Essays on International Trade and Factor Flows

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Chapter 1

Introduction

This thesis consists of eight self-contained essays on international trade and factor flows. In these essays, I address three topics that center around the following questions: What determines the boundaries of the firm in the global economy? What type of migration can countries expect to receive in the future, depending on their current migration profile? Can the labor market effects of protection explain individual attitudes towards international trade? The topics, though all drawn from the field of international economics, are not significantly related to each other. If one is tempted to identify a common thread running through all topics, one could argue that in all of them optimal (i.e. welfare-maximizing) levels of international trade or factor flows are not achieved (due to market imperfections) or at least in danger of not being achieved (due to trade protection). I shall present brief summaries of all essays in turn.[1]

What determines the boundaries of the firm in the global economy? In the first part of this thesis (CHAPTERS 2, 3, AND 4), I use firm-level data from Spain in order to investigate the boundaries of the firm in the global economy. Roughly one-third of world trade is intra-firm trade (i.e., trade within multinational firms). Its distribution across *countries* and across *sectors* is not random, but responds to some underlying structural features of the economy. Antràs (2003) finds that capital-intensive goods and goods imported from capital-abundant countries are often traded within the boundaries of the firm, whereas labor-intensive goods and goods imported from labor-intensive countries are traded at arm's length (i.e., between independent parties).

In this thesis, I look into the distribution of intra-firm trade across *firms*, and I show that it is systematically related to the productivity of the firm. The Spanish data set that I use

[1] I discuss the specific contributions of all the essays collected in this thesis (and their related literature) more comprehensively in the corresponding chapters.

is exceptionally rich in terms of firms' sourcing activities. It records whether a firm acquires inputs within the firm or at arm's length, and it does so separately for the inputs acquired in the Spanish economy and, if applicable, for the inputs imported from a foreign economy. This allows me to provide novel insights into the behavior of firms in terms of where and how they acquire their inputs in the global economy.

Chapter 2: Sourcing premia with incomplete contracts: Theory and evidence. In this chapter, I provide an in-depth exploration of the Spanish firm-level data. I try to identify regularities in the input sourcing of firms, in order to establish key stylized facts that have so far gone unnoticed in the literature due to lack of data. I document, first, that on average across industries highly productive firms tend to engage in intra-firm sourcing and in foreign sourcing, whereas low productive firms engage in arm's length sourcing and in domestic sourcing; second, that the different sourcing strategies appear to be complementary to one another (rather than mutually exclusive, as often assumed in the theoretical literature on input sourcing); and third, that the more productive firms tend to pursue various sourcing channels simultaneously (for example foreign sourcing in addition to domestic sourcing). The association between intra-firm sourcing and firm productivity found in the Spanish data must be explained by a model that features firm heterogeneity, as in Melitz (2003). Such models have been proposed by Grossman & Helpman (2004) and Antràs & Helpman (2004), to name the most influential papers. I briefly review these models in this chapter, and I spell out—in the most general way possible—the conditions that result in an unambiguous mapping of a firm's productivity into the ownership structure of input sourcing (intra-firm or arm's length).

Chapter 3: Global sourcing and firm selection. The Spanish data set is a panel data set that observes firms over several periods of time. In this chapter, I exploit the time variation in the data in order to address firm selection into sourcing strategies. By this I mean that firms self-select into their sourcing strategy based on their productivity (in the sense that causation runs from productivity to sourcing and not the other way around). The correlations between productivity and sourcing found in Chapter 2 of this thesis could be due to firms self-selecting into their sourcing strategies, or it could be the result of firms becoming more productive subsequent to their sourcing decisions (or both). In this chapter, I report evidence that on average across industries firms that select strategies of intra-firm sourcing and foreign sourcing ex post have been more productive ex ante. This finding supports the notion of firm selection, which is a central ingredient in theoretical models of input sourcing.

Chapter 4: Global sourcing: Towards a firm-level test of the hold-up model. In this chapter, I take a structural approach to the analysis of intra-firm trade in a cross-section of firms. In particular, I look at the Spanish firm-level data through the lens of the Antràs & Helpman (2004) model, the workhorse model of global sourcing under hold-up problems. It features incomplete contracts and relationship-specific investments that lead to a hold-up problem (and a corresponding efficiency loss) in the firm-supplier relationship. Minimization of this efficiency loss commands the firm to acquire property rights over the supplier's input (and thus trade the input within the firm boundaries of control), if the firm's own input in the production of a final good is sufficiently important (i.e., if what is called the "headquarter intensity" is sufficiently large).

I first develop a novel representation of the model that draws upon the modularity properties of the firm's maximum profit function with respect to the key parameters of the model, as in Mrázowá & Neary (2013). These parameters are the firm's productivity; the industry's headquarter intensity; the ex-post distribution of revenue between the firm and the supplier; and the unit cost of sourcing abroad (relative to the unit cost of sourcing domestically). I then use this representation to derive novel firm-level predictions from the model. These predictions point to relevant cross-industry heterogeneity in the effect of productivity on the likelihood of a firm to rely on intra-firm sourcing and on foreign sourcing, respectively. In particular, the headquarter intensity of the industry is supposed to govern the productivity effect in a systematic way, at least for a very large and plausible parameter subspace. This suggests that the positive associations between productivity and intra-firm sourcing as well as foreign sourcing, as described in Chapters 2 and 3, hide important cross-industry variation that has gone unnoticed in existing literature.

I explore this possibility in a series of discrete choice models that I estimate with the Spanish firm-level data. I find, first, that for a given sourcing location the productivity effect on intra-firm sourcing is ambiguous: it is strictly positive in headquarter-intensive industries and strictly negative in all other industries. I find, second, that the productivity effect on foreign sourcing is strictly positive across all industries, while it is the weaker, the larger the headquarter intensity of production. These empirical regularities that I find in all relevant sourcing dimensions of the data are consistent with the predictions of the Antràs & Helpman (2004) model.

What type of migration can countries expect to receive in the future, depending on their current migration profile? In the second part of this thesis (Chapters 5, 6, and 7), I use Spanish migration data to study network externalities in the international migration of people. Network externalities occur when already settled migrants provide help in the migration endeavors of those left behind. This reduces the costs of migration for those left behind, which means that a country's current endowment with migrants will have an impact on the type of migration countries can expect to receive in the future.

I use publicly available administrative migration data from Spain, in order to shed light on this phenomenon in a recent migration boom to Spain. I shall inform about the extremely fascinating period from the mid-1990s up to the rise of the Global Financial Crisis in 2007/08. Within a little more than a decade, Spain received about six million new migrants, and its total population surged from less than 40 million people to more than 45 million people. In the history of humans, there are arguably not many examples of a similarly dramatic influx of people into a country over such a short period of time.

Chapter 5: Facts and figures on a recent migration boom to Spain. This chapter is intended to provide some background information for the more substantial Chapters 6 and 7. It starts with a very brief discussion of the institutional background in Spain. It then provides a short descriptive analysis of the Spanish migration phenomenon. I am interested in the development of the number of migrants over time (gross flows and stocks); migrants' countries of origin as well as their provinces of destination within Spain, and how these have changed through time; and differences in the settlement pattern between migrants and natives, as well as between the major migrant populations themselves. My results uncover some interesting regularities that can inspire future empirical work on migration.

Chapter 6: Networks and selection in international migration to Spain. In this chapter, I provide new evidence on migrant networks as determinants of both the scale and skill composition of migration. In the received literature, migrant networks, defined as the migrants that are already settled in a certain destination, constantly rank among the most important factors shaping migration; see for example Beine et al. (2011). Migrants feel strongly attracted to destinations hosting other migrants that are culturally alike, for example because they receive assistance in finding jobs or housing.

I develop and apply a three-level nested multinomial logit (NMNL) model of migration that accommodates varying degrees of substitutability across alternative destinations. I purport it is easier for migrants to substitute one destination by another one if the two destinations belong to the same country or region, since they will share a common cultural, legal, and economic background. Also, I argue that two destinations belonging to a region with a very high degree of political autonomy (such as Catalonia) will be easier to substitute for one another, because the set of shared rules will be larger for such destinations than for others.

The three-level NMNL model that I propose can account for these features. It belongs to the class of random utility models pioneered by McFadden (1974, 1978, 1984). Through its nesting structure, the model introduces unobserved heterogeneity into the function describing aggregate migration flows, and it suggests estimated coefficients of the migrant network variable to differ across destinations. These are important challenges in the estimation of migration functions based on aggregate data (rather than micro-level data). I estimate the model with the Spanish migration data, and I find strong positive network effects on the scale of migration, as well as a strong negative effect on the ratio of high-skilled to low-skilled migrants. Both types of effects appear to be robust across different estimators, samples, and control variables. I find significant heterogeneity in the estimated network elasticity across regions, a result that would put the use of a simpler random utility framework into doubt.

Chapter 7: Co-national and cross-national pulls in international migration to Spain. In this chapter, I extend the analysis presented in Chapter 6 to allow for a more flexible definition of a migrant network. The received literature typically assumes that the network effect applies to migrants who share the same nationality (or the same country of origin), but is muted across nationalities (or countries of origin). This is a very strong assumption, and I relax this assumption in this chapter. In particular, I expand the perspective of the attraction of a migrant network from co-national migrants to co-national migrants along with migrants from "adjacent" nationalities. For example, I hypothesize that a group of migrants from Ecuador will not only attract further migration from Ecuador, but that it will also attract migration from other Latin American countries. In the estimations based on the Spanish migration data, I find evidence for the network externality to operate across nationalities, both independently and in conjunction with the usual co-national network externality. This opens up an entirely new perspective on the composition of future migration flows in relation to the current stocks of migrants in countries around the globe.

Can the labor market effects of protection explain individual attitudes towards international trade? Individuals hold vastly different opinions about international trade and protection. A recent example is the highly controversial (and highly emotional) debate about the free trade agreement between the United States and the European Union. Policy makers argue the free trade agreement will make both regions better off. This argument is backed by economic theory. Trade economists point out routinely that global economic integration unlocks welfare gains, the so-called gains from trade, through a more efficient use of resources and more products becoming available in both countries. However, economic theory also tells us that the free trade agreement has the potential to benefit some groups at the expense of others (in either country). The gains from trade will not be evenly distributed. This might explain why some people and countries hold more sympathetic views towards free trade than others.

In the third and final part of this thesis, I study whether the labor market effects of protection can explain the sorting of individuals into groups of trade skeptics and free traders. In particular, I relate individual preferences towards international trade and protection to the factor price effects of protection in the neoclassical trade model. For this purpose, I draw on large-scale survey data on public opinion derived from two different sources, namely the 2005 wave of the International Social Survey Program (ISSP) and the 2007 wave of the Pew Global Attitudes Project (GAP). These data are internationally comparable and include a large number of individuals from many different countries.

Chapter 8: Individual attitudes towards trade: Stolper-Samuelson revisited. In this chapter, I draw upon the standard neoclassical trade model with two factors of production and two goods. This model highlights the role of relative factor endowments as a source of comparative advantage. The labor market effects of protection in this model are summarized in the famous Stolper-Samuelson theorem. It states that protection of domestic import-competing industries will hurt (in real terms) the relatively abundant factor, while it will benefit the other factor.

I look into the Pew GAP survey data, in order to see if this logic is reflected in how individuals perceive international trade in a large number of countries across the entire world income distribution. I aim at improving upon an influential paper by Mayda & Rodrik (2005), which does a similar job based on a different survey data source. I advance the literature both methodologically (through a more convincing choice of estimator), as well as in terms of the data employed (broader country coverage and more accurate measures of relative factor endowments). In the model, I distinguish between two factors of production, high-skilled labor and low-skilled labor. I find that high-skilled individuals are substantially more pro-trade than low-skilled individuals in high-skilled labor abundant countries, and vice versa in a considerable share of low-skilled labor abundant countries. This finding strengthens the results found in Mayda & Rodrik (2005) in that they are consistent with the predictions of the neoclassical trade model.

CHAPTER 9: DOES FACTOR ABUNDANCE SHAPE FREE TRADERS? THEORY AND EVIDENCE. In this chapter, I broaden the analysis presented in CHAPTER 8, and I aim at an empirical implementation that is as close as possible to economic theory. As an attempt to embrace the highly segmented nature of modern labor markets, I split labor into many distinct factors of production. Also, I allow for countries to differ in their technology level (i.e., their productivity). I first show how in this general version of the neoclassical trade model (the so-called Heckscher-Ohlin-Vanek model) trade protection produces groups of winners and losers within a country (relative to each other). Whether individuals of a specific skill belong to one or the other group depends on the relative abundance of their skill (i.e., their domestic supply relative to the world supply). I then translate this result into an empirical model of preference formation for individuals of different skill in different countries. Finally, I estimate this model based on the ISSP data set as well as the Pew GAP data set. In either data set, I find that the group of individuals whose skills are relatively abundant hold more positive views towards free trade than other individuals. Importantly, my empirical design allows me to differentiate this effect from other (potentially confounding) effects specific to individuals' labor market skills; see Hainmueller & Hiscox (2006) for a discussion. Hence, my findings provide novel and strong evidence in favor of the neoclassical trade model.

CHAPTER 10: SUMMARY AND OUTLOOK. In the final chapter of this thesis, I provide a very brief summary of selected aspects of my thesis and a short outlook on future research.

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Chapter 2

Sourcing premia with incomplete contracts: Theory and evidence

This chapter is based on joint work with Wilhelm Kohler. It was published as an article in February 2011 in the B.E. Journal of Economic Analysis & Policy (Contributions), 11(1), 1-39.

2.1 Introduction

In OECD countries, the share of intermediate inputs in total trade has steadily increased over the past decades, reaching a level of 56.2 percent for goods trade and 73.2 percent for services trade in 2006. From 1995 to 2006, intermediate goods trade has grown in real terms at an average annual rate of 6.2 percent, while the corresponding figure for both final consumption goods and capital goods is 5.9 percent. Over the same period, real trade in services has increased by 7.0 percent per annum, compared to 6.3 percent for final services.[1]

This chapter sheds light on the global sourcing strategies of Spanish manufacturing firms. Arguably, this is an interesting case to look at. Spain has seen above OECD-average real growth rates for each year from 1997 up to 2008.[2] Starting out from below OECD-average shares of intermediates in total trade, Spain has also experienced strong growth in input trade for both goods and services, to reach levels close to, or even above the OECD-average in 2005. From 1995 to 2005, its average annual volume growth of intermediate input trade was 7.3 percent for goods and 10.7 percent for services, compared to 6.2 percent and 7 percent for the average of OECD countries. By 2006, the share of intermediates in total Spanish imports has

[1] Lanz & Ragoussis (2009).

[2] OECD Economic Outlook 2010, Annex Table 1.

reached values of 0.92 for the primary goods industry, 0.47 for manufacturing, and a value of 0.87 for services, compared to OECD-averages of 0.87, 0.52, and 0.77, respectively.[3]

In this chapter, we use a survey-based data set for the years 2006-2008, in order to highlight the micro-structure of input sourcing in Spanish manufacturing. We take a "high-resolution-perspective" in two dimensions. First, our data set includes firm-level observations on input sourcing. And secondly, we observe a firm's organizational mode of sourcing, in addition to whether it is sourcing domestically or abroad. More specifically, our data distinguish between a contractual relationship with an independent supplier (outsourcing), and sourcing from a related party (vertical integration). We provide an in-depth exploration of firms' global sourcing decisions and investigate the link between performance and sourcing behavior, covering both the organizational and the location dimension.

The theoretical literature stresses the importance of a firm's level of productivity, not just for the global reach of its operations, but also for the organizational form of its sourcing activities. This literature focuses on various forms of contractual imperfections that arise from input specificity, which often follows from product differentiation of final goods, a hallmark of modern trade theory. The pioneering contributions are Antràs (2003), Grossman & Helpman (2004), and Antràs & Helpman (2004). These and other models of input sourcing differ in the details of what is contractible as well as the organizational forms assumed available, but they share a common implication: Production relationships are not brought to their full economic potentials because of inefficient levels and composition of inputs. Inefficiency derives from distorted incentives of input providers, due to holdup or agency problems, and the choice of a specific organizational form aims at reducing this inefficiency. Although we do not dwell on normative implications in this chapter, it is worth pointing out that these inefficiencies have recently sparked interest also in new trade policy issues and a new rationale for trade agreements; see Antràs & Staiger (2012). In this chapter, our focus lies on the relationship between firms' productivity levels and their choice of sourcing strategies. In Section 2.2, we set the stage for our subsequent empirical analysis through a comparative review of existing models that deal with the productivity-sourcing nexus, with special emphasis on incomplete contracts.[4]

Our empirical analysis comes in two steps. In Section 2.3 we first portray a stylized picture of sourcing heterogeneity among Spanish manufacturing firms, as observed in 2006-2008. In doing so, we highlight a number of patterns that, in our view, have so far not received sufficient attention in the literature. We slice our data set along several dimensions, including

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[3] Lanz & Ragoussis (2009), Tables 7 and 11.

[4] For extensive surveys, see Spencer (2005) and Helpman (2006).

the number of sourcing strategies simultaneously pursued by any one firm. More specifically, we explore the relative frequencies of different types of pure and combined strategies regarding the location and organizational form of input sourcing, as well as their prevalence among small and large, or exporting and non-exporting firms. In addition, we investigate the pattern of interdependence between four principle sourcing strategies by estimating the "probabilities" that a firm pursues any one strategy of input sourcing, say vertical integration, conditional on pursuing others.

The second step of our empirical analysis is inspired by the literature on so-called "exporter premia", which was pioneered in the 1990s by Andrew Bernard and others and which has subsequently lead to the development of theoretical models of trade that feature firm heterogeneity, most notably by Melitz (2003). A stylized fact brought to light by this literature is that in many countries and industries the bulk of exports is concentrated among relatively few firms that are typically larger and more productive than non-exporting firms. Bernard et al. (2007) report similar patterns also for US imports, but overall, empirical research on firm heterogeneity on the import side is somewhat scant, compared to exports. In Section 2.4 of this chapter, we contribute to this literature by providing econometric estimates of performance premia on different strategies of input sourcing. We shall henceforth speak of "sourcing premia", and we shall cover both the location as well as the organizational form of input sourcing.

