + (1-\alpha) \ln \left\{ \frac{1-\alpha}{p} [(1+a_i)\,p - c] \right\} - \gamma\epsilon \\ =& \alpha \ln(\alpha) + \ln[(1+a_i)\,p - c] + (1-\alpha) \ln(1-\alpha) - (1-\alpha) \ln(p) - \gamma\epsilon \end{aligned} \tag{2.46}$$

Occupational Choice

In the following, we proceed as in Section 2.2 in order to derive the cut-off ability levels for the three groups of individuals in the open economy setting. To this end, we initially assume that migration will take place. The conditions that ensure the migration of some individuals with intermediate ability levels are presented thereafter.

An individual will prefer to work in sector Y in Foreign over working in sector X in Home if:

$$u_{i,Y}^{f} > u_{i,X} \tag{2.47}$$

$$\alpha \ln(\alpha) + \ln[(1+a_i)\,p - c] + (1-\alpha)\ln(1-\alpha) - (1-\alpha)\ln(p) - \gamma\epsilon$$

$$> \alpha \ln(\alpha) + \ln(1+\beta a_i) + (1-\alpha)\ln(1-\alpha) - (1-\alpha)\ln(p)$$

$$\ln\left[\frac{(1+a_i)\,p - c}{1+\beta a_i}\right] > \gamma\epsilon$$

$$a_i < a^* = \frac{e^{\gamma\epsilon} - p - c)}{p - \beta e^{\gamma\epsilon}} = \frac{p - c - e^{\gamma\epsilon}}{\beta e^{\gamma\epsilon} - p} \tag{2.48}$$

$$p = \frac{(1+\beta a^*)\,e^{\gamma\epsilon} + c}{1+a^*} \tag{2.49}$$

given that:

$$\beta > pe^{-\gamma\epsilon} \tag{2.50}$$

An individual will prefer to work in sector Y in Foreign over working in sector Y in Home if:

$$u_{i,Y}^{f} > u_{i,Y} \tag{2.51}$$

$$\alpha \ln(\alpha) + \ln[(1+a_i)\,p - c] + (1-\alpha)\ln(1-\alpha) - (1-\alpha)\ln(p) - \gamma\epsilon$$

$$> \alpha \ln(\alpha) + \ln(1+a_i) + (1-\alpha)\ln(1-\alpha) + \alpha\ln(p) - \epsilon$$

$$\ln\left[\frac{(1+a_i)\,p}{(1+a_i)\,p - c}\right] < \epsilon(1-\gamma)$$

$$\frac{(1+a_i)\,p}{(1+a_i)\,p - c} < e^{\epsilon(1-\gamma)}$$

$$a_i > a^{**} = \frac{e^{\epsilon(1-\gamma)} - \frac{c}{p}e^{\epsilon(1-\gamma)} - 1}{1 - e^{\epsilon(1-\gamma)}} = \frac{\frac{c}{p}e^{\epsilon(1-\gamma)} - \left(e^{\epsilon(1-\gamma)} - 1\right)}{e^{\epsilon(1-\gamma)} - 1} \tag{2.52}$$

Thus, given that condition (2.50) is fulfilled (i.e., given that the productivity parameter β is sufficiently high), individuals with a very high ability level, $a_i \geq a^*$, will have a comparative advantage to work in sector X in Home also in the open economy setting, thereby totally avoiding occupational stigma.[8] Inequality (2.52) suggests that individuals with a very low productivity, $0 \leq a_i < a^{**}$, will choose to work in sector Y in Home in the open economy setting although they now face the possibility of migration. Given

[8] As above, we assume that the individual who is indifferent between working in sector X in Home or in sector Y in Foreign will work in sector X, and that the individual who is indifferent between working in sector Y in Foreign or in Home will emigrate to work in Foreign.

that $a^{**} < a^{*}$ (the condition for which is derived below), all individuals with intermediate ability levels, $a^{**} \leq a_i < a^{*}$, will choose to migrate to Foreign and work in sector Y.

Noting that $\beta > 1$ and that $a \in (0,1)$, we can infer from (2.49) that $p^o \in \left(\frac{(1+\beta)e^{\gamma\epsilon}+c}{2}; e^{\gamma\epsilon}+c\right)$.

The following Proposition summarizes the choice of the heterogeneous individuals concerning both the sector and the country of employment in the open economy setting:

Proposition 3. *Under the assumption that two-way migration occurs in the open economy setting, all individuals with ability*

$$a_i \geq \frac{p - c - e^{\gamma\epsilon}}{\beta e^{\gamma\epsilon} - p}$$

will work in the domestic sector X, while all individuals with ability

$$0 \leq a_i < \frac{\frac{c}{p}e^{\epsilon(1-\gamma)} - \left(e^{\epsilon(1-\gamma)} - 1\right)}{e^{\epsilon(1-\gamma)} - 1}$$

will work in the domestic sector Y. Individuals characterized by an ability level

$$\frac{\frac{c}{p}e^{\epsilon(1-\gamma)} - \left(e^{\epsilon(1-\gamma)} - 1\right)}{e^{\epsilon(1-\gamma)} - 1} \leq a_i < \frac{p - c - e^{\gamma\epsilon}}{\beta e^{\gamma\epsilon} - p}$$

will find it optimal to migrate to the other country and work in sector Y.
The equilibrium relative price for good y, p^o, will lie in the interval $\left(\frac{(1+\beta)e^{\gamma\epsilon}+c}{2}; e^{\gamma\epsilon}+c\right)$.

The result that the individuals with the largest ability levels of the group of individuals working in sector Y will migrate to Foreign is directly linked to the assumptions of a logarithmic utility function and individual-specific productivities: The higher the ability level a_i, the smaller is the reduction in utility due to migration costs and the more likely it is that the reduction in disutility from occupational stigma at least compensates for the reduction in utility caused by migration costs.

In order to derive the conditions that ensure the existence of two-way migration in the open economy setting, we depart from the closed economy situation in which $p = p^c$. For an individual with a migration preference to exist, inequalities (2.48) and (2.52) need to specify a non-empty interval for a_i, i.e., $a^{*} > a^{**}$:

$$\frac{p^c - c - e^{\gamma\epsilon}}{\beta e^{\gamma\epsilon} - p^c} > \frac{\frac{c}{p^c}e^{\epsilon(1-\gamma)} - \left(e^{\epsilon(1-\gamma)} - 1\right)}{e^{\epsilon(1-\gamma)} - 1} \tag{2.53}$$

Given that

$$\beta > p^c e^{-\gamma\epsilon}, \tag{2.54}$$

this yields the following condition:

$$\begin{aligned}
\left(p^c - c - e^{\gamma\epsilon}\right)\left(e^{\epsilon(1-\gamma)} - 1\right) &> \left[\frac{c}{p^c}e^{\epsilon(1-\gamma)} - \left(e^{\epsilon(1-\gamma)} - 1\right)\right]\left(\beta e^{\gamma\epsilon} - p^c\right) \\
\beta e^{\epsilon} - \beta e^{\gamma\epsilon} - \left(e^{\epsilon} - e^{\gamma\epsilon}\right) &> \frac{c}{p^c}\left(\beta e^{\epsilon} - p^c\right) \\
c < c^{prohib} &= \frac{p^c\left(\beta - 1\right)\left(e^{\epsilon} - e^{\gamma\epsilon}\right)}{\left(\beta e^{\epsilon} - p^c\right)} \qquad (2.55)
\end{aligned}$$

Substituting the upper bound for p^c, $\frac{(1+\beta)}{2}e^{\epsilon}$, into condition (2.54), and the lower bound for p^c, e^{ϵ}, into condition (2.55), we obtain the following proposition:

Proposition 4. *Sufficient conditions for migration to take place in the open economy setting are given by:*

$$\beta > \frac{e^{\epsilon}}{2e^{\gamma\epsilon} - e^{\epsilon}} \tag{2.56}$$

$$e^{\epsilon} - e^{\gamma\epsilon} < e^{\gamma\epsilon} \leftrightarrow \gamma < \frac{\epsilon - \ln(2)}{\epsilon} \tag{2.57}$$

$$c < e^{\epsilon} - e^{\gamma\epsilon} \tag{2.58}$$

Summing up, if the productivity parameter β is sufficiently high, if the stigma-reducing factor γ is sufficiently low, and if the cost of migration c is lower than the difference in the stigma-induced "discount factors" of migrants' utility $(e^{\epsilon} - e^{\gamma\epsilon})$[9], some individuals with intermediate ability levels will choose to migrate. In this situation, $p = p^o \neq p^c$.

With a^{*o} denoting the ability level of the individual who is just indifferent between work in sector X in Home and work in sector Y in Foreign in the open economy equilibrium, the ability range of the individuals choosing to migrate is given by:

$$[a^{**}, a^{*o}) = \left[\frac{\frac{c}{p^o}e^{\epsilon(1-\gamma)} - \left(e^{\epsilon(1-\gamma)} - 1\right)}{e^{\epsilon(1-\gamma)} - 1}, \frac{p^o - c - e^{\gamma\epsilon}}{\beta e^{\gamma\epsilon} - p^o}\right) \tag{2.59}$$

Since Home and Foreign are identical in all respects, in the open economy setting the equilibrium "range of individuals" from Foreign working in sector Y in Home is equal to the "range of individuals" from Home working in sector Y in Foreign. In addition, the abilities of the former type of individuals are distributed over the same interval as the

[9] Note that the un-logarithmized expression for migrants' individual utility is given by: $u^f_{i,Y} = \frac{x^{\alpha}y^{1-\alpha}}{e^{\gamma\epsilon}}$.

abilities of the latter type of individuals.

Concerning the comparative statics of a^* with respect to p in the open economy setting, we have the following Proposition:

Proposition 5. *The sufficient conditions for the existence of migration (summarized in Proposition 4) ensure that a^* is increasing in p in the open economy setting.*

Proof. See Section 2.5.2 in the appendix.

Goods Market Equilibrium

As explained above, we assume that migration costs reduce the supply of both goods that is available for consumption in the same proportion in which individuals demand the two goods. Under this assumption, the goods market equilibrium condition in the open economy setting must take the same form as the one in the closed economy setting (2.43):

$$p = \frac{(1-\alpha)\left[1+\frac{\beta}{2}-a^*-\frac{\beta(a^*)^2}{2}\right]}{\alpha\left[a^*+\frac{(a^*)^2}{2}\right]} = \frac{(1-\alpha)x}{\alpha y}$$

Comparison of the Open Economy Equilibrium to the Closed Economy Equilibrium

In the following, we derive the effects of the introduction of migration on the equilibrium labor allocation across sectors and on the equilibrium relative price. Our assumption about the neutrality of migration costs for the relative price ensures that the relative price is only influenced via the channel of occupational choice when the possibility of migration is introduced. Therefore, the effects on the key variables in equilibrium can be derived with the help of a graphical illustration that is similar to Figure 2.5.

Figure 2.7 illustrates the general equilibrium in the open economy setting in comparison to the equilibrium in the closed economy setting. It can be easily shown that the occupational indifference locus in the open economy setting (2.49) (discontinuous locus) is less concave than the corresponding locus in the closed economy setting (2.38) (continuous locus). The goods market equilibrium locus is the same in the open economy setting as in the closed economy setting.

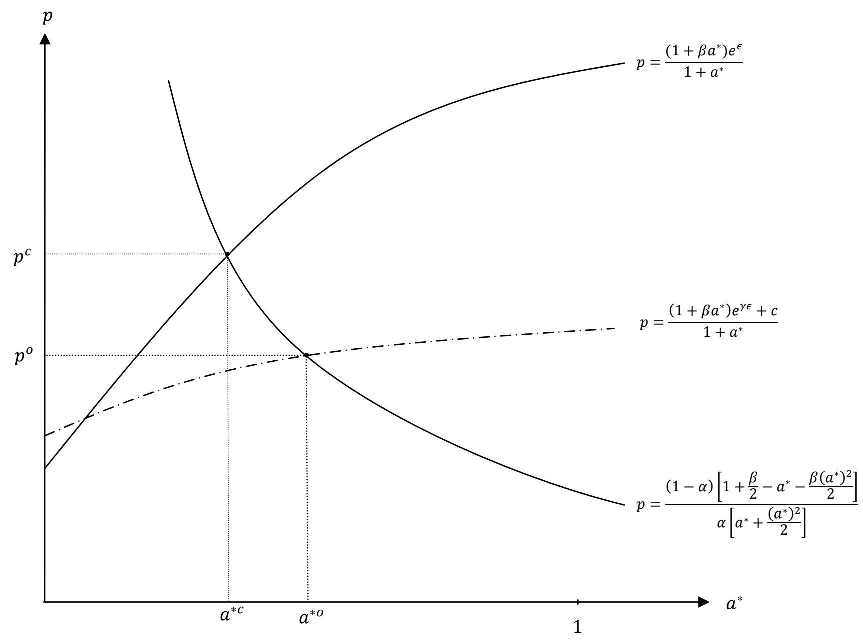

Figure 2.7: Joint Determination of the Cut-off Ability Level and the Relative Price in the Open Economy Setting Compared to the Closed Economy Setting

Own illustration based on a variant of the Fan and Stark (2011) model.

Since the goods market equilibrium locus is downward-sloping in the (a^*, p)-space, the condition ensuring that a^{*o} will be larger than a^{*c} is as follows: The occupational indifference locus in the open economy setting must lie below the occupational indifference locus in the closed economy setting for $a^* = a^{*c}$. Put differently, a^{*o} will be larger than a^{*c} if the two occupational indifference loci intersect at some $a^* < a^{*c}$. In Section 2.5.3 in the appendix we show that inequality (2.55) reflects exactly the condition required for this result. We thus have the following Proposition:

Proposition 6. *In the open economy setting with migration of some individuals, $a^{*o} > a^{*c}$. This implies that more individuals will choose to work in the stigmatized sector Y and less individuals will opt for work in sector X compared to the closed economy setting. In this situation, $p^o < p^c$.*

In Section 2.5.4 in the appendix, we show that if the costs of migration are assumed to affect the relative price in the same way as in the reference model, the same mathematical tools and reasoning as in Fan and Stark (2011, 567-568 and 568-569) can be applied to derive that $p^o < p^c$ and $a^{*o} > a^{*c}$ also in the modified set-up.

2.3.3 Comparative Statics

We next explore how the equilibrium values in the open economy setting change for different values of the parameters β, c, and γ.

Concerning the effect of a change in β on the equilibrium values in the open economy setting, we have a similar proposition as in the closed economy setting:

Proposition 7. *The relative price for good y in the open economy setting will be the higher the larger β. The effect of an increase in β on the sectoral labor allocation is ambiguous.*

Proof. See Section 2.5.5 in the appendix.

We next look at the sensitivity of the equilibrium values in the open economy setting with respect to changes in the costs of migration c or in the stigma-reducing parameter γ.

Proposition 8. *In the open economy setting, the lower the costs of migration c, the more individuals will choose to work in sector Y and the lower will be the relative price for good y, ceteris paribus. Similarly, the smaller γ and thus the larger the stigma-reducing effect of migration, the more individuals will work in sector Y, such that the relative price for the stigmatized good y unambiguously decreases. The effect of a decrease in c or γ on the number of native workers in sector Y is indeterminate.*

Proof. See Section 2.5.6 in the appendix.

Note that in contrast to Fan and Stark (2011), Proposition 8 states that the effect of a change in migration costs on the relative price in the open economy setting is unambiguous in this framework. This is due to the fact that migration costs have been modified such that they do not distort the relative price in the open economy setting.

Figure 2.8 illustrates the condition of indifference between the two occupations for the critical agent in the closed economy setting (gray surface) and in the open economy setting (dark surface), as well as the goods market equilibrium condition (light surface) for different values of c and the case in which $\alpha = 0.5$, $\beta = 2$, $\epsilon = 1$, and $\gamma = 0.5$. The equilibrium values of a^{*c}, p^c, a^{*o}, and p^o for different values of c are determined at the intersection of the respective surfaces. It can be seen that $a^{*o} > a^{*c}$ and $p^o < p^c$ is only guaranteed for small values of c (compare the sufficient conditions for the existence of migration). Furthermore, as stated in Proposition 8, a^{*o} increases and p^o decreases as c decreases. Figure 2.9 is the corresponding illustration for the sensitivity of the equilibrium values of p^o and a^{*o} with respect to a change in γ.

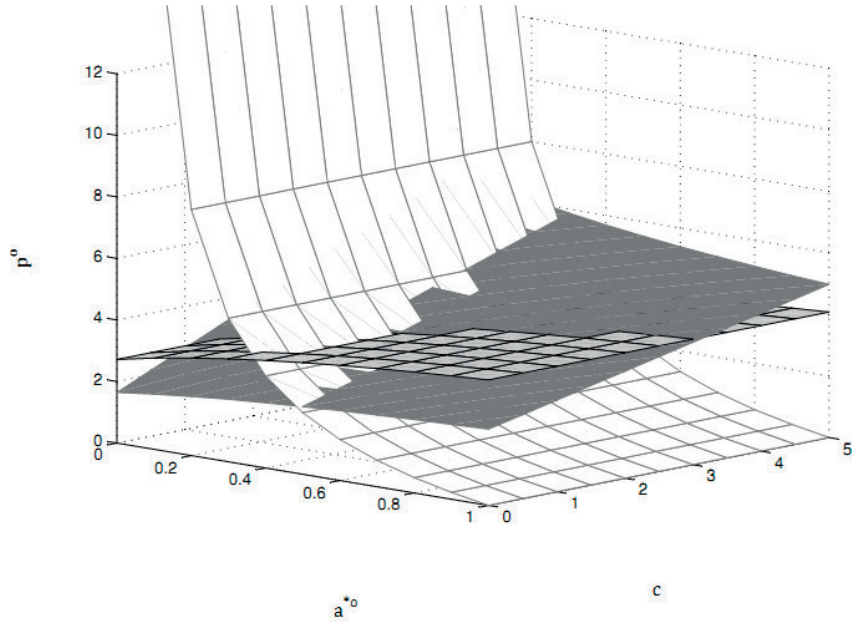

Figure 2.8: Equilibrium Values of p^o and a^{*o} for Different Values of c ($\alpha = 0.5,\ \beta = 2,\ \epsilon = 1,\ \gamma = 0.5$)

Own illustration based on a variant of the Fan and Stark (2011) model.

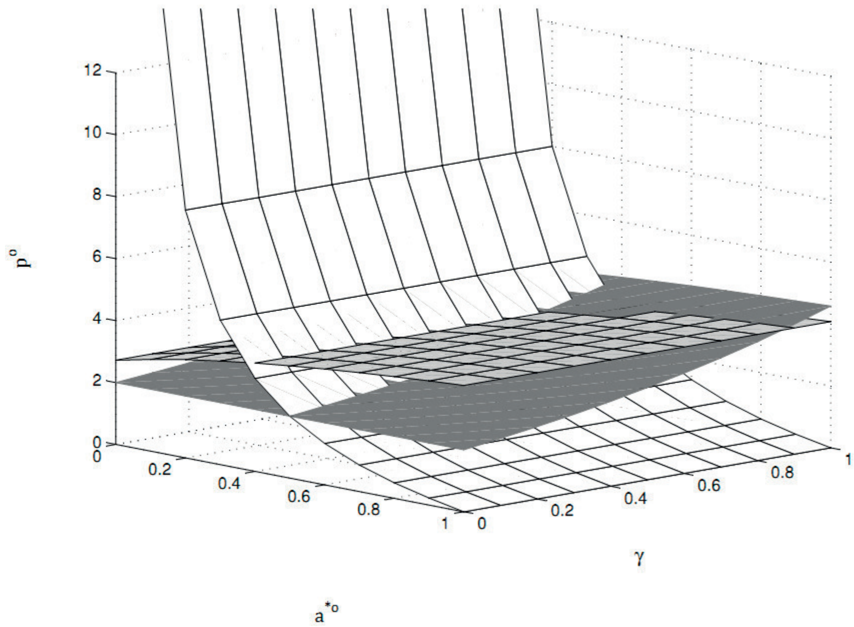

Figure 2.9: Equilibrium Values of p^o and a^{*o} for Different Values of γ ($\alpha = 0.5,\ \beta = 2,\ \epsilon = 1,\ c = 1$)

Own illustration based on a variant of the Fan and Stark (2011) model.

2.3.4 Welfare Analysis

Welfare Effects for the Different Types of Workers

As in the reference model, four groups of individuals are of interest for the study of the welfare implications of migration:

1. Individuals who work in sector X in Home in both the closed economy setting and the open economy setting
2. Individuals who work in sector X in Home in the closed economy setting but work in sector Y in Foreign in the open economy setting
3. Individuals who work in sector Y in Home in the closed economy setting but work in sector Y in Foreign in the open economy setting
4. Individuals who work in sector Y in Home in both the closed economy setting and the open economy setting

It can be derived from expression (2.52) that individuals of type 4 only exist in the open economy equilibrium if:

$$c > c^{crit} = \frac{(e^{\epsilon(1-\gamma)} - 1)}{e^{\epsilon(1-\gamma)}} p^{o} \tag{2.60}$$

By contrast, if $c \leq c^{crit}$, all individuals who choose to work in sector Y will migrate, such that the workforces of sector Y of the two economies will be "interchanged".

Figure 2.10 schematically illustrates the different types of workers for the interval $c \in \left[0, c^{prohib}\right]$, where c^{prohib} is defined by expression (2.55).

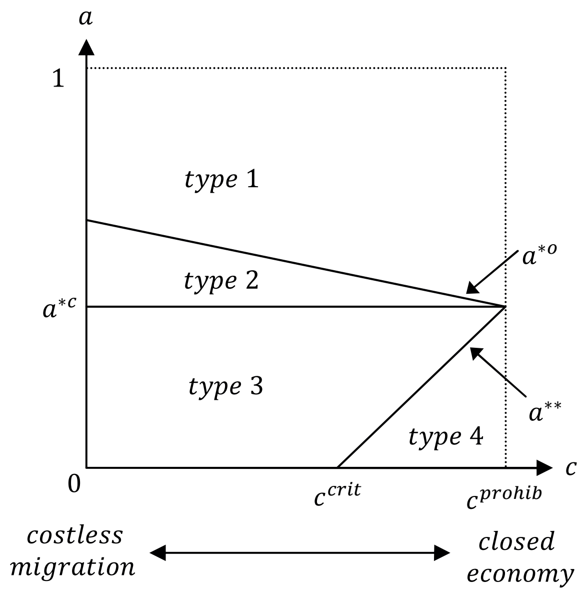

Figure 2.10: Classification of Individuals for Welfare Analysis

Own illustration based on a variant of the Fan and Stark (2011) model.

The following Proposition summarizes the welfare effects that arise when two-way migration between the two identical economies becomes possible:

Proposition 9. *In the open economy setting with migration, all individuals of type 1 and type 2 are better off compared to the closed economy setting. Of the individuals of type 3, only those with*

$$a_i > \overline{\overline{a}} = \frac{\frac{c}{p^o}\left(\frac{p^o}{p^c}\right)^{\alpha} e^{\epsilon(1-\gamma)} - \left[\left(\frac{p^o}{p^c}\right)^{\alpha} e^{\epsilon(1-\gamma)} - 1\right]}{\left(\frac{p^o}{p^c}\right)^{\alpha} e^{\epsilon(1-\gamma)} - 1}$$

will be better off, while all individuals of type 4 will be worse off.

Proof. See Section 2.5.7 in the appendix.

The driving force behind Proposition 9 is that $p^o < p^c$ when migration takes place. Therefore, all high-ability workers who either work in the domestic sector X or in the foreign sector Y are definitely better off in the open economy setting compared to the closed economy setting. Of the individuals working in the domestic sector Y only those characterized by a rather high ability level $a_i > \overline{\overline{a}}$ (with $a^{**} < \overline{\overline{a}} < a^{*c}$) will be better off in the open economy setting. This result is in line with the result in the reference model, where only the individuals with a rather high aversion to occupational stigma are better off in the open economy setting

Aggregate Welfare Effect

After having shown that workers with rather high ability levels are better off while workers with low ability levels are worse off in the open economy situation compared to the closed economy situation, we now analyze the overall welfare effect for different values of migration costs c. In order to aggregate individual welfare, we choose a utilitarian welfare function. Given that migration costs are assumed to be wasteful, the difference between aggregate welfare in the open economy setting with $c \in \left[0, c^{prohib}\right]$ and aggregate welfare in the closed economy setting can be expressed as:

$$\begin{aligned}\Delta W = W^o - W^c = \sum_i u_i^o - \sum_i u_i^c = \sum_i \Delta u_i = \int_{a^{*o}}^{1} -(1-\alpha)\left[\ln\left(p^o\right) - \ln\left(p^c\right)\right] da \\ + \int_{a^{*c}}^{a^{*o}} \left\{-(1-\alpha)\left[\ln\left(p^o\right) - \ln\left(p^c\right)\right] + \ln\left[\left(1+a_i\right)p^o - c\right] - \ln\left(1+\beta a_i\right) - \gamma\epsilon\right\} da \\ + \int_{a^{**}}^{a^{*c}} \left\{-(1-\alpha)\ln\left(p^o\right) - \alpha\ln\left(p^c\right) + \ln\left[\left(1+a_i\right)p^o - c\right] - \ln\left(1+a_i\right) + (1-\gamma)\epsilon\right\} da \\ + \int_{0}^{a^{**}} \alpha[\ln\left(p^o\right) - \ln(p^c)]da \qquad (2.61)\end{aligned}$$

$$
\begin{aligned}
\Delta W &= (1-\alpha)[\ln(\mathrm{p^c}) - \ln(p^o)] - a^{*c}\ln(p^c) + a^{**}\ln(p^o) \\
&+ \left(a^{*o} + 1 - \frac{c}{p^o}\right)\ln(p^o a^{*o} + p^o - c) - \left(a^{**} + 1 - \frac{c}{p^o}\right)\ln(p^o a^{**} + p^o - c) \\
&- \left(\frac{1}{\beta} + a^{*o}\right)\ln(1+\beta a^{*o}) + \left(\frac{1}{\beta} + a^{*c}\right)\ln(1+\beta a^{*c}) - (1+a^{*c})\ln(1+a^{*c}) \\
&+ (1+a^{**})\ln(1+a^{**}) + (a^{*c} - a^{**})\,\epsilon - (a^{*o} - a^{**})\,\gamma\epsilon \qquad (2.62)
\end{aligned}
$$

Since it is not possible to find an explicit solution to the optimization problem $\frac{\partial \Delta W}{\partial c} = 0$, we continue our considerations with some numerical examples. To this end, we assume that $\alpha = 0.5$ and that $\beta = 10$. Figure 2.11 distinguishes four different parameter constellations for ϵ and γ and illustrates the difference in aggregate welfare ΔW (solid curves) for different values of migration costs $c \in \left[0, c^{prohib}\right]$. In addition, Figure 2.11 shows the respective sectoral cut-off ability level in the closed economy setting, a^{*c} (gray lines), and in the open economy setting, a^{*o} (dotted curves), as well as the ability level of the individual who is indifferent between work in the domestic sector Y or the foreign sector Y, a^{**} (dashed curves), for different values of c.

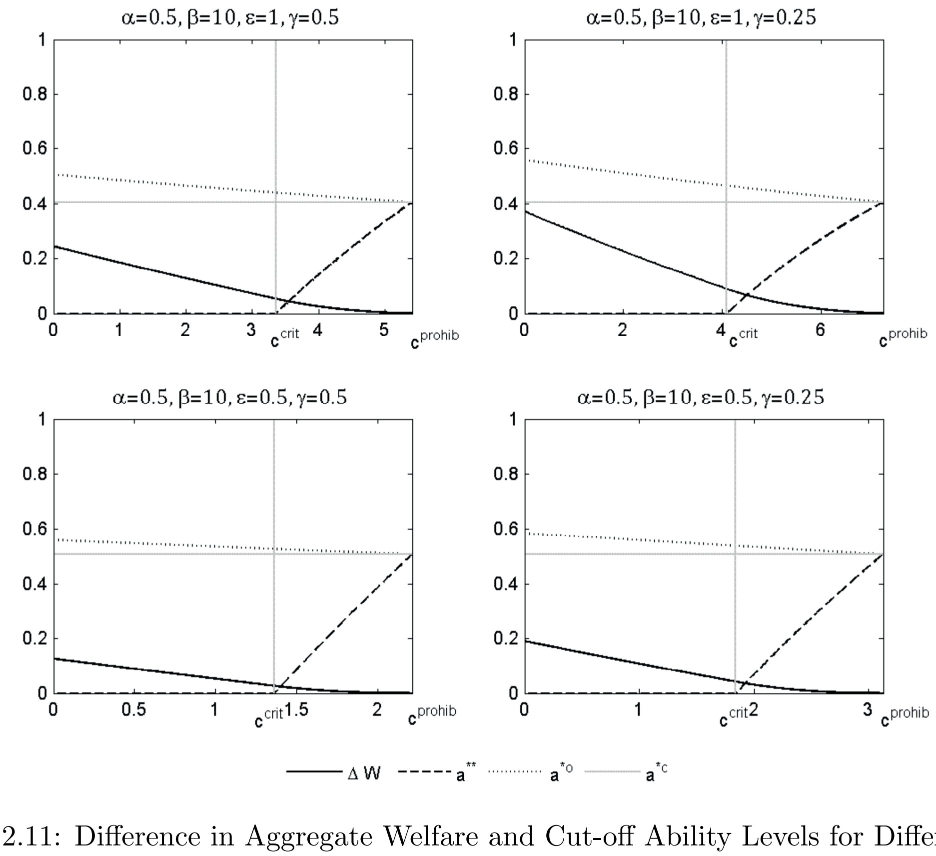

Figure 2.11: Difference in Aggregate Welfare and Cut-off Ability Levels for Different Values of c

Own illustration based on a variant of the Fan and Stark (2011) model.

In the four cases considered, the curve ΔW seems to be continuous and monotonically downward-sloping. The vertical lines that indicate the levels of c^{crit} each mark the change from a situation with complete migration of all workers of sector Y (i.e., a situation in which the workforces of sector Y of both economies are "interchanged") to a situation in which only some individuals working in sector Y optimally choose to migrate. The closed economy situation with $\Delta W = 0$ and $a^{*o} = a^{**} = a^{*c}$ is reached for $c = c^{prohib}$. The difference in aggregate welfare, ΔW, is positive in the relevant interval for migration costs c in all cases considered. This welfare gain is the larger, the lower the cost of migration and hence the more workers migrate. At $c = 0$, the welfare gain is maximal.

2.3.5 Some Further Considerations Concerning the Costs of Migration

There exists a lot of evidence that skills are only imperfectly transferable internationally – even between very similar countries; see, e.g., Basilio and Bauer, 2010, Mattoo et al., 2008, Chiswick et al., 2003, Bratsberg and Ragan, 2002, Friedberg, 2000, as well as Chapter 7 of this thesis. Therefore, modeling the costs of migration in a way that reduces a migrant's productivity might constitute a further interesting modification to the reference model.

Let us assume that migration costs no longer solely occur at the demand side as in the reference model, but now origin at the supply side and are thus defined in units of good y.[10] Since individuals are not only producers but also consumers, the decrease in a migrant's productivity will also involve a reduction of each migrant's wage and thus of his purchasing power. However, since supply of good y will decrease by more than demand for y in the presence of the second good x, the modified migration costs will exert an upward pressure on the price of good y and consequently on the equilibrium relative price in the open economy setting for any given labor allocation across sectors. Graphically speaking, in this scenario the goods market equilibrium locus in the open economy setting will lie above the goods market equilibrium locus in the closed economy setting in Figure 2.7. This has two direct implications: On the one hand, the considered modification will further reinforce the result that the occupational cut-off ability level in the open economy setting , a^{*o}, is higher than the cut-off ability level in the closed economy setting, a^{*c}, because a higher price for good y will incite more individuals to work in this sector, ceteris paribus. On the other hand, however, this modification will render the final impact on the equilibrium relative price ambiguous. The reason for this is that an increase in the level

[10] It has to be stressed that the change of the base unit in which migration costs are measured *per se* does not introduce any change to the mechanisms of the model.

of employment and thus in the supply of good y will countervail the described upward pressure on the price of good y. This is neither the case in Fan and Stark (2011) nor in the model variants presented in Sections 2.2 and 2.3. Whereas in the latter variants the relative price of good y is only influenced via changes in the sectoral labor allocation, in the former model both the effect of migration costs on the relative price and the change in the sectoral labor allocation work in the same direction. Therefore, the equilibrium relative price in the open economy setting lies unambiguously below the relative price in the closed economy setting in these model variants.

2.4 Conclusion

This chapter has presented an alternative case for migrants' positive selection on skills that is unrelated to international (or inter-regional) income differences. Considering a variant of the model by Fan and Stark (2011), we have shown that the individuals with the highest ability levels of those working in a stigmatized sector have an incentive to migrate if this reduces their disutility from occupational stigma. The intuition underlying the reduction of the disutility from occupational stigma is that migration increases the geographical distance between an individual and his social environment. In order to emphasize this argument and following Fan and Stark (2011), the two economies in the model have been assumed to be identical in all respects. As a consequence, the equilibrium in the open economy setting has featured two-way migration between these economies. It has been shown that the main results of Fan and Stark (2011) are preserved if individuals select into sectors of production and countries on the basis of heterogeneous abilities rather than on the basis of heterogeneous degrees of stigma aversion.

The empirical assessment of the predictions evolving from this model framework constitutes an interesting yet challenging avenue for future research. The central prediction is that individuals may migrate to another country or region in order to increase the "distance" to their social environment, thereby reducing the perceived disutility from occupational stigma. Abstracting from the specific type of individual heterogeneity underlying this motive for migration, there are two possibilities how this prediction can be assessed empirically. One possibility is to test for a positive causal relationship between the incidence of occupational stigma and the *decision to migrate*. This approach is most closely related to the model's central prediction. Another, less obvious possibility is to analyze the relationship between the incidence of occupational stigma and the *distance* *moved*. On the basis of the model considered in this chapter, we should expect to find a positive relationship between occupational stigma and the decision to migrate or the distance moved.

2.5 Appendix to Chapter 2

2.5.1 Proof of Proposition 2

The differentiation of conditions (2.38) and (2.43) with respect to β reveals that both loci in Figure 2.5 will shift upwards as β increases:

$$\frac{\partial p}{\partial \beta} = \frac{e^{\epsilon} a^*}{1 + a^*} > 0 \tag{2.63}$$

$$\frac{\partial p}{\partial \beta} = \frac{(1-\alpha)}{2\alpha} \left[\frac{1 - (a^*)^2}{a^* + \frac{(a^*)^2}{2}} \right] > 0 \tag{2.64}$$

Whereas these upward shifts unambiguously imply that the two loci will intersect at a higher price p^c as β increases, the effect on a^{*c} is ambiguous and depends on the other model parameters. ■

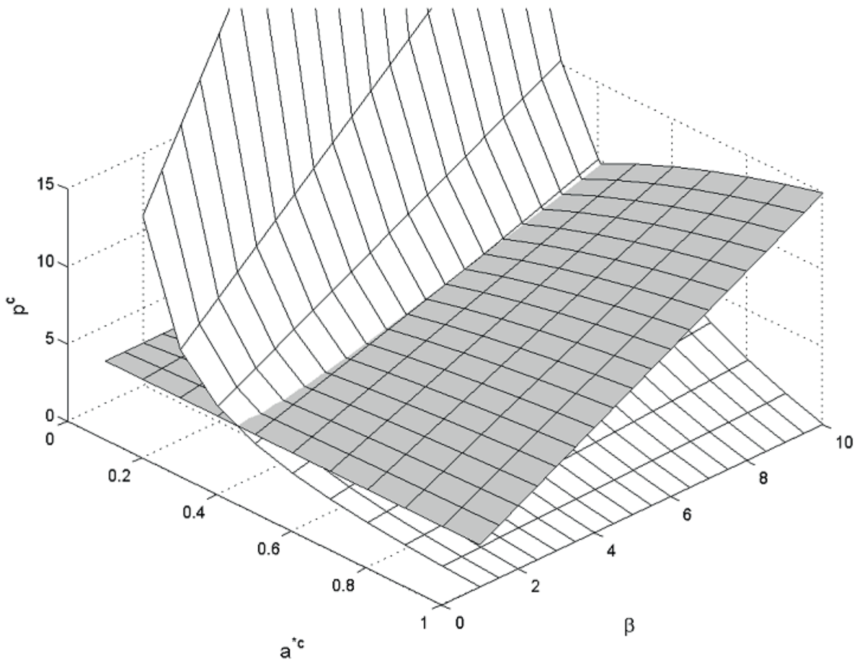

Figure 2.12: Equilibrium Values of p^c and a^{*c} for Different Values of β ($\alpha = 0.5$, $\epsilon = 1$)

Own illustration based on a variant of the Fan and Stark (2011) model.

Figure 2.12 illustrates the condition of indifference between the two occupations (2.38, dark surface) as well as the goods market equilibrium condition (2.43, light surface) for different values of β for the case of $\alpha = 0.5$ and $\epsilon = 1$. The equilibrium values of a^{*c} and p^c for different values of β are determined at the intersection of the two surfaces. It can be seen that a^{*c} moderately increases as the productivity parameter β increases in the interval from 1 to 5 or in the interval from 7 to 10, but that a^{*c} stays constant for $5 \leq \beta \leq 7$. p^c increases with a higher β over the entire interval considered.

2.5.2 Proof of Proposition 5

In order to guarantee that a^* is increasing in p in the open economy setting, the following condition must hold:

$$\frac{\partial a^*}{\partial p} = \frac{(\beta e^{\gamma\epsilon} - p) + (p - c - e^{\gamma\epsilon})}{(\beta e^{\gamma\epsilon} - p)^2} = \frac{(\beta - 1)e^{\gamma\epsilon} - c}{(\beta e^{\gamma\epsilon} - p)^2} > 0 \tag{2.65}$$

$$c < (\beta - 1)e^{\gamma\epsilon} \tag{2.66}$$

It can easily be verified that the latter condition is non-binding if the conditions ensuring the existence of migration hold. ■

2.5.3 Proof Related to Proposition 6

A comparison of the sectoral cut-off ability levels in the closed economy setting and in the open economy setting, both evaluated at $p = p^c$, yields:

$$\begin{aligned}
a^{*c}|_{p=p^c} &< a^{*o}|_{p=p^c} \\
\frac{p^c - e^\epsilon}{\beta e^\epsilon - p^c} &< \frac{p^c - e^{\gamma\epsilon} - c}{\beta e^{\gamma\epsilon} - p^c} \\
(p^c - e^\epsilon)(\beta e^{\gamma\epsilon} - p^c) &< (p^c - e^{\gamma\epsilon} - c)(\beta e^\epsilon - p^c) \\
p^c\beta e^{\gamma\epsilon} + p^c e^\epsilon &< p^c\beta e^\epsilon + p^c e^{\gamma\epsilon} - c(\beta e^\epsilon - p^c) \\
c &< \frac{p^c(\beta - 1)(e^\epsilon - e^{\gamma\epsilon})}{\beta e^\epsilon - p^c}
\end{aligned} \tag{2.67}$$

A glance at condition (2.55) reveals that the latter is equivalent to condition (2.67). Thus, if migration takes place, $a^{*o} > a^{*c}$ and $p^o < p^c$. ■

2.5.4 Proof Related to Alternative Migration Costs

We now consider the case in which migration costs exert a downward pressure on the relative price of good y as assumed in Fan and Stark (2011). Figure 2.13 illustrates the determination of the equilibrium values of the sectoral cut-off ability level and the relative price in the open economy setting compared to the closed economy setting for this case. The pressure of migration costs on the relative price is reflected in the downward shift of the goods market equilibrium locus.

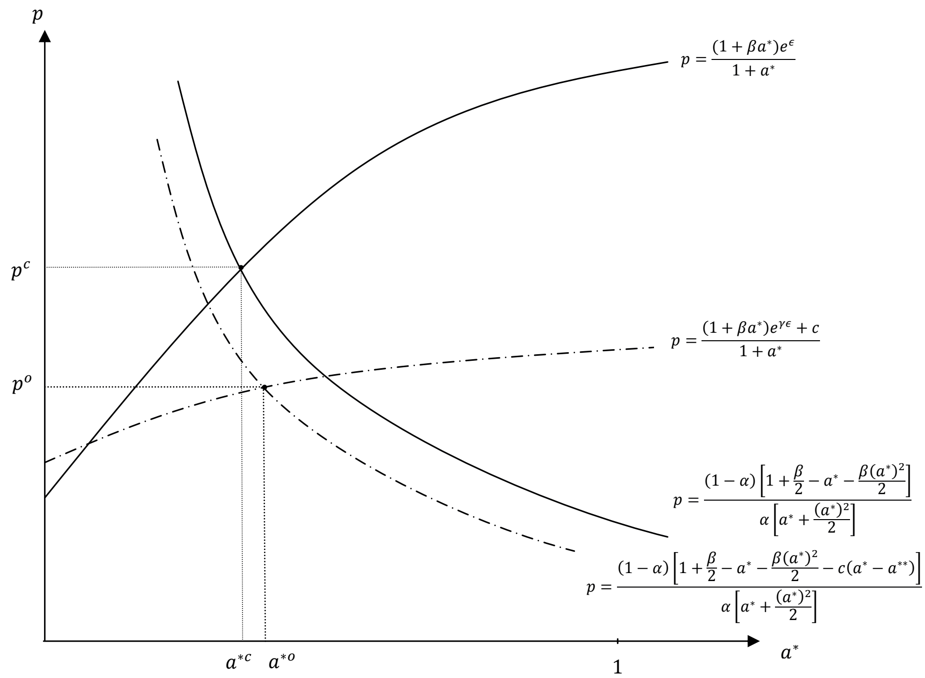

Figure 2.13: Joint Determination of the Cut-off Ability Level and the Relative Price in the Open Economy Setting Compared to the Closed Economy Setting with Alternative Migration Costs

Own illustration based on a variant of the Fan and Stark (2011) model.

Note that the structure of the following proof that $p^o < p^c$ is the same as in Fan and Stark (2011, 567-568).

Rewriting the goods market equilibrium condition in the open economy setting in the case that migration costs exert a downward pressure on the relative price of good y yields:

$$\alpha\left[a^{*o}+\frac{(a^{*o})^2}{2}\right]-\frac{1-\alpha}{p^o}\left[1+\frac{\beta}{2}-a^{*o}-\frac{\beta\,(a^{*o})^2}{2}\right]=-\frac{1-\alpha}{p^o}c(a^{*o}-a^{**}) \qquad (2.68)$$

If there is migration in the open economy setting, i.e., if conditions (2.54) and (2.55) hold, the right-hand side of equation (2.68) will be negative. Thus, we can write:

$$\alpha\left[a^{*o}+\frac{(a^{*o})^2}{2}\right]<\frac{1-\alpha}{p^o}\left[1+\frac{\beta}{2}-a^{*o}-\frac{\beta\,(a^{*o})^2}{2}\right] \tag{2.69}$$

Solving inequality (2.69) for $(1-\alpha)$ yields:

$$p^o\alpha\frac{a^{*o}+\frac{(a^{*o})^2}{2}}{1+\frac{\beta}{2}-a^{*o}-\frac{\beta(a^{*o})^2}{2}}<1-\alpha \tag{2.70}$$

Similarly, solving the goods market equilibrium condition in the closed economy setting (2.43) for $(1-\alpha)$ yields:

$$p^c\alpha\frac{a^{*c}+\frac{(a^{*c})^2}{2}}{1+\frac{\beta}{2}-a^{*c}-\frac{\beta(a^{*c})^2}{2}}=1-\alpha \tag{2.71}$$

Relating inequality (2.70) to the latter expression, we obtain the following inequality:

$$p^o\frac{a^{*o}+\frac{(a^{*o})^2}{2}}{1+\frac{\beta}{2}-a^{*o}-\frac{\beta(a^{*o})^2}{2}}<p^c\frac{a^{*c}+\frac{(a^{*c})^2}{2}}{1+\frac{\beta}{2}-a^{*c}-\frac{\beta(a^{*c})^2}{2}} \tag{2.72}$$

Inserting the expressions for the cut-off ability levels a^{*o} and a^c into (2.72) yields:

$$p^o\left[\frac{\frac{p^o-c-e^{\gamma\epsilon}}{\beta e^{\gamma\epsilon}-p^o}+\frac{(p^o-c-e^{\gamma\epsilon})^2}{2(\beta e^{\gamma\epsilon}-p^o)^2}}{1+\frac{\beta}{2}-\frac{p^o-c-e^{\gamma\epsilon}}{\beta e^{\gamma\epsilon}-p^o}-\frac{\beta(p^o-c-e^{\gamma\epsilon})^2}{2(\beta e^{\gamma\epsilon}-p^o)^2}}\right]<p^c\left[\frac{\frac{p^c-e^{\epsilon}}{\beta e^{\epsilon}-p^c}+\frac{(p^c-e^{\epsilon})^2}{2(\beta e^{\epsilon}-p^c)^2}}{1+\frac{\beta}{2}-\frac{p^c-e^{\epsilon}}{\beta e^{\epsilon}-p^c}-\frac{\beta(p^c-e^{\epsilon})^2}{2(\beta e^{\epsilon}-p^c)^2}}\right] \tag{2.73}$$

Let us assume that $p^o \geq p^c$. Given that migration takes place, i.e., that conditions (2.54) and (2.55) are fulfilled, it can be shown that the left-hand side of expression (2.73) will be larger than the right-hand side of expression (2.73), which contradicts the inequality sign.

For inequality

$$p^o\left[\frac{\frac{p^o-c-e^{\gamma\epsilon}}{\beta e^{\gamma\epsilon}-p^o}+\frac{(p^o-c-e^{\gamma\epsilon})^2}{2(\beta e^{\gamma\epsilon}-p^o)^2}}{1+\frac{\beta}{2}-\frac{p^o-c-e^{\gamma\epsilon}}{\beta e^{\gamma\epsilon}-p^o}-\frac{\beta(p^o-c-e^{\gamma\epsilon})^2}{2(\beta e^{\gamma\epsilon}-p^o)^2}}\right]>p^c\left[\frac{\frac{p^c-e^{\epsilon}}{\beta e^{\epsilon}-p^c}+\frac{(p^c-e^{\epsilon})^2}{2(\beta e^{\epsilon}-p^c)^2}}{1+\frac{\beta}{2}-\frac{p^c-e^{\epsilon}}{\beta e^{\epsilon}-p^c}-\frac{\beta(p^c-e^{\epsilon})^2}{2(\beta e^{\epsilon}-p^c)^2}}\right] \tag{2.74}$$

to hold true for $p^o \geq p^c$, it must be true that:

$$\frac{p^o-c-e^{\gamma\epsilon}}{\beta e^{\gamma\epsilon}-p^o}>\frac{p^c-e^{\epsilon}}{\beta e^{\epsilon}-p^c} \tag{2.75}$$

This can be reformulated as:

$$\frac{\beta-1}{\beta e^{\epsilon}-p^c}>\frac{c}{p^o e^{\epsilon}-p^c e^{\gamma\epsilon}} \tag{2.76}$$

From condition (2.55) we know that in the presence of migration we have:

$$\frac{\beta - 1}{\beta e^{\epsilon} - p^c} > \frac{c}{p^c e^{\epsilon} - p^c e^{\gamma\epsilon}} \tag{2.77}$$

Thus, for $p^o \geq p^c$ in the presence of migration we would indeed have that:

$$\frac{p^o - c - e^{\gamma\epsilon}}{\beta e^{\gamma\epsilon} - p^o} > \frac{p^c - e^{\epsilon}}{\beta e^{\epsilon} - p^c}$$

and hence inequality (2.74) would hold true. Since this would contract inequality (2.73), it must be true that $p^o < p^c$. ■

With $p^o < p^c$ in the presence of migration, the same line of argumentation as in Fan and Stark (2011, 568-569) can be applied to reason that the sectoral cut-off ability level in the open economy setting is higher than the cut-off level in the closed economy setting, $a^{*o} > a^{*c}$. This implies that more individuals will choose to work in the stigmatized sector Y and less individuals will opt for work in sector X. The intuition for this result is that migration partly corrects for the "wedge" in terms of utility that is put between the two occupations by the stigma.

2.5.5 Proof of Proposition 7

Differentiation of condition (2.49) with respect to β yields:

$$\frac{\partial p}{\partial \beta} = \frac{e^{\gamma\epsilon} a^*}{1 + a^*} > 0 \tag{2.78}$$

Furthermore, the locus for the goods market equilibrium is the same in the open economy setting as in the closed economy setting. It has been shown in the Proof of Proposition 2 that the latter is increasing in β. Therefore, the relative price in the open economy equilibrium p^o is increasing in β. However, the effect on the cut-off ability level a^{*o} is ambiguous – just as it is the case in the closed economy setting. ■

2.5.6 Proof of Proposition 8

Differentiation of condition (2.49) with respect to c yields:

$$\frac{\partial p}{\partial c} = \frac{1}{1+a^{*}} > 0 \tag{2.79}$$

Thus, in the open economy setting with two-way migration of some individuals taking place, a decrease in the cost of migration c will induce a downward shift of the occupational indifference locus in Figure 2.7. By contrast, the goods market equilibrium locus is unaffected. Since the latter locus is downward-sloping in the (a^{*}, p)-space, this implies a decrease in p^{o} and an increase in a^{*o}, ceteris paribus.

Similarly, differentiation of condition (2.49) with respect to γ yields:

$$\frac{\partial p}{\partial \gamma} = \frac{(1+\beta a^{*})\,\epsilon e^{\gamma\epsilon}}{1+a^{*}} > 0 \tag{2.80}$$

Thus, in the open economy setting with two-way migration of some individuals taking place, a decrease in γ will induce a downward shift of the occupational indifference locus in Figure 2.7, while the goods market equilibrium locus is unaffected. Since the latter locus is downward-sloping in the (a^{*}, p)-space, a decrease in γ is accompanied by a decrease in p^{o} and an increase in a^{*o}, ceteris paribus. ■

In the following, we argue that the effects of a decrease in either c or γ on the individual who is indifferent between work in the domestic sector Y and the foreign sector Y are indeterminate without further simplifying assumptions. The differentials of a^{**} as given in expression (2.52) with respect to c and γ, respectively, are defined as follows:

$$\frac{da^{**}}{dc} = \frac{\partial a^{**}}{\partial p} \cdot \frac{dp^{o}}{dc} + \frac{\partial a^{**}}{\partial c} \tag{2.81}$$

$$\frac{da^{**}}{d\gamma} = \frac{\partial a^{**}}{\partial p} \cdot \frac{dp^{o}}{d\gamma} + \frac{\partial a^{**}}{\partial \gamma} \tag{2.82}$$

It has been derived above that $\frac{dp^{o}}{dc}$ and $\frac{dp^{o}}{d\gamma}$ must both be positive. Furthermore, it can be easily checked that $\frac{\partial a^{**}}{\partial c}$ and $\frac{\partial a^{**}}{\partial \gamma}$ are also positive, and that $\frac{\partial a^{**}}{\partial p^{o}}$ is negative. Given that the detailed algebraic expressions of (2.81) and (2.82) are very complicated, it seems impossible to determine the definitive signs of these expressions without any further assumptions on the model parameters.

2.5.7 Proof of Proposition 9

***Ad* type 1.** Individuals who work in sector X in Home both in the closed economy setting and in the open economy setting will be better off in the open economy setting if:

$$\begin{aligned} u^o_{i,X} &> u^c_{i,X} \\ \alpha\ln(\alpha) + \ln(1+\beta a_i) + (1-\alpha)\ln(1-\alpha) - (1-\alpha)\ln(p^o) & \\ > \alpha\ln(\alpha) + \ln(1+\beta a_i) + (1-\alpha)\ln(1-\alpha) - (1-\alpha)\ln(p^c) & \\ p^o &< p^c \end{aligned} \tag{2.83}$$

Since the purchasing power in terms of good x of the individuals who continue to work in sector X will be unchanged when the possibility of migration is introduced, these individuals are better off in the open economy setting as the relative price of good y decreases, because this raises their purchasing power in terms of good y.

***Ad* type 2.** Individuals who work in sector X in Home in the closed economy setting but work in sector Y in Foreign in the open economy setting will be better off in the open economy setting if:

$$\begin{aligned} u^{f,o}_{i,Y} &> u^c_{i,X} \\ \alpha\ln(\alpha) + \ln[(1+a_i)\,p^o - c] + (1-\alpha)\ln(1-\alpha) - (1-\alpha)\ln(p^o) - \gamma\epsilon & \\ > \alpha\ln(\alpha) + (1-\alpha)\ln(1-\alpha) + \ln(1+\beta a_i) - (1-\alpha)\ln(p^c) & \\ \frac{1+\beta a_i}{(1+a_i)\,p^o - c} &< \left(\frac{p^c}{p^o}\right)^{1-\alpha} e^{-\gamma\epsilon} \\ a_i\left[\beta e^{\gamma\epsilon} - p^c\left(\frac{p^o}{p^c}\right)^{\alpha}\right] &< (p^o - c)\left(\frac{p^c}{p^o}\right)^{1-\alpha} - e^{\gamma\epsilon} \end{aligned}$$

Given that β is large enough, i.e., given that condition (2.54) holds, we obtain for $p^o < p^c$:

$$a_i < \bar{a} = \frac{(p^o - c)\left(\frac{p^c}{p^o}\right)^{1-\alpha} - e^{\gamma\epsilon}}{\beta e^{\gamma\epsilon} - p^c\left(\frac{p^o}{p^c}\right)^{\alpha}} \tag{2.84}$$

Recalling that individuals of type 2 are characterized by the following ability range:

$$\begin{aligned} a^{*c} < a_i &< a^{*o} \\ \frac{p^c - e^{\epsilon}}{\beta e^{\epsilon} - p^c} < a_i &< \frac{p^o - c - e^{\gamma\epsilon}}{\beta e^{\gamma\epsilon} - p^o} \end{aligned} \tag{2.85}$$

it can be easily seen that inequality (2.84) is non-binding for $p^o < p^c$. This implies in turn that $p^c \left(\frac{p^o}{p^c}\right)^{\alpha} > p^o$:

$$\bar{a} = \frac{(p^o - c)\left(\frac{p^c}{p^o}\right)^{1-\alpha} - e^{\gamma\epsilon}}{\beta e^{\gamma\epsilon} - p^c\left(\frac{p^o}{p^c}\right)^{\alpha}} > \frac{p^o - c - e^{\gamma\epsilon}}{\beta e^{\gamma\epsilon} - p^o} = a^{*o} \tag{2.86}$$

Thus, with $p^o < p^c$, all individuals of type 2 will be better off in the open economy setting compared to the closed economy setting. This result is intuitive and in line with the result in the benchmark model: If $p^o < p^c$, all individuals of type 1 are better off in the open economy setting. Therefore, individuals who switch from sector X in Home in the closed economy setting to the stigmatized sector Y in Foreign in the open economy setting must experience a welfare gain that is at least as high as the gain they would experience from the lower price for good y had they kept working in sector X. Otherwise, there would be no economic rationale for them to switch to sector Y in Foreign in the open economy setting.

***Ad* type 3.** Individuals who work in sector Y in Home in the closed economy setting but work in sector Y in Foreign in the open economy setting will be better off in the open economy setting if:

$$u_{i,Y}^{f,o} > u_{i,Y}^{c}$$

$$\alpha \ln(\alpha) + (1-\alpha)\ln(1-\alpha) + \ln[(1+a_i)\,p^o - c] - (1-\alpha)\ln(p^o) - \gamma\epsilon$$

$$> \alpha \ln(\alpha) + (1-\alpha)\ln(1-\alpha) + \ln(1+a_i) + \alpha \ln(p^c) - \epsilon$$

$$\frac{1+a_i}{(1+a_i)\,p^o - c} < \left(\frac{p^o}{p^c}\right)^{\alpha} \frac{e^{\epsilon(1-\gamma)}}{p^o}$$

$$a_i\left[1 - \left(\frac{p^o}{p^c}\right)^{\alpha} e^{\epsilon(1-\gamma)}\right] < (p^o - c)\left(\frac{p^o}{p^c}\right)^{\alpha} \frac{e^{\epsilon(1-\gamma)}}{p^o} - 1$$

Assuming that $p^o > p^c$, we would obtain:

$$a_i > \bar{\bar{a}} = \frac{(p^o - c)\left(\frac{p^o}{p^c}\right)^{\alpha} \frac{e^{\epsilon(1-\gamma)}}{p^o} - 1}{-\left[\left(\frac{p^o}{p^c}\right)^{\alpha} e^{\epsilon(1-\gamma)} - 1\right]} = \frac{\frac{c}{p^o}\left(\frac{p^o}{p^c}\right)^{\alpha} e^{\epsilon(1-\gamma)} - \left[\left(\frac{p^o}{p^c}\right)^{\alpha} e^{\epsilon(1-\gamma)} - 1\right]}{\left(\frac{p^o}{p^c}\right)^{\alpha} e^{\epsilon(1-\gamma)} - 1} \tag{2.87}$$

Recalling that individuals of type 3 are characterized by the following ability range:

$$a^{**} < a_i < a^{*c}$$

$$\frac{\frac{c}{p^c} e^{\epsilon(1-\gamma)} - \left(e^{\epsilon(1-\gamma)} - 1\right)}{e^{\epsilon(1-\gamma)} - 1} < a_i < \frac{p^c - e^{\epsilon}}{\beta e^{\epsilon} - p^c} \tag{2.88}$$

it can be easily seen that inequality (2.87) would be non-binding for $p^o > p^c$:

$$\overline{\overline{a}} = \frac{\frac{c}{p^o}\left(\frac{p^o}{p^c}\right)^{\alpha} e^{\epsilon(1-\gamma)} - \left[\left(\frac{p^o}{p^c}\right)^{\alpha} e^{\epsilon(1-\gamma)} - 1\right]}{\left(\frac{p^o}{p^c}\right)^{\alpha} e^{\epsilon(1-\gamma)} - 1} < \frac{\frac{c}{p^c} e^{\epsilon(1-\gamma)} - \left(e^{\epsilon(1-\gamma)} - 1\right)}{e^{\epsilon(1-\gamma)} - 1} = a^{**} \tag{2.89}$$

However, as we know from above that $p^o < p^c$, inequality (2.87) must be binding for some individuals. This implies that only individuals of type 3 with a rather high ability, $a_i > \overline{\overline{a}}$, will be better off in the open economy setting.

***Ad* type 4.** Individuals who work in sector Y in Home in both the closed economy setting and the open economy setting will be better off in the open economy setting if:

$$u^o_{i,Y} > u^c_{i,Y} \tag{2.90}$$

$$\alpha \ln(\alpha) + (1-\alpha)\ln(1-\alpha) + \ln(1+a_i) + \alpha \ln(p^o) - \epsilon$$

$$> \alpha \ln(\alpha) + (1-\alpha)\ln(1-\alpha) + \ln(1+a_i) + \alpha \ln(p^c) - \epsilon$$

$$p^o > p^c \tag{2.91}$$

Contrasting the individuals of type 1, individuals of type 4 will be worse off in the open economy setting because of the decrease in the equilibrium price for good y. With a lower equilibrium price, their purchasing power in terms of good x decreases while their purchasing power in terms of good y remains constant. ■

CHAPTER 3

Low Occupational Prestige and Internal Migration in Germany

3.1 Introduction

In this chapter we ask whether empirically observed migration moves are driven by individuals' concerns for their occupational status. Such concerns may arise if an individual's occupational status is considered relatively low by his social environment and if the individual cares about the opinion of his social environment. The idea that migration may serve to reduce disutility from being employed in a low-prestige ("stigmatized") occupation was developed by Fan and Stark (2011) and has been revisited in Chapter 2. Disutility from occupational stigma may constitute a push factor of migration, but its empirical relevance is yet to be explored. We study how individuals' concerns for occupational status affect internal migration in Germany, using data from the German Socio-Economic Panel (SOEP 2012) provided by Deutsches Institut für Wirtschaftsforschung (DIW) Berlin. Given that the two identical countries in the theoretical model of reference can just as well be interpreted as two identical regions or cities within the same country (Fan and Stark, 2011, 554), our analysis of internal migration is compatible with this theoretical model. In particular, analyzing internal migration rather than international migration allows us to abstract from large income differences.

We exploit detailed information on individuals' occupations and education paths, in addition to data on their residential histories. In the absence of any reliable information on

This chapter is based on SOEPpapers No. 562, see Neubecker (2013).

occupational stigma, we use available information on occupational prestige to construct an indicator for *low occupational prestige* and employ this measure as a proxy for *occupational stigma*. Our indicator is based on the assumption that an individual's occupational standing is measured as his occupational achievement within the broad occupational category to which his vocational training belongs. We expect to find a positive effect of low occupational prestige as measured by this indicator on the probability of internal migration in Germany.

In line with the theoretical model considered in Chapter 2, our interest lies on migration that is likely to serve as a means to change an individual's social environment. Therefore, we only consider moves over a certain distance as moves and focus on workers who do not improve upon their occupational situations in the considered periods. We thus abstract from migration that is related to occupational upgrading.[1] Furthermore, given our interest in the residential histories of workers with vocational training, Germany appears to be an appropriate case for our analysis because of its strong dual education system.[2]

Our estimations reveal a statistically significant and robust negative relationship between the probability of internal migration in Germany and the incidence of low prestige associated with a worker's occupation. This finding rejects our working hypothesis according to which individuals in occupations with relatively low prestige are more likely to migrate compared to individuals in occupations with relatively high prestige. Given the specific assumptions and data considered for our empirical analysis, however, our finding does not necessarily reject the more general prediction of the theoretical model of reference. We provide possible explanations for our finding, but are unable to empirically discriminate between them.

By analyzing the role of occupational prestige for the migration decisions of German residents, this chapter contributes to the literature on the determinants of internal

[1] For a study investigating the joint decision of residential and job mobility in the United States, see Kan (2003).