Empirical knowledge of sourcing premia is important for two reasons. First, the presence of such sourcing premia indicates the general empirical relevance of the above mentioned strand of literature, even though, as we shall argue, they cannot per se be interpreted as lending support to any one specific model, and even though we cannot establish the direction of causality. And secondly, sourcing premia point to aggregate productivity effects through firm selection. In particular, changes in the quality of the contractual environment or the costs of operating certain organizational forms, domestically and abroad, will change the aggregate productivity of an industry, by complete analogy to the selection effects of trade and FDI in Melitz (2003) and Helpman et al. (2004). The empirical pattern of sourcing premia should thus give an indication also for the pattern of such selection-based productivity effects.

However, empirical estimation of sourcing premia turns out to be less straightforward than perhaps expected. We need a flexible econometric framework that allows us to estimate premia with respect to both the location and the organizational dimension of sourcing in a unified way. An important aspect of the empirical landscape is that firms tend to pursue multiple strategies of input sourcing. This negates a straightforward mapping of firms into a unique sourcing channel, thus complicating the estimation of sourcing premia. We develop a two-tier framework that also allows us to deal with this situation. Tier one aims at sourcing premia on single strategies in a way comparable to the traditional exporter premia. Tier two exploits information on multiple strategies in estimating marginal effects that derive from adding further sourcing channels to a given sourcing strategy. In our estimations, we apply labor productivity and total factor productivity (TFP) as measures of firm performance. TFP is calculated through firm-specific residuals from econometric estimations of industry-specific production functions.

In the empirical section, this chapter is related to a number of papers that have also explored the productivity-sourcing nexus. Tomiura (2007) provides evidence on the relationship between foreign sourcing and the productivity level of Japanese firms, based on a 1998 survey. He finds that firms which engage in foreign sourcing tend to be more productive, but he does not formally estimate sourcing premia in a multi-sourcing context, as we do in this chapter. In addition, his analysis does not cover different organizational modes of domestic sourcing. Fariñas et al. (2010) show that the productivity distribution of offshoring firms dominates that of non-offshoring firms at first order. The authors refer to the same Spanish data source as we do, but for the years 1990-2002. For this early period, however, the data do not allow distinguishing firms' organizational modes of sourcing, which lies at the heart of recent innovations in trade theory and our empirical analysis. Defever & Toubal (2013) aim at a test of the Antràs & Helpman (2004, 2008) model by evaluating the explanatory potential of firm-level productivity for the cross-firm variation in organizational modes of foreign sourcing, based on French firm-level data for 1999. As we shall explain in Section 2.2, our purpose here is not to test any specific model of sourcing. Instead, we pursue on "open search" for sourcing premia. The study that comes closest to what we do in our empirical section is Federico (2010) who estimates sourcing premia in a cross-section of Italian firms in 1997. In this chapter, we explore a much more recent unbalanced panel of firms, which seems important in an area where so much change has occurred in recent years. And it seems of particular relevance in the present case, since the Spanish economy has experienced above average dynamics in intermediate inputs trade over the past decade, as we have argued above.

2.2 Theory of sourcing under input specificity

Product differentiation often affords market power, as stressed in modern trade theory, but in most cases it comes with the need to secure provision of *specific* inputs, tailored to the features of the differentiated final good. The detailed nature of the input required and the legal and institutional environment determine available contractual forms of input procurement. Very often, complete contracts for production and delivery of inputs with idiosyncratic specifications cannot be written. Typically, firms face a discrete choice between a limited number of organizational forms. Theoretical models of input sourcing mostly assume two forms that go by the names of *vertical integration*, or intra-firm provision, and *outsourcing*, or arms-length provision through an independent supplier. Loosely speaking, in these models vertical integration features an advantage of greater control of the final goods producer over input provision. But in one form or another, this comes at the expense of impairing the incentive for the other party to put up effort and investment in securing the necessary quality or quantity of the input. Therefore, if incentivizing the other party is sufficiently important, an outsourcing relationship may be more advantageous for the final goods producer, even though it implies a partial loss of control.

Under certain conditions the choice between vertical integration and outsourcing may be influenced by a firm's productivity level. Generally, we may conceive *maximum* profits Π as a function of a firm's productivity level θ as well as other characteristics of production, such as the prices of various types of inputs and their importance for production. For simplicity, we assume the contribution of these characteristics to be one-dimensional and measured through a continuous variable Q. The key point then is that the profit function is specific to the organizational form of sourcing, for reasons following below. We may write maximum profits as $\Pi_\Omega = \Pi_\Omega(\theta, Q)$, where $\Omega = V, O$ indicates the organizational mode, i.e., vertical integration or outsourcing.[5] Without loss of generality, we assume that both θ and Q are non-negative and parametric to the firm. A sufficient condition for a firm's productivity level to play no role for its choice of the organizational form is

$$[\Pi_V(\theta, Q) - \Pi_O(\theta, Q)][\Pi_{V\theta}(\theta, Q) - \Pi_{O\theta}(\theta, Q)] > 0 \tag{2.1}$$

for all θ- and Q-values that satisfy $\Pi_\Omega(\theta, Q) > 0$, where we use a subscript to denote partial derivatives. If vertical integration delivers a profit advantage for the minimum level of productivity required to make a profit at all, then inequality (2.1) states that this advantage gets reinforced if the productivity level increases. And accordingly if the profit advantage lies with outsourcing.

If this condition is violated, then each of the two organizational forms may be advantageous only for certain sub-ranges of the productivity level. In turn, these sub-ranges remain

[5]The notion of *maximum* profits implies that the firm (credibly) anticipates choosing profit-maximizing production levels etc., given its choice of organizational form.

unaffected by production characteristics other than productivity if

$$[\Pi_V(\theta, Q) - \Pi_O(\theta, Q)][\Pi_{VQ}(\theta, Q) - \Pi_{OQ}(\theta, Q)] > 0 \tag{2.2}$$

Obviously, this inequality follows the same logic as inequality (2.1), but with respect to changes in the production characteristic Q instead of the productivity level θ.

Why might these conditions be violated? A possible reason is highlighted in Grossman & Helpman (2004) who model sourcing of inputs in a *principle-agent framework*. They assume that in an outsourcing (arms-length) relationship the principal (firm) cannot monitor the agent's (input provider's) efforts to ensure satisfactory quality of inputs. In contrast, vertical integration facilitates monitoring and contractibility of effort for a subset of the tasks required. The outcome of the relationship is binary in nature. If the input is of sufficient quality, then total revenue is determined by the firm's productivity level, otherwise it is zero. The likelihood of sufficient quality depends on the agent's effort level. An outsourcing contract features a success-contingent payment serving as a "high-powered" incentive, in addition to an unconditional payment (restricted to non-negative values) that secures participation. With integration, the contract specifies a wage, to be paid conditional on contracted effort for the sub-range of tasks where monitoring is possible, alongside a success-contingent bonus payment that serves as a "high-powered" incentive for non-monitored tasks.

Integration appears advantageous because of contractibility of at least some tasks, but it also means that the firm must bear the cost of material inputs directly, whereas with outsourcing these inputs are acquired by the supplier, and the firm pays for the cost indirectly through the participation constraint. Expected profits are equal to expected revenue, net of effort-related as well as unconditional payments that secure participation of the agent, and – with integration – net of material input costs, which are given independently of a firm's productivity.

Importantly, Grossman & Helpman (2004) assume that the marginal return of effort in terms of a higher success probability is diminishing. For the firm, this implies an increasing marginal cost of eliciting effort from the agent through the "high-powered" incentive. It also implies that the agent is able to extract a rent from the contractual relationship. The higher the productivity of the firm, the more it pays to elicit high effort from the agent. But high effort implies high rent sharing. Intuitively, then, the fact that outsourcing allows to shift the (fixed) input cost to the supplier becomes increasingly attractive to the firm as its productivity increases. It is a vehicle to retard rent sharing.

In terms of the above notation, if integration seems more attractive because of contractibility of at least some of the tasks, i.e., $\Pi_V(\theta, Q) > \Pi_O(\theta, Q)$, for high productivity levels we may observe $\Pi_{V\theta}(\theta, Q) < \Pi_{O\theta}(\theta, Q)$, eventually leading to $\Pi_V(\theta, Q) < \Pi_O(\theta, Q)$ for very high productivity levels. Conversely, for a sufficiently low initial level of productivity, shifting the materials cost onto the supplier may be useful for a different reason: It is a useful "high-powered" incentive vehicle when, due to low productivity, the optimal effort level, and thus the rent to be extracted, is small. For low enough productivity values, we may therefore observe $\Pi_V(\theta, Q) < \Pi_O(\theta, Q)$ coupled with $\Pi_{V\theta}(\theta, Q) > \Pi_{O\theta}(\theta, Q)$. Thus, the above condition is violated and the productivity level becomes an important determinant in the organizational choice.

Given the dominance of outsourcing for low, as well as for high productivity levels, the question is whether the key advantage of integration, viz. observability and contractibility of some tasks, will ever become large enough to render integration a superior form of sourcing. Grossman & Helpman (2004) show that under certain conditions, particularly if the share of tasks for which integration permits contractibility is large enough, this is true for intermediate levels of productivity. Figure 2.1 borrows from Grossman & Helpman (2004) in depicting maximum expected profits (solid lines) for alternative productivity-levels and organizational forms of sourcing.[6]

<<Figure 2.1 about here>>

In very influential papers, Antràs (2003) and Antràs & Helpman (2004) tell a different story of why productivity might be important for organizational choice. They focus on a *holdup-problem* that arises from a concurrence of incomplete contracts and relationship-specificity of inputs. Production of final goods requires two essential inputs: a headquarter service provided by the final goods producer herself, and an intermediate input provided by a second party. Both inputs have zero value outside the production relationship, and lack of contractibility pits the two parties against each other in ex post negotiation about revenue sharing. Revenue from the production relationship derives from selling the final good in a market with monopolistic competition. Since neither party may expect to fully appropriate the marginal revenue of her input, both inputs will be provided in less than optimal amounts. Moreover, production will also suffer from a distorted input mix. A clever choice of the organizational form will minimize the loss due to this inefficiency.

Available organizational forms differ in terms of the outside option in the bargaining process. Following the property rights literature, Antràs & Helpman (2004) define integration

[6]The piecewise linear profit-line for outsourcing reflects a two-step piecewise linearity of the concave relationship between individual effort and the probability of successful completion of the final good.

as affording residual claims on the input, should bargaining break down. With this outside option, the expected revenue share accruing to the final goods producer (input supplier) is higher (lower) with vertical integration than with outsourcing. However, vertical integration tends to erode the incentive for the non-headquarter input, hence it does not clearly dominate the outsourcing strategy. If the input is sufficiently important, the final goods producer will find outsourcing to be a more profitable sourcing strategy. In terms of the above notation, if we identify Q as the intensity of the production relationship in the headquarter input, then for low values of Q we have $\Pi_V(\theta, Q) < \Pi_O(\theta, Q)$ with $\Pi_{VQ}(\theta, Q) > \Pi_{OQ}(\theta, Q)$, which will eventually lead to $\Pi_V(\theta, Q) > \Pi_O(\theta, Q)$ for high enough values of Q. We cannot, therefore, expect an *unambiguous* relationship between a firm's productivity level and its organizational form of input sourcing.

However, for a given value of Q the incentive implications of the two organizational forms will either favor outsourcing or integration. In Antràs & Helpman (2004), the productivity level of the firm then acts as an unambiguous leverage for this incentive advantage: $\partial|\Pi_V(\theta, Q) - \Pi_O(\theta, Q)|/\partial\theta$. But it is the expected profit, not the incentive advantage alone, that determines the organizational form. Assuming, plausibly, that there are fixed costs of running the production relationship and that these costs are specific to the organizational form then renders a decisive influence of productivity. For instance, if $\Pi_{V\theta}(\theta, Q) > \Pi_{O\theta}(\theta, Q)$ and if vertical integration entails a higher fixed cost, then the firm needs a sufficient leverage from a high level of productivity for the incentive advantage to choose vertical integration.

In this model, the leverage property of θ implies linear profit lines for either organizational form, as opposed to the strictly convex line for outsourcing in Grossman & Helpman (2004). Figure 2.1 anchors the comparison of the two models through a common profit line $\Pi_V(\theta, Q)$ and a dashed profit line $\Pi'_O(\theta, Q)$ for outsourcing, as emerging in Antràs & Helpman (2004). This latter framework assumes unavoidable organizational fixed costs for both of the two forms, whereas in Grossman & Helpman (2004) outsourcing avoids all fixed cost by shifting upfront purchasing of materials to the agent. Hence, in Antràs & Helpman (2004) there exists a unique cut-off level θ_b which separates outsourcing from integration, whereas the principle-agent framework has outsourcing "reappear" as an optimal form of sourcing for high-enough productivity levels larger than θ_d.[7]

It is now relatively straightforward to envisage an extension of these models to include a foreign source of input provision. It seems plausible that some (or all) of the structural details that govern the choice of vertical integration or outsourcing in the above frameworks are different for foreign sourcing (offshoring) compared to domestic sourcing. For instance,

[7] There also exists a threshold level for positive profits.

in the Grossman & Helpman (2004) framework, the range of monitored tasks, the cost of material inputs and the outside option of partners may all be lower abroad than in the domestic economy. In the Antràs & Helpman (2004) framework, the fixed cost of operating the two alternative modes of sourcing, as well as the cost of the input as such, may be different for foreign compared to domestic sourcing.[8] The same may apply for the residual claims afforded by vertical integration, or the range of contractible inputs in the generalized framework presented in Antràs & Helpman (2008). It is relatively obvious that superimposing an "offshoring equivalent" to the above organizational choice generates a richer pattern of sourcing strategies, with associated ranges of productivity levels.

Even with this extension, however, a profit-maximizing firm with a given productivity level would see no reason for pursuing multiple modes of sourcing. This contrasts with casual observation, and we shall see below that multiple-mode sourcing strategies are quite common also among Spanish firms. On a very general level, some explanatory candidates seem straightforward. For instance, a risk-averse principal may want to hedge against the risk associated with the cost of materials inputs. She may also consider running multiple-mode strategies to build up a fallback position so as to enhance her outside option for the bargaining in any one of the organizational modes. For reasons of space, we abstain from any detailed theoretical reasoning for the occurrence of multiple-mode sourcing, but we shall return to this issue in our empirical section below.[9]

While it is thus clear why a firm's productivity level should have an influence on organizational choice, it is also obvious that available models do not permit a clear-cut and *unconditional* prediction on the ranking of organizational forms in terms of the firm's productivity level.[10] The predictions vary across models, as witnessed by Figure 2.1, and even within a given model the ranking depends on a host of variables, many of which are difficult, if not impossible, to observe. In the next sections, we turn to a micro-level empirical analysis of input sourcing strategies pursued by Spanish manufacturing firms. Although our analysis cannot purport to test any specific model of input sourcing, it will nonetheless reveal informative insights into the Spanish case, and it should give us a general impression of the empirical relevance of recent literature on global sourcing which stresses the role of a firm's

[8]In view of the Spanish case, we want to stress that in a multi-factor context the foreign cost advantage may well lie with *comparatively* cheap high-skilled labor. Moreover, it may also have to do with the search process for suppliers of suitably specified inputs, whence issues of market thickness and country size may play a role; see Grossman & Helpman (2005).

[9]For a model focusing on the fallback position, see Du et al. (2009). We deliberately abstain from calling such multi-mode sourcing a *complex sourcing* strategy, so as to avoid confusion with the term *complex integration* strategy as used in the literature on multinational firms; see Grossman et al. (2006).

[10]Feenstra & Hanson (2005) present a holdup-model of inputs trade akin to the models portrayed above, but without any explicit role for productivity levels to influence the organizational form of sourcing.

productivity level for organizational choice.

2.3 Stylized facts of input sourcing

Before turning to an econometric analysis of sourcing premia, we want to highlight the specific advantages of our data as well as some important stylized facts pertaining to Spanish firms' input sourcing. This section provides a comprehensive picture of Spanish firms' sourcing behavior, including several new features that should inspire refinement of existing and development of new theoretical models of input sourcing.

2.3.1 Data description

The data come from the *"Encuesta Sobre Estrategias Empresariales"* (ESEE)[11], an annual survey of Spanish manufacturing firms carried out by the SEPI Foundation, Madrid.[12] The survey generates an unbalanced panel of some 4,600 legal entities with information on firms' strategies of input sourcing, as well as revenue and balance sheet statistics, covering the years 2000-2008. The SEPI Foundation applies a complex random sampling procedure, sending out survey questionnaires[13] to *all* firms with more than 200 employees, and to a *subset* of firms with 200 or less but more than 10 employees. This subset is selected according to a stratified sampling scheme, in which each combination of a single industry (out of a total of 20 industries, each formed by a group of products at NACE-1993 level)[14] and a single size group (out of four)[15] is fixed as a distinct and independent stratum in advance, giving rise to a total of 80 strata. This way of sampling guarantees that we can establish representativeness of the data for different industries (at distinct points in time) and the manufacturing sector at large. Importantly, the SEPI Foundation preserves these highly desirable sample properties over time by controlling for the dynamics in the panel due to market entry and exit.[16] In both, the descriptive data exploration and the econometric analysis, we always use the sampling information in order to obtain consistent and efficient estimates, and to draw conclusions

[11] "Survey on Business Strategies".

[12] "Sociedad Estatal de Participaciones Industriales". The SEPI Foundation promotes research and study opportunities in Spain. For more information, see `http://www.funep.es`.

[13] The SEPI Foundation uses an extended questionnaire every four years and a reduced annual questionnaire for the years in between.

[14] See Table A.1 in Appendix A for a comprehensive list of industries.

[15] Size groups are (i) between 10 and 20 employees, (ii) between 21 and 50 employees, (iii) between 51 and 100 employees, and (iv) between 101 and 200 employees.

[16] For more information on this procedure, see `http://www.funep.es/esee/en/einfo_que_es.asp`.

about the Spanish manufacturing industry as a whole.[17]

The key advantage of our data is that from 2006 onwards they fully cover both, the location and the organization dimension of firms' sourcing decisions. To avoid ambiguity as to the precise meaning of the various organizational modes, we list the questions to which firms were responding in the questionnaire.[18]

- Of the total amount of purchases of goods and services that you incorporate (transform) in the production process, indicate according to the type of supplier the percentage which these represent in the total amount of purchases of your firm in [year].

    1. Spanish suppliers which belong to your group of companies or which participate in your firm's joint capital. [yes/no] / [if yes, then percentage rate]
    2. Other suppliers located in Spain. [yes/no] / [if yes, then percentage rate]

- For the year [year], indicate whether you imported goods and services that you incorporate (transform) in the production process, and the percentage which these imports – according to the type of supplier – represent in the total value of your imports. [yes/no]

    1. From suppliers which belong to your group of companies and/or from foreign firms which participate in your firm's joint capital. [yes/no] / [if yes, then percentage rate]
    2. From other foreign firms. [yes/no] / [if yes, then percentage rate]

Since the survey also includes information on the total amount of purchases as well as the total value of imports for each observation, we can compute – for each firm and each year (2006,2007,2008) – the extent to which intermediate inputs were acquired from a related or an unrelated party, respectively, in the home and in a foreign economy. Note that the framing of the above questions defines an input supplier as a *different legal entity* (either related or unrelated to the firm). In turn, inputs are defined such that the good in question is *transformed in the production process*.[19] In what follows, we distinguish among four

[17]Specifically, we weight each observation by the inverse of its probability of being sampled, using size-group-specific information on the total number of firms in a given NACE-1993 industry (provided by the Social Security Directorate through the SEPI Foundation) and the representation of each size group in the sample.

[18]The original survey questions are given in Spanish. The original questionnaires are downloadable at `http://www.funep.es/esee/sp/svariables/indice.asp`.

[19]The sourcing information obtained from this survey does not refer to single, well-defined transactions of firms. Hence, we cannot trace a firm's acquisition of a certain input at a specific point in time back to a particular sourcing mode. What we observe are the pure extensive and intensive margins of firms (with a

sourcing options: foreign integration (FI), foreign outsourcing (FO), domestic integration (DI), and domestic outsourcing (DO). Coherent coverage of all sourcing modes generates a comprehensive picture of global sourcing behavior that goes well beyond existing studies which are mostly restricted to a subset of sourcing strategies. The precise way in which we exploit the sourcing information contained in the data will become evident below.

An important further improvement made possible by our data relates to the strategic relationship between headquarter firms and affiliated firms. Earlier studies typically lack information on which party occupies the parental status and, thus, has complete discretion over the strategic decision of interest; see, for example, Federico (2010) and Nunn & Trefler (2008). Models of global sourcing typically do not consider situations in which the input supplier has a controlling stake in a producer's joint capital and may therefore manipulate the sourcing decision to her own advantage. In our data, all firms are categorized by the extent to which other companies participate in a firm's joint capital. Hence, we can construct a unique subsample of *true* headquarter firms, which helps us circumvent this entire issue in a straightforward way. A related question has to do with the distinction between firms and establishments or plants. Note that our survey collects data at the level of the firm (a unique legal entity), whereby about five out of six firms in the sample operate by means of a single establishment only. Naturally, a single firm/legal entity may well be part of a group of companies, but the data always refer to a single firm's sourcing strategy and balance sheet statements, instead of consolidated information for conglomerates.

2.3.2 Stylized facts

In what follows, we want to establish what we believe to be important stylized facts that may be drawn from our data set. We slice our data in the sourcing dimensions (domestic vs. foreign and outsourcing vs. integration), and we draw lines between small and large firms, as well as exporting and non-exporting firms. As we have emphasized above, the survey underlying our data provides for firms to report multiple sourcing strategies. We exploit this by looking at sourcing strategies in two different ways. First, we identify all possible strategies spanned by our two-by-two dimension of sourcing. This gives rise to the distinction between single-mode-and-location strategies, denoted in a self-explanatory way by FI, FO, DI and DO, and combined strategies where firms pursue more than one mode or location of sourcing. Overall, there are 15 different strategies that may arise, with a one-to-one mapping

potentially large number of different products, inputs, and/or sourcing markets), not product-country-firm combinations. As a consequence, our econometric analysis cannot exploit information on firms' sourcing markets other than the distinction between the home and a foreign economy.

of firms into strategies, as in Table 2.1. The second approach simply asks about the number of times any one of our four principle combinations of sourcing mode and location arises, irrespective of whether it is observed as a single-mode-and-location strategy, or as part of a combined strategy. With this approach, followed in Table 2.2, each firm is potentially observed more than once.

<<Tables 2.1 and 2.2 about here>>

The first question we want to ask is how likely small and large firms are to pursue pure outsourcing modes, meaning that they acquire intermediates exclusively from unrelated parties. Conversely, how likely are they to entirely abstain from independent suppliers (vertical integration)? Summing up percentages for DO, FO and $DOFO$ (and correspondingly for DI, FI and $DIFI$), we summarize the following observation.

Stylized fact 1. *Pure outsourcing strategies are relatively common, while pure integration is a very rare phenomenon. This pattern is largely independent of firm size.*[20]

How likely are firms to pursue combined strategies that involve two or more combinations of organizational mode and location of sourcing? Comparing columns (1) through (4) and (5) through (15), the answer may be stated as

Stylized fact 2. *Combined strategies are almost as prevalent as single organization and location strategies, whereby large firms and exporting firms, respectively, are more likely to pursue multiple ways of sourcing than are small and non-exporting firms.*

The most common example of multiple sourcing is a combination of domestic and foreign outsourcing ($DOFO$). One might be tempted to explain multiple ways of sourcing by the presence of multi-product firms maintaining multiple contractual relationships with various suppliers. Our data allow us to examine this explanation, and we find contrary evidence. For instance, 85 percent of firms in the 2008 sample report production of a "single good" (using the 3 digit NACE-1993 product level). And of these single-product firms, almost one-half are engaged in multiple ways of sourcing.

Counting our four principle ways of sourcing independently of whether or not they appear in multi-mode or multi-location strategies, Table 2.2 reveals that provision of inputs from independent domestic suppliers looms large in the sourcing modes, appearing in more than 90 percent of all reporting firms. In contrast, foreign outsourcing is reserved to a minority

[20]Note that the percentages of Tables 2.1 and 2.2 relating to all firms weight the number of firms in each size class by the inverse probability of being sampled, based on the size distribution of all Spanish firms.

(37 percent) of all firms. However, Spanish manufacturing firms' overall engagement in international sourcing is still quite pronounced, if compared to other developed countries. For example, Tomiura (2007) reports that only five percent of Japan's manufacturing firms in 1998 are engaged in foreign sourcing, whether through offshore outsourcing, vertical FDI, or both.[21] This remarkable difference reflects the strong economic integration in Europe, and we provide further support for this statement later in this section.

Vertical integration is significantly less prevalent among Spanish firms. To the extent present, it is more likely to be found for domestic input provision than for offshoring. Moreover, there are huge differences between small and large firms. More than a third (fourth) of large firms purchase intermediates through vertical integration at home (abroad), with percentages that are larger by the factor four (seven) than those for small firms. Almost two thirds of large firms do offshore outsourcing, with percentages almost twice as high as those for small firms. These differences between small and large firms are reduced somewhat once we drop small non-exporting firms from the sample. Indeed, the smallest share of firms engaging in international sourcing can be found among small firms with purely domestic sales. However, the ranking of the relative importance of each of the four sourcing categories is preserved across size and export status groups. We may summarize these findings as

Stylized fact 3. *Domestic sourcing is significantly more common than foreign sourcing, independently of the organizational form of sourcing. Outsourcing is significantly more common than integration, independently of the location choice. And large as well as exporting firms are much more likely to pursue strategies of offshoring and vertical integration than are small and non-exporting firms.*

Although of a purely descriptive nature, Stylized fact 3 is a hint towards a fixed cost ranking of global sourcing strategies, if interpreted against models of global sourcing such as those presented in Section 2.2. Since, arguably, fixed costs should constitute an especially high hurdle for smaller firms, our data point towards an ordering that satisfies $f_V^l > f_O^l$ and $f_\Omega^F > f_\Omega^D$, $\ell \in \{F, D\}$, where f represents fixed costs and superscripts F and D refer to the foreign and the domestic economy, respectively. The type of ranking is essential for deriving predictions from any model of global sourcing that allows for firm heterogeneity.

Table 2.2 brings up a further interesting feature of our data worth discussing: It refers to firms that we classify as "non-sourcing". These are firms that do not report acquiring any intermediate inputs from a different legal entity. Such firms appear as pursuing a particularly

[21] We should add a caveat in that the data in Tomiura (2007) do not impose any threshold value on firm size, while the Spanish data do not include manufacturing firms with less than ten employees.

deep vertical integration strategy in the home economy, incorporating all steps of the production chain into a single legal entity. For our purpose, the question arises as to whether we should treat such firms on the same footing as firms that follow domestic integration in input provision. For example, such firms might seem as having full discretion over all decisions related to provision of inputs, which would in turn rule out any kind of hold-up problem. However, we argue that such non-sourcing firms should still be regarded as pursuing domestic integration, as long as the economic nature of the production relationship (and thus the strategic game) between headquarter and supplier is not affected by whether or not the legal system treats the supplier as a different legal entity.[22] We shall return to this point in our econometric analysis below.

What is the likelihood that a firm pursues foreign integration, conditional upon also including foreign outsourcing among its sourcing modes, compared to the unconditional probability of choosing vertical integration? This question can be asked for all four principle sourcing modes, leading to a whole matrix of unconditional and conditional probabilities. To answer these questions, we estimate a multivariate probit model, regressing all relevant indicator variables for sourcing strategies on year dummies, and using the Geweke-Hajivassiliou-Keane (GHK) simulator to evaluate higher-order integrals of the multivariate normal distribution; see Cappellari & Jenkins (2003) for details on this estimation. We do so separately for each firm size group, and we subsequently calculate unconditional and conditional probabilities, based on estimated correlations of the residuals across equations (and thus sourcing categories). Table 2.3 summarizes the essential results, averaging out the estimates across the years 2006, 2007, and 2008.[23] A first message from this table is that, with the sole exception domestic outsourcing, the probability is higher for large firms than for small firms for any sourcing channel.

<<Table 2.3 about here>>

More interestingly, a row-wise comparison of the numbers presented in Table 2.3 suggests a significant degree of interdependence between sourcing strategies. For instance, the probability of a large (small) firm pursuing foreign integration increases from 27 (4) percent to

[22]Still, this interpretation is challenged by the question of why, after all, we should then observe this kind of heterogeneity of different legal regimes between headquarters and suppliers in the data. This concern is strengthened by the fact that it does not appear to follow a random distribution: 0.7 percent of small firms report a single domestic integration sourcing strategy, whereas as much as about 5 percent report no sourcing at all.

[23]In the interest of clarity, we abstain from presenting all estimated conditional probabilities of being active in a specific sourcing mode. Instead, we show each estimated "success probability", conditional on the firm also using the mode indicated in the row or column label as a further sourcing mode. This gives rise to the two 4×4 matrices for large and small firms presented in Table 2.3.

36 (9) percent, if this firm outsources internationally, and to 32 (12) percent if it integrates domestically. Similarly, the probability of offshore outsourcing and domestic integration, conditional on foreign integration, is higher than the corresponding unconditional probability. This basic pattern is independent on firm size. However, what does depend on firm size is the relationship between the foreign outsourcing and the domestic integration group. For small firms, there is a positive correlation between the two modes, while for large firms this is not the case. We summarize this as

Stylized fact 4. *There is a strong interdependence between all sourcing strategies other than domestic outsourcing. In particular, there is positive correlation between the probabilities of (i) vertically integrating a foreign supplier (ii) outsourcing internationally, and (iii) vertically integrating domestically.*

Theoretical accounts of global sourcing tend to characterize firms' offshoring decisions in a set-up in which final-good producers in high-cost North may relocate part of their production chain to low-cost South. Against this backdrop, we examine the breakdown of total imports (including imported inputs) of each firm according to four regions of origin: European Union (EU), Latin America, other OECD countries (excluding EU countries and Latin America), and the rest of the world (ROW; excluding EU countries, countries in Latin America, and other OECD countries).[24]

<<Table 2.4 about here>>

Table 2.4 compares the regional distribution of aggregate Spanish imports of the manufacturing sector with that of the Spanish economy as a whole. What we can learn from this is, in our view, a major qualification of the common understanding of offshoring as a phenomenon involving relocation of input production from high wage to low wage countries. Indeed, from each Euro-equivalent imported by the Spanish manufacturing industry in 2006, 75 cents came from a member state of the European Union.[25] Of the overall value of imports in that year, less than six percent originate in low wage countries such as the Czech Republic, Estonia, Hungary, Lithuania, Latvia, Poland, Slovenia, and Slovakia, while the top five source countries are Germany (22 percent), France (20), Italy (13), United Kingdom (8), and

[24] In 2006, roughly 60 percent of Spanish manufacturing imports are classified as inputs *incorporated (transformed) in the production process.*

[25] To make sure that this figure is not overstated due to imports of final goods, we restrict the sample to firms for which the total value of imports is equal to the total value of imports of intermediate inputs. Then, the share of the value of imports from the European Union in the overall value of imports is even higher (83 percent); see Table 2.4.

the Netherlands (6). Generally speaking, high technology EU-countries seem to matter more for input provision in the manufacturing sector than for supply of finals and inputs in the Spanish economy at large. We summarize

Stylized fact 5. *Offshoring in Spain mainly takes place by means of importing intermediate inputs from high wage countries in the European Union.*

<<Table 2.5 about here>>

In Table 2.5 we again differentiate between large and small firms and their imports from different world regions, independently of the amount of imports. First, we see that more than 90 percent of importing firms source from member states of the European Union, with a much smaller fraction of goods and services coming from elsewhere. This observation reinforces our above statements. Second, a significantly higher share of large firms than of small firms imports from Latin American countries (12 versus 6 percent), other OECD countries (42 vs. 20 percent), and countries of the rest of the world (42 vs. 27 percent). Third, large firms are more likely to import simultaneously from two, three, or all four world regions than small firms. We can draw similar conclusions from distinguishing small exporters from small non-exporters. We thus have

Stylized fact 6. *Virtually all importers source from EU countries. Large firms and exporting firms have well above-average probabilities of (i) acquiring intermediate inputs from distant, non EU countries and (ii) spreading their sourcing activities among a large number of import regions.*

2.4 Estimating sourcing premia

In this section, we turn to an econometric analysis of the relationship between a firm's productivity level and its sourcing behavior. Following the literature on exporter premia, we estimate sourcing premia.[26] By this we mean differences in estimated means of productivity across firms, conditional on how and where a firm obtains its inputs. Such premia are suggested by the models of input sourcing that we have briefly reviewed in Section 2.2 above. According to these models, vertical integration and outsourcing entail different incentive patterns in sourcing relationships that are plagued by incomplete contracts. In turn, under

[26]Our approach borrows from Bernard & Jensen (1999) who focus on exporter status of a firm. The methodology has also been applied in a refined way by Helpman et al. (2004) who distinguish between multinational and non-multinational exporters.

plausible conditions a firm's productivity level is an important determinant of whether one or the other organizational form of sourcing (incentive pattern) is more attractive in terms of expected profits. We should thus expect to observe a systematic pattern of productivity differences between firms that pursue different sourcing strategies.

However, as emphasized in Section 2.2, the precise pattern of sourcing premia depends on several characteristics that we do not observe, such as organizational fixed cost. Hence, the subsequent econometric analysis should not be interpreted as an empirical test of any one model of input sourcing. Nor do we intend to establish causality running from a firm's sourcing behavior to its productivity level. Rather, we examine whether our Spanish data for 2006-2008 lend empirical support to the general idea of within-industry firm heterogeneity in productivity and sourcing. More specifically, our econometric results reveal the detailed pattern of correlation, if any, between Spanish firms' productivity levels and their global sourcing decisions, consistently covering both, the location and the organization dimension of sourcing.

2.4.1 Measures of firm productivity

We must first clarify how to measure firm productivity in our subsequent regression analysis. Our first measure is labor productivity, computed as the log of real value added over the hours effectively worked. Real value added is defined as production plus other operating income net of total outlays for intermediate inputs and external services, everything expressed in prices of the year 2000. As an alternative measure, we compute a firm's level of total factor productivity (TFP) relative to the industry average, relying on estimation of sector-specific production functions. Taking advantage of several convenient features of our data, we apply the Olley & Pakes (1996) three-step estimation algorithm in order control for the estimation biases originating in endogenous selection into markets (selection bias) and simultaneous choice of input factors (simultaneity bias).

We feed the Olley & Pakes (1996) estimation routine with the ESEE firm-level data from 2000-2008, using year-specific information on each firm's real value added, real investment, real capital stock, labor employment, and exit decisions. Real value added is defined as above. Real investment is the value of investment (in Euros) in real estate, construction, and equipment. The real capital stock is the value (in Euros) of real estate, constructions, and equipment, net of depreciation. Labor employment enters the production function in terms of effective work hours, which reduces the probability of non-stochastic measurement errors. Exit decisions are well documented in the Spanish data, so that we can differentiate between firms shutting down production, i.e., market exit, and mere panel exit.

For deflation of production and other operating income, we use firm-level variations in goods prices as reported by the ESEE. For years in which a firm is not sampled, we use an industry-level price index from the Spanish National Statistics Institute (INE). Relying on a firm-specific goods price index is important for at least three reasons. First, if firms have market power (say due to product differentiation) and if firm-specific mark-ups behave differently over time, then the use of industry price indexes results in a correlation between the input choices and the error term. Second, if unobserved firm-specific demand shocks cause price fluctuations, then estimation based on industry-level deflation would lead to inconsistent estimates; see Klette & Griliches (1996) and De Loecker (2007). The same holds true, thirdly, if different firms within the same industry (say exporters versus non-exporters) face different market structures; see De Loecker (2007). For deflation of variables other than real value added, we use industry-level price indexes from the Spanish INE.

2.4.2 Econometric specifications

We apply a simple unified econometric framework in which we regress firm productivity on up to four binary variables which fully describe a firm's sourcing strategy. In much of the theoretical literature on global sourcing, firms face a discrete choice of intermediate input production according to which the unique profit-maximizing strategy is *either* foreign integration (FI), *or* foreign outsourcing (FO), *or* domestic integration (DI), *or* domestic outsourcing (DO). We operationalize this concept by computing "sourcing dummies" in a *mutually exclusive* way. If a firm is active in two or more sourcing modes simultaneously, we assign it to the category which is the least prevalent one in the overall sample.[27] Technically speaking, when observing multiple sourcing strategies, we apply a strict *"sourcing hierarchy"* that states $FI > DI > FO > DO$. As a robustness check, we have applied an alternative hierarchy, viz. $FI > FO > DI > DO$. This requires that we re-label four percent of firms in the weighted sample. We comment briefly on relevant similarities and differences in the text. Detailed results for this alternative case are available from the authors upon request. All of this implies that, for the time being, we ignore the empirical fact that some firms do combine different sourcing channels at a given point in time. We do so deliberately, however, so as to mimic the theoretical case of pure sourcing strategies. We turn to a more differentiated approach geared towards multiple sourcing strategies below.