[2] According to figures for Germany for 2007 from OECD (2009, 304, Table C1.4), 57.1% of students in upper secondary education were enrolled in ISCED-97 category 3B, providing essentially access to practical or occupation-specific tertiary education, and 0.3% were enrolled in ISCED-97 category 3C. Only 42.6% were enrolled in ISCED-97 category 3A, providing access to theory-based tertiary programs; see UNESCO (2006) for details on these categories. The OECD combined average for practical secondary education is much lower (7.9 % for category 3B and 25.6 % for category 3C), while the OECD average for general upper secondary education is much higher (70.2% for category 3A) (OECD, 2009, 304, Table C1.4). In the German dual education system apprentices typically spend 3 to 4 days per week in a firm providing them with practical training, and further 12 hours per week in a part-time school where they receive general as well as occupation-specific education (Hoeckel and Schwartz, 2010, 10).

migration in Germany.[3] As the costs of migration are generally lower in the case of internal migration as opposed to international migration, it is not surprising that we observe much more internal migration as opposed to international migration of German residents: According to figures from the German Federal Statistical Office (2011, 64), in the year 2009 a total of 2,555,165 residents in Germany changed their cities of residence within a given German Federal Land (*Bundesland*), and further 1,081,286 residents moved to another German Federal Land. In the same year, only 733,796 (German and non-German) residents left Germany to move to another country (Federal Statistical Office, 2011, 69). In what follows, we refer to studies on internal migration in Germany that are based on the same database as the analysis in this chapter. Given the rich information available in the SOEP, these studies differ in various content-related dimensions, such as the definition of migration (accomplished migration versus intended migration), the factors of major interest (socio-economic factors versus psychological/non-economic factors), or the sample of individuals considered (working population versus university graduates, East Germans versus West Germans). The majority of these studies exploit information on accomplished moves documented in the SOEP. Studies investigating individuals‘ intentions to move within Germany include Bönisch and Schneider (2010), who look at general migration intentions, as well as Burda (1993) and Büchel and Schwarze (1994), whose focus is on East Germans' intentions to move to West Germany.[4] Concerning the determinants of migration, the focus of most studies using data from the SOEP is on socio-economic factors.[5] A recent exception is the work by Jäger et al. (2010), who analyze the role of an individual's propensity to take risks for migration. Their estimation results suggest that individuals who are more willing to take risks are more likely to move to another German region (*Raumordnungsregion*), ceteris paribus.[6] However, none of the aforementioned studies has looked at the role of low occupational prestige for internal migration.

The analysis presented in this chapter is also related to the literature studying the effects of social status inconsistencies. In particular, the sociological literature has long

[3] For a survey on internal migration in developed countries, see Greenwood (1997).
[4] For studies using data from the SOEP on individuals‘ intentions to move abroad, see Niefert et al. (2001) and Übelmesser (2006).
[5] For example, Hunt (2006) studies the mobility of East Germans after reunification with a focus on increases in Eastern wages and unemployment.
[6] A follow-up study by Bauernschuster et al. (2012) assesses the reasons underlying the comparatively high mobility of highly educated and risk-loving individuals by disentangling the psychic costs of moving from the pure geographic costs of moving. Their findings suggest that the lower overall distance sensitivity in the migration decision of more educated and risk-loving persons is essentially explained by their smaller sensitivity to the cultural costs of moving.

been studying the relationship between the determinants of social status – education, occupation, and income – as well as the effects of potentially implied status inconsistencies; see, e.g., Lenski (1954). According to Lee et al. (2009, 35), a classical case of status inconsistency is when a highly educated individual works in a job associated with relatively low prestige and/or low income. While there exist several studies on the effects of status inconsistency on wages or job mobility, there is relatively little evidence on the effect of status inconsistency on geographical mobility. An exception is the study by Quinn and Rubb (2005), which investigates the effect of education-occupation mismatches on migration decisions in Mexico. To measure education-occupation mismatches, the authors calculate an individual's amount of overeducation or undereducation as the positive or negative difference between the years of education completed by the individual and the years of education required in the occupation[7] held by the individual, respectively, see Quinn and Rubb (2005, 157). Their findings suggest that overeducation leads to a higher incidence of migration, while undereducation leads to a lower incidence of migration.[8] In a follow-up study, Quinn and Rubb (2011) study overeducation[9] both as a potential cause and as a consequence of the migration decisions of U.S. households. They report that the reduction of overeducation of husbands and wives seems to be an important factor motivating migration. Furthermore, migration is found to involve more wives than husbands exiting full-time paid employment, and to more robustly reduce the level of overeducation for men compared to women.

In light of the theoretical model presented in Chapter 2, the measures of status inconsistency employed in Quinn and Rubb (2005, 2011) and in other studies entail the shortcoming that they do not allow for a distinction between the *pecuniary dimension* and the *prestige dimension* of status inconsistency. Put differently, these measures effectively compound the possible effects of status-inconsistent wages and of status-inconsistent occupational prestige, both of which can originate in an education-occupation mismatch. Lee et al. (2009) partly overcome this problem by adopting the inconsistency definition by Brown et al. (1988), which incorporates the notion that an individual's occupation

[7] The level of education that is required in some occupation is measured by the mean level of schooling in the respective occupation, see Quinn and Rubb (2005, 157).

[8] Quinn and Rubb (2005) regard these findings as a possible explanation for the different effects of education on migration that have been obtained in the empirical literature. Depending on the incidence of overeducation and undereducation at different education levels in the considered sample, one might either obtain a positive or a negative effect of education on migration if overeducation and undereducation are not controlled for (Quinn and Rubb, 2005, 153-154).

[9] In order to determine the extent of overeducation, Quinn and Rubb (2011, 39) rely on two different measures of required education: the mean and the mode of education by occupation.

and income constitute two forms of compensation for his investment in education. Lee et al. (2009, 36-37) refer to individuals with high education status but low occupational and income status as "under-rewarded inconsistents", and characterize individuals whose occupational prestige and/or income significantly exceeds the respective measure of individuals with comparable education as "over-rewarded inconsistents". Individuals with one typical and one atypical relationship between education and occupation/income are labeled "mixed inconsistents". The empirical findings of Lee et al. (2009) suggest that under-rewarded individuals in the United States are more likely to migrate, while over-rewarded individuals are less likely to migrate compared to status consistent individuals. Thus, whereas Lee et al. (2009) consider both the pecuniary dimension and the prestige dimension of occupational status (inconsistency), they do not, however, disentangle the associated effects in their empirical analysis.

The empirical analysis presented in this chapter contributes to the literature studying the effects of social status inconsistencies in that it discriminates between the potential effects of relatively low occupational prestige and of relatively low income on the migration decision. In doing so, the focus of the analysis is on migration as a means to change one's social environment. As a consequence, and different from the related empirical studies, we explicitly disregard the possibility of migration linked to status improvements in terms of occupational prestige. The empirical measures of low occupational prestige and low income employed in our analysis are closely related to the measures of status inconsistencies reviewed above, because they are also based on a comparison of the characteristics of an individual's job with his (vocational) education.

To the best of our knowledge, our empirical analysis is the first of this kind that is based on a large sample of individuals. Closely related anecdotal evidence is provided by Fan and Stark (2011). They report that high-status ship building engineers in Nikolayev/Ukraine accepted to work as low-status welders only afield but not in their home town as the demand for shipbuilding engineers declined. The evidence presented in Parkins (2010) matches this anecdotal evidence: In her interviews with 40 highly educated Jamaicans, occupation/skill mismatch arises as one of the important push factors of intended or accomplished emigration.

The remainder of this chapter is organized as follows. In Section 3.2 we develop a testable hypothesis that can be brought to our data and that is inspired by the model laid out in detail in Chapter 2. In Section 3.3 we describe the empirical model and the data that we use in our analysis. In Section 3.4 we present and discuss our estimation results. Section 3.5 concludes.

3.2 Towards a Testable Hypothesis

In the following, we develop an empirically testable hypothesis that is motivated by the model in Chapter 2 and that can be brought to the data.

We depart from the model's general prediction that migration may be motivated by an individual's desire to avoid disutility from occupational stigma by changing his social environment. Importantly, we are not aware of any reliable empirical measure of occupational stigma, while we dispose of several indicators to measure occupational prestige. Therefore, we translate all considerations about occupational stigma into considerations about (low) occupational prestige. We make two central assumptions.

First, in line with the theoretical model in Chapter 2, we assume that individuals care about occupational prestige in the sense that they attribute some utility to the prestige of their occupation. This assumption seems to be compatible with the views on self-definition in social psychology. According to Ashforth and Kreiner (1999, 417), "[...] job titles serve as prominent identity badges. The robustness of occupational prestige rankings attests to the salience and importance that society ascribes to occupational identities."

Second, we assume that individuals evaluate both the prestige of their own occupation as well as the prestige of other individuals' occupations on the basis of comparisons with "similar" individuals. More specifically, we assume that individuals evaluate occupational prestige as the achievement in terms of prestige within the broad occupational category to which an individual's vocational training belongs. This means that the individuals considered for comparison work in occupations related to the considered category of vocational training.[10] To give an example, our assumption implies that an individual with a vocational training related to *Surface or underground construction* compares his current occupational prestige to that of individuals working in occupations related to *Surface or underground construction*, but not to individuals working in occupations related to *Electronics*. Thereby, the considered comparison is independent of the broad occupational category to which the individual's *current* occupation belongs, because it is meant to account for self-selection in terms of vocational training. At the same time,

[10] Even though we do not explicitly account for these individuals' vocational trainings when implementing the described comparison, it is likely that most of the individuals working in a specific occupational category have a related vocational training and are thus similar in terms of their vocational trainings.

by relating an individual's current occupation to his (vocational) training, the proposed comparison is closely related to the definitions of status inconsistencies reviewed in the introduction of this chapter.[11] Our second assumption seems to be consistent with social comparison theory in social psychology, which goes back to Festinger (1954).[12] Whereas Festinger (1954) is known for pointing out the role of similar individuals in terms of the "critical dimension" for social comparisons, subsequent research has emphasized the role of similar individuals in terms of "related attributes" (Corcoran et al., 2011, 124). Related attributes are "[...] closely associated with the critical dimension and partially determine the performance on the critical dimension" (Corcoran et al., 2011, 124). In our context, the "critical dimension" is current occupational prestige and the "related attribute" is the occupational prestige associated with the individual's vocational training. Clearly, the type of vocational training is a determinant of occupational prestige achieved in later occupations. Contrasting social comparison theory, which focuses on social comparisons as a means of individuals to evaluate their own abilities and opinions (see, e.g., Festinger, 1954), we presume that individuals also evaluate the prestige of the occupations held by members of their social environment in the above described way. We thus assume that individuals account for the fact that the members of their social environment have selected themselves into specific occupational fields via their vocational trainings. Based on the above assumptions and considerations, we formulate the following working hypothesis:

Hypothesis: *Individuals working in occupations with low prestige relative to the prestige of the occupations associated with their vocational training category are, ceteris paribus, more likely to migrate compared to individuals working in occupations with relatively high prestige. Migration in this context refers to a residential move that does not involve an improvement of occupational prestige.*

The logic underlying this hypothesis – as well as the more general prediction of the theoretical model – is that migration may serve as a means to change an individual's social environment. Thus, a sound test of this hypothesis in the described context requires us to abstract from any migration decision that is related to occupational upgrading. We will therefore focus on workers (migrants and non-migrants) who do not improve upon their

[11] For example, while Quinn and Rubb (2005) relate an individual's years of education to the average years of education in his occupation, we compare the prestige of an individual's current occupation to the average prestige of the occupations associated with the individual's vocational training. This will be explained in more detail in Section 3.3.

[12] Research on social comparisons in social psychology is concerned with the causes and consequences of individuals' comparisons to other individuals, as well as with the type of individuals considered for comparisons (Corcoran et al., 2011, 119).

occupational situations. In the next section, we describe in detail how we measure the two components of our hypothesis – the incidence of migration and relatively low occupational prestige – as well as the relevant set of control variables.

3.3 Empirical Model and Data

This section presents the empirical model and the data used in our analysis. We use information from the SOEP-Geocode database[13] to identify residential moves within Germany. All other variables are based on information that is also available in the regular SOEP database. The SOEP is a representative survey of households in Germany. Initiated in 1984, it is a panel study with a focus on individuals' well-being that tracks households over time and space; see Wagner et al. (2007) for a detailed description of the SOEP.

3.3.1 Migration

Our dependent variable is a binary variable indicating whether individual i has moved within Germany in a given period (MIG_i).[14] We only consider residential moves over a distance of at least 20 kilometers (km) as moves. Hence, our dependent variable is characterized as follows:

$$MIG_i = \begin{cases} 1 & \text{if } movedist_i \geq 20\,\text{km} \\ 0 & \text{if } 0 \leq movedist_i < 20\,\text{km}, \end{cases}$$

where $movedist_i$ is the moving distance observed for individual i. We employ a Probit model to estimate the conditional probability of a residential move for individual i:

$$\Pr\left(MIG_i = 1|\boldsymbol{x}\right) = \Phi\left(\boldsymbol{x_i'}\boldsymbol{\beta}\right)$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function, $\boldsymbol{x_i}$ is a vector of individual-level characteristics, and $\boldsymbol{\beta}$ is a vector of parameters to be estimated.[15]

3.3.2 Low Occupational Prestige

Our explanatory variable of main interest is an indicator variable for (relatively) low occupational prestige (LOP_i). This variable takes on the value one if the prestige level P_i associated with individual i's occupation at the beginning of a period does not exceed

[13] We accessed this information via remote computer access on the basis of an expanded data distribution contract with DIW Berlin.
[14] Information on the time frame is provided below.
[15] See Cameron and Trivedi (2005, Chapter 14) for further details on the Probit model.

the average prestige level of the occupations associated with the individual's vocational training V_i, $\bar{P}_{V_i}$; it takes on the value zero otherwise:

$$LOP_i = \begin{cases} 1 \text{ if } P_i \leq \bar{P}_{V_i} \\ 0 \text{ if } P_i > \bar{P}_{V_i}. \end{cases}$$

The sociological literature offers three scale types to measure occupational status: prestige measures, socioeconomic scales, and nominal class categories (Ganzeboom and Treiman, 1996, 203). Since we consider low occupational prestige as the flip side of occupational stigma, we rely on the first scale type and measure occupational prestige based on the Magnitude Prestige Scale (MPS), which is a prestige scale specifically constructed for Germany. This scale was originally developed by Wegener (1984) for the occupations of the International Standard Classification of Occupations 1968 (ISCO-68). To construct the scale, Wegener used information from three surveys in which individuals in Germany were asked to rank 50 different occupations in terms of their prestige. We rely on an updated version of this scale by Christoph (2005), MPS88, which was developed to match the revised classification ISCO-88. The values of MPS88 range from 20.0 (ISCO-88 unit group 9312, *Construction and maintenance labourers: roads, dams and similar constructions*; ISCO-88 unit group 9311, *Mining and quarrying labourers*) to 186.8 (ISCO-88 unit group 2422, *Judges*) (see Christoph, 2005, 119-126), with higher values indicating higher prestige.[16] We match the MPS88 values as given in Christoph (2005) to the ISCO-88 codes of individuals' occupations reported in the SOEP.[17] Ideally, we would proceed in a similar way concerning individuals' completed vocational trainings, and then compare the prestige of an individual's current occupation to the prestige of his vocational training.[18] However, we cannot do so because information on vocational training is only available at a rather aggregated level, which is the one of *Berufsabschnitte* of the German classification of occupations *Klassifikation der Berufe 1992* (KldB-92). Therefore, we calculate mean values of MPS88 for the different vocational training categories based on the matching of

[16] The matching of the English occupation titles is based on `http://doku.iab.de/fdz/EGS/Klassifikation_Berufe.xls`, accessed on 04/02/2012.

[17] In principle, individuals' occupations are classified at the ISCO-88 4-digit level such that we can directly match the values of MPS88 reported in Christoph (2005). However, for 2.7% of the sample observations (44 person-periods; see below), occupations are only reported at the ISCO-88 3-digit or 2-digit level. In order to retain these observations, we construct and consider mean values of MPS88 over the associated detailed occupations for these broader occupational categories.

[18] We summarize the following types of training in Germany under the heading of vocational training: *Lehre, Berufsfachschule, Schule des Gesundheitswesens, Fachschule (Meister, Techniker), Beamtenausbildung.*

the ISCO-88 4-digit occupations to the broad occupational classes of KldB-92 included in the SOEP.[19] Table 3.4 in the appendix reports the mean values for the relevant categories of vocational training, along with the minimum and maximum values of MPS88 as well as the numbers of observations. Based on these mean values, we classify the prestige of an individual's current occupation as low if the associated prestige level does not exceed the mean prestige level of the individual's vocational training category. Thereby, we have to exclude individuals with a vocational training in two KldB-92 categories because the variation of MPS88 within these categories is zero.[20] We rely on an indicator variable rather than on a continuous variable to measure (relatively) low occupational prestige because we do not want to put too much weight on precise prestige differences calculated on the basis of MPS88. Table 3.5 in the appendix lists individuals' occupations categorized as occupations with relatively low prestige by broad category of the individuals' vocational trainings. Two types of low-prestige occupations may be distinguished: occupations related to the individuals' vocational training categories and those unrelated to the individuals' vocational training categories. We treat these two types on an equal footing when constructing LOP_i, assuming that occupational prestige is judged on the basis of an individual's achievement relative to his training.[21]

To give an example, consider two individuals, each with a vocational training in the field of *Metal construction and machine construction* (KldB-92 *Berufsabschnitt* IIIg, $\bar{P}_{V_i} = 50.7$). One individual is working as an *Agricultural- or industrial-machinery mechanic and fitter* (ISCO-88 unit group 7233, $P_i = 47.4$), and the other one as a *Tool-maker and related worker* (ISCO-88 unit group 7222 $P_i = 52.6$). As the prestige level of an *Agricultural- or industrial-machinery mechanic and fitter* is smaller than the mean prestige level of occupations associated with *Metal construction and machine construction*, the indicator LOP_i is one for the first individual, indicating low occupational prestige. By contrast, the prestige level of a *Tool-maker and related worker* is larger than the relevant benchmark value. Therefore, LOP_i takes on the value zero for the second individual. Note that the

[19] We construct these mean values as weighted averages of MPS88 by KldB-92 *Berufsabschnitte* considering information from the entire SOEP on individuals aged 18 or older in the period 2001-2009 and applying the provided weighting factors. We exclude ISCO-88 occupations generally requiring tertiary education (occupations of ISCO-88 majors 2 and 3, see ILO, 1990, 3-4), as well as occupations classified as *Legislators, senior officials and managers* (ISCO-88 major 1).

[20] These are KldB-92 categories IIIs (*Helpers without further information on their activities*) and IVb (*Technicians, technical specialists*). Note that the English names of all KldB-92 categories are own translations by the author.

[21] 49.2% of the individuals working in occupations with low prestige ($LOP_i = 1$) work in occupations that are related to their vocational trainings.

occupations of both individuals pertain to the field of their vocational training.

3.3.3 Control Variables

A major challenge for our empirical analysis is the choice of an adequate set of control variables. Given that we intend to explicitly discriminate between a prestige dimension and an income dimension of (relatively) low status, we include indicator variables for (relatively) low and high income into our empirical model. These variables take on the value one for individuals with a net income that is lower (higher) than or equal to the 25-% (75-%) percentile of the net income earned in the occupations associated with the individuals' vocational training categories, and zero otherwise.[22]

Furthermore, our empirical model has to account for an individual's ability as well as his moving costs. These factors are likely to be correlated not only with the propensity to migrate, but also with the incidence of low occupational prestige. In our most demanding model specifications, we control for a rich set of socio-demographic and job characteristics, usually measured at the beginning of a migration period. We expect several of these variables to implicitly control for an individual's ability, such as the highest education level, the log of income, or the absolute prestige level of an individual's occupation.

We also control for other job and dwelling characteristics, as well as for an individual's attachment to his place of residence and social environment. These control variables are usually measured at the beginning of a migration period. In terms of job characteristics, we control for tenure, for whether an individual works in a different occupational field than his vocational training, for whether the individual has at least changed his occupation once, and for the satisfaction with his current job. Concerning the characteristics of the individual's dwelling and his attachement to his place of residence, we account for whether an individual has changed his district of residence (*Kreis*) in the previous year, for the number of years of residence in the current dwelling, for dwelling ownership, for satisfaction with the dwelling, and for whether the indivdiual judges his neighbourhood as good. In terms of the individual's attachment to his social environment, we control for the number of close friends and for whether he frequently meets his friends and relatives. The last two variables are included because individuals with strong local ties could have

[22] We construct these percentiles by KldB-92 *Berufsabschnitte* on the basis of the net labor income of individuals aged 18 or older with a full-time employment observed at the beginning of a given period. As for the construction of LOP_i, we consider information from the entire SOEP and apply the provided weighting factors. Similarly as above, we exclude ISCO-88 occupations generally requiring tertiary education (occupations of ISCO-88 majors 2 and 3), as well as occupations classified as *Legislators, senior officials and managers* (ISCO-88 major 1).

higher moving costs, making them less likely to move. Our last specification additionally includes indicator variables for the different Federal Lands in which the individuals were living at the beginning of a migration period.

In all specifications, we control for standard socio-demographic and household characteristics such as sex, age, German citizenship, whether an individual lives in East Germany at the beginning of a migration period, the presence of children in the household, marital status, as well as for an individual's willingness to take risks. Table 3.6 in the appendix provides detailed source information for all variables.

3.3.4 Sample

Our sample comprises individuals aged 18 or older with completed vocational training (but no university education) who work in a full-time job at the beginning of a period and for whom the SOEP reports the type of vocational training.[23] As explained above, we focus on individuals who did not improve upon their occupational prestige in a given period.[24] Due to reasons of data availability, we only consider individuals from sample F of the SOEP ("Innovation", initiated in 2000). One reason is that since 2001, the reported vocational trainings are based on more recent information obtained from the individuals, see Haisken-DeNew and Frick (2005, 70-71). Another reason is that information on individuals' moving distance is only available from 2001 onward. In line with other migration studies, we aggregate the yearly residential information, considering two five-year periods (2001-2005, 2005-2009).[25] An individual is identified as a mover by our dependent variable if he moved at least once over a distance of 20 km in a given period.[26] In principle, our sample consists of 1,636 person-periods for which we have information on the two variables of interest, MIG_i and LOP_i. Depending on the set of control variables included, the sample size is reduced in some estimations due to missing information for some control variables. We pool our data for the two periods in order to maximize the number of observations.[27]

Our analysis of residential moves within Germany with data from the SOEP is possible due to the "follow-up concept" of the household survey. This concept implies that indi-

[23] We exclude individuals with university education because we cannot apply the same definition of low occupational prestige to these individuals.

[24] In order to see whether an individual improved his occupational prestige, we compare the prestige levels of the individual's occupations at the beginning and at the end of a period.

[25] According to Long and Boertlein (1990, 5), such aggregation of information from several years avoids a strong influence of chronic movers and corrects for return and repeat migration.

[26] We do not consider individuals for whom the residential information contains gaps.

[27] The 1,636 person-periods cover 452 individuals whom we observe in both periods, and further 732 individuals whom we observe in only one period.

viduals are generally followed geographically in case they move within Germany (Haisken-DeNew and Frick, 2005, 22). Yet in some cases individuals cannot be re-interviewed because they have moved and no information on their places of residence is available. From an econometric point of view, panel attrition will constitute a problem in the context of our analysis if the attrition does not occur randomly but is indeed related to residential moves. Our concern about this type of problem is weakened, however, because the relative frequencies of successful follow-ups tabulated in Table 1 in Kroh (2011, 27) are quite high.

3.3.5 Descriptive Evidence

Table 3.1 provides a cross-tabulation of the indicator variables for migration and for low occupational prestige. It reports 58 migration events, correponding to 3.55% of the person-periods included in our sample.[28] We observe a single move within a given five-year period for 47 migration events, and two moves for the remaining 11 migration events. The average moving distance across the 58 migration events[29] is 121.42 km.[30]

Table 3.1: Cross-tabulation of the Indicator Variables MIG_i and LOP_i

		Above-average occupational prestige $LOP_i = 0$	Below-/average occupational prestige $LOP_i = 1$	Total
No move $MIG_i = 0$	absolute	1,145	433	1,578
	% row	72.56	27.44	100.00
	% column	95.98	97.74	96.45
Move $MIG_i = 1$	absolute	48	10	58
	% row	82.76	17.24	100.00
	% column	4.02	2.26	3.55
Total	absolute	1,193	443	1,636
	% row	72.92	27.08	100.00
	% column	100.00	100.00	100.00

Source: Author's tabulations using data from the SOEP.

[28] This incidence is lower than the incidence of migration reported in Jäger et al. (2010, 686), which amounts to 5.8%. We relate this observation to differences in the definition of migration (we consider a threshold for the moving distance rather than the criterion whether an individual has moved to another German region), in the length of the considered period (we look at two five-year intervals rather than at a single seven-year interval), as well as in the considered sub-sample of information from the SOEP.

[29] For person-periods with two moves, we consider the average moving distance in order to construct this value.

[30] For 26 migration events the (average) moving distance lies in the interval [20 km, 50 km), for 12 migration events in the interval [50 km , 99 km), and for 20 migration events the (average) distance is larger than 100 km.

Table 3.1 shows that person-periods characterized by above-average occupational prestige (in comparison to their vocational training) exhibit a higher incidence of migration (4.02%) compared to person-periods characterized by average or below-average occupational prestige (2.26%). This observation stands in contrast to our working hypothesis. 27.08% of all person-periods work in occupations with average or below-average occupational prestige. This percentage is about the same for non-movers (27.44%), but smaller for movers (17.24%). Movers and non-movers differ substantially with respect to their vocational trainings and occupational categories. Although the vocational trainings and occupations of movers do not cover each of the considered categories, their distributions neither exhibit a particular pattern, see Tables 3.4 and 3.5 in the appendix.

Table 3.2 provides summary statistics for the variables considered in our estimations. Looking at the mean values of some key variables, we see that most of our person-periods refer to individuals from West Germany (79%), who are male (69%), and on average aged 42. The majority of these individuals have a last schooling degree from the lowest or second-lowest schooling level (41% *Hauptschulabschluss* and 46% *Realschulabschluss*) and work in occupations with an average prestige level of 71. The average prestige gap relative to the minimum prestige level associated with the individuals' vocational trainings is positive and amounts to 34. 46% of the individuals work in an occupation that is not associated with their vocational training. 47% of the individuals are dwelling owners and the average length of residence in the current dwelling is 13 years. It is important to keep in mind that 55% of our person-periods consist of observations on individuals who are being observed in both periods.

Table 3.2: Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
MIG_i	1636	.035	.185	0	1
LOP_i	1636	.271	.444	0	1
Income $\leq p25$	1636	.181	.385	0	1
Income $\geq p75$	1636	.427	.495	0	1
Male	1636	.693	.462	0	1
Age	1636	41.537	9.831	19	70
German	1636	.983	.127	0	1
East Germany	1636	.212	.409	0	1
Hauptschulabschluss	1634	.412	.492	0	1
Realschulabschluss	1634	.460	.499	0	1
Fachhochschulreife/Abitur	1634	.103	.305	0	1
Other/no schooling degree	1634	.024	.155	0	1
Children in household	1636	.597	.491	0	1
Married, living together	1523	.675	.469	0	1
Married, living separated	1523	.012	.108	0	1
Single	1523	.259	.438	0	1
Divorced	1523	.039	.193	0	1
Widowed	1523	.015	.122	0	1
Tenure	1635	12.402	9.970	0	55.3
Absolute prestige level	1636	70.647	25.832	24.7	153.5
Log of net income	1631	7.301	.447	3.912	8.732
Work in different occupational field than vocational training	1636	.464	.499	0	1
Occupational change	1615	.446	.497	0	1
Prestige gap relative to min. prestige of vocational training	1636	33.624	26.476	-21.6	130.8
Dwelling owner	1590	.474	.499	0	1
Years in current dwelling	1514	12.900	11.428	0	64
Good neighbourhood	1626	.916	.277	0	1
Change of Kreis in previous year	1630	.028	.166	0	1
Frequent meetings with friends/ relatives	1632	.791	.407	0	1
Number of close friends	1574	4.179	3.688	0	50
Satisfaction with flat	1629	8.036	1.781	0	10
Satisfaction with job	1625	7.368	2.014	0	10
Willingness to take risks	1629	4.850	2.170	0	10

Source: Author's tabulations using data from the SOEP.

3.4 Estimation Results

This section presents and discusses our estimation results.

3.4.1 Results from Probit Estimation

Table 3.3 presents average marginal effects from Probit estimations of the incidence of migration along with robust standard errors. In all estimations we apply cross-sectional weighting factors.[31] The estimated specifications differ with respect to the included control

[31] As we only consider information from sample F of the SOEP, we obtain these factors by multiplying the cross-sectional weighting factors provided in the SOEP by the factor 2.22 as suggested in Haisken-DeNew

variables and, as a consequence, with respect to the sample size.

The average marginal effect of the incidence of low occupational prestige is negative throughout the different specifications, ranging from -0.037 to -0.022. It is always statistically significant at the 5-% or 10-% level. This implies that the probability of migration is smaller by 2.2 to 3.7 percentage points for an individual with an occupation characterized by average or below-average prestige relative to the occupations associated with his vocational training, compared to an individual with above-average occupational prestige, ceteris paribus. This finding confirms the unconditional negative relationship between these two variables reported above, but it clearly contradicts our working hypothesis. Before discussing this finding in more detail, we first look at the average marginal effects of the other explanatory variables.

The average marginal effects of the variables accounting for low and high income are never statistically significant at any reasonable significance level. This suggests that in our context the income dimension of (relative) occupational status is unrelated to residential mobility, ceteris paribus. The only dimension of (relative) occupational status that seems relevant for residential mobility is occupational prestige.

Table 3.3: Average Marginal Effects from Probit Estimations of the Incidence of Migration. Dependent Variable: MIG_i.

	(1)	(2)	(3)	(4)	(5)	(6)
Occupational prestige *(reference: $LOP_i = 0$)*						
$LOP_i = 1$	-.037**	-.034**	-.037**	-.022*	-.022*	-.022*
	(.015)	(.014)	(.015)	(.013)	(.013)	(.013)
Income position *(reference: p25 < Income < p75)*						
Income $\leq$ p25		-.006	-.006	.007	.008	.002
		(.014)	(.018)	(.015)	(.015)	(.015)
Income $\geq$ p75		.002	.002	-.013	-.015	-.010
		(.013)	(.014)	(.011)	(.012)	(.011)
Socio-demographic characteristics						
Male *(reference: female)*		.004	.003	-.025**	-.024**	-.020**
		(.012)	(.014)	(.011)	(.011)	(.010)
Age		-.000	-.000	-.000	-.000	-.001
		(.001)	(.001)	(.001)	(.001)	(.001)
German *(reference: non-German)*		.024	.026	omitted	omitted	omitted
		(.033)	(.033)			

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and Frick (2005, 177-178).

Table 3.3 *continued*

	(1)	(2)	(3)	(4)	(5)	(6)
East Germany *(reference: West Germany)*		-.011	-.012	-.004	-.003	.015
		(.014)	(.014)	(.011)	(.011)	(.024)
Realschulabschluss *(reference: Hauptschulabschluss)*		.039***	.040***	.035***	.033***	.035***
		(.015)	(.015)	(.013)	(.012)	(.013)
Fachhochschulreife/Abitur *(reference: Hauptschulabschluss)*		.019	.021	.033**	.032**	.029*
		(.018)	(.019)	(.016)	(.016)	(.018)
Other/no schooling degree *(reference: Hauptschulabschluss)*		.012	.015	omitted	omitted	omitted
		(.033)	(.033)			
Household characteristics						
Children in household *(reference: no children in household)*		-.031***	-.032***	-.025**	-.025**	-.030**
		(.012)	(.012)	(.011)	(.011)	(.012)
Married, living separated *(reference: married, living together)*		.074***	.074***	.038*	.037*	.047**
		(.026)	(.026)	(.021)	(.021)	(.022)
Single *(reference: married, living together)*		.022	.021	-.003	-.003	-.011
		(.016)	(.016)	(.011)	(.011)	(.011)
Divorced *(reference: married, living together)*		.025	.026	-.015	-.014	-.011
		(.026)	(.027)	(.025)	(.025)	(.024)
Widowed *(reference: married, living together)*		.047	.046	.054**	.056**	.052**
		(.031)	(.032)	(.024)	(.024)	(.025)
Job characteristics						
Tenure		-.003***	-.003***	-.001**	-.001**	-.001*
		(.001)	(.001)	(.001)	(.001)	(.001)
Absolute prestige level			-.000	-.000*	-.000	-.000
			(.000)	(.000)	(.001)	(.001)
Log of net income			.001	.034*	.037**	.030*
			(.021)	(.018)	(.018)	(.017)
Work in different occupational field than vocational training *(reference: work in same field)*				-.002	-.002	-.001
				(.011)	(.011)	(.012)
Occupational change *(reference: no change)*				.013	.014	.019
				(.012)	(.012)	(.014)
Prestige gap relative to min. prestige of vocational training category					-.000	-.000
					(.000)	(.000)

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Table 3.3 *continued*

	(1)	(2)	(3)	(4)	(5)	(6)
Dwelling characteristics						
Dwelling owner *(reference: no dwelling owner)*				-.021*	-.021*	-.023*
				(.012)	(.012)	(.013)
Years in current dwelling				-.002*	-.002*	-.002**
				(.001)	(.001)	(.001)
Good neighbourhood				-.009	-.010	-.004
				(.013)	(.013)	(.015)
Change of *Kreis* in previous year				-.010	-.012	-.015
				(.024)	(.024)	(.026)
Other personal characteristics						
Frequent meetings with friends/relatives *(reference: no frequent meetings)*				-.037***	-.037***	-.043***
				(.011)	(.011)	(.012)
Number of close friends				.001	.000	.000
				(.002)	(.002)	(.002)
Satisfaction with flat				-.009***	-.009***	-.011***
				(.003)	(.003)	(.003)
Satisfaction with job				.000	.000	-.000
				(.002)	(.002)	(.002)
Willingness to take risk				.001	.001	.001
				(.002)	(.002)	(.003)
Period 2005-2009 *(reference: 2001-2005)*				.006	.006	.006
				(.010)	(.010)	(.010)
Regional dummies	no	no	no	no	no	yes
Observations	1636	1520	1515	1219	1219	1129
Pseudo R^2	0.020	0.211	0.211	0.316	0.318	0.358

*,**,*** denote significance at the 10-%, 5-%, 1-% levels, respectively. Robust standard errors are reported in parentheses. The average marginal effects are based on the Delta method. Refer to Section 3.3 for a detailed description of the variables.

The effects of the control variables mostly have the expected signs. However, not all effects are statistically significant. In the following, our focus is on the average marginal effects that are statistically signficant at least at the 10-% level. All interpretations are ceteris paribus-interpretations. Men have a lower probability of migration than women. Individuals with intermediate or high schooling (*Realschulabschluss* or *Fachhochschulreife/Abitur)* are, on average, more likely to migrate relative to individuals with the lowest schooling degree (*Hauptschulabschluss*). In terms of household characteristics, we find that individuals with children in their household are on average less likely to move compared to individuals without children in their household. Married individuals living separated from their partner as well as widowed individuals have a higher probability to migrate compared to married individuals living together with their partner. Furthermore, concerning the different job characteristics, only tenure and the absolute level of income exhibit statistically significant average marginal effects. The probability of migration is on average larger for individuals with a large net income or only few years of tenure. In terms of dwelling characteristics, we find that individuals who have their own dwelling are characterized by, on average, a lower probability of moving than individuals without their own dwelling. Also, the probability of migration is decreasing in the number of years an individual has been living in his current dwelling. Our estimation results furthermore provide evidence that individuals who are attached to their social environment and current place of residence are characterized by low mobility: Individuals who frequently meet their friends and relatives or who are highly satisfied with their dwelling have, on average, a lower probability to move compared to individuals who are less attached to their current place of residence.

3.4.2 Robustness Analysis

We have argued above that we expect some of our control variables to implicitly control for individual ability. If this is not the case, individual ability may interfere with the incidence of low occupational prestige. As individual ability is likely to be positively correlated with the propensity to migrate but negatively correlated with the incidence of low occupational prestige, the coefficient for LOP_i may be estimated with a downward bias. If the bias is large enough, it will lead to an overall negative marginal effect of low occupational prestige on the incidence of migration. On the basis of this consideration, we additionally include a further proxy variable for indivdiual ability, defined as the difference between the prestige level of an individual's occupation and the minimum prestige level associated with his vocational training category, $P_i - Min(P_{V_i})$ (columns 5 and 6 in Table 3.3). If the estimated coefficients of our prestige indicator and the proxy variable for individual ability were to differ in terms of sign, this would indicate the presence of the above-described omitted variables problem. However, the average marginal effect of the proxy variable for individual ability turns out statistically insignificant, while at the same time the negative effect of LOP_i remains virtually unchanged. This weakens our concern about a possible omitted variable bias due to unobserved individual ability.

Furthermore, we have repeated our estimations additionally controlling for individuals' categories of vocational training with a set of indicator variables (not reported). The negative effect of LOP_i is robust to the inclusion of these additional control variables.

In another robustness check we have based our indicator variable for low occupational prestige on Treiman's Standard International Occupational Prestige Scale (SIOPS) instead of MPS88.[32] Using this alternative indicator variable, we have repeated the estimations from Table 3.3 (not reported).[33] The obtained average marginal effects for the alternative prestige indicator are negative, but they lose their statistical significance in the specifications of columns (2) to (6).[34]

We have also assessed the robustness of our results using the Logistic (Logit) and Ordinary Least Squares (OLS) estimators instead of the Probit estimator. The obtained estimates (not reported) are in line with those from the Probit estimations, both in terms of sign and in terms of magnitude. In particular, they confirm the negative relationship between the incidence of low occupational prestige and the propensity to move.

3.4.3 Discussion

The estimation results for our indicator variable of low occupational prestige attest to a negative effect of low occupational prestige on the propensity to migrate rather than to a positive or zero effect.[35] In the following, we present two possible explanations for this finding.

The first explanation is related to the costs of moving. Individuals employed in low-prestige occupations could face additional costs of moving deriving from a particularly strong attachment to their social (non-work) environment, within which their low-prestige occupation may be accepted. A move over a distance of at least 20 km may involve additional costs for this group of workers because – unlike other workers – they may have more difficulties in building up a new social environment.[36] In terms of the theoretical model considered in Chapter 2, this argument is equivalent to the existence of prohibitively high migration costs for the workers in the stigmatized sector. In the model, such high costs

[32] Based on 85 occupational prestige studies conducted in 51 countries, this international scale was originally established for the occupational categories of the International Standard Classification of Occupations 1968 (ISCO-68) by Treiman (1977). Several years later, Ganzeboom and Treiman (1996) updated the SIOPS for the revised International Standard Classification of Occupations ISCO-88. The updated SIOPS ranges from 6 to 78, with higher values indicating higher prestige; see the listing in Ganzeboom and Treiman (1996, 221-237).

[33] For the sake of consistency, we also measure the absolute level of occupational prestige (which enters as a control variable) using the SIOPS in these estimations.

[34] This may be due to the fact that our sample is slightly decreased when using the alternative prestige scale to construct our variables of major interest. We are left with 1520 person-periods for whom we observe the two variables of major interest. A migration event is reported for 54 of these person-periods.

[35] One could argue that due to cheap communication and transportation technologies, these days a residential move within Germany does not necessarily imply a displacement from an individual's social environment. However, on the basis of this argument, we would expect to find a zero average marginal effect and not a negative effect for the indicator variable of low occupational prestige.

[36] Note that the costs associated with dealing with occupation-related prejudices by unknown individuals (e.g., potential landlords) should be already captured by the variable controlling for the absolute prestige level of an individual's occupation.

would discourage any incentive to migrate associated with the desire to reduce disutility from occupational stigma. The existence of additional migration costs for workers in low-prestige occupations could thus explain the lower propensity to migrate for these workers relative to workers in occupations with higher prestige.

The second possible explanation is inspired by Ashforth and Kreiner (1999, 419-420), who argue that individuals performing "dirty work" may develop "strong occupational or workgroup cultures". One could argue that strong occupational cultures alleviate the disutility from low occupational prestige, eventually confering a positive utility to the workers concerned. If this effect is large enough for workers in occupations with low prestige ("dirty work"), i.e., if the positive effect due to a strong occupational culture dominates the negative effect due to low occupational prestige, this may as well explain our estimation results.[37]

Although either one of the above explanations appears plausible, we are not in a position to give a final answer to the question of what is responsible for the negative effect of low occupational prestige on migration. In particular, as far as we know the SOEP does not provide information on the strength of occupational cultures. Whatever type of mobility-impeding force is at work, it is strong enough to dominate any mobility-enhancing motive related to disutility from low occupational prestige.

3.5 Conclusion

This chapter has presented a first attempt to empirically assess a recent prediction from the theoretical migration literature, according to which migration may be driven by a desire to avoid disutility associated with occupational stigma, see Fan and Stark (2011). Thereby, the role of migration is to bring about a change in an individual's social environment. Using individual-level data from the German SOEP, we have tested the hypothesis that individuals working in occupations with low prestige relative to the occupations associated with their vocational training category are more likely to migrate compared to individuals in occupations with relatively high prestige – even if this migration does not involve an improvement in terms of occupational prestige. Our estimations for the likelihood of moving over a distance of at least 20 kilometers within Germany have included a rich set of control variables. The results obtained from these estimations robustly reject our

[37] In a similar vein, one could argue that leaving such an occupational subculture confers additional costs in the case of migration, because it takes some time until a worker integrates into a corresponding occupational subculture at his new place of residence.

working hypothesis. They suggest that workers in occupations with low prestige relative to the prestige of the occupations associated with their vocational training are on average characterized by a smaller propensity to migrate within Germany, ceteris paribus. We have argued that our finding could derive from particularly high costs of moving or particularly strong occupational cultures relevant for the considered group of workers.

Our empirical analysis is the first to discriminate between the potential effects of relative occupational prestige and relative income on the migration decision, in addition to the effects of absolute prestige and absolute income. On the one hand, our results reveal a negative relationship between the incidence of relatively low occupational prestige and migration, while they do not reveal any significant relationship between an individual's relative income position and his propensity to migrate. Absolute income, on the other hand, is a significant predictor of migration. The effect of absolute occupational prestige, by contrast, is not significantly different from zero. These results appear to be compatible with the observation that individuals in Germany talk more openly about (and thus are more likely to compare) their occupations and education levels than they talk about their incomes.

In future work on this topic it would be interesting to look at internal migration in a different country. Due to the comparatively high residential mobility of individuals in the United States (see, e.g., Molloy et al., 2011), a thorough analysis of the status-related determinants of internal migration in the United States might constitute a worthwhile empirical exercise. Thereby, a distinction between the potential effects of relative occupational prestige and income may complement the work of Lee et al. (2009). Another interesting avenue for future work would be to study the exact forces underlying our main finding. This involves high data requirements. Lastly, it would also be interesting to extend the conventional survey questions on individuals' motives for migration by a question on the role of status considerations.

3.6 Appendix to Chapter 3

Table 3.4: Prestige Characteristics of Individuals' Vocational Training Categories

Occupational category of vocational training (KldB-92 *Berufsabschnitte*, author's translations)		**Mean MPS88 ($\bar{P}_{V_i}$)**	**Min MPS88**	**Max MPS88**	**Observations (migrants)**
Ia	Occupations in agriculture, animal husbandry, forestry and horticulture	38.1	23.9	60.0	55 (1)
IIa	Occupations related to mining and mineral extraction	41.3	20.0	45.9	5
IIIb	Occupations concerned with ceramic and glass	36.8	36.1	45.6	2
IIIc	Occupations concerned with chemicals and syntheticals	43.8	39.9	46.8	9
IIId	Occupations related to the manufacturing and processing of paper and print	52.9	31.6	64.2	15 (1)
IIIe	Occupations related to the manufacturing and processing of paper and print	39.8	31.6	58.8	1
IIIf	Occupations related to the production and processing of metals	43.2	33.9	49.6	27 (1)
IIIg	Occupations related to metal construction and machine construction	50.7	31.9	63.0	338 (5)
IIIh	Occupations related to electronics	53.9	49.9	62.3	123 (4)
IIIi	Occupations related to assembling and metals	39.7	31.9	42.7	4
IIIk	Occupations in the textile and apparel industry	42.7	41.5	58.8	25 (1)
IIIl	Occupations related to the production of leather and the processing of leather and fur	50.4	41.5	51.1	8 (1)
IIIm	Occupations related to alimentation	50.6	48.3	55.0	82 (5)
IIIn	Occupations related to surface or underground construction	41.7	20.0	53.4	60 (4)
IIIo	Occupations related to finishes and upholsterers	49.7	35.6	56.8	37 (3)
IIIp	Occupations related to the processing of wood and plastics	51.2	29.3	53.1	30
IIIq	Painters and lacquerers	52.2	36.1	52.5	37 (2)
IIIr	Inspectors and distribution workers	44.8	31.8	46.7	3
IIIt	Machine operators and related occupations	38.1	31.8	51.6	1
Va	Merchants	53.9	38.3	73.1	163 (7)
Vb	Service merchants and related occupations	85.5	35.6	92.1	82 (3)
Vc	Occupations in transportation	43.2	26.7	76.6	28
Vd	Occupations concerned with organization, administration and office	74.3	32.4	93.6	245 (9)
Ve	Occupations in public order and security	60.8	36.8	85.3	23
Vf	Writers and producers of art	47.3	36.1	75.7	5
Vg	Occupations related to health services	57.5	56.9	60.2	114 (6)
Vh	Occupations in welfare and education, and others	57.0	56.9	57.3	51 (3)
Vi	Other service occupations	46.0	28.6	77.9	63 (2)

Source: Author's tabulations using data from the SOEP. See Section 3.3 for details.

Table 3.5: Individuals Working in Occupations with Relatively Low Prestige, by Vocational Training Category and Current Occupation

Occupational category of vocational training (KldB-92 *Berufsabschnitte*, author's translations)		Mean MPS88 ($\bar{P}_{V_i}$)	Occupation (ISCO-88 4-digit level)		MPS88 (P_i)	Observations (migrants)
Ia	Occupations in agriculture, animal husbandry, forestry and horticulture	38.1	8122	Metal melters, casters and rolling-mill operators	33.9	2
			6112	Gardeners, horticultural and nursery growers	36.6	7
IIId	Occupations related to the manufacturing and processing of paper and print	52.9	9132	Helpers and cleaners in offices, hotels and other establishments	30.0	1
			8232	Plastic-products machine operators	39.9	1
			8211	Machine-tool operators	42.7	1
IIIf	Occupations related to the production and processing of metals	43.2	7212	Welders and flame cutters	38.3	1
			8324	Heavy truck and lorry drivers	40.7	4
IIIg	Occupations related to metal construction and machine construction	50.7	9313	Building construction labourers	24.7	2
			8334	Lifting-truck operators	26.7	1
			9330	Transport labourers and freight handlers	26.9	9
			8290	Other machine operators not elsewhere classified	31.8	2
			9320	Manufacturing labourers	32.4	2
			8332	Earth-moving and related plant operators	36.8	3
			9152	Doorkeepers, watchpersons and related workers	36.8	2
			7212	Welders and flame cutters	38.3	2
			8322	Car, taxi and van drivers	38.3	7
			8232	Plastic-products machine operators	39.9	1
			8323	Bus and tram drivers	40.5	3
			8324	Heavy truck and lorry drivers	40.7	13
			7143	Building structure cleaners	41.2	1
			8333	Crane, hoist and related plant operators	41.5	3
			8211	Machine-tool operators	42.7	9
			8121	Ore and metal furnace operators	43.7	1
			9141	Building caretakers	44.7	5
			4142	Mail carriers and sorting clerks	45.1	1
			7122	Bricklayers and stonemasons	45.3	2
			7214	Structural-metal preparers and erectors	45.4	15
			7134	Insulation workers	45.6	1

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Table 3.5 *continued*

Occupational category of vocational training (KldB-92 *Berufsabschnitte*, author's translations)		**Mean MPS88 ($\bar{P}_{V_i}$)**	**Occupation (ISCO-88 4-digit level)**		**MPS88 (P_i)**	**Observations (migrants)**
			8159	Chemical-processing-plant operators not elsewhere classified	46.0	3
			4131	Stock clerks	46.7	9
			7213	Sheet-metal workers	47.1	6
			7233	Agricultural- or industrial-machinery mechanics and fitters	47.4	42
			8278	Brewers, wine and other beverage machine operators	48.3	1
			7223	Machine-tool setters and setter-operators	48.5	5
			7124	Carpenters and joiners	48.7	1
			8163	Incinerator, water-treatment and related plant operators	49.0	2
			7241	Electrical mechanics fitters and services	49.9	1
IIIh	Occupations related to electronics	53.9	9132	Helpers and cleaners in offices, hotels and other establishments	30.0	2
			8322	Car, taxi and van drivers	38.3	1
			8324	Heavy truck and lorry drivers	40.7	3
			6100	Skilled agricultural and fishery workers	44.0	1
			4142	Mail carriers and sorting clerks	45.1	4
			7241	Electrical mechanics fitters and services	49.9	10 (1)
			7136	Plumbers and pipe fitters	51.0	4
IIIk	Occupations related to textile and apparel industry	42.7	9320	Manufacturing labourers	32.4	2
			7143	Building structure cleaners	41.2	4 (1)
			7436	Sewers, embroiderers and related workers	41.5	1
IIIm	Occupations related to alimentation	50.6	8334	Lifting-truck operators	26.7	1
			9330	Transport labourers and freight handlers	26.9	1
			9132	Helpers and cleaners in offices, hotels and other establishments	30.0	1
			8290	Other machine operators not elsewhere classified	31.8	1
			8253	Paper-products machine operators	36.1	1
			8322	Car, taxi and van drivers	38.3	2
			8323	Bus and tram drivers	40.5	4
			8211	Machine-tool operators	42.7	2

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Table 3.5 *continued*

Occupational category of vocational training (KldB-92 *Berufsabschnitte*, author's translations)		**Mean MPS88 ($\bar{P}_{V_i}$)**	**Occupation (ISCO-88 4-digit level)**		**MPS88 (P_i)**	**Observations (migrants)**
			8159	Chemical-processing-plant operators not elsewhere classified	46.0	2
			4131	Stock clerks	46.7	2
			8221	Pharmaceutical-and toiletry-products machine operators	46.8	1
			7233	Agricultural- or industrial-machinery mechanics and fitters	47.4	2
			5122	Cooks	49.8	7 (1)
			7411	Butchers, fishmongers and related food preparers	49.9	5
IIIn	Occupations related to surface or underground construction	41.7	9330	Transport labourers and freight handlers	26.9	1
			8332	Earth-moving and related plant operators	36.8	5
			8322	Car, taxi and van drivers	38.3	1
			8323	Bus and tram drivers	40.5	1
IIIo	Occupations related to finishes and upholsterers	49.7	9313	Building construction labourers	24.7	1
			7437	Upholsterers and related workers	35.6	1
			8324	Heavy truck and lorry drivers	40.7	2
			6100	Skilled agricultural and fishery workers	44.0	4
			7131	Roofers	47.2	4
			7124	Carpenters and joiners	48.7	4
IIIp	Occupations related to the processing of wood and plastics	51.2	8143	Papermaking-plant operators	31.6	1
			8290	Other machine operators not elsewhere classified	31.8	1
			9320	Manufacturing labourers	32.4	1
			8122	Metal melters, casters and rolling-mill operators	33.9	1
			8323	Bus and tram drivers	40.5	3
			8324	Heavy truck and lorry drivers	40.7	1
			8231	Rubber-products machine operators	41.4	1
			7423	Woodworking machine setters and setter-operators	42.1	1
			6100	Skilled agricultural and fishery workers	44.0	1
			9141	Building caretakers	44.7	2

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Table 3.5 *continued*

Occupational category of vocational training (KldB-92 *Berufsabschnitte*, author's translations)		**Mean MPS88 ($\bar{P}_{V_i}$)**	**Occupation (ISCO-88 4-digit level)**		**MPS88 (P_i)**	**Observations (migrants)**
IIIq	Painters and lacquerers	52.2	9320	Manufacturing labourers	32.4	1
			8324	Heavy truck and lorry drivers	40.7	2
			8151	Crushing-, grinding- and chemical-mixing-machinery operators	44.8	1 (1)
			4142	Mail carriers and sorting clerks	45.1	1
			7214	Structural-metal preparers and erectors	45.4	1
Va	Merchants	53.9	9330	Transport labourers and freight handlers	26.9	1
			9320	Manufacturing labourers	32.4	2
			8322	Car, taxi and van drivers	38.3	1 (1)
			8232	Plastic-products machine operators	39.9	1
			8324	Heavy truck and lorry drivers	40.7	1
			6100	Skilled agricultural and fishery workers	44.0	1
			4131	Stock clerks	46.7	4
			7124	Carpenters and joiners	48.7	2
			7442	Shoe-makers and related workers	51.1	1
			5220	Shop, stall and market salespersons and demonstrators	53.8	24
Vb	Service merchants and related occupations	85.5	6112	Gardeners, horticultural and nursery growers	36.6	1
			4142	Mail carriers and sorting clerks	45.1	1
			5220	Shop, stall and market salespersons and demonstrators	53.8	1
			4221	Travel agency and related clerks	60.2	1
			3431	Administrative secretaries and related associate professionals	73.2	3
			4133	Transport clerks	76.6	4
Vc	Occupations in transportation	43.2	8332	Earth-moving and related plant operators	36.8	1
			8322	Car, taxi and van drivers	38.3	1
			6129	Animal producers and related workers not elsewhere classified	39.2	1
			8324	Heavy truck and lorry drivers	40.7	2
			8211	Machine-tool operators	42.7	1

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Table 3.5 *continued*

Occupational category of vocational training (KldB-92 *Berufsabschnitte*, author's translations)		**Mean MPS88 ($\bar{P}_{V_i}$)**	**Occupation (ISCO-88 4-digit level)**		**MPS88 (P_i)**	**Observations (migrants)**
Vd	Occupations concerned with organization, administration and office	74.3	8290	Other machine operators not elsewhere classified	31.8	1
			9320	Manufacturing labourers	32.4	1
			8324	Heavy truck and lorry drivers	40.7	1
			4142	Mail carriers and sorting clerks	45.1	5
			4131	Stock clerks	46.7	3
			4141	Library and filing clerks	47.9	1
			7124	Carpenters and joiners	48.7	1
			7231	Motor vehicle mechanics and fitters	52.9	2
			5220	Shop, stall and market salespersons and demonstrators	53.8	4
			5123	Waiters, waitresses and bartenders	55.4	1
			7137	Building and related electricians	56.0	1
			4221	Travel agency and related clerks	60.2	1 (1)
			4222	Receptionists and information clerks	60.2	1
			4223	Telephone switchboard operators	60.2	2
			3152	Safety, health and quality inspectors	66.0	1
			4212	Tellers and other counter clerks	67.1	4
			4211	Cashiers and ticket clerks	67.4	2
			4111	Stenographers and typists	73.1	2
			4115	Secretaries	73.1	10
			4190	Other office clerks	73.1	27 (1)
			3431	Administrative secretaries and related associate professionals	73.2	13 (1)
Vg	Occupations related to health services	57.5	5132	Institution-based personal care workers	57.3	15 (1)
Vh	Occupations in welfare and education, and others	57.0	5122	Cooks	49.8	1
			7231	Motor vehicle mechanics and fitters	52.9	1
			7422	Cabinetmakers and related workers	53.1	1
			5131	Child-care workers	56.9	2
			5139	Personal care and related workers not elsewhere classified	56.9	1

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Table 3.5 *continued*

Occupational category of vocational training (KldB-92 *Berufsabschnitte*, author's translations)		**Mean MPS88 ($\bar{P}_{V_i}$)**	**Occupation (ISCO-88 4-digit level)**		**MPS88 (P_i)**	**Observations (migrants)**
Vi	Other service occupations	46.0	8322	Car, taxi and van drivers	38.3	1
			7143	Building structure cleaners	41.2	1
			8261	Fibre-preparing-, spinning- and winding-machine operators	44.2	1 (1)
			7134	Insulation workers	45.6	1

Source: Author's tabulations using data from the SOEP. See Section 3.3 for details.

Table 3.6: Data Sources

Variable	**Source: *Variable* (Dataset) in the SOEP (v28)**
MIG_i: Indicator for residential move over at least 20 km, periods 2001-2005 and 2005-2009	Own variable construction based on *resmove* and *distance* (movedist)
LOP_i: Indicator for low occupational prestige, 2001 and 2005	Own variable construction based on *is8801, traina01, trainb01, trainc01, traind01, rpbbil02* (rpgen), *is8805, traina05, trainb05, trainc05, traind05, vpbbil02* (vpgen); matching of MPS88 to *is8801, is8805* based on Christoph (2005)
Indicator for low or high income, 2001 and 2005	Own variable construction based on *labnet01* (rpgen), *labnet05* (vpgen)
Indicator for being male	*sex* (ppfad)
Age	Own variable construction based on *gebjahr* (ppfad)
Indicator for German citizenship, 2001 and 2005	*rp115* (rp), *vp135* (vp)
Indicator for East Germany, 2001 and 2005	*rsampreg, vsampreg* (ppfad)
Indicators for different schooling levels attained, 2001 and 2005	*rpsbil* (rpgen), *vpsbil* (vpgen) (own recoding)
Indicator for household with children, 2001 and 2005	*typ1hh01* (rhgen), *typ1hh05* (vhgen) (own recoding)
Indicators for different types of family status, 2001 and 2005	*rfamstd* (rpgen), *vfamstd* (vpgen)
Tenure, 2001 and 2005	*rerwzeit* (rpgen), *verwzeit* (vpgen)
Magnitude prestige scale	*is8801* (rpgen), *is8805* (vpgen); matching of MPS88 to *is8801, is8805* based on Christoph (2005)
(Ln of) Net income, 2001 and 2005	*labnet01* (rpgen), *labnet05* (vpgen)
Indicator for work in different occupational field than vocational training	Own variable construction based on *klas01, traina01, trainb01, trainc01, traind01, rpbbil02* (rpgen) and *klas05, traina05, trainb05, trainc05, traind05, vpbbil02* (vpgen)
Indicator for at least one occupational change	*occmove* (biojob) (own recoding)

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Table 3.6 *continued*

Variable	**Source: *Variable* (Dataset) in the SOEP (v28)**
Prestige gap relative to minimum prestige of vocational training category	Own variable construction based on *is8801, traina01, trainb01, trainc01, traind01* (rpgen), *is8805, traina05, trainb05, trainc05, traind05* (vpgen); matching of MPS88 to *is8801, is8805* based on Christoph (2005)
Indicator for dwelling ownership, 2002 and 2007	*sp85a01* (sp), *xp126a01* (xp)
Years in current dwelling	Own variable construction based on *brmovein, erhebj* (bioresid) and *resmove* (movedist)
Indicator for whether household is located in good neighbourhood, 2001 and 2005	*rh5311* (rh), *vh5413* (vh)
Indicator for whether household changed *Kreis* in previous year, 2001 and 2005	Own variable construction based on *kkz* (kreise_l)
Indicator for frequent meetings with friends/relatives, 2001 and 2005	*rp0305* (rp), *vp0305* (vp) (own recoding)
Number of close friends, 2003 and 2008	*tp06* (tp), *yp06* (yp)
Satisfaction with dwelling, 0-10, 2001 and 2005	*rp0105* (rp), *vp0106* (vp)
Satisfaction with job, 0-10, 2001 and 2005	*rp0102* (rp), *vp0102* (vp)
Willingness to take risks, 0-10, 2004	*up119* (up)
Indicators for the Federal Lands of residence, 2001 and 2005	*nuts2* (ror_l) (own recoding)

See Section 3.3 for details on the construction of the variables.

CHAPTER 4

Migration to Spain in the Period 1997-2009

4.1 Introductory Remarks

Spain has long been a classical country of emigration. Yet, its strong economic growth over the past twenty years and its liberal immigration policy have put Spain among the world's major countries of immigration. From 1995 to 2010, the stock of foreign-born individuals residing in Spain has risen by 5.3 million people. This is by far the largest increase experienced by any country in the world, the United States being the only exception.[1] This chapter presents key stylized facts on the recent Spanish immigration boom, evaluating migration data from the period 1997-2009. We draw attention to both the country and the province margin of migration in order to motivate the Spanish experience as a unique case for an empirical study of network effects in migration. We start out with a brief description of the policy setting and subsequently provide a first systematic look at the data, paving the way for the econometric analyses presented in Chapters 5 and 6.

This chapter is based on a joint work with Marcel Smolka. The concept for this chapter was developed jointly, while the empirical analysis and writing were shared equally.

[1] Besides Spain, the countries with the largest increase in the stock of foreign-born individuals from 1995 to 2010 are the United States (14.3 million additional people), Italy (2.7), the United Kingdom (2.3), Canada (2.2), and Germany (1.8). These figures come from the World Development Indicators 2010, The World Bank. From 2000 to 2008, Spain experienced the highest growth rate of the foreign-born population recorded in any OECD country over a short period of time after World War II (OECD, 2010, 240).

4.2 The Spanish Immigration Policy

It was not until the 1990s that immigration became a vital policy issue in Spain; see Ortega Pérez (2003) for this and the following information. Before, European legislation had prompted the socialist government to approve the restrictive *"Law on the Rights and Freedoms of Aliens in Spain"* in 1985 (*Ley Orgánica 7/1985*). Its 1996 amendment marks a relevant political turning point in that it recognizes immigration as a "structural phenomenon" and grants foreigners important rights such as access to education and legal counsel. This more liberal stance towards immigration is reflected in the *"Law on the Rights and Freedoms of Aliens in Spain and their Social Integration"* (*Ley Orgánica 4/2000*), which was meant to foster integration and further expanded the rights of foreigners in Spain. The law provoked a controversial debate, and the rights it granted to undocumented immigrants were partly withdrawn by the conservative party after winning the absolute majority in the general elections of March 2000, see *Ley Orgánica 8/2000.* In recent years, the socialist government has initiated measures to counteract undocumented immigration and to better integrate documented immigrants, see OECD (2006, 214). For example, in 2005, an unprecedented regularization process took place and a well-endowed integration fund was introduced. A recent reform of the *"Law on the Rights and Freedoms of Aliens in Spain and their Social Integration"* provides immigrants, whether legally or illegally residing in Spain, with rights of assembly, demonstration, unionization, and strike, see OECD (2010, 240) and *Ley Orgánica 2/2009.* In addition, it facilitates sanctions against people housing visa overstayers (OECD, 2010, 240).