[27]The prevalence of sourcing strategies in the data is found in the final column of Table 2.2 above. Thus, since FI is the least prevalent of all strategies, any firm pursuing FI is treated as an FI-firm, regardless of whether it relies on FI alone or as part of a more complex strategy. Analogously for all other strategies.

Formally, we estimate the following panel model.

$$\theta_{it} = \beta_0 + \beta_1 FI_{it} + \beta_2 FO_{it} + \beta_3 DI_{it} + \beta_4 Age_{it} + \beta_5 Export_{it} + \gamma_j + \gamma_t + \mu_{it}, \tag{2.3}$$

where θ_{it} is firm i's productivity level at time t, FI_{it}, FO_{it}, DI_{it} are mutually exclusive sourcing dummies as explained above, Age_{it} is the age of the firm, $Export_{it}$ is a dummy variable that controls for a firm's exporter status, γ_j is an industry fixed effect, γ_t is a year fixed effect, and $\mu_{it} = c_i + \epsilon_{it}$ is a composite error term including an unobserved firm-effect c_i and an idiosyncratic error ϵ_{it}.

Since our sample spans several industries, we need to control for industry-specific determinants of a firm's performance by including industry dummies. We do so in all regressions. The exporter status appears in our set of regressors in order to capture the traditional exporter premium; see Bernard et al. (2007). This reduces the probability of observing spurious positive correlation between foreign sourcing modes and performance measures. This could happen, for instance, if firms obtain access to new information through exporting, and if that information reduces the fixed cost of offshoring. We shall return to this below when comparing results obtained upon including and excluding exporter status in the estimated equation.

Finally, we also follow the empirical literature on productivity premia in that we control for a firm's age, and by including year dummies which isolate our estimates from any year-specific productivity shocks that equally affect all Spanish manufacturing firms in the sample.

Equation (2.3) describes a model in which domestic-outsourcing firms ($FI_{it} = FO_{it} = DI_{it} = 0$) serve as the baseline category against which all potential performance premia need to be interpreted. To give an example, the premium (in percent) of foreign-integration firms relative to domestic-outsourcing firms is equal to $\lambda_{DO}^{FI} = 100 \times [\exp(\beta_1) - 1]$. Thus, an estimated coefficient of $\beta_1 = 0.5$ means that, other things equal, foreign-integration firms are roughly 65 percent more productive than domestic-outsourcing firms.

With mutually exclusive sourcing dummies, we see three plausible ways of dealing with what we have classified as "non-sourcing" firms before. The first is to argue that these firms are acquiring all inputs in the home economy without reverting to independent suppliers and to treat them on an equal footing with domestic-integration firms. The second way simply drops "non-sourcing" firms from the estimation sample, given that they do not acquire any inputs from a party that would be considered a legal entity in our sample. A third possibility is to treat them as an entirely distinct group of firms which serves as the baseline category in estimating sourcing premia. For this last case, the regression model (2.3) turns into

$$\theta_{it} = \beta_0 + \beta_1 FI_{it} + \beta_2 FO_{it} + \beta_3 DI_{it} + \beta_4 DO_{it} + \beta_5 Age_{it} + \beta_6 Export_{it} + \gamma_j + \gamma_t + \mu_{it}, \quad (2.4)$$

where DO_{it} is an indicator variable for domestic outsourcing, again based on mutually exclusive coding. Here, we only report estimates for the first type of coding and comment on what seem to be interesting differences in the text; see Tables 2.6 and 2.7. The regression results for the alternative firm codings can be found in Appendix B.

Mutually exclusive coding has the advantage of being in line with the theoretical models reviewed in Section 2.2. However, it does not fully exploit all information contained in the data. In the previous section, we have therefore suggested broaden the analysis by alternatively constructing our sourcing indicators in what we call mutually inclusive coding; see Tables 2.8 and 2.9. To see the difference, consider a firm that engages in both vertical FDI and offshore outsourcing, but not in domestic sourcing. With mutually inclusive coding, the dummies FI and FO both take on a value of one, and the dummies for DI and DO a value of zero. In comparison with the more restrictive coding structure that satisfies mutual exclusion, this opens up an entirely new perspective on sourcing premia. It uncovers marginal effects from adding a new specific location and/or organizational form to the firm's existing sourcing activities. With mutually inclusive sourcing dummies, non-sourcing firms form the baseline group throughout all regressions, as in equation (2.4).[28]

We conduct the entire empirical analysis twice, relying on two types of samples. The first is restricted to true headquarter firms, meaning that we exclude a firm if some other company owns more than 50 percent of the firm's capital and/or if the firm is subject to foreign ownership.[29] Restricting the sample along this dimension seems important in the present context, since we would otherwise risk including firms whose sourcing strategies are in fact dictated by their parental companies. The presence of such firms in the sample is a potentially troubling source of estimation bias that, to the best of our knowledge, has not been addressed rigorously in existing empirical studies. We regard the possibility to avoid this bias as a key advantage of our data set. Since this comes at the expense of a lower number of observations, we also run all regressions on the unrestricted sample.[30] It turns out

[28]Re-labeling or excluding non-sourcing firms in this estimation would not allow for a unique baseline category.

[29]The threshold value of control is not decisive. For example, in 2008 we exclude roughly 30 percent of the total number of firms ($N = 1,976$). Reducing the threshold value to 25 percent would eliminate only a slightly larger number of firms but leave any of our results unchanged.

[30]Restricting the sample along the ownership dimension also significantly decreases the share of large firms in the sample.

that the restriction matters less for estimation outcomes than we have expected. A possible explanation is that the bulk of firms which are subject to external ownership still have full control over their very sourcing decisions. We report estimation results for both the restricted and the unrestricted sample in the text.

We implement three routines for estimating sourcing premia. The first simply pools the data and applies ordinary least squares (OLS). This estimator yields consistent estimates as long as there is no systematic contemporaneous correlation between the composite error term and the explanatory variables. Second, we explicitly treat the data as a panel and account for unobserved heterogeneity across firms by estimating a population-averaged model (PA). This model allows incorporating different correlation structures for the error term but is asymptotically equivalent to the random-effects model if estimated with an equal-correlation linear regression estimator.[31] Provided that all explanatory variables are (i) independent from the firm-specific fixed effect c_i and (ii) strictly exogenous, conditional on c_i, the model delivers consistent and efficient estimates. Lastly, we allow for correlation between the realization of each sourcing dummy of firm i at time t and time-varying firm unobservables c_{it} at time t by adopting a simple instrumental variables (IV) approach whereby each sourcing dummy is instrumented by its lagged value.

We deliberately abstain from estimating a fixed-effects panel model in which we could get rid of the constant firm-effect c_i. In a world with two sourcing strategies, a fixed-effects estimator would no doubt lead to well identified parameter estimates that may be interpreted as indicating the presence of a sourcing premium. However, with multiple sourcing strategies, fixed effects estimation runs into a problem of interpretation with respect to the indicator variables for sourcing strategies. A given change in such a variable, say a firm dropping out of the foreign integration category, no longer has a clear-cut interpretation. It obtains economic meaning only if we know the category it drops into. As a result, fixed-effects parameter estimates do not lend themselves to ready conclusions about sourcing premia in the same way as estimates based on "between-variation" do. Therefore, our focus squarely lies on between-, not within-variation in our data.

2.4.3 Regression results for mutually exclusive sourcing dummies

Table 2.6 presents the first set of results with mutually exclusive sourcing dummies and with non-sourcing firms coded as domestic-integration firms. The estimation sample is restricted to true headquarter firms. A first observation is that in virtually all regressions all three

[31] We report regression results with this estimator below but have also experimented with an autoregressive correlation structure for the panels. The results are available from the authors upon request.

sourcing dummies (FI, FO, DI) are positively and significantly correlated with both firm productivity measures. We conclude that, on average, firms which pursue a plain outsourcing strategy in the home economy (baseline category) exhibit the lowest level of labor and total factor productivity.

<<Table 2.6 about here>>

More importantly, however, we recognize a robust ranking of coefficients for sourcing dummies: Throughout almost all regressions, coefficients for FI are largest and those for DI are lowest. Loosely speaking, firms which rely on foreign affiliates in organizing intermediate input production abroad perform better than all other firms in terms of productivity. At the same time, firms engaging in offshore outsourcing are doing better than firms sourcing from related parties in the domestic economy. Interestingly, this general pattern does not depend on the productivity measure, the estimator, or the exporter status of a firm.

What is especially sensitive to a firm's exporter status, however, is the magnitude of the foreign sourcing premium, as we would expect. To give an example, column (7), which employs total factor productivity as the dependent variable and does not control for exporter status, tells us that foreign-integration (foreign-outsourcing) firms are 60 (30) percent more productive than domestic-outsourcing firms. Column (8) suggests that controlling for whether or not the firm is an exporter reduces both premia by about 30 percent.

By contrast, controlling for exporter status reduces the estimated sourcing premium for domestic-integration firms relative to domestic outsourcers by a mere point from 14 to 13 percent.[32] Relatedly, in the majority of cases the exporter premium is highly significant and larger than that of domestic-integration firms, but comparable in size to the average of the premia for foreign-integration and foreign-outsourcing firms, ranging from 15 to 23 percent for the two productivity measures.[33]

In Table 2.6, the second panel from below reports p-values for two-tailed tests of equality across sourcing dummy coefficients. Dropping the exporter dummy as a regressor, we find that in the majority of cases the differences among sourcing premia are statistically significant

[32] We checked whether controlling for a firm's age is responsible for these changes, and we found it is not.

[33] As a robustness check, we have also employed firm-size in terms of the number of employees as a measure of firm performance. Recent trade theory on firm heterogeneity (Melitz, 2003) stipulates perfect correlation between firm size and firm productivity. Estimated sourcing premia with this alternative measure (not reported) are larger than those obtained with labor and total factor productivity. We find that foreign-integration firms are on average almost five times as large as firms which outsource domestically. Analogously, foreign-outsourcing (domestic-integration) firms are more than 60 (30) percent larger than domestic outsourcers. This finding complements the result established in Bernard & Jensen (1999) that the employment premium of exporters (in percent) is larger than the corresponding TFP premium, and it is in line with the results reported in Federico (2010).

at the ten percent confidence level. Yet, controlling for exporter status typically increases the corresponding p-values, so that we often fail to reject the null hypothesis of equal values across sourcing dummy coefficients. Looking at the OLS estimates of TFP premia, however, we still find significant performance differentials among all types of firms, even after segregating these differentials from the exporter premium. The IV approach comes with a sizable loss of precision in estimation and thus makes it difficult to establish differences among sourcing dummies at reasonable levels of confidence. More importantly, however, even our IV regressions leave the ranking of estimated sourcing dummy coefficients unchanged.

The results for the same regression exercise, but with the alternative sourcing hierarchy (not reported: $FI > FO > DI > DO$) are very similar, with a single exception. The sourcing premia of firms engaging in domestic integration are significantly reduced while those of firms labeled as pursuing foreign outsourcing are slightly increased. This renders the ranking of sourcing dummy coefficients even more distinct than before, with mode-wise productivity differentials significant at the ten percent confidence level in the overwhelming majority of regressions. We interpret this as an indication that firms which combine strategies of foreign outsourcing and domestic integration perform better than those which use either of the two sourcing channels alone.

Table 2.7 reports regression results obtained by imposing the original sourcing hierarchy ($FI > DI > FO > DO$) but employing the unrestricted estimation sample which includes both headquarter and non-headquarter firms. Most of our previous qualitative and quantitative observations survive or become even stronger, given that the precision with which coefficients are estimated increases with the sample size. An exception is the relative ranking of estimated coefficients for the foreign-outsourcing and domestic-integration categories. In particular, point estimates of the coefficient on DI are significantly larger than before, exceeding those for FO in several specifications. This finding is consistent with empirical evidence reported by Federico (2010), who cannot identify true headquarter status in his sample of Italian manufacturing firms.

<<Table 2.7 about here>>

Similar and instructive changes in estimated coefficients are also obtained by excluding non-sourcing firms from the estimation sample; see Tables B.1 and B.3 in Appendix B. These results suggest relevant productivity differentials even between "true" domestic-integration firms and non-sourcing firms. The fact that non-sourcing firms, which are included again in Tables B.2 and B.4 in Appendix B as the baseline category, appear to be no more productive than domestic-outsourcing firms is additional support for this interpretation. Indeed, our results suggest robust productivity premia relative to non-sourcing firms for all categories other than domestic outsourcing. Comparing sourcing premia from these regressions across performance measures, and evaluating the significance of potential differences in these premia across sourcing modes, we find that "true" domestic-integration firms and foreign-outsourcing firms are comparable to each other in labor productivity and TFP. Similar conclusions can be drawn from regressions in which we impose the alternative sourcing hierarchy.

To conclude this subsection, our point estimates of sourcing dummy coefficients with mutually exclusive coding feature a general pattern of productivity differentials according to which foreign-integration firms perform best and domestic-outsourcing firms perform worst, while foreign-outsourcing and domestic-integration firms exhibit intermediate performance levels both in terms of labor and total factor productivity. This result is independent of the estimation sample, sourcing hierarchy, and the way in which we deal with non-sourcing firms. Thus, for a given sourcing location (organizational form), there is a productivity premium for integrating (offshoring) over outsourcing (non-offshoring) firms.

2.4.4 Regression results for mutually inclusive sourcing dummies

In this subsection we explicitly address the large incidence of combined sourcing strategies, i.e., firms that source inputs from both locations and/or through both organizational forms. Such firms are quite common in our data, and we now capture this feature by coding sourcing dummies in a mutually inclusive way. We argue that this opens up a new perspective, allowing us to extract further information from our data set.

Tables 2.8 and 2.9 reveal the importance of distinguishing between the two types of coding structures. We recognize significant correlation between firm productivity and the various sourcing indicators. The coefficient of the FI dummy lacks significance in some specifications, but this only reflects the small number of single-mode foreign-integration firms in the restricted sample. We find reassuring evidence for this statement from regressions with the unrestricted sample, where we obtain similar point estimates and reject the null hypothesis of a zero FI-coefficient at the ten percent confidence level in virtually all specifications; see Table 2.9.

More importantly, however, our estimates in Tables 2.8 and 2.9 no longer suggest a robust ranking of sourcing dummy coefficients, although the evidence still detects "pure" domestic outsourcers and non-sourcing firms as the least productive firms in the entire Spanish manufacturing industry. Among the other types of firms, we do not find any productivity differentials that are robustly significant at the ten percent confidence level. This last finding leads us to the conclusion that, strictly speaking, any sourcing category contributes equally to a firm's productivity premium, relative to single mode domestic outsourcers and non-sourcing firms. For each additional sourcing channel, the performance premium rises by roughly 15 percentage points.

<<Tables 2.8 and 2.9 about here>>

Foreign-integration firms thus appear to be performing exceptionally well with mutually exclusive sourcing dummies, because they simultaneously combine various sourcing channels more often than any other type of firm in the sample; see also Table 2.1. That said, from unreported regressions in which we use firm-employment as a measure of firm performance, we find comparatively large and significant size differentials between firms which outsource in a foreign economy and those which adopt strategies of integrating input production into the firm boundaries at home and abroad, even after controlling for exporter status. There, the ranking of sourcing dummy coefficients that we have found using the earlier approach, i.e., $FI > DI > FO > DO$, is largely reproduced. Again, this is consistent with Federico (2010). Indeed, these differentials are even more significant in our estimates with the unrestricted sample.

Naturally, the appearance of multi-mode and multi-location sourcing strategies at the level of the individual firm goes unattended with aggregate data on intra-firm trade and offshoring. Yet, it points to the need for further refinements to theory, so that it may explain the incidence of such sourcing behavior at the micro-level and contribute to the understanding of its implications for the aggregate economy. It would be interesting to explore in more detail the dynamics of how firms develop their sourcing behavior over their lifecycles. Indeed, our data show that firm performance is positively correlated with the degree to which a firm combines organizational modes and locations when organizing its intermediate input production. However, with the short period of time for which the data were available at the time this chapter was written, a more extensive empirical investigation of this phenomenon is not within reach of this chapter.

2.5 Final remarks

What have we learned from this analysis? First, we find pronounced heterogeneity among Spanish manufacturing firms in terms of where and how they source their inputs of goods and services. Heterogeneity is not random, but has conspicuous patterns. A phenomenon that we have been able to describe in detail, but has so far not received much attention in theory, is firms' tendency to pursue sourcing strategies that combine domestic and offshore supply of inputs as well as different organizational forms of sourcing, viz. arms-length relationships and vertical integration. We find that firms seldom rely on vertically integrated input supply as their only form of sourcing. Conversely, strategies that avoid integrating input suppliers altogether are relatively common. In a similar vein, strategies that include offshoring are far less common than strategies that rely entirely on domestic sourcing. In turn, combined sourcing strategies are particularly common among exporting and large firms. We also observe a characteristic pattern of interdependence across modes and locations of sourcing. Specifically, once a firm takes up any mode or location beyond pure domestic outsourcing, it also becomes more likely to pursue any of the remaining combinations of sourcing channels.

A second major lesson that we learn from our empirical analysis is that there are significant performance premia on certain sourcing strategies over others. Theoretical models lead us to expect such premia, reflecting firms' sourcing decisions in an environment of incomplete contracts. Most models would predict that under plausible conditions there should be premia on offshore sourcing as well as sourcing through vertical integration, relative to domestic arms-length sourcing. By and large, the sourcing premia that we estimate on micro-level data for Spanish manufacturing firms corroborate this view. Although we are careful to point out that this finding should not be interpreted as a test of any specific model of global input sourcing, it is still reassuring to find a robust picture of such premia. Conditional means of productivity levels are generally largest (lowest) for firms pursuing foreign integration (domestic outsourcing). This ranking generally survives controlling for the exporter status of firms. Moreover, estimated premia are larger if defined in terms of employment than in terms of labor or total factor productivity. For productivity, we find premia on foreign integration and foreign outsourcing in the vicinity of 60 percent or 30 percent, respectively.

A third empirical lesson relates to marginal effects of increasing the number of sourcing channels. Utilizing information on single firms pursuing multiple combinations of sourcing channels, as available in our firm-level data set, we find that such marginal effects are quite pervasive. Starting out with a zero premium of domestic outsourcing, relative to a baseline category of non-sourcing firms, adding any further combination of sourcing channels increases this premium by about 15 percentage points. This is a sizable effect, and it is quite robust. However, beyond this we do not find a clear ranking of premia associated with any specific combination of sourcing channels. This points to a premium on the number of utilized sourcing channels as such. Available theoretical models of input sourcing are unable to explain such marginal effects. Indeed, they imply that a given firm would always find a single dominating channel of sourcing.

Where to move from here? We see a theoretical and an empirical challenge. We are convinced and, indeed, we present some empirical evidence that the picture of multiple sourcing strategies is not simply an artifact of aggregation over products and transactions. The pervasiveness of sourcing strategies that combine several sourcing channels, as well as the evidence of marginal effects on performance premia, calls for a corresponding refinement of theoretical models. On the empirical side, the challenge is to construct micro-level data sets and develop suitable empirical frameworks that would permit a proper test of, and statistical discrimination between, specific models of input sourcing under incomplete contracts.

Figures and tables

Figure 2.1. Maximum profits for different sourcing regimes

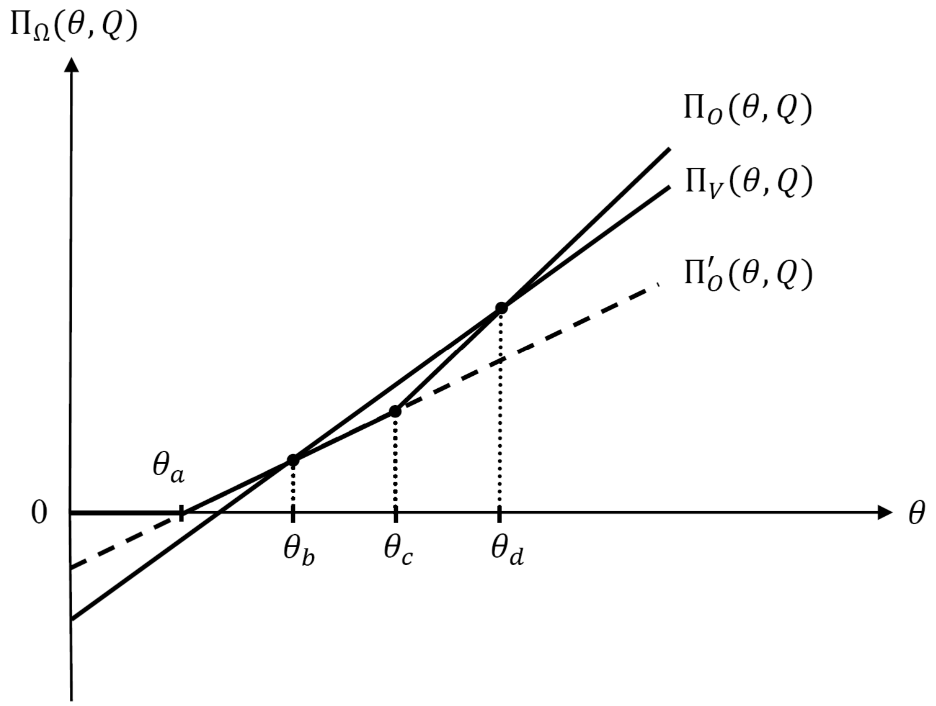

Table 2.1. Spanish manufacturing firms' sourcing strategies in 2008

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Large Firms (> 200 Employees)														
DO	*DI*	*FO*	*FI*	*DODI*	*DOFO*	*DOFI*	*DODIFO*	*DODIFI*	*DOFOFI*	*DIFO*	*DIFI*	*DIFOFI*	*FOFI*	*DODIFOFI*
95	8	13	2	52	131	8	68	6	74	3	1	2	4	49
18.0	1.5	2.5	0.4	9.8	24.8	1.5	12.9	1.1	14.0	0.6	0.2	0.4	0.8	9.3
Small Firms (< 201 Employees)														
DO	*DI*	*FO*	*FI*	*DODI*	*DOFO*	*DOFI*	*DODIFO*	*DODIFI*	*DOFOFI*	*DIFO*	*DIFI*	*DIFOFI*	*FOFI*	*DODIFOFI*
793	10	19	0	38	401	7	51	1	33	2	0	0	3	15
54.9	0.7	1.3	0.0	2.6	27.8	0.5	3.5	0.1	2.3	0.1	0.0	0.0	0.2	1.0
Exporting Firms Among Small Firms														
DO	*DI*	*FO*	*FI*	*DODI*	*DOFO*	*DOFI*	*DODIFO*	*DODIFI*	*DOFOFI*	*DIFO*	*DIFI*	*DIFOFI*	*FOFI*	*DODIFOFI*
307	3	16	0	22	304	7	39	1	32	2	0	0	3	15
39.3	0.4	2.0	0.0	2.8	38.9	0.9	5.0	0.1	4.3	0.3	0.0	0.0	0.4	1.9
Non-Exporting Firms Among Small Firms														
DO	*DI*	*FO*	*FI*	*DODI*	*DOFO*	*DOFI*	*DODIFO*	*DODIFI*	*DOFOFI*	*DIFO*	*DIFI*	*DIFOFI*	*FOFI*	*DODIFOFI*
485	7	3	0	16	96	0	12	0	1	0	0	0	0	0
73.3	1.1	0.5	0.0	2.4	14.5	0.0	1.8	0.0	0.2	0.0	0.0	0.0	0.0	0.0
All Firms (Weighted)														
DO	*DI*	*FO*	*FI*	*DODI*	*DOFO*	*DOFI*	*DODIFO*	*DODIFI*	*DOFOFI*	*DIFO*	*DIFI*	*DIFOFI*	*FOFI*	*DODIFOFI*
53.8	0.7	1.3	0.0	2.8	27.7	0.5	3.8	0.1	2.6	0.2	0.0	0.0	0.2	1.3

Note: In each panel of the table the second and third rows give the numbers and the percentages of firms in the various sourcing categories, respectively. All percentages are of the total number of firms in the respective size or export status category in the 2008 sample (N=529 for large firms, N=1,445 for small firms, N=781 for small exporting firms, N=662 for small non-exporting firms; two small firms do not report export status). We represent foreign integration (FI), foreign outsourcing (FO), domestic integration (DI), and domestic outsourcing (DO), as well as all combinations thereof. Percentages in the last row have been obtained after weighting the number of firms in each size category by the inverse of the probability of being sampled, given the size distribution of all Spanish firms. Percentage points in each row do not sum up to 100 percent due to non-sourcing firms.

Table 2.2. Spanish manufacturing firms in mutually inclusive sourcing categories in 2008

	Large Firms		*Small Firms*		*Small Exporters*		*Small Non-Exporters*		*All Firms (Weighted)*
	Number	*in %*	*Number*	*in %*	*Number*	*in %*	*Number*	*in %*	*in %*
Domestic Outsourcing	483	91.3	1,339	92.7	727	93.1	610	92.1	92.6
Domestic Integration	189	35.7	117	8.1	82	10.5	35	5.3	8.9
Foreign Outsourcing	344	65.0	524	36.3	411	52.6	112	16.9	37.1
Foreign Integration	146	27.6	59	4.1	58	7.4	1	0.2	4.7
Non-Sourcing	13	2.5	72	5.0	30	3.8	42	6.3	4.9

Note: With mutually inclusive strategies, a single firm may show up in more than one sourcing category. All percentages are of the total number of firms in the respective size or export status category in the 2008 sample (N=529 for large firms, N=1,445 for small firms, N=781 for small exporting firms, N=662 for small non-exporting firms; two small firms do not report export status). Large firms have more than 200 employees. We obtain percentages in the last column after weighting the number of firms in each size category by the inverse of the probability of being sampled.

Table 2.3. Estimated probabilities of the use of sourcing channels (2006-2008)

	Foreign Integration		*Foreign Outsourcing*		*Domestic Integration*		*Domestic Outsourcing*	
Foreign Integration	**26.9**	**3.7**	35.8	9.0	31.5	12.1	27.3	3.8
Foreign Outsourcing	86.4	82.1	**64.8**	**34.3**	64.2	49.8	66.6	35.5
Domestic Integration	41.1	28.1	34.7	12.6	**35.0**	**8.7**	35.3	8.5
Domestic Outsourcing	92.5	94.2	93.5	95.7	91.8	90.1	**91.0**	**92.4**

Note: The table gives estimated probabilities of being active in each of the four sourcing modes, averaged across years. In each cell of the above 4×4 matrix, the first number refers to large firms (> 200 employees) and the second number to small firms (< 201 employees). The numbers are percentage rates and give the estimated probabilities that a randomly selected firm (within firm size groups) is active in the sourcing modes indicated in rows, conditional on being active in the sourcing modes indicated in columns. All numbers on the leading diagonal (in bold letters) represent unconditional estimated success probabilities.

Table 2.4. Regional distribution of aggregate Spanish import values in 2006

	Manufacturing Sector	*All Sectors*
European Union	75 (83)	44
Latin America	3 (3)	5
OECD Rest	11 (6)	11
Rest of the World	10 (7)	40

Note: All numbers represent percentage rates. Data for the manufacturing sector come from the ESEE, data for all sectors come from the Spanish National Statistics Institute (Instituto Nacional de Estadística de España). We obtain the numbers in parentheses by exclusively considering firms for which the total value of imports is equal to the total value of imports of intermediate inputs. There are almost no differences between large and small firms in terms of the regional distribution of aggregate import values, which is why we do not report them separately here.

Table 2.5. Import characteristics of Spanish manufacturing firms in 2006

	Large Firms		*Small Firms*		*Small Exporters*		*Small Non-Exporters*		*All Firms (Weighted)*
	Number	*in %*	*Number*	*in %*	*Number*	*in %*	*Number*	*in %*	*in %*
Import Region									
European Union	469	95.7	671	90.4	502	91.4	169	86.7	90.7
Latin America	59	12.0	44	5.9	36	6.6	8	4.1	6.2
OECD Rest	206	42.0	148	20.0	121	22.0	27	13.8	21.0
Rest of the World	204	41.6	202	27.2	177	32.2	26	13.3	27.9
# of Import Regions									
1	169	34.5	444	59.8	302	55.0	144	73.9	58.6
2	201	41.0	205	27.6	172	31.3	33	16.9	28.3
3	79	16.1	54	7.3	50	9.1	4	2.1	7.7
4	41	8.4	39	5.3	25	4.6	14	7.2	5.4
Total Number of Importers	490	92.5	742	51.4	549	74.6	195	27.6	52.57

Note: Overall numbers of large and small firms in the 2006 sample equal 530 and 1,443, respectively. Large firms have more than 200 employees. Overall numbers of small exporters and small non-exporters equal 736 and 707, respectively. All percentage numbers except those in the last row are relative to importing firms in the respective size and export status group. All percentage numbers in the last row are relative to all firms in the respective size and export status group.

Table 2.6. Sourcing premia with mutually exclusive hierarchical sourcing dummies ($FI > DI > FO > DO$) (true headquarter firms, 2006-2008)†

	Baseline Category: Domestic-Outsourcing Firms; Non-Sourcing Firms Coded as Domestic-Integration Firms (DI)											
	Dependent Variable: Labor Productivity						*Dependent Variable: Total Factor Productivity*					
	OLS		PA		IV		OLS		PA		IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
<u>*Sourcing Dummies*</u>												
FI	0.432^{A}	0.280^{B}	0.316^{A}	0.236^{B}	0.364	0.134	0.472^{A}	0.343^{A}	0.274^{A}	0.228^{B}	0.571^{B}	0.389
	(0.121)	(0.118)	(0.116)	(0.109)	(0.271)	(0.254)	(0.130)	(0.125)	(0.096)	(0.092)	(0.279)	(0.253)
FO	0.239^{A}	0.150^{A}	0.159^{A}	0.103^{A}	0.326^{A}	0.221^{A}	0.273^{A}	0.198^{A}	0.121^{A}	0.088^{A}	0.373^{A}	0.292^{A}
	(0.021)	(0.022)	(0.024)	(0.024)	(0.043)	(0.047)	(0.022)	(0.023)	(0.022)	(0.022)	(0.049)	(0.053)
DI	0.147^{A}	0.134^{A}	0.092^{A}	0.083^{B}	0.190^{B}	0.182^{B}	0.132^{A}	0.121^{A}	0.063^{C}	0.057	0.148	0.143
	(0.036)	(0.035)	(0.036)	(0.035)	(0.092)	(0.088)	(0.038)	(0.037)	(0.037)	(0.037)	(0.107)	(0.105)
<u>*Other Variables*</u>												
Age		0.004^{A}		0.005^{A}		0.004^{A}		0.004^{A}		0.004^{A}		0.003^{A}
		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)
$Export$		0.211^{A}		0.202^{A}		0.185^{A}		0.185^{A}		0.163^{A}		0.144^{A}
		(0.021)		(0.026)		(0.032)		(0.022)		(0.027)		(0.037)
Constant	2.831^{A}	2.629^{A}	2.855^{A}	2.651^{A}	2.769^{A}	2.610^{A}	0.075	-0.059	0.067	-0.110	0.107	-0.027
	(0.058)	(0.057)	(0.081)	(0.078)	(0.086)	(0.084)	(0.084)	(0.083)	(0.120)	(0.122)	(0.136)	(0.142)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$H0: FI = FO$	0.11	0.27	0.18	0.22	0.89	0.73	0.13	0.25	0.11	0.13	0.48	0.70
$H0: FI = DI$	0.02	0.23	0.06	0.18	0.55	0.86	0.01	0.09	0.03	0.07	0.16	0.38
$H0: FO = DI$	0.02	0.67	0.08	0.60	0.14	0.66	0.00	0.06	0.14	0.42	0.04	0.18
Observations	4,050	4,032	4,050	4,032	2,491	2,480	3,995	3,978	3,995	3,978	2,454	2,443
R^2	0.13	0.17	.	.	0.13	0.18	0.05	0.09	.	.	0.05	0.08

† *Note: The table gives estimation results obtained with the Bernard & Jensen (1999) methodology. Each column represents a separate regression where the dependent variable is a function of dummy variables for foreign integration (FI), foreign outsourcing (FO), domestic integration (DI), and a firm's age (Age) and export status (Export). Labor productivity is the natural log of real value added over the hours effectively worked. Total factor productivity is estimated with the Olley & Pakes (1996) three-step algorithm. The sourcing dummies are mutually exclusive. If a firm is active in two or more sourcing modes simultaneously, we assign it to the category which is the least prevalent one in the data; see Table 2.2. The estimation sample excludes firms with domestic or foreign parental companies. Non-sourcing firms are coded as domestic-integration firms (DI). The lower part of the table gives p-values of tests for equality of coefficients. Robust standard errors are given in parentheses. Superscripts C, B, and A indicate significance at the 10%, 5%, 1% levels, respectively.*

Table 2.7. Sourcing premia with mutually exclusive hierarchical sourcing dummies ($FI > DI > FO > DO$) (all firms, 2006-2008)†

	Baseline Category: Domestic-Outsourcing Firms; Non-Sourcing Firms Coded as Domestic-Integration Firms (DI)											
	Dependent Variable: Labor Productivity						*Dependent Variable: Total Factor Productivity*					
	OLS		PA		IV		OLS		PA		IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
<u>Sourcing Dummies</u>												
FI	0.495^{A}	0.338^{A}	0.332^{A}	0.229^{A}	0.612^{A}	0.457^{A}	0.440^{A}	0.298^{A}	0.216^{A}	0.145^{B}	0.558^{A}	0.427^{A}
	(0.048)	(0.048)	(0.066)	(0.063)	(0.085)	(0.087)	(0.048)	(0.049)	(0.061)	(0.060)	(0.091)	(0.094)
FO	0.234^{A}	0.141^{A}	0.137^{A}	0.084^{A}	0.343^{A}	0.238^{A}	0.269^{A}	0.185^{A}	0.099^{A}	0.070^{A}	0.393^{A}	0.305^{A}
	(0.020)	(0.021)	(0.022)	(0.022)	(0.041)	(0.045)	(0.021)	(0.022)	(0.022)	(0.022)	(0.047)	(0.051)
DI	0.277^{A}	0.227^{A}	0.174^{A}	0.149^{A}	0.354^{A}	0.299^{A}	0.251^{A}	0.207^{A}	0.122^{A}	0.106^{A}	0.318^{A}	0.272^{A}
	(0.031)	(0.029)	(0.032)	(0.031)	(0.069)	(0.065)	(0.032)	(0.031)	(0.033)	(0.032)	(0.077)	(0.075)
<u>Other Variables</u>												
Age		0.004^{A}		0.005^{A}		0.004^{A}		0.003^{A}		0.004^{A}		0.003^{A}
		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)
$Export$		0.221^{A}		0.212^{A}		0.178^{A}		0.211^{A}		0.174^{A}		0.164^{A}
		(0.019)		(0.024)		(0.030)		(0.021)		(0.025)		(0.035)
Constant	2.834^{A}	2.652^{A}	2.866^{A}	2.676^{A}	2.792^{A}	2.640^{A}	0.024	-0.119	0.042	-0.124	0.057	-0.067
	(0.058)	(0.058)	(0.085)	(0.082)	(0.091)	(0.089)	(0.078)	(0.078)	(0.110)	(0.111)	(0.126)	(0.131)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$H0: FI = FO$	0.00	0.00	0.00	0.02	0.00	0.01	0.00	0.02	0.06	0.20	0.08	0.20
$H0: FI = DI$	0.00	0.04	0.03	0.25	0.02	0.13	0.00	0.10	0.17	0.56	0.04	0.18
$H0: FO = DI$	0.19	0.01	0.27	0.05	0.88	0.37	0.60	0.51	0.52	0.31	0.35	0.68
Observations	5,914	5,876	5,914	5,876	3,637	3,612	5,827	5,790	5,827	5,790	3,582	3,557
R^2	0.14	0.19	.	.	0.15	0.20	0.05	0.09	.	.	0.05	0.08