4.3 The Extensive Margin and the Intensive Margin of Migration to Spain

We explore Spanish data from 1997 to 2009 on both the volume of immigrant inflows and the size of the migrant population, detailed by year, nationality, and Spanish province (*provincia*) or region (*comunidad o ciudad autónoma*). Information on migration flows and stocks come from the Spanish Residential Variation Statistics and the Municipal Register, respectively. Both series are freely available from the website of the Spanish Instituto Nacional de Estadística (INE).[2] A major advantage of these data relative to those from

[2] The only exception is the migration stock data reported for 1997, which we separately requested from INE. These stocks are actually observed at May 1, 1996. From 1998 on, stocks are observed at January, 1. For the internet sources of the data, see Table 6.7 in the appendix to Chapter 6 (Section 6.6.5).

other countries is that they are likely to include both documented and undocumented immigrants who registered at Spanish municipalities (*municipios*) from 2000 onwards.[3]

From 1997 to 2009, a total of 5,960,312 immigrants registered at Spanish municipalities. By immigrants we mean people who were born outside Spain, hold a foreign nationality, and come from a foreign country. Abstracting from a stagnation of the inflow in 2003, the data series from 1997 to 2007 report a strictly monotone upward trend in both the size of the total immigrant population and the number of new immigrants per year. This fact suggests that Spanish immigration is more of a permanent nature, rather than just temporary. The inflow peaked in 2007 at 915 thousand immigrants, a number that is 26 times the inflow in 1997. Beginning in 2007, the global financial and economic crisis has hit the Spanish economy hard, with many firms shutting down or reducing production and laying off workers. The economic downturn coincides with a sharp decline in the number of newly arriving immigrants in 2008 and 2009, relative to the pre-crisis years. We may summarize these findings as

Stylized Fact 1. *From 1997 to 2007, continuous and considerable increases in annual immigrant inflows have boosted the foreign-born population in Spain. The global financial and economic crisis marks a preliminary end to the Spanish immigration boom.*

Aggregate numbers on immigrant stocks and flows hide important cross-country variation. The following statistics paint a more differentiated picture of the Spanish immigration experience. More precisely, we portray changes both at the *intensive margin* and at the *extensive margin* of migration. By intensive margin we mean annual migration flows from a given subset of traditional migrant-sending countries, while we refer to the number of migrant-sending countries as the extensive margin. From 1997 to 2009, a total of 39 countries have sent at least 100 migrants to Spain in each and every year. The aggregate inflow of these countries was equal to 32.5 thousand people in 1997, and climbed to 762.6 thousand in 2007. Figure 4.1 compares yearly stock and flow data for the six major origin countries over the period considered. Together, these countries account for more than 2.9 million new immigrants in Spain, which is roughly half of the overall immigration to Spain.[4] Leaving aside the year 2009, we see a steady and significant increase in the immigrant population of people with Romanian, Moroccan, Bolivian, and British nationality.

[3] This issue will be explained and discussed in more detail in Chapters 5 and 6.

[4] Romanians make up 13.6% of all new immigrants from 1997-2009, followed by Moroccans (11.1%), Ecuadorians (8.2%), Colombians (6.1%), Britons (5.3%), and Bolivians (4.7%).

In contrast, the number of immigrants born in Ecuador (Colombia) stagnates around 450 (250) thousand people since 2004 (2003). The development of migrant inflows over time is more heterogeneous across origin countries than that of migrant stocks. The general upward trend in the number of new immigrants beginning in 1997 applies to all nationalities, but it is most extensive (in time and size) for Romanian and Moroccan people. Such differences must be due to time-variant source country characteristics or time-variant bilateral factors. In contrast, the joint decrease in the number of new immigrants in 2009 can be attributed to the global financial and economic crisis. This time-specific shock has, at least in principle, a uniform impact on all migration flows to Spain.

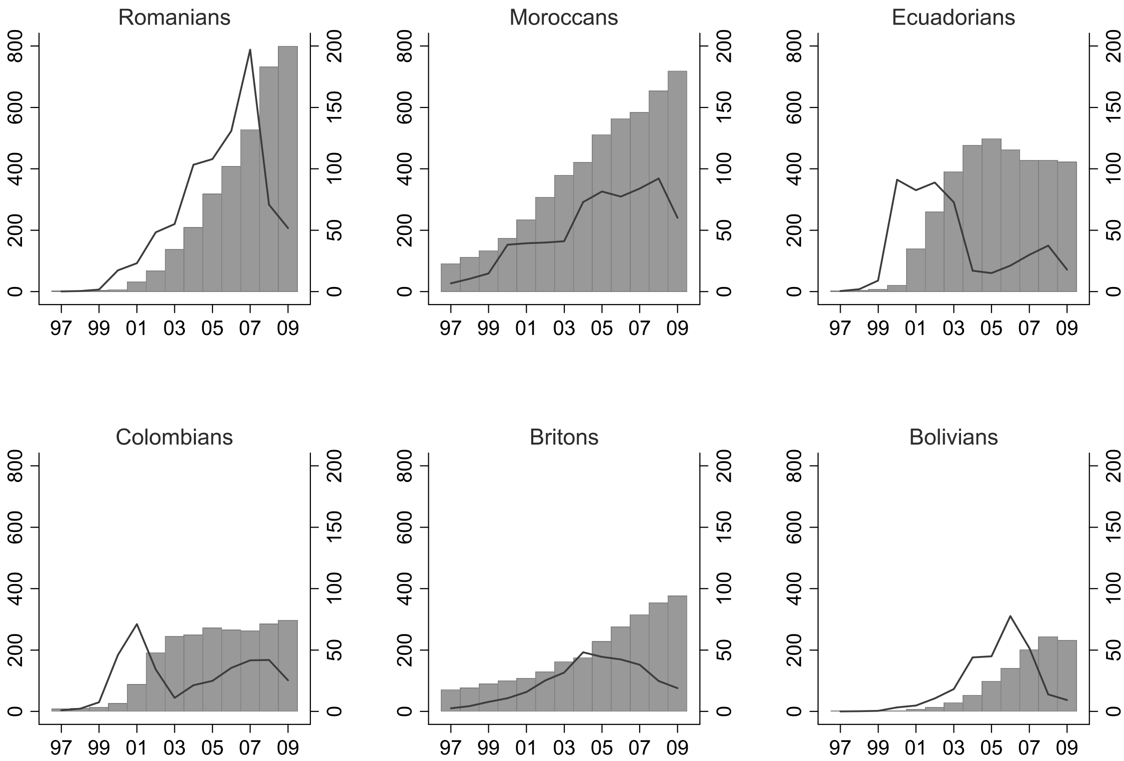


Figure 4.1: Migration Stocks and Inflows in Thousands, Spain 1997 to 2009

This figure shows immigrant stocks in Spain (bars, left ordinate) and inflows to Spain (lines, right ordinate) by nationality for the six major origin countries over the period 1997-2009. Numbers are given in thousands ('000s). *Source:* Authors' tabulations using data from INE.

In addition to the voluminous increases at the intensive margin, Spain has also experienced considerable changes at the extensive margin of migration over the time span considered. In 1997, Spain was the destination of at least 100 migrants from each of a total of 39 countries. For 2009, this number was 100 countries. At the same time, immigrants have targeted ever more provincial destinations in Spain. For example, in 1997, individuals from the 39 traditional migrant-sending countries moved to approximately 30 of a total of 52 different Spanish provinces on average. For 2007, this number was 48 provinces, and it remained that high in the two subsequent years. This same trend can also be observed for all origin countries, albeit on a lower level.[5] We summarize this as

Stylized Fact 2. *In quantitative terms, the Spanish immigration boom is borne by huge increases at the intensive margin of migration. Changes at the extensive margin have, however, greatly expanded the degree of ethnic diversification of recent migration flows. On average, new immigrants have spread over an ever more extensive set of destination provinces.*

4.4 The Regional Distribution of Migrants in Spain

We next take a closer look at the regional distribution of foreign-born individuals in Spain relative to the regional distribution of natives. Figure 4.2 depicts "concentration curves" for each of the six major source countries. Each subfigure plots the cumulative proportion of Spanish nationals (ordinate) against the cumulative proportion of foreign nationals (abscissa), separately for the years 1999 (dashed curves) and 2009 (solid curves). The units of geographical reference are Spanish provinces, sorted in descending order based on the share of immigrants in the total province's population, see Duncan and Duncan (1955, 210-211) for the same approach.[6] The 45-degree line is a benchmark indicating no difference in the spatial concentration between immigrants and natives, or zero clustering. Two patterns stand out. First, all concentration curves deviate from the 45-degree line to a significant extent. Hence, the spatial diffusion of each of the groups of immigrants differs from that of natives both at the beginning and the end of the Spanish immigration boom. These differences are more pronounced for some sources than for others. For example, in 1999, approximately 70% of all immigrants from Ecuador resided in provinces in which only 20% of all Spanish people lived, while the same number for Moroccan and Colombian immigrants is only 50%. Second, each source country's concentration curve for the year 1999 lies strictly to the right of the corresponding curve for the year 2009. We conclude that the geographical distributions of the major immigrant populations have become more similar to that of natives over time, although there are again relevant differences across

[5] In 1997, immigrants from all different origin countries moved to nine destination provinces in Spain on average. In 2008, this number peaked at 25 provinces.

[6] We do not follow Duncan and Duncan (1955) in labeling the curve "segregation curve" because we study spatial concentration of immigrants at a higher level of aggregation than is usually done in the residential segregation or assimilation literature. We rather employ the term "concentration curve" as done by Jones (1967).

source countries. This convergence may be the result of changes in new immigrants' location choices but also that of internal migration.[7]

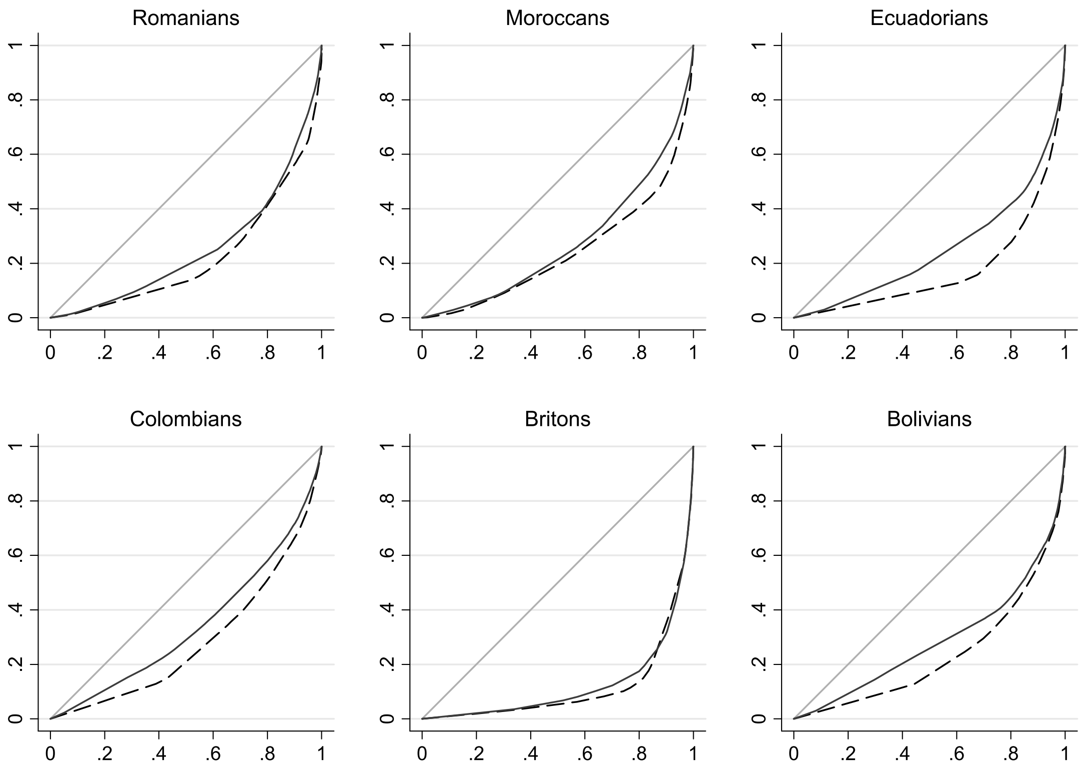


Figure 4.2: Concentration Curves for Foreign Nationals in Spain, 1999 and 2009

This figure shows concentration curves for foreign nationals in Spain for the years 1999 (dashed curves) and 2009 (solid curves). Each subfigure plots the cumulative proportion of Spanish people (ordinate) against the cumulative proportion of foreign nationals (abscissa). The units of geographical reference are Spanish provinces. In total there are 52 provinces, sorted in descending order based on the share of immigrants in the total province's population. *Source:* Authors' tabulations using data from INE.

This trend can also be seen by tracking indices of spatial diffusion over time. In our context, the "index of dissimilarity" reads as $D = 0.5 \sum_1^N |x_j - y_j|$, where x_j is the share of a certain immigrant group residing in province j, y_j is the corresponding share for Spanish nationals, and N is the total number of provinces in Spain, see Duncan and Duncan (1955, 211). Graphically speaking, D measures the maximum vertical distance between a given immigrant group's concentration curve as in figure 4.2 and the 45-degree line. Alternatively, D gives the minimum share of immigrants who have to move to other Spanish provinces in order to replicate the spatial distribution of Spanish nationals, see Duncan and Duncan (1955, 211). Thus, D can only take on values in the closed unit interval, with higher numbers indicating stronger dissimilarity in location choices between immigrants and natives. The left panel of figure 4.3 depicts the index of dissimilarity

[7] We have also looked at concentration curves where we do not distinguish among different source countries. Both observations, clustering and convergence, carry over to the immigrant population at large.

for the four major immigrant sources from 1997 to 2009. For these countries, the index takes on values between 0.2 and 0.6. For Ecuadorian and Romanian immigrants the index reports the highest degree of spatial dissimilarity, but the values for 2009 are always smaller than those for 1997. From 2001 onwards, we observe a general downward trend in spatial dissimilarity over time.[8]

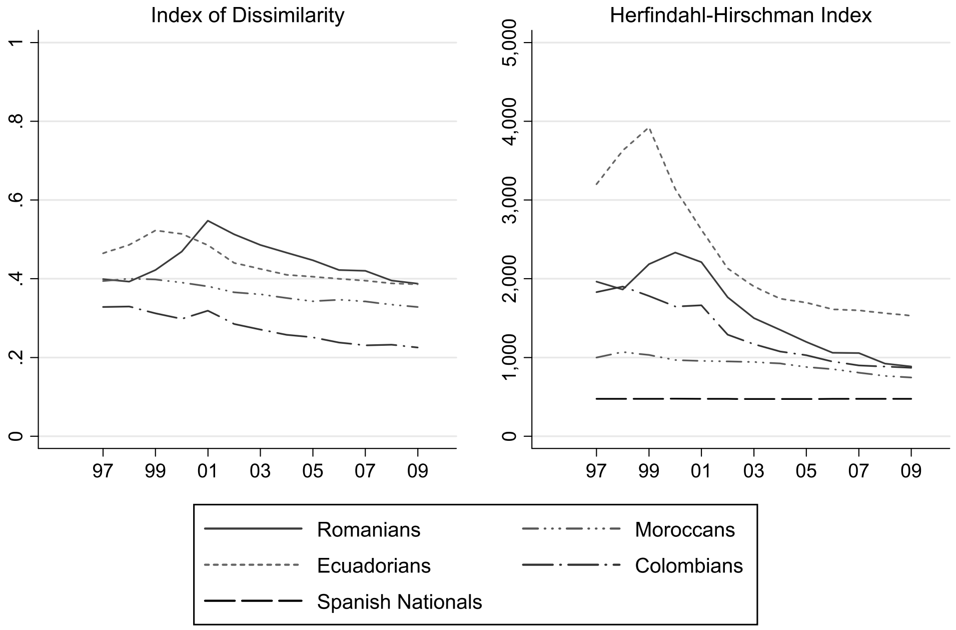


Figure 4.3: Spatial Clustering of Immigrant Groups in Spain, 1997 to 2009

This figure shows the index of dissimilarity (left panel) and the Herfindahl-Hirschman index (right panel) for the stocks of selected ethnic groups in Spain over the period 1997-2009. Both indices use Spanish provinces as units of geographical reference. *Source:* Authors' tabulations using data from INE.

We thus have

Stylized Fact 3. *Immigrants' location choices in Spain do not match the spatial distribution of natives. The degree of this dissimilarity steadily declined since the early 2000s.*

The index of dissimilarity proves useful in detecting differences in location choices between natives and immigrants. Yet, it has its limits in describing the extent of spatial concentration. For example, positive values of the index of dissimilarity do not imply that a larger proportion of immigrants than of natives is located in each group's single most attractive province. The right panel of figure 4.3 therefore shows the development of the

[8] We have also computed the coefficient of geographic association, which is another common measure of spatial diffusion. Among other things, it differs from the index of dissimilarity in its choice of reference group, which slightly changes its interpretation, see Haggett et al. (1977, 299-300) for details. The values of the coefficient of geographic association are very similar to those of the index of dissimilarity for all major immigrant groups in Spain both in terms of the order of magnitude and the development over time, which is why we do not report them here.

"migration Herfindahl-Hirschman Index" (Conway and Rork, 2010; henceforth migration HHI) for different ethnic groups over time. It allows us to assess differences in spatial concentration both across groups of immigrants and natives and over time.[9] Following Conway and Rork (2010, 768), we calculate this index as the total sum of the squared shares of immigrants in each province in total immigrants in Spain, separately for the different ethnic groups in Spain. In our case of $N = 52$ destination provinces, the index may range from $N \cdot (1/N \cdot 100)^2 \approx 192$ (individuals are evenly distributed across all provinces) to 10,000 (individuals are completely concentrated in a single province). Since the HHI for a given immigrant group is independent of the spatial distribution of natives in Spain, we also compute the HHI for Spanish nationals as a reference group. For them, the HHI is very stable over time and takes on values in the vicinity of 475 in each year from 1997 to 2009. For each of the four major immigrant groups, the HHI is above that of the reference group, indicating stronger spatial concentration of immigrants relative to natives. The most concentrated groups of immigrants are people with Ecuadorian and Romanian nationality. We also see a time trend similar to that of the index of dissimilarity. We may state these findings as

Stylized Fact 4. *The major immigrant groups in Spain are more strongly concentrated in space than natives. The degree of concentration steadily declined since the early 2000s.*

The descriptive analyses presented so far provide valuable information on immigrants' tendency to cluster in space. However, they cannot identify immigrants' preferred geographical subunits. Figure 4.4 illustrates differences in the spatial distribution of each of the four major immigrant groups in Spain and the group of natives in each of 52 Spanish provinces for the year 1999. The darker a province's color, the larger is an immigrant group's provincial population share relative to that of Spanish natives. The maps reflect that Colombians, Ecuadorians, Moroccans, and Romanians were more strongly concentrated in Madrid compared to the native population. The differences in the population shares of these groups and the population share of natives living in Madrid amounted to 48.2 percentage points for Ecuadorians and to 31.6 (26.0) percentage points for Romanians (Colombians). By contrast, the degree of concentration of Moroccans exceeded the one of natives by only 4.6 percentage points in Madrid. Concerning the other Spanish provinces, immigrants' location preferences relative to those of natives were quite hetero-

[9] As a drawback, the HHI cannot detect pure location choice differences between immigrants and natives as long as the exact same shares of population are simply located in different provinces.

geneous across the considered ethnic groups. Moroccans were concentrated to a similar degree in Murcia as in Madrid, and they lived significantly more often in Barcelona and Girona relative to Spanish natives. Romanians, by contrast, also settled to a significantly larger extent in Castellón relative to natives. Of the four immigrant groups, the spatial distribution of Ecuadorians ressembled the one of Spanish natives most. The differences across the considered immigrant groups notwithstanding, each of these groups was less likely to settle in Sevilla relative to Spanish natives.

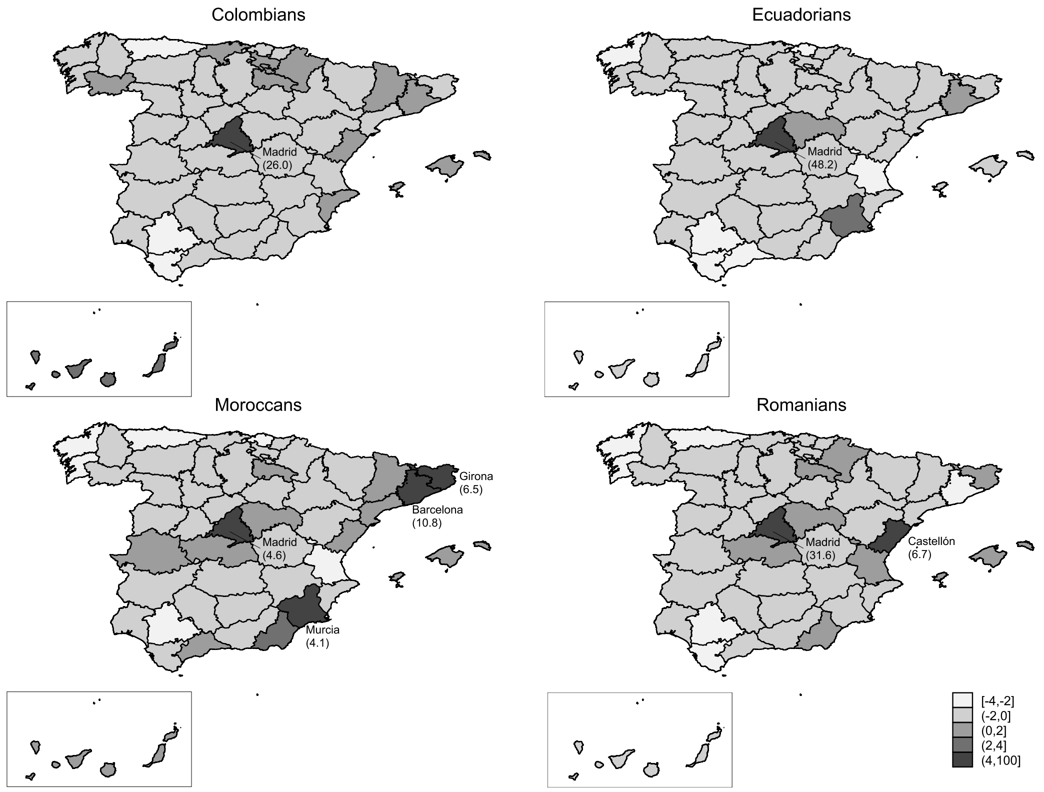


Figure 4.4: Comparison of the Spatial Distribution of Major Immigrant Groups in Spain and of Natives, 1999

This figure illustrates differences in the spatial distribution of natives and major immigrant groups in Spain for the year 1999. The units of geographical reference are Spanish provinces. The numbers are percentage points and computed from the difference between the share of immigrants living in a certain province and the corresponding share for natives. Dark colors represent strong concentration of immigrants relative to natives. Light colors represent strong concentration of natives relative to immigrants. The provinces Las Palmas and Santa Cruz de Tenerife are grouped together as Islas Canarias. *Source:* Authors' tabulations using data from INE.

We sum these observations up as

Stylized Fact 5. *Each of the four major immigrant groups in Spain (Colombians, Ecuadorians, Moroccans, Romanians) was to a significantly larger extent concentrated in Madrid compared to the Spanish native population in 1999. At the same time, each of these groups had settled relatively less often in Sevilla compared to natives. Beyond that, the location choices in Spain differed across the considered ethnic groups to a significant extent.*

CHAPTER 5

Co-national and Cross-national Pulls in International Migration to Spain

5.1 Introduction

Migrants are attracted to destinations hosting migrants of the same nationality as their own (co-national migrants). In this chapter, we provide evidence that migrants are also attracted to destinations hosting migrants from nationalities adjacent to their own nationality (namely, migrants from countries neighboring their own country of origin). We draw on rich migration data from the Spanish Instituto Nacional de Estadística (INE) on large scale migration to Spain in the period 1996-2006.

A large literature, starting with Nelson (1959) and Greenwood (1969, 1970), documents that, other things held equal, individuals tend to migrate to where other migrants from the same place of origin are present. An explanation of this inclination is that in all sorts of ways, past migrants alleviate the burden of migration by transmitting information and providing help in obtaining jobs, housing, and the like. Other explanations are that settled migrants foster follow-up migration by remitting to those left behind, thereby financing the latter's move (Stark and Jakubek, 2013), and by building up certain ethnic-specific institutions in the host country.[1] We argue that whatever the precise support

This chapter is based on an article jointly written with Marcel Smolka, which is available online in the *International Review of Economics & Finance* (doi: 10.1016/j.iref.2013.05.007), see Neubecker and Smolka (2013). The concept for this chapter was developed jointly, while the empirical analysis and writing were shared equally. An earlier version of this work has appeared as University of Tübingen Working Papers in Economics and Finance No. 46, see Neubecker and Smolka (2012).

[1] For the role of ethnic-specific institutions in migrants' integration, see Breton (1964).

channel, the migrants who promote further migration include not only past co-national migrants but also past migrants from adjacent nationalities.

There are good reasons to believe that the pull effect attributed to established migrants is not limited to co-national migrants but, rather, that it extends to migrants from adjacent nationalities. The economic globalization of the recent decades has led to more frequent interactions and cross references among individuals from adjacent nationalities, thus expanding the set of contacts beyond one's own nationality. Cross-national interactions are more likely to arise the smaller the geographical and cultural distance between the nationalities concerned.[2] Relatedly, suppose that migrants from Ecuador easily integrate into the Spanish labor market due to their language, skills, work ethics, culture, norms, and other characteristics. Then, migrants from other Latin American countries could reasonably expect to integrate well too, assuming that their skills and other productive attributes are comparable to those of Ecuadorian migrants.

The idea of a multi-nationality pull squares well with descriptive evidence on the geographical distribution of migrants in Spain. We show that migrants from adjacent nationalities tend to cluster in specific Spanish provinces. We also show that the geographical settlement patterns of migrants from two different nationalities are more similar the smaller the geographical distance between their countries of origin.

Methodologically, we draw upon the discrete choice literature in order to derive an empirical migration function based on the multinomial logit model described in McFadden (1984, 1411-1415). We hypothesize that the value of this function depends positively on the pull of co-national migrants. However, we augment the migration function by a cross-national pull term so as to capture the influence of migrants from adjacent nationalities on migration flows. We define this term as the log of the sum of all migrants settled in a certain destination (excluding co-national migrants), weighting each migrant by the inverse distance between his country of origin and the country of origin of a potential migrant. The migration function is estimated with Spanish migration data detailed by country of origin and by province of destination for the period 1996-2006.

Our estimations reveal that both the size and composition (in terms of nationalities)

[2] Interactions among individuals from adjacent nationalities may be more likely than perhaps expected. In the year 2000, for example, 7.0% of all the individuals living in Costa Rica held a foreign nationality of another country in Latin America or the Caribbean. The corresponding numbers for larger countries such as Venezuela (3.2%), Paraguay (3.0%), or Argentina (2.0%) are smaller but still not negligible; see World Bank's Global Bilateral Migration Database at http://data.worldbank.org/data-catalog/global-bilateral-migration-database, accessed on 09/26/2012.

of the migrant population at destination are significant determinants of migration flows. Apart from the expected pull effect due to co-national migrants, we find that migrants move to destinations with large representations of other migrants, ceteris paribus, when these migrants are from adjacent nationalities. Failing to account for this cross-national pull leads to a small omitted variable bias in the estimation of the co-national pull effect. Interestingly, we also find evidence for a positive interaction between the co-national pull and the cross-national pull.

This chapter is related to recent estimates of network effects in migration with aggregate (macro-level) migration data. Studies in this literature define migrant networks in terms of a common country of origin, a common country of birth, or a common nationality (see, e.g., Clark et al., 2007, Lewer and Van den Berg, 2008, Pedersen et al., 2008, Beine et al., 2011a,b). The studies find strong support for the importance of networks in determining the scale of migration.[3] Another strand of the literature on network effects in migration employs micro-level data. For instance, Bauer et al. (2007, 2009) look at Mexican migrants in the United States, measuring migrant networks in terms of a common village of origin. Several empirical studies have looked at the effect of migrant networks measured at the family level, exploiting detailed information on the precise type of social ties. Davis et al. (2002) find that closer kinship bonds result in a larger impact of the migrant network. Dolfin and Genicot (2010) find that family networks provide information on jobs and act as a source of credit, and that community networks are important sources of information on border-crossing. By focusing on common origin defined at the country or sub-country level, all the afore-mentioned studies have ignored the role of migrant networks that include adjacent nationalities in shaping migration flows.[4]

The remainder of this chapter is organized as follows. Section 5.2 describes the settlement patterns of migrants from different nationalities in Spain. Section 5.3 presents our estimation approach, the data used for estimation, and the estimation results. Section 5.4 concludes.

[3] Grogger and Hanson (2011), Beine et al. (2011a,b), and the analysis presented in Chapter 6 also find that migrant networks bias the skill structure of migration toward the low-skill individuals.

[4] Åslund (2005) finds that migrants in Sweden are attracted both to regions hosting co-national migrants as well as to regions hosting foreigners in general. However, he does not distinguish between different nationalities of these foreigners.

5.2 Geographical Distribution Patterns of Migrants in Spain

In this section we provide descriptive evidence on the geographical distribution of different migrant populations in Spain, showing that migrants prefer to settle in provinces with large populations of migrants from adjacent nationalities.[5] Information on the migrants is elicited from the Spanish Municipal Register; it is available from the INE website. For information on all data sources used in this chapter, see Table 6.7 in the appendix to Chapter 6 (Section 6.6.5).

Our first observation is that migrants are not uniformly distributed across the 52 Spanish provinces. The four major destination provinces account for 47% of all migrants registered in Spanish municipalities in the year 2009. These provinces are Madrid (18.8%), Barcelona (14.2%), Alicante (8.2%), and Valencia (5.6%) and rank also among the most populous provinces in Spain in general; the corresponding shares of the native population are 13.0% in Madrid, 11.4% in Barcelona, 3.5% in Alicante, and 5.5% in Valencia. Still, the migrants' concentration is considerably more pronounced than that of the native population; see also Chapter 4.

Our second observation is that migrants from adjacent nationalities tend to concentrate in specific provinces. For instance, migrants from South America, Sub-Saharan Africa, Eastern Europe, and East Asia are all significantly more concentrated in Madrid and in Barcelona than Spanish nationals.[6] For each of these four world regions, the share of migrants residing in either of these two provinces exceeds the corresponding share of Spanish nationals by more than 15 percentage points. Migrants from these world regions also reside more often than Spanish nationals in several Northern provinces (Vizcaya, Zaragoza, Girona), as well as in several provinces along the Spanish Mediterranean coast (Tarragona, Valencia, Alicante, Murcia, Málaga). We refer to this pattern of concentration of migrants relative to Spanish nationals as *clustering*.

In order to find out a little more about differences in the settlement patterns across migrant groups, we compare in Figure 5.1 the geographical distribution of migrants from each of the four world regions with the distribution of all migrants in Spain in 2009 (in each case, excluding migrants from the world region under consideration). For example, we compare the share of all migrants from South America settled in Madrid to the corre-

[5] Migrants are people who live in Spain and who are of a foreign nationality.

[6] South America is the most important region of origin of migrants in Spain (1.6 million migrants in the year 2009). Eastern Europe ranks second (1.3 million), Western Europe third (1.2 million), North Africa fourth (779,000), Sub-Saharan Africa fifth (227,000), and East Asia sixth (155,000).

sponding share of all other migrants in Madrid. Dark colors indicate a strong concentration of migrants from a given world region relative to all other migrants, whereas light colors indicate a relatively weak concentration. We see, for example, that migrants from South America, Eastern Europe, and East Asia are more strongly clustered in Madrid than migrants from other world regions. The opposite holds true for migrants from Sub-Saharan Africa. In Barcelona, migrants from South America, Sub-Saharan Africa, and East Asia are more strongly clustered than other migrants, whereas migrants from Eastern Europe are clustered less than migrants from other world regions. Differences in the degree of concentration also apply for other provinces.

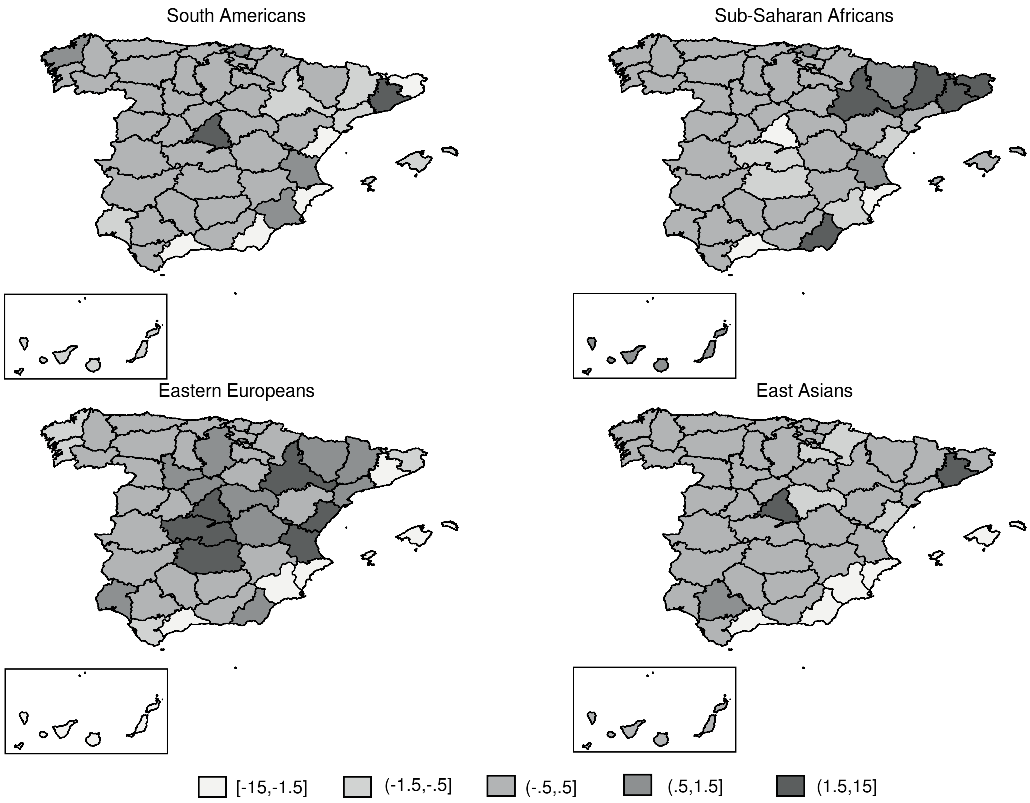


Figure 5.1: Differences in the Geographical Concentration of Migrant Populations in Spain, 2009

This Figure illustrates differences in the geographical distributions of migrants in Spain from four different world regions relative to the distribution of all migrants in Spain in the year 2009 (in each case excluding migrants from the world region under consideration). For example, we compare the share of all migrants from South America settled in each province to the corresponding share of all other migrants in the same province (upper left panel). The numbers are percentage point differences between the two shares. Dark colors indicate a strong concentration of migrants from a given world region relative to all other migrants, while light colors indicate a relatively weak concentration. The provinces Las Palmas and Santa Cruz de Tenerife are grouped together as Islas Canarias. *Source*: Authors' tabulations using data from INE.

We also take a slightly more formal approach to look at the relationship between the settlement patterns of migrants in Spain and the geographical proximity of their countries of origin. In particular, we ask whether differences in the geographical distribution of migrants originating from any pair of two countries correlate with the distance between the two countries. Figure 5.2 plots the country-pair-specific "index of dissimilarity" à la Duncan and Duncan (1955) for any two migrant populations settled in Spain in 2009 against the log of the distance (measured in kilometers) between the considered countries of origin. The index of dissimilarity is a summary statistic for the differences in the geographical distributions of two populations. It is defined as $D = 0.5 \sum_1^N |x_j - y_j|$ where x_j is the share of migrants from a specific nationality residing in province j, y_j is the corresponding share of migrants from a second nationality, and N is the total number of provinces in Spain. The index gives the share of migrants from the x-nationality who would have to move to other Spanish provinces in order to replicate the geographical distribution of migrants from the y-nationality (see Duncan and Duncan, 1955, 211). Thus, D can only take on values in the unit interval, with a higher value indicating a stronger dissimilarity in location choices between migrants from two nationalities.

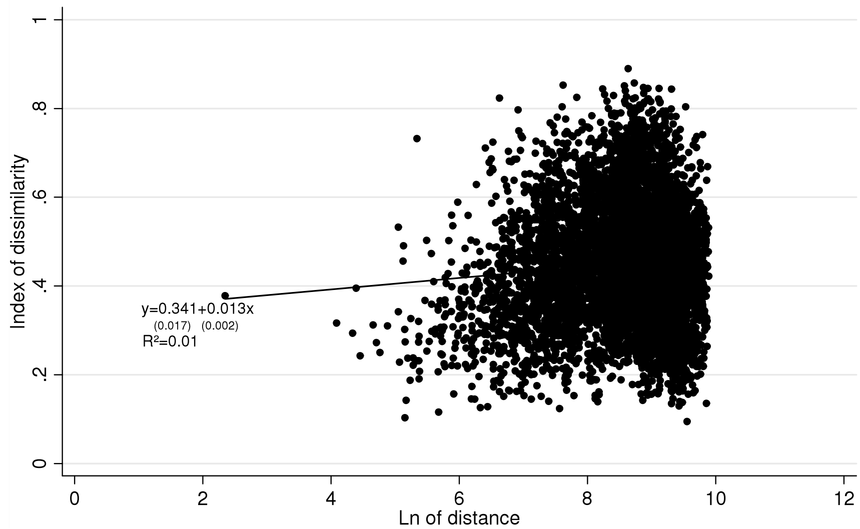


Figure 5.2: Index of Dissimilarity of Migrant Populations in Spain and Distance between Countries of Origin, 2009

Source: Authors' tabulations using data from INE and CEPII.

The linear best fit in Figure 5.2 indicates a positive albeit small correlation between the dissimilarity index and the distance variable (statistically significant at the 1-% level), showing that migrants from a certain nationality tend to settle in provinces where other migrants from adjacent nationalities settle.

5.3 Empirical Analysis

In this section we first describe our empirical model and the data that we use, and we then present and discuss our estimation results. We also conduct a robustness analysis.

5.3.1 Empirical Model and Data

Consider a large number of origin countries (indexed by i or $\ell = 1, \dots, I$) and a large number of destinations at the sub-country level (indexed by j or $k = 1, \dots, J$).[7] Let an individual's origin country i represent one element in the set of destinations, so that we actually have a model of location choice for all individuals (including non-migrants). Let individuals originating from country i be indexed by $o = 1, \dots, m_i$.

Assume that individuals form expectations about the utility to be derived from migrating to (and living in) each destination based on observable variables such as wages, employment, and the presence of other migrants. We write the expected utility of individual o when migrating from country i to destination j in an additively separable form:

$$U_{ij}^o = V_{ij} + e_{ij}^o, \tag{5.1}$$

where the term V_{ij} summarizes all utility components common to individuals migrating from country i to destination j, and e_{ij}^o is an individual-specific stochastic taste variable for migrating from i to j.

Individuals are assumed to be utility maximizers, so that each individual moves to the destination where he expects to receive the highest utility:

$$j^o = \text{argmax}(U_{i1}^o, \dots, U_{iJ}^o), \quad j^o \in \{1, \dots, J\}. \tag{5.2}$$

The probability that individual o migrates from country i to destination j can thus be written as:

$$\begin{aligned} P_i^o(j^o = j) &= \Pr(U_{ij}^o > U_{ik}^o \quad \forall k \in \{1, \dots, J\} : k \neq j) \\ &= \Pr(e_{ik}^o - e_{ij}^o < V_{ij} - V_{ik} \quad \forall k \in \{1, \dots, J\} : k \neq j). \end{aligned} \tag{5.3}$$

[7] Strictly speaking, each origin country i is associated with a unique set of destinations, so the number of destinations and the indexing of destinations should be i-specific. We omit this index in order to avoid notational clutter.

This probability depends on the distribution assumed for the stochastic taste variables, $e^o_{i1}, \ldots, e^o_{iJ}$. Let $\mathbf{g}_i = (g_{i1}, \ldots, g_{iJ})$ be a $(1 \times J)$ row vector with non-negative entries, and let H_i be a non-negative function of $\mathbf{g}_i$ with

$$\lim_{g_{ij} \to \infty} H_i(\mathbf{g}_i) = +\infty \quad \text{for} \quad j = 1, \ldots, J. \tag{5.4}$$

Let H_i be linearly homogeneous in $\mathbf{g}_i$, and let it have mixed partial derivatives of all orders, with non-positive even and non-negative odd mixed derivatives. McFadden (1978, 80-81) has shown that under this set of assumptions the function

$$F_i(e^o_{i1}, \ldots, e^o_{iJ}) = \exp\left[-H_i\left(\exp[-e^o_{i1}], \ldots, \exp[-e^o_{iJ}]\right)\right] \tag{5.5}$$

is a multivariate extreme value distribution function and that, if $(e^o_{i1}, \ldots, e^o_{iJ})$ is distributed F_i, (5.3) can be written as:

$$P^o_i(j^o = j) = \frac{\exp[V_{ij}]}{H_i(\exp\left[V_{i1}\right], \ldots, \exp\left[V_{iJ}\right])} \frac{\partial H_i(\exp\left[V_{i1}\right], \ldots, \exp\left[V_{iJ}\right])}{\partial \exp[V_{ij}]}; \tag{5.6}$$

see also McFadden (1981, 226-230). Following the received literature, we assume that

$$H_i(\exp\left[V_{i1}\right], \ldots, \exp\left[V_{iJ}\right]) = \sum_{j=1}^{J} \exp[V_{ij}], \tag{5.7}$$

so that we end up with the response probabilities of the multinomial logit (MNL) model:

$$P^o_i(j^o = j) = \frac{\exp[V_{ij}]}{\sum_{j=1}^{J} \exp[V_{ij}]} \tag{5.8}$$

Aggregating over all individuals from country i, taking logs, and rearranging terms, we obtain the following migration function:

$$\ln\left(m_{ij}\right) = V_{ij} - \ln \sum_{j=1}^{J} \exp[V_{ij}] + \ln\left(m_i\right), \tag{5.9}$$

where m_{ij} is the number of migrants from country i to destination j and m_i is the initial population size of country i. Importantly, from the term $\ln \sum_{j=1}^{J} \exp[V_{ij}]$ we see that the migrant flow from i to j is a function of the expected utility in all destinations $j = 1, \ldots, J$. Borrowing from the international trade literature, we refer to this term as a "multilateral resistance term" (see Anderson and van Wincoop, 2003). Differentiating equation (5.9) with respect to V_{ik} yields

$$\frac{\partial \ln(m_{ij})}{\partial V_{ik}} = \begin{cases} 1 - \frac{\exp[V_{ij}]}{\sum_{j=1}^{J} \exp[V_{ij}]} = 1 - m_{ij}/m_i \geq 0 \quad \text{for} \quad k = j, \\ -\frac{\exp[V_{ik}]}{\sum_{j=1}^{J} \exp[V_{ij}]} = -m_{ik}/m_i \leq 0 \quad \text{for} \quad k \neq j. \end{cases} \tag{5.10}$$

Hence, any increase in the expected utility of destination j for individuals from country i stimulates migration from country i to destination j, while it discourages migration from country i to all other destinations $k \neq j$.

One may think of the non-stochastic part of the expected utility, V_{ij}, as being composed of a number of pull factors and cost factors. Among other things, these factors include the wage rate, employment opportunities, social security and health care provisions, migration policies, and the cultural and geographical distance between origin and destination. Other variables such as trade and capital flows might be important, too. Trade is not only facilitated by, but is also conducive to a good infrastructure for traveling and transportation. Capital invested by foreign firms could create demand for specific types of labor, especially foreign labor. More importantly, the pull and cost factors are likely to depend on the size as well as on the composition (in terms of nationalities) of the migrant population at destination j. Using equation (5.9), we assume that the log number of migrants from country i to destination j can be approximated linearly by the following expression:

$$\ln(m_{ij}) = \beta_0 \ln(M_{ij}) + \beta_1 \ln\left(\sum_{\ell \neq i} \eta_{i\ell} M_{\ell j}\right) + \lambda \cdot \mathbf{X}_{ij} + \varepsilon_{ij}, \tag{5.11}$$

where M_{ij} is the number of established migrants from country i in destination j, $\eta_{i\ell}$ is the proximity between countries i and ℓ, $\mathbf{X}_{ij} = (X_{ij1}, \ldots, X_{ijS})'$ is a vector of control variables, $\lambda = (\lambda_1, \ldots, \lambda_S)$ is a vector of parameters to be estimated along with β_0 and β_1, and ε_{ij} is an error term. As explained in more detail below, the vector $\mathbf{X}_{ij}$ controls for the multilateral resistance term, for the initial population size in the country of origin, and for a number of other pull and cost factors.

The variable $\ln(M_{ij})$ is meant to capture all types of pull effects that originate from the stock of established co-national migrants. This variable is akin to the standard network variable used in the related empirical literature. We cannot discriminate among different types of pull effects because some of them are unobserved (such as social ties between migrants). We refer to the variable $\ln(M_{ij})$ as the *co-national pull*.

Different from the received literature, the migration model given by equation (5.11) includes the term $\ln\left(\sum_{\ell\neq i}\eta_{i\ell}M_{\ell j}\right)$, which measures the pull of migrants in destination j from countries that are culturally and geographically close to country i. This variable is a weighted log sum of all foreign nationals living in destination j, where the weights measure the proximity between countries i and ℓ. It is meant to be a first-order approximation of all types of pull effects that derive from the stock of established migrants from adjacent nationalities. By analogy to the co-national pull, we refer to $\ln\left(\sum_{\ell\neq i}\eta_{i\ell}M_{\ell j}\right)$ as the *cross-national pull*. We expect to find a positive cross-national pull effect on migration, $\hat{\beta}_1 > 0$, in addition to a positive co-national pull effect on migration, $\hat{\beta}_0 > 0$.

In order to estimate equation (5.11), we use data for the 55 most important countries of origin in terms of the number of migrants in Spain in 1996.[8] Spain is divided into 52 provinces (*provincias*) that are nested in 19 regions (*comunidades autónomas*). We exclude the provinces (enclaves) of Ceuta and Melilla due to their specific geographical location and thus we end up with 50 provinces.[9]

The migration data are taken from the local registry of Spanish municipalities provided through INE. We have reason to believe that these data include both documented and undocumented migrants from 2000 onwards. The *"Law on the Rights and Freedoms of Aliens in Spain and their Social Integration"* provided a particular incentive for migrants to register. When registered, migrants were entitled to free medical care under the same terms as Spanish nationals, conditional only on registration in their municipality but not on their legal residence status (see *Ley Orgánica 4/2000, artículo 12*). In addition, registration was one of the requirements for regularization during the large-scale regularization process in 2005 (OECD, 2006, 214). The dependent variable in equation (5.11) is the log of the migration flow into Spanish provinces, obtained from the Spanish Residential Variation Statistics and aggregated from the beginning of 1997 until the end of 2006.[10] We measure migrant stocks, M_{ij}, by the number of individuals from nationality i who live in destination j as of May 1, 1996, as reported by the Spanish Municipal Register. To retain observations with a zero co-national pull, we add one to the number of co-national

[8] These countries are listed in Table 6.6 in the appendix to Chapter 6 (Section 6.6.5).

[9] See `http://www.ine.es/daco/daco42/codmun/cod_provincia.htm`, accessed on 04/17/2012, for a list of these provinces.

[10] We define migrants as individuals whose last country of residence (other than Spain) corresponds to their country of birth and nationality.

migrants.

We proxy the cultural and geographical proximity between any two nationalities, η_{il}, by the inverse of the geographical distance (in kilometers) between the most populous cities of the corresponding countries. We assume that cultural proximity (including linguistic proximity) and geographical proximity are closely related. Data on distances are taken from the French Centre d'Études Prospectives et d'Informations Internationales (CEPII). We control for several other potential determinants of the scale of migration, captured by the vector $\mathbf{X}_{ij}$. In particular, we account for the impact of trade and FDI flows using data from the Spanish Ministry of Industry, Tourism and Trade. Trade flows are measured as the sum of exports and imports (in Euros) between country i and province j in the year 1996. Data on FDI are observed as inflows into Spanish regions for the year 1997, detailed by country of origin. We add one to both variables before taking logs so as to retain observations with zero trade or FDI flows. Furthermore, in order to control for destination-specific pull factors other than the "pure" presence of co-national or cross-national migrants such as wages, employment opportunities, weather conditions, and the like, we include a set of province fixed effects. Finally, we control for the initial population size in the country of origin, $\ln(m_i)$, as well as for the multilateral resistance term, $\ln \sum_{j=1}^{J} \exp[V_{ij}]$, that is common to all provincial destinations in Spain. We do so using the familiar fixed effects approach, computing all variables as deviations from their country means (within-transformation). Because our migration data refer to a single destination country, this approach wipes out all effects specific to a given country of origin and Spain at large (for example, the Spanish migration policy towards Ecuador). Also, this fixed effects approach has the advantage that it is compatible with a less restrictive structure of substitutability across alternatives than is assumed in the standard MNL model (see Ortega and Peri, 2013, and Chapter 6).

More demanding specifications of our fixed effects model control for all effects specific to pairs of origin countries and destination regions in Spain. These effects are eliminated by computing all variables as deviations from their country-and-region means. This approach greatly reduces the probability of omitted variables bias because it controls for all determinants of migration relevant for pairs of origin countries and destination regions in Spain. These determinants include a number of prominent cultural factors (language, habits, historical ties) as well as geographical factors (especially distance).[11]

[11] For example, Cataluña is closer to France than Andalucía both culturally and geographically.

Given the potential endogeneity of the co-national pull, we also employ instrumental variables regression techniques. As excluded instruments, we use historical migration flows within Spain, defined as the log of the number of people holding country i's nationality and migrating from destination j in Spain to any other destination $k \neq j$ in Spain in 1988 and 1989, respectively. Regarding the relevance of these instruments, a large historical migrant flow from some province j to other Spanish provinces is an indicator of a high level of the historical migrant stock of province j, even though accounting logic tells us that it also reduces that province's historical migrant stock. The historical migrant stock can in turn be expected to correlate with the contemporaneous migrant stock. We thus expect to find a correlation also between the historical migration flows within Spain and the contemporaneous migrant stocks. Our first-stage regressions attest to a positive and significant (partial) correlation between our excluded instruments and the contemporaneous migrant stocks. For our instruments to be valid, they must, of course, be uncorrelated with the structural error term. One could argue that considerable historical migration within Spain reflects (and signals) a poor matching quality (for example in terms of jobs), thus discouraging further migration today. However, it is unlikely that this signaling effect, whether empirically relevant or not, renders our instruments endogenous. This is so because, first, to the extent that the matching quality is specific to a pair of origin country and destination region, it is absorbed into our fixed effects; and second, because the signal as such should be captured by the (observable) co-national pull term, given that this term itself is a function of the entire set of historical migration flows. Hence, the signaling effect should not be part of the structural error term.

5.3.2 Estimation Results

Table 5.1 shows the results of the fixed effects (FE) estimations (columns (a) to (f)) and of the fixed effects two stage least squares (FE 2SLS) estimations (columns (g) to (l)). For each estimator, the first three columns control for country-fixed effects and the last three columns control for country-and-region fixed effects through a conventional within-transformation of the data. 5.7% of the observations had to be dropped due to zero migrant flows.[12]

[12] In the specifications that control for country-and-region fixed effects, additional observations need to be dropped due to regions consisting of a single province. Excluding then the provinces Ceuta and Melilla, the full matrix would have included 55×50 observations.

Table 5.1: Estimations Based on the Inverse-distance-weighted Cross-national Pull

	Dependent Variable: Migration Inflow (Province-level 1997-2006)											
	Fixed Effects						Fixed Effects Two Stage Least Squares					
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
Co-national Pull	0.682***	0.660***	0.639***	0.539***	0.524***	0.515***	0.953***	0.945***	0.903***	0.825***	0.820***	0.868***
(Province-level 1996)	(0.028)	(0.030)	(0.030)	(0.029)	(0.030)	(0.030)	(0.070)	(0.065)	(0.049)	(0.080)	(0.079)	(0.093)
Cross-national Pull		0.539***	0.321***		0.486***	0.335**		0.293***	0.252**		0.229*	0.236
(Province-level 1996)		(0.134)	(0.118)		(0.131)	(0.136)		(0.107)	(0.128)		(0.136)	(0.152)
Co-n. x *Cross-n. Pull*			0.032***			0.022***			0.010			-0.007
(Province-level 1996)			(0.010)			(0.008)			(0.010)			(0.011)
Trade Flow	0.005	0.008	0.011	0.004	0.004	0.005	0.004	0.005	0.007	0.005	0.006	0.006
(Province-level 1996)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
FDI Flow	0.012**	0.012**	0.011**				0.004	0.004	0.004			
(Region-level 1997)	(0.005)	(0.005)	(0.005)				(0.005)	(0.005)	(0.005)			
Country Effects	Yes	Yes	Yes	Nested	Nested	Nested	Yes	Yes	Yes	Nested	Nested	Nested
Country-and-Region E.	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Province Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,592	2,592	2,592	2,199	2,199	2,199	2,592	2,592	2,592	2,199	2,199	2,199
Centered R^2	0.792	0.796	0.798	0.670	0.673	0.674	0.770	0.773	0.768	0.635	0.637	0.624
Hansen J Test							0.023	0.028	1.070	0.379	0.247	1.710
- p-value							0.880	0.866	0.586	0.538	0.619	0.425
Kleib.-Paap LM Test							20.13	16.79	10.95	24.27	22.38	16.31
- p-value							0.000	0.000	0.012	0.000	0.000	0.001
Kleib.-Paap W. F Test							30.70	23.75	7.741	18.48	16.78	6.371
Exogeneity Test							14.29	14.81	10.31	11.03	11.19	11.45
- p-value							0.000	0.000	0.001	0.001	0.001	0.001

All variables are in natural logs. Heteroskedasticity-robust standard errors (clustered by countries or pairs of countries and Spanish regions) are given in parentheses. *,**,*** denote significance at the 10-%, 5-%, 1-% levels, respectively. The regressions include all countries with at least 630 nationals residing in Spain in the year 1996 (55 countries of origin). In columns (g)-(l), the co-national pull and its interaction with the cross-national pull are instrumented with historical migration flows within Spain (and the corresponding interactions). Refer to Section 5.3 for a detailed description of the variables. In column (i), two province effects are partialled out in order to ensure full rank of the estimated covariance matrix of moment conditions.

For the sake of comparison, we report estimation results for specifications in which we: (i) exclude the cross-national pull; (ii) estimate the full model as given by equation (5.11); and (iii) interact the co-national and cross-national pulls. The third set of estimations allows us to gauge whether the two types of effects reinforce each other.

In all the specifications employed, the co-national pull effect is positive and statistically significant at the 1-% level. The estimated coefficient, roughly interpretable as an elasticity, ranges between 0.52 and 0.68 in the FE estimations, and between 0.82 and 0.95 in the FE 2SLS estimations. The exact elasticity is $\frac{\partial \ln(m_{ij})}{\partial \ln(M_{ij})} = \beta_0(1 - \frac{m_{ij}}{m_i})$ and thus it is smaller than the estimated coefficient; see also equation (5.10). In the analysis that follows, we plausibly assume that the fraction m_{ij}/m_i is close to zero.

The cross-national pull effect is positive and statistically significant at least at the 10-% level, the FE 2SLS model with the interaction term included being the only exception. The estimated coefficient ranges between 0.32 and 0.54 in the FE estimations, and between 0.23 and 0.29 in the FE 2SLS estimations. Our estimates thus seem to support the hypothesis that new migrants are attracted to destinations hosting migrants from the same nationality as well as from adjacent nationalities.

In order to evaluate the cross-national pull effect in terms of its quantitative importance, we differentiate the estimated migration function with respect to the log of the migrant pull of a certain nationality $\ell \neq i$:

$$\frac{\partial \ln(m_{ij})}{\partial \ln(M_{\ell j})} \cong \beta_1 \times \frac{\eta_{i\ell} M_{\ell j}}{\sum_{\ell \neq i} \eta_{i\ell} M_{\ell j}}. \tag{5.12}$$

This elasticity can be compared to the elasticity of the co-national pull, $\frac{\partial \ln(m_{ij})}{\partial \ln(M_{ij})} \cong \beta_0$. Given that $\hat{\beta}_0 > \hat{\beta}_1$ and $\frac{\eta_{i\ell} \mathrm{M}_{\ell \mathrm{j}}}{\sum_{\ell \neq \mathrm{i}} \eta_{i\ell} \mathrm{M}_{\ell \mathrm{j}}} \leq 1$, the marginal effect due to co-national migrants is strictly larger than the marginal effect due to migrants from adjacent nationalities. Take, as an example, established Peruvian migrants in Barcelona and their impact on future migration from Ecuador to Barcelona. By plugging in the relevant values for the weights, $\eta_{i\ell}$, and the migrant stocks, $M_{\ell j}$, and by using the estimate for β_1 in column (e), we get an estimated elasticity of approximately 0.11 for the cross-national pull.

As to the interaction term between the co-national pull and the cross-national pull, we find a positive and significant interaction effect in the FE estimations. The results should though be interpreted with caution because the interaction effect does not survive in the FE 2SLS estimations. Figure 5.3 plots the marginal co-national pull effect on follow-up migration against the size of the cross-national pull. It is based on the parameter estimates reported in column (f). The marginal effect (straight line) is shown together with the 90-% confidence interval (dashed lines). Figure 5.3 also includes the estimated density of the cross-national pull (dotted line). We see that the estimated elasticity is positive and that it is significantly different from zero for relevant values of the cross-national pull, lying in the interval between 0.42 and 0.63. Furthermore, we see that this elasticity is larger the larger the cross-national pull. Hence, Figure 5.3 lends support to the idea that co-national migrants exert an independent positive influence on migration, but that this influence is more important the larger the presence of migrants from adjacent nationalities.

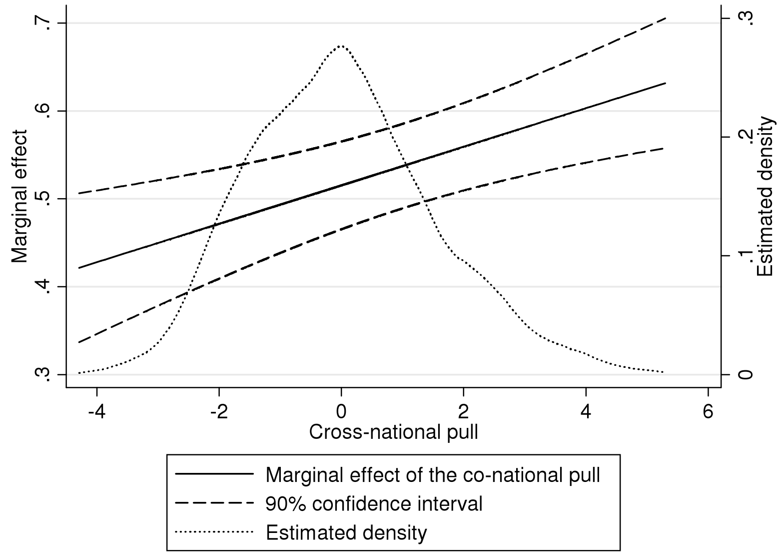


Figure 5.3: Marginal Effect of the Co-national Pull

With regard to the control variables, we do not find a statistically significant effect of trade on migration. Yet, the estimated coefficient for the FDI variable is positive and marginally statistically significant in the FE estimations. This suggests that, other things held constant, migrant flows are slightly larger for country-province pairs characterized by a high inflow of FDI at the regional level. However, the effect of FDI is insignificant in the FE 2SLS estimations.

The instruments used in the FE 2SLS estimations seem to be valid, relevant, and strong according to various test statistics. In order to test for the validity of the instruments, we perform over-identification tests of all instruments in the form of Hansen J tests. We can never reject the null hypothesis of instrument exogeneity at any reasonable level of confidence. Furthermore, the values of the Kleibergen-Paap LM statistic indicate that our excluded instruments are relevant, given that we always have to reject the null hypothesis of under-identification. The Kleibergen-Paap Wald F test provides information on the strength of the instruments. The corresponding test statistic is above the critical value of 10 when the interaction term is not included (columns (g), (h), (j) and (k)).[13] This suggests that there is no problem of weak instruments. Following Baum et al. (2007, 490), we compare the values of the Kleibergen-Paap Wald F statistic to the critical values for the Cragg-Donald Wald F statistic provided by Stock and Yogo (2005) in the specifications in which both the co-national pull and its interaction with the cross-national pull are instrumented (columns (i) and (l)).[14] Based on this comparison, the instruments seem to lead to a bias of the FE 2SLS estimator relative to the bias of the FE estimator of at most 10% and 20% in the specifications reported in columns (i) and (l), respectively. Based on exogeneity tests for the instrumented co-national pull, we always have to reject the null hypothesis that this regressor is exogenous at the 1-% level.

5.3.3 Robustness Analysis

By construction, most of the variation in the cross-national pull used for identification stems from differences in the number of migrants from adjacent nationalities (large weights), not from differences in the number of migrants from far-removed nationalities (small weights). Hence, the results reported in Table 5.1 are informative about the role of the former group of established migrants, but not the latter.

In order to gain further insight into possible differences between the effects of the two types of migrants, we applied an alternative weighting scheme, using as weights the distance (instead of the inverse distance) between the two countries considered. Hence, the weights are shifted away from migrants from adjacent nationalities to those from far-removed nationalities. If the estimates obtained with this alternative weighting scheme were to look similar to those reported above, we would have had reason to believe that it is established migrants in general who foster follow-up migration, independently of the composition of the stock of migrants in terms of nationalities.

We find the opposite. Table 5.2 reports the corresponding estimation results. They indicate a statistically significant negative coefficient for the (alternative) cross-national pull in the FE estimations, and a statistically insignificant coefficient in the FE 2SLS estimations. Hence, it is not established migrants per se who attract follow-up migration.

[13] This comparison follows the "rule of thumb" suggested by Staiger and Stock (1997), see Baum et al. (2007, 490).

[14] The Cragg-Donald Wald F statistic is the relevant F statistic in the case that the errors are independent and identically distributed (Baum et al., 2007, 489).

Table 5.2: Estimations Based on the Distance-weighted Cross-national Pull

	Dependent Variable: Migration Inflow (Province-level 1997-2006)											
	Fixed Effects						Fixed Effects Two Stage Least Squares					
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
Co-national Pull	0.682***	0.630***	0.305	0.539***	0.489***	0.121	0.953***	0.942***	1.137***	0.825***	0.800***	1.273***
(Province-level 1996)	(0.028)	(0.027)	(0.239)	(0.029)	(0.031)	(0.213)	(0.070)	(0.084)	(0.220)	(0.080)	(0.106)	(0.387)
Cross-national Pull		-0.929***	-0.989***		-1.019***	-1.055***		-0.128	-0.023		-0.189	0.128
(Province-level 1996)		(0.171)	(0.173)		(0.153)	(0.156)		(0.241)	(0.202)		(0.316)	(0.384)
Co-n. x *Cross-n. Pull*			0.019			0.022*			-0.010			-0.022
(Province-level 1996)			(0.014)			(0.012)			(0.013)			(0.018)
Trade Flow	0.005	0.006	0.007	0.004	0.003	0.004	0.004	0.004	0.003	0.005	0.005	0.005
(Province-level 1996)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
FDI Flow	0.012**	0.009*	0.009*				0.004	0.004	0.004			
(Region-level 1997)	(0.005)	(0.005)	(0.005)				(0.005)	(0.005)	(0.005)			
Country Effects	Yes	Yes	Yes	Nested	Nested	Nested	Yes	Yes	Yes	Nested	Nested	Nested
Country-and-Region E.	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Province Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,592	2,592	2,592	2,199	2,199	2,199	2,592	2,592	2,592	2,199	2,199	2,199
Centered R^2	0.792	0.796	0.797	0.670	0.677	0.678	0.770	0.772	0.755	0.635	0.641	0.610
Hansen J Test							0.023	0.023	0.235	0.379	0.302	0.836
- p-value							0.880	0.879	0.889	0.538	0.583	0.658
Kleib.-Paap LM Test							20.13	19.13	10.57	24.27	21.49	17.29
- p-value							0.000	0.000	0.014	0.000	0.000	0.001
Kleib.-Paap W. F Test							30.70	24.73	9.282	18.48	13.88	5.443
Exogeneity Test							14.29	13.43	14.27	11.03	7.662	12.10
- p-value							0.000	0.000	0.000	0.001	0.006	0.001

All variables are in natural logs. Heteroskedasticity-robust standard errors (clustered by countries or pairs of countries and Spanish regions) are given in parentheses. *,**,*** denote significance at the 10-%, 5-%, 1-% levels, respectively. The regressions include all countries with at least 630 nationals residing in Spain in the year 1996 (55 countries of origin). In columns (g)-(l), the co-national pull and its interaction with the cross-national pull are instrumented with historical migration flows within Spain (and the corresponding interactions). Refer to Section 5.3 for a detailed description of the variables. In column (i), two province effects are partialled out in order to ensure full rank of the estimated covariance matrix of moment conditions.

What matters is composition in terms of nationalities. A stock composed of migrants from far-removed nationalities has a strictly non-positive effect on follow-up migration.

In another robustness check, we have used an indicator variable for a common official language as a weight in the cross-national pull. The results from these estimations are reported in Table 5.3 in the appendix. The FE estimations suggest a positive cross-national pull effect on follow-up migration, which is again weaker than the co-national pull effect. However, the results are not robust in the FE 2SLS estimations.

5.4 Conclusion

We expand the perspective of the attraction of a migrant pool from co-national migrants to co-national migrants together with migrants from adjacent nationalities. We find that cross-national links are relevant predictors of international migration flows, both independently and in conjunction with co-national links. Our analysis is based on macro-level data on migrant stocks and flows during the era of the migration boom to Spain, and is drawing on data by countries of origin and provinces of destination.

The two novel findings of our analysis are, first, that migrants from a certain nationality are attracted to destinations hosting migrants from adjacent nationalities. Importantly, this holds true even when the co-national pull is small or zero. In terms of magnitude, this effect is large enough to be relevant, but smaller than the pull effect due to co-national migrants. The second novel finding is non-linearity in precisely this co-national pull effect, which appears to be stronger the larger the presence of migrants from adjacent nationalities.

An obvious drawback of our analysis is that we cannot explore the precise channels underlying the pull effects. The received literature attributes a prominent role to networks fostering follow-up migration. Identification of the relative importance of each of the possible channels of migration dynamics is left for future research.

5.5 Appendix to Chapter 5

Table 5.3: Estimations Based on the Language-weighted Cross-national Pull

	Dependent Variable: Migration Inflow (Province-level 1997-2006)											
	Fixed Effects						Fixed Effects Two Stage Least Squares					
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)	(j)	(k)	(l)
Co-national Pull	0.682***	0.663***	0.650***	0.539***	0.532***	0.503***	0.953***	0.929***	1.042***	0.825***	0.820***	1.035***
(Province-level 1996)	(0.028)	(0.028)	(0.036)	(0.029)	(0.029)	(0.051)	(0.070)	(0.073)	(0.069)	(0.080)	(0.084)	(0.130)
Cross-national Pull		0.108***	0.091*		0.069*	0.032		0.044	0.104*		0.012	0.129*
(Province-level 1996)		(0.037)	(0.047)		(0.036)	(0.051)		(0.035)	(0.057)		(0.038)	(0.067)
Co-n. x *Cross-n. Pull*			0.003			0.006			-0.012**			-0.023**
(Province-level 1996)			(0.006)			(0.007)			(0.006)			(0.010)
Trade Flow	0.005	0.005	0.005	0.004	0.003	0.004	0.004	0.004	0.003	0.005	0.005	0.005
(Province-level 1996)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
FDI Flow	0.012**	0.012**	0.012**				0.004	0.005	0.002			
(Region-level 1997)	(0.005)	(0.005)	(0.005)				(0.005)	(0.005)	(0.005)			
Country Effects	Yes	Yes	Yes	Nested	Nested	Nested	Yes	Yes	Yes	Nested	Nested	Nested
Country-and-Region E.	No	No	No	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Province Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,592	2,592	2,592	2,199	2,199	2,199	2,592	2,592	2,592	2,199	2,199	2,199
Centered R^2	0.792	0.794	0.794	0.670	0.671	0.671	0.770	0.774	0.751	0.635	0.636	0.599
Hansen J Test							0.023	0.029	1.017	0.379	0.353	0.445
- p-value							0.880	0.864	0.601	0.538	0.552	0.800
Kleib.-Paap LM Test							20.13	19.31	18.74	24.27	24.13	25.51
- p-value							0.000	0.000	0.000	0.000	0.000	0.000
Kleib.-Paap W. F Test							30.70	24.72	14.04	18.48	17.28	8.562
Exogeneity Test							14.29	13.02	17.08	11.03	9.977	14.16
- p-value							0.000	0.000	0.000	0.001	0.002	0.000

All variables are in natural logs. Heteroskedasticity-robust standard errors (clustered by countries or pairs of countries and Spanish regions) are given in parentheses. *,**,*** denote significance at the 10-%, 5-%, 1-% levels, respectively. The regressions include all countries with at least 630 nationals residing in Spain in the year 1996 (55 countries of origin). In columns (g)-(l), the co-national pull and its interaction with the cross-national pull are instrumented with historical migration flows within Spain (and the corresponding interactions). Refer to Section 5.3 for a detailed description of the variables. In column (i), two province effects are partialled out in order to ensure full rank of the estimated covariance matrix of moment condition.

CHAPTER 6

Networks and Selection in International Migration to Spain

6.1 Introduction

An established body of literature argues that already settled migrants, often simply labeled as a migrant network, alleviate the burden of migration for prospective newcomers, for example through informal job referrals among co-national peers, see, e.g., Munshi (2003).[1] In this chapter, we provide new evidence on migrant networks as determinants of the total size (scale) and skill structure of migration, drawing on aggregate data from a recent migration boom to Spain. Spain is an interesting case to look at. The country has become one of the world's most attractive destination for migrants due to its strong economic growth ahead of the global financial crisis. From 1997 to 2009, Spain received roughly six million new migrants.[2] The foreign-born share among the total population grew at a rate not seen in any OECD country for a short period of time after World War II, increasing from 4.9% in 2000 to 14.1% in 2008 (OECD, 2010, 240).

This chapter is based on a joint work with Marcel Smolka and Anne Steinbacher, which has appeared as DIW Discussion Papers no. 1306, see Neubecker et al. (2013). The concept for this chapter was developed by Marcel Smolka and the author of this dissertation. The data management on the basis of the survey data and the estimation of the skill model was mainly carried out by Anne Steinbacher. Most of the remaining empirical work and writing were shared between Marcel Smolka and the author of this dissertation. An earlier version of this work has appeared as University of Tübingen Working Papers in Economics and Finance No. 35 (see Neubecker et al., 2012) and as IAW Discussion Paper No. 83.

[1] Massey (1988, 396) defines migrant networks as "[...] sets of interpersonal ties that link migrants, former migrants, and nonmigrants in origin and destination areas through the bonds of kinship, friendship, and shared community origin."

[2] Of these migrants, 13.6% are Romanians, followed by Moroccans (11.1%), Ecuadorians (8.2%), Colombians (6.1%), Britons (5.3%), and Bolivians (4.7%). Unless stated otherwise, all migration figures in this chapter are own calculations based on data from the Spanish Instituto Nacional de Estadística (INE).

In order to identify network effects in migration to Spain, we develop and apply a three-level nested multinomial logit (NMNL) migration model along the lines of McFadden (1984, 1422-1428). The model is more general than the standard multinomial logit (MNL) model described in McFadden (1984, 1411-1415). The standard MNL model has been extensively applied to the migration literature but assumes that, in principle, any two migration destinations are equally substitutable for one another. This assumption is at odds with the fact that destinations belonging to the same *territorial entity* (e.g., a sovereign state or a country subdivision with independent legislative authority) are similar in many respects. They share, by definition, the same legal and political framework; they have a common cultural background; and they engage in the same economic activities. Our NMNL framework allows for such multi-level similarities, with cross-alternative substitutability being largest for destinations located in the same region of a given country, and lowest for destinations located in different countries. Our model introduces unobserved heterogeneity into the migration function that challenges previous identification strategies based on cross-sectional migration data.

Another challenge in terms of modeling cross-alternative substitutability derives from the so-called "Dispositive Principle", an important feature of the Spanish political system. As part of the Spanish constitution, it grants regional authorities the right to define the extent of their legislative autonomy (Morales and Molés, 2002, 180). Hence, destinations in regions with a high demand for self-government are rendered more similar to each other than destinations in other regions. Related arguments derive from the fact that some, but not all, regions have a second official language that is actively used by the population (in addition to *castellano*). In general, destinations in regions with a pronounced political and cultural autonomy should appear as close substitutes, relative to destinations in other regions. Our NMNL framework, while remaining tractable, allows us to model these features of the Spanish economy in a very convenient way, namely by introducing similarity parameters that are specific to the different regions of destination in Spain.[3] Although we cannot estimate these parameters directly, our model suggests that estimated network coefficients are not homogeneous across destinations, a possibility that we explore in detail and that challenges previous interpretations of the quantitative importance of the network

[3] To the best of our knowledge, no other random utility model that could be estimated with our data would allow us to do likewise. For example, the generalized nested logit (GNL) model by Wen and Koppelman (2001) could be used to closely approximate our three-level NMNL, but its estimation is not feasible with our data.

effect.

Obtaining consistent and unbiased estimates of network effects in migration is not trivial. The main endogeneity concern is the two-way relationship between migration costs and migrant networks, defined as the number of migrants from a certain nationality already settled in a certain destination. On the one hand, the migrant network appears as an argument in the migration cost function determining future migration. On the other hand, the migrant network is the result of past migration and thus itself influenced by migration costs. Our data distinguish among both different countries of origin and different provinces of destination in Spain. This allows us to go beyond the existing literature in the way we control for unobserved heterogeneity in migration costs through fixed effects. By grouping countries of origin into world regions, we control for all migration costs specific to the world region of origin and the province of destination (e.g., Latin American people being especially well-received in the province of Murcia).[4] By grouping provinces of destination into regions, we control for all migration costs specific to the country of origin and the region of destination in Spain (e.g., the short distance between France and Cataluña). To further strengthen our analysis, we instrument migrant networks by historical internal migration flows in Spain.

The first finding of this chapter is that migrant networks exert a strong positive effect on the scale of migration. This finding squares well with the popular idea that already settled migrants reduce the migration costs for those left behind.[5] However, we find significantly upward-biased estimates of the network effect when unobserved heterogeneity is not controlled for through fixed effects. The second finding of this chapter is that migrant networks exert a strong negative effect on the skill structure of migration, defined as the ratio of high-skilled to low-skilled migrants. This finding is consistent with the idea that high-skilled individuals have lower effective migration costs than low-skilled individuals, see Chiswick (1999). Intuitively, migrant networks are more important for low-skilled individuals than they are for high-skilled individuals, biasing the skill structure of migration toward the low-skilled individuals.

Our estimation results strongly reject a constant degree of cross-alternative substi-

[4] This approach also controls for the fact that migrants are attracted to destinations hosting migrants from countries that are culturally and geographically close to their own country of origin; see Chapter 5.

[5] Carrington et al. (1996) and Chau (1997) study the dynamics of migration when network effects are treated as a positive externality, which generates a welfare loss in the laissez-faire transition path equilibrium. From a social planner perspective, this calls for policy intervention in the form of migration subsidies that accelerate the speed of migration.

tutability, working against the standard MNL model in our application to the Spanish case. The extent of cross-regional heterogeneity in the elasticity of migration with respect to migrant networks (network elasticity) is striking. The estimated network elasticity is lowest for the destinations located in the region of Extremadura, slightly exceeding a value of 0.1; it is highest for the destinations located in the region of Cataluña, lying in the vicinity of 0.55. The highest degree of cross-alternative substitutability is thus found for the set of destinations belonging to Cataluña, arguably the region with the highest degree of political and cultural autonomy in Spain.

This chapter is related to the recent literature estimating network effects based on aggregate migration data. Beine et al. (2011a) investigate the determinants of the scale and skill structure of migration between the years 1990 and 2000 to 30 OECD countries. They find that economies hosting migrants from a given country attract both a larger number of new migrants as well as a larger fraction of low-skilled migrants from that country.[6] Similar results are obtained by Beine and Salomone (2013) who study potential gender differences in network effects. The paper by Beine et al. (2011b) employs a data structure similar to ours, focusing on U.S. migration. It separately identifies what the authors call local and national network externalities, saying that local migrant networks facilitate assimilation, while nation-wide migrant networks reduce visa costs. However, all of these papers derive the estimated migration functions from a standard MNL model that assumes a constant degree of cross-alternative substitutability.[7]

This chapter is also related to a number of macro-level studies that are more generally concerned with the determinants of international migration.[8] In this literature, migrant networks constantly rank among the most important factors shaping migration, but the estimated migration functions often lack an explicit micro-foundation (Clark et al., 2007, Lewer and Van den Berg, 2008, Pedersen et al., 2008, Mayda, 2010). Two recent papers,

[6] See also Grogger and Hanson (2011, 53) for complementary evidence. Mckenzie and Rapoport (2010) find positive self-selection on education from Mexican migrants to the United States to be more likely, the larger the number of return migrants in the origin community. Bertoli (2010) finds a positive interaction between the number of migrants abroad and the extent of negative self-selection, using individual-level data on Ecuadorian emigrants.

[7] Bertoli and Fernández-Huertas Moraga (2012) use the same migration data as Beine et al. (2011a) in order to estimate network effects in migration, relaxing the assumption of a constant degree of cross-alternative substitutability. The most general version of their estimated model reduces to a two-level NMNL model with a single similarity parameter for all "nests" (territorial entities in this chapter) to have equal similarity parameters; see Section 6.6.1 in the appendix for details.

[8] For the location choice of migrants within borders, see Bartel (1989), Zavodny (1997, 1999), Chiswick and Miller (2004), Card and Lewis (2007), and Jayet et al. (2010). Selected survey-based studies on migration decisions at the micro-level include Åslund (2005), Baghdadi (2005), Bauer et al. (2005, 2009), and Dolfin and Genicot (2010).

Bertoli and Fernández-Huertas Moraga (2013) and Ortega and Peri (2013), estimate the determinants of migration based on micro-founded random utility models. In both papers, the standard MNL assumption of a constant degree of cross-alternative substitutability is relaxed. Bertoli and Fernández-Huertas Moraga (2013) consult the same Spanish data source as we do in this chapter. They show how panel methods can be used to obtain consistent estimates of the migration function under arbitrary specifications of the cross-nested logit (CNL) model due to Vovsha (1997). The CNL model allocates a “portion” of each destination to a set of “nests” (territorial entities in this chapter), assuming, contrary to our model, that there is a single similarity parameter, see Wen and Koppelman (2001, 628).[9] Ortega and Peri (2013) investigate the impact of income and immigration policies on migration to OECD countries, using panel data detailed by country of origin and country of destination.[10] Their model, best understood as a two-level NMNL model with a single similarity parameter for all nests, allows for a higher degree of cross-alternative substitutability for any two destinations outside the individual’s country of origin. However, neither Bertoli and Fernández-Huertas Moraga (2013) nor Ortega and Peri (2013) identify the effects of migrant networks on the scale and skill structure of migration, as we do in this chapter.

The remainder of this chapter is organized as follows. Section 6.2 characterizes individual decision making in a three-level NMNL model. We derive estimable equations from this model for the scale and skill structure of migration. In Section 6.3 we present our estimation strategy and introduce in detail the data that we employ in our econometric analysis. Section 6.4 presents our estimation results; we provide a structural interpretation of these results in terms of our NMNL migration model. Section 6.5 concludes.

6.2 The Model

In this section we develop a multi-country random utility framework with many countries of origin and many provinces of destination at the sub-country level. The framework takes the form of a nested multinomial logit (NMNL) model along the lines of McFadden (1984, 1422-1428).

[9] The CNL model is a special case of the GNL model; unlike the GNL model, the CNL model cannot be used to approximate our three-level NMNL model (see Wen and Koppelman, 2001). Bertoli, Brücker, and Fernández-Huertas Moraga (2013) employ the CNL model in order to study the effect of the recent economic crisis in Europe on migration to Germany.

[10] In Ortega and Peri (2009), a previous version of Ortega and Peri (2013), the authors also study the effects of migration on employment, investment, and productivity.

6.2.1 Basic Setup

We assume that the decision making process leading to migration follows a hierarchical structure in which provinces of destination (the final migration destinations) are grouped into higher-level territorial entities (nests). Individuals "eliminate" nests until a single province remains. Decision making can be described in a hierarchical manner[11]: first to which country to migrate (including the country of origin), second which region to move to within the chosen country, and third which province to pick within the preferred region.[12] Let $i = 1, \ldots, I$ index countries of origin, j or $k = 1, \ldots, J$ index provinces of destination, z or $y = 1, \ldots, Z$ index the primary nests (countries of destination), and r or $\ell = 1, \ldots, R$ index the secondary nests (regions of destination within countries), as perceived by individuals living in country i.[13] Let the country of origin i be one element in each of the sets $\{1, \ldots, Z\}$, $\{1, \ldots, R\}$, and $\{1, \ldots, J\}$; it represents a degenerate nest with a single final migration destination. Define A_{zr} as the set of provinces belonging to region r in country z, and A_z as the set of regions belonging to country z.

We write the utility of individual o who migrates from country i to province j and lives in province j as:

$$U_{ij}^{o} = Y_j - C_{ij} + e_{ij}^{o}, \tag{6.1}$$

where the index $o = 1, \ldots, m_i$ identifies individuals originating from country i, the terms Y_j and C_{ij} are sub-utility functions relevant for moving from country i to province j and living in province j, and the term e_{ij}^{o} is a stochastic (random) utility variable with individual-specific realizations for each province $j = 1, \ldots, J$. The function Y_j summarizes utility-relevant characteristics of province j such as the wage rate, the state of the housing market, and the climate. It is assumed to be independent of the individual's country of origin. The function C_{ij} captures the costs of moving and assimilation, henceforth called migration costs. Similar to Beine et al. (2011a, 33-34), we hypothesize that these costs are a decreasing and globally convex function of the migrant network, M_{ij}, defined as the number of co-national migrants already settled in province j. A convenient specification of migration costs that incorporates the idea of positive but diminishing returns to the

[11] We assume that each decision in this hierarchy is made conditional on both the fixed preceding decisions and the optimal succeeding decisions. Hence, one can think of individuals as deciding on all aspects of their migration moves simultaneously (see Domencich and McFadden, 1975, 33-46).

[12] In Ortega and Peri (2013), the first decision of individuals is between going abroad and staying at home. Our econometric implementation is compatible with this additional structure.

[13] Strictly speaking, the final migration destinations j and the nests r and z are i-specific. We omit this index in order to avoid notational clutter.

migrant network uses the log of M_{ij}:

$$C_{ij} = c_{iz} + c_{ir} + c_{ij} - \theta \ln(1 + M_{ij}), \quad j \in A_{zr}, r \in A_z, \tag{6.2}$$

where the parameter $\theta > 0$ is a measure for the strength of the network effect, and where we add one to the variable M_{ij} before taking logs in order to abstract from infinitely large migration costs. The other cost components not related to the migrant network will be described in more detail below. Suffice it to say here that, for a given country of origin i, they vary either across countries of destination (c_{iz}), across regions of destination (c_{ir}), or across provinces of destination (c_{ij}). For expositional convenience, we define $U_{ij} \equiv U^o_{ij} - e^o_{ij} = Y_j - C_{ij}$ and $\xi_{ij} \equiv Y_j - c_{ij} + \theta \ln(1 + M_{ij})$.

Individuals are assumed to choose from the set of provinces the alternative from which they derive the highest utility:

$$j^o = \text{argmax}(U^o_{i1}, \dots, U^o_{iJ}), \quad j^o \in \{1, \dots, J\}. \tag{6.3}$$

The probability that individual o from country i migrates to province j is equal to the probability that this individual associates the largest utility with moving to province j:

$$\begin{aligned} P^o_i(j^o = j) &= \Pr(U^o_{ij} > U^o_{ik} \ \ \forall\, k \in \{1, \dots, J\} : k \neq j) \\ &= \Pr(e^o_{ik} - e^o_{ij} < U_{ij} - U_{ik}; \quad \forall\, k \in \{1, \dots, J\} : k \neq j). \end{aligned} \tag{6.4}$$

By the laws of conditional probability, we can express this probability as a product of transition probabilities:

$$P^o_i(j^o = j) = P^o_i(j^o = j | j^o \in A_{zr}) P^o_i(j^o \in A_{zr} | r \in A_z) P^o_i(r \in A_z), \quad j \in A_{zr}, r \in A_z. \tag{6.5}$$

These probabilities depend on the distribution assumed for the random utility variables, $e^o_{i1}, \dots, e^o_{iJ}$. Let $\mathbf{g}_i = (g_{i1}, \dots, g_{iJ})$ be a $(1 \times J)$ row vector with non-negative entries, and let H_i be a non-negative function of $\mathbf{g}_i$ with:

$$\lim_{g_{ij} \to \infty} H_i(\mathbf{g}_i) = +\infty \quad \text{for } j = 1, \dots, J. \tag{6.6}$$

Furthermore, assume that H_i is homogeneous of degree one in $\mathbf{g}_i$, and let H_i have mixed partial derivatives of all orders, with non-positive even and non-negative odd mixed derivatives. It can be shown that the function

$$F_i(e^o_{i1},\ldots,e^o_{iJ}) = \exp\left[-H_i\left(\exp[-e^o_{i1}],\ldots,\exp[-e^o_{1J}]\right)\right] \tag{6.7}$$

is a multivariate extreme value distribution function, and that, if $(e^o_{i1},\ldots,e^o_{iJ})$ is distributed F_i, (6.4) can be written as:

$$\begin{aligned} P^o_i(j^o = j) &= \frac{\exp[U_{ij}]}{H_i(\exp[U_{i1}],\ldots,\exp[U_{iJ}])}\frac{\partial H_i(\exp[U_{i1}],\ldots,\exp[U_{iJ}])}{\partial \exp[U_{ij}]} \\ &= \frac{\partial \ln H_i(\exp[U_{i1}],\ldots,\exp[U_{iJ}])}{\partial U_{ij}}; \end{aligned} \tag{6.8}$$

see McFadden (1978, 80-81) and McFadden (1981, 226-230).[14]

We depart from the received literature in that we introduce a function H_i that generates the response probabilities of a three-level NMNL model. It allows for the random utilities associated with provinces belonging to the same region (or the same country) to be mutually correlated, whereas the random utilities associated with provinces in different countries are independent.

Define on the half-open unit interval two parameters, λ_z and κ_r $(0 < \kappa_r, \lambda_z \leq 1)$, measuring the similarity of the provinces located in country z and region r, respectively. These parameters govern the degrees of cross-alternative substitutability in our model; they are allowed to vary across countries and across regions, respectively. High parameter values indicate little similarity among provinces (and weak correlations among the random utilities), low parameter values indicate much similarity (and strong correlations). As we have argued in the introduction, cross-regional differences in the similarity parameter κ_r in Spain could derive, for example, from the constitutionally anchored "Dispositive Principle", which allows for region-specific degrees of legislative autonomy. We assume:

$$\begin{aligned} H_i(\exp[U_{i1}],\ldots,\exp[U_{iJ}]) &= \sum_z \left(\sum_{r\in A_z}\left(\sum_{j\in A_{zr}} \exp[U_{ij}/(\kappa_r\lambda_z)]\right)^{\kappa_r}\right)^{\lambda_z} \\ &= \sum_z \exp[-c_{iz}]\left(\sum_{r\in A_z}\exp[-c_{ir}/\lambda_z]\left(\sum_{j\in A_{zr}}\exp[\xi_{ij}/(\kappa_r\lambda_z)]\right)^{\kappa_r}\right)^{\lambda_z} \end{aligned} \tag{6.9}$$

[14]We show in Section 6.6.2 in the appendix how to derive (6.8).

It is instructive to note that the function $H_i(\cdot)$ nests the generating function for the response probabilities of the standard MNL model as a special case with $\kappa_r = \lambda_z = 1\ \forall r, z$. We shall return to this in more detail below. From equations (6.8) and (6.9) it follows that each transition probability in equation (6.5) has a closed-form analytical solution[15]:

$$P_i^o(r \in A_z) = \exp[\Omega_{iz}\lambda_z - c_{iz} - \Psi_i], \tag{6.10}$$

$$P_i^o(j^o \in A_{zr} | r \in A_z) = \exp[\Phi_{ir}\kappa_r - c_{ir}/\lambda_z - \Omega_{iz}], \tag{6.11}$$

$$P_i^o(j^o = j | j^o \in A_{zr}) = \exp[\xi_{ij}/(\lambda_z\kappa_r) - \Phi_{ir}], \tag{6.12}$$

where Φ_{ir}, Ω_{iz}, and Ψ_i are "inclusive values" defined as:

$$\Phi_{ir} \equiv \ln \sum_{k \in A_{zr}} \exp[\xi_{ik}/(\lambda_z\kappa_r)], \tag{6.13}$$

$$\Omega_{iz} \equiv \ln \sum_{\ell \in A_z} \exp[\Phi_{i\ell}\kappa_\ell - c_{i\ell}/\lambda_z], \tag{6.14}$$

$$\Psi_i \equiv \ln \sum_z \exp[\Omega_{iz}\lambda_z - c_{iz}]. \tag{6.15}$$

The inclusive values Φ_{ir}, Ω_{iz}, and Ψ_i summarize, respectively, the characteristics of all provinces belonging to region r, all provinces belonging to country z, and all provinces belonging to the complete set of final migration destinations. Using equation (6.5) together with equations (6.10) to (6.15) and aggregating over all individuals from country i, we can write the rate of migration from country i to province j as:

$$\frac{m_{ij}}{m_i} = \frac{\exp[\xi_{ij}/(\lambda_z\kappa_r) - c_{ir}/\lambda_z - c_{iz}]}{\exp[\Psi_i + (1-\kappa_r)\Phi_{ir} + (1-\lambda_z)\Omega_{iz}]}, \tag{6.16}$$

where m_{ij} is the number of individuals migrating from i to j, and m_i is the initial population size of country i. This ij-specific migration rate depends on the attractiveness of all provinces $k = 1, \dots, J$, whether in the same region r (or the same country z) or not. For example, consider the elasticity of m_{ij}/m_i, $j \in A_{zr}, r \in A_z$, with respect to Y_k, the utility-relevant characteristics of province k, $k \in A_{y\ell}, \ell \in A_y$. Straightforward though cumbersome differentiation yields[16]:

[15] For example, in order to derive $P_i^o(r \in A_z)$, one simply has to compute $\partial \ln H_i(\cdot)/\partial(-c_{iz})$, and similarly for the other transitional probabilities. We show in Section 6.6.3 in the appendix how to compute $P_i^o(j^o = j) = \partial \ln H_i(\cdot)/\partial U_{ij}$.

[16] We show in Section 6.6.4 in the appendix how to compute this elasticity.

$$\frac{\partial \ln(m_{ij}/m_i)}{\partial \ln(Y_k)} = Y_k \left[\frac{I(j,k)}{\lambda_z \kappa_r} - \left(\frac{m_{ik}}{m_i}\right) \right.$$
$$\left. - \frac{I(\ell,r)}{\lambda_z \kappa_r}(1-\kappa_r)\left(\frac{m_{ik}}{m_{ir}}\right) - \frac{I(y,z)}{\lambda_z}(1-\lambda_z)\left(\frac{m_{ik}}{m_{iz}}\right)\right], \tag{6.17}$$

where $m_{ir} = \sum_{j \in A_{zr}} m_{ij}$, $m_{iz} = \sum_{r \in A_z} m_{ir}$, and $I(a,b) = 1$ if $a = b$ and zero otherwise.[17] Given that $0 < \kappa_r, \lambda_z \leq 1$, this elasticity is positive for $k = j$ and negative for all provinces $k \neq j$. It is in this sense that we refer to the inclusive values Ψ_i, Φ_{ir}, and Ω_{iz} in equation (6.16) as "multilateral resistance" terms.[18]

Changes in the conditions in some province $k \neq j$ induce *non-uniform* effects on the ij-specific migration rate, depending on whether this province belongs to the same country or region as province j. In particular, the elasticity in (6.17) is largest (in absolute terms) for changes in the conditions in other provinces in the same region, $I(\ell, r) = I(y, z) = 1$. The fact that such substitution effects are strongest within regions and weakest across countries is due to the similarity of provinces within the same region (and within the same country). In the standard MNL model with $\lambda_z = \kappa_r = 1 \ \forall r, z$, the pattern of cross-elasticities becomes strikingly simple. For $k \neq j$, (6.17) collapses to $\partial \ln(m_{ij}/m_i)/\partial \ln(Y_k) = -Y_k m_{ik}/m_i$, independently of whether or not the provinces j and k are located in the same region or the same country.

The rich patterns of cross-alternative substitutability in the NMNL model notwithstanding, the issue of multilateral resistance is not a special feature of the NMNL model. It is a key element of the standard MNL model as well. To see this, note that with $\lambda_z = \kappa_r = 1 \ \forall r, z$, the ij-specific migration rate reads as:

$$\left.\frac{m_{ij}}{m_i}\right|_{\lambda_z, \kappa_r = 1} = \frac{\exp[\xi_{ij} - c_{ir} - c_{iz}]}{\exp[\Psi_i]} = \frac{\exp[U_{ij}]}{\sum_k \exp[U_{ik}]}, \tag{6.18}$$

which depends not only on the conditions in i and j, but also on the conditions in all other provinces through the multilateral resistance term Ψ_i. Based on the standard MNL model of equation (6.18), a common approach in the literature is to compute the ij-specific migration rate (namely, the fraction of the population in i who migrate to j) relative to the i-specific stay rate (namely, the fraction of non-migrants of the population in i):

[17] Notice that $I(j,k) = 1$ implies that $I(\ell,r) = I(y,z) = 1$ but not the other way around.

[18] Mayda (2010) speaks of "multilateral pull" effects. The idea of multilateral resistance here is similar to that in the gravity equation for international trade flows (see Anderson and van Wincoop, 2003). Anderson (2011) sketches a general equilibrium migration model with multilateral resistance. See also Hanson (2010, 4373-4375) for a discussion.

$$\frac{m_{ij}}{m_{ii}} = \exp[U_{ij} - U_{ii}], \tag{6.19}$$

where the multilateral resistance term cancels out. In the standard MNL model, the odds ratio between any two provinces is thus independent of the number and characteristics of other provinces, a property known as the independence of irrelevant alternatives (IIA) assumption (McFadden, 1974, 1978).[19] Thus, estimating a log-linearized version of equation (6.19) (instead of estimating a log-linearized version of equation (6.18)) has the advantage that no attention needs to be paid to the multilateral resistance term, provided that the IIA assumption is not violated. In our more general NMNL modeling framework, the relative odds becomes:

$$\frac{m_{ij}}{m_{ii}} = \frac{\exp[\xi_{ij}/(\lambda_z \kappa_r) - \xi_{ii} - c_{ir}/\lambda_z + c_{i\ell} - c_{iz} + c_{iy}]}{\exp[(1-\kappa_r)\Phi_{ir} + (1-\lambda_z)\Omega_{iz}]}, \tag{6.20}$$

where $j \in A_{zr}, r \in A_z$, and $i \in A_{y\ell}, \ell \in A_y$, and where we have used the fact that the country of origin i represents a degenerate nest representing a single final migration destination. It is thus easy to verify that the odds ratio between any two provinces belonging to two different regions is not independent of the number and characteristics of other provinces. This involves a partial relaxation of the IIA assumption. Hence, in our NMNL framework, the issue of multilateral resistance needs to be addressed explicitly, whether we estimate a log-linearized version of equation (6.16) or of equation (6.20).[20] Given that the variable m_i in equation (6.16) is exogenous, while the variable m_{ii} in equation (6.20) is endogenous and potentially difficult to observe, we use the ij-specific migration rate in equation (6.16) for our econometric implementation.

6.2.2 Scale of Migration

Substituting ξ_{ij} in equation (6.16), taking logs, and rearranging terms yields the following migration function for $j \in A_{zr}, r \in A_z$:

$$\begin{aligned}\ln(m_{ij}) =& \frac{\theta}{\lambda_z \kappa_r} \ln(1 + M_{ij}) + \ln(m_i) + \frac{1}{\lambda_z \kappa_r} Y_j - c_{iz} - \frac{1}{\lambda_z} c_{ir} - \frac{1}{\lambda_z \kappa_r} c_{ij}, \\ & \underbrace{-\Psi_i - (1-\lambda_z)\Omega_{iz} - (1-\kappa_r)\Phi_{ir}}_{\text{Multilateral resistance}}. \end{aligned} \tag{6.21}$$

[19] Strictly speaking, the standard MNL model as such does not imply the IIA property. The IIA property would indeed be absent in the standard MNL model if U_{ij} was a function of any of the characteristics of province $k \neq i, j$.

[20] The same applies to the CNL migration model estimated in Bertoli and Fernández-Huertas Moraga (2013).

Identification of the network effect is thus complicated by the presence of both the different cost components and the multilateral resistance terms. Moreover, the network coefficient, defined as $\eta_{zr} \equiv \eta(\lambda_z, \kappa_r) = \frac{\theta}{\lambda_z \kappa_r}$, is a decreasing function of λ_z and κ_r; it is larger the larger the similarities of provinces in country z and region r, respectively. For low values of λ_z and κ_r, it is easy to substitute one province for another one in the same country or region, respectively. In this case, a small increase in the migrant network in province $k \in A_{zr}, r \in A_z$, leads a large number of individuals to substitute another province $j \in A_{zr}$ by province k, other things held constant. We expect to find higher degrees of cross-alternative substitutability (and thus larger network coefficients) in regions that put a lot of emphasis on their political and cultural autonomy.

6.2.3 Skill Structure of Migration

We now distinguish between high-skilled and low-skilled individuals, denoted by h and l, respectively. We augment the utility function by a parameter $\gamma^s > 0, s \in \{h, l\}$, representing the ease with which individuals are able to cope with migration costs (decreasing with higher values):

$$U^o_{ij} = Y_j - \gamma^s C_{ij} + e^o_{ij}, \tag{6.22}$$

where $s = h$ if individual o is high-skilled and $s = l$ otherwise. We assume that $\gamma^h < \gamma^l$, so high-skilled individuals have lower effective migration costs than low-skilled individuals. This assumption is in line with Chiswick (1999), who argues that the high-skilled can handle their migration process more efficiently than the low-skilled. We can thus derive one migration function for each skill group by complete analogy to equation (6.21). Subtracting the equation for low-skilled migrants from the same equation for high-skilled migrants, we obtain:

$$\begin{aligned} \ln\left(\frac{m^h_{ij}}{m^l_{ij}}\right) =& \frac{\theta\gamma^*}{\lambda_z\kappa_r}\ln(1+M_{ij}) + \ln\left(\frac{m^h_i}{m^l_i}\right) - \gamma^* c_{iz} - \frac{\gamma^*}{\lambda_z}c_{ir} - \frac{\gamma^*}{\lambda_z\kappa_r}c_{ij} \\ &- \Psi^*_i - (1-\lambda_z)\Omega^*_{iz} - (1-\kappa_r)\Phi^*_{ir}, \end{aligned} \tag{6.23}$$

where the variables with an asterisk (*) are differences between the corresponding parameters (or variables) for high-skilled and low-skilled individuals. Since $\gamma^* < 0$, the ratio of new high-skilled to new low-skilled migrants is a decreasing function of the migrant network. This result is due to the fact that individuals differ in their effective costs of migration, and that this difference is less important for low levels of migration costs. Hence, it is the low-skilled individuals who benefit the most from a reduction in migration costs through a larger migrant network.[21]

6.3 Estimation Strategy and Data

In this section we describe our estimation strategy and we present the different variables that we use in the estimation. We estimate different variants of the models given by equations (6.21) and (6.23), each augmented by a stochastic error term. We consider two different aggregation levels for final migration destinations in Spain. The model for the scale of migration is estimated at the level of provinces in Spain. Due to reasons of data availability, the model for the skill structure of migration is estimated at the level of regions in Spain.[22] For both models, our benchmark estimates are based on a sample comprising the 55 most important countries of origin listed in Table 6.6 in Section 6.6.5 in the appendix.[23] All migration data come from the Spanish Instituto Nacional de Estadística (INE). The full internet sources of our data are listed in Table 6.7 in Section 6.6.5 in the appendix.

6.3.1 Scale of Migration

The dependent variable is the log of the migration flow to provinces of destination in Spain, obtained from the Spanish Residential Variation Statistics and aggregated from the beginning of 1997 until the end of 2006.[24] This period covers Spain's unprecedented migration boom, which was eventually attenuated by the global financial and economic crisis starting in 2007. The migrant network, M_{ij}, is measured by the number of settled migrants in 1996, as reported by the Spanish Municipal Register. We rely on population figures disaggregated by nationalities and by provinces in Spain as of May 1, 1996.

From the year 2000 onwards, our migration data are likely to include both docu-

[21] This is reflected in the following inequality: $\partial U_{ij}(\gamma^l)/\partial M_{ij} > \partial U_{ij}(\gamma^h)/\partial M_{ij}$. In this respect, our modeling approach is akin to the one in Beine et al. (2011a).

[22] Spain is divided into 52 provinces that are nested in 19 regions. We exclude the provinces (enclaves) of Ceuta and Melilla due to their specific geographical location and thus we end up with 50 provinces nested in 17 regions. See http://www.ine.es/daco/daco42/codmun/cod_provincia.htm and http://www.ine.es/daco/daco42/codmun/cod_ccaa.htm (both accessed on 04/17/2012) for a list of provinces and regions, respectively.

[23] These are all countries with at least 630 migrants in Spain in the year 1996. We apply alternative selection criteria in a robustness analysis.

[24] Migrants are defined as individuals whose last country of residence (other than Spain) corresponds to their country of birth and nationality. In their raw form, the migration flow data are observed for periods of less than a year. We aggregate the data over time because the model cannot deal with a time dimension in any convenient way, unless we impose the extremely strong assumption that in every period individuals left in the home country draw new realizations of the random variables $e^o_{i1}, \ldots, e^o_{iJ}$.

mented and undocumented migrants due to the incentives deriving from the *"Law on the Rights and Freedoms of Aliens in Spain and their Social Integration"* (*Ley Orgánica 4/2000, artículo 12*). This law became effective in 2000 and entitled all registered foreigners to free medical care under the same conditions as Spanish nationals, irrespective of their legal status.[25] Each registrant must provide his or her name, surname, sex, usual domicile, nationality, passport number, as well as the place and date of birth.[26] Since this information is confidential and must not be communicated to other administrative units, the probability of forced repatriation is independent of registration.

We identify the model from the within-cluster variation across provinces in the data. We start with a parsimonious fixed effects (FE) specification in which we define as clusters the different countries of origin, computing all variables in equation (6.21) as deviations from their country means (within-transformation).[27] This approach wipes out, first, all terms with subscript i and thus controls for the initial population size in the country of origin as well as for the multilateral resistance term Ψ_i; and second, it wipes out all terms with subscript iz because our migration data refer to a single country of destination z. By eliminating c_{iz}, it thus controls, for example, for the impact of country-specific migration policies and the geographical and cultural distance between the country of origin and the country of destination. By eliminating Ω_{iz}, it is compatible with a model in which the degree of cross-alternative substitutability is larger within than across countries of destination.

In more demanding specifications of our FE model, we define as clusters the different pairs of countries of origin and regions of destination, computing all variables as deviations from their country-and-region means. In addition to the above-described country effects, this approach wipes out all terms with subscript ir. These terms include, first, the multilateral resistance term Φ_{ir}, so that this approach is fully compatible with our three-level NMNL model; and second, they include the cost term c_{ir} representing the geographical and cultural distance between the country of origin and the region of destination. Important elements of this distance derive from a cultural, political, and historical context. For

[25] As part of its austerity measures in 2012, the Spanish government has restricted this access to health care for undocumented migrants from September 2012 onwards. Exceptions are made in the case of pregnant women, minors, and emergency care (`http://www.presseurop.eu/en/content/news-brief/2614611-no-more-free-treatment-undocumented-migrants` based on `http://elpais.com/elpais/2012/08/29/opinion/1346265472_538020.html`, accessed on 08/31/2012).

[26] See INE at `http://www.ine.es/en/metodologia/t20/t203024566_en.htm`, accessed on 08/19/2011.

[27] When zero values inflate the dependent variable, the FE estimator delivers inconsistent estimates (see Santos Silva and Tenreyro, 2006). In our sample we observe only a modest number of zero migration flows (5.75% of all country-province pairs) and therefore apply the FE estimator.

example, the different regions in Spain feature substantial heterogeneity in terms of native languages; the Basque Autonomous Community and Navarre both have strong cultural ties with the Northern Basque Country that is part of French national territory[28]; the region of Galicia has long been suffering from a chronic growth weakness leading to mass emigration in the 19th and 20th century, in particular to Latin American countries.

All other migration costs are summarized in the term c_{ij}. Some of these costs, for example the attitudes of the native population toward migrants, may be specific to the province of destination j but independent of the country of origin i. We control for these province-specific migration costs by including a set of province fixed effects in the estimation; the province fixed effects also absorb the impact of province-specific pull factors summarized in the term Y_j. Some other migration costs may be specific to both the province of destination and the world region of origin (grouping countries of origin). An example would be that individuals from Ecuador feel attracted not only by a network of co-national migrants (i.e., migrants from Ecuador) but also by a network of migrants from other Latin American countries; see Chapter 5. This additional effect, a "cross-national" network externality, would lower the migration costs for potential migrants from Ecuador, leading to a higher incidence of migration. In more demanding specifications of our model, we therefore control for these other migration costs through a set of world region-and-province fixed effects.[29]

As further control variables, we include bilateral trade and capital flows where possible. Both variables could be part of the cost term c_{ij}. Trade is not only facilitated by, but is also conducive to a good infrastructure for traveling and transportation. Capital invested by foreign firms could create demand for specific types of labor, especially foreign labor. Data on both trade and foreign direct investment (FDI) are provided by the Spanish Ministry of Industry, Tourism and Trade. We measure ij-specific trade flows by the sum of exports and imports (in Euros) in the year 1996. These information are taken from DataComex Statistics on Spanish Foreign Trade. Ideally, we would like to use FDI stocks to measure inward investment but we only have information on gross FDI inflows (in Euros). These are detailed by the country of the last owner and by the region of des-

[28] The Basque Autonomous Community and Navarre form the Spanish part of the Basque Country (*País Vasco* in Spanish; *Euskal Herria* in Basque language).

[29] In terms of world regions, we distinguish among East Asia & Pacific; Eastern Europe & Central Asia; Latin America & Caribbean; Middle East & North Africa; North America, Australia & New Zealand; South & South-East Asia; Sub-Saharan Africa; as well as Western Europe. For a similar classification used by the IMF, see `http://www.imf.org/external/datamapper/region.htm`, accessed on 07/25/2012.

tination in Spain[30]; they are available from DataInvex Statistics on Foreign Investments in Spain. Due to limited data availability, we have to use FDI flows for the year 1997. We argue, however, that endogeneity is unlikely, given that firms base their investment decisions on long-term considerations instead of short-term or medium-term forecasts.

In case we omit ij-specific variables that are correlated with both m_{ij} and M_{ij}, the migrant network is endogenous to the subsequent migrant flow. In view of our extended FE specification, it is difficult to think of any such omitted variable. However, suppose there is a province-specific labor demand for workers from a certain nationality, such as the demand for German engineers in SEAT's car production in Barcelona. Then, the FE model may produce biased and inconsistent estimates. Consistent estimation would call for an instrument that is uncorrelated with the structural error term but correlated with the endogenous regressor. We adopt an instrumental variables approach in which we instrument country i's migrant network in province j with historical internal migration flows in Spain, defined as the log of the number of people holding country i's nationality and migrating from province j to any other province $k \neq j$ in Spain in 1988 (henceforth simply called internal migration); see also Chapter 5.[31]

Because it indicates a large historical network, internal migration can be expected to correlate positively with the migrant network in 1996.[32] Our first-stage regressions attest to a statistically significant positive (partial) correlation. Its significance is also reflected in relatively high values for the first-stage F statistics. For internal migration to be a valid instrument, it must be uncorrelated with the structural error term.[33] This assumption could be violated if a large internal migration observed for a certain province reflects and signals a poor matching quality (for example in terms of jobs) between this province and the corresponding migrants, thus leading to a lower incidence of migration today. However, this signaling effect does not necessarily render our instruments endogenous. One reason is that most, if not all, of the variation in the matching quality across countries and across provinces is absorbed into our fixed effects. Another, probably more important, reason is that the signaling effect should be captured by the (observable) migrant network itself,

[30] Hence, the effect of FDI on migration is not identified in the model controlling for country-and-region fixed effects.

[31] The year 1988 is the first year for which these information are available. It is well before the start of the Spanish migration boom. We add one to the number of people before taking logs in order to keep observations with zero migration flows.

[32] It follows from its definition, however, that internal migration also reduces the size of the historical network.

[33] Therefore, the focus on *internal* migration is on purpose because it excludes return migrants who could shape future migration in one way or the other.

given that this network is a function of all past migration flows. We use internal migration in 1989 as a second excluded instrument. This allows us to perform tests on overidentifying restrictions and check for instrument exogeneity.

6.3.2 Skill Structure of Migration

Aggregate migration data with reliable information on the skill structure of migration can only be constructed at the level of regions rather than at the level of provinces. In principle, there are two alternative ways to estimate equation (6.23) at the regional level. The first is to rule out regions as secondary nests from the very beginning, and to consider the set of regions in Spain to form the set of final migration destinations within the primary nest of Spain. This is equivalent to setting κ_r equal to one for all r and letting each region in Spain be a destination $j \in A_z$, where country z is Spain. The second way is to derive the migration function for regions of destination from the model's existing three-level nesting structure. The starting point is to use equations (6.10) and (6.11) in order to compute the probability $P_i^o(j^o \in A_{zr}) = P_i^o(j^o \in A_{zr}|r \in A_z)P_i^o(r \in A_z)$. It is easy to show that the two alternative approaches lead to two different migration functions. In what follows, we lay out our estimation strategy for the first approach and report the corresponding results in the next section. We have checked the robustness of our results using the second approach, but we abstain from providing detailed estimation results.[34]

The dependent variable in equation (6.23), $\ln\left(\frac{m_{ij}^h}{m_{ij}^l}\right)$, measures the skill structure of migration. Skill-specific migration flows are obtained from the National Immigrant Survey 2007 (NIS). The survey gathers unique information on a total of 15,465 migrants through field interviews conducted between November 2006 and February 2007; see Reher and Requena (2009, 255-261) for this and the following information.[35] Migrants report, amongst others, their year of arrival in Spain, their first destination in Spain, as well as their highest level of education they completed before migrating. They are defined as individuals aged 16 years or older who were born abroad and have lived in Spain for more than a year, or at least intended to stay for more than a year at the time the survey was conducted.[36] Importantly, this definition is independent of the individual's legal status, so the data again include documented and undocumented migrants. We aggregate the

[34] Section 6.4.2 includes a short description of these robustness checks.

[35] The sample was obtained through a relatively complex three-stage sampling scheme designed to offer reliable and representative data to policy makers and researchers. More detailed information on the sampling can be found in Reher and Requena (2009) as well as in INE (2007).

[36] Foreign-born individuals with Spanish nationality from birth who migrated to Spain within two years after birth are not considered as migrants.

number of migrants by country of birth and region of destination, distinguishing between individuals with completed tertiary education before migrating (high-skilled) and all other individuals (low-skilled) and applying the provided population weights. Although the data can be considered representative of migrants who arrived shortly before the survey was taken, the numbers for earlier cohorts are less reliable due to the lack of information on migrants who died, returned, or migrated onward. We deal with the trade-off between a large number of individuals and data representativeness in that we consider only migrants who arrived in Spain between January 1, 2002, and December 31, 2006.

The migrant network, M_{ij}, is measured by the number of settled migrants as of January 1, 2002. These data, detailed by country of origin and region of destination, are taken from the Spanish Municipal Register. The sum of import and export values in 2001 is collected at the level of regions. Investment stocks as of 2001 are approximated by gross FDI inflows from the beginning of 1998 until the end of 2001. Country-specific fixed effects are wiped out by applying the corresponding within-transformation to the data. Hence, cross-regional differences in the migrant network of a given country of origin are used as identifying variation so that we cannot control for country-and-region fixed effects. We instead augment the model by observable variables that are likely to influence the migration costs. In particular, we control for the geographical distance between the country of origin i and the region of destination in Spain[37], as well as for a common language through an indicator variable. This indicator variable is equal to one if at least 80% of the region's total population are native speakers of a language spoken by at least 20% of the people living in the country of origin, and zero otherwise. The information on native languages in Spain are taken from a number of recent survey studies.[38] Language information on the countries of origin come from Mayer and Zignago (2006). The influence of all terms indexed j is absorbed by a set of dummy variables for the different regions of destination. The complete specification of our model furthermore controls for world region-and-region fixed effects.

We also apply the instrumental variables approach to this model, by analogy to the model for the scale of migration. In particular, we instrument the migrant network in 2002, M_{ij}, with the log of the number of people holding country i's nationality and migrating

[37] Distances are constructed using the STATA module GEODIST by Picard (2010). Latitudinal and longitudinal data of the countries of origin are taken from Mayer and Zignago (2006). Coordinates for the regions of destination are obtained from the Spanish Wikipedia/GeoHack website.

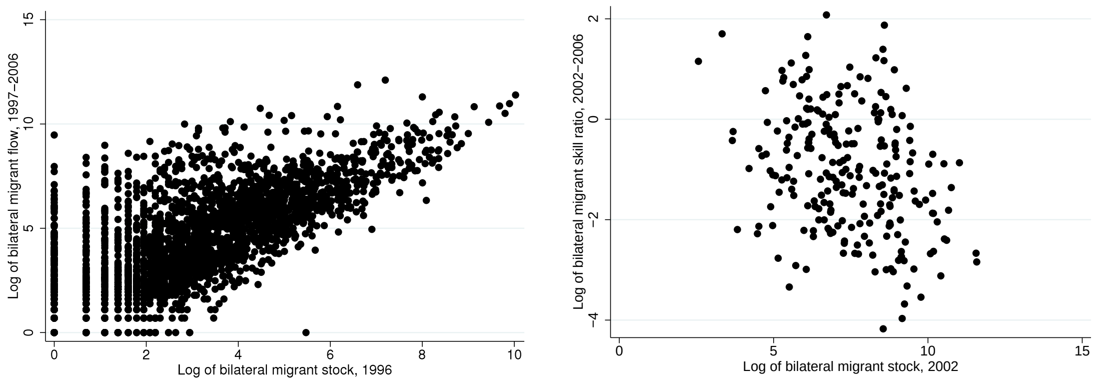
[38] See Table 6.7 in Section 6.6.5 in the appendix for a list of surveys.

from region j in Spain to any other region $k \neq j$ in Spain in 1988. As before, we use the corresponding migration flow in 1989 as a second excluded instrument.

For some pairs of countries of origin and regions of destination we lack information on the skill ratio due to the limited sample size of the NIS. Hence, the dependent variable is sometimes unobserved, which raises concerns of endogenous sample selection. Technically, the well-known two-step Heckman procedure for testing and correcting for sample selection bias could be applied if the country fixed effects were not differenced out but, rather, if they were estimated by including a set of country dummy variables. However, this approach would result in inconsistent estimates due to the incidental parameters problem described in Neyman and Scott (1948). We therefore implement a procedure for identifying a potential sample selection bias akin to the one proposed by Wooldridge (1995, 123-124) for panel data. A description of our procedure can be found in Section 6.6.6 in the appendix.

6.4 Estimation Results

In this section we present and discuss our estimation results. We start with a descriptive look at the relationship between migrant networks and the scale and skill structure of migration to different destinations in Spain. Figure 6.1(a) is a scatter plot for migration between 1997 and 2006 versus migrant networks in 1996, where each dot represents a different pair of country of origin and province of destination.



(a) $\ln(m_{ij})$ plotted against $\ln(1+M_{ij})$, province-level (b) $\ln\left(\frac{m^h_{ij}}{m^l_{ij}}\right)$ plotted against $\ln(1+M_{ij})$, region-level

Figure 6.1: Migrant Networks and the Scale and Skill Structure of Migration

Source: Author's tabulations using data from INE.

We observe a positive correlation between the two variables. Figure 6.1(b) is a scatter plot for the skill structure of migration between 2002 and 2006 versus migrant networks at the beginning of 2002, where now each dot represents a different pair of country of origin and region of destination. The figure suggests a weak negative correlation between the two variables. In what follows, we test whether these correlations reflect a causal relationship running from migrant networks to the scale and skill structure of migration, and we provide a structural interpretation of our estimation results in terms of our NMNL model.

6.4.1 Results for the Scale of Migration

In this section we present the estimation results of the model for the scale of migration as specified in equation (6.21). We first estimate an *average* network coefficient, abstracting from potential differences in the parameter κ_r across regions. Tables 6.1 and 6.2 show the results from the FE model and the two stage least squares (2SLS) FE model, respectively. In columns (a) and (b) of both tables, we eliminate country fixed effects via an adequate within-transformation of the data. The number of observations is equal to 2,592, which is the result of having 55 countries of origin, 50 provinces of destination, and 158 undefined values for the dependent variable due to zero migrant flows ($55 \times 50 - 158 = 2,592$). In columns (c) to (f), we eliminate country-and-region fixed effects by modifying the within-transformation accordingly. This excludes all regions consisting of a single province and thus reduces the number of observations to 2,209.[39]

In the most parsimonious specification of the FE model in column (a) of Table 6.1, the estimated network coefficient is equal to 0.688.[40]. The coefficient is statistically significant at the 1-% level and estimated with very high precision (heteroskedasticity-robust standard error, clustered by countries of origin, equal to 0.029). When we augment the model by FDI and trade flows in column (b), we find a positive and statistically significant coefficient of the FDI variable, statistically significant at the 5-% level. Yet, the point estimate of this coefficient is equal to 0.012 and thus implies a moderate quantitative importance only. Trade relations, instead, do not seem to have a significant impact on the scale of migration. More importantly, the estimates of the network coefficient are virtually unchanged in this version of the model. However, once we control for country-and-region fixed effects in columns (c) and (d), we see a drop in the estimated network coefficient down to 0.539, which corresponds to a decrease by roughly 20%. We see a further reduction by more

[39] Seven regions consist of a single province. Applying the within-transformation to such observations yields all zeros.

[40] This estimate of the average network coefficient is virtually identical to the local network externality estimated by Beine et al. (2011b).

than 10-% once we take out the variation that is constant for each pair of world regions of origin and provinces of destination via dummy variables.

Table 6.1: Scale of Migration – FE Model

	Dependent Variable: Migration Flow (Province-level 1997-2006)					
	(a)	(b)	(c)	(d)	(e)	(f)
Stock of Migrants	0.688***	0.682***	0.539***	0.539***	0.469***	0.469***
(Province-level 1996)	(0.029)	(0.029)	(0.029)	(0.029)	(0.035)	(0.035)
FDI Flow		0.012**				
(Region-level 1997)		(0.005)				
Trade Flow		0.005		0.004		0.008
(Province-level 1996)		(0.007)		(0.007)		(0.007)
Constant	2.357***	2.215***	2.566***	2.619***	2.322***	2.313***
	(0.124)	(0.171)	(0.089)	(0.139)	(0.125)	(0.162)
Province Effects	Yes	Yes	Yes	Yes	Nested	Nested
Country Effects	Yes	Yes	Nested	Nested	Nested	Nested
Country-and-Region Effects	No	No	Yes	Yes	Yes	Yes
World R.-and-Province E.	No	No	No	No	Yes	Yes
Observations	2,592	2,592	2,209	2,209	2,209	2,209
Within R^2	0.791	0.792	0.670	0.670	0.764	0.764

All variables are in natural logs. Heteroskedasticity-robust standard errors (clustered by countries of origin or pairs of countries of origin and regions of destination) are given in parentheses. *,**,*** denote significance at the 10-%, 5-%, 1-% levels, respectively. The regressions include all countries of origin with at least 630 nationals residing in Spain in 1996 (55 countries of origin). See Section 6.3 for a detailed description of all variables.

Unobserved heterogeneity in our model has two sources: first, the multilateral resistance terms, and second, the different cost components. Failing to account for the multilateral resistance terms leads to downward-biased estimates of the network coefficient due to a positive covariance between the migrant network and the terms Ψ_i, Ω_{iz}, and Φ_{ir}, respectively. Failing to account for the different cost components, in turn, leads to upward-biased estimates of the network coefficient due to a negative covariance between the migrant network and the terms c_{iz}, c_{ir}, and c_{ij}, respectively. Given that our estimation results point towards a sizeable upward bias in the estimation of the network coefficient in specifications (a)-(d), the second source of unobserved heterogeneity clearly "dominates" the first one.

The 2SLS FE estimations in Table 6.2 strengthen our interpretation of a quantitatively important causal effect of migrant networks on the scale of migration. They suggest a somewhat larger role for the network effect, with a coefficient ranging between 0.732 and 0.958. The difference between the FE estimates and the 2SLS FE estimates could be due to stochastic measurement errors in the migrant network, which would result in downward-biased estimates of the network coefficient when applying the FE estimator; see

Hausmann (2001). As in the FE estimations, the network coefficient is lowest when we control for country-and-region effects as well as for world region-and-province effects. The loss in precision from using the 2SLS FE approach is fairly small if interpreted relative to the FE model. The effects of both trade and FDI on the scale of migration are essentially zero.

Table 6.2: Scale of Migration – 2SLS FE Model

	Dependent Variable: Migration Flow (Province-level 1997-2006)					
	(a)	(b)	(c)	(d)	(e)	(f)
Stock of Migrants	0.958***	0.955***	0.826***	0.829***	0.732***	0.735***
(Province-level 1996)	(0.068)	(0.069)	(0.078)	(0.079)	(0.096)	(0.097)
FDI Flow		0.004				
(Region-level 1997)		(0.005)				
Trade Flow		0.005		0.007		0.010
(Province-level 1996)		(0.007)		(0.008)		(0.007)
Constant	0.169	0.156	0.107	0.112	0.047	0.053
	(0.117)	(0.120)	(0.097)	(0.098)	(0.103)	(0.103)
Province Effects	Yes	Yes	Yes	Yes	Nested	Nested
Country Effects	Yes	Yes	Nested	Nested	Nested	Nested
Country-and-Region Effects	No	No	Yes	Yes	Yes	Yes
World R.-and-Province E.	No	No	No	No	Yes	Yes
Observations	2,592	2,592	2,209	2,209	2,209	2,209
Within R^2	0.769	0.769	0.632	0.631	0.740	0.740
Robust first-stage F test	32.33	31.70	19.18	19.15	12.92	12.91
Test on Overidentifying R.						
Robust score χ^2 test	0.014	0.022	0.467	0.416	0.308	0.243
- p-value	0.905	0.881	0.494	0.519	0.579	0.622
Exogeneity Test						
Robust regression F test	20.14	19.40	12.33	12.43	5.29	5.37
- p-value	0	0	0.001	0.001	0.022	0.021

All variables are in natural logs. Heteroskedasticity-robust standard errors (clustered by countries of origin or pairs of countries of origin and regions of destination) are given in parentheses. *,**,*** denote significance at the 10-%, 5-%, 1-% levels, respectively. The regressions include all countries of origin with at least 630 nationals residing in Spain in 1996 (55 countries of origin). The (log) stock of migrants in 1996 is instrumented with the (log) migration flows of foreign nationals within Spain in 1988 and in 1989. See Section 6.3 for a detailed description of all variables.

The 2SLS diagnostics are all encouraging. The first-stage F statistic for the joint significance of the excluded instruments is relatively high and thus points to the relevance and strength of the instruments. It exceeds the critical value of 10 in all specifications, which is required for reliable inference in the case of a single endogenous regressor (Stock et al., 2002, 522). Wooldridge's robust score χ^2 test of overidentifying restrictions checks for instrument exogeneity. The null hypothesis (exogeneity) of this test can never be rejected at any reasonable significance level. This suggests that our instruments are uncorrelated with the structural error term, and that our structural equation is correctly specified. We also report the results from an exogeneity test for the migrant network.

The robust regression-based F test rejects the null hypothesis that the migrant network is exogenous at the 1-% level. It should thus be treated as endogenous.