† *Note: The table gives estimation results obtained with the Bernard & Jensen (1999) methodology. Each column represents a separate regression where the dependent variable is a function of dummy variables for foreign integration (FI), foreign outsourcing (FO), domestic integration (DI), and a firm's age (Age) and export status (Export). Labor productivity is the natural log of real value added over the hours effectively worked. Total factor productivity is estimated with the Olley & Pakes (1996) three-step algorithm. The sourcing dummies are mutually exclusive. If a firm is active in two or more sourcing modes simultaneously, we assign it to the category which is the least prevalent one in the data; see Table 2.2. The estimation sample includes firms with domestic or foreign parental companies. Non-sourcing firms are coded as domestic-integration firms (DI). The lower part of the table gives p-values of tests for equality of coefficients. Robust standard errors are given in parentheses. Superscripts C, B, and A indicate significance at the 10%, 5%, 1% levels, respectively.*

Table 2.8. Sourcing premia with mutually inclusive sourcing dummies (true headquarter firms, 2006-2008)†

	Baseline Category: Non-Sourcing Firms											
	Dependent Variable: Labor Productivity						*Dependent Variable: Total Factor Productivity*					
	OLS		PA		IV		OLS		PA		IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
<u>Sourcing Dummies</u>												
FI	0.147	0.065	0.151	0.106	0.044	0.166	0.203^{C}	0.132	0.182^{B}	0.156^{C}	0.149	0.052
	(0.117)	(0.118)	(0.112)	(0.109)	(0.277)	(0.260)	(0.115)	(0.117)	(0.085)	(0.087)	(0.283)	(0.255)
FO	0.244^{A}	0.156^{A}	0.170^{A}	0.114^{A}	0.322^{A}	0.220^{A}	0.268^{A}	0.193^{A}	0.118^{A}	0.085^{A}	0.374^{A}	0.297^{A}
	(0.020)	(0.021)	(0.023)	(0.024)	(0.041)	(0.046)	(0.022)	(0.023)	(0.022)	(0.022)	(0.047)	(0.052)
DI	0.250^{A}	0.251^{A}	0.171^{B}	0.170^{B}	0.291^{B}	0.308^{A}	0.206^{A}	0.207^{A}	0.107	0.105	0.176	0.190
	(0.063)	(0.062)	(0.072)	(0.071)	(0.114)	(0.114)	(0.070)	(0.071)	(0.070)	(0.071)	(0.168)	(0.169)
DO	-0.014	-0.012	-0.021	-0.017	0.078	0.073	-0.015	-0.013	-0.006	-0.003	0.024	0.020
	(0.034)	(0.032)	(0.033)	(0.032)	(0.096)	(0.088)	(0.036)	(0.035)	(0.040)	(0.040)	(0.098)	(0.094)
<u>Other Variables</u>												
Age		0.004^{A}		0.005^{A}		0.004^{A}		0.004^{A}		0.004^{A}		0.003^{A}
		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)
$Export$		0.203^{A}		0.196^{A}		0.176^{A}		0.179^{A}		0.162^{A}		0.133^{A}
		(0.021)		(0.026)		(0.032)		(0.022)		(0.026)		(0.037)
Constant	2.824^{A}	2.628^{A}	2.880^{A}	2.656^{A}	2.675^{A}	2.531^{A}	0.092	-0.059	0.080	-0.114	0.060	-0.058
	(0.065)	(0.064)	(0.086)	(0.083)	(0.123)	(0.118)	(0.088)	(0.089)	(0.124)	(0.128)	(0.161)	(0.163)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$H0: FI = FO$	0.42	0.45	0.87	0.94	0.20	0.15	0.59	0.62	0.49	0.44	0.44	0.36
$H0: FI = DI$	0.47	0.19	0.89	0.64	0.30	0.13	0.98	0.61	0.51	0.66	0.94	0.68
$H0: FO = DI$	0.93	0.15	1.00	0.45	0.80	0.47	0.39	0.85	0.87	0.77	0.27	0.56
$H0: FI = DO$	0.19	0.53	0.14	0.28	0.68	0.39	0.07	0.24	0.04	0.09	0.68	0.91
$H0: DI = DO$	0.00	0.00	0.01	0.01	0.14	0.09	0.00	0.00	0.16	0.18	0.41	0.35
$H0: FO = DO$	0.00	0.00	0.00	0.00	0.02	0.17	0.00	0.00	0.01	0.07	0.00	0.02
Observations	4,049	4,031	4,049	4,031	2,491	2,480	3,994	3,977	3,994	3,977	2,454	2,443
R^2	0.13	0.18	.	.	0.14	0.19	0.06	0.09	.	.	0.06	0.09

† *Note: The table gives estimation results obtained with the Bernard & Jensen (1999) methodology. Each column represents a separate regression where the dependent variable is a function of dummy variables for foreign integration (FI), foreign outsourcing (FO), domestic integration (DI), domestic outsourcing (DO), and a firm's age (Age) and export status (Export). Labor productivity is the natural log of real value added over the hours effectively worked. Total factor productivity is estimated with the Olley & Pakes (1996) three-step algorithm. The sourcing dummies are mutually inclusive. The estimation sample excludes firms with domestic or foreign parental companies. Non-sourcing firms are coded as the baseline category. The lower part of the table gives p-values of tests for equality of coefficients. Robust standard errors are given in parentheses. Superscripts C, B, and A indicate significance at the 10%, 5%, 1% levels, respectively.*

Table 2.9. Sourcing premia with mutually inclusive sourcing dummies (all firms, 2006-2008)†

	Baseline Category: Non-Sourcing Firms											
	Dependent Variable: Labor Productivity						*Dependent Variable: Total Factor Productivity*					
	OLS		PA		IV		OLS		PA		IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
<u>Sourcing Dummies</u>												
FI	0.239^{A}	0.160^{A}	0.170^{B}	0.110^{C}	0.277^{A}	0.207^{B}	0.173^{A}	0.102^{B}	0.105^{C}	0.058	0.189^{C}	0.133
	(0.050)	(0.048)	(0.069)	(0.065)	(0.095)	(0.090)	(0.051)	(0.050)	(0.062)	(0.060)	(0.097)	(0.096)
FO	0.206^{A}	0.124^{A}	0.131^{A}	0.083^{A}	0.273^{A}	0.179^{A}	0.250^{A}	0.177^{A}	0.096^{A}	0.070^{A}	0.358^{A}	0.281^{A}
	(0.019)	(0.020)	(0.021)	(0.022)	(0.039)	(0.043)	(0.020)	(0.021)	(0.021)	(0.021)	(0.045)	(0.049)
DI	0.282^{A}	0.253^{A}	0.201^{A}	0.183^{A}	0.314^{A}	0.292^{A}	0.232^{A}	0.206^{A}	0.141^{A}	0.127^{A}	0.227^{A}	0.209^{A}
	(0.039)	(0.037)	(0.045)	(0.043)	(0.070)	(0.065)	(0.041)	(0.040)	(0.047)	(0.047)	(0.079)	(0.079)
DO	-0.036	-0.031	-0.029	-0.027	0.046	0.047	-0.056^{C}	-0.052	-0.036	-0.036	-0.004	-0.002
	(0.030)	(0.028)	(0.028)	(0.028)	(0.081)	(0.074)	(0.033)	(0.032)	(0.035)	(0.035)	(0.089)	(0.083)
<u>Other Variables</u>												
Age		0.004^{A}		0.005^{A}		0.004^{A}		0.003^{A}		0.004^{A}		0.003^{A}
		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)
$Export$		0.215^{A}		0.207^{A}		0.181^{A}		0.201^{A}		0.171^{A}		0.157^{A}
		(0.019)		(0.024)		(0.030)		(0.021)		(0.025)		(0.035)
Constant	2.821^{A}	2.662^{A}	2.893^{A}	2.668^{A}	2.755^{A}	2.595^{A}	0.009	-0.080	0.076	-0.119	0.061	-0.065
	(0.062)	(0.062)	(0.086)	(0.084)	(0.112)	(0.109)	(0.080)	(0.081)	(0.112)	(0.116)	(0.143)	(0.145)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$H0\colon FI = FO$	0.56	0.51	0.61	0.71	0.98	0.80	0.19	0.20	0.91	0.86	0.15	0.21
$H0\colon FI = DI$	0.52	0.15	0.71	0.35	0.76	0.47	0.40	0.13	0.66	0.39	0.78	0.58
$H0\colon FO = DI$	0.08	0.00	0.16	0.04	0.63	0.15	0.68	0.51	0.38	0.25	0.18	0.46
$H0\colon FI = DO$	0.00	0.00	0.01	0.05	0.06	0.16	0.00	0.01	0.04	0.17	0.14	0.28
$H0\colon DI = DO$	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.05	0.06
$H0\colon FO = DO$	0.00	0.00	0.00	0.00	0.02	0.15	0.00	0.00	0.00	0.01	0.00	0.01
Observations	5,913	5,875	5,913	5,875	3,637	3,612	5,826	5,789	5,826	5,789	3,582	3,557
R^2	0.15	0.19	.	.	0.16	0.21	0.06	0.09	.	.	0.06	0.09

† *Note: The table gives estimation results obtained with the Bernard & Jensen (1999) methodology. Each column represents a separate regression where the dependent variable is a function of dummy variables for foreign integration (FI), foreign outsourcing (FO), domestic integration (DI), domestic outsourcing (DO), and a firm's age (Age) and export status (Export). Labor productivity is the natural log of real value added over the hours effectively worked. Total factor productivity is estimated with the Olley & Pakes (1996) three-step algorithm. The sourcing dummies are mutually inclusive. The estimation sample includes firms with domestic or foreign parental companies. Non-sourcing firms are included as the baseline category. The lower part of the table gives p-values of tests for equality of coefficients. Robust standard errors are given in parentheses. Superscripts C, B, and A indicate significance at the 10%, 5%, 1% levels, respectively.*

Appendices

A Data appendix

Table A.1. List of Spanish manufacturing industries

NACE-1993 Classification	*Industry*
151	Meat
159	Beverage
361	Furniture Industry
152-158, 160	Food Products & Tobacco
171-177, 181-183	Textile
191-193	Leather & Footwear
201-205	Timber & Wooden Products
211-212	Pulp & Paper Products
221-223	Publishing & Graphics Design
241-247	Chemical Products
251-252	Plastic & Rubber Products
261-268	Mineral Products (Non-Metal Products)
271-275	Ferrous Metals & Non-Ferrous Metals
281-287	Metal Products
291-297	Industry & Agricultural Machinery
300, 331-335	Office Machinery & Data Processing
311-316, 321-323	General & Electric Machinery
341-343	Motorized Vehicles
351-355	Other Transportation Equipment
362-366, 371-372	Miscellaneous Manufacturing

B Further estimation results

Table B.1. Sourcing premia with mutually exclusive hierarchical sourcing dummies ($FI > DI > FO > DO$) (true headquarter firms, 2006-2008)†

	Baseline Category: Domestic Outsourcing Firms; Non-Sourcing Firms Excluded											
	Dependent Variable: Labor Productivity						*Dependent Variable: Total Factor Productivity*					
	OLS		PA		IV		OLS		PA		IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Sourcing Dummies												
FI	0.429[A]	0.287[B]	0.345[A]	0.260[B]	0.345	0.137	0.471[A]	0.347[A]	0.297[A]	0.246[B]	0.561[B]	0.397
	(0.121)	(0.118)	(0.118)	(0.112)	(0.268)	(0.252)	(0.130)	(0.125)	(0.100)	(0.097)	(0.279)	(0.254)
FO	0.241[A]	0.157[A]	0.172[A]	0.113[A]	0.319[A]	0.225[A]	0.276[A]	0.204[A]	0.130[A]	0.094[A]	0.370[A]	0.298[A]
	(0.021)	(0.022)	(0.024)	(0.024)	(0.043)	(0.047)	(0.022)	(0.023)	(0.022)	(0.022)	(0.048)	(0.052)
DI	0.346[A]	0.313[A]	0.234[A]	0.211[A]	0.448[A]	0.421[A]	0.318[A]	0.288[A]	0.155[B]	0.139[C]	0.364[B]	0.344[C]
	(0.067)	(0.066)	(0.076)	(0.074)	(0.128)	(0.124)	(0.073)	(0.073)	(0.072)	(0.071)	(0.177)	(0.176)
Other Variables												
Age		0.004[A]		0.005[A]		0.004[A]		0.004[A]		0.004[A]		0.003[A]
		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)
$Export$		0.195[A]		0.197[A]		0.163[A]		0.174[A]		0.166[A]		0.125[A]
		(0.021)		(0.027)		(0.033)		(0.023)		(0.028)		(0.038)
Constant	2.770[A]	2.627[A]	2.838[A]	2.643[A]	2.757[A]	2.613[A]	0.046	(0.111	0.053	(0.123	0.071	(0.052
	(0.059)	(0.060)	(0.082)	(0.079)	(0.086)	(0.086)	(0.088)	(0.091)	(0.124)	(0.125)	(0.145)	(0.150)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$H0\!: FI = FO$	0.12	0.27	0.14	0.19	0.92	0.73	0.14	0.25	0.10	0.12	0.50	0.70
$H0\!: FI = DI$	0.55	0.85	0.41	0.70	0.74	0.33	0.30	0.68	0.20	0.32	0.57	0.87
$H0\!: FO = DI$	0.12	0.02	0.42	0.19	0.33	0.13	0.57	0.26	0.73	0.53	0.97	0.80
Observations	3,829	3,811	3,829	3,811	2,308	2,297	3,777	3,760	3,777	3,760	2,275	2,264
R^2	0.13	0.18	.	.	0.14	0.18	0.06	0.09	.	.	0.06	0.09

† *Note: The table gives estimation results obtained with the Bernard & Jensen (1999) methodology. Each column represents a separate regression where the dependent variable is a function of dummy variables for foreign integration (FI), foreign outsourcing (FO), domestic integration (DI), and a firm's age (Age) and export status (Export). Labor productivity is the natural log of real value added over the hours effectively worked. Total factor productivity is estimated with the Olley & Pakes (1996) three-step algorithm. The sourcing dummies are mutually exclusive. If a firm is active in two or more sourcing modes simultaneously, we assign it to the category which is the least prevalent one in the data; see Table 2.2. The estimation sample excludes firms with domestic or foreign parental companies. Non-sourcing firms are excluded. The lower part of the table gives p-values of tests for equality of coefficients. Robust standard errors are given in parentheses. Superscripts C, B, and A indicate significance at the 10%, 5%, 1% levels, respectively.*

Table B.2. Sourcing premia with mutually exclusive hierarchical sourcing dummies ($FI > DI > FO > DO$) (true headquarter firms, 2006-2008)[†]

	Baseline Category: Non-Sourcing Firms											
	Dependent Variable: Labor Productivity						*Dependent Variable: Total Factor Productivity*					
	OLS		PA		IV		OLS		PA		IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
<u>Sourcing Dummies</u>												
FI	0.398^{A}	0.249^{B}	0.313^{B}	0.234^{B}	0.376	0.141	0.444^{A}	0.316^{B}	0.267^{B}	0.222^{B}	0.591^{B}	0.405
	(0.126)	(0.121)	(0.122)	(0.115)	(0.289)	(0.269)	(0.134)	(0.129)	(0.107)	(0.104)	(0.297)	(0.271)
FO	0.205^{A}	0.118^{A}	0.132^{A}	0.080^{B}	0.346^{A}	0.234^{B}	0.244^{A}	0.170^{A}	0.094^{B}	0.065	0.398^{A}	0.310^{A}
	(0.040)	(0.038)	(0.039)	(0.038)	(0.114)	(0.106)	(0.041)	(0.040)	(0.043)	(0.043)	(0.116)	(0.112)
DI	0.309^{A}	0.276^{A}	0.197^{B}	0.179^{B}	0.471^{A}	0.432^{A}	0.286^{A}	0.256^{A}	0.116	0.106	0.389^{C}	0.357^{C}
	(0.076)	(0.073)	(0.082)	(0.080)	(0.165)	(0.156)	(0.080)	(0.080)	(0.080)	(0.080)	(0.208)	(0.204)
DO	-0.034	-0.034	-0.029	-0.026	0.026	0.016	-0.030	-0.030	-0.029	-0.025	0.029	0.019
	(0.038)	(0.036)	(0.036)	(0.035)	(0.116)	(0.106)	(0.039)	(0.038)	(0.042)	(0.042)	(0.117)	(0.110)
<u>Other Variables</u>												
Age		0.004^{A}		0.005^{A}		0.004^{A}		0.004^{A}		0.004^{A}		0.003^{A}
		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)
$Export$		0.208^{A}		0.201^{A}		0.181^{A}		0.182^{A}		0.163^{A}		0.140^{A}
		(0.021)		(0.026)		(0.032)		(0.022)		(0.027)		(0.036)
Constant	2.854^{A}	2.654^{A}	2.874^{A}	2.669^{A}	2.735^{A}	2.590^{A}	0.093	-0.039	0.090	-0.090	0.071	-0.050
	(0.067)	(0.066)	(0.087)	(0.084)	(0.136)	(0.129)	(0.091)	(0.089)	(0.126)	(0.128)	(0.169)	(0.169)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$H0: FI = FO$	0.11	0.26	0.12	0.17	0.91	0.71	0.13	0.24	0.08	0.10	0.49	0.71
$H0: FI = DI$	0.52	0.84	0.38	0.67	0.76	0.32	0.28	0.67	0.17	0.28	0.56	0.88
$H0: FO = DI$	0.13	0.02	0.39	0.18	0.34	0.12	0.57	0.25	0.76	0.57	0.96	0.80
$H0: FI = DO$	0.00	0.02	0.00	0.02	0.19	0.62	0.00	0.01	0.00	0.01	0.04	0.13
$H0: DI = DO$	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.04	0.06	0.04	0.06
$H0: FO = DO$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	4,050	4,032	4,050	4,032	2,491	2,480	3,995	3,978	3,995	3,978	2,454	2,443
R^2	0.13	0.18	.	.	0.14	0.18	0.06	0.09	.	.	0.06	0.09

[†] *Note: The table gives estimation results obtained with the Bernard & Jensen (1999) methodology. Each column represents a separate regression where the dependent variable is a function of dummy variables for foreign integration (FI), foreign outsourcing (FO), domestic integration (DI), domestic outsourcing (DO), and a firm's age (Age) and export status (Export). Labor productivity is the natural log of real value added over the hours effectively worked. Total factor productivity is estimated with the Olley & Pakes (1996) three-step algorithm. The sourcing dummies are mutually exclusive. If a firm is active in two or more sourcing modes simultaneously, we assign it to the category which is the least prevalent one in the data; see Table 2.2. The estimation sample includes firms with domestic or foreign parental companies. Non-sourcing firms are included as the baseline category. The lower part of the table gives p-values of tests for equality of coefficients. Robust standard errors are given in parentheses. Superscripts C, B, and A indicate significance at the 10%, 5%, 1% levels, respectively.*