Our next specification allows for cross-regional differences in the similarity parameter κ_r leading to region-specific network coefficients, η_{zr}. The specification employed is equivalent to the one reported in column (f) of Table 6.1, except for the fact that we now interact the migrant network with dummy variables for the different regions of destination. Table 6.3 reveals substantial heterogeneity in the estimated network coefficient across regions. It is largest for the region of Cataluña (0.795) and smallest for the region of Extremadura (0.155).[41] Hence, individuals seem to consider the provinces in the region of Cataluña (Barcelona, Girona, Lleida, and Tarragona) to be very similar to each other, relative to the provinces in the region of Extremadura (Badajoz and Cáceres). This result accords with the pronounced autonomy of Cataluña in terms of its political and cultural life. It is not surprising either that two other regions with a second official language, Comunitat Valenciana and Galicia, rank next to Cataluña in terms of the size of the estimated network coefficient. At any rate, the large and significant cross-regional differences in the estimated network coefficient show that the assumption of a constant degree of cross-alternative substitutability featured in the standard MNL model is too restrictive to hold in the Spanish case.

Table 6.3: Estimated Network Coefficients, by Spanish Region

Spanish Region r	Estimate of η_{zr}	Spanish Region r	Estimate of η_{zr}
Cataluña	0.795	Andalucía	0.507
Comunitat Valenciana	0.699	Castilla y León	0.447
Galicia	0.544	País Vasco	0.287
Canarias	0.525	Castilla-La Mancha	0.186
Aragón	0.509	Extremadura	0.155

This table reports region-specific estimates of the network coefficient η_{zr}. The specification employed is equivalent to that reported in column (f) of Table 6.1, except that we interact the migrant network with dummy variables for the different regions of destination. F tests reveal that each of the above-reported network coefficients – with the exception of the one for Extremadura – is significant at least at the 5-% level. The number of observations is 2,209, and the within R^2 is 0.771.

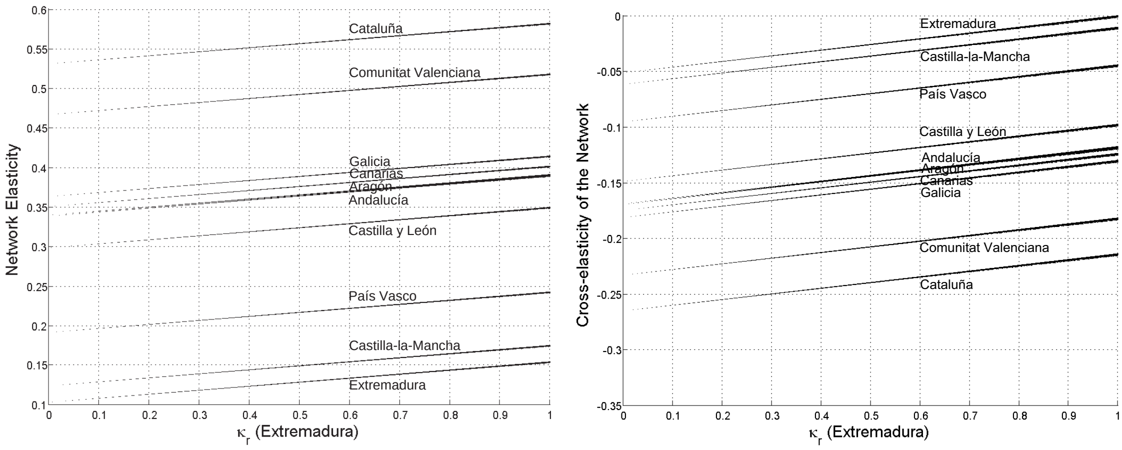
[41] In the estimation, the region of Cataluña serves as the reference region. The differences between the network coefficients estimated for Cataluña and for either of the other regions (except for the regions of Comunitat Valenciana and Canarias) are statistically significant at least at the 10-% level according to t-tests.

The estimated network coefficients can be used to compute the *network elasticity* of migration defined as:

$$\frac{\partial \ln (m_{ij})}{\partial \ln (1+M_{ik})} = \theta \left[\frac{I(j,k)}{\lambda_z \kappa_r} - \left(\frac{m_{ik}}{m_i}\right) - \frac{I(\ell,r)}{\lambda_z \kappa_r}(1-\kappa_r)\left(\frac{m_{ik}}{m_{ir}}\right) - \frac{I(y,z)}{\lambda_z}(1-\lambda_z)\left(\frac{m_{ik}}{m_{iz}}\right)\right]. \tag{6.24}$$

The network elasticity ($j = k$) is a function of *(i)* the network parameter θ, *(ii)* the similarity parameters κ_r and λ_z, and *(iii)* the relative attractiveness of the province of destination j (reflected by the shares m_{ij}/m_i, m_{ij}/m_{ir}, and m_{ij}/m_{iz}). Neither κ_r nor λ_z can be estimated directly due to the use of aggregate migration data. This implies an uncertainty about the true network *elasticity*, which would be present even if the true network *coefficient*, η_{zr}, was known with certainty. However, we can compute estimates of the upper and lower bounds for this elasticity, separately for each region of destination. For this purpose, we use the fact that table 6.3 allows us to compute estimates of the ratio $\kappa_r/\kappa_\ell = \eta_{z\ell}/\eta_{zr}, \forall r, \ell \in A_z$. Since the region of Extremadura features the lowest estimated network coefficient, its similarity parameter κ_r can take on any value between zero and one; the similarity parameters for all other regions $\kappa_\ell, \ell \neq r$, must be strictly lower than one. For example, the range of permissable similarity parameter values for the region of Cataluña runs from zero to $0.155/0.795 = 0.195$.

Figure 6.2(a) shows counterfactual network elasticities by region of destination as a function of the similarity parameter of the region of Extremedura, κ_r. The exact value of κ_r is unknown, but fixing this parameter also fixes the similarity parameters of all other regions. In order to focus on the heterogeneity in the network elasticity that is due to differences in the similarity parameters across regions, we have imposed the following assumptions: first, there are 200 countries of destination outside the country of origin i; second, each of these countries consists of 51 provinces that are uniformly distributed across 17 regions; and third, all provinces abroad are equally attractive destinations, with an overall fraction of migrants in the total population equal to three percent, $\sum_{j\neq i} m_{ij}/m_i = 0.03$. These assumptions imply: $m_{ij}/m_i = 1/340,000$, $m_{ij}/m_{ir} = 1/3$, and $m_{ij}/m_{iz} = 1/51$. For the provinces in the region of Extremadura, we find a network elasticity that slightly exceeds a value of 0.1; for the provinces in the region of Cataluña, the elasticity lies in the vicinity of 0.55. These are quite large differences. For any given region, the difference between the upper and the lower bound (i.e., the permissable range) of the network elasticity is roughly equal to 0.05, so the uncertainty about the network elasticity is not a real issue here. Importantly, the figure also incorporates the uncertainty about the country-specific similarity parameter λ_z, which can take on any value between zero and one. This uncertainty, which turns out to be almost irrelevant for the computation of the network elasticity, is reflected in the thickness of the upward-sloping lines.[42]



(a) Network Elasticities

(b) Cross-Elasticities for $j, k \in A_{zr}$

Figure 6.2: Counterfactual Network Elasticities and Cross-elasticities

We have also computed the cross-elasticities of the network based on (6.24), by analogy to the network elasticity. Cross-elasticities for two provinces belonging to one of the regions listed in table 6.3 are depicted in figure 6.2(b). For the provinces in the region of Extremadura, we find an extremely low cross-elasticity, ranging between 0.0 and -0.05; for the provinces in the region of Cataluña, it lies between -0.22 and -0.27. In figures 6.3(a) and 6.3(b) in Section 6.6.7 in the appendix, we also depict the cross-elasticities when the two provinces j and k are located in different regions of the same country and when they are located in different countries, respectively. These cross-elasticities are *(i)* not specific to any region of destination in Spain, *(ii)* lower (in absolute terms) than the cross-elasticities depicted in figure 6.2(b), and *(iii)* characterized by a higher uncertainty about their true values.

Robustness Analysis

We have conducted two robustness checks, both of which indicate a slightly larger average network coefficient than do our estimates in tables 6.1 and 6.2. The first robustness check addresses a potential estimation bias due to non-stochastic measurement errors in our migration data. The migration data that we have considered above covers the period 1997-

[42] Individual lines are upward-sloping because, for a given similarity parameter λ_z and a given estimate of the network coefficient η_{zr}, a larger κ_r is only compatible with a larger network parameter θ.

2006. To the extent that undocumented migrants arrived in or before 1996 and registered in later years (especially due to the *Ley Orgánica 4/2000* in 2000), we understate the true size of the migrant network in 1996 and overstate the true size of the migrant flow over the period 1997-2006. We show in appendix 6.6.8 that our extended FE specification is entirely immune to both types of measurement errors under a relatively mild assumption, namely that the ratio of "mismeasured" to observed migrants is constant within clusters. However, we have also employed the migrant network as of January 2002 along with the migrant flow from 2002 to 2006.[43]

In a second robustness check, we have applied alternative sample selection criteria in order to see whether our results suffer from endogenous sample selection. In particular, we have considered all observations (country-province pairs) with a migrant network of more than either 10, 20, or 50 migrants in the year 1996.[44][45] Applying these criteria results in unbalanced samples of 98, 90, or 74 countries, respectively.

6.4.2 Results for the Skill Structure of Migration

Table 6.4 reports the results from FE estimations of our model for the skill structure of migration as specified in equation (6.23). We employ regional data instead of provincial data in the following estimations, defining regions as final migration destinations. The FE estimator is applied to 241 observations with non-missing values for the migrant skill ratio (the dependent variable). The full data matrix contains 935 pairs of 55 countries of origin and 17 regions of destination. In all the specifications employed in table 6.4, we find a robustly significant negative impact of migrant networks on the skill structure of migration, as suggested by theory. The estimated coefficient varies between -0.506 and -0.637, so the differences across specifications are rather small in magnitude. Neither the trade variable nor the FDI variable turns out to be statistically significant. This finding is not surprising in light of the poorly suggestive evidence in favor of a positive effect of trade or FDI on the scale of migration. Maybe surprisingly, the effects of a common language and geographical proximity are often estimated to be zero and have an unexpected sign, but one should keep in mind here that identification comes only from within-cluster variation.

[43] For trade and FDI flows we have used the observations from 2001.

[44] Sample selection based on explanatory variables is a type of exogenous sample selection (see Wooldridge, 2009, 323).

[45] Identification requires, of course, that we have at least two observations within each cluster.

Table 6.4: Skill Structure of Migration – FE Model

	Dependent Variable: Migrant Skill Ratio (Region-level 2002-2006)					
	(a)	(b)	(c)	(d)	(e)	(f)
Stock of Migrants	-0.513***	-0.510***	-0.506***	-0.626***	-0.637***	-0.621***
(Region-level 2002)	(0.090)	(0.089)	(0.093)	(0.110)	(0.106)	(0.115)
FDI Flow			-0.006			-0.012
(Region-level 1998-2001)			(0.020)			(0.018)
Trade Flow			-0.001			0.080
(Region-level 2001)			(0.084)			(0.112)
Language		0.248	0.246		0.463**	0.559***
(Region-level)		(0.221)	(0.223)		(0.175)	(0.154)
Distance		-0.636	-0.657		-1.450	-1.388
(Region-level)		(0.394)	(0.392)		(1.358)	(1.353)
Constant	2.991***	8.216**	8.443**	3.733***	15.770	13.755
	(0.729)	(3.388)	(3.894)	(0.857)	(11.275)	(11.692)
Region Effects	Yes	Yes	Yes	Nested	Nested	Nested
Country Effects	Yes	Yes	Yes	Yes	Yes	Yes
World R.-and-Region E.	No	No	No	Yes	Yes	Yes
Observations	241	241	241	241	241	241
Within R^2	0.245	0.261	0.261	0.466	0.477	0.481

All variables except for the language dummy are in natural logs. Heteroskedasticity-robust standard errors (clustered by countries of origin) are given in parentheses. *,**,*** denote significance at the 10-%, 5-%, 1-% levels, respectively. See Section 6.3 for a detailed description of all variables.

Table 6.5 reports the results from the 2SLS FE estimations. They do not alter our causal interpretation in any significant way. As with the previous model for the scale of migration, the first-stage F test and the test on overidentifying restrictions suggest that our instruments are both relevant and exogenous. In all the specifications considered, the estimated coefficient of the migrant network is negative and statistically significant at the 5-% level. The point estimates range between -0.374 and -0.609 and are thus found to be slightly smaller than those obtained from the FE estimations. In the full specification of the model in columns (e) and (f), the migrant network is the only structural explanatory variable whose effect is statistically different from zero.

In order to interpret our results in terms of elasticities, we compute:

$$\frac{\partial \ln(m_{ij}^h/m_{ij}^l)}{\partial \ln(1+M_{ij})} = \theta\gamma^* \left[\frac{1}{\lambda_z} - \left(\frac{m_{ij}}{m_i}\right) - \frac{1-\lambda_z}{\lambda_z}\left(\frac{m_{ij}}{m_{iz}}\right)\right], \tag{6.25}$$

where we have assumed, for simplicity, that $m_{ij}/m_i = m_{ij}^h/m_i^h = m_{ij}^l/m_i^l$ and $m_{ij}/m_{iz} = m_{ij}^h/m_{iz}^h = m_{ij}^l/m_{iz}^l$. We assume, as before, that there are 200 countries of destination outside the country of origin i; that each of these countries consists of 17 regions; and that all regions abroad are equally attractive destinations, with an overall fraction of migrants in the total population equal to three percent.[46] Then, given that the similarity parameter λ_z can take on any value between zero and one, an estimated coefficient of the migrant network equal to -0.621 (as in column (f) of table 6.4) implies an elasticity value somewhere in the range between -0.621 and -0.584.

Table 6.5: Skill Structure of Migration – 2SLS FE Model

	Dependent Variable: Migrant Skill Ratio (Region-level 2002-2006)					
	(a)	(b)	(c)	(d)	(e)	(f)
Stock of Migrants	-0.374***	-0.382***	-0.405**	-0.506**	-0.579**	-0.609**
(Region-level 2002)	(0.144)	(0.145)	(0.169)	(0.214)	(0.238)	(0.265)
FDI Flow			0.005			-0.003
(Region-level 1998-2001)			(0.022)			(0.022)
Trade Flow			0.063			0.094
(Region-level 2001)			(0.070)			(0.074)
Language		0.134	0.158		0.010	0.084
(Region-level)		(0.205)	(0.199)		(0.353)	(0.313)
Distance		-0.649*	-0.562		-0.927	-0.824
(Region-level)		(0.386)	(0.380)		(0.573)	(0.552)
Constant	0.077	0.077	0.033	0.143	0.194	0.137
	(0.177)	(0.183)	(0.173)	(0.206)	(0.226)	(0.214)
Region Effects	Yes	Yes	Yes	Nested	Nested	Nested
Country Effects	Yes	Yes	Yes	Yes	Yes	Yes
World R.-and-Region E.	No	No	No	Yes	Yes	Yes
Observations	241	241	241	241	241	241
Within R^2	0.208	0.220	0.225	0.412	0.417	0.419
Robust first-stage F test	24.11	19.77	13.57	14.48	11.42	10.34
Test on Overidentifying R.						
Robust score χ^2 test	1.070	0.769	0.909	0.310	0.284	0.430
- p-value	0.301	0.381	0.340	0.577	0.594	0.512
Exogeneity Test						
Robust regression F test	0.794	0.867	0.860	0.873	0.678	0.618
- p-value	0.070	0.029	0.032	0.026	0.175	0.253

All variables except for the language dummy are in natural logs. Heteroskedasticity-robust standard errors (clustered by countries of origin) are given in parentheses. *,**,*** denote significance at the 10-%, 5-%, 1-% levels, respectively. The (log) stock of migrants in 2002 is instrumented with the (log) migration flows of foreign nationals within Spain in 1988 and in 1989. See Section 6.3 for a detailed description of all variables.

Robustness Analysis

We have checked the robustness of these results and the validity of some underlying assumptions in various ways. First, we have tested for sample selection bias and found contrary evidence, using a Heckman (1976)-style procedure similar to the one proposed by Wooldridge (1995, 123-124). This procedure is described in Section 6.6.6 in the appendix. Second, following the methodology proposed by Grogger & Hanson (2011, 53-54), we have

[46]This implies that $m_{ij}/m_i = 3/340,000$ and $m_{ij}/m_{iz} = 1/17$.

excluded the possibility that individuals group regions of destinations into nests at the sub-country level. To do so, we have repeatedly estimated the scale model as given by equation (6.21), using regional data instead of provincial data and each time excluding the observations for one region. The estimated network coefficient is very stable across regressions, ranging from 0.665 to 0.719. Third, we have restricted the sample to observations for which the dependent variable is constructed on the basis of at least ten migrants in the underlying survey data. The negative and significant effect of migrant networks on the skill structure of migration proves to be robust to this restriction, even though it reduces the sample size down to 110 observations.

Finally, we have estimated a migration function that describes migration into regions of destination but derives from the three-level NMNL model featuring provinces as the final migration destinations; see also the discussion at the beginning of Section 6.3.2. A complication in this framework is that this migration function depends, among other things, on the number of provinces in each regional nest and the within-nest distribution of migrant networks across provinces. This last argument is part of a highly non-linear term, which collapses to zero if we look at regions that consist of a single province. Hence, we have estimated the model excluding all regions that consist of more than one province.[47] In spite of the reduced number of observations, our estimates continue to reflect a negative and statistically significant impact of migrant networks on the skill structure of migration.[48]

6.5 Conclusion

Using rich data from a recent migration boom to Spain, we have shown that migrant networks increase the scale of migration and decrease the skill content of migration. Both effects are economically significant and robust across a number of different specifications. Our identification strategy is based on a three-level NMNL model that allows for varying degrees of cross-alternative substitutability among final migration destinations. The ease with which one destination in Spain can be substituted by another one depends on whether or not the two destinations are located in the same region; in case they are, it also depends on the degree of political and cultural autonomy of that region. Our ap-

[47] This is a valid approach as long as individuals do not group regions of destination into nests at the sub-country level.

[48] We have also experimented with two alternative estimation approaches following Quigley (1976) and Lerman (1976). Both include the full set of regions in Spain and are summarized in McFadden (1978, 91-94). Again, we have obtained a robustly significant, negative impact of migrant networks on the skill structure of migration.

proach is corroborated by the significant degree of heterogeneity in the estimated network elasticities across regions.

Our findings add to the understanding of the recent migration phenomenon in Spain. This migration has gained momentum through Spain's strong economic growth in the years prior to the global financial crisis. It has led to a change in the size and composition of the country's population and labor supply, with potentially important effects on a number of key macroeconomic variables such as wages, unemployment, and production, as well as on the national welfare state. The recent economic recession in Spain is reflected in a sharp decline in new migration and a significant amount of return migration in the very short run. The conjoint analysis of the structural relationships among past migration, future migration, wages, and employment involves non-trivial dynamics. Attempts to study these dynamics in a unified framework seem to appear as a challenging yet promising avenue for future research.

6.6 Appendix to Chapter 6

6.6.1 Comparison with Bertoli and Fernández-Huertas Moraga (2012)

We show that our three-level NMNL model is more general than the migration model estimated in Bertoli and Fernández-Huertas Moraga (2012) (henceforth BFM, 2012). The response probability generating function in BFM (2012) can be written as:

$$H_i = \sum_z \left(\sum_{j \in A_z} a_{ijz}^{1/\lambda_z} \exp[U_{ij}/\lambda_z] \right)^{\lambda_z}, \tag{6.26}$$

where we use the notation employed in our paper but should stress that in BFM (2012) the final migration destinations are countries (indexed here by j) while the nests (indexed here by z) have no specific interpretation. In BFM (2012), the $J \times Z$ matrix $\mathbf{A}_i$ collects the allocation parameters a_{ijz} that characterize the portion of destination j assigned to nest z for individuals from country i. The most general version of H_i used to estimate the determinants of migration in BFM (2012) assumes *(i)* that there is a single similarity parameter for all nests, $\lambda_z = \lambda$, *(ii)* that the nest corresponding to the country of origin i includes the country of origin i as a single element, and *(iii)* that all row vectors of $\mathbf{A}_i$ contain only a single non-zero element (assumed to be equal to one).[49] These assumptions

[49] Bertoli and Fernández-Huertas Moraga (2013) invoke assumptions *(i)* and *(ii)* as well, but they relax *(iii)* in the spirit of the CNL model.

imply that equation (6.26) becomes:

$$H_i = \sum_z \left(\sum_{j \in A_z} \exp[U_{ij}/\lambda] \right)^{\lambda}, \tag{6.27}$$

where the number and composition of nests is chosen arbitrarily by the authors. Equation (6.27) gives rise to a two-level NMNL model with a single similarity parameter for all nests. The pattern of cross-elasticities generated by equation (6.27) is thus more restrictive than the one generated by our three-level NMNL model with heterogeneous similarity parameters across nests; see equation (6.9).

6.6.2 Derivation of the Probability of Migration $P_i^o(j^o = j)$

We show that

$$P_i^o(j^o = j) = \frac{\exp[U_{ij}]}{H_i(\cdot)} \frac{\partial H_i(\cdot)}{\partial \exp[U_{ij}]}. \tag{6.28}$$

The proof follows McFadden (1978, 81). The probability that individual o chooses destination 1 is equal to:

$$\begin{aligned} P_i^o(j^o = 1) &= \Pr(U_{i1}^o > U_{ik}^o \ \ \forall\, k \in \{2, \ldots, J\}) \\ &= \Pr(U_{i1} - U_{ik} + e_{i1}^o > e_{ik}^o \ \forall\, k \in \{2, \ldots, J\}) \\ &= \Pr(U_{i1} - U_{i2} + e_{i1}^o > e_{i2}^o, \ldots, U_{i1} - U_{iJ} + e_{i1}^o > e_{iJ}^o). \end{aligned} \tag{6.29}$$

Since $F_i(e_{i1}^o, \ldots, e_{iJ}^o) = \exp[-H_i(\exp[-e_{i1}^o], \ldots, \exp[-e_{iJ}^o])]$ is a joint cumulative distribution function, (6.29) can be written as:

$$P_i^o(j^o = 1) = \int_{-\infty}^{\infty} \left(\int_{-\infty}^{U_{i1}-U_{i2}+e_{i1}^o} \cdots \left(\int_{-\infty}^{U_{i1}-U_{iJ}+e_{i1}^o} f(e_{i1}^o, \ldots, e_{iJ}^o) de_{iJ}^o \right) \ldots de_{i2}^o \right) de_{i1}^o, \tag{6.30}$$

where $f(e_{i1}^o, \ldots, e_{iJ}^o)$ is the joint probability density function corresponding to $F(e_{i1}^o, \ldots, e_{iJ}^o)$. Since

$$f(e_{i1}^o, \ldots, e_{iJ}^o) = \frac{\partial^J F(e_{i1}^o, \ldots, e_{iJ}^o)}{\partial e_{i1}^o \ldots \partial e_{iJ}^o} \tag{6.31}$$

(6.30) can be written as:

$$P_i^o(j^o = 1) = \int_{-\infty}^{\infty} \left(\int_{-\infty}^{U_{i1}-U_{i2}+e_{i1}^o} \cdots \left(\int_{-\infty}^{U_{i1}-U_{iJ}+e_{i1}^o} \frac{\partial^J F(e_{i1}^o, \ldots, e_{iJ}^o)}{\partial e_{i1}^o \ldots \partial e_{iJ}^o} de_{iJ}^o \right) \ldots de_{i2}^o \right) de_{i1}^o$$

$$= \int_{-\infty}^{\infty} \frac{\partial F(e^o_{i1}, U_{i1} - U_{i2} + e^o_{i1}, \ldots, U_{i1} - U_{iJ} + e^o_{i1})}{\partial e^o_{i1}} de^o_{i1}$$

$$= \int_{-\infty}^{\infty} \frac{\partial \left(\exp\left[-H_i\left(e^{-e^o_{i1}}, e^{U_{i2}-U_{i1}-e^o_{i1}}, \ldots, e^{U_{iJ}-U_{i1}-e^o_{i1}}\right)\right]\right)}{\partial e^o_{i1}} de^o_{i1}$$

$$= \int_{-\infty}^{\infty} e^{-e^o_{i1}} \frac{\partial H_i(e^{-e^o_{i1}}, e^{U_{i2}-U_{i1}-e^o_{i1}}, \ldots, e^{U_{iJ}-U_{i1}-e^o_{i1}})}{\partial e^{-e^o_{i1}}} \times$$

$$\times \exp\left[-H_i\left(e^{-e^o_{i1}}, e^{U_{i2}-U_{i1}-e^o_{i1}}, \ldots, e^{U_{iJ}-U_{i1}-e^o_{i1}}\right)\right] de^o_{i1}, \tag{6.32}$$

where

$$\frac{\partial H_i(e^{-e^o_{i1}}, e^{U_{i2}-U_{i1}-e^o_{i1}}, \ldots, e^{U_{iJ}-U_{i1}-e^o_{i1}})}{\partial e^{-e^o_{i1}}} = \sum_j \left(e^{U_{ij}-U_{i1}} \frac{\partial H_i(\cdot)}{\partial e^{U_{ij}-U_{i1}-e^o_{i1}}}\right). \tag{6.33}$$

Recall that H_i is linearly homogeneous. Hence,

$$H_i\left(e^{-e^o_{i1}}, e^{U_{i2}-U_{i1}-e^o_{i1}}, \ldots, e^{U_{iJ}-U_{i1}-e^o_{i1}}\right) = e^{-e^o_{i1}-U_{i1}} H_i\left(e^{U_{i1}}, e^{U_{i2}}, \ldots, e^{U_{iJ}}\right) \tag{6.34}$$

and

$$\frac{\partial H_i(e^{-e^o_{i1}}, e^{U_{i2}-U_{i1}-e^o_{i1}}, \ldots, e^{U_{iJ}-U_{i1}-e^o_{i1}})}{\partial e^{-e^o_{i1}}} = \frac{\partial H_i(e^{U_{i1}}, e^{U_{i2}}, \ldots, e^{U_{iJ}})}{\partial e^{U_{i1}}}. \tag{6.35}$$

Thus, (6.32) can be written as:

$$P^o_i(j^o=1) = \int_{-\infty}^{\infty} e^{-e^o_{i1}} \frac{\partial H_i(e^{U_{i1}}, e^{U_{i2}}, \ldots, e^{U_{iJ}})}{\partial e^{U_{i1}}} \exp\left[-e^{-e^o_{i1}-U_{i1}} H_i\left(e^{U_{i1}}, e^{U_{i2}}, \ldots, e^{U_{iJ}}\right)\right] de^o_{i1}$$

$$= \frac{\partial H_i(\cdot)}{\partial \exp[U_{i1}]} \int_{-\infty}^{\infty} e^{-e^o_{i1}} \exp\left[-e^{-e^o_{i1}-U_{i1}} H_i\left(e^{U_{i1}}, e^{U_{i2}}, \ldots, e^{U_{iJ}}\right)\right] de^o_{i1}$$

$$= \frac{\partial H_i(\cdot)}{\partial \exp[U_{i1}]} \int_{-\infty}^{\infty} e^{-\zeta+U_{i1}-\ln H_i(\cdot)} \exp\left[-e^{-\zeta}\right] d\zeta$$

$$= \frac{\partial H_i(\cdot)}{\partial \exp[U_{i1}]} \frac{\exp[U_{i1}]}{H_i(\cdot)}, \tag{6.36}$$

where we have changed variables according to $\zeta \equiv e^o_{i1} + U_{i1} - \ln H_i(\cdot)$ in the third line. Finally, notice that this argument can be applied to any other alternative $j \neq 1$ as well.

6.6.3 Derivation of the Partial Derivative $\partial \ln H_i(\cdot)/\partial U_{ij}$

Since

$$\ln H_i(\cdot) = \ln \sum_z \left(\sum_{r \in A_z} \left(\sum_{j \in A_{zr}} \exp[U_{ij}/(\kappa_r \lambda_z)] \right)^{\kappa_r} \right)^{\lambda_z} \tag{6.37}$$

we have

$$\frac{\partial \ln H_i(\cdot)}{\partial U_{ij}} = H_i(\cdot)^{-1} \exp[U_{ij}/(\kappa_r \lambda_z)] Q X, \tag{6.38}$$

where

$$\begin{aligned} Q &= \left(\sum_{j \in A_{zr}} \exp[U_{ij}/(\kappa_r \lambda_z)] \right)^{\kappa_r - 1} \\ &= (\exp[(-c_{iz} - c_{ir})/(\kappa_r \lambda_z)])^{\kappa_r - 1} \left(\sum_{j \in A_{zr}} \exp[\xi_{ij}/(\kappa_r \lambda_z)] \right)^{\kappa_r - 1} \end{aligned} \tag{6.39}$$

and

$$\begin{aligned} X &= \left(\sum_{r \in A_z} \left(\sum_{j \in A_{zr}} \exp[U_{ij}/(\kappa_r \lambda_z)] \right)^{\kappa_r} \right)^{\lambda_z - 1} \\ &= (\exp[-c_{iz}/\lambda_z])^{\lambda_z - 1} \left(\sum_{r \in A_i} (\exp[-c_{ir}/\lambda_z]) \left(\sum_{j \in A_{zr}} \exp[\xi_{ij}/(\kappa_r \lambda_z)] \right)^{\kappa_r} \right)^{\lambda_z - 1}. \end{aligned} \tag{6.40}$$

By defining $\Phi_{ir} = \ln \sum_{k \in A_{zr}} \exp[\xi_{ik}/(\kappa_r \lambda_z)]$ and $\Omega_{iz} = \ln \sum_{\ell \in A_z} \exp[\Phi_{i\ell}\kappa_\ell - c_{i\ell}/\lambda_z]$, equation (6.38) can be written as:

$$\frac{\partial \ln H_i(\cdot)}{\partial U_{ij}} = \frac{\exp[\xi_{ij}/(\kappa_r \lambda_z) - c_{ir}/\lambda_z - c_{iz}]}{H_i(\cdot) \exp[(1 - \kappa_r)\Phi_{ir} + (1 - \lambda_z)\Omega_{iz}]}, \tag{6.41}$$

which gives $P_i^o(j^o = j)$, where $j \in A_{zr}, r \in A_z$; see equations (6.8) and (6.16).

6.6.4 Derivation of the Elasticity $\partial \ln(m_{ij}/m_i)/\partial \ln Y_k$

In the following, we derive $\partial \ln(m_{ij}/m_i)/\partial \ln Y_k$ for $k = j \in A_{zr}, r \in A_z$. The other (simpler) derivatives where $k \neq j$ can be derived analogously. They depend on whether or not $k \in A_{zr}$ and whether nor not $z = y$ if $k \in A_{y\ell}$,$\ell \in A_y$. Since

$$\ln\left(\frac{m_{ij}}{m_i}\right) = \xi_{ij}/(\lambda_z \kappa_r) - c_{ir}/\lambda_z - c_{iz} - \Psi_i - (1 - \kappa_r)\Phi_{ir} - (1 - \lambda_z)\Omega_{iz} \tag{6.42}$$

we have

$$\begin{aligned}\frac{\partial \ln (m_{ij}/m_i)}{\partial \ln Y_k} &= \frac{Y_k}{\lambda_z \kappa_r} - \frac{\exp[\Omega_{iz}\lambda_z - c_{iz}]\lambda_z}{\exp[\Psi_i]}\frac{\partial \Omega_{iz}}{\partial \ln Y_k} - (1-\kappa_r)\frac{\partial \Phi_{ir}}{\partial \ln Y_k} \\ &\quad - (1-\lambda_z)\frac{\partial \Omega_{iz}}{\partial \ln Y_k} \\ &= \frac{Y_k}{\lambda_z \kappa_r} - \frac{m_{iz}\lambda_z}{m_i}\frac{\partial \Omega_{iz}}{\partial \ln Y_k} - (1-\kappa_r)\frac{\partial \Phi_{ir}}{\partial \ln Y_k} - (1-\lambda_z)\frac{\partial \Omega_{iz}}{\partial \ln Y_k}. \qquad (6.43)\end{aligned}$$

Since

$$\frac{\partial \Phi_{ir}}{\partial \ln Y_k} = \frac{\exp[\xi_{ik}/(\lambda_z\kappa_r)]}{\sum_{k\in A_{zr}}\exp[\xi_{ik}/(\lambda_z\kappa_r)]}\frac{Y_k}{\lambda_z\kappa_r} = \frac{m_{ik}}{m_{ir}}\frac{Y_k}{\lambda_z\kappa_r} \qquad (6.44)$$

and

$$\frac{\partial \Omega_{iz}}{\partial \ln Y_k} = \frac{\exp[\Phi_{ir}\kappa_r - c_{ir}/\lambda_z]\kappa_r}{\sum_{\ell\in A_z}\exp[\Phi_{i\ell}\kappa_\ell - c_{i\ell}/\lambda_z]}\frac{\partial \Phi_{ir}}{\partial \ln Y_k} = \frac{m_{ir}\kappa_r}{m_{iz}}\frac{\partial \Phi_{ir}}{\partial \ln Y_k} \qquad (6.45)$$

equation (6.43) can be written as:

$$\frac{\partial \ln (m_{ij}/m_i)}{\partial \ln Y_k} = Y_k\left(\frac{1}{\lambda_z\kappa_r} - \frac{m_{ik}}{m_i} - \frac{(1-\kappa_r)}{\lambda_z\kappa_r}\frac{m_{ik}}{m_{ir}} - \frac{(1-\lambda_z)}{\lambda_z}\frac{m_{ik}}{m_{iz}}\right). \qquad (6.46)$$

6.6.5 Data Sources

Table 6.6: List of the 55 Countries Considered in the Estimations of Chapters 5 and 6, by World Region

EAST ASIA & PACIFIC	Cuba	NORTH AMERICA,	WESTERN EUROPE
China	Dominican Republic	AUSTRALIA	Austria
Japan	Ecuador	& NEW ZEALAND	Belgium
Korea	El Salvador	Australia	Denmark
Philippines	Honduras	Canada	Finland
	Mexico	United States	France
EASTERN EUROPE	Peru		Germany
& CENTRAL ASIA	Uruguay	SOUTH & SOUTH-	Ireland
Bosnia and Herzegowina	Venezuela	EAST ASIA	Italy
Bulgaria		India	Netherlands
Poland	MIDDLE EAST	Pakistan	Norway
Romania	& NORTH AFRICA		Portugal
Russia	Algeria	SUB-SAHARAN	Sweden
	Egypt	AFRICA	Switzerland
LATIN AMERICA	Iran	Angola	United Kingdom
& CARIBBEAN	Lebanon	Cape Verde	
Argentina	Morocco	Equatorial Guinea	
Bolivia	Syria	Gambia	
Brazil		Guinea	
Chile		Mauritania	
Colombia		Senegal	

Table 6.7: Data Sources of Chapters 4, 5, and 6

Variable	Definition	Data Sources
Migrant Flow (m_{ij})	Migrants who registered at municipalities in Spain between January 1, 1997 (or January 1, 2002), and December 31, 2006, by province of destination (or region of destination) and by country of origin. Migrants are defined as individuals whose last country of residence (other than Spain) corresponds to their country of birth and nationality.	Spanish Residential Variation Statistics, INE, `http://www.ine.es/en/prodyser/micro_varires_en.htm`, accessed on 10/05/2010
Migrant Network (M_{ij})	Number of settled migrants as of May 1, 1996 (or January 1, 2002) [or of January 1, 1999, or January 1, 2009, for Chapters 4 and 5] by province of destination (or region of destination) in Spain and by nationality.	Population by Nationality, Autonomous Communities and Provinces, Sex and Year, Municipal Register, Main Population Series since 1998, INE, `http://www.ine.es/jaxi/menu.do?type=pcaxis&path=%2Ft20%2Fe245&file=inebase&L=0`, accessed on 10/07/2010
Trade Flow	Sum of exports and imports, by province (or region) in Spain and by country of destination/origin.	DataComex Statistics on Spanish Foreign Trade, Spanish Government, Ministry of Industry, Tourism and Trade, `http://datacomex.comercio.es/principal_comex_es.aspx`, accessed on 10/20/2010
FDI Flow	Gross FDI flow in Euros, by region in Spain and by country of the last owner.	DataInvex Statistics on Foreign Investments in Spain, Spanish Government, Ministry of Industry, Tourism and Trade, `http://datainvex.comercio.es/principal_invex.aspx`, accessed on 10/20/2010
Historical Internal Migrant Flow	People moving from one province (or region) to another province (or region) in Spain in 1988 and 1989, by province (or region) in Spain and by nationality.	Spanish Residential Variation Statistics, INE, `http://www.ine.es/en/prodyser/micro_varires_en.htm`, accessed on 10/05/2010
Geographical Distance (between Countries)	Geographical distance (measured in kilometers) between the most populous cities of two countries.	GeoDist dataset of dyadic variables, CEPII, `http://www.cepii.fr/anglaisgraph/bdd/distances.htm`, accessed on 10/13/2010
Common Official Language (of Countries)	This indicator variable is equal to one if two countries have a common official language; it is zero otherwise.	GeoDist dataset of dyadic variables, CEPII, `http://www.cepii.fr/anglaisgraph/bdd/distances.htm`, accessed on 10/13/2010

Continuation on the next page

Table 6.7 *continued*

Variable	Definition	Data Sources
Migrant Skill Ratio (m_{ij}^h/m_{ij}^l)	Ratio of new high-skilled migrants over new low-skilled migrants, aggregated from 2002 to 2006, by region of destination in Spain and by country of birth. Migrants are individuals aged 16 years or older who were born abroad and have lived in Spain for more than a year, or at least intended to stay for more than a year at the time the survey was conducted.	National Immigrant Survey 2007, INE, `http://www.ine.es/prodyser/micro_inmigra.htm`, accessed on 10/05/2010
Geographical Distance (between Spanish Regions and Countries)	Distances are constructed on the basis of latitudinal and longitudinal data for regions in Spain and countries of origin and using the STATA module GEODIST by Picard (2010).	SpanishWikipedia/GeoHack, `http://es.wikipedia.org`, accessed on 09/05/2011; Mayer & Zignago (2006)
Common Lanuage (of Spanish Regions and Countries)	This indicator variable is equal to one if at least 80% of a region's population in Spain are native speakers of a language spoken by at least 20% of the people in the country of origin; it is zero otherwise.	*Cataluña*: Generalitat de Catalunya, Institut d'Estadística de Catalunya (2008). Enquesta d'usos lingüístics de la població 2008. *Comunidad Foral de Navarra*: Instituto de Estadística de Navarra (2001). Censo 2001 de Población y Viviendas en Navarra. *Comunitat Valenciana*: Universidad de Salamanca (2007). Estudio CIS No. 2.667. La identitad nacional en España. *Galicia*: Instituto Galego de Estatística (2008). Enquisa de condicións de vida das familias. Coñecemento e uso do galego. Edición 2008. *Illes Balears*: Villaverde i Vidal, J. A. (2003). L'Enquesta Sociolingüística 2003. Principals Resultats. *País Vasco*: Universidad de Salamanca (2007). Estudio CIS No. 2.667. La identitad nacional en España. *Countries of origin*: Mayer & Zignago (2006).

6.6.6 Testing for Sample Selection Bias

We briefly present our procedure for identifying a potential sample selection bias in the model for the skill structure of migration. It is a slight modification of Wooldridge (1995, 123-124), who proposes a method for testing for sample selection bias in panel data. It will become evident below that we impose very strong assumptions on the selection equation and the mechanism governing selection. These assumptions would often be inappropriate if we were to derive *corrections* for a sample selection bias in models with fixed effects. It turns out, however, that they do not pose a threat to the correct *testing* for a sample selection bias. For further details on this, the reader is referred to Wooldridge (1995).

We start by rewriting the model for the skill structure of migration as:

$$y_{ij} = \mu_i + \mathbf{x}_{ij}\boldsymbol{\beta} + u_{ij}, \qquad j = 1, \ldots, J, \tag{6.47}$$

where y_{ij} is the ij-specific log of the ratio of high-skilled migrations to low-skilled migrants, μ_i is an unobserved country fixed effect, $\mathbf{x}_{ij}$ is a $1 \times K$ vector of explanatory variables (including region dummies and interactions between region dummies and world region dummies), $\boldsymbol{\beta}$ is a $K \times 1$ vector of parameters to be estimated, and u_{ij} is an independent and identically distributed error term. We explicitly allow for $E(\mu_i|\mathbf{x}_{i1}, \ldots, \mathbf{x}_{iJ}) \neq E(\mu_i)$. Since J is fixed, the asymptotic analysis is valid for $I \to \infty$. Now suppose that $(y_{ij}, \mathbf{x}_{ij})$ is sometimes unobserved, and that $\mathbf{s}_{ij} = (s_{i1}, \ldots, s_{iJ})'$ is a vector of selection indicators with $s_{ij} = 1$ if $(y_{ij}, \mathbf{x}_{ij})$ is observed and zero otherwise. Define $\mathbf{x}_i \equiv (\mathbf{x}_{i1}, \ldots, \mathbf{x}_{iJ})$ and $\mathbf{s}_i \equiv (\mathbf{s}_{i1}, \ldots, \mathbf{s}_{iJ})$ and suppose that $E(u_{ij}|\mu_i, \mathbf{x}_i, \mathbf{s}_i) = 0 \; \forall j$, which implies that the selection process is strictly exogenous conditional on μ_i and $\mathbf{x}_i$. Then, our FE estimator employed in the main text is consistent and asymptotically normal even when selection arbitrarily depends on $(\mu_i, \mathbf{x}_i)$ (Wooldridge, 1995, 118).

In our application, the explanatory variables $\mathbf{x}_{ij}$ are observed for all regions $j = 1, \ldots, J$. The variable y_{ij} is observed if $s_{ij} = 1$, but not otherwise. For each $j = 1, \ldots, J$, define an unobserved latent variable

$$h^*_{ij} = \boldsymbol{\delta}_{j0} + \mathbf{x}_{i1}\boldsymbol{\delta}_{j1} + \cdots + \mathbf{x}_{iJ}\boldsymbol{\delta}_{jJ} + v_{ij}, \tag{6.48}$$

where v_{ij} is a stochastic term independent of $(\mu_i, \mathbf{x}_i)$, and $\boldsymbol{\delta}_{jp}$ is a $(K + 1) \times 1$ vector of unknown parameters, $p = 1, 2, \ldots, J$.[50] The binary selection indicator is defined as $s_{ij} \equiv 1[h_{ij}^* > 0]$. Since $\mathbf{s}_i$ is a function of $(\mathbf{x}_i, \mathbf{v}_i)$, where $\mathbf{v}_i \equiv (v_{i1}, \ldots, v_{iJ})'$, a sufficient condition for the selection process to be strictly exogenous conditional on μ_i and $\mathbf{x}_i$ is:

$$E(u_{ij}|\mu_i, \mathbf{x}_i, \mathbf{v}_i) = 0, \qquad j = 1, \ldots, J. \tag{6.49}$$

Under (6.49), there is no sample selection bias. An alternative that implies sample selection bias is:

$$E(u_{ij}|\mu_i, \mathbf{x}_i, \mathbf{v}_i) = E(u_{ij}|v_{ij}) = \rho v_{ij}, \qquad j = 1, \ldots, J, \tag{6.50}$$

where $\rho \neq 0$ is some unknown scalar. Under the alternative (6.50) we have:

$$E(y_{ij}|\mu_i, \mathbf{x}_i, \mathbf{s}_i) = \mu_i + \mathbf{x}_{ij}\boldsymbol{\beta} + \rho E(v_{ij}|\mu_i, \mathbf{x}_i, \mathbf{s}_i) = \mu_i + \mathbf{x}_{ij}\boldsymbol{\beta} + \rho E(v_{ij}|\mathbf{x}_i, \mathbf{s}_i). \tag{6.51}$$

Let $E(v_{ij}|\mathbf{x}_i, \mathbf{s}_i) = E(v_{ij}|\mathbf{x}_i, s_{ij})$ and assume a standard uniform distribution for v_{ij}. Then,

$$E(v_{ij}|\mathbf{x}_i, s_{ij} = 1) = E(v_{ij}|\mathbf{x}_i, v_{ij} > -\mathbf{x}_i\boldsymbol{\delta}_j) = (1 + \mathbf{x}_i\boldsymbol{\delta}_j)/2. \tag{6.52}$$

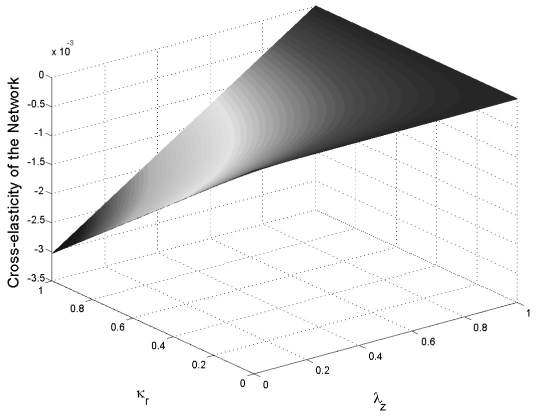
and

$$E(y_{ij}|\mu_i, \mathbf{x}_i, s_{ij} = 1) = \rho^* + \mu_i + \mathbf{x}_{ij}\boldsymbol{\beta} + \rho^*\mathbf{x}_i\boldsymbol{\delta}_j, \tag{6.53}$$

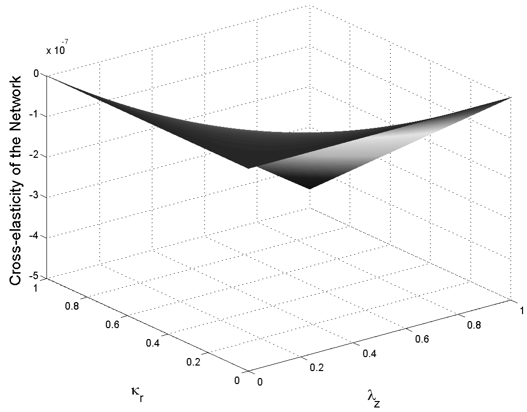
where $\rho^* \equiv \rho/2$ and $\mathbf{x}_i$ now includes unity as its first element. The procedure to test for sample selection bias is as follows. We first obtain estimates of $\mathbf{x}_i\boldsymbol{\delta}_j$ by estimating region-specific selection equations (where s_{ij} is the dependent variable) derived from equation (6.48), using linear probability models for the full data matrix. We then estimate equation (6.53) in a fixed effects framework (within-transformed data), using only observations with $s_{ij} = 1$. We finally test $H_0 : \rho = 0$, using the t-statistic for ρ^*.

[50] In the following, $\mathbf{x}_{ij}$ includes one element more than in equation (6.47), despite the fact that we use the same notation for convenience. We thus assume that there is exactly one exclusion restriction in equation (6.47). In the estimation, we use the log of the number of people holding country i's nationality and migrating from region j in Spain to any other region $k \neq j$ within or outside Spain over the period from January 1, 2006, to December 31, 2007, as an exclusion restriction.

6.6.7 Counterfactual Cross-Elasticities



(a) Cross-Elasticities for $j \in A_{zr}$ and $k \in A_{z\ell},\ r \neq \ell$



(b) Cross-Elasticities for $j \in A_{zr}$ and $k \in A_{y\ell},\ z \neq y$

Figure 6.3: Counterfactual Cross-elasticities for the Network Effect

6.6.8 Measurement Error

We argue that the potential non-stochastic measurement errors discussed at the end of section 6.4.1 are unlikely to result in biased estimates. Let $\tilde{m}_{ij} < m_{ij}$ and $\tilde{M}_{ij} > M_{ij}$ denote the unobserved true size of the migrant flow and the migrant network, respectively. Let the relationship between the migrant flow and the migrant network be given by the following equation:

$$\ln(\tilde{m}_{ij}) = \eta_{zr} \ln(\tilde{M}_{ij}). \tag{6.54}$$

Let y_{ij} denote the ratio of unobserved (i.e. "excess") migrants to observed migrants in the flow, and let x_{ij} denote the ratio of unobserved (i.e. unregistered) migrants to observed migrants in the network. Hence, $\tilde{m}_{ij} = (1 - y_{ij})m_{ij}$ and $\tilde{M}_{ij} = (1 + x_{ij})M_{ij}$ and thus:

$$\ln((1 - y_{ij})m_{ij}) = \eta_{zr} \ln((1 + x_{ij})M_{ij}), \tag{6.55}$$

which can be rewritten as:

$$\ln(m_{ij}) = \eta_{zr} \ln(M_{ij}) + \eta_{zr} \ln(1 + x_{ij}) - \ln(1 - y_{ij}). \tag{6.56}$$

The last two terms in equation (6.56), if not controlled for, may introduce a bias in the estimation of the network coefficient η_{zr}. Obviously, a sufficient condition for our FE model controlling for country-and-region fixed effects to deliver unbiased estimates is:

$$v_{ij} = v_{ir}, \quad v = \{x, y\}. \tag{6.57}$$

Hence, the type of mismeasurement potentially present in our migration data is not a problem *per se* for the estimation. For example, suppose that migrants are possibly measured with error, so that $x_{ij} \leq 0$ and $y_{ij} \leq 0$ for all provinces in Spain. Furthermore suppose that these errors are large for some regions of destination but small for others, and that they are large for some countries of origin but small for others. Then, a mild but sufficient condition for our estimates to be unbiased is: $x_{ij} = x_{ik}$ and $y_{ij} = y_{ik}$, where $j \neq k$ and $j, k \in A_{zr}$.

CHAPTER 7

Occupation-specific South-North Migration

7.1 Introduction

When compared to international trade or capital flows, international migration is often considered as the least complete aspect of globalization (see, e.g., Freeman, 2006, 149-151). However, migration from developing countries to member countries of the Organisation for Economic Co-operation and Development (OECD) and particularly the extent of migration of high-skilled workers are important phenomena of globalization (see Carrington and Detragiache, 1998, and Docquier and Marfouk, 2006). In developing and developed countries, politicians are particularly concerned about the emigration of their highly skilled workers, considered as an important resource for economic development. Yet several empirical studies find that the propensity to emigrate is increasing in the skill level; an observation that Dos Santos (2006, 19-21) attributes to the fact that migration costs are decreasing in the skill level, as well as to the existing selective immigration policies.

The migration of high-skilled workers is generally known as "brain drain" [or "brain gain"][1] if "[...] the net flow is heavily in one direction [...]" (Salt, 1997, 5). This term was originally used to describe the migration of scientists from the United Kingdom to the United States and was characterized by a strong connotation of loss (Johnson, 1965, 299). According to the more recent definition by Docquier and Rapoport (2008), it generally

This chapter is a slightly revised version of Tübinger Diskussionsbeitrag No. 328, see Heuer (2010).

[1] Note that we use the term "brain gain" in this thesis in order to refer to the incentive to invest in human capital that is induced by the prospect of migration, see Chapter 8.

refers to "[...] the international transfer of resources in the form of human capital and mainly applies to the migration of relatively highly educated individuals from developing to developed countries." Recently created datasets of south-north migration rates based on information on immigrants in OECD countries by country of origin and – partly imputed – educational attainment (Carrington and Detragiache, 1998, Adams, 2003, Docquier and Marfouk, 2006, Defoort, 2006, Beine et al., 2007, Docquier et al., 2009) have made it possible to empirically analyze the extent of the brain drain and to test several hypotheses of the theoretical brain drain literature. This improvement notwithstanding, the available cross-country datasets do not allow to analyze which professions are disproportionately represented among the brain drain. Due to restricted data availability, these datasets draw on the pure educational definition given above and define all tertiary-educated individuals as high-skilled, thus considering only one aggregate type of brain drain. The existing evidence of the occupation-specific brain drain is mainly of anecdotal nature: Several case studies analyze one or a few specific occupations or sectors in one or at most a few countries of emigration or immigration (Commander et al., 2004, Bhorat et al., 2002, Thomas-Hope, 2002, Alburo and Abella, 2002, Pellegrino, 2002, Meyer et al., 2000, Watanabe, 1969). The sector that has been most thoroughly analyzed is the medical sector; see, e.g., Bhargava and Docquier, 2008, Kangasniemi et al., 2007, Awases et al., 2004.

Benefiting from richer data on immigrants in OECD countries, this chapter presents two new datasets on south-north migration rates by occupational category at two distinct levels of disaggregation according to the International Standard Classification of Occupations 1988 (ISCO-88). The datasets combine information about the labor market outcomes and educational attainments of immigrants in OECD countries around the year 2000 provided by the Database on Immigrants in OECD Countries (DIOC) by the OECD with employment data for the developing migrant-sending countries from the International Labour Organization (ILO). They constitute the first comprehensive datasets on south-north migration by major and sub-major occupational categories for cross-sections of, respectively, 91 and 17 developing countries of emigration. These data at hand, we are able to break down south-north migration along both the skill and the occupational dimension and thus to distinguish and compare several types of brain drain. We furthermore use the gathered employment data to study differences in the employment distributions of the developing migrant-sending and the developed migrant-receiving countries in order to sketch the structural context within which this south-north migration has taken place. Comparisons of the employment distributions of the native and the foreign-born OECD population are used to study the degree of “overeducation” among tertiary-educated south-north migrants, and serve as an indicator of whether skills that are specific to certain professional categories exhibit a rather low or high degree of international transferability. Stylized facts are derived based on mean values for different populations as well as on parametric and non-parametric statistics for distributional differences.

This chapter is organized as follows: Section 7.2 assesses the extent of south-north migration and brain drain with data from the DIOC adopting an educational point of view. This serves as a benchmark for the occupation-specific analysis. Section 7.3 focuses on the occupational distribution of south-north migrants relative to the one of OECD natives. Particular attention is paid to the two types of human capital *Professionals* as well as *Technicians and associate professionals*. Section 7.4 introduces the new datasets of occupation-specific emigration rates. It studies the extent and composition of south-north migration and brain drain against the backdrop of the employment distributions in the migrant-sending countries. Section 7.5 concludes. The appendix (Section 7.6) documents the data preparation and presents summary statistics. Unless stated otherwise, all figures in this chapter are own calculations based on data from OECD and ILO. The detailed data sources are provided in Section 7.6.1.

7.2 An Education-based Assessment of the Brain Drain

This section summarizes employment data and emigration rates from the DIOC in order to point out the extent of south-north migration from the perspective of both the receiving and the sending countries. Particular attention is paid to the migration of the most highly skilled. The assessment of the brain drain in this section is based on educational attainment as it is standard in the related literature. It will serve as a benchmark for the stylized facts derived in Sections 7.3 and 7.4, where the definition of brain drain rests upon the educational qualification required in the occupations that are actually exercised.

The Perspective of the North

The extent of south-north migration exceeds that of north-north migration by far: In 2000, workers who had emigrated from developing countries[2] to the OECD represented about 65.7% of the total immigrant labor force in the OECD, whereas employees who had left

[2] All countries classified as low- or middle-income countries in 2000 by the Worldbank are considered as *developing countries*. A detailed definition is provided in Section 7.6.2 in the appendix.

high-income (OECD or non-OECD) countries to work in an OECD country accounted for only 25.4% of the total immigrant labor force in the OECD.[3]

A glance at the educational distribution of south-north migrants reveals the importance of the brain drain phenomenon: Highly skilled migrants, defined as foreign-born individuals with tertiary education (comprising ISCED-97 levels 5 and 6, see UNESCO 2006), born in developing countries represented 28.8% of the total south-north migrants working in the OECD in 2000 for whom educational attainment is known. If only low-income countries are considered, the percentage of tertiary-educated migrants rises to 41.7%, with emigration of secondary (primary) educated workers amounting to 31.7% (26.6%). Thus, for the poorest sending countries, employment of south-north migrants was rising in qualification.

Since the considered version of the DIOC only contains data on immigration to OECD member countries, it can neither be used to study south-south migration (migration from developing to other developing countries), nor can it be used to study migration from developing to non-OECD high-income countries.[4] However, disregarding the brain drain from the south to the "non-OECD-north" might not be too problematic: Docquier and Marfouk (2006, 154) estimate from non-OECD census data that 90% of worldwide high-skilled migrants live in the OECD.

The Perspective of the South

The following summary statistics point out that the relative incidence of high-skilled migration from developing countries to developed countries is generally higher than the relative incidence of total south-north migration. The DIOC provides tertiary emigration rates, defined as the percentage of a country's tertiary-educated native population living in the OECD, for 75 low- and middle-income countries in 2000. On average, the tertiary emigration rate amounted to 16.0%, while the total emigration rate from the same developing countries was 3.9% in 2000. Yet there were large regional differences. Figure 7.1 illustrates mean (total) emigration rates and mean tertiary emigration (brain drain) rates for these 75 developing countries by region of origin. Sub-Saharan Africa as well as Latin America and the Caribbean are the regions with the highest average brain drain around

[3] The remaining 8.9% can be attributed to migration from dependent territories, not further specified regions, or no-longer existing states that cannot be assigned to specific income groups.

[4] The OECD and the Worldbank have recently launched a project to extend the DIOC, especially to include data on south-south migration. This extended database has become available as *DIOC-E* from the OECD.

2000. This observation is in line with the evidence reported in Docquier and Marfouk (2006, 170-171).

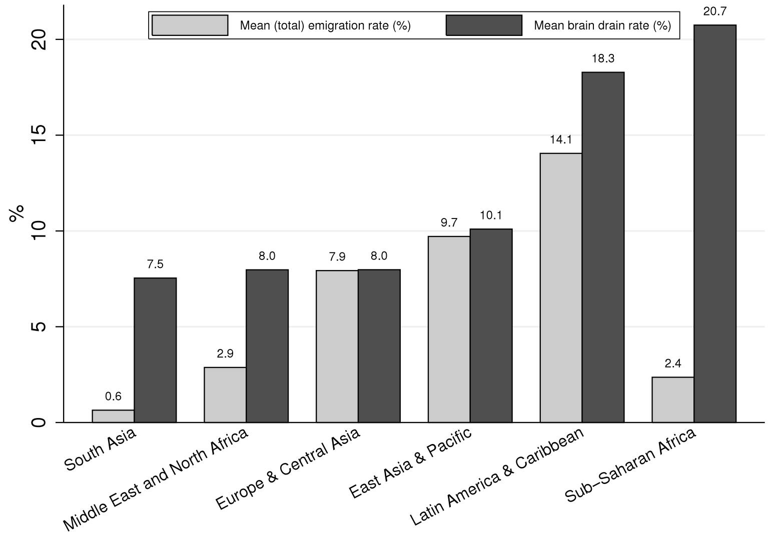


Figure 7.1: Mean South-North Migration and Brain Drain Rates around 2000 (%), by Region of Origin

Source: Author's tabulations using data from the DIOC.

Table 7.1 reports different percentiles of the brain drain by region of origin. The interregional and intraregional differences are striking for the considered sample: The highest brain drain rate is reported for Latin America and the Caribbean and amounted to 76.9% (Guyana). By contrast, the maximal rates in Eastern Europe and Central Asia, in the Middle East and North Africa, and in South Asia were less than 20%. From the comparison of the different percentiles, one can further conclude that intraregional differences were highest in Latin America and the Caribbean, in Sub-Saharan Africa, and in East Asia and the Pacific. In general, the highest rates can be attributed to small countries or islands.

Table 7.1: Different Percentiles of the Brain Drain in 2000 (%), by Region of Origin

Region	**5%**	**50%**	**75%**	**Max.(100%)**	**# Countries**
East Asia & Pacific	1.5	5.2	13.2	38.3	8
Eastern Europe & Central Asia	3.2	8.4	12.3	12.3	3
Latin America & Caribbean	1.9	6.2	14.1	76.9	22
Middle East & North Africa	3.7	6.8	11.3	15.4	8
Sub-Saharan Africa	3.8	15.5	26.5	71.5	28
South Asia	3.0	4.9	9.8	19.4	6

Source: Author's tabulations using data from the DIOC.

7.3 An Occupation-specific Assessment of the Brain Drain

This section turns to the notion of *high-skilled* based on the educational qualification that is generally required in the different occupational categories of ISCO-88. Using data from the DIOC, we compare the occupational employment distributions of total south-north migrants as well as of tertiary-educated south-north migrants to the ones of the native-born OECD populations in order to assess the incidence of formal "overeducation"[5] and the degree of transferability of higher education. Using sign test statistics, this assessment goes beyond the descriptive evidence presented in OECD (2008). We then focus on *Professionals* and *Technicians and associate professionals*, the two most skill-intensive occupational categories, in order to shed some light on possible differences in the transferability of professionals' skills.

On the Relation between ISCO-88 and ISCED-76

The major advantage of the International Standard Classification of Occupations 1988 (ISCO-88)[6] by the ILO in the context of this assessment of the brain drain is its relation to the formal education levels of the International Standard Classification of Education 1976 (ISCED-76) by UNESCO: According to ILO (1990, 3-4), *Professionals* (ISCO-88 major 2) are associated with ISCED-76 levels 6 and 7, and *Technicians and associate professionals* (major 3) mostly require education at ISCED-76 level 5.[7] This implies that at the ISCO-88 major level, one can distinguish between two occupational categories requiring tertiary education, thus between two types of human capital and brain drain, which can be further broken down into eight sub-major and 39 minor occupational groups.

Clerks, *Service workers and shop and market sales workers*, *Skilled agricultural and fishery workers*, *Craft and related trades workers*, as well as *Plant and machine operators and assemblers* (majors 4-8) require skills that are often attained through formal education at ISCED-76 levels 2 or 3 (secondary education). *Elementary occupations* (major 9) are associated with ISCED-76 level 1 (primary education). "Although ISCO-88 avoids the terminology, 'Elementary Occupations' can be regarded as 'Unskilled', and 'Manual' or 'Blue-collar' occupations are concentrated within major groups 6 to 9" (Elias, 1997, 7).

[5] In line with the review of the overeducation/undereducation literature in Chiswick and Miller (2009, 163), employees are regarded as "overeducated" if their educational attainment exceeds the educational reference level of the occupational categories of ISCO-88.

[6] For a summary of the principles underlying ISCO-88 and a list of the sub-major categories, see Section 7.6.4 in the appendix.

[7] Note that under the current version ISCED-97 tertiary education is included in levels 5 and 6.

The *Armed forces* and *Legislators, senior officials and managers* (majors 0 and 1) do not have a skill coding because the skills required in these categories exhibit great variation.

Whereas these broad skill categories allow to distinguish two skill-intensive and two less skill-intensive categories, it is important to highlight that the coding of occupations to the aggregated ISCED skill levels only applies "[...] where the necessary occupational skills are acquired through formal education or vocational training", and that "[...] the focus in ISCO-88 is on the skills required to carry out the tasks and duties of an occupation – and not on whether a worker having a particular occupation is more or less skilled than another worker in the same occupation" (ILO, 1990, 2).

7.3.1 The Occupational Distribution of Total South-North Migrants

Table 7.2 reports the distribution of employees in the OECD around 2000 for total foreign-borns from developing countries and for OECD natives by ISCO-88 sub-major category.