Table B.3. Sourcing premia with mutually exclusive hierarchical sourcing dummies ($FI > DI > FO > DO$) (all firms, 2006-2008)†

	Baseline Category: Domestic-Outsourcing Firms; Non-Sourcing Firms Excluded											
	Dependent Variable: Labor Productivity						*Dependent Variable: Total Factor Productivity*					
	OLS		PA		IV		OLS		PA		IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
<u>*Sourcing Dummies*</u>												
FI	0.500^{A}	0.355^{A}	0.363^{A}	0.254^{A}	0.601^{A}	0.466^{A}	0.446^{A}	0.313^{A}	0.238^{A}	0.161^{A}	0.552^{A}	0.439^{A}
	(0.048)	(0.048)	(0.065)	(0.063)	(0.085)	(0.087)	(0.048)	(0.049)	(0.061)	(0.059)	(0.092)	(0.095)
FO	0.237^{A}	0.151^{A}	0.155^{A}	0.098^{A}	0.331^{A}	0.241^{A}	0.271^{A}	0.193^{A}	0.111^{A}	0.078^{A}	0.382^{A}	0.307^{A}
	(0.020)	(0.021)	(0.022)	(0.023)	(0.041)	(0.044)	(0.021)	(0.022)	(0.022)	(0.022)	(0.047)	(0.051)
DI	0.435^{A}	0.362^{A}	0.324^{A}	0.274^{A}	0.497^{A}	0.429^{A}	0.390^{A}	0.324^{A}	0.231^{A}	0.198^{A}	0.439^{A}	0.383^{A}
	(0.042)	(0.040)	(0.050)	(0.048)	(0.077)	(0.073)	(0.045)	(0.044)	(0.051)	(0.051)	(0.090)	(0.089)
<u>*Other Variables*</u>												
Age		0.004^{A}		0.005^{A}		0.004^{A}		0.003^{A}		0.004^{A}		0.003^{A}
		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)
$Export$		0.197^{A}		0.203^{A}		0.149^{A}		0.192^{A}		0.175^{A}		0.139^{A}
		(0.020)		(0.025)		(0.031)		(0.021)		(0.025)		(0.036)
Constant	2.817^{A}	2.607^{A}	2.850^{A}	2.658^{A}	2.782^{A}	2.645^{A}	0.011	-0.136^{C}	0.028	-0.209^{C}	0.026	-0.082
	(0.059)	(0.058)	(0.084)	(0.082)	(0.092)	(0.090)	(0.079)	(0.080)	(0.111)	(0.113)	(0.132)	(0.137)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$H0: FI = FO$	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.01	0.04	0.16	0.08	0.17
$H0: FI = DI$	0.29	0.90	0.62	0.79	0.36	0.74	0.38	0.86	0.94	0.63	0.38	0.67
$H0: FO = DI$	0.00	0.00	0.00	0.00	0.04	0.02	0.01	0.00	0.02	0.02	0.54	0.43
Observations	5,630	5,596	5,630	5,596	3,399	3,378	5,548	5,515	5,548	5,515	3,350	3,329
R^2	0.16	0.19	.	.	0.16	0.20	0.06	0.09	.	.	0.06	0.09

† *Note: The table gives estimation results obtained with the Bernard & Jensen (1999) methodology. Each column represents a separate regression where the dependent variable is a function of dummy variables for foreign integration (FI), foreign outsourcing (FO), domestic integration (DI), and a firm's age (Age) and export status (Export). Labor productivity is the natural log of real value added over the hours effectively worked. Total factor productivity is estimated with the Olley & Pakes (1996) three-step algorithm. The sourcing dummies are mutually exclusive. If a firm is active in two or more sourcing modes simultaneously, we assign it to the category which is the least prevalent one in the data; see Table 2.2. The estimation sample includes firms with domestic or foreign parental companies. Non-sourcing firms are excluded. The lower part of the table gives p-values of tests for equality of coefficients. Robust standard errors are given in parentheses. Superscripts C, B, and A indicate significance at the 10%, 5%, 1% levels, respectively.*

Table B.4. Sourcing premia with mutually exclusive hierarchical sourcing dummies ($FI > DI > FO > DO$) (all firms, 2006-2008)†

	Baseline Category: Non-Sourcing Firms											
	Dependent Variable: Labor Productivity						*Dependent Variable: Total Factor Productivity*					
	OLS		PA		IV		OLS		PA		IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Sourcing Dummies												
FI	0.435^{A}	0.291^{A}	0.308^{A}	0.208^{A}	0.574^{A}	0.429^{A}	0.376^{A}	0.245^{A}	0.187^{A}	0.118^{C}	0.505^{A}	0.384^{A}
	(0.058)	(0.056)	(0.071)	(0.069)	(0.130)	(0.123)	(0.059)	(0.059)	(0.070)	(0.069)	(0.137)	(0.132)
FO	0.172^{A}	0.091^{B}	0.101^{A}	0.054	0.311^{A}	0.213^{B}	0.202^{A}	0.128^{A}	0.060	0.033	0.345^{A}	0.264^{B}
	(0.038)	(0.036)	(0.037)	(0.036)	(0.105)	(0.097)	(0.040)	(0.038)	(0.041)	(0.041)	(0.111)	(0.105)
DI	0.371^{A}	0.304^{A}	0.266^{A}	0.226^{A}	0.473^{A}	0.402^{A}	0.321^{A}	0.261^{A}	0.169^{A}	0.143^{B}	0.395^{A}	0.337^{A}
	(0.053)	(0.050)	(0.057)	(0.055)	(0.122)	(0.112)	(0.056)	(0.055)	(0.062)	(0.062)	(0.135)	(0.129)
DO	-0.063^{C}	-0.054	-0.042	-0.036	-0.025	-0.022	-0.067^{C}	-0.059	-0.045	-0.041	-0.042	-0.039
	(0.037)	(0.035)	(0.034)	(0.033)	(0.107)	(0.098)	(0.038)	(0.036)	(0.039)	(0.039)	(0.112)	(0.104)
Other Variables												
Age		0.004^{A}		0.005^{A}		0.004^{A}		0.003^{A}		0.004^{A}		0.003^{A}
		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)		(0.001)
$Export$		0.212^{A}		0.207^{A}		0.170^{A}		0.203^{A}		0.172^{A}		0.157^{A}
		(0.019)		(0.024)		(0.030)		(0.021)		(0.025)		(0.034)
Constant	2.875^{A}	2.691^{A}	2.901^{A}	2.696^{A}	2.806^{A}	2.655^{A}	0.072	(0.074	0.070	(0.095	0.090	(0.035
	(0.067)	(0.065)	(0.089)	(0.087)	(0.133)	(0.126)	(0.085)	(0.084)	(0.116)	(0.117)	(0.159)	(0.159)
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$H0: FI = FO$	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.02	0.03	0.15	0.09	0.21
$H0: FI = DI$	0.30	0.82	0.61	0.82	0.38	0.81	0.39	0.81	0.82	0.75	0.39	0.72
$H0: FO = DI$	0.00	0.00	0.00	0.00	0.05	0.02	0.01	0.00	0.04	0.04	0.60	0.44
$H0: FI = DO$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00
$H0: DI = DO$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$H0: FO = DO$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observations	5,914	5,876	5,914	5,876	3,637	3,612	5,827	5,790	5,827	5,790	3,582	3,557
R^2	0.15	0.19	.	.	0.17	0.21	0.06	0.09	.	.	0.06	0.09

† *Note: The table gives estimation results obtained with the Bernard & Jensen (1999) methodology. Each column represents a separate regression where the dependent variable is a function of dummy variables for foreign integration (FI), foreign outsourcing (FO), domestic integration (DI), domestic outsourcing (DO), and a firm's age (Age) and export status (Export). Labor productivity is the natural log of real value added over the hours effectively worked. Total factor productivity is estimated with the Olley & Pakes (1996) three-step algorithm. The sourcing dummies are mutually exclusive. If a firm is active in two or more sourcing modes simultaneously, we assign it to the category which is the least prevalent one in the data; see Table 2.2. The estimation sample includes firms with domestic or foreign parental companies. Non-sourcing firms are included as the baseline category. The lower part of the table gives p-values of tests for equality of coefficients. Robust standard errors are given in parentheses. Superscripts C, B, and A indicate significance at the 10%, 5%, 1% levels, respectively.*

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Chapter 3

Global sourcing and firm selection

A discussion paper of this chapter is available as University of Tübingen Working Papers in Economics and Finance No. 63.

3.1 Introduction

The sourcing of inputs is of key importance for a firm's success. Firms face a two-dimensional choice problem: they decide about the location of sourcing (foreign *vs.* domestic) as well as the ownership structure of sourcing (vertical integration *vs.* outsourcing). Which firms select which sourcing strategy has been the subject of intensive research, but remains an open question. This letter aims to provide novel empirical evidence on this interesting question by exploring the relationship between *pre-existing* productivity differentials across manufacturing firms in Spain and *subsequent choice (or selection)* of different sourcing strategies.

Identification of productivity-based firm selection is important, because it points to aggregate productivity effects. Changes in the costs of operating a strategy of vertical integration or of outsourcing, domestically or abroad, have the potential to change the aggregate productivity of an industry, by analogy to the selection effects of trade and foreign direct investment discussed in Melitz (2003) and Helpman et al. (2004).

We use data from the Spanish "Encuesta Sobre Estrategias Empresariales" (ESEE) from 2006-2011 to investigate how firms' selection of sourcing strategies in year t is related to their productivity in years *prior to* t. Overall, we find evidence that firms that select strategies of vertical integration and of offshoring ex post tend to have been more productive ex ante. We call this an *"ex ante sourcing premium"* of vertical integration and offshoring, respectively. It points to causation running from productivity to sourcing modes, as required for the above mentioned aggregate productivity effects.

This finding is in line with the recent literature on global sourcing by heterogeneous firms. This literature studies the boundaries of the firm—a classical question in economics dating back to Coase (1937)—against the backdrop of a global economy that allows for firms to move the source of their inputs abroad; see Helpman (2006) and Antràs (2013) for surveys. In an application of the property-rights theory of the firm (Grossman & Hart, 1986; Hart & Moore, 1990), Antràs & Helpman (2004) introduce a monopolistic competition model in which vertical integration and offshoring can be advantageous in terms of variable production costs, but disadvantageous in terms of fixed costs. Hence there is a trade-off, and the optimal sourcing strategy depends on the firm's productivity.

Existing empirical literature focuses on the *contemporaneous* relationship between a firm's productivity and its sourcing behaviour, and it has produced mixed evidence. Defever & Toubal (2013) find that French firms relying on an outsourced (rather than an integrated) foreign supplier tend to be more productive. Corcos et al. (2013) document the opposite pattern in an extended sample of the same French data source. Federico (2010, 2012) provides evidence that firms choosing strategies of vertical integration and of offshoring tend to be more productive than firms that source their inputs domestically and from independent suppliers. Tomiura (2007) and Kohler & Smolka (2011, 2012) find similar patterns in Japanese data and ESEE data, respectively. A common feature of these studies is that time-series information is not available or, where available, has not been exploited to address firm selection. Hence causality remains an open issue. Fariñas et al. (2010) and Wagner (2011) find evidence for productivity-based firm selection into offshoring. However, they do not study (or condition on) the ownership structure of sourcing due to lack of data. We contribute to the literature by addressing firm selection in both dimensions of sourcing, location and ownership structure, and by exploiting panel data towards estimating the corresponding "ex ante sourcing premia".

3.2 Data and identification

ESEE is a longitudinal dataset of Spanish manufacturing firms with 10 or more employees. There are at least three advantages of using ESEE data for this work. The first is that it is based on a truly representative sample. The initial selection of firms in 1990 was carried out through a two-way sampling scheme, distinguishing between large firms (more than 200 employees; exhaustive sampling) and small firms (10-200 employees; stratified, proportional, and systematic sampling with a random seed). Subsequent sampling was carried out in a way that preserves representativeness of the sample with respect to the Spanish manufacturing sector with 10 or more employees.[1]

The second advantage of this data set is the level of detail. The ESEE survey collects data on a large set of firm characteristics, including firms' main activities, their accounting statements, as well as information on their customers and suppliers. Importantly, information on output and the use of labor as well as capital allow for firms' productivity levels to be estimated using standard estimation routines. Of special importance for the present purpose, the survey obtains answers to the following questions:

- *Of the total amount of purchases of goods and services that you incorporate (transform) in the production process, indicate – according to the type of supplier – the percentage that these represent in the total amount of purchases of your firm in* [year].
  - (a) *Spanish suppliers that belong to your group of companies or that participate in your firm's joint capital.* [yes/no] / [if yes, then percentage rate]
  - (b) *Other suppliers located in Spain.* [yes/no]/[if yes, then percentage rate]
- *For the year* [year]*, indicate whether you imported goods and services that you incorporate (transform) in the production process, and the percentage that theses imports – according to the type of supplier – represent in the total value of your imports.* [yes/no]
  - (a) *From suppliers that belong to your group of companies and/or from foreign firms that participate in your firm's joint capital.* [yes/no]/[if yes, then percentage rate]
  - (b) *From other foreign firms.* [yes/no]/[if yes, then percentage rate]

We are thus able to identify foreign integration (FI), foreign outsourcing (FO), domestic integration (DI) and domestic outsourcing (DO) as distinct sourcing strategies. In 2011, 5.0% of small firms and 34.1% of large firms have relied on FI. The corresponding numbers are 40.2% and 70.1% for FO, 10.9% and 33.6% for DI, and 93.6% and 93.5% for DO. Thus, the sourcing strategies are not mutually exclusive, but appear complementary to one another (Kohler & Smolka, 2011).

The third advantage of our data is given by its panel structure and time horizon. Firms rarely change their sourcing from one year to another. This means that a relatively long time horizon is essential in order to have sufficient variation in the data that can be exploited for identification purposes. ESEE data on both dimensions of sourcing (location and ownership

[1] More information on ESEE data and its sampling properties are available at `http://www.fundacionsepi.es/esee/en/epresentacion.asp` (accessed on 25/10/2013).

structure) has been collected for six consecutive years from 2006 to 2011. The average number of sourcing strategies used in 2006 was 1.37 for small firms and 2.11 for large firms. In 2011, the same numbers were 1.50 and 2.31, respectively. This trend towards a stronger fragmentation of the production process was largely driven by firms adding either FI or FO to their existing sourcing portfolios, which indicates growing importance of offshoring.

We use regression analysis in order to compare the ex ante productivity across firms that select the same sourcing strategy in year $t-1$ (the pre-selection period), but select different sourcing strategies in year t (the selection period). Key to our approach are suitable sample restrictions imposed to identify productivity-based firm selection into both vertical integration (conditional on the location of sourcing) and foreign sourcing (conditional on the ownership structure of sourcing). Figure 3.1 illustrates the identification of firm selection into vertical integration, conditional on the firm sourcing abroad: we first restrict the sample to firms that select FO, DI, and DO at both $t-1$ and t, and to firms that do not select FI at $t-x$, with $x = 1, \ldots, t-1$. This sample restriction leaves us with a sufficient number of firms that differ in their FI status (the strategy of interest) in the selection period, but that behave identical otherwise, both in the pre-selection period as well as in the selection period.[2] We then estimate the pre-selection productivity differences (in both levels and first differences) between firms choosing to select FI in the selection period and firms choosing not to change their sourcing strategy, controlling for a host of other firm characteristics. We do so in a linear regression framework where selection into FI is captured through a $(0,1)$ indicator variable (the selection variable).[3]

We apply the Olley & Pakes (1996) estimation algorithm, henceforth called OPA, in order to estimate total factor productivity (TFP) as a firm-specific, time-variant variable. The OPA avoids estimation biases due to endogenous selection into markets and simultaneous choice of input factors. We feed the OPA with ESEE data from 2000-2011, using annual information on each firm's real output, real investment, real capital stock, real purchases, labor employment, and exit decisions. *Real output* is the total production value plus other operating income (income from rent and leasing, industrial property, commissions, and certain services), expressed in terms of prices of the year 2000. We deflate production values and other types of operating revenue by using firm-level ESEE data on goods price variations along with an industry-level price index from the Spanish Instituto Nacional de Estadística

[2] We include firms that—in addition to sourcing abroad—choose to source domestically as well, since we would otherwise be left with an almost empty set of firms.

[3] Notice that for a given firm the selection variable can be equal to zero in one period and equal to one in another (subsequent) period. In principle, the model could therefore be identified even in case we observed just a single firm through time.

(INE) for years with missing data. This avoids estimation biases due to firm-specific mark-up pricing, firm-specific demand shocks, or firm-specific market access (Klette & Griliches, 1996; De Loecker, 2007). *Real investment* is the total investment value in real estate, construction, and equipment, deflated with an industry-level INE price index. The *real capital stock* is the reported value of real estate, construction, and equipment, deflated with an industry-level INE price index. We use a firm-level price index along with industry-level INE data to compute *real purchases*, defined as the total expenditure on intermediate inputs and external services. *Labor employment* is measured by effectively worked hours. *Exit decisions* of firms documented in ESEE data allows us to distinguish firms shutting down production from firms staying in the market, but exiting the sample.

3.3 Results

Table 3.1 reports the main results from the analysis of firm selection into vertical integration. There is strong evidence that the more productive firms self-select into strategies of vertical integration, whether in the foreign or in the domestic economy. We obtain an estimated coefficient of the selection variable which is above 0.2 and significantly different from zero, when estimating TFP differences in *levels* and not including any firm-level controls. If we control for a firm's age, skill intensity, capital intensity, technological effort, export status, and foreign ownership, the estimated coefficient of the selection variable is slightly below 0.2, but with a strictly positive lower confidence limit. This means that in the pre-selection period the firms self-selecting into vertical integration are on average somewhat less than twenty percent more productive than their competitors in the same industry with otherwise identical characteristics. These are quite strong and interesting results, also because the two samples employed in Table 3.1 are entirely disjunct. There is, however, no evidence that pre-selection TFP *growth* is larger for firms selecting vertical integration—the estimated coefficient of the respective selection variable has a negative sign throughout and is not significantly different from zero. This is in line with existing theory, where sourcing is driven by productivity levels, not productivity growth.