Aggregating these numbers, we find that 23.9% of all south-north migrants with reported occupation worked in occupations requiring tertiary education (ISCED levels 5-7). This share is 4.9 percentage points lower than the share of tertiary-educated south-north migrants (see Section 7.2). Thus, from the perspective of the sending countries, there was 17% "overeducation" on the aggregate level. By contrast, there was no aggregate "overeducation" among OECD natives (26.9% of OECD natives with known education levels received tertiary education and 26.1% of those with known sub-major occupational categories worked in occupations requiring tertiary education). This observation suggests the existence of "brain waste"[8] due to the imperfect transferability of skills: Even though several south-north migrants held university degrees enabling them to work as *Professionals/Technicians and associate professionals* at least in their countries of birth, they did not find adequate jobs in the OECD and worked in occupations requiring less than tertiary education.

14.0% of total south-north migrants worked in occupations presupposing primary education (ISCED level 1), and a majority of 54.4% worked in occupations requiring secondary education (ISCED levels 2, 3). This latter proportion falls only slightly short of the percentage of OECD natives in occupations requiring secondary education (55.7%). Yet the relative numbers of south-north migrants working in occupations requiring primary education are considerably larger, while the numbers for those working as *Legislators,*

[8] The understanding of this term is based on Salt (1997, 5), see also Section 7.4.

senior officials and managers (sub-majors 11-13) are slightly smaller than the ones of OECD natives.

Table 7.2: Occupational Distributions of South-North Migrants (F) and OECD Natives (N) around 2000, by ISCO-88 Sub-major Occupational Category (%)

ISCO-88 Sub-Major Occupational Category		**F**	**N**	
Armed forces	(0)	0.2	0.7	
Legislators and senior officials	(11)	0.1	0.2	
Corporate managers	(12)	6.1	7.1	
General managers	(13)	1.4	2.1	
Physical, mathematical and engineering science professionals	(21)	4.5	2.8	ISCED 5-7
Life science and health professionals	(22)	3.3	2.1	ISCED 5-7
Teaching professionals	(23)	2.7	4.2	ISCED 5-7
Other professionals	(24)	3.8	4.5	ISCED 5-7
Physical and engineering science associate professionals	(31)	1.9	2.4	ISCED 5-7
Life science and health associate professionals	(32)	2.0	2.3	ISCED 5-7
Teaching associate professionals	(33)	0.7	0.8	ISCED 5-7
Other associate professionals	(34)	5.0	7.0	ISCED 5-7
Office clerks	(41)	7.2	9.2	ISCED 2,3
Customer service clerks	(42)	3.2	2.8	ISCED 2,3
Personal and protective services workers	(51)	11.7	8.6	ISCED 2,3
Models, salespersons and demonstrators	(52)	3.2	5.0	ISCED 2,3
Market-oriented skilled agricultural and fishery workers	(61)	3.6	8.3	ISCED 2,3
Subsistence agricultural and fishery workers	(62)	0.0	0.0	ISCED 2,3
Extraction and building trades workers	(71)	5.4	4.8	ISCED 2,3
Metal, machinery and related trades workers	(72)	7.0	6.0	ISCED 2,3
Precision, handicraft, printing and related trades workers	(73)	0.7	0.8	ISCED 2,3
Other craft and related trades workers	(74)	1.7	1.7	ISCED 2,3
Stationary-plant and related operators	(81)	0.6	0.9	ISCED 2,3
Machine operators and assemblers	(82)	6.3	3.4	ISCED 2,3
Drivers and mobile-plant operators	(83)	3.8	4.2	ISCED 2,3
Sales and services elementary occupations	(91)	8.5	4.8	ISCED 1
Agricultural, fishery and related labourers	(92)	0.3	0.2	ISCED 1
Labourers in mining, construction, manufacturing and transport	(93)	5.2	3.1	ISCED 1

Source: Author's tabulations using data from the DIOC.

Concerning the sub-major categories of the skill-intensive major *Professionals*, foreign-born employees in the OECD worked relatively more often as *Physical, mathematical and engineering science professionals* or as *Life science and health professionals*, and relatively less often as *Teaching professionals* or as *Other professionals* compared to the native OECD population. This observation is likely related to a smaller international transferability of skills associated with teaching professions relative to professions in the natural sciences. This issue will be further assessed and discussed in Sections 7.3.3 and 7.4.3. In all sub-major categories of the major *Technicians and associate professionals*, south-north migrants were relatively less frequent than OECD natives.

Concerning the occupational categories generally requiring less than tertiary education, pronounced differences are observed for sub-majors 82, 91, and 61: Whereas the percentages of south-north migrants working as *Machine operators and assemblers* or in *Sales and services elementary occupations* were considerably larger than the ones of OECD natives, the percentage of OECD natives working as *Market-oriented skilled agricultural and fishery workers* was more than twice the respective percentage of south-north migrants. This observation is not astonishing when one recognizes that the former types of occupations in general do not require many skills or prior experience, but can be easily learned by anyone. By contrast, the latter type of occupations are likely to require skills that substantially differ between developed and developing countries.

A glance at the most frequent sub-major occupational categories of south-north migrants by region of origin reveals two interesting deviations from the overall distribution: Whereas the most common occupational categories among total south-north migrants figure in major categories requiring less than tertiary education, emigrants from South Asia most often worked as *Physical, mathematical and engineering science professionals* (sub-major 21) in the OECD in 2000. Furthermore, large proportions of emigrants from South Asia as well as from the Middle East and North Africa in the OECD worked in sub-major 12 (*Corporate managers*), which might be considered as a skill-intensive category, too.

7.3.2 The Occupational Distribution of Tertiary-educated South-North Migrants

This section takes advantage of the cross-classification of the OECD population by occupational category and educational attainment in the DIOC in order to further assess the incidence of "overeducation" among south-north migrants and the international transferability of higher education. We make use of the sign test statistic to check whether the employment distributions of tertiary-educated south-north migrants significantly differed from the ones of OECD natives. This serves as a test of whether south-north migrants were affected by "overeducation" to a comparable extent as OECD natives. Our analysis complements the one in OECD (2008, 139), which relates aggregate overqualification rates (calculated as the percentage of employed holding a job for which they are formally overqualified) of foreign-born individuals to the ones of OECD natives.

Since occupations in ISCO-88 majors 2 (*Professionals*) and 3 (*Technicians and as-*

sociate professionals) normally require tertiary education, we expect that most tertiary-educated OECD natives and south-north migrants worked in these occupational categories. Table 7.3 presents mean values for the occupational distributions of the foreign-born (F) and the native (N) OECD population with tertiary education (ISCED-97 levels 5/6)[9].

Table 7.3: Occupational Distributions of South-North Migrants (F) and OECD Natives (N) around 2000, Mean Values across OECD Countries by ISCED-97 Level (%)

		ISCED 6		**ISCED 5**		**ISCED 5/6**	
Occupation, ISCO-88 Major		**F**	**N**	**F**	**N**	**F**	**N**
Armed forces	(0)	0.9	0.5	0.5	0.7	0.5	1.5
Legislators, senior officials and managers	(1)	10.8	11.5	11.9	12.6	14.7	16.1
Professionals	(2)	72.4	76.9	37.3	43.5	46.1	45.9
Technicians and associate professionals	(3)	7.8	6.8	17.8	20.8	17.4	21.1
Clerks	(4)	3.0	1.9	7.4	7.7	4.8	5.0
Service workers, shop and market sales workers	(5)	2.8	1.1	9.7	5.8	6.4	3.2
Skilled agricultural and fishery workers	(6)	0.4	0.4	0.9	1.6	0.4	1.4
Craft and related trade workers	(7)	1.0	0.4	5.1	3.9	3.5	3.9
Plant and machine operators and assemblers	(8)	0.8	0.3	3.6	1.8	2.1	1.0
Elementary occupations	(9)	1.6	0.4	6.1	1.7	4.0	0.8

Source: Author's tabulations using data from the DIOC.

As expected, most tertiary-educated migrants (ISCED-97 levels 5/6) from developing countries in the OECD worked as *Professionals* or *Technicians and associate professionals*: On average 46.1% and respectively 17.4% worked in these skill-intensive categories around 2000. In addition, a non-negligible share (on average 14.7%) worked as *Legislators, senior officials and managers*, whereas the shares of highly educated migrants working in occupations requiring only secondary or primary education (majors 4-9) were considerably smaller. South-north migrants with education at ISCED-97 level 6 were even more strongly concentrated in ISCO-88 major 2, while the distributional peak of the occupations of south-north migrants with education at ISCED-97 level 5 in the high-skill intensive occupational categories was less pronounced.

Using the sign test statistic[10] for the populations with education at ISCED-97 levels 6 and 5 separately, we find that the shares of tertiary-educated south-north migrants working in ISCO-88 majors 5, 7, 8, and 9 (occupational categories generally requiring less than tertiary education) were significantly larger than the respective shares of the OECD

[9] For some individuals, the exact level of tertiary education – ISCED-97 level 5 or 6 – has not been reported. Therefore, the populations considered in columns 7 and 8 exceed the combined populations considered in columns 3/5 and 4/6.

[10] This is a non-parametric test statistic that does not impose distributional assumptions and that is suitable in the context of two matched samples of metric data with small sample sizes (n_1,n_2 < 30) (Bamberg et al., 2009, 171 and 188). The null hypothesis of this test statistic is that the median of the differences between the values of the two considered criteria is equal to zero.

native population.[11] In addition, south-north migrants with education at ISCED-97 level 6 were more often employed in ISCO-88 majors 3 and 4, but less often in major 2 compared to OECD natives with the same educational attainment.[12] South-north migrants with education at ISCED-97 level 5 were relatively less represented in majors 2 and 3.[13] The sign tests yield no significant differences for major category 6, nor for the aggregated employment shares of south-north migrants and OECD natives with education at ISCED-97 levels 5/6.

The outlined distributional differences between the tertiary-educated foreign-born and native OECD population point out that significantly more tertiary-educated south-north migrants than OECD natives worked in occupational categories requiring less than tertiary education. This is in line with the observation that the percentage of total south-north migrants working in occupational categories generally requiring tertiary education was lower than the percentage of total south-north migrants with tertiary education (see Sections 7.2 and 7.3.1). From the point of view of the sending countries, these emigrants worked in professions for which they were "overeducated". One plausible explanation of this finding is the imperfect transferability of human capital in general, and, in this context, of formal tertiary education in certain professions acquired in the migrant-sending countries. Whereas Chiswick and Miller (2009) explicitly consider the transferability of language skills and of pre-immigration labor market experience in addition to formal education for foreign-borns in the United States, the data from the DIOC only enable us to assess the transferability of human capital accumulated through formal education. We suppose that the importance of a high proficiency of the receiving country's official language in the case of some high-skilled occupational categories (such as teaching, legal, or social services professions) contributes to the observation that relatively more highly educated south-north migrants than OECD natives worked in occupational categories for which they were formally "overeducated". Similar considerations apply to acquired work experience and to the knowledge of the receiving country's institutions. According to the review of overeducation theories in Chiswick and Miller (2009, 164), the theory of technological change predicts that overeducation is more common for immigrants from less developed countries.

[11] The null hypothesis of the one-sided test that the median of the differences is zero against the alternative hypothesis that the median of the differences between foreign-born and native employment shares is larger than zero can be rejected at the 1- and 5-% levels, respectively.

[12] The null of the respective one-sided sign tests can be rejected at the 1-, 5-, and 10-% level, respectively.

[13] The null of the respective one-sided sign tests can be rejected at the 10- and 1-% level, respectively.

7.3.3 Assessing the International Transferability of ***Professionals'*** Skills

This section examines differences in the disaggregated employment distributions of the skill-intensive majors 2 and 3 (*Professionals* and *Technicians and associate professionals*) between south-north migrants and OECD natives on the one hand, and between south-north migrants and the respective populations in the origin countries on the other hand. The intention of these analyses is to provide some tentative evidence on the different degrees of international transferability of tertiary education. Professional categories that were relatively more frequent among south-north migrant *Professionals* than among OECD-native *Professionals* or among *Professionals* residing in the sending countries will be considered to require skills with a relatively high degree of international transferability. Sub-major categories that were relatively less frequent among foreign-born *Professionals* in the OECD will be considered to require skills that are rather country-specific.

Professionals (2) | Technicians and associate professionals (3)

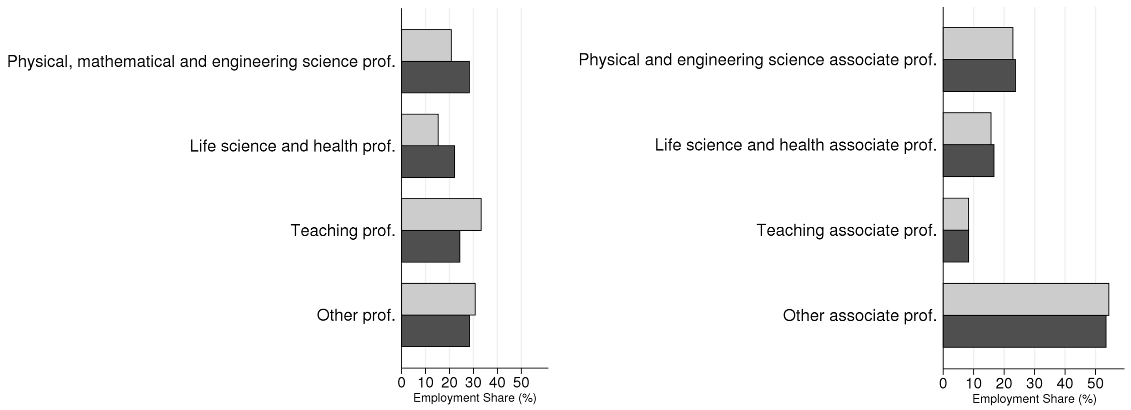


Figure 7.2: Mean Values of the Distributions of South-North Migrants (dark) and Natives (light) in OECD Countries (2000) in ISCO-88 majors 2 and 3, over Sub-majors

Source: Author's tabulations using data from the DIOC.

Whereas Figure 7.2 shows larger mean shares of *Professionals* working as *Physical, mathematical and engineering science professionals* (sub-major 21) or as *Life science and health professionals* (sub-major 22) for the immigrant OECD population born in developing countries than for the native OECD population around 2000, the mean proportion of native *Professionals* working as *Teaching professionals* (sub-major 23) exceeded the one of foreign-born *Professionals.* In line with these observations, the application of the sign test statistic[14] reveals that the shares of foreign-born *Professionals* working in sub-majors

[14]The reasoning for the adequacy of this test statistic is the same as in Section 7.3.2.

21 and 22 were significantly larger, and that the ones of those working in sub-majors 23 and 24 were significantly smaller than the respective shares of native-born *Professionals*.[15]

By contrast, the differences in the mean employment shares of foreign-born and native *Technicians and associate professionals* (sub-majors 31-34) were less pronounced: Significant (positive) differences between foreign-born and native employment shares can only be confirmed for sub-major category 31 (at the 5-% level of statistical significance).

Given that we had to recode the occupational categories reported for some countries,[16] we test the robustness of some of the above findings. To this end, we exploit the similar occupational structures of ISCO-88 majors 2 and 3 and aggregate their sub-major categories into four broad types of *(Associate) Professionals*. The results from sign tests confirm those obtained for sub-major categories 21-24: The shares of aggregate *(Associate) Professionals* working as *Physical, mathematical and engineering science (associate) professionals* or as *Life science and health (associate) professionals* in the OECD were significantly larger for south-north migrants than for OECD natives. Native-born *Professionals*, however, worked more often as *Teaching (associate) professionals* or as *Other (associate) professionals*.[17]

We also relate the distributions of *(Associate) Professionals* from 17 developing countries working in the OECD over these four aggregated occupational categories to the respective distributions in the countries of origin and test for equality of distributions.[18] The results from sign tests partly confirm the above picture: The shares of aggregate *(Associate) Professionals* from the considered developing countries working as *Life science and health (associate) professionals* were significantly larger (at the 1-% level) for those working in the OECD compared to those in the origin countries around 2000. The proportions of *(Associate) Professionals* working as *Teaching (associate) professionals* in the sending countries significantly exceeded the ones of the emigrant *(Associate) Professionals* in the OECD (at the 1-% level).

The significant differences in the occupational distributions of south-north migrants and OECD natives working as *(Associate) Professionals* on the one hand, and between

[15] The null hypotheses of the relevant one-sided tests can be rejected at the 1- and 5-% level for sub-majors 22, 23 and 21, 24, respectively.

[16] In particular, we had to recode the minor categories of ISCO-1968 to the sub-major categories of ISCO-88 for some countries. For a detailed description of the data preparation and the encountered problems, see Sections 7.6.5 and 7.6.6 in the appendix.

[17] The null of the respective one-sided sign tests can be rejected at the 5-% level for *Physical, mathematical and engineering science (associate) professionals* and *Teaching (associate) professionals*, and at the 1-% level for *Life science and health (associate) professionals* and *Other (associate) professionals*.

[18] For a description of the considered data and countries, see Section 7.6.7 in the appendix.

(Associate) Professionals from developing countries working in the OECD and those working in the origin countries on the other hand likely suggest that skills related to *Physical, mathematical and engineering science professions* and to *Life science and health professions* exhibit a larger degree of international transferability than skills related to *Teaching occupations*. This has already been indicated by the aggregated figures in Section 7.3.1.

Unfortunately, it is not clear whether the immigrant *Professionals* acquired their tertiary education before or after migration. The reason is that the DIOC does not distinguish between foreign-borns who pursued their studies in the sending countries and those who went to university in the OECD. The subsequent considerations suggest, however, that the ignorance of the country where (higher) education has been acquired may not be so problematic in this context.

There are essentially two plausible explanations for the distributional differences outlined in this section. On the one hand, *Professionals* who acquired their university degrees in the sending countries and who managed to find jobs as *Professionals* in the OECD most likely belong to occupational categories whose (formal and on-the-job) skills exhibit a high degree of international transferability, such as it is plausibly the case in the natural sciences. This may be partly related to selective immigration policies that favor the immigration of specific types of professionals, such as engineers or doctors. By contrast, *Teaching professionals* face the problem that educational systems greatly differ across countries. It is unlikely that permissions to teach acquired in developing sending countries are accredited in the OECD without further requirements. On the other hand, *Professionals* born in developing countries who pursued their university degrees in the OECD are likely to have mainly chosen fields of study procuring internationally transferable skills, such that the acquired qualifications are also of use in the case of return migration. On the basis of these considerations, south-north migrants should thus be relatively more represented in occupational categories requiring internationally transferable skills – irrespective of where they have pursued their studies. Furthermore, a high proficiency of the receiving country's official language is of less importance for *Physical, mathematical, engineering*, *Life science and health professionals* than for *Teaching professionals*. Especially in the natural sciences, English is very often the working language. An empirical study that systematically analyzes the occupational choice of high-skilled immigrants in the United States is Chiswick and Taengnoi (2007). They find that high-skilled immigrants who have limited proficiency of the host country's language – which is English in this case – and whose first language is linguistically distant from English are more likely to exercise professions in which English communication skills are not so important.

7.4 Two New Datasets on South-North Migration by Occupational Category

This section presents south-north migration rates by occupational category at the major and sub-major level of ISCO-88. These data allow for a comparison of the extent of emigration in different occupational categories for several developing sending countries, which was not possible with the existing migration datasets until now. Occupation-specific emigration rates that can be compared across several developing sending countries are only available for doctors and nurses from the OECD.[19] Furthermore, data on the medical brain drain from sub-Saharan African countries is provided, e.g., in Docquier and Bhargava (2007), Clemens and Pettersson (2008), and in Hagopian et al. (2004).

In order to analyze the extent of south-north migration from the perspective of the sending countries for various occupational categories, we combine data on immigrants in OECD countries from the DIOC with data on employment in the sending countries from the ILO database on labor statistics (LABORSTA) and calculate *occupation-specific emigration rates*. In analogy to the approach in Docquier and Marfouk (2006, 166), we relate the stock of migrants working in a specific occupational category in the OECD to the stock of total natives, defined as migrants in the OECD (M_{ij}) plus residents in the sending country (R_{ij}), in the same occupational category around the year 2000:

$$m_{ij} = \frac{M_{ij}}{M_{ij} + R_{ij}}. \tag{7.1}$$

Thus, m_{ij} gives the likelihood that an individual from country i with occupation j worked in the OECD around 2000. In statistical terms, m_{ij} gives the conditional probability that an individual from country i had emigrated to the OECD by 2000 (event B) given that he was working in occupational category j in 2000 (event A): $P(B|A)$. Depending on the level of disaggregation, j either refers to the ISCO-88 major (1-digit) or sub-major (2-digit) occupational categories.

The constructed dataset of occupation-specific emigration rates at the major level includes information for 91 developing countries around the year 2000. We are also able

[19] See the list of data sources in Section 7.6.1 for the reference of this dataset.

to calculate analogous emigration rates at the ISCO-88 sub-major level. However, due to scarce data availability, these emigration rates can only be constructed for 17 developing countries around 2000.

Using data from countries of immigration in order to study emigration is very common in the related empirical literature. This can be justified with the argument that emigration data are less reliable than immigration data because emigration declarations are often not compulsory and also include tourists (Beine et al., 2001, 284).

Whereas flow data would allow to capture the brain drain in terms of "sunk costs" of higher education, i.e., foregone taxes etc. that were invested into the higher education of the future emigrants, this is not possible with the stock data from the DIOC. The reason for this is that the available data do not allow to distinguish between the foreign-borns who acquired their tertiary education in the developing sending countries or in the OECD receiving countries. However, south-north migrants who received at least part of their pre-tertiary education in the sending countries also produced educational costs borne by the latter that are captured in the data. Unlike flow data, the available stock data on the OECD's foreign-born population in 2000 provide *accumulated* information on migration to the OECD over the past years, excluding return migrants as well as migrants who arrived in the relevant period but who had already deceased by 2000. Since it is impossible to statistically evaluate emigration and return migration, stock data can be considered as more reliable than flow data (Docquier and Marfouk, 2006, 156).

On the basis of these considerations, we consider the stock of migrants from developing countries in the OECD working in occupational categories requiring tertiary education (ISCO-88 majors 2 and 3) as potential but inavailable human capital of the developing sending countries. Hence, this is a broad notion of the brain drain that accounts for the extent to which the most able left the developing sending countries because it comprises also emigrants who acquired their (tertiary) education in the host country. According to Meyer and Brown (1999), "[...] it is clear, today, that the majority of skilled people of foreign origin acquire their professional qualifications in the host country". In this context, Bhorat et al. (2002, 10) argue that stock data "[They] simply reveal the extent of the diasporas, which should not be confused with a basic result of earlier highly skilled outflows".

A further issue is the ignorance of the occupations performed by migrants in their origin countries prior to emigration. These occupations are not reported in the DIOC. In order to be able to interpret m_{ij} as occupation-specific emigration rate, we therefore have to assume that migrants who acquired their highest education certificate in the sending countries would perform occupations in the same reported occupational category in their origin country if they had not emigrated. While the findings from Section 7.3.3 suggest that this assumption may not be very problematic in the case of high-skilled occupations such as business or engineering professions that require internationally transferable skills, it will be so in the case of occupations demanding skills that are rather country-specific, such as several teaching or legal professions. In this context, the term "brain waste" describes the "[...] deskilling that occurs when highly skilled workers migrate into forms of employment not requiring the application of the skills and experience applied in the former job" (Salt, 1997, 5). For the type of occupations that are associated with "brain waste" due to the imperfect transferability of acquired skills and diplomas, our emigration rates will be likely to underestimate the absence of certain types of professionals from the migrant-sending countries. Being unaware of the place where (higher) education has been acquired, the interpretation of m_{ij} as occupation-specific emigration rate furthermore requires the implicit assumption that all emigrants who went to university in the OECD would have pursued the same studies and acquired the same skills in the origin countries if they had not emigrated.

Using employment data from LABORSTA and the DIOC, we also calculate *resident employment shares* at the level of the ISCO-88 major and sub-major categories, i.e., employment shares for the resident populations in developing countries and OECD countries:

$$r_{ij} = \frac{R_{ij}}{\sum_j R_{ij}}. \tag{7.2}$$

In addition, we construct *native employment shares*, i.e., employment shares for total natives (residents plus migrants) from developing migrant-sending countries. These shares give the probability $P(A)$ that an individual born or residing in country i worked in occupational category j around 2000:

$$n_{ij} = \frac{R_{ij} + M_{ij}}{\sum_j R_{ij} + \sum_j M_{ij}}. \tag{7.3}$$

Native employment shares are instructive in two respects. First, n_{ij} can be interpreted as the total human capital of type j that would be available to country i if no emigration had occurred and if all emigrants who went to university or acquired an occupational training in the OECD had acquired the same skills in the origin country. This measure of human capital can then be related to the incidence of south-north migration as observed for human capital type j, m_{ij}. Second, the comparison of native employment shares and resident employment shares of the sending countries provides some indication on the selectivity of south-north migration.

7.4.1 The Extent of High-Skilled Emigration Revisited with Occupational Data

Before we present descriptive evidence on occupation-specific south-north migration, in this section we reassess the extent of the *aggregate* brain drain with the employment data from ILO and OECD. To this end, we aggregate the occupation-specific employment data by the broad skill (ISCED-76) levels that are associated with ISCO-88 (see Section 7.3). We then compare the obtained (employment-based) evidence on the aggregate brain drain to the (population-based) evidence presented in Section 7.2.

Whereas the emigration rates available with the DIOC rest upon educational attainment to capture the brain drain, in the following analysis the definition of *high-skilled* is based on the educational qualification required in the occupations that are actually exercised. This entails the advantage that we can use employment data from ILO in order to measure the relevant populations in the migrant-sending countries. By contrast, in OECD (2008, 174) the information on origin populations by educational attainment had to be constructed using population data from the United Nations along with the Barro-Lee database for the educational structure of the populations in the origin countries.

Table 7.4 shows that the mean south-north migration rate was highest for occupational categories requiring tertiary education (ISCED-76 levels 5-7), while developing countries' mean employment shares of residents and natives were highest for occupations requiring secondary education (ISCED-76 levels 2, 3) in 2000. The application of one-sample (paired difference) t tests[20] yields the following: The mean emigration rate in occupations presupposing tertiary education was significantly larger (at the 1- and 5-% level) than the mean rates in the low-skill categories (ISCED-76 levels 2, 3 and level 1).

[20] In the present case, the numbers of observations of the matched samples are sufficiently large ($n_1, n_2 > 30$). This allows us to use this parametric test statistic for asymptotic normality, whereas with smaller samples sizes the sign test is appropriate (see Section 7.3.2). The null hypothesis of the one-sample (paired difference) t statistic is that the means of the two considered distributions are equal (Bamberg et al., 2009, 171).

Table 7.4: Mean Values of Resident and Native Employment Shares (%), Mean Emigration Rates (%) of Developing Countries around 2000, by ISCED-76 Levels Associated with ISCO-88

ISCED-76 Level	**Employment Residents**	**Employment Natives**	**Emigration Rate**	**# Dev. Countries**
Tertiary (5-7)	15.6	16.3	11.5	83
Secondary (2, 3)	64.5	64.0	6.7	83
Primary (1)	16.2	16.0	8.9	73

Source: Author's tabulations using data from the DIOC and LABORSTA.

Concerning the employment distributions of residents and natives by broad skill category, we find for both distribution types that the mean employment shares were significantly smaller for occupations requiring tertiary or primary education compared to the mean share for occupations requiring secondary education.[21]

Thus, in addition to the observation that employment of south-north migrants from low-income countries was rising in qualification (see Section 7.2), aggregate south-north migration rates were on average highest for the most skill-intensive occupational categories. This means, people from developing countries with professional skills specific to occupations figuring in the high-skill categories were more likely to work in the OECD compared to their fellow countrymen with occupations in the low-skill categories.[22] This trend is in line with the immigration policies of many OECD countries that favor either high-skilled immigration in general, or immigration of specific types of professionals. Our second observation describes the relatively low importance of highly skill-intensive occupations in total employment in the sending countries with which the brain drain has to be contrasted.

Table 7.4 suggests that the mean employment share of residents in skill-intensive occupations was somewhat smaller compared to the mean share of natives, with the opposite being true for the categories summarizing the less skill-intensive occupations. However, the application of paired difference t tests yields that the hypothesis that the mean employment shares of residents and natives are equal cannot be rejected at reasonable significance levels.

Taken together, whereas on average 16.3% of natives from developing countries were employed in occupations requiring education at the highest ISCED-76 levels, 11.5% of

[21] The null hypothesis of the relevant one-sided tests that the mean employment shares are equal in the aggregated skill categories for residents and respectively natives can be rejected at the 1-% level.

[22] Note that the assumption that migrants in the OECD execute the same jobs that they would execute in their origin countries had they not emigrated is not restrictive in this context. If some highly educated migrants from developing countries secured jobs in the low-skill occupational categories in the OECD, the emigration rates for ISCED-76 levels 5-7 will be underestimated.

these lived and worked in the OECD around 2000. This employment-based average number of the brain drain is 4.5 percentage points lower than the corresponding population-based number (see Section 7.2). In Section 7.3, a similar picture has emerged when we compared the respective aggregate shares of south-north migrants from the considered developing countries. This makes us conclude that the emigration rates for the skill-intensive occupational categories are likely to be downward biased from the point of view of the sending countries due to an imperfect transferability of (formal) skills. Put differently, the employment-based brain drain rates presented in Table 7.4 are by construction lower than the population-based counterparts because the former account for the fact that formal skills are not always transferable internationally.

7.4.2 South-North Migration by ISCO-88 Major Occupational Category

This section presents mean emigration rates and employment shares by ISCO-88 major occupational category for 91 developing countries around 2000, as well as for the different world regions in which these countries are located. This disaggregation allows to distinguish two broad types of human capital and brain drain (ISCO-88 majors 2 and 3), which generally require tertiary education. Moreover, it provides additional insights on emigration and employment in occupational categories presupposing secondary education (ISCO-88 majors 4-8), as well as for *Legislators, senior officials and managers* and the *Armed forces*, which are not assigned any general skill category.[23]

Concerning the two types of brain drain, Table 7.5 shows a higher mean emigration rate for *Professionals* than for *Technicians and associate professionals*: On average, 14.1% of the former and 10.6% of the latter born or living in developing countries worked in the OECD around 2000. The application of the paired difference t test to the distributions underlying the mean values yields that this difference is statistically significant at the 1-% level. The mean employment shares of natives were only marginally larger than the ones of residents in these two categories; these differences are also statistically significant (at the 1-% level).

Table 7.5 furthermore reveals large differences across the emigration rates of occupational categories generally requiring secondary education (majors 4-8): Whereas the probability that a *Clerk* residing or born in one of the included developing countries lived and worked in the OECD around the year 2000 was 13.2% on average, the analogous

[23] Sub-major 0 (*Armed forces*) has been excluded from the regional statistics due to small numbers of observations.

probability for a *Skilled agricultural and fishery worker* was only 1.7%. Applying paired difference t tests for equality of mean values yields that the mean emigration rate of *Clerks* was significantly larger (at the 1-% level) than the mean rates in ISCO-88 majors 5-8, while the mean emigration rate of *Skilled agricultural and fishery workers* was significantly smaller (at the 1-% level) than the mean values in the other majors requiring secondary education. The mean emigration rate of *Plant and machine operators and assemblers* was with 11.4% on a high level, too, and it was significantly larger than the mean emigration rates in major categories 5-7.[24]

By contrast, employment of residents in developing countries in occupational categories generally requiring secondary education was concentrated to a large extent in the occupational category *Skilled agricultural and fishery workers* (the mean employment share in the sample is 24.0%) around 2000. Yet, on average only 6.1% of those employed in developing countries worked as *Clerks*. The differences between the mean employment shares of these two majors and the mean shares of the other majors requiring secondary education are statistically significant (at the 1-% level). Comparing these mean employment shares to the ones of OECD countries, large differences are observed for all major categories except for the *Armed forces*, *Service workers and shop and market sales workers*, *Craft and related trades workers*, and for *Plant and machine operators and assemblers*. Testing for equality of distributions with the Kolmogorov-Smirnov test statistic[25], we find that OECD countries exhibited significantly larger employment shares in the most skill-intensive majors 1-4, as well as in major categories 5 and 8.[26] By contrast, resident employment shares in major categories 6, 9, and 0 were significantly larger for developing countries than for OECD countries.[27] Thus, in addition to the relatively small importance of *Professionals* and *Technicians and associate professionals* in total employment, developing countries exhibited smaller employment shares of *Legislators, senior officials and managers*, *Clerks*, and *Service workers and shop and market sales workers* compared to OECD countries.

The comparison of mean resident employment shares and mean native employment

[24] The null hypothesis of equal means of the respective one-sided tests can be rejected at the 5-% and 1-% level for majors 5 and 6, 7, respectively.

[25] This non-parametric test statistic is appropriate in the context of two independent samples of metric data with continuous distribution functions and small samples sizes ($n_1, n_2 < 30$) (Bamberg et al., 2009, 170). The null hypothesis of the one-sided tests for this statistic is that the values of one distribution are smaller/larger or equal the values of the second distribution (Büning and Trenkler, 1978, 133-134).

[26] Equality of distributions can be rejected at the 1-% level for majors 1-4, at the 5-% level in the case of major 5, and at the 10-% level for major 8.

[27] Equality of distributions can be rejected at the 1-% level for majors 6 and 9, and at the 5-% level in the case of major 0.

shares of developing countries reveals marginal differences (< 0.5 percentage points), which are statistically significant (according to paired difference t tests): On average, the probability of being employed in either major category 1, 2, or 3 (which include the most skill-intensive occupations) or in either major category 4, 5, or 8 was larger for natives than for residents of developing countries. At the same time, the probability of being employed in either major 0, 6, 7, or 9 was smaller for natives than for residents.[28]

When we relate the mean emigration rate of *Professionals* to the respective value for the mean native employment share, it turns out that while *Professionals* on average made up only 8.2% of total native employment of developing countries, on average 14.1% of the native *Professionals* from developing countries (i.e., of the *Professionals* being potentially available to these countries) worked in the OECD around 2000.

Given that we had to recode the occupational categories reported for some countries,[29] we test the robustness of the above findings by excluding information that is not reported according to ISCO-88. Although we obtain larger mean emigration rates and employment shares for some major occupational categories from the reduced sample, these differences are rather small (< 1 percentage point). In addition, the results from the t tests applied to the smaller sample confirm the above-described distributional differences. Furthermore, we consider the summary statistics presented in Section 7.4.1 as a second robustness check for the observation of considerably large emigration rates for *(Associate) Professionals*. The reason is that due to the aggregation by ISCED-76 education categories, most objections regarding the recoding of occupational categories should be dispelled (see Section 7.6.5 in the appendix).

[28] The hypothesis of equal means across distributions can be rejected at the 1-% level for majors 1, 2, 3, 4, and 6, at the 5-% level for majors 0, 7, 8, and 9, and at the 10-% level for major 5.

[29] In particular, we had to recode the major categories of ISCO-68 to the ones of ISCO-88 for some countries. For a detailed discussion of the recoding procedures, see Section 7.6.6 in the appendix.

Table 7.5: Mean Values of Resident Employment Shares (%) of Developing Countries and of OECD Countries, Mean Native Employment Shares of Developing Countries (%), Mean South-North Migration Rates (%) around 2000, by ISCO-88 Major

ISCO-88 Major Occupational Category j		**Employment Residents** $\sum_{i=1}^{I} r_{ij}/I$	**Employment Natives** $\sum_{i=1}^{I} n_{ij}/I$	**Employment OECD** $\sum_{i^*=1}^{I^*} r_{i^*j}/I^*$	**Emigration Rate** $\sum_{i=1}^{I} m_{ij}/I$	**# Dev. Countries** I	**# OECD Countries** I^*
Armed forces	(0)	1.6	1.5	0.7	2.9	86	24
Legislators, senior officials and managers	(1)	4.8	5.0	8.6	13.7	91	27
Professionals	(2)	7.8	8.2	13.1	14.1	91	27
Technicians and associate professionals	(3)	8.0	8.2	14.8	10.6	91	27
Clerks	(4)	6.1	6.5	11.1	13.2	91	27
Service workers, shop and market sales workers	(5)	13.5	13.6	13.8	8.5	91	27
Skilled agricultural and fishery workers	(6)	24.0	22.9	6.0	1.7	91	27
Craft and related trades workers	(7)	14.8	14.6	14.1	7.5	91	27
Plant and machine operators and assemblers	(8)	7.9	8.1	8.6	11.4	90	27
Elementary occupations	(9)	16.2	15.8	9.2	9.0	91	27

Source: Author's tabulations using data from the DIOC and LABORSTA.

According to Table 7.6, for ISCO-88 major categories 1-7 south-north migration rates were on average largest for developing countries situated in Latin America and the Caribbean. For majors 8 and 9, south-north migration rates were on average largest for developing countries in East Asia and the Pacific. On average, 23.6% of the *Professionals* and 18.5% of the *Technicians and associate professionals* being potentially available to developing countries in Latin America and the Caribbean lived in the OECD around 2000. Mean migration rates of countries in East Asia and the Pacific were also on a high level (with mostly two-digit percentages) for most occupational categories.

A trend common to many regions of origin (except East Asia and the Pacific as well as Eastern Europe and Central Asia) is that the largest mean emigration rates around 2000 are observed for the most skill-intensive occupational categories *Professionals* and *Technicians and associate professionals*, for *Legislators, senior officials and managers*, or for *Clerks*. For East Asia and the Pacific, the mean emigration rate was largest for the less skill-intensive occupational category *Plant and machine operators and assemblers*; for Eastern Europe and Central Asia, the mean emigration rate was largest for *Elementary occupations* and *Craft and related trades workers*.[30]

For *Professionals* and *Technicians and associate professionals*, the mean resident employment shares were largest for developing countries in Eastern Europe and Central Asia (approximately 11%). The same employment shares were smallest for sub-Saharan Africa: On average, *Professionals* made up only 2.9% and *Technicians and associate professionals* 4.3% of employment in sub-Saharan African countries. *Skilled agricultural and fishery workers* on average accounted for the largest employment shares in all regions of origin. An exception is Latin America and the Caribbean, where most employees (19.9% on average) worked in *Elementary occupations*. Whereas for *Skilled agricultural and fishery workers* the largest mean resident employment shares are observed for sub-Saharan Africa and South Asia (42.0% and 38.3%, respectively), this share was only 10.5% in Latin America and the Caribbean.[31]

[30] When considering only employment data classified according to ISCO-88, the largest mean emigration rates for East Asia and Pacific are observed for majors 4, 8, 1, and 2.

[31] When considering only employment data originally classified according to ISCO-88, the highest mean resident employment shares of *Skilled agricultural and fishery workers* is observed for East Asia and the Pacific (44.1%).

Table 7.6: Mean Values of South-North Migration Rates and Resident Employment Shares of Developing Countries around 2000, by ISCO-88 Major and Region of Origin (%)

Mean South-North Migration Rates, by ISCO-88 Major and Region of Origin (%)

ISCO-88 Major Occupational Category		East Asia & Pacific	Eastern Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	South Asia	Sub-Saharan Africa
Legislators, senior officials and managers	(1)	17.2	4.5	21.2	10.2	1.4	17.4
Professionals	(2)	16.5	4.3	23.6	8.6	6.3	16.1
Technicians and associate professionals	(3)	12.7	3.9	18.5	6.1	1.5	11.4
Clerks	(4)	19.0	5.7	21.6	5.1	2.8	10.4
Service and shop and market sales workers	(5)	10.1	4.8	15.4	4.0	2.1	4.1
Skilled agricultural and fishery workers	(6)	1.7	1.8	2.9	0.3	0.0	0.6
Craft and related trades workers	(7)	9.4	6.5	12.9	2.2	0.4	2.2
Plant and machine operators and assemblers	(8)	24.0	5.7	17.0	5.2	2.2	5.4
Elementary occupations	(9)	17.0	7.3	12.9	3.1	0.6	3.0

Mean Resident Employment Shares of Developing Countries, by ISCO-88 Major and Region (%)

ISCO-88 Major Occupational Category		East Asia & Pacific	Eastern Europe & Central Asia	Latin America & Caribbean	Middle East & North Africa	South Asia	Sub-Saharan Africa
Legislators, senior officials and managers	(1)	4.0	6.1	5.5	4.7	5.7	1.8
Professionals	(2)	7.7	11.1	7.1	9.3	4.2	2.9
Technicians and associate professionals	(3)	5.7	11.3	9.0	7.4	4.6	4.3
Clerks	(4)	5.6	4.9	8.0	7.0	5.8	3.9
Service and shop and market sales workers	(5)	10.6	11.6	18.2	16.0	7.9	10.8
Skilled agricultural and fishery workers	(6)	37.7	19.7	10.5	20.0	38.3	42.0
Craft and related trades workers	(7)	13.9	13.7	16.9	17.0	14.8	10.8
Plant and machine operators and assemblers	(8)	6.0	9.6	8.6	9.4	4.4	5.3
Elementary occupations	(9)	15.3	11.3	19.9	13.6	16.7	20.4

Source: Author's tabulations using data from the DIOC and LABORSTA.

Table 7.6 furthermore shows that employment was on average very polarized in sub-Saharan Africa (with on average 20.4% of total employment in occupations requiring primary education, but only 2.9% in the most skill-intensive category *Professionals*), in Latin America and the Caribbean, in East Asia and the Pacific, as well as in South Asia. By contrast, the “skill gap” was much smaller in Eastern Europe and Central Asia, as well as in the Middle East and North Africa.

Summing up, the disaggregation of south-north migration rates by ISCO-88 major category has produced the following additional insights: The average incidence of south-north migration around 2000 was largest for the skill-intensive occupational categories *Professionals* and *Technicians and associate professionals*, as well as for *Legislators, senior officials and managers*, *Clerks*, and *Plant and machine operators and assemblers.* For the considered migrant-sending countries, the employment shares of *Professionals*, *Technicians and associate professionals*, *Legislators, senior officials and managers*, *Clerks*, *Service workers and shop and market sales workers*, and of *Plant and machine operators and assemblers* were significantly smaller than the ones for OECD countries. By contrast, the shares of *Skilled agricultural and fishery workers* and of workers in *Elementary occupations* were significantly larger in the developing countries than in the OECD countries. The regional summary statistics have revealed that developing countries in Latin America and the Caribbean as well as in East Asia and the Pacific exhibited the largest emigration rates around 2000, and that sub-Saharan Africa experienced relatively strong brain drain.

7.4.3 South-North Migration by ISCO-88 Sub-Major Occupational Category

Table 7.7 reports mean south-north migration rates and employment shares of residents and natives of developing migrant-sending countries and of the resident OECD population around 2000 by ISCO-88 sub-major category.[32] This disaggregation allows us to study eight different types of human capital and brain drain (sub-majors 21-24 and 31-34), as well as 16 less skill-intensive occupational categories (sub-majors 41-93) and the three sub-majors contained in major category 1 (11-13).

[32] Observations with zero reported resident employment and positive migrant employment have been excluded for the summary statistics reported in Table 7.7, because the resulting emigration rates of 100% are considered as distorting outliers. Most often, this concerned the *Armed forces*, for which data on resident employment was missing or reported ambiguously.

Table 7.7: Mean Values of Resident Employment Shares (%) of Developing Countries and OECD Countries, Mean Native Employment Shares of Developing Countries (%), Mean South-North Migration Rates (%) around 2000, by ISCO-88 Sub-major

ISCO-88 Sub-Major Occupational Category j		Employment Residents $\sum_{i=1}^{I} r_{ij}/I$	Employment Natives $\sum_{i=1}^{I} n_{ij}/I$	Employment OECD $\sum_{i^*=1}^{I^*} r_{i^*j}/I^*$	Emigration Rate $\sum_{i=1}^{I} m_{ij}/I$	# Dev. Countries I	# OECD Countries I^*
Legislators and senior officials	(11)	0.3	0.3	0.3	3.8	17	24
Corporate managers	(12)	3.2	3.2	5.2	9.7	17	23
General managers	(13)	2.8	2.7	3.2	7.4	15	21
Physical, mathematical and engineering science professionals	(21)	1.7	1.8	2.8	10.5	17	25
Life science and health professionals	(22)	1.1	1.1	2.0	11.1	17	25
Teaching professionals	(23)	3.6	3.6	4.2	3.8	17	25
Other professionals	(24)	2.9	2.9	4.2	5.9	17	25
Physical and engineering science associate professionals	(31)	2.4	2.4	3.4	4.8	17	24
Life science and health associate professionals	(32)	2.1	2.1	2.4	6.2	16	25
Teaching associate professionals	(33)	1.0	0.9	1.3	4.1	16	22
Other associate professionals	(34)	4.3	4.4	7.5	5.5	17	25
Office clerks	(41)	4.6	4.6	8.8	5.0	17	25
Customer service clerks	(42)	1.2	1.2	2.3	7.6	16	23
Personal and protective services worker	(51)	6.6	6.6	8.5	5.7	17	25
Models, salespersons and demonstrators	(52)	7.1	7.0	5.4	2.6	17	25
Market-oriented skilled agricultural and fishery workers	(61)	10.6	10.4	6.4	1.6	17	24
Subsistence agricultural and fishery workers	(62)	12.7	12.7	0.4	0.0	6	4
Extraction and building trades workers	(71)	4.9	4.8	5.4	3.3	17	25
Metal, machinery and related trades workers	(72)	5.4	5.4	5.4	3.8	17	25
Precision, handicraft, printing and related trades workers	(73)	1.0	1.0	0.8	3.9	17	24
Other craft and related trades workers	(74)	4.0	3.9	2.3	2.5	16	24
Stationary-plant and related operators	(81)	1.2	1.2	1.0	4.2	17	24
Machine operators and assemblers	(82)	3.3	3.3	3.5	6.6	17	25
Drivers and mobile-plant operators	(83)	6.0	5.9	4.1	2.5	17	25
Sales and services elementary occupations	(91)	6.5	6.5	5.4	4.5	17	25
Agricultural, fishery and related labourers	(92)	3.3	3.2	0.4	1.8	16	19
Labourers in mining, construction, manufacturing and transport	(93)	4.6	4.6	3.2	4.5	17	23

Source: Author's tabulations using data from the DIOC and LABORSTA.

Of the skill-intensive sub-major categories, *Life science and health occupations* exhibited the largest emigration rates: On average, 11.1% and, respectively, 6.2% of the native population of developing countries working in sub-majors 22 and 32 worked in the OECD around 2000. Similarly high brain drain rates are observed for *Physical, mathematical and engineering science professionals*: On average, 10.5% of the native population of developing countries working in sub-major 21 worked in the OECD around 2000. By contrast, the mean south-north migration rate for *Teaching professionals* and for *Teaching associate professionals* was only 3.8% and 4.1%, respectively. Somewhat larger mean emigration rates (5.9% and 5.5%) are obtained for *Other professionals* and *Other associate professionals* (sub-majors 24 and 34), comprising, amongst others, economists and lawyers. The use of the sign test statistic to test for distributional differences within ISCO-88 major 2 (*Professionals*) confirms that the emigration rates of *Physical, mathematical and engineering science professionals* and of *Life science and health professionals* were higher than the ones of *Teaching professionals* and *Other professionals*.[33] In addition, emigration rates of *Other professionals* were significantly larger than the ones of *Teaching professionals* (at the 1-% level). In major category 3 (*Technicians and associate professionals*), emigration rates of *Other associate professionals* significantly exceeded the emigration rates of *Physical and engineering science associate professionals* (at the 1-% level).

Given that we had to recode the occupational categories reported for some countries,[34] we test the robustness of some of the above findings by aggregating the eight ISCO-88 sub-major categories generally requiring tertiary education into four broad types of *(Associate) Professionals*. Table 7.8 contains the mean emigration rates calculated for these four aggregated categories. On average, 8.0% of the *Life science and health (associate) professionals* and 6.8% of the *Physical, mathematical and enigneering science (associate) professionals* born in one of the 17 considered developing countries worked in the OECD around 2000. The mean emigration rate of *Other (associate) professionals* amounted to 5.3%, whereas only 2.8% of the *Teaching (associate) professionals* from developing countries worked in the OECD. The application of sign tests to these four categories strenghtens our findings from above: The emigration rates of *Teaching (associate) professionals* were

[33] The hypothesis that the median of the differences in the distributions is zero can be rejected at the 1-% level.

[34] In particular, we had to recode the minor categories of ISCO-1968 to the sub-major categories of ISCO-88 for some countries. For a detailed description of the data preparation and the encountered problems, see Sections 7.6.5 and 7.6.6 in the appendix.

significantly smaller than the ones of all other types of *(Associate) Professionals* (at the 1-% level).

Table 7.8: Mean Values of South-North Migration Rates (%) for 17 Developing Countries in 2000, by Aggregated ISCO-88 Sub-major Category of Professionals

Aggregated Category of Professionals and Associate Professionals	ISCO-88 Sub-Major	Emigration Rate
Physical, mathematical and engineering science (associate) professionals	21, 31	6.8
Life science and health (associate) professionals	22, 32	8.0
Teaching (associate) professionals	23, 33	2.8
Other (associate) professionals	24, 34	5.3

Source: Author's tabulations using data from the DIOC and LABORSTA.

The observation that emigration rates are higher for health professionals and for engineers than for teaching professionals is in line with the many studies focusing on these professionals. Due to different educational systems across countries and the importance of a good proficiency of the host country's language in contact with pupils and administrations, skills of teachers are less easily applicable in foreign countries than skills related to natural sciences. Therefore, it is not surprising that a medical doctor or an engineer from a developing country was more likely to find a job as a doctor or engineer in the OECD than a teacher from a developing country found a position corresponding to his education. At the same time, south-north migrants have probably studied more often natural sciences in the OECD than they have become teachers.

Table 7.7 furthermore reveals high emigration rates (9.7% and 7.4% on average) for the sub-majors *Corporate managers* and *General managers* (12 and 13), which can be considered to require relatively high education levels, too. Other occupational categories exhibiting high mean migration rates (>5%) are *Office clerks* and *Customer service clerks*, *Personal and protective services workers*, as well as *Machine operators and assemblers* (sub-majors 41, 42, 51 and 82). In the case of *Service workers* and *Machine operators and assemblers*, the high rates might be due to a high degree of international transferability of (formal) skills acquired in the sending countries or a strong preference for these occupations of those south-north migrants who acquired their higher education in the OECD. The high rates for *Clerks* and *Managers*, however, are most likely related to a preference for these occupations coupled with the intention of permanent stay in the case that higher education was acquired in the OECD, because the skills associated with these occupations are likely to be relatively country-specific.

The lowest emigration rates (<2%) can be attributed to occupational categories related to agriculture (sub-majors 61, 62, and 92).

When we compare the more disaggregated resident employment shares of developing countries to the ones of OECD countries using Kolmogorov-Smirnov tests, we can confirm our finding that employment shares of *Professionals* (major 2) and of *Clerks* (major 4) were significantly higher in OECD countries than in developing countries (see Section 7.4.2) for all sub-categories except *Teaching professionals.* Concerning the sub-major categories of *Technicians and associate professionals* (major 3), we obtain significantly higher employment shares for OECD countries compared to developing countries for *Physical and engineering science associate professionals* and for *Other associate professionals.* Furthermore, the employment shares of *Corporate managers* and of *Personal and protective services workers* (sub-majors 12 and 51) were significantly smaller in developing countries than in OECD countries. The opposite is true for *Models, salespersons and demonstrators*, *Other craft and related trades workers*, *Drivers and mobile-plant operators*, as well as for *Agricultural, fishery and related labourers* (sub-majors 52, 74, 83, and 92).[35]

Testing for distributional differences between resident and native employment shares, we find that the probability of being employed in sub-majors 21, 22, 24, or 34 was significantly higher for natives than for residents of developing countries (at the 1-% level). The same observation is made for sub-majors 41 and 42.[36]

Summing up, the distinction between eight different types of brain drain and human capital as well as the aggregation of these types into four broad categories has revealed that *Physical and engineering science (associate) professionals*, *Life science and health (associate) professionals*, as well as *Other (associate) professionals* exhibited significantly larger emigration rates compared to *Teaching (associate) professionals.* This is in line with the considerations about the different degrees of international transferability of professionals' skills presented in Section 7.3. Furthermore, the comparison of resident employment shares confirms the relatively small endowment with human capital in developing migrant-sending countries compared to OECD countries for all types of *Professionals* except *Teaching professionals*, for some *Technicians and associate professionals*, as well as for *Clerks.* When we relate the mean emigration rate of *Life science and health professionals* to the

[35] Equality of distributions can be rejected at the 1-% level for sub-major categories 21, 22, 24, 41, 42, 74, 83, 92, at the 5-% level for sub-majors 31, 34, 51, 52, and at the 10-% level for category 12.

[36] The corresponding significance levels at which the null hypothesis of the sign tests can be rejected are the 1-% level (21, 22, 41), the 5-% level (24, 42), and the 10-% level (34).

respective value for the mean native employment share, we obtain the following numerical example of the medical brain drain: Whereas *Life science and health professionals* on average made up only 1.1% of total native employment of the developing countries in our sample, on average 11.1% of these worked in the OECD around 2000.

7.5 Conclusion

This chapter has introduced two new datasets of south-north migration rates at the level of the major and sub-major occupational categories of ISCO-88 for cross-sections of, respectively, 91 and 17 developing countries around the year 2000. Most interestingly, these disaggregated data have allowed us to study south-north migration for two broad and eight more specific types of brain drain.

The combination of the evidence on occupation-specific south-north migration with data on south-north migration by educational attainment as well as with the distributional differences observed between foreign-born and native employees in the OECD has produced the following major insights:

The percentage of total south-north migrants with tertiary education exceeded the percentage of south-north migrants working in occupational categories generally requiring tertiary education. Furthermore, the shares of tertiary-educated south-north migrants working in occupational categories requiring less than tertiary education were significantly larger than the respective shares among tertiary-educated natives in the OECD. These findings are most likely related to the fact that the skills and diplomas acquired by the most highly educated in developing countries are only imperfectly transferable internationally, resulting in "overeducation" and "brain waste" from the perspective of the migrant-sending countries.

The mean value of aggregate south-north migration rates for occupations presupposing tertiary education was significantly larger compared to the mean rates for occupations requiring primary or secondary education. The incidence of south-north migration was highest for the occupational category *Professionals* – one of the two broad types of human capital that generally require tertiary education – as well as for *Clerks* (presupposing secondary education) and for *Legislators, senior officials and managers*. Whereas developing countries situated in Latin America and the Caribbean and in East Asia and the Pacific exhibited the largest emigration rates for all occupational categories, sub-Saharan Africa experienced relatively strong brain drain around 2000.

At the more disaggregated level, the comparison of the distributions of south-north migrants and OECD natives in the most skill-intensive occupational category *Professionals* has revealed that south-north migrants working as *Professionals* were with a higher probability employed in the *Physical, mathematical and engineering sciences* and in *Life science and health professions*, and worked with a lower probability as *Teaching professionals* compared to OECD natives. In line with these observations, *Physical and engineering science (associate) professionals*, *Life science and health (associate) professionals*, as well as *Other (associate) professionals* have been found to exhibit significantly larger emigration rates than *Teaching (associate) professionals*.

Worryingly from a development perspective, this migration took place in the context of relatively small shares accruing to most types of *Professionals*, some *Technicians and associate professionals*, to *Clerks*, and to *Corporate managers* in the total employment of the developing sending countries around 2000. This has been revealed by the comparison of resident employment shares of developing and of OECD countries.

The critical discussion on the occupation-specific emigration rates has revealed the following: On the one hand, these rates constitute rather broad measures of the brain drain due to the ignorance of both the country where south-north migrants acquired (higher) education and the occupation performed in the origin country prior to emigration. Clearly, the ignorance of the country where migrants pursued their studies impedes the assessment of whether south-north migrants working as *Professionals* preferentially chose the relevant fields before or after migration. We have argued, however, that the ignorance of this information does not necessarily impede the assertion about the different degrees of transferability of professional skills. On the other hand, the presented emigration rates allow for both an inter-country and an inter-occupation comparison of the extent to which the most able left developing countries to work in the OECD until 2000. Therefore, they can be used to study the effects of occupation-specific brain drain on different types of human capital in the sending countries. Alternatively, they can be used to study the effects of professional diaspora networks on economic development in the migrant-sending countries.

Given that the definition of high-skilled underlying the occupation-specific migration rates is based on the educational qualifications that are generally required in the occupational categories, we have been able to use employment data in order to measure the relevant populations in the migrant-sending countries. This is an advantage relative to the emigration rates conventionally used in the literature. The definition of the latter rests upon educational attainment, such that the required information on the origin populations has to be constructed from several data sources. We have also argued that the brain drain rates constructed from employment data are – by construction – lower than the rates constructed from educational data. The reason is that the former account for the fact that formal skills are only imperfectly transferable internationally.

7.6 Appendix to Chapter 7

7.6.1 Data Sources

Country groups by region
The World Bank, Data & Statistics
http://go.worldbank.org/D7SN0B8YU0, accessed on 11/17/2008.

Database on Immigrants in OECD Countries (DIOC)
OECD, 2008
http://www.oecd.org/document/51/0,3343,en_2649_33931_40644339_1_1_1_1,00.html, accessed on 11/05/2008.

Employment for detailed occupational groups by sex (SEGREGAT)
Total employment, by occupation (Main statistics, annual, 2C)
ILO, LABORSTA Internet
http://laborsta.ilo.org/, accessed on 10/15/2009.

Expatriation rates by country of birth for nurses and doctors, circa 2000
OECD, 2008
http://www.oecd.org/statisticsdata/0,3381,en_2649_33931_1_119656_1_1_1,00.html, accessed on 11/05/2008.

International Migration by Educational Attainment (1990-2000) - Release 1.1
F. Docquier and A. Marfouk, 2006
http://perso.uclouvain.be/frederic.docquier/oxlight.htm, accessed on 11/15/2008.

Translation from US OCC 2000 to ISCO-88
J. Elliott and V. Gerova, 2006
Centre for Longitudinal Studies, Institute of Education, Research Archive
http://www.cls.ioe.ac.uk/text.asp?section=00010001000500160002,
accessed on 11/20/2008.

World Bank GNI per capita Operational Guidelines & Analytical Classifications
(low, lower middle, upper middle, and high income countries in 2000)
The World Bank, Data & Statistics
http://go.worldbank.org/U9BK7IA1J0, accessed on 01/22/2009.

World Development Indicators (WDI)
The World Bank, 2008.

7.6.2 Definition of *Developing Countries*

In 2000, the World Bank considered all countries with a GNI per capita ≤755 US$ (Atlas methodology) as "low-income" countries, and all countries with a GNI per capita between 756 and 9,265 US$ as "middle-income" countries, differentiating between "lower middle income" (756 up to 2,995 US$) and "upper middle income" (2,996 up to 9,265 US$) countries. Following this grouping, we consider all countries classified as low- or middle-income countries in 2000 as *developing countries* in this chapter.

7.6.3 Developing Countries by World Region

Developing countries have been grouped into six world regions according to the (developing) country groups defined by the World Bank on its website. Countries that fell into the group of developing countries in 2000 as defined by the above definition but that are not listed in the World Bank's current list of developing countries by region have been assigned separately. The resulting grouping for the 91 countries included in the dataset at the ISCO-88 major level is the following:

East Asia and the Pacific (16 countries):

Cambodia, China, Fiji, Indonesia, Kiribati, Laos, Malaysia, Marshall Islands, Mongolia, Palau, Papua New Guinea, Philippines, Samoa, Thailand, Tonga, Viet Nam.

Eastern Europe and Central Asia (21 countries):

Armenia, Azerbaijan, Bulgaria, Croatia, Czech Republic, Estonia, Georgia, Hungary, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Former Yugoslav Republic of Macedonia, Republic of Moldova, Poland, Romania, Russian Federation, Serbia and Montenegro, Slovakia, Turkey, Ukraine.

Latin America and the Caribbean (27 countries):

Antigua and Barbuda, Argentina, Belize, Bolivia, Brazil, Chile, Colombia, Costa Rica, Cuba, Dominica, Dominican Republic, Ecuador, El Salvador, Grenada, Guyana, Honduras, Jamaica, Mexico, Nicaragua, Panama, Peru, Puerto Rico, Saint Lucia, Suriname, Trinidad and Tobago, Uruguay, Venezuela.

Middle East and North Africa (11 countries):

Algeria, Bahrain, Arab Republic of Egypt, Islamic Republic of Iran, Lebanon, Morocco, Oman, Occupied Palestinian Territory, Saudi Arabia, Syrian Arab Republic, Yemen.

Sub-Saharan Africa (11 countries):

Botswana, Eritrea, Ethiopia, Lesotho, Madagascar, Mauritius, Namibia, South Africa, Uganda, United Republic of Tanzania, Zambia.

South Asia (5 countries):

Bangladesh, Maldives, Nepal, Pakistan, Sri Lanka.

7.6.4 The International Standard Classification of Occupations 1988

The International Standard Classification of Occupations 1988 (ISCO-88) is a revised version of the International Standard Classification of Occupations 1968, the successor of ISCO 1958, and was endorsed by the fourteenth International Conference of Labour Statistics (ICLS) (Hoffmann, 2003, 138).

ISCO-88 is based on the two concepts *job* and *skill* (see ILO, 1990, 2-4 for this and the following information). A *job*, consisting of a set of tasks and duties executed, is the statistical unit of the classification. A set of similar jobs constitutes an *occupation*. The concept of *skill*, considered as the ability to carry out the tasks and duties of a job and comprising the dimensions *skill level* and *skill specialization*, is used to further delineate and aggregate occupational groups.

Occupational categories are grouped into four broad *skill levels* with reference to the educational categories and levels of the International Standard Classification of Education (ISCED-76) by UNESCO; see Section 7.3. The four skill levels reflect information about the complexity and the range of tasks and duties (with priority on complexity over range).

The second dimension of skill, *skill specialization*, defined by the field of knowledge required, the materials and machinery worked with, and the type of goods and services produced, is used for the successive disaggregation of the occupational groups. By this means, the ISCO-88 distinguishes 10 broad occupational groups (majors), which can be further broken down into 28 sub-major, 116 minor, and 390 unit groups. Even the finest categories often consist of more than one occupation. Two rules apply to the classification of jobs with a broad range of tasks and duties (ILO, 1990, 8-9): If the tasks and duties concern different stages of the production and distribution process, the tasks and duties related to the production process should be given priority over associated ones. Furthermore, if the involved tasks and duties require skills that are acquired by different levels of training and experience, priority should be on those tasks and duties requiring the highest level of skills. Since the number and delineation between occupations will depend on the size of an economy, its level of economic development etc., no detailed descriptions of the occupations at the level of the unit groups are provided for ISCO-88 (ILO, 1990, 4).

As to the appropriateness of cross-country comparisons of occupation-specific data, Elias (1997, 15-17) notes that the reliability of such comparisons can be improved by aggregating data, whereby the sub-major level represents a useful level of aggregation. This notwithstanding, Elias stresses that misinterpretation of the international standard within the national context is a major problem in this context.

Table 7.9 provides a list of the major and sub-major categories of ISCO-88.

Table 7.9: International Standard Classification of Occupations (ISCO-88): Major and Sub-major Groups

ISCO-88 Major and Sub-Major	**ISCO-88** Occupation Description
0	**Armed forces**
01	Armed forces
1	**Legislators, senior officials and managers**
11	Legislators and senior officials
12	Corporate managers
13	General managers
2	**Professionals**
21	Physical, mathematical and engineering science professionals
22	Life science and health professionals
23	Teaching professionals
24	Other professionals
3	**Technicians and associate professionals**
31	Physical and engineering science associate professionals
32	Life science and health associate professionals
33	Teaching associate professionals
34	Other associate professionals
4	**Clerks**
41	Office clerks
42	Customer services clerks
5	**Service workers and shop and market sales workers**
51	Personal and protective services workers
52	Models, salespersons and demonstrators
6	**Skilled agricultural and fishery workers**
61	Market-oriented skilled agricultural and fishery workers
62	Subsistence agricultural and fishery workers
7	**Craft and related trades workers**
71	Extraction and building trades workers
72	Metal, machinery and related trades workers
73	Precision, handicraft, printing and related trades workers
74	Other craft and related trades workers
8	**Plant and machine operators and assemblers**
81	Stationary-plant and related operators
82	Machine operators and assemblers
83	Drivers and mobile-plant operators
9	**Elementary occupations**
91	Sales and services elementary occupations
92	Agricultural, fishery and related labourers
93	Labourers in mining, construction, manufacturing and transport

Source: ILO (1990).

7.6.5 Employment Data for OECD Countries from the DIOC

The Database on Immigrants in OECD Countries (DIOC) has been made available online in May 2008 and constitutes an extension of the OECD Database on Foreign-born and Expatriates, published in 2005. The latter was the first comprehensive database containing information on the educational attainment of the populations of all OECD countries by place of birth, and thus allowed for an assessment of south-north and north-north migration by educational level. The DIOC provides supplementary information on several demographic and labor market characteristics of the native and foreign-born population in OECD countries around the year 2000: In addition to the place of birth and educational attainment, the DIOC includes information on the age and gender, duration of stay, fields of study, as well as on labor market outcomes (such as labor market status, sector of activity, or occupational category) in separate datafiles. Data was mainly collected from population censuses and population registers of the OECD member countries (see OECD, 2008, 3).

We consider foreign-born employees who are working in the OECD around 2000 as immigrants, or, respectively, as emigrants when taking the perspective of the source countries. This definition thus abstracts from nationality and seems preferable to a nationality-based definition of immigrants because the concept of nationality varies between countries, see OECD, 2008, 56.

In Sections 7.2-7.4, we make use of the broad educational categories reported in dataset D of the DIOC in order to distinguish primary-educated workers (ISCED-97 levels 0, *Pre-primary education*, 1, *Primary education or first stage of basic education*, and 2, *Lower secondary or second stage of basic education*), secondary-educated workers (ISCED-97 levels 3, *Secondary education*, and 4, *Post-secondary non-tertiary education*), and tertiary-educated employees (ISCED-97 levels 5, *First stage of tertiary education*, and 6, *Second stage of tertiary education*).

The DIOC records occupations of native and foreign-born employees according to the International Standard Classification of Occupations 1988 (ISCO-88). In dataset D, which contains data on 463,758,788 employees at the sub-major (2-digit) level, occupations have been reported from 28 OECD countries, excluding Iceland and Korea, covering 39,911,124 immigrants (8.6% of total employees). At the minor (3-digit) level, comparable information on occupations is available from 22 OECD countries and for 33,583,212 foreign-born workers (dataset E). In addition to containing information from less OECD countries, the latter dataset does not provide educational attainments. Yet, this information is simultaneously available for occupations reported at the 2-digit level in dataset D. Therefore, the information from dataset D has been preferred for the calculation of the occupation-specific emigration rates and for the summary statistics presented in Sections 7.2 and 7.3.

For 8.1% of the foreign-borns in the OECD only the region but not the country of origin is reported, and for 1.1% of the foreign-borns information on occupational categories is missing in dataset D. These observations have not been further considered for the calculation of the emigration rates. Furthermore, for 9.4% of the foreign-borns, employment is only reported at the ISCO-88 major level in datafile D. This concerns, e.g., the employment data reported for Germany and Italy. When calculating the occupation-specific emigration rates at the ISCO-88 sub-major level on the basis of the information from dataset D, we have recoded the reported major occupational categories as missing. Therefore, these migrants are still included in the total number of considered migrants. Comparable information at the ISCO-88 sub-major level is available for 150 developing countries around 2000.

For most OECD countries that did not report professions according to ISCO-88 but made use of national classification systems instead, dataset D of the DIOC already contains the information matched with ISCO-88 if the national classifications are close to it. However, for the United States and Japan, occupations are reported according to national classifications, and for Turkey according to ISCO-68, a former version of ISCO-88.

As to the U.S. employment data, we have matched the occupational categories from the U.S. census reported in datafile E to the ISCO-88 unit groups based on a table of translation between US OCC 2000 and ISCO-88 by Elliott and Gerova (2006). We then have aggregated the recoded U.S. employment data over the corresponding ISCO-88 sub-major categories and used the resulting data instead of the U.S. employment data reported in dataset D. In doing so, we miss information on 1% of the U.S. employees reported in dataset D. However, the resulting data are of better quality than could be obtained by establishing a recoding scheme of the broad U.S. OCC 2000 major groups reported in datafile D to the ISCO-88 sub-major groups. Somewhat more inconvenient, however, is the fact that due to this data substitution, we cannot include information on U.S. employment in Section 7.3.2, because information on educational attainment is not simultaneously available with the employment data in datafile E.

Since the reported categories from the Japan Standard Classification of Occupations (JSOC) are very broad, they cannot be appropriately matched to the ISCO-88 sub-major groups. Most impedimental is the fact that the Japanese occupational category *Professionals and technical workers* does not allow for a distinction between occupations that are included in ISCO-88 majors 2 (*Professionals*) and 3 (*Technicians and associate professionals*). Thus, this prevents an appropriate matching even at the 1-digit level, see OECD (2008, Annex A). Since the focus of this chapter is on ISCO-88 majors 2 and 3, we have decided to exclude foreign-born employees working in Japan. These account for only 1.7% of the foreign-born employees included in the dataset. Our resulting dataset contains information on native and foreign-born workers in 26 OECD countries.[37]

We have matched the 83 occupational categories reported at the ISCO-68 minor (2-digit) level to the 28 ISCO-88 sub-major (2-digit) categories by drawing on the table of correspondence between the ISCO-68 occupational (5-digit) categories and the ISCO-88 unit (4-digit) groups provided in ILO (1990). Based on this table of translation for the more disaggregated occupations, we have assigned the mode in terms of ISCO-88 sub-major category to each ISCO-68 minor category. More specifically, to each ISCO-68 minor category we have assigned the ISCO-88 sub-major category that appears most frequently among the ISCO-88 4-digit categories corresponding to the 5-digit categories of the ISCO-68 minor category under consideration. Table 7.10 provides the resulting recoding. For 13 ISCO-68 minor categories, we have obtained an unambiguous match and thus did not have to rely on the mode.[38] In nearly all cases in which we had to deal with multiple matches, the mode was with a relative frequency of at least 50% very prominent. This weakens the concerns about the ambiguity of our assigned mappings to some extent. Importantly, when our recoded data is aggregated by ISCO-88 major category, these concerns can be relaxed even further because multiple matches in terms of the major categories are seldom. In addition, multiple matches mostly concern ISCO-88 major categories related to the same broad ISCED-76 educational category, such as, e.g., majors 2/3 or 7/8. This is not astonishing given that the skill-intensive majors 2 and 3 exhibit similar structures concerning their occupational sub-categories. In Sections 7.3.3 and 7.4.3, we have therefore exploited this similarity for robustness checks (by combining sub-majors 21+31, 22+32,

[37] Note that no information about the country of origin is available for foreign-born employees in Norway.

[38] Considering the mode as an adequate selection criterion, we implicitly assume that there is no imbalance of the total number of sub-categories assigned to the aggregate occupational groups by ISCO-88.

23+33, and 24+34). The relative frequencies of the mode are much less distinguished in the case of recoding ISCO-68 minor categories 16, 33, 40, and 94. Yet, when we inspect the ISCO-88 sub-majors with the second highest relative frequencies, we conclude that our concerns about observed ambiguities will again be weakened in the cases in which we consider data aggregated by ISCO-88 major category.

Table 7.10: ISCO-68 Minor and ISCO-88 Sub-major Groups

ISCO-68 Occupation Description	**ISCO-68 Minor**	**ISCO-88 Sub-Major**
Professional, Technical and Related Workers	01	21
Architects, Engineers and Related Technicians	02-03	21
Aircraft and Ships' Officers	04	31
Life Scientists and Related Technicians	05	22
Medical, Dental, Veterinary and Related Workers	06-07	22
Statisticians, Mathematicians, Systems Analysts and Related Technicians	08	21
Economists	09	24
Accountants	11	24
Jurists	12	24
Teachers	13	23
Workers in Religion	14	24
Authors, Journalists and Related Writers	15	24
Sculptors, Painters, Photographers and Related Creative Artists	16	34
Composers and Performing Artists	17	24
Athletes, Sportsmen and Related Workers	18	34
Professional, Technical and Related Workers Not Elsewhere Classified	19	24
Legislative Officials and Government Administrators	20	11
Managers	21	12
Clerical Supervisors	30	41
Government Executive Officials	31	34
Stenographers, Typists and Card- and Tape-Punching Machine Operators	32	41
Bookkeepers, Cashiers and Related Workers	33	41
Computing Machine Operators	34	41
Transport and Communications Supervisors	35	41
Transport Conductors	36	51
Mail Distribution Clerks	37	91
Telephone and Telegraph Operators	38	31
Clerical and Related Workers Not Elsewhere Classified	39	41
Managers (Wholesale and Retail Trade)	40	12
Working Proprietors (Wholesale and Retail Trade)	41	13
Sales Supervisors and Buyers	42	34
Technical Salesmen, Commercial Travellers and Manufacturers' Agents	43	34
Insurance, Real Estate, Securities and Business Services Salesmen and Auctioneers	44	34
Salesmen, Shop Assistants and Related Workers	45	52
Sales Workers Not Elsewhere Classified	49	91
Managers (Catering and Lodging Services)	50	13
Working Proprietors (Catering and Lodging Services)	51	13

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Table 7.10 *continued*

ISCO-68 Occupation Description	**ISCO-68 Minor**	**ISCO-88 Sub-Major**
Housekeeping and Related Service Supervisors	52	51
Cooks, Waiters, Bartenders and Relaters Workers	53	51
Maids and Related Housekeeping Service Workers Not Elsewhere Classified	54	51
Building Caretakers, Charworkers, Cleaners and Related Workers	55	91
Launderers, Dry-Cleaners and Pressers	56	82
Hairdressers, Barbers, Beauticians and Related Workers	57	51
Protective Service Workers	58	51
Service Workers Not Elsewhere Classified	59	51
Farm Managers and Supervisors	60	13
Farmers	61	61
Agricultural and Animal Husbandry Workers	62	61
Forestry Workers	63	61
Fishermen, Hunters and Related Workers	64	61
Production Supervisors and General Foremen	70	82
Miners, Quarrymen, Well Drillers and Related Workers	71	81
Metal Processers	72	81
Wood Preparation Workers and Paper Makers	73	81
Chemical Processers and Related Workers	74	81
Spinners, Weavers, Knitters, Dyers and Related Workers	75	82
Tanners, Fellmongers and Pelt Dressers	76	74
Food and Beverage Processers	77	82
Tobacco Preparers and Tobacco Product Makers	78	74
Tailors, Dressmakers, Sewers, Upholsterers and Related Workers	79	74
Shoemakers and Leather Goods Makers	80	74
Cabinetmakers and Related Woodworkers	81	74
Stone Cutters and Carvers	82	71
Blacksmiths, Toolmakers and Machine-Tool Operators	83	72
Machinery Fitters, Machine Assemblers and Precision Instrument Makers (except Electrical)	84	72
Electrical Fitters and Related Electrical and Electronics Workers	85	72
Broadcasting Station and Sound Equipment Operators and Cinema Projectionists	86	31
Plumbers, Welders, Sheet Metal and Structural Metal Preparers and Erectors	87	72
Jewellery and Precious Metal Workers	88	73
Glass Formers, Potters and Related Workers	89	73
Rubber and Plastics Product Makers	90	82
Paper and Paperboard Products Makers	91	82
Printers and Related Workers	92	73
Painters	93	71
Production and Related Workers Not Elsewhere Classified	94	73
Bricklayers, Carpenters and Other Construction Workers	95	71
Stationary Engine and Related Equipment Operators	96	81
Material-Handling and Rel. Equipment Operators, Dockers and Freight Handlers	97	83
Transport Equipment Operators	98	83
Labourers Not Elsewhere Classified	99	93

Source: Own mapping drawing on ILO (1990). Note that the recoding of ISCO-68 minor categories 30 and 70 is self-contained, because these occupations are not included in the considered table of correspondence from ILO (1990).

The resulting recoding does not provide any matching for ISCO-88 sub-majors 32, 33, 42, 62, and 92. This does not imply that the considered occupational categories do not exist under ISCO-68, but is due to the fact that for these specific occupational groups, ISCO-88 provides more detailed 2-digit categories than ISCO-68 (even though the total number of 2-digit categories of ISCO-68 exceeds the one of ISCO-88).

In order to assess the quality of our recoding, in Table 7.11 we report the occupational distribution of total employment in Turkey at the ISCO-88 major level for the years 2000 and 2001. As to the data reported for 2000, we have recoded the employment data from the DIOC according to the above-described rules and then aggregated the data by ISCO-88 major category. As to the data reported for 2001, we have taken data that is reported at the ISCO-88 major level from LABORSTA. When we compare the employment distributions for 2000 and 2001, we observe only small differences ($\leq$ 1.5 percentage points) for the most skill-intensive majors 2 and 3, as well as for majors 4 and 8. However, there seems to be a recoding bias from major 3 to 2, because the employment share of *Professionals* is higher and the one of *Technicians and associate professionals* is smaller for the recoded data relative to the data originally reported at ISCO-88. The differences in the employment shares are more striking for majors 5, 6, 7, and 9, which generally require secondary or primary education, respectively, as well as for major category 1. These differences are likely to constitute biases that are due to the proposed recoding rather than significant changes in employment in Turkey. Given that the focus of this chapter is on the skill-intensive occupational categories, we have decided to include the recoded employment data for Turkey into our dataset.

Table 7.11: Distribution of Total Employment in Turkey over ISCO-88 Major Categories (%)

ISCO-88 Major Occupational Category		**2000**	**2001**
Legislators, senior officials and managers	(1)	5.3	8.0
Professionals	(2)	7.2	5.7
Technicians and associate professionals	(3)	3.7	4.9
Clerks	(4)	4.9	4.4
Service workers, shop and market sales workers	(5)	6.3	9.0
Skilled agricultural and fishery workers	(6)	47.9	36.1
Craft and related trades workers	(7)	12.9	15.3
Plant and machine operators and assemblers	(8)	7.5	8.0
Elementary occupations	(9)	4.3	8.5

Source: Author's tabulations with data from the DIOC (2000) and LABORSTA (2001).

7.6.6 Employment Data for Developing Countries from LABORSTA

The employment data that has been used to calculate the south-north migration rates as well as the resident and native employment shares for the countries of emigration originate from LABORSTA, the main ILO database on labor statistics. Employment by detailed occupational category is available at the major and sub-major level of ISCO-88. Contrasting the data from the DIOC, these data do not simultaneously provide information on the educational attainments of the employees.

Employment data at the ISCO-88 major level is available from the file “Total employment, by occupation” (Main statistics, annual, 2C). We considered data from the period 1995-2005 in order to maximize observations. The exact years from which data has been considered for each of the 91 developing countries are reported in Table 7.13. As to the data at the ISCO-88 sub-major level, we have considered data from the file “Employment for detailed occupational groups by sex” (SEGREGAT). For 13 countries of the considered 17 developing countries the data refer to the year 2000. For the other countries, data refer to some year in the period 1996-2001.

We have obtained the samples of 91 and, respectively, 17 developing migrant-sending countries on the basis of the following order of priority: If available, data classified according to ISCO-88 has been preferred to data coded at ISCO-68. For countries for which data was only available at ISCO-68, the occupational categories have been recoded to match ISCO-88 according to the above described rules. As to the sub-major level, only the employment data for Colombia has been recoded. As to the major level, the employment data of 21 developing sending countries has been recoded (see Tables 7.13 and 7.14). Table 7.12 provides the mode-based translation between the major groups of ISCO-68 and -88. An unambiguous match in terms of all involved sub-categories (the relative frequency of the mode is 100%) is obtained for administrative and managerial workers (major 2 of ISCO-68 and, respectively, major 1 of ISCO-88). For all other ISCO-68 major groups, the relative frequencies of the mode exceed 50%. Problematic, however, is the fact that in these cases there are even multiple matches in terms of aggregate ISCED-76 education levels: For example, whereas in the case of ISCO-68 minor 3 (Clerical and related workers) the mode ISCO-88 major category 4 is appropriate in 64.7% of the involved ISCO-68 5-digit categories, further 25.1% of the involved 5-digit categories should be rather attributed to ISCO-88 major 3 at the aggregate level. In addition, no satisfying recoding is obtained for the most skill-intensive occupational categories. Therefore, in order to assess the robustness of our findings derived from the data at the major level, we have excluded the recoded data from our sample in the robustness check reported in Section 7.4.2.

If data was available from several sources or covered different worker populations, data from labor force surveys and data covering total employment has been preferred.

Similarly as for the immigrant data, observations with missing occupational categories have been excluded. Also, reported sub-major categories that turned out to be major categories have been recoded as missing. For some countries, employment was classified at the ISCO-88 minor level and had to be transferred to the sub-major level.

Whereas data on employment in the Republic of Korea is in principle available, it has not been further considered. The reason is that the data on employees in the OECD who were born in the Republic of Korea is not utilizable because they do not always allow to distinguish among individuals born in North Korea or South Korea.

Table 7.12: Major Groups of ISCO-68 and ISCO-88

ISCO-68 Occupation Description	**ISCO-68 Major**	**ISCO-88 Major**
Professional, technical and related workers	0/1	2
Administrative and managerial workers	2	1
Clerical and related workers	3	4
Sales workers	4	3
Service workers	5	5
Agriculture, animal husbandry and forestry workers, fishermen and hunters	6	6
Production and related workers, transport and equipment operators and labourers	7/8/9	7

Source: Own mapping drawing on ILO (1990).

7.6.7 Description of the Datasets

Tables 7.13 and 7.14 provide some aggregated information on the compiled data as well as on the underlying data sources for the constructed datasets at the major and sub-major level of ISCO-88.

Table 7.13: Description of the Data at the ISCO-88 Major Level

Country	Residents	S-N Migrants	Emigration Rate (%)	# ISCO Majors	Years Residents	Original Class. Residents	Source Residents
East Asia and the Pacific (16)							
Cambodia	5,275,176	128,120	2.4	10	2000	ISCO-88	Labour force survey
China	668306176	964,159	0.1	4	2005	ISCO-88	Official estimates
Fiji	217,178	74,682	25.6	9	1996	ISCO-88	Population census
Indonesia	90,412,000	109,271	0.1	7	2001	ISCO-1968	Labour force survey
Kiribati	9,200	310	3.3	7	2000	ISCO-1968	Population census
Laos	2,144,951	149,988	6.5	9	1995	ISCO-88	Population census
Malaysia	9,357,000	129,264	1.4	9	2001	ISCO-88	Labour force survey
Marshall Islands	9,928	14	0.1	7	1999	ISCO-1968	Population census
Mongolia	779,100	1,083	0.1	10	2000	ISCO-88	Population census
Palau	9,383	54	0.6	7	2000	ISCO-1968	Population census
Papua New Guinea	2,344,734	15,071	0.6	10	2000	ISCO-88	Population census
Philippines	29,020,750	1,241,153	4.1	9	2001	ISCO-88	Labour force survey
Samoa	50,325	33,806	40.2	10	2001	ISCO-88	Population census
Thailand	33,469,400	133,534	0.4	9	2001	ISCO-88	Labour force survey
Tonga	34,570	19,729	36.3	10	2003	ISCO-88	Labour force survey
Viet Nam	37,913,748	812,768	2.1	9	2000	ISCO-88	Labour force survey
Eastern Europe and Central Asia (21)							
Armenia	840,730	37,136	4.2	10	2001	ISCO-88	Population census
Azerbaijan	3,377,800	14,190	0.4	9	2003	ISCO-88	Labour force survey
Bulgaria	2,581,582	318,214	11.0	10	2001	ISCO-88	Population census
Croatia	1,552,000	195,497	11.2	10	2000	ISCO-88	Labour force survey
Czech Republic	4,730,000	94,967	2.0	10	2000	ISCO-88	Labour force survey
Estonia	571,000	8,407	1.5	9	2000	ISCO-88	Labour force survey
Georgia	1,813,500	39,483	2.1	10	2000	ISCO-88	Labour force survey
Hungary	3,849,100	113,819	2.9	10	2000	ISCO-88	Labour force survey
Kazakhstan	6,680,000	191,037	2.8	9	2001	ISCO-88	Labour force survey

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Table 7.13 *continued*

Country	Residents	S-N Migrants	Emigration Rate (%)	# ISCO Majors	Years Residents	Original Class. Residents	Source Residents
Kyrgyzstan	1,850,101	14,894	0.8	9	2002	ISCO-88	Labour force survey
Latvia	939,700	18,962	2.0	9	2000	ISCO-88	Labour force survey
Lithuania	1,397,900	32,176	2.2	10	2000	ISCO-88	Labour force survey
Macedonia	561,341	79,294	12.4	10	2002	ISCO-88	Labour force survey
Moldova	1,514,600	23,494	1.5	10	2000	ISCO-88	Labour force survey
Poland	14,527,000	982,918	6.3	10	2000	ISCO-88	Labour force survey
Romania	10,763,300	476,199	4.2	8	2000	ISCO-88	Labour force survey
Russian Federation	65,069,000	668,469	1.0	9	2000	ISCO-88	Labour force survey
Serbia and Montenegro	3,092,506	271,980	8.1	10	2003	ISCO-88	Labour force survey (Serbia)
							Population census (Montenegro)
Slovakia	2,101,500	152,762	6.8	9	2000	ISCO-88	Labour force survey
Turkey	21,525,000	811,939	3.6	9	2001	ISCO-88	Labour force survey
Ukraine	20,175,000	246,208	1.2	9	2000	ISCO-88	Labour force survey
Latin America and the Caribbean (27)							
Antigua and Barbuda	36,233	15,835	30.4	10	2001	ISCO-88	Population census
Argentina	8,192,028	177,061	2.1	10	2000	ISCO-88	Labour force survey
Belize	77,755	26,767	25.6	9	1999	ISCO-88	Labour force survey
Bolivia	2,096,000	44,414	2.1	10	2000	ISCO-88	Labour force survey
Brazil	64,678,400	347,133	0.5	10	2000	ISCO-88	Population census
Chile	4,693,899	116,573	2.4	10	2002	ISCO-88	Population census
Colombia	15,585,537	389,114	2.4	6	2001	ISCO-88	Labour force survey
Costa Rica	1,312,280	44,949	3.3	9	2000	ISCO-88	Labour force survey
Cuba	4,379,274	442,213	9.2	3	2000	ISCO-1968	Labour force survey
Dominica	25,096	15,054	37.5	9	2001	ISCO-88	Population census
Dominican Republic	3,000,200	338,622	10.1	9	2000	ISCO-88	Labour force survey
Ecuador	3,376,122	307,832	8.4	10	2000	ISCO-88	Labour force survey
El Salvador	2,192,657	492,922	18.4	9	2000	ISCO-88	Labour force survey
Grenada	33,068	27,582	45.5	9	1998	ISCO-88	Labour force survey

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Table 7.13 *continued*

Country	Residents	S-N Migrants	Emigration Rate (%)	# ISCO Majors	Years Residents	Original Class. Residents	Source Residents
Guyana	232,409	193,661	45.5	10	2002	ISCO-88	Population census
Honduras	2,334,391	157,152	6.3	7	2001	ISCO-1968	Labour force survey
Jamaica	934,800	491,366	34.5	6	2000	ISCO-88	Labour force survey
Mexico	38,034,400	4,514,403	10.6	10	2000	ISCO-88	Labour force survey
Nicaragua	1,916,345	127,046	6.2	10	2003	ISCO-88	Labour force survey
Panama	984,144	85,114	8.0	9	2001	ISCO-88	Labour force survey
Peru	7,128,375	251,713	3.4	10	2000	ISCO-88	Labour force survey
Puerto Rico	1,162,000	595,463	33.9	9	2000	ISCO-88	Labour force survey
Saint Lucia	62,425	14,572	18.9	9	2000	ISCO-88	Labour force survey
Suriname	156,705	593	0.4	10	2004	ISCO-88	Population census
Trinidad and Tobago	502,800	177,380	26.1	8	2000	ISCO-88	Labour force survey
Uruguay	1,067,600	43,774	3.9	10	2000	ISCO-88	Labour force survey
Venezuela	8,924,710	130,970	1.4	7	2000	ISCO-1968	Labour force survey
Middle East and North Africa (11)							
Algeria	6,229,412	536,052	7.9	10	2001	ISCO-88	Labour force survey
Bahrain	286,780	3,095	1.1	8	2001	ISCO-88	Population census
Arab Republic of Egypt	17,203,300	160,847	0.9	9	2000	ISCO-88	Labour force survey
Islamic Republic of Iran	14,571,572	299,872	2.0	9	1996	ISCO-88	Population census
Lebanon	1,107,958	163,751	12.9	10	2004	ISCO-88	Household survey
Morocco	9,818,987	644,794	6.2	9	2004	ISCO-88	Labour force survey
Oman	280,462	410	0.1	9	2000	ISCO-88	Labour force survey
Palestinian Territory (occupied)	596,756	5,922	1.0	9	2000	ISCO-88	Labour force survey
Saudi Arabia	5,710,931	12,083	0.2	7	2000	ISCO-1968	Labour force survey
Syrian Arab Republic	4,723,000	59,045	1.2	3	2001	ISCO-1968	Labour force survey
Yemen	3,620,154	15,141	0.4	10	1999	ISCO-88	Labour force survey
Sub-Saharan Africa (11)							
Botswana	466,695	921	0.2	9	2000	ISCO-88	Labour force survey
Eritrea	57,205	25,904	31.2	9	1996	ISCO-88	Labour-rel. establ. survey

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Table 7.13 *continued*

Country	Residents	S-N Migrants	Emigration Rate (%)	# ISCO Majors	Years Residents	Original Class. Residents	Source Residents
Ethiopia	24,851,416	73,308	0.3	9	1999	ISCO-88	Labour force survey
Lesotho	617,235	331	0.1	9	1999	ISCO-88	Labour force survey
Madagascar	9,570,397	40,942	0.4	10	2005	ISCO-88	Household survey
Mauritius	465,570	52,526	10.1	9	2000	ISCO-88	Population census
Namibia	428,981	1,384	0.3	10	2000	ISCO-88	Labour force survey
South Africa	12,179,000	230,300	1.9	9	2000	ISCO-88	Labour force survey
Tanzania, United Republic of	16,914,806	45,056	0.3	9	2001	ISCO-88	Labour force survey
Uganda	9,259,800	54,478	0.6	9	2003	ISCO-88	Labour force survey
Zambia	2,692,376	20,427	0.8	7	2000	ISCO-1968	Population census
South Asia (5)							
Bangladesh	44,323,000	131,631	0.3	6	2003	ISCO-88	Labour force survey
Maldives	71,700	35	0.0	10	2000	ISCO-88	Population census
Nepal	9,891,838	15,606	0.2	9	2001	ISCO-88	Population census
Pakistan	37,481,000	312,970	0.8	9	2001	ISCO-88	Labour force survey
Sri Lanka	6,452,013	176,223	2.7	9	2002	ISCO-88	Labour force survey

Source: Author's tabulations using data from the DIOC and LABORSTA.

Coverage of workers is total employment for all countries except Eritrea (all persons engaged). Employment data reported without the information on occupational categories have been disregarded. Ambiguous occupational codings have have been recoded as missing.

The total population of the 91 considered developing countries (excluding Palau) amounted to 3.4 billion people in 2000. This corresponds to circa 67% of the total population living in the 150 low- or middle-income countries for which data are available from the WDI in 2000. The average GDP per capita in PPP (available for 88 of the 91 developing countries) was 6118 constant 2005 international \$ in 2000 (data is missing for Cuba, Palau, and Puerto Rico). This exceeds the average GDP per capita in PPP in the 142 developing countries for which data is available from the WDI, which amounts to 5043 constant 2005 international \$ in 2000.

Table 7.14: Description of the Data at the ISCO-88 Sub-major Level

Country	Residents	S-N Migrants	Emigration Rate (%)	# ISCO Sub-Majors	Year Residents	Original Class. Residents	Source Residents
East Asia and the Pacific (2)							
Mongolia	752,299	1,083	0.1	25	2000	ISCO-88	Population census
Thailand	33,027,200	133,534	0.4	28	2000	ISCO-88	Labour force survey
Eastern Europe and Central Asia (9)							
Bulgaria	2,863,809	318,214	10.0	26	2000	ISCO-88	Labour force survey
Czech Republic	4,670,181	94,967	2.0	27	2000	ISCO-88	Labour force survey
Estonia	604,406	8,407	1.4	26	2000	ISCO-88	Labour force survey
Hungary	3,805,976	113,819	2.9	26	2000	ISCO-88	Labour force survey
Latvia	968,095	18,962	1.9	26	2000	ISCO-88	Labour force survey
Lithuania	1,524,657	32,176	2.1	26	2000	ISCO-88	Labour force survey
Poland	14,455,840	982,918	6.4	26	2000	ISCO-88	Labour force survey
Slovakia	2,082,780	152,762	6.8	26	2000	ISCO-88	Labour force survey
Ukraine	20,191,500	246,208	1.2	26	2000	ISCO-88	Labour force survey
Latin America and the Caribbean (2)							
Colombia	17,231,066	389,114	2.2	22	2001	ISCO-1968	Labour force survey
Ecuador	5,526,205	307,832	5.3	28	2000	ISCO-88	Labour force survey
South Asia (1)							
Pakistan	22,443,546	312,970	1.4	27	1998	ISCO-88	Population census
Middle East and North Africa (1)							
Islamic Republic of Iran	13,328,872	299,872	2.2	27	1996	ISCO-88	Population census
Sub-Saharan Africa (2)							
Mauritius	465,400	52,526	10.1	25	2000	ISCO-88	Population census
Seychelles	30,969	3,545	10.3	28	1997	ISCO-88	Population census

Source: Author's tabulations using data from the DIOC and LABORSTA.
Coverage of workers is total employment for all countries except Ecuador (economically active population). Employment data reported without the information on occupational categories have been disregarded. Employment data reported only with information on ISCO-88 major occupational categories have not been disregarded; the occupational codes have been recoded as missing.
The total population of the considered 17 developing countries amounted to 449 million people in 2000. This corresponds to 8.8% of the total population living in developing countries in 2000. The average GDP per capita in PPP of the considered 17 developing countries was 8641 constant 2005 international $.

CHAPTER 8

The Effect of Occupation-specific Brain Drain on Human Capital

8.1 Introduction

Emigration of high-skilled individuals from developing countries to developed countries – or "brain drain" (Docquier and Rapoport, 2008) – initially reduces the human capital of the migrant-sending economies. Especially firms and policy-makers are concerned about such loss of scientists, physicians, teachers, and other high-skilled individuals due to these professionals' relevance for, e.g., research, production, and the provision of services, see Batista et al. (2012, 32). Economists put the brain drain in a wider perspective when stressing the positive externalities of human capital including its importance for economic growth.[1] However, the economic migration literature has also identified several positive feedback effects of brain drain on the source countries. These include remittances, network effects, and return migration of individuals with enhanced skills. Stark et al. (1997, 1998) and Mountford (1997) were the first to argue that there might even be a "brain gain" in the sense of an increase in the human capital of the sending economies that is induced by the emigration of high-skilled workers. The reason is that the prospect of migration to countries with higher wages increases expected returns to education, which might incentivize people in developing countries to invest more in education. If the brain gain exceeds the brain drain, this is called a "beneficial brain drain" (see Beine et al., 2001, 2008).

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[1] See the endogenous growth literature with the seminal articles by Romer (1986) and Lucas (1988).

To our knowledge, the brain drain literature has not yet studied differences in the effect of brain drain on human capital formation across various types of human capital. This can be partly attributed to a lack of comparable disaggregated data. Intuitively, the effect of brain drain on human capital accumulation in the sending economies is likely to differ across different human capital types. While the classical brain gain hypothesis refers to human capital considered as perfectly transferable internationally, empirically, human capital types differ with respect to their degree of international transferability. For instance, a scientist or engineer is more likely to obtain a job matching his qualification in a foreign country compared to a lawyer. In addition, the immigration legislations of many OECD countries are designed in a way that is meant to attract specific types of immigrant professionals (such as physicians, engineers, and other scientists). Based on these considerations, the additional question emerges by how much the effect of brain drain on the formation of human capital differs across different types of human capital.

Contributions of this Chapter

This chapter provides an empirical test of the brain gain hypothesis for four different types of human capital. We analyze the impact of occupation-specific brain drain on enrollment in four aggregated types of tertiary education[2] for a sample of 38 developing migrant-sending economies. To give an example, this approach allows us to answer the question of whether a higher probability of emigration for scientists and engineers increases or reduces enrollment in *Science & Engineering* programs in the sending economies, ceteris paribus, and on whether this effect is stronger than the corresponding effect for health professionals.

In order to proxy the prospect of migration to high-income countries for graduates of different fields of tertiary education in developing countries, we construct south-north migration rates that are similar to those presented in Chapter 7. To this end, we combine occupation-specific employment data of migrants in OECD countries with data on employment and tertiary enrollment of resident populations in the respective origin countries. This approach is possible due to sufficient similarities between the sub-major occupational categories requiring tertiary education according to the International Standard Classification of Occupations 1988 (ISCO-88) on the one hand, and the fields of tertiary education distinguished by the International Standard Classification of Education 1997 (ISCED-97) on the other hand. The construction of emigration rates on the basis of employment data

[2] These are *Science & Engineering*, *Health & Agriculture*, *Education*, and *Humanities & Social Sciences*.

entails the advantage that these rates include only immigrant professionals who managed to find a job matching their qualifications at destination. This does not apply to the emigration rates that are commonly used in related studies, because the latter generally rely on data on the total population with tertiary education, irrespective of their status of employment. In order to be able to compare the employment-based emigration rates to the conventionally used measures that are based on population data by education, we present benchmark analyses in which we separately estimate the effects of the aggregated variants of both measures on aggregate human capital formation.

In our empirical model for tertiary enrollment by field of education, we control for the pool of potential students who might enroll in tertiary education, for the supply of different types of tertiary education, as well as for effects that are specific to the different types of tertiary education but uniform across countries. Even though our data are in principle cross-sectional, the implied cluster-sample structure allows us to extract observed and unobserved heterogeneity at the country level by applying fixed effects estimation. To mitigate endogeneity concerns even further, we also present fixed effects instrumental variables estimations, in which we instrument our brain drain measure with two new instrument variables. These are calculated using information on the number of migrants in the OECD who originate from all countries in the world except the considered sending country.

Related Literature

The distinction between four types of human capital in our analyses constitutes the major contribution of this chapter and adds to the empirical literature on the effects of brain drain on the sending economies. In this literature, an empirical test of the brain gain hypothesis for a cross-section of developing countries has been exclusively carried out either for the total tertiary-educated population, the number of physicians, or enrollment in sciences up until now. Studies assessing the brain gain hypothesis at the aggregate level commonly use the proportion of tertiary educated natives (residents plus migrants) from developing countries who live in OECD countries in order to account for the prospect of high-skilled emigration.[3] Relying on different empirical counterparts for the formation of human capital, these studies present mixed results: Studies that proxy investments in

[3] These south-north migration rates of the highly skilled are based on macro-level information on immigrants in OECD countries by country of origin and – partly imputed – educational attainment. See Carrington and Detragiache (1998), Adams (2003), Docquier and Marfouk (2006), Beine et al. (2007), Docquier et al. (2009), Defoort (2008), and OECD (2008) for descriptions of the different datasets.

human capital with the growth rate of the proportion of tertiary-educated natives find that the brain drain rate measured in the base period exerts a positive effect on the growth rate of the *ex ante* stock of human capital in cross-sectional analyses (Beine et al., 2003, 2008, Docquier et al., 2008), and in a panel data analysis if countries are poor (Beine, Docquier, and Oden-Defoort, 2011). By contrast, the same brain drain measure is found to have a negative impact on the formation of human capital if the latter is accounted for by tertiary school enrollment rates measured in the same period as the brain drain in cross-sectional analyses (Groizard and Llull, 2006, 2007a), and in a panel data analysis (Checchi et al., 2007).[4] This can be interpreted as a "disincentive effect" to invest in higher education (Checchi et al., 2007, 20). Although appearing contradictory, these findings could derive from a time lag with which individuals acquire tertiary education for given observed emigration. A high emigration rate in some base period would thus coincide with a decreased tertiary school enrollment rate (many emigrants from poor countries leave their home countries to study in the OECD) – reflecting the brain drain effect, but also with a potential increase in the proportion of the tertiary educated native population over time – reflecting a dynamic brain gain effect. However, the different results also have to be seen in light of the fact that the two measures of human capital formation relate to different populations. The growth rate of the proportion of tertiary-educated natives captures a possible brain gain effect for the total population originating from a given country, irrespective of where tertiary education has been acquired. By contrast, the enrollment measure focuses on relatively few age cohorts that pursue tertiary education in the developing countries of origin. Therefore, the latter yields more conservative estimates when used to asses the brain gain hypothesis. We think that if the eventual interest lies on the impact of brain drain on the *ex post* level of human capital, the results from analyses using enrollment data can better anticipate the effect of high-skilled emigration on the availability of high-skilled workers in the origin countries than analyses relying on education-specific population data. The reason for this is that the number of students enrolled in tertiary education who will emigrate after graduation is rather small, because the enrollment measure captures only very few age cohorts. By contrast, the population (share) of tertiary-educated natives includes the tertiary-educated emigrants of all age cohorts living in the OECD, of whom a large proportion is likely to stay abroad.

[4] Faini (2005) estimates a random effects model of a similar specification, but measures the emigration rate with a five-year lag relative to the enrollment rate. He does not find any significant effect of the lagged tertiary emigration rate on tertiary school enrollment.

Empirical studies testing the brain gain hypothesis with more disaggregated data are scarce. Using panel data on the number of physicians in migrant-sending countries as well as on physician immigrants in 18 (mainly OECD) receiving countries, Bhargava et al. (2011) estimate the effect of physician emigration on the number of physicians trained in the respective sending economies (residents plus migrants). In line with the above studies that estimate a similar model for the growth rate of the relative number of tertiary-educated natives, their estimation results point to the existence of a "physician brain gain".[5] Evaluating survey data of overseas doctors in the United Kingdom, Kangasniemi et al. (2007) only find weak support for the hypothesis of a physician brain gain effect. With the intention to study the impact of high-skilled emigration on the composition of human capital, Di Maria and Lazarova (2012) estimate the effect of brain drain as measured by Docquier and Marfouk (2006) on the proportion of students enrolled in tertiary education who study science and technology. Their findings suggest that the possibility of high-skilled emigration decreases the contemporaneous enrollment in science and technology specialties compared to a situation in which emigration is inhibited for countries further away from the technological frontier, whereas the opposite is the case for countries that are closer to the frontier. Further evidence on occupation-specific brain drain comprises several case studies analyzing one or a few specific occupations or sectors in one or at most a few countries of emigration or immigration.[6] The most comprehensive data seem to be available for the medical sector.[7]

Empirical studies assessing the effect of brain drain on the *ex post* level of human capital in migrant-sending countries, and thus the hypothesis of a beneficial brain drain (BBD), do not reach a consensus, either. Beine et al. (2008) and Docquier et al. (2008) conduct counterfactual experiments in which they compare observed proportions/numbers of skilled residents to hypothetical ones, which they calculate using predictions of their human capital estimations and the emigration rates of low-skilled workers. They find that a BBD is most likely if the probability of emigration is not too high and if the level of human capital was previously low. Based on parameter estimates obtained from a regression of the growth rate of the *ex ante* stock of human capital on the high-skilled

[5] In a very similar study, Chojnicki and Oden-Defoort (2010) confirm this incentive effect for Sub-Saharan African countries.

[6] See, e.g., Watanabe (1969), Meyer et al. (2000), Bhorat et al. (2002), Thomas-Hope (2002), Alburo and Abella (2002), Pellegrino (2002), and Commander et al. (2004).

[7] See Hagopian et al. (2004), Bhargava and Docquier (2008), Clemens and Pettersson (2008), and OECD (2008).

emigration rate, Beine, Docquier, and Oden-Defoort (2011) simulate the impact of high-skilled emigration on the steady state level of *ex post* human capital. From this numerical exercise they specify a concrete threshold range for the brain drain rate (20% to 30%) below which countries experience a BBD. Groizard and Llull (2006, 2007b) rely on an estimation approach to study the hypothesis of a BBD in terms of highly educated individuals. They find evidence for a negative impact of the brain drain rate on the *ex post* level of human capital, proxied by the proportion of the population aged 25+ with more than 13 years of school (excluding emigrants).[8] This result contradicts the BBD hypothesis.

In their study on physician emigration, Bhargava et al. (2011) use the parameter estimate of the effect of physician emigration on the number of physicians trained in the sending economies to make inferences about the *ex post* numbers of physicians. Their calculations suggest that the obtained "physician brain gain" effect was too small to generate a "beneficial physician brain drain", implying thus a net brain drain.[9] Clemens (2007) studies the hypothesis of a beneficial physician brain drain with a different dataset for African sending countries around the year 2000 in a cross-sectional estimation analysis. His results are less pessimistic than those by Bhargava et al. (2011), because they do not reveal a robust significant impact of per capita physician emigration on the per capita number of physicians in the sending countries. An obvious disadvantage of such estimation approaches is that they can only produce some average effect for the considered countries in the sample, while simulation studies are capable of providing more differentiated results for countries that differ with respect to specific characteristics. However, both approaches at best produce crude approximations for the net effect of the brain drain on the *ex post* level of human capital. To our knowledge, there does not yet exist any evidence from survey questions on the hypothesis of a BBD for several developing countries of emigration.

The remainder of this chapter is organized as follows: Section 8.2 presents descriptive evidence on human capital specific brain drain and enrollment in different types of tertiary education for developing migrant-sending countries. Section 8.3 revisits the hypotheses of brain gain and BBD theoretically. Section 8.4 presents our empirical strategy, the data

[8] In addition to using the *ex post* level of human capital, the empirical models in Groizard and Llull (2006, 2007b) differ from the one in Beine et al. (2003, 2008), Beine, Docquier, and Oden-Defoort (2011), and Docquier et al. (2008) in that they do not include human capital in the baseline period as a regressor.

[9] The results of a similar study are also rather pessimistic: Relying on the same methodology as Beine et al. (2008), Chojnicki and Oden-Defoort (2010) conclude from their counterfactual experiments that only some African countries might have benefited from physician emigration.

we employ, as well as the estimation results from our main model and two benchmark specifications. Section 8.5 summarizes the main results and concludes.

8.2 Descriptive Evidence

To highlight the extent of heterogeneity inherent in the brain drain phenomenon, in this section we present summary statistics for our human capital specific migration rates from developing countries to OECD countries. In addition, we provide scatter plots that illustrate the unconditional relationship between these measures for the prospect of emigration and our dependent variable for human capital formation, which measures enrollment in different fields of tertiary education.

Figure 8.1 illustrates average south-north migration rates around the year 2000 by type of human capital and region. Ignoring South Asia (which is represented here only by Bangladesh), in four world regions the prospect of migration to the OECD was highest or second highest for professionals working in occupations related to *Health & Agriculture*. This is in line with the predominant concern about medical brain drain in other empirical studies. Concerning the other types of human capital that we distinguish, the picture is less uniform for the different regions. It has to be mentioned that the presented region-specific averages are calculated over relatively few developing countries (see the numbers in parentheses).[10] The differences in the relative incidence of south-north migration across the four types of human capital have two major determinants: On the one hand, the probability of a perfect job match is higher for those high-skilled individuals with occupations requiring skills that are easily transferable across borders (such as engineers) compared to those with rather country-specific skills (such as lawyers), ceteris paribus. On the other hand, these differences are partly reinforced by the immigration legislations of many OECD countries, which try to attract specific types of immigrant professionals by easing their work and residence conditions.

[10] See Section 8.4.1 for a detailed description of how we calculated the human capital specific emigration rates. For the construction of Figure 8.1, we excluded four observations with implausible values (larger than 100%).

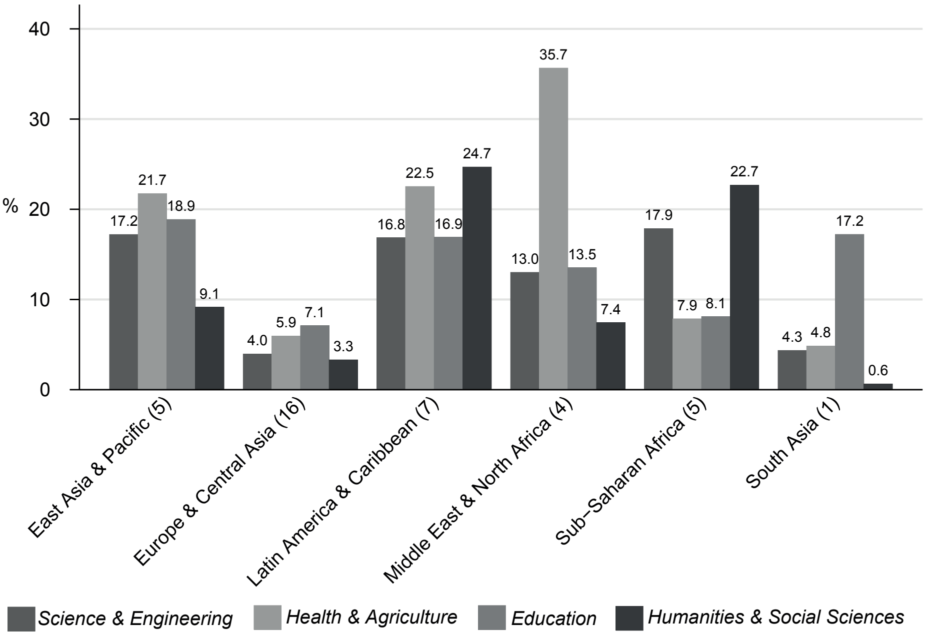

Figure 8.1: South-North Migration, by Type of Human Capital and Region of Origin
This figure shows mean values of occupation-specific emigration rates to the OECD around the year 2000, by type of human capital and region of origin. The numbers of countries considered for each region are displayed in parentheses. The emigration rates have been calculated on the basis of employment data from the OECD and the ILO, combined with enrollment data from the UNESCO. For a detailed description of the data, see Section 8.4.1.

Figure 8.2 plots the ln of enrollment in different fields of tertiary education around the year 2005 against the ln of the corresponding employment-based emigration rates around the year 2000. We take the former variable as a measure for human capital formation, which is the dependent variable in our estimation analyses presented in Section 8.4. For each type of human capital, we observe a significant negative relationship between the two variables. The slopes of the corresponding linear best fit lines are steepest for *Humanities & Social Sciences*, and for *Science & Engineering*. Figure 8.2 can be regarded as tentative evidence against the hypothesis of a brain gain for the considered types of human capital. It suggests that the negative relationship between tertiary enrollment and human capital specific emigration might have been strongest for *Humanities & Social Sciences*. Our multivariate econometric model in Section 8.4 is set up to test whether these correlations still hold if we condition on confounding factors such as the supply of education.

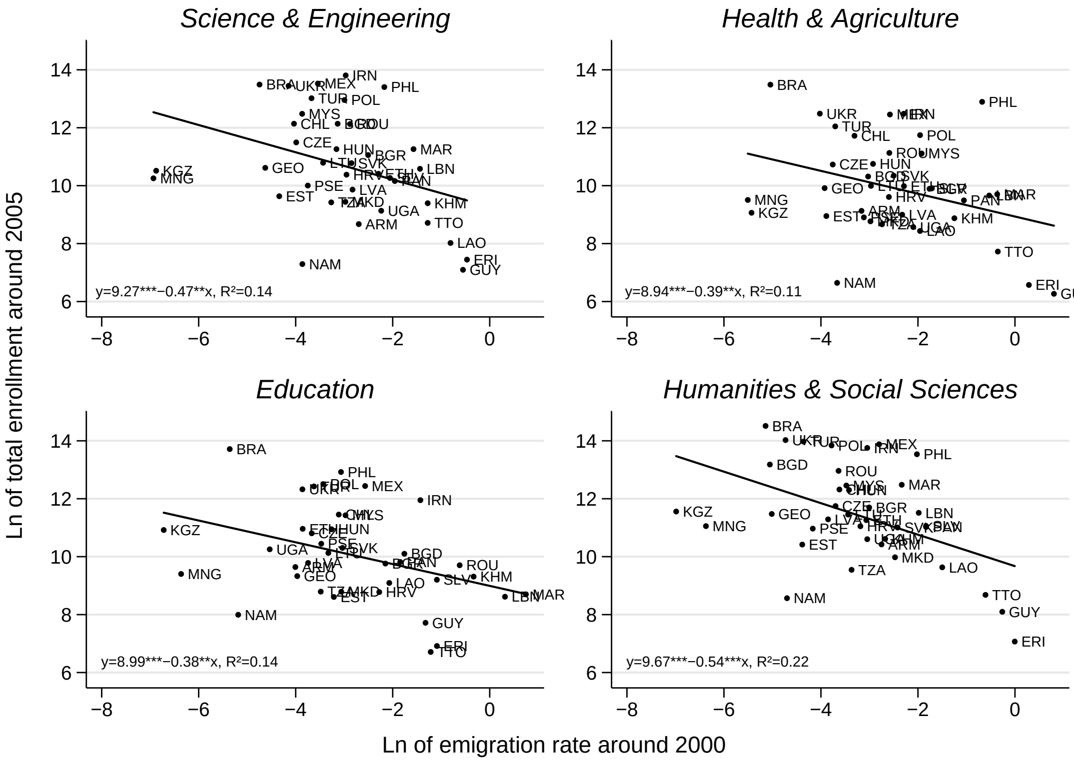

Figure 8.2: Tertiary Enrollment and South-North Migration, by Type of Human Capital

Each sub-figure plots the ln of total enrollment in the considered type of tertiary education around the year 2005 against the ln of the corresponding human capital-specific emigration rate to the OECD around 2000. Each dot characterizes the respective observation for one of 38 developing countries in our sample. The solid lines represent linear best fit lines from simple regressions of the enrollment variable on the emigration rate. The corresponding regression results are displayed in the lower left corner of each sub-figure. For a detailed description of the data, see Section 8.4.1.

8.3 The Hypotheses of Brain Gain and Beneficial Brain Drain Revisited

Since the late 1990s, the brain drain literature argues that the emigration of the most highly educated individuals from developing countries to developed countries might motivate a positive effect on the formation of human capital in the migrant-sending countries, see, e.g., Stark et al. (1997, 1998) and Mountford (1997). The models commonly study the brain drain in a context of high inter-country wage differences, probabilistic migration, and perfect transferability of skills across countries. Most of the models consider some type of positive externality to human capital. Their central argument is that the prospect of emigration, by increasing expected returns to education, might incentivize people in developing countries to invest more in education (brain gain hypothesis).[11]

[11] In models with homogeneous individuals, this effect takes the form of an increase in an individual's investment in education due to the migration perspective. In models with heterogeneous individuals, the brain gain is modeled as an increase in the share of individuals who acquire education.

In the following, we present a consolidated version of the theoretical model presented in Mountford (1997, 289-296) and derive the hypotheses of brain gain and BBD along with the conditions under which a BBD arises. We chose this model because of its simplicity, and because it considers individuals to be heterogeneous. By measuring the amount of human capital in an economy with the share of individuals becoming educated, this model captures a brain gain in terms of an increase in the share of educated individuals. Using data on enrollment in tertiary education in our subsequent econometric analysis, we are confident that we can adequately capture this notion of human capital formation.

Consider a small open economy in a world with one consumption good, free capital mobility, and limited mobility of labor. Production requires the input factors capital (K) and labor (L), which is measured in efficiency units, and is characterized by constant returns to scale:

$$Y_t = F(K_t, \lambda_t L_t) = f(k_t)\lambda_t L_t \quad \text{with} \quad k_t = \frac{K_t}{\lambda_t L_t} \tag{8.1}$$

λ_t denotes the productivity of labor or, alternatively, the state of technology in period t. $f(k_t)$ is positive, concave in k_t, and satisfies the Inada conditions[12]. With factors being paid their marginal product, the wage rate per efficiency unit of labor is given by $w_t = \lambda_t[f(k) - kf'(k)] \equiv \lambda_t w(k)$. In a steady state equilibrium, the world interest rate r^* is constant. It follows that $r_t = r^*$, and $k_t = k\ \forall t$. The labor force is recruited from overlapping generations, whereby the continuum of heterogeneous agents in each generation is normalized to 1. The model abstracts from population growth. There are two types of agents, the educated and the uneducated. This implies that the education decision is a simple discrete choice. An individual i differs from other individuals with respect to his level of latent ability e^i, which is independent of his parents' abilities and distributed over the interval $[0, E]$ according to the (positive) density function $g(e^i)$, whereby $\int_0^E g(e^i)de^i = 1$. All agents live for three periods. In their first period, they can acquire education at a constant cost of c units of output by borrowing on the world capital markets. In the second period agents work, repay their possible debt from the first period, and save for consumption during their retirement in the third period. Individuals who invest in education are rewarded with an amount of efficiency units of labor equal to their level of latent ability e^i when working in the second period, while uneducated workers have

[12] $\lim_{k\to 0} f(k) = 0$, $\lim_{k\to 0} f'(k) = \infty$, $\lim_{k\to\infty} f'(k) = 0$.

only one efficiency unit of labor. From the condition that individual i will only invest in education if this increases his level of consumption in the third period,

$$\lambda_t w(k)e^i - c(1+r^*) > \lambda_t w(k), \tag{8.2}$$

one can determine the threshold latent ability e^{*NM} that separates individuals who acquire education from those who do not in the absence of migration possibilities:[13]

$$e^{*NM} = \frac{\lambda_t w(k) + c(1+r^*)}{\lambda_t w(k)} \tag{8.3}$$

The economy-wide amount of human capital is given by the proportion of educated workers:

$$s_t^{NM} = \int_{e_t^{*NM}}^{E} g(e^i)de^i \tag{8.4}$$

This proportion is decisive for growth through an intergenerational externality which relates productivity in one period to the level of human capital in the previous period: $\lambda_t = \lambda(s_{t-1})$, with $\lambda_t' > 0$. The implication of this assumption for the dynamics of the human capital stock can be derived as follows:

$$\frac{ds_t^{NM}}{ds_{t-1}^{NM}} = \frac{ds_t^{NM}}{de_t^{*NM}} \cdot \frac{de_t^{*NM}}{d\lambda_t} \cdot \frac{d\lambda_t}{ds_{t-1}^{NM}} = [-g(e_t^*)] \cdot \left[-\frac{c(1-r^*)}{\lambda^2(s_{t-1}^{NM})w(k)}\right] \cdot \lambda'(s_{t-1}^{NM}) > 0; \tag{8.5}$$

see Mountford (1997, 291-292). Thus, in the benchmark case without the possibility of emigration, human capital in t is a positive function of human capital in *t-1*.[14]

Mountford (1997, 293-295) models the case of a brain drain by assuming that only educated agents successfully emigrate with probability π, which is motivated by a higher wage per efficiency unit of labor in the world economy compared to the wage in the home economy: $w^F > \lambda_t w^H$. This emigration probability is meant to reflect immigration quotas imposed by the receiving countries. It transforms the agent's decision problem into an expected utility problem. Anticipating the opportunity to migrate in their second period of life, risk-neutral individuals will opt for education if:

$$[\pi w^F + (1-\pi)\lambda_t w^H]e^i - c(1+r^*) > \lambda_t w^H \tag{8.6}$$

[13] Mountford (1997, 291) assumes that $e^{*NM} \in [0+\varepsilon, E-\varepsilon]$, where $0 < \varepsilon < E/2$.

[14] Depending on the functional form of $\lambda(s_{t-1})$, there will exist either a single or multiple steady state equilibria for the economy's level of human capital (Mountford, 1997, 292).

The threshold latent ability in the presence of migration possibilities for the educated is then given by:

$$e^* = \frac{\lambda_t w^H + c(1+r^*)}{\pi w^F + (1-\pi)\lambda_t w^H} < e^{*NM} \tag{8.7}$$

Thus, in the presence of a positive probability of emigration for the educated, more individuals will opt for education. The economy's *ex post* level of human capital is:

$$s_t = \frac{(1-\pi)\int_{e_t^*}^{E} g(e^i)de^i}{1-\pi\left(\int_{e_t^*}^{E} g(e^i)de^i\right)} \tag{8.8}$$

s_t is decreasing in education costs c and in the domestic wage rate w^H, yet it is increasing in the foreign wage rate w^F. Contrasting the baseline situation without the possibility of emigration, the dynamics of the human capital stock in the presence of the brain drain are less clear. This can be easily seen from the following derivative:

$$\frac{ds_t}{ds_{t-1}} = \frac{\partial s_t}{\partial e_t^*}\cdot\frac{\partial e_t^*}{\partial \lambda_t}\cdot\frac{\partial \lambda_t}{\partial s_{t-1}} = \frac{-(1-\pi)g(e^i)}{\left[1-\pi\int_{e_t^*}^{E} g(e^i)de^i\right]^2}\cdot\frac{w^H[\pi w^F-(1-\pi)c(1+r^*)]}{[\pi w^F+(1-\pi)\lambda w^H]^2}\cdot\lambda'(s_{t-1}) \tag{8.9}$$

Given that the first fraction on the right-hand side of (8.9) is unambiguously negative and the last term by assumption positive, it depends on the sign of the second fraction whether the derivative (8.9) is positive as in the baseline case, or not. If π is lower than $\frac{c(1+r^*)}{c(1+r^*)+w^F}$, the *ex post* level of human capital will be increasing in the human capital of the previous period.

In order to derive the condition for a brain drain to be beneficial for the economy's *ex post* level of human capital (and ultimately for growth), we compare the share of educated individuals in the case when the latter are allowed to migrate with probability π to the share of the educated when no such emigration is possible. In terms of comparative statics, the condition for a BBD is:

$$\left.\frac{ds_t}{d\pi}\right|_{\pi=0} > 0 \quad \text{where} \quad \frac{ds_t}{d\pi} = \frac{\partial s_t}{\partial \pi} + \frac{\partial s_t}{\partial e^*}\cdot\frac{\partial e^*}{\partial \pi}, \tag{8.10}$$

see Mountford (1997, 294). The first component of (8.10) gives the negative brain drain effect:

$$\frac{\partial s_t}{\partial \pi} = -\frac{\int_{e_t^*}^{E} g(e^i)de^i[1-\int_{e_t^*}^{E} g(e^i)de^i]}{[1-\pi\int_{e_t^*}^{E} g(e^i)de^i]^2} < 0 \tag{8.11}$$

The second component of (8.10) captures the positive brain gain effect: By reducing the threshold ability level e^*, any increase in the emigration probability of the educated π is accompanied by a positive impact on the proportion of educated individuals s_t:

$$\frac{\partial e^*}{\partial \pi} = -\frac{[\lambda_t w^H + c(1+r^*)](w^F - \lambda_t w^H)}{[\pi w^F + (1-\pi)\lambda_t w^H]^2} < 0 \tag{8.12}$$

and

$$\frac{\partial s_t}{\partial e^*} = -\frac{(1-\pi)g(e^*)}{[1-\pi\int_{e_t^*}^{E} g(e^i)de^i]^2} < 0 \tag{8.13}$$

Evaluating these countervailing effects at $\pi = 0$ and noting that the numerator of (8.11) is at most $\frac{1}{4}$ (see footnote 13) yields the following condition for a BBD:

$$\frac{g(e^{*NM})[\lambda_t w^H + c(1+r^*)](w^F - \lambda_t w^H)}{(\lambda_t w^H)^2} > \frac{1}{4}, \tag{8.14}$$

see Mountford (1997, 294). Thus, if inequality (8.14) is satisfied, there exists a positive optimal emigration probability for the educated such that the brain gain effect dominates the brain drain.

The additional assumption of uniformly distributed abilities allows to illustrate the countervailing effects in a simple diagram: In Figure 8.3, the dark area represents the brain drain and the light area characterizes the brain gain. A BBD arises if the latter area is of larger size than the former.

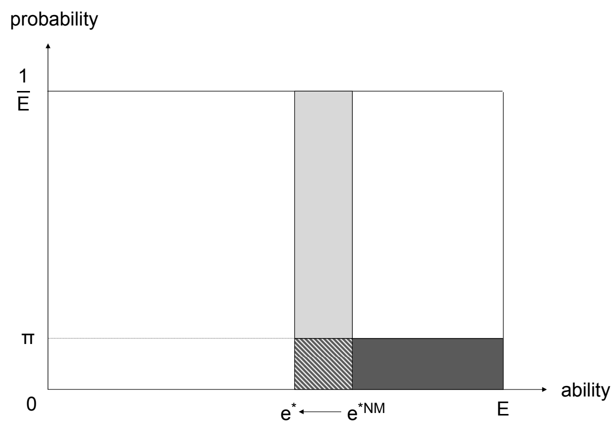

Figure 8.3: Brain Drain vs. Brain Gain Effect

Source: Mountford (1997, 295)

With uniformly distributed abilities, the condition for a BBD simplifies to:

$$1 - \frac{e^*}{E} < (1-\pi)\frac{w^F - \lambda_t w^H}{\pi w^F + (1-\pi)\lambda_t w^H}, \tag{8.15}$$

where the level of human capital has become $\left(1 - \frac{e^*}{E}\right)$, see Mountford (1997, 295). The circumstances under which this condition is likely to hold can be described as follows: If the probability of emigration for the educated is low, the level of human capital was previously low, and the foreign wage is very high relative to the home wage, a brain drain will benefit the human capital in the home economy (BBD).