Table 3.2 looks at firm selection into foreign sourcing. While there is again little evidence for differences in TFP *growth* in the pre-selection period, we find clear evidence for differences in TFP *levels* prior to selecting into strategies of foreign sourcing. The estimated coefficient of the corresponding selection variable is between +0.074 and +0.139 when we condition on firms relying exclusively on an outsourced production structure, and between +0.219 and

+0.279 when we condition on firms operating an integrated production structure.[4] With a single exception, the estimated coefficients are statistically significant at least at the 5% level. These results strongly suggest that the more productive firms self-select into strategies of foreign sourcing, whether they operate an integrated or an outsourced production structure.

3.4 Conclusions

We present novel evidence on sourcing behavior, based on direct observation of firms' self-selection. Using panel data information on Spanish firms, we find that among the firms that abstain from vertical integration to start with, it will be the more productive ones that subsequently self-select into strategies of vertical integration (at home or abroad). The same pattern is found for self-selection of firms into foreign sourcing (integrated or outsourced).

Two comments on these findings are in order. First, our results only hold *on average* across industries. Hence, it is possible that in some industries it is the less productive firms (rather than the highly productive ones) that select into vertical integration. This could explain the seemingly contradictory results found in Defever & Toubal (2013) and Corcos et al. (2013). Second, and relatedly, while the productivity-based firm selection evidenced by our data supports a central tenet of the recent heterogeneous-firm literature on global sourcing, it should not be interpreted as lending support to any specific model of sourcing. To see whether the selection patterns found in this chapter are in line with the predictions of a certain theoretical model of sourcing, we need an empirical strategy that goes beyond establishing the mere presence and direction of self-selection. In particular, we must establish a connection between the detailed pattern of self-selection and certain industry- and firm-specific variables that theoretical models propose, over and above a firm's productivity level, as key explanatory variable for the ownership structure and the location of sourcing.

[4] In this latter case, we include firms that—in addition to domestic integration—rely on domestic outsourcing as well, in order to have a sufficiently large number of firms in the sample. The two samples employed in Table 3.2 are nevertheless entirely disjunct.

Figures and tables

Figure 3.1. Identification of productivity-based firm selection into vertical integration (conditional on foreign sourcing)

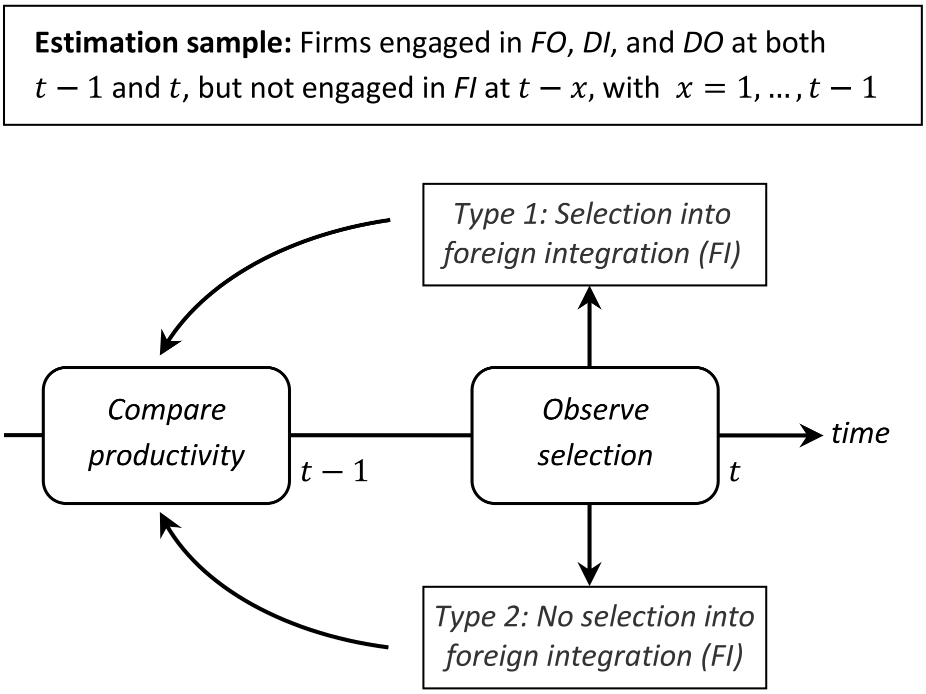

Table 3.1. Productivity-based firm selection into vertical integration

	Offshore production				*Domestic production*			
	Sample restrictions:				*Sample restrictions:*			
	at t-x: FI status=0, with x=1,…,t-1				*at t-x: DI status=0, with x=1,…,t-1*			
	at t-1 and t: FO status=1 & DI status=1 & DO status=1				*at t-1 and t: FI status=0 & FO status=0 & DO status=1*			
	TFP level		*TFP growth*		*TFP level*		*TFP growth*	
Selection variable	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
FI status at t (left panel) OR	0.216**	0.182**	-0.023	-0.031	0.242**	0.169*	-0.043	-0.047
DI status at t (right panel)	(0.101)	(0.092)	(0.025)	(0.030)	(0.097)	(0.093)	(0.041)	(0.041)
Firm-level controls	No	Yes	No	Yes	No	Yes	No	Yes
No. of observations	379	359	379	359	3,359	3,331	3,351	3,323
% of switching firms	>5%	>5%	>5%	>5%	>1%	>1%	>1%	>1%
R-squared	0.532	0.649	0.429	0.468	0.047	0.124	0.059	0.061

The table reports estimated coefficients of the selection variable for vertical integration, as explained in Section 3.2. The left panel *(offshore production)* looks at vertical integration conditional on the firm sourcing abroad; the right panel *(domestic production)* looks at vertical integration conditional on the firm sourcing domestically only. The variables *FI status* , *FO status* , *DI status,* and *DO status* are dummy variables for the respective sourcing strategies. Industry-year constants are always included. Firm-level controls are a firm's age, skill intensity (graduate workers over total workers, in logs), capital intensity (capital assets over average number of workers, in logs), technological effort (R&D costs plus technology imports over total sales, in logs), export status, and an ordered variable for the ratio of foreign capital in the firm's joint capital (zero;one:0-25;two:25-50;three:>50). Robust standards errors (clustered by firm) are given in parenthesis. *,**,*** indicate statistical signficance at the 10%, 5%, and 1% level, respectively.

Table 3.2. Productivity-based firm selection into foreign sourcing

	Outsourced production				*Integrated production*			
	Sample restrictions:				*Sample restrictions:*			
	at t-x: FO status=0; with x=1,…,t-1				*at t-x: FI status=0; with x=1,…,t-1*			
	at t-1 and t: DI status=0 & FI status=0 & DO status=1				*at t-1 and t: FO status=0 & DI status=1 & DO status=1*			
	TFP level		*TFP growth*		*TFP level*		*TFP growth*	
Selection variable	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
FO status at t (left panel) OR	0.139***	0.074***	0.003	0.001	0.279**	0.219	0.112	0.112
FI status at t (right panel)	(0.026)	(0.026)	(0.015)	(0.015)	(0.137)	(0.142)	(0.157)	(0.151)
Firm-level controls	No	Yes	No	Yes	No	Yes	No	Yes
No. of observations	3,287	3,260	3,281	3,254	289	280	286	277
% of switching firms	>8%	>8%	>8%	>8%	>1%	>1%	>1%	>1%
R-squared	0.054	0.129	0.058	0.060	0.437	0.507	0.555	0.573

The table reports estimated coefficients of the selection variable for foreign sourcing, as explained in Section 3.2. The left panel *(outsourced production)* looks at foreign sourcing conditional on the firm operating an outsourced production structure only; the right panel *(integrated production)* looks at foreign sourcing conditional on the firm operating an integrated production structure. The variables *FI status* , *FO status* , *DI status,* and *DO status* are dummy variables for the respective sourcing strategies. Industry-year constants are always included. Firm-level controls are a firm's age, skill intensity (graduate workers over total workers, in logs), capital intensity (capital assets over average number of workers, in logs), technological effort (R&D costs plus technology imports over total sales, in logs), export status, and an ordered variable for the ratio of foreign capital in the firm's joint capital (zero;one:0-25;two:25-50;three:>50). Robust standards errors (clustered by firm) are given in parenthesis. *,**,*** indicate statistical signficance at the 10%, 5%, and 1% level, respectively.

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Chapter 4

Global sourcing: Towards a firm-level test of the hold-up model

This chapter is based on joint work with Wilhelm Kohler (previously unpublished).

4.1 Introduction

Modern trade theory emphasizes that buyers and sellers of intermediate inputs enter a contractual relationship that is fundamentally different from a transaction in final goods. Input specifications often do not lend themselves to third-party verification, which rules out enforceable contracts. At the same time, product differentiation implies that such inputs have little, if any, use outside the production relationship they have been specifically designed for. As a result, trade in intermediate inputs is often plagued by a hold-up problem, and the gains from this trade are not fully exploited.

The canonical model of input trade under such hold-up problems is due to Antràs (2003) who draws on the property rights theory of the firm as developed by Grossman & Hart (1986). The model explains a firm's decision to vertically integrate (rather than outsource) the input supply as an attempt to minimize the efficiency loss that derives from the hold-up problem.[1] Through integration, also called intra-firm sourcing, the firm acquires a residual property right in the input produced, which enhances its relative bargaining position vis-

[1]Policy implications of hold-up problems in input trade have been addressed in Ornelas & Turner (2008, 2012) and Antràs & Staiger (2012). The general thrust of this literature is that hold-up problems may justify subsidization or taxation of imported inputs, depending on whether the problem is more severe (or present only) for foreign sourcing, as in Antràs & Staiger (2012), or domestic sourcing, as in Ornelas & Turner (2008). However, as emphasized by Ornelas & Turner (2012), the optimal policy also depends on how firms react to the hold-up problem by choosing a specific ownership structure of input trade.

à-vis the supplier in ex-post negotiation over the production surplus. However, integration is costly because it reduces the supplier's incentive to invest in the production relationship at the time this relationship is established. Hence, integration tends to be favored in industries where the supplier's contribution to the production relationship is small relative to the contribution made by the firm, so-called headquarter-intensive industries (as opposed to component-intensive industries).

This chapter develops and applies an empirical strategy towards a firm-level test of the hold-up model of global sourcing proposed by Antràs & Helpman (2004), henceforth called AH model. The AH model extends Antràs (2003) by allowing for firms to differ in their productivity, as in Melitz (2003), and by explaining a firm's decision on the location of sourcing (domestic *versus* foreign) along with the ownership structure of sourcing (integration *versus* outsourcing). The model delivers an intriguing set of *industry-level predictions* on how the prevalence of intra-firm sourcing and foreign sourcing (as fractions of firms) is determined through the headquarter intensity of the industry and the dispersion of productivity across firms within the industry. In this chapter we propose a novel representation of the AH model that allows us to rigorously derive *firm-level predictions*, which we test on a unique survey data set of Spanish firms covering both the location and the ownership structure of sourcing over the period from 2006-2011.

At the industry level, a proper test of the AH model allowing for discrimination against other models of input sourcing hinges on two assumptions.[2] The first is that in any given industry the productivity distribution of firms has a certain shape (such as Pareto). This is a relatively mild assumption that can be verified with observable (or estimable) data, although such verification is rarely carried out in practice. The second assumption is that the true ranking of fixed costs associated with alternative locations and ownership structures of sourcing is in line with the ranking imposed by the researcher when formulating the tested hypothesis. This is a problematic assumption because the fixed costs are impossible to observe, nor is there a natural ranking of fixed costs that could safely be assumed to apply.

Knowledge of the fixed cost ranking is in fact crucial for an industry-level test of the AH model. To see why, suppose that integration demands *higher* fixed costs than outsourcing, a case discussed in detail in Antràs & Helpman (2004). In headquarter-intensive industries,

[2]Other models are presented, for example, in Grossman & Helpman (2002, 2003) where firms avoid search and contracting costs by vertically integrating (rather than outsourcing) its input supply, at the expense of foregone specialization gains. Grossman & Helpman (2004) invoke a principal-agent framework in which the nature (and subject) of a contract between firm and manager are different for the two ownership structures available. Grossman & Helpman (2005) develop a model that focuses on the trade-off between a cost advantage of foreign sourcing on the one hand and the disadvantage of a more difficult search for a suitable input supplier in an incomplete contracts environment.

there will be firm selection into different ownership structures of sourcing, since integration is beneficial in terms of variable production costs. High-productivity firms choose integration and low-productivity firms choose outsourcing.[3] In component-intensive industries, where the variable cost advantage lies with outsourcing, there will be no selection at all. Now suppose, instead, that integration demands *lower* fixed costs than outsourcing. In this case the above statement is reversed: Firm selection occurs only in component-intensive industries and, strikingly, it occurs in reverse fashion. This possibility of reversed predictions is a strength of the AH model, since it reflects great generality, but it also makes the model hard to test empirically.[4]

The industry-level predictions derived by Antràs & Helpman (2004) are based on the assumption that firms in the same industry are identical in all respects but their productivity. What emerges from this assumption is a characteristic sequence of "productivity cut-offs" that uniquely separates firms into groups that pursue different sourcing strategies. In this chapter, we allow for the fixed costs of sourcing to include a randomly distributed firm-specific component, a channel by which we introduce a second dimension of firm heterogeneity into the model. This extension is part of an empirical strategy towards a firm-level test of the AH model that is robust across all possible rankings of fixed costs for the different sourcing strategies. Nor does our strategy depend on any assumptions regarding the distribution of productivity across firms.

The key to our approach is to first pin down the difference in a firm's maximum profit across alternative locations and ownership structures, respectively, and to then study the variation in this difference induced by exogenous changes in the industry's headquarter intensity and the firm's productivity level. While Antràs & Helpman (2004) carve out productivity cut-offs that eliminate the difference in maximum profits across any two sourcing strategies, we explore the variation in this difference across the entire parameter space. In so doing, we exploit the fact that this variation is independent of the fixed costs of sourcing, whether specific to the industry or the firm. Technically speaking, our approach involves examining the modularity properties of the firm's maximum profit function with respect to key parameters of the model, as in Mrázowá & Neary (2013). These are the industry's headquarter

[3]If productivity is distributed Pareto, this equilibrium implies that a higher dispersion of productivity across firms will lead to a higher prevalence of intra-firm sourcing. An alternative equilibrium involving no selection will arise in headquarter-intensive industries, if the fixed cost disadvantage of integration relative to outsourcing is sufficiently small.

[4]In a regression analysis of industry-level data, this possibility of reversed predictions renders any attempt to "control" for the fixed cost ranking (for example through fixed effects in a panel estimation) meaningless. The reason for this is that in theory the sign of the effect of a greater productivity dispersion across firms on the prevalence of intra-firm sourcing depends on this very fixed cost ranking.

intensity; the firm's productivity level; the ex-post distribution of revenue between the firm and the input supplier; and the unit cost of sourcing abroad (relative to the unit cost of sourcing domestically). For a very large and plausible parameter subspace, we find modularity properties that are straightforward to translate into a firm-level probability model of sourcing.

The firm-level predictions that we derive from the AH model are reminiscent of the industry-level predictions derived in Antràs & Helpman (2004), but they are novel in several important ways. First, for a given ownership structure of sourcing the probability of a firm to source its input abroad (rather than domestically) is monotonically decreasing in the industry's headquarter intensity. The effect of the firm's productivity is strictly positive throughout, but it is the weaker, the larger the headquarter intensity of production. Second, for a given sourcing location the probability of a firm to vertically integrate (rather than outsource) its input supply is monotonically increasing in the industry's headquarter intensity, while the effect of the firm's productivity is ambiguous: it is strictly positive in headquarter-intensive industries and strictly negative in component-intensive industries. This prediction is the firm-level analogue to what has been dubbed the Antràs effect by Nunn & Trefler (2008). With minor qualifications rooted in the empirical fact that firms pursue more than one sourcing strategy at a time (Kohler & Smolka, 2011), the patterns that we find in the Spanish firm-level data are fully compatible with all of these predictions. Importantly, since these predictions do not hinge upon unobserved fixed cost rankings across alternative sourcing strategies, our approach amounts to a proper test of the AH model. And the outcome is strong empirical support of the model.

Our data are drawn from an annual survey of about 2,000 manufacturing firms in Spain. They are particularly well suited for a firm-level test of the AH model, for two reasons. First, the firms report the ownership structure of their input sourcing (integration *versus* outsourcing) separately for either sourcing location (domestic *versus* foreign). Hence, we can test the firm-level predictions of the AH model in all relevant sourcing dimensions. Secondly, the survey classifies firms into 20 different industries based on the three-digit NACE Rev. 2 standard industrial classification of the European Union. This allows us to exploit the cross-industry variation in headquarter intensity for identification purposes, and to treat unobserved fixed cost differences across alternative sourcing strategies as a constant, industry-specific probability shifter in favor of one or the other sourcing alternative.

This chapter is related to a series of papers that have tried, in one way or another, to bring the AH model to the data. Studies using data at the industry-level (widely or narrowly defined) are Yeaple (2006), Nunn & Trefler (2008), Bernard et al. (2010), and Nunn & Trefler

(2013).[5] These studies robustly find that measures of an industry's headquarter intensity, especially capital intensity, are positively associated with the prevalence of intra-firm trade in the industry. A subset of these studies also finds that firm heterogeneity, captured by the dispersion of productivity in the industry, plays an important role for the prevalence of intra-firm trade. By and large, the conclusion drawn in these studies is that the evidence lends support to the AH model. However, this conclusion rests on untested assumptions about the fixed cost ranking of alternative sourcing strategies as well as about the shape of the productivity distribution of firms. Furthermore, these studies focus exclusively on the choice between integration and outsourcing abroad. They do not look at the same choice in the domestic economy, nor do they study the trade-off between domestic and foreign sourcing in relation to the AH model.

Studies using data at the firm-level fall into two parts. The studies by Tomiura (2007), Federico (2010), Kohler & Smolka (2011), and Kohler & Smolka (2012) search for characteristic differences across groups of firms pursuing different sourcing strategies. It turns out that for a given sourcing location there are robust "performance premia" in terms of productivity, size, capital intensity and the like on vertical