8.4 Econometric Implementation

This section describes the data we employ, our econometric model, and the estimation strategy, and then proceeds with a discussion of the estimation results. As a benchmark, we present estimation results based on aggregate data on human capital formation and brain drain. Contrasting these benchmark analyses as well as the reviewed empirical analyses that rely on aggregate data about high-skilled south-north migration, our main analysis aims at uncovering heterogeneity in the effect of brain drain on human capital formation across different types of human capital.

The core theoretical prediction of Section 8.3 is that due to an anticipated opportunity of migration to a high-wage economy for the highly educated, more individuals in developing countries will opt for higher education compared to the hypothetical situation in which no migration is possible. If this incentive effect exceeds the pure outflow of human capital, the sending economies will experience a net gain in human capital with enhanced growth perspectives.

The descriptive evidence presented in Section 8.2 tentatively suggests a negative relationship between the relative incidence of human capital specific emigration and subsequent enrollment in the corresponding fields of tertiary education, which appears to be strongest for the field *Humanities & Social Sciences*. This seems to contradict the hypothesis of a brain gain. In the following, we test this hypothesis within a multivariate econometric analysis and thereby provide an implicit test of the effect captured by expression (8.12). In addition, we test the hypothesis that a brain gain is more likely for those types of human capital whose skills are easily transferable internationally (*Sciences & Engineering*, *Health & Agriculture*), compared to those types that rely more heavily on a good proficiency of the receiving country's language and on country-specific skills (*Education*, *Humanities & Social Sciences*).

8.4.1 Data and Econometric Model

We measure the formation of human capital of type j with the number of students in country i enrolled in tertiary education of type j around 2005, $enrollter_{ij,2005}$.[15] This information is taken from the UNESCO.[16] Subscript i refers to developing countries of emigration[17], and subscript j distinguishes between four (aggregated) types of tertiary education: *Science & Engineering*, *Health & Agriculture*, *Education*, and *Humanities & Social Sciences*.[18] We measure the formation of human capital with data on enrollment, because we think that this measure is well suited to capture a possible brain gain that may eventually result in a BBD. In particular, data on enrollment captures the relevant segment of a country's population that could be affected by a brain gain in terms of an increased incentive to acquire tertiary education. This does not apply to the growth rate of a country's population share with tertiary education, which is the most frequent measure for aggregate human capital formation in the empirical literature on the brain drain. Even though the latter measure will also react in response to a brain gain in terms of an increase in the number of tertiary graduates, this effect will interfere with other effects that influence the size of the native population with tertiary education. For instance, this measure will also increase with the number of nationals from a given developing country who graduate in the OECD. In principle, it would also be possible to use data on graduates in different fields of tertiary education rather than enrollment data. However, the advantage of enrollment data as opposed to graduate data is that the former provides a snapshot of the intention to pursue different types of tertiary education for several age cohorts, while the latter does the same for only one cohort.

In analogy to the existing literature, we would ideally like to use south-north migration rates at the level of the four fields of study in order to capture the prospect

[15] In an earlier version of this chapter, we relied on occupation-specific employment shares to measure the availability of different types of human capital, see Heuer (2011). Due to very scarce availability of employment data at the ISCO-88 sub-major level, we decided to replace this measure by data on tertiary enrollment. This has changed the focus of our analysis from considerations about the net effect of brain drain on human capital in the sending countries to an assessment of the brain gain hypothesis.

[16] See Table 8.4 in the appendix for detailed data descriptions and data sources.

[17] We consider countries that are classified as low- or middle-income countries in 2000 by the World Bank as developing countries. These are countries with a GNI per capita $\leq$ 755 US$ (low-income countries), and with a GNI per capita between 756 and 9,265 US$ (middle-income countries). See the World Bank GNI per capita Operational Guidelines & Analytical Classifications at `http://go.worldbank.org/U9BK7IA1J0, accessed on 01/22/2009.`

[18] We obtain these four categories by aggregating the different fields of study distinguished by the ISCED-97. We consider all fields except *General Programmes* and *Services* because these cannot be adequately matched to the considered ISCO-88 sub-major categories. See Table 8.5 in the appendix for a detailed description of how we aggregate and match the relevant categories.

of emigration for tertiary graduates in the different fields. We would furthermore like to measure these migration rates with a five-year lag relative to the dependent variable in order to allow the incentive effect to materialize gradually over time. This is common practice in the literature.[19] Unfortunately, such disaggregated migration rates are not available.[20] Therefore, we use migration rates constructed from employment data to proxy the prospect of migration to the OECD for tertiary graduates of the four aggregated fields. This approach is possible due to the fact that the relevant classification of occupations, ISCO-88, explicitly distinguishes between several occupational categories that generally require tertiary education.[21] Following our strategy in Chapter 7, we combine employment data classified according to the ISCO-88 from the OECD and LABORSTA to construct occupation-specific south-north migration rates in analogy to Docquier and Marfouk (2006).[22] These rates are defined as the share of individuals from country i (resident employees R plus emigrants M employed in the OECD) who work in an occupational category related to human capital type j and who are employed in the OECD around the year 2000:

$$m_{ij,2000} = \frac{M_{ij,2000}}{R_{ij,2000} + M_{ij,2000}} \tag{8.16}$$

$m_{ij,2000}$ captures the conditional probability that an individual from country i was working in the OECD around the year 2000 given that the individual was working in an occupation related to human capital type j. Due to scarce data availability concerning employment reported at the ISCO-88 sub-major level for developing countries, we have been able to construct such migration rates for only 17 developing countries in Chapter 7. To increase the number of countries in our sample, in this chapter we proxy the number of total natives employed in occupations related to human capital type j as follows:

$$(R_{ij,2000} + M_{ij,2000}) \approx \sum_j (R_{ij,2000} + M_{ij,2000}) \cdot \frac{enrollter_{ij,2000}}{\sum_j enrollter_{ij,2000}}, \tag{8.17}$$

[19] The only exceptions that use contemporaneous measures of human capital and brain drain are Groizard and Llull (2006, 2007a) and Checchi et al. (2007).

[20] Whereas data on the fields of study of tertiary-educated migrants in the OECD are available from several OECD countries for the year 2000 by OECD (2008), the absence of data on the fields of study of the tertiary-educated population in the migrant-sending countries impedes the construction of such disaggregated migration rates.

[21] According to ILO (1990, 3-4), *Professionals* (ISCO-88 major 2) are associated with ISCED-76 levels 6 and 7, and *Technicians and associate professionals* (major 3) mostly require education at ISCED-76 level 5. Note that under ISCED-97, tertiary education is included in levels 5 and 6.

[22] To maximize the available data on immigrants employed in OECD countries, we recode occupations reported for Turkey at the ISCO-68 minor level, as well as occupations reported for the United States according to the national classification scheme US OCC 2000. See Section 7.6.5 in the appendix to Chapter 7 for details.

where $\sum_j (R_{ij,2000} + M_{ij,2000})$ refers to the total number of native employees who worked in occupational categories requiring tertiary education. The last term in expression (8.17) is the share of students enrolled in tertiary education in country i around the year 2000 whose field of study belongs to human capital type j. The proposed approximation relies on the assumption that tertiary enrollment shares constitute suitable proxies for employment shares of occupations generally requiring tertiary education.[23] We prefer to rely on this approximation rather than to abstain from the normalization of the migrant stocks by human capital specific employment of the corresponding native populations.[24] The reason is that ignoring this information may result in biased estimates because a large number of migrants working in occupations related to some type of human capital may not necessarily reflect a large probability of human capital specific south-north migration. The large number could simply be due to a large incidence of employment related to this type of human capital. Table 8.5 in the appendix documents how we attributed the eight occupational categories at the ISCO-88 sub-major level that generally require tertiary education to the four types of human capital distinguished above.

At the aggregate level, emigration rates based on employment data exhibit an important advantage when compared to emigration rates constructed from education-specific population data. By construction, the former account for the fact that skills are only imperfectly transferable internationally because they exclude emigrated professionals who did not manage to find a job as a professional in the OECD. Therefore, the former emigration rates are lower than the latter (see Chapter 7). Whereas this implies that the employment-based emigration rates are more conservative empirical measures of the migration prospect than the population-based counterparts, the former capture the emigration potential that is relevant for the decision to enroll in some type of tertiary education more precisely: The incentive mechanism is likely to operate in the case of observed south-north migration with a perfect job match for professionals. However, it is unlikely to be at work in the case of observed emigration of professionals from developing countries who work, for instance, as a taxi driver or caretaker in the receiving OECD countries. According to Beine et al. (2008, 632), the incentive effect is not determined solely by a

[23] Di Maria and Lazarova (2012) rely on a similar assumption when they use the share of students enrolled in tertiary education who study science and technology as a proxy for the share of technically skilled workers in the population.

[24] In four cases, we obtain implausible values for $m_{ij,2000}$ (larger than 100%) based on this approach. Therefore, we repeat our estimations excluding these observations as a robustness check. Our results remain qualitatively robust to the change in the sample.

higher probability of emigration when educated, but it is also linked to the possibility of accessing legal, high-skilled jobs. At the same time, the employment-based measure of the probability of emigration to the OECD is a less conservative estimate of the brain drain effect compared to the population-based counterpart. This tendency is weakened to some extent, however, because the employment-based emigration rate also includes individuals who obtained their university degree in one of the receiving OECD countries.[25] [26]

Having described the empirical measures for our variables of main interest, we propose the following log-linear econometric model in order to assess the effect of brain drain on the formation of different types of human capital:

$$\begin{aligned} \ln(enrollter_{ij,2005}) =& \alpha + \beta_1 \cdot \ln(m_{ij,2000}) + \beta_2 \cdot \ln(enrollsec_{i,2000}) \\ &+ \beta_3 \cdot \ln(gradter_{ij,2000}) + \gamma_i + \delta_j + \epsilon_{ij}, \end{aligned} \tag{8.18}$$

where $\ln(enrollter_{ij,2005})$ and $\ln(m_{ij,2000})$ refer to the natural logs of the variables described above. Model (8.18) includes the ln of the total number of students enrolled in secondary education in i five years before enrollment in tertiary education is observed, $\ln(enrollsec_{i,2000})$. This variable is taken from the UNESCO, and it controls for the pool of students who might potentially pursue tertiary education in country i around the year 2005. A similar approach can be found in Checchi et al. (2007).[27]

We proxy the supply of education of type j in country i with the ln of the number of graduates of country i in tertiary education of type j around the year 2000, $\ln(gradter_{ij,2000})$. Note that we use graduate data rather than data on teachers in tertiary education by field of study to proxy the supply of education because data on teachers is not available at the same level of disaggregation from the UNESCO. This variable can also be considered as an implicit control for the cost of acquiring tertiary education of type j in country i. It is measured with a five-year lag relative to the dependent variable in order to mitigate endogeneity concerns.

γ_i refers to country-specific effects that do not vary across human capital types j (e.g.

[25] Whereas the same is true for the widely used data by Docquier and Marfouk (2006), Beine et al. (2007) explicitly take into account immigrants' ages at immigration as a proxy for the country where they acquired their education.

[26] It is thus implicitly assumed that the emigrants who went to university in the OECD would have pursued the same studies and acquired the same skills in the home countries if they had not emigrated.

[27] In their panel analyses, Checchi et al. (2007) use enrollment rates rather than the ln of absolute enrollments and consider an earlier period.

public subsidies for tertiary education).

A set of dummy variables identifying the different types of human capital is represented by δ_j. These dummy variables capture effects that are specific to the different types of tertiary education and that are common to all countries in the sample (e.g. reputation associated with a specific field of tertiary education). Lastly, ϵ_{ij} is an error term.

Our first hypothesis on the existence of a brain gain or incentive effect is reflected in the expectation that the estimated coefficient of the migration rate, $\widehat{\beta_1}$, turns out positive. In order to test our second hypothesis, according to which a brain gain is more likely for certain types of human capital compared to others, we estimate a second specification of model (8.18) in which we interact the migration rate with the set of dummy variables for the considered types of human capital, δ_j. Human capital type j =$\{$*Humanities & Social Sciences*$\}$ serves as a reference category. Furthermore, in a third specification of model (8.18), we interact the migration rate with a single dummy variable that takes on the value one if j belongs to either category of $\{$*Science & Engineering, Health & Agriculture*$\}$; it takes on the value zero if j belongs to either one of $\{$*Education, Humanities & Social Sciences*$\}$. The latter specification is motivated by the following considerations: Occupations related to the fields *Science & Engineering* or *Health & Agriculture* generally seem to be characterized by rather universal knowledge, whereas occupations related to the fields *Education* or *Humanities & Social Sciences* often require good language skills (e.g. teachers) or country-related skills (e.g. business professions), or even country-specific education (e.g. legal professionals). Thus, we want to assess the hypothesis that a brain gain is more likely for human capital types characterized by internationally transferable skills as opposed to country-specific skills. From a rather technical point of view, the joint estimation of several interaction effects usually entails multicollinearity, which increases the estimated standard errors. Therefore, the specification with a single interaction effect may yield more significant estimates than the specification with the three interaction effects.

We prefer this interaction approach to separate estimations of model (8.18) for the different types of human capital for two reasons: First, separate estimations impede the application of panel data estimation techniques, which we prefer to cross-sectional techniques as we will argue below. Second, as the number of countries for which information on all variables is available is rather small, separate estimations would have to rely on very few observations.

In order to test the robustness of our results, we conduct estimations in which we additionally control for the ln of the average monthly wage of male workers in occupations related to human capital type j around the year 2000, $\ln(w_{ij,2000})$.[28] Furthermore, to allow for non-linearities in the relationship between the formation of human capital and brain drain, we add the square of the latter variable to model (8.18) in an additional specification. We also interact the migration rate with a set of dummy variables for the different world regions[29], γ_r, to allow for inter-regional heterogeneity in the effect of brain drain on human capital formation.

We provide a list of the countries included in our sample, summary statistics of all variables, and some additional estimation results in the appendix.

8.4.2 Econometric Concerns and Estimation Strategy

As the nature of our dataset is in principle cross-sectional, we first estimate model (8.18) with ordinary least squares (OLS), pooling the data on the four types of human capital. To mitigate concerns about omitted variables bias, we next exploit the fact that we dispose of four observations for each country, or cluster. This allows us to estimate model (8.18) with fixed effects because the panel data estimation techniques fixed effects (FE) and random effects (RE) can generally be applied to cluster-sample data. Since it is very likely that the outcomes within a cluster are correlated, one should allow for an unobserved cluster effect (Wooldridge, 2009, 495). In this context, an unobserved effect at the country level could, e.g., be the reputation enjoyed by university graduates in general. This effect, however, is likely to be correlated with the included explanatory variables in model (8.18). Therefore, FE seems preferable to RE. FE estimation is also more appropriate because the available sample cannot be considered as a random sample from a much larger universe of countries, see Wooldridge (2009, 493). We implement FE estimation by applying a variant of the standard within-transformation to our cluster data. This means that we subtract cluster-level averages from all observed variables.[30]

Despite this possibility to extract the country-specific effects γ_i, we are still concerned

[28] We are grateful to Daniela Harsch and Jörn Kleinert for making their standardized wage data available. See Harsch and Kleinert (2011) for details on the wage data. In order to calculate average wages for the different types of human capital described in Table 8.5, we assign equal weights to the wage rates reported by detailed occupations. The recoding of the detailed occupations to the ISCO-88 sub-major occupational categories is based on the table of translations of the ILO October Inquiry.

[29] These are the regional country groups defined by the World Bank, see `http://go.worldbank.org/D7SN0B8YU0`, accessed on 11/17/2008.

[30] The within-transformation of the cluster data used to estimate our log-linear model renders the consideration of variables measured in relative terms dispensable. This implies that in all FE estimations, our measure of human capital formation is closely related to the relevant theoretical variable considered in Section 8.3, as well as to the enrollment rates employed in earlier studies.

about the exogeneity of the migration rate. The migration rate in equation (8.18) will be endogenous if one or more relevant explanatory variables of tertiary enrollment that vary over both countries and fields of study and that are correlated with the migration rate are omitted, or if the latter variable is measured with an error. In order to address this concern, we additionally estimate model (8.18) with the technique of fixed effects instrumental variables (FE IV).[31] For these estimations we need at least one excluded instrument with dimensions i and j that is correlated with the migration rate, but that is uncorrelated with the error term in model (8.18). Using data on migrant stocks in OECD countries from OECD (2008), for each combination of sending country i and human capital type j in our sample we construct the following two information: First, the number of migrants from all other countries in the world except i who are employed in sub-major occupational categories related to human capital type j in the OECD around 2000, $mig_{ij,2000} = \sum_{k \neq i} M_{kj,2000}$. Second, the squared number of migrants who are employed in sub-majors related to j in the OECD around 2000 summed over all origin countries other than i: $sqmig_{ij,2000} = \sum_{k \neq i} \left(M_{kj,2000}\right)^2$.[32] We argue that the relative incidence of migration to OECD countries from a given developing country i is likely to be codetermined by the incidence of migration from other countries in the world to the OECD. However, there is no plausible reason to suppose that the latter incidence has a direct impact on the formation of human capital in country i. Therefore, we use $\ln(mig_{ij,2000})$ and $\ln(sqmig_{ij,2000})$ as excluded instruments in FE IV estimations of model (8.18). We test the exogeneity assumption for the migration rate with a standard endogeneity test. Since we have more excluded instruments than instrumented regressors, we can assess the validity of the constructed instruments via a test on overidentifying restrictions. The relevance of our instruments is analyzed using the Kleibergen-Paap LM statistic, whereas the Kleibergen-Paap Wald F test provides some information on the strength of the considered instruments (in the case of one endogenous regressor).[33] We report heteroskedasticity-robust standard errors for all estimated coefficients.

[31] All FE and FE IV estimations are performed relying on STATA module xtivreg2 by Schaffer (2010).

[32] We are grateful to Ronald Davies for the suggestion of these instruments.

[33] Baum et al. (2007, 490) suggest the use of this test statistic in combination with the "rule of thumb" by Staiger and Stock (1997) to test for weak identification in the case of heteroskedasticity. According to the "rule of thumb", the F statistic should be at least 10 in the case of one endogenous regressor.

8.4.3 Benchmark Analyses

Before we proceed with the estimation results for model (8.18), we present benchmark estimations in which we use aggregate data on human capital formation and brain drain. With these benchmark analyses, we intend to check whether we can reproduce the contrasting empirical results on the brain gain hypothesis found in the literature with the data that we consider in our analysis at a more disaggregated level. In particular, we compare results from estimations in which we measure the brain drain either with conventional education-specific population data, or on the basis of the occupation-specific employment data. To this end, we aggregate the information on employment in occupations that generally require tertiary education.

Testing the Brain Gain Hypothesis with Aggregate Population Data

We first reassess the test of the brain gain hypothesis at the aggregate level with the model proposed in Beine et al. (2008), in which the formation of human capital is measured by the change in the share of the native population with tertiary education. Since we want to consider the period from 2000 to 2005 as we do in our main analysis, we cannot rely on data on the native population (residents at origin plus migrants in the OECD) by education level, but have to use data on resident populations in the sending countries instead. We take the share of resident populations with tertiary education ($popter_{i,t}$) as well as the emigration rate of the tertiary-educated populations ($m_{i,2000}$) from different databases provided by the World Bank, respectively.[34] Table 8.1 contains the estimation results. In columns (1) and (2), we measure the prospect of migration to the OECD for the highly skilled with the emigration rate of the tertiary-educated population from the World Bank. In columns (3) and (4), we measure the same prospect with the share of the native population that worked in occupations requiring tertiary education and that lived in the OECD around 2000. Following Beine et al. (2008), in columns (2) and (4) we instrument the migration rate with the ln of the population size in 2000 (from the World Bank), $\ln(pop_{i,2000})$, and the ln of the migrant stock in OECD countries in 2000 (from OECD, 2008), $\ln(mstock_{i,2000})$.

[34]See Table 8.4 in the appendix for detailed data descriptions and data sources.

Table 8.1: Estimation Results from Benchmark Analysis with Aggregate Population Data
Dependent variable: Growth rate of population share with tertiary education, $\ln\left(\frac{popter_{i,2005}}{popter_{i,2000}}\right)$

	(1)	(2)	(3)	(4)
	Population Data		*Employment Data*	
$\ln(m_{i,2000})$	0.025	0.000	0.017**	0.005
	(0.016)	(0.013)	(0.008)	(0.008)
$\ln(popter_{i,2000})$	-0.073**	-0.084**	-0.074**	-0.081**
	(0.027)	(0.035)	(0.031)	(0.034)
SSA_i	-0.028	-0.042	-0.030	-0.039
	(0.050)	(0.065)	(0.052)	(0.061)
Constant	-0.018	-0.097	-0.021	-0.076
	(0.059)	(0.108)	(0.079)	(0.102)
Observations	38	38	38	38
R^2	0.449	0.410	0.448	0.428
Kleibergen-Paap Wald F test		26.29		30.39
Kleibergen-Paap LM test		11.53		10.88
Kleibergen-Paap LM p-value		0.003		0.004
Hansen J test		7.423		6.627
Hansen J test p-value		0.006		0.010
Endogeneity test		0.049		0.982
Endogeneity test p-value		0.825		0.322

*,**,*** denote significance at the 10-%, 5-%, 1-% levels, respectively. Heteroskedasticity-robust standard errors are given in parentheses. Columns (1) and (3) report results from OLS estimation. Columns (2) and (4) report results from IV estimations in which $\ln(m_{i,2000})$ is instrumented with $\ln(pop_{i,2000})$ and $\ln(mstock_{i,2000})$, and in which small sample corrections are implemented.

Despite the fact that we consider a slightly different measure for human capital accumulation, a much smaller sample[35], and a shorter, more recent period compared to Beine et al. (2008), our OLS estimates reported in column (1) are qualitatively similar to theirs: The elasticity of the growth rate of the population share with tertiary education between 2000 and 2005 with respect to the conventional brain drain rate in 2000 is 0.025. The estimate in the benchmark study is 0.042 for the larger period 1990-2000. Our estimated coefficients for the tertiary-educated population share in the baseline period are negative, but the absolute value is lower compared to the estimate in the study of reference. Contrasting the results in the reference study, our coefficient estimates for the brain drain rate based on population data and for the dummy variable for Sub-Saharan African countries, SSA_i, are found to be statistically insignificant in Table 8.1. In the IV estimations reported in columns (2) and (4), the Hansen J tests suggest that the considered excluded instruments are not exogenous. Similarly as in the study of reference, the endogeneity tests suggest that the brain drain rates can be considered exogenous. In our IV estima-

[35]The sample considered for the benchmark analyses covers the 38 developing countries for which we conduct our main analysis.

tions, the positive effect of the brain drain rate decreases, while in the IV estimations of the reference study it stays almost unaltered.

As expected, the coefficient estimate for the employment-based brain drain rate in column (3) is lower compared to the estimate for the conventional measure reported in column (1). We attribute this finding to the fact that our employment-based measure of the brain drain accounts for the imperfect international transferability of skills. The coefficient estimate of the employment-based measure is statistically significant at the 5-% level in column (3), while the coefficient of the population-based counterpart in column (1) is not significant. The estimated coefficients of the control variables are almost unaffected by the change of the brain drain measure.

Testing the Brain Gain Hypothesis with Aggregate Enrollment Data

In a second benchmark analysis, we conduct a test for the brain gain hypothesis at the aggregate level using data on total enrollment in tertiary education from the UNESCO, and the two different measures of brain drain described above. We do not follow the empirical studies that performed similar analyses with this type of data[36] as closely as we followed Beine et al. (2008) above, but we rather estimate a variant of model (8.18) in which dimension j is omitted and to which we add dummy variables for the different world regions. Table 8.2 reports the results.

We find a significantly negative elasticity of tertiary enrollment around 2005 with respect to high-skilled emigration in 2000. This elasticity amounts to -0.13 for the conventional brain drain rate, and is slightly smaller in absolute terms if the brain drain rate is constructed from employment data. The order of magnitude for our estimate is comparable to estimates obtained from different models with similar data by Groizard and Llull (2007a) and Checchi et al. (2007). The control variables for enrollment in secondary education, $\ln(enrollsec_{i,2000})$, and the number of graduates in tertiary education around 2000, $\ln(gradter_{i,2000})$, are both significantly positively correlated with absolute enrollment in tertiary education in 2005. This suggests that cross-country variation in tertiary enrollment is partly explained by differences in the countries' pool of potential applicants for tertiary education, as well as by differences in their potential to supply tertiary education.

[36] See Faini (2005), Groizard and Llull (2006, 2007a), and Checchi et al. (2007).

Table 8.2: Estimation Results from Benchmark Analysis with Aggregate Enrollment Data
Dependent variable: Ln of absolute enrollment in tertiary education, $\ln(enrollter_{i,2005})$

	(1)	(2)	(3)	(4)
	Population Data		*Employment Data*	
$\ln(m_{i,2000})$	-0.130*	-0.202***	-0.109***	-0.128***
	(0.066)	(0.072)	(0.035)	(0.046)
$\ln(enrollsec_{i,2000})$	0.511***	0.495***	0.539***	0.539***
	(0.117)	(0.116)	(0.108)	(0.110)
$\ln(gradter_{i,2000})$	0.475***	0.471***	0.455***	0.450***
	(0.093)	(0.094)	(0.087)	(0.087)
Constant	-0.175		-0.412	
	(0.774)		(0.742)	
Regional dummies γ_r	Yes	Yes	Yes	Yes
Observations	38	38	38	38
R^2	0.973	0.972	0.976	0.975
Kleibergen-Paap Wald F test		17.16		8.386
Kleibergen-Paap LM test		10.32		10.67
Kleibergen-Paap LM p-value		0.006		0.005
Hansen J test		0.385		1.121
Hansen J test p-value		0.535		0.290
Endogeneity test		1.910		0.681
Endogeneity test p-value		0.167		0.409

*,**,*** denote significance at the 10-%, 5-%, 1-% levels, respectively. Heteroskedasticity-robust standard errors are given in parentheses. Columns (1) and (3) report results from OLS estimation. Columns (2) and (4) report results from IV estimations in which $\ln(m_{i,2000})$ is instrumented with $\ln(mig_{i,2000})$ and $\ln(sqmig_{i,2000})$, and in which small sample corrections are implemented.

In columns (2) and (4) we instrument the brain drain rate with the aggregated variants of the excluded instruments proposed for our analysis with the more disaggregated data. These instruments are the ln of the total stock of migrants employed in ISCO-88 majors 2 and 3 in the OECD who were born in all sending countries other than i, $\ln(mig_{i,2000})$, and the ln of the sum of squared migrant stocks in majors 2 and 3 from countries other than i, $\ln(sqmig_{i,2000})$. According to the reported test statistics, these instruments perform quite well. In particular, we cannot reject the hypothesis of the Hansen J test that the excluded instruments are exogenous at any reasonable level of statistical significance. Based on endogeneity tests, we cannot reject the hypothesis that the brain drain rate is exogenous at any reasonable level of statistical significance, either.

8.4.4 Estimation Results

The estimation results for model (8.18) are reported in Table 8.3. Applying three different estimation techniques, we first estimated the original model. We then estimated two further specifications that include interaction terms of the emigration rate with dummy variables for the different human capital types. These interactions allow for differences in the effect of human capital specific brain drain on enrollment in tertiary education. Columns (1)-(3) contain results from pooled ordinary least squares (POLS) estimation, columns (4)-(6) those from FE estimation, and columns (7)-(9) those from FE IV estimation. In the FE IV estimations, the brain drain variable and – if applicable – its interactions are instrumented with $\ln(mig_{ij,2000})$, $\ln(sqmig_{ij,2000})$, and with the interactions of these instruments with the set of dummies δ_j in the case that interaction terms are included.

The estimates obtained from POLS estimation on the cluster dataset are very similar to our benchmark results from the aggregate data reported in Table 8.2. The estimated coefficient of the human capital specific emigration rate amounts to -0.11 and is statistically significant at the 1-% level in column (1). The same coefficient estimate was obtained in the benchmark estimation. Lagged enrollment in secondary education and the lagged number of tertiary graduates are both significantly positively related to enrollment in different fields of tertiary education around the year 2005. However, the estimated coefficients quantitatively differ from the benchmark results.

In columns (2) and (3), the hypothesis that the coefficient estimates of the brain drain variable and its interactions are jointly equal to zero can be rejected at the 1-% and 5-% level, respectively (see the reported joint tests). In column (2), the coefficients of the interaction terms suggest that the negative relationship between brain drain and enrollment in tertiary education was stronger for enrollment in *Education*, but weaker for enrollment in *Health & Agriculture* and *Science & Engineering* compared to the reference category *Humanities & Social Sciences.* In line with this ranking, column (3) suggests that the negative relationship was twice as high for the aggregated field *Education, Humanities & Social Sciences* compared to the aggregated field *Science & Engineering, Health & Agriculture.*

The results from FE estimation reported in columns (4)-(6) reveal a larger negative relationship between human capital specific brain drain and tertiary enrollment than the results from POLS. The estimated elasticity of human capital specific enrollment in tertiary education with respect to brain drain is about -0.5. This suggests a substantial upward bias for the estimates obtained from OLS estimation, which is likely to result from unobserved heterogeneity at the country level. As in the case of the POLS estimations, the coefficient of the emigration rate has high statistical significance (at the 1-% level) in all three reported FE estimations. In addition, the joint tests reported in columns (5) and (6) suggest that the coefficients of the brain drain variable and the interaction terms are jointly significant at the 1-% level. The ranking of the considered types of human capital on the basis of the elasticity of tertiary enrollment with respect to brain drain is qualitatively the same as in the case of POLS. The estimated coefficients of our proxy for the supply of education, the ln of the lagged number of graduates in tertiary education, are smaller in the FE estimations than in the POLS estimations. In all specifications, the coefficient of this variable is statistically significant at the 1-% level. A 1-% increase in the capacity of tertiary education around 2000, measured by the number of tertiary graduates, is associated with a 0.18-% increase in tertiary enrollment around the year 2005, ceteris paribus.

The negative relationship between human capital specific enrollment in tertiary education and brain drain is robust to the instrumentation of the brain drain variable and its possible interactions. This makes us confident in refering to this relationship as a causal effect. In the FE IV estimations reported in columns (7)-(9), the estimated elasticities of tertiary enrollment with respect to brain drain are smaller than in the FE estimations, but they still exceed the estimates obtained from POLS. The hypothesis that the brain drain variable and its interactions are exogenous can be rejected at the 5-% level of statistical significance in column (9). The same hypothesis cannot be rejected in columns (7) and (8), indicating that the results from FE estimation in columns (4) and (5) should be preferred to those from FE IV estimation. The null hypothesis of valid instruments of the Hansen J statistic cannot be rejected at reasonable levels of statistical significance in specifications (7)-(9). This suggests that the excluded instruments are exogenous in model (8.18). The reported Kleibergen-Paap LM statistics indicate that our excluded instruments are relevant in two of the considered three specifications: The null hypothesis of underidentification can be rejected at the 5-% and 1-% level in columns (7) and (9), respectively. It cannot be rejected in column (8) at any reasonable significance level. The result for the latter specification may be related to the fact that we rely on artificial additional instrument variables, constructed as interactions between our two excluded instruments and the human capital fixed effects. In column (7), the Kleibergen-Paap Wald F test exceeds the critical value of 10 proposed by Staiger and Stock (1997). This points to strong instruments. However, we cannot apply this rule of thumb for the first-stage F test to columns (8) and (9), in which the brain drain measure as well as its interactions are instrumented. To our knowledge, there exist no critical values for this statistic and the case of multiple endogenous regressors.[37]

Table 8.9 in the appendix contains estimation results from additional variants of model (8.18). In columns (1) and (4) of this table, we additionally control for the ln of the average wage rate around the year 2000. Due to scarce wage data availability, the inclusion of this variable dramatically decreases the number of observations. The wage variable is never found to be statistically significant. In columns (2) and (5) we add the square of the brain drain variable in order to control for non-linearities in the effect of human capital specific brain drain on enrollment in tertiary education. Based on the endogeneity test in column (5), we cannot reject the hypothesis that both the emigration rate and the squared rate are exogenous. In the FE estimation reported in column (2), the emigration rate and the squared rate are jointly significant at the 1-% level in the latter estimation. However, the coefficient estimate suggests a zero impact of the squared emigration variable on tertiary enrollment. Thus, we conclude that the effect of human capital specific brain drain on tertiary enrollment is linear in our sample. In columns (3) and (6), we interact the brain drain variable with dummy variables for the different world regions. Sub-Saharan Africa serves as a reference region. In the FE IV estimation reported in column (6), we cannot reject the hypothesis that the brain drain variable and its interactions are exogenous. However, this result is obtained in the presence of underidentification as implied by the Kleibergen-Paap LM test. In the FE estimations reported in columns (3) and (6), the brain drain variable and its interactions are jointly significant at the 1-% level. This suggests important heterogeneity in the effect of brain drain on tertiary enrollment across developing countries pertaining to different world regions. The negative effect of the brain drain on tertiary enrollment appears to be relatively strong for countries in Middle East & North Africa, in Eastern Europe & Central Asia, as well as in South Asia (Bangladesh) compared to Sub-Saharan Africa. By contrast, the negative effect is found to be significantly weaker for countries in East Asia & Pacific.

[37] Stock and Yogo (2005) provide critical values for the Cragg-Donald Wald F statistic, which is the relevant F statistic in the case that the errors are independent and identically distributed. Even though Baum et al. (2007, 490) suggest the application of these critical values with caution also for the Kleibergen Paap Wald F test, we cannot do so because these critical values are not available for all cases considered in our estimations.

Table 8.3: Estimation Results from Disaggregated Data on Tertiary Enrollment and Human Capital Specific Brain Drain
Dependent variable: Ln of absolute enrollment in (aggregated) fields of tertiary education, $\ln(enrollter_{ij,2005})$

	Ordinary Least Squares			*Fixed Effects*			*Fixed Effects Instrumental Variables*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$^{\dagger}\ln(m_{ij,2000})$	-0.110***	-0.132***	-0.143**	-0.513***	-0.500***	-0.532***	-0.269	-0.308*	-0.418***
	(0.038)	(0.048)	(0.058)	(0.083)	(0.080)	(0.081)	(0.171)	(0.166)	(0.136)
$^{\dagger}\ln(m_{ij,2000})\times\delta_{\{Science\ \&\ Engineering\}}$		0.044			0.032			0.293	
		(0.065)			(0.046)			(0.209)	
$^{\dagger}\ln(m_{ij,2000})\times\delta_{\{Health\ \&\ Agriculture\}}$		0.078			0.074			0.185	
		(0.070)			(0.049)			(0.156)	
$^{\dagger}\ln(m_{ij,2000})\times\delta_{\{Education\}}$		-0.021			-0.052			-0.223	
		(0.104)			(0.066)			(0.178)	
$^{\dagger}\ln(m_{ij,2000})\times\delta_{\{Science\ \&\ Engin.,\ Health\ \&\ Agric.\}}$			0.073			0.080*			0.400***
			(0.064)			(0.041)			(0.123)
$\ln(enrollsec_{i,2000})$	0.353***	0.361***	0.357***						
	(0.063)	(0.064)	(0.063)						
$\ln(gradter_{ij,2000})$	0.618***	0.614***	0.616***	0.185***	0.176***	0.182***	0.353***	0.241**	0.300***
	(0.052)	(0.052)	(0.051)	(0.067)	(0.066)	(0.065)	(0.132)	(0.110)	(0.108)
Constant	0.637	0.508	0.494						
	(0.480)	(0.498)	(0.483)						
Field dummies δ_j	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	152	152	152	152	152	152	152	152	152
Countries	38	38	38	38	38	38	38	38	38
R^2	0.937	0.938	0.938	0.867	0.875	0.873	0.847	0.774	0.765
†Joint test		3.596	4.570		12.23	21.89		4.967	6.881
†Joint test p-value		0.008	0.012		0.000	0.000		0.001	0.002

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Table 8.3 *continued*

	Ordinary Least Squares			*Fixed Effects*			*Fixed Effects Instrumental Variables*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Kleibergen-Paap Wald F test							16.31	0.465	9.183
Kleibergen-Paap LM test							8.502	5.096	12.61
Kleibergen-Paap LM p-value							0.014	0.404	0.006
Hansen J test							1.416	4.587	2.824
Hansen J test p-value							0.234	0.332	0.244
Endogeneity test							2.093	5.988	7.632
Endogeneity test p-value							0.148	0.200	0.022

*,**,*** denote significance at the 10-%, 5-%, 1-% levels, respectively. Heteroskedasticity-robust standard errors are given in parentheses. In columns (2), (5) and (8), *Humanities & Social Sciences* serves as a reference category. In columns (3), (6) and (9), the aggregated field *Education, Humanities & Social Sciences* serves as a reference category. In columns (7)-(9), $\ln(m_{ij,2000})$ and its interactions are instrumented with $\ln(mig_{ij,2000})$, $\ln(sqmig_{ij,2000})$, and if applicable with the interactions of these variables with the dummies δ_j. In all IV estimations, small sample corrections are implemented.

8.5 Conclusion

This chapter has tested the hypothesis of a brain gain induced by the emigration of high-skilled workers for four types of human capital and a sample of 38 developing countries. Based on a regression framework, it has addressed the question of whether higher prospects of migration to the OECD, accounted for by human capital-specific emigration rates constructed from employment data, lead to larger numbers of enrollment in the associated fields of tertiary education in the origin countries. The obtained estimation results suggest a negative effect of the prospect of migration to the OECD on tertiary enrollment in developing origin countries. This negative effect is robust across various specifications and estimation techniques, and thus rejects the hypothesis of a brain gain. This finding may be interpreted as a "disincentive effect" to pursue higher education that arises because the populations in the sending countries interpret the observed incidence of high-skilled emigration as evidence for a shortage of adequate local jobs (Checchi et al., 2007, 20). At the same time, this finding may be related to the observation that many individuals from developing countries emigrate to enroll in tertiary education abroad; see, e.g., OECD (2011, 318). In the absence of substantial return migration of highly skilled emigrés, this disincentive effect will further aggravate concerns about brain drain.

We find that the disincentive effect was significantly stronger for the fields *Education* and *Humanities & Social Sciences*, compared to the fields *Science & Engineering* and *Health & Agriculture*. It is the latter fields that are likely to be characterized by skills with a high degree of international transferability. We regard this as tentative evidence in favor of our second hypothesis, according to which a brain gain is more likely for human capital types characterized by internationally transferable skills as opposed to country-specific skills. Whether this weaker negative effect for the former types of human capital also results in a weaker net brain drain or not, however, depends on the scale of migration of young individuals after graduation (both to OECD countries and from OECD countries to the origin countries in case that tertiary education is obtained abroad).

Our estimation results for the effect of brain drain on tertiary enrollment obtained from the (cross-sectional) cluster dataset replicate the estimate obtained from a cross-sectional benchmark analysis with aggregated data. However, the analysis on the basis of the cluster dataset has two advantages relative to the one that is based on aggregated data. Most importantly, it has allowed us to detect heterogeneity inherent in the effect of brain drain on tertiary enrollment. In addition, it has allowed us to extract unobserved heterogeneity at the country level by applying panel data estimation techniques. Our estimation results suggest that both aspects are relevant in our analysis of the impact of brain drain on tertiary enrollment.

In another benchmark analysis, we have shown that the aggregated variant of our employment-based brain drain rates yields a positive estimate for the effect of brain drain on the growth rate of the tertiary-educated population share. Yet the estimate is more conservative compared to the one obtained with the conventional population-based brain drain measure. We attribute this finding to the fact that the employment-based measure, by construction, accounts for the fact that skills are only imperfectly transferable internationally because it excludes emigrated individuals with tertiary education who did not manage to find adequate jobs in the OECD. This additional analysis has replicated the more prevalent empirical approach in the literature, which assesses the brain gain hypothesis with data on the tertiary-educated total population. We have argued that the observation that evidence obtained from this approach favors the hypothesis of a brain gain has to be seen in light of its relation to a different population of interest. Analyses that rely on population data test the brain gain argument for the total population originating from a given country, irrespective of where tertiary education has been acquired. By contrast, analyses that rely on enrollment data as the present study provide a more conservative test of the brain gain argument because they focus only on a few age cohorts in the migrant-sending countries.

As data availability improves, it would be desirable to re-assess the hypothesis of a brain gain using richer enrollment data or population figures disaggregated by professions for more migrant-sending countries. Furthermore, future work on this topic might include the analysis of spillover effects of human capital specific brain drain on the formation of other types of human capital: For instance, it might be possible that a higher probability of emigration of physicians incentivizes some individuals in developing countries, who otherwise would have studied law, to study medicine, ceteris paribus. This type of research question might be best addressed with individual-level data. To our knowledge, Batista et al. (2012) are the first to have conducted a household survey with questions tailored to the study of the brain gain mechanism. Their estimation and counterfactual analyses reveal that the probability of completing intermediate secondary schooling in Cape Verde is increasing in the probability of own future migration.

8.6 Appendix to Chapter 8

Table 8.4: Data Sources

Variable	Definition	Data Sources
$enrollter_{ij,2005}$	Enrollment in tertiary education by field of study. If available, data from the year 2005 is considered. Else, data from 2006, 2004, 2007, 2003, 2008 or 2002 is taken.‡	UNESCO Institute for Statistics. http://www.uis.unesco.org, accessed on 01/06/2012.
$enrollter_{ij,2000}$	Enrollment in tertiary education by field of study. If available, data from the year 2000 is considered. Else, data from 2001, 1999, 2002, 1998, 2003 or 2004 is taken.‡	
$enrollter_{i,2005}$	Enrollment in total tertiary education (public and private, full and part time). If available, data from the year 2005 is considered. Else, data from 2006, 2004, 2007 or 2003 is taken.‡	
$gradter_{ij,2000}$	Graduates in tertiary education by field of study. If available, data from the year 2000 is considered. Else, data from 1999, 1998 or some year in the period 2001-2004 is taken.‡	
$gradter_{i,2000}$	Total graduates in all programs of tertiary education. If available, data from the year 2000 is considered. Else, data from 1999, 1998 or some year in the period 2001-2004 is taken.‡	
$enrollsec_{i,2000}$	Enrollment in total secondary education (public and private, all programmes). If available, data from the year 2000 is considered. Else, data from 2001, 1999, 2002, 1998 or 1997 is taken.‡	

‡ Entries reporting data as "nil or negligible" or "category not applicable" are recoded as zero. Only entries reporting "data missing" are considered as real missings.

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Table 8.4 *continued*

Variable	Definition	Data Sources
$m_{ij,2000}$	Occupation-specific emigration rate to OECD countries. See Section 8.4.1 for details on how this variable is constructed.	Own calculations based on: • Database on Immigrants in OECD Countries (DIOC), OECD (2008). `http://www.oecd.org/document/51/0,3343,en_2649_33931_40644339_1_1_1_1,00.html.`, accessed on 10/15/2009. • Total employment, by occupation (Main statistics, annual, 2C. ILO, LABORSTA Internet. `http://laborsta.ilo.org/`, accessed on 10/15/2009. • Enrollment in tertiary education by field of study around 2000. UNESCO Institute for Statistics. `http://www.uis.unesco.org`, accessed on 01/06/2012.
$m_{i,2000}$ (*emp*)	Share of the native population (resident population plus emigrants in the OECD) employed in occupations requiring tertiary education (ISCO-88 majors 2 and 3) who lived in the OECD around 2000.	
$mig_{ij,2000}$	Total stock of migrants employed in sub-major occupational categories related to human capital type j in the OECD around 2000 who were born in countries other than i.	
$sqmig_{ij,2000}$	Sum of squared stocks of migrants employed in sub-major occupational categories related to human capital type j in the OECD around 2000 who were born in countries other than i.	
$mig_{i,2000}$	Total stock of migrants employed in ISCO-88 majors 2 and 3 in the OECD around 2000 who were born in countries other than i.	
$sqmig_{i,2000}$	Sum of squared stocks of migrants employed in majors 2 and 3 in the OECD around 2000 who were born in countries other than i.	
$mstock_{i,2000}$	Stock of migrants born in i who were living in OECD countries around 2000.	
$w_{ij,2000}$	Average monthly wage rate of male workers in occupations related to human capital type j around the year 2000. The recoding of occupations is based on ILO October Inquiry: Industry groups and occupations, LABORSTA Internet. `http://laborsta.ilo.org/applv8/data/to1ae.html`, accessed on 01/08/2012.	Own calculations based on a dataset by Harsch and Kleinert (2011).

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Table 8.4 *continued*

Variable	Definition	Data Sources
$m_{i,2000}$ (*pop*)	Emigration rate of the tertiary educated (proportion of total tertiary educated population) in 2000.	The World Bank, World Development Indicators (WDI) & Global Development Finance. `http://databank.worldbank.org`, accessed on 02/04/2012.
$pop_{i,2005}$, $pop_{i,2000}$	Total population in 2005/2000.	
$popter_{i,2005}$, $popter_{i,2000}$	Proportion of population aged 15+ with tertiary education in 2005/2000. If available, data for the year 2005/2000 from the IIASA/VID Projection is taken. Else, corresponding population shares from Barro-Lee are employed. For Georgia (Occupied Palestinian Territory), we use data on the tertiary-educated labor force from the WDI for 2004/1999 (2006/2001). Data for Lebanon is approximated based on figures from Docquier and Marfouk (2006).	The World Bank, Education Statistics. `http://databank.worldbank.org`, accessed on 02/04/2012.

Table 8.5: Mapping of Data Disaggregated by either Field of Education or Occupation to Four Types of Human Capital

	Tertiary Enrollment *Tertiary Graduates* Fields of Study ISCED-97 Majors**	*Migration Rates* Occupations ISCO-88 Sub-Majors
Science & Engineering	Science (4), Engineering, manufacturing and construction (5)	Physical, mathematical and engineering science professionals (21), Physical and engineering science associate professionals (31)
Health & Agriculture	Health and welfare (7), Agriculture (6)	Life science and health professionals (22), Life science and health associate professionals (32)
Education	Education (1)	Teaching professionals (23), Teaching associate professionals (33)
Humanities & Social Sciences	Humanities and arts (2), Social sciences, business and law (3)	Other professionals (24), Other associate professionals (34)

* Please refer to UNESCO (2006) and ILO (1990) for detailed listings of the sub-categories included in the major categories of ISCED-97 and the sub-major categories of ISCO-88, respectively.

** We do not consider the field General Programmes (0), because it refers to non-tertiary education, and the field Services (8), because this category cannot be adequately matched to the considered ISCO-88 sub-major categories.

Table 8.6: List of Countries Included in the Estimations, by World Region

Eastern Europe & Central Asia (EECA)	**East Asia & Pacific (EAP)**	**Middle East & North Africa (MENA)**
Armenia	Cambodia	Iran
Bulgaria	Laos	Lebanon
Croatia	Malaysia	Morocco
Czech Republic	Mongolia	Occ. Palestinian Territory
Estonia	Philippines	
Georgia		**South Asia (SA)**
Hungary	**Latin America &**	Bangladesh
Kyrgyzstan	**Caribbean (LAC)**	
Latvia	Brazil	**Sub-Saharan Africa**
Lithuania	Chile	**(SSA)**
Macedonia	El Salvador	Eritrea
Poland	Guyana	Ethiopia
Romania	Mexico	Namibia
Slovakia	Panama	Tanzania
Turkey	Trinidad and Tobago	Uganda
Ukraine		

Table 8.7: Summary Statistics of Aggregated Data Used in Benchmark Analyses

Variable	Mean	Std. Dev.	Min	Max	Observations
$\ln\left(\frac{popter_{i,2005}}{popter_{i,2000}}\right)$	.1113886	.1116595	-.4519851	.2816078	38
$\ln(popter_{i,2000})$	-2.552739	.9376326	-5.004096	-.8722738	38
$\ln(m_{i,2000})$ (employment data)	-3.085368	1.40214	-6.725728	-.2478418	38
$\ln(m_{i,2000})$ (population data)	-2.113064	.9490599	-4.688284	-.1138625	38
$\ln(mstock_{i,2000})$	11.51761	1.734554	6.98749	15.32278	38
$\ln(pop_{i,2000})$	16.12074	1.459388	13.50504	18.97701	38
SSA_i	.1315789	.34257	0	1	38
$\ln(enrollter_{i,2005})$	12.25052	1.670804	8.436417	15.33553	38
$\ln(enrollsec_{i,2000})$	13.56848	1.46994	11.18481	17.07733	38
$\ln(gradter_{i,2000})$	10.07909	1.768304	6.22059	12.9741	38
$\ln(mig_{i,2000})$	16.12146	.0091615	16.08624	16.12761	38
$\ln(migsq_{i,2000})$	28.44693	.015381	28.3757	28.45227	38

Table 8.8: Summary Statistics of Disaggregated Data

Variable		Mean	Std. Dev.	Min	Max	Observations
$\ln(enrollter_{ij,2005})$	overall	10.53382	1.820118	6.267201	14.51328	N = 152
	between		1.678108	7.000904	13.80131	i = 38
	within		.7434586	8.697459	12.47855	j = 4
$\ln(m_{ij,2000})$	overall	-2.915283	1.523155	-6.984723	.8041051	N = 152
	between		1.410879	-6.503418	-.3183147	i = 38
	within		.6074275	-4.724404	-1.103028	j = 4
$\ln(enrollsec_{i,2000})$	overall	13.56848	1.455265	11.18481	17.07733	N = 152
	between		1.46994	11.18481	17.07733	i = 38
	within		0			j = 4
$\ln(gradter_{ij,2000})$	overall	8.35894	1.891693	3.89182	12.13681	N = 152
	between		1.77932	4.647657	11.3883	i = 38
	within		.6895094	6.381148	10.24782	j = 4
$\ln(enrollter_{ij,2000})$	overall	10.16332	1.918792	5.817111	14.26232	N = 152
	between		1.775333	6.519703	13.54683	i = 38
	within		.7697876	7.871765	12.28387	j = 4

Table 8.9: Additional Estimation Results. Dependent Variable: $\ln(enrollter_{ij,2005})$

	Fixed Effects			*Fixed Effects Instrumental Variables*		
	(1)	(2)	(3)	(4)	(5)	(6)
$^{\dagger}\ln(m_{ij,2000})$	-0.453***	-0.515***	-0.558***	-0.118	-0.484	-0.467***
	(0.094)	(0.140)	(0.079)	(0.139)	(0.413)	(0.134)
$\ln(w_{ij,2000})$	-0.057			-0.004		
	(0.209)			(0.241)		
$^{\dagger}[\ln(m_{ij,2000})]^2$		-0.000			-0.038	
		(0.019)			(0.090)	
$^{\dagger}\ln(m_{ij,2000})\times\gamma_{\{\mathrm{EAP}\}}$			0.366***			0.463**
			(0.132)			(0.181)
$^{\dagger}\ln(m_{ij,2000})\times\gamma_{\{\mathrm{EECA}\}}$			-0.057			-0.312
			(0.096)			(0.220)
$^{\dagger}\ln(m_{ij,2000})\times\gamma_{\{\mathrm{LAC}\}}$			0.145			0.265
			(0.169)			(0.412)
$^{\dagger}\ln(m_{ij,2000})\times\gamma_{\{\mathrm{MENA}\}}$			-0.156			-0.061
			(0.114)			(0.208)
$^{\dagger}\ln(m_{ij,2000})\times\gamma_{\{\mathrm{SA}\}}$			-0.039			-0.194
			(0.110)			(0.176)
$\ln(gradter_{ij,2000})$	0.239***	0.186***	0.157***	0.446***	0.345***	0.181
	(0.075)	(0.063)	(0.054)	(0.114)	(0.132)	(0.114)
Field dummies δ_j	Yes	Yes	Yes	Yes	Yes	Yes
Observations	79	152	152	79	152	152
Countries	20	38	38	20	38	38
R^2	0.876	0.867	0.887	0.838	0.847	0.870
†Joint test		22.71	31.33		2.378	7.869
†Joint test p-value		0.000	0.000		0.098	0.000

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Table 8.9 *continued*

	Fixed Effects			*Fixed Effects Instrumental Variables*		
	(1)	(2)	(3)	(4)	(5)	(6)
Kleibergen-Paap Wald F test				32.98	2.854	0.799
Kleibergen-Paap LM test				6.959	8.764	7.967
Kleibergen-Paap LM p-value				0.031	0.033	0.336
Hansen J test				1.712	1.750	4.131
Hansen J test p-value				0.191	0.417	0.659
Endogeneity test				3.422	1.980	7.355
Endogeneity test p-value				0.064	0.372	0.289

*,**,*** denote significance at the 10-%, 5-%, 1-% levels, respectively. Heteroskedasticity-robust standard errors are given in parentheses. In columns (3) and (6), Sub-Saharan Africa (SSA) serves as a reference category. In column (4), $\ln(m_{ij,2000})$ is instrumented with $\ln(mig_{ij,2000})$ and $\ln(sqmig_{ij,2000})$. In column (5), $\ln(m_{ij,2000})$ and $[\ln(m_{ij,2000})]^2$ are instrumented with $\ln(mig_{ij,2000})$, $\ln(sqmig_{ij,2000})$ and the squared instruments. In column (6), $\ln(m_{ij,2000})$ and its interactions are instrumented with $\ln(mig_{ij,2000})$, $\ln(sqmig_{ij,2000})$, and with the interactions of these variables with the set of regional dummies γr. In all IV estimations, small sample corrections are implemented.

CHAPTER 9

Concluding Remarks

This chapter concludes this thesis by summarizing the evidence and answers that the presented research adds to the existing literature that addresses the questions outlined in the introduction. In addition, this chapter outlines possible avenues for future research.

What Determines Migration?

The question of what determines migration has been addressed both from the perspective of individual workers and for aggregate migration flows.

The Role of Occupational Status. Chapters 2 and 3 have studied the desire to reduce disutility associated with unfavorable occupational status as a determinant of an individual's decision to migrate. The underlying intuition is that the migration-induced increase in the "distance" to an individual's familiar social environment decreases the disutility associated with unfavorable occupational status. This motive for migration has been proposed in Fan and Stark (2011) and has been revisited in the theoretical Chapter 2. Chapter 3 has presented an empirical assessment of this motive for migration using individual-level data on internal migration in Germany. The estimation results from this assessment reveal that individuals working in occupations with rather low prestige levels (relative to the prestige associated with their vocational training) have a lower probability to move over a distance of at least 20 kilometers within Germany compared to invididuals working in high-prestige occupations. This result contrasts with the expectation derived from the related theoretical model. As possible explanations of this finding, the existence of particularly high costs of moving or a strong occupational culture for workers in occupations with relatively low prestige have been discussed. The presented estimation results furthermore suggest that an individual's propensity to migrate is positively related to his absolute labor income and his level of schooling, while it is negatively related to his tenure. Dwelling ownership, a long period lived in the current dwelling, satisfaction with one's flat, and frequent meetings with friends and relatives decrease the probability of a move.

In future research it would be interesting to test the prediction of migration that is motivated by unfavorable occupational status with a different dataset or within a different empirical framework. Depending on whether the results obtained with different data were to confirm the negative relationship obtained with the German data and if data availability was appropriate, the analysis could be accompanied by a test of the relevance of the two explanations outlined above. Furthermore, rather than assessing the decision to migrate, one may as well study the relationship between the distance moved and the incidence of unfavorable occupational status.

The Role of Established Migrants. Chapter 5 has assessed the relevance of a cross-national pull effect as a determinant of the scale of aggregate migration flows to Spanish provinces in the period 1996-2006, in addition to a co-national pull effect. The provided evidence suggests that the scale of migration to Spanish provinces from a given origin country depends positively on the number of established migrants from proximate origin countries, as well as on the network of migrants from the same origin country. This finding on the relevance of cross-national pull effects in international migration to Spain complements the existing evidence on network effects in migration, and it thereby adds a further determinant of aggregate migration flows to the literature.

Chapter 6 has studied further heterogeneity inherent in network effects in aggregate migration to Spain. Focusing on the pull effect of co-national migrants on follow-up migration, this chapter has assessed whether the network effect differs across Spanish regions. The estimation results confirm the existence of substantial heterogeneity in the network effect across Spanish regions. According to the considered theoretical model, this finding reflects differences in the degree of substitutability of alternative migration destinations across Spanish regions. The positive coefficient of the network variable is largest for Cataluña, Comunitat Valenciana, and Galicia, suggesting high degrees of cross-alternative substitutability for these regions. An intuition that has been provided for this finding is that each of these regions has a second official language in addition to *castellano*, such that migrants may perceive the provinces in these regions as relatively close substitutes as opposed to the provinces in other Spanish regions.

A worthwhile avenue for future research would be the attempt to disentangle the different channels underlying the revealed network effects in migration. Despite the relatively large array of empirical analyses studying network effects in migration, relatively little is known about how established migrants promote follow-up migration. Potential channels of influence include, e.g., the provision of information, remittances, or ethnic-specific institutions by established migrants to potential followers. A major challenge for any estimation analysis assessing the relative importance of each of these channels is the issue of measurement. The design of adequate survey questions for migrants may therefore constitute a more viable approach.

Who Migrates?

The question of who migrates has been picked up in several chapters of this thesis, which have adopted different foci.

Characterizing Migrants in the Absence of International Wage Differences. The theoretical Chapter 2 has provided a case for the positive selection of migrants in terms of their abilities that is unrelated to international wage differences. It has been shown that in the case in which work in one of two sectors is stigmatized and confers disutility to its workers, the workers with the highest ability levels of the workers employed in this sector will migrate to an identical foreign country. The underlying intuition is that migration reduces the disutility from occupational stigma. Given that migration is costly, however, workers with low ability levels will not find it worthwhile to migrate.

While the subsequent Chapter 3 has empirically assessed this motive for migration, it has not addressed the prediction concerning the selection of migrants in terms of ability. This prediction could thus serve as a starting point for future research. One way to test the selection prediction could be to study the interaction effect between the incidence of occupational stigma (or low occupational prestige) and a worker's skill level in a model for the incidence of migration. According to the theoretical model considered in Chapter 2, this interaction effect should be positive.

Characterizing Migrants to Spain. Chapter 4 has presented stylized facts on migration to Spain in the period 1997-2009 using stock as well as flow data detailed by country of origin and province of destination. These data reveal that the recent Spanish immigration boom was driven by increases both at the intensive and at the extensive margin of migration. The six major origin countries in the considered period were Romania, Morocco, Ecuador, Colombia, Britain, and Bolivia. The dissimilarity in the location choices of these immigrant groups relative to the ones of Spanish nationals as well as their stronger spatial concentration have declined over time.

In addition to assessing the impact of established (co-national) migrants on the scale of recent migration flows to Spain, Chapter 6 has studied the influence of established migrants on the skill composition of migration to Spain in the period 2002-2006. The obtained results reveal a negative effect of the stock of established migrants on the ratio of high-to-low-skilled follow-up migrants from the same origin country. This finding implies that origin countries with large migrant networks in Spain at the beginning of 2002 sent relatively more low-skilled migrants to Spain in the subsequent period compared to origin countries with low migrant networks in Spain at the beginning of 2002. This finding is compatible with the assumptions in the theoretical model that the costs of migration are decreasing in the size of the established migrant network and that low-skilled individuals have higher effective costs of migration than high-skilled individuals.

In future research it could be interesting to exploit the dimensions of age and gender available in the microdata that have been used to construct the migrant flows. In doing so, one might be able to estimate the extent of migration that is related to family reunification, relative to the extent of migration that is primarily driven by economic motives. Also, one could analyze the impact of migrant networks on these two types of migration.

Characterizing South-North Migrants. Chapter 7 has presented descriptive evidence on occupation-specific south-north migration around the year 2000 with a focus on high-skilled migration. This evidence suggests that the incidence of south-north migration was highest among *Professionals*, one of the two occupational categories generally requiring tertiary education, and among *Clerks* and *Legislators, senior officials and managers*. Evidence from more disaggregated data reveals that the probability that a *Professional* in the OECD worked as a *Physical, mathematical and engineering science professional* or as a *Life science and health professional* was significantly larger for a south-north migrant compared to an OECD native. It is exactly these occupational categories that exhibit significantly larger brain drain rates than the occupational category *Teaching professionals*. The employment shares of most types of *Professionals* and *Technicians and associate professionals*, as well as of *Clerks* and *Corporate managers* were significantly smaller in the migrant-sending countries than in the receiving countries.

As data availability improves, the compiled datasets could be complemented with more recent information on the extent of occupation-specific migration. On the one hand, this would allow to study the development of occupation-specific brain drain over time. On the other hand, an extended dataset could be used to further analyze the effects of occupation-specific south-north migration on the migrant-sending countries and thus to extend the analysis presented in Chapter 8.

How Does Migration Impact on the Sending Countries?

The question of how migration impacts on the sending countries has been studied in Chapter 8.

The Effect of Brain Drain on Human Capital. Relying on the same occupation-specific employment data as Chapter 7, Chapter 8 has studied the effect of brain drain on enrollment in tertiary education in the sending countries for four types of human capital. The estimation results suggest a negative effect of the relative incidence of high-skilled emigration on enrollment in tertiary education in the sending countries, thereby rejecting the hypothesis of a brain gain. This finding seems to reflect a trend to reduce investments in human capital in the sending countries in response to the brain drain. Evidence on tertiary enrollment in OECD countries suggests that investments may to some extent be relocated abroad. The negative effect was significantly stronger for *Education* and *Humanities & Social Sciences*, compared to *Science & Engineering* and *Health & Agriculture*. This finding is likely related to a relatively high degree of international transferability of skills associated with the latter types of human capital.

Future work on this topic may revisit the conducted analysis with an extended dataset. Depending on the availability of appropriate data, it would be particularly interesting to consider more disaggregated types of human capital than could be sensibly studied with the data at hand. Furthermore, analyses of how the different types of brain drain impact on growth and other development indicators in the sending countries constitute an interesting avenue for future research.

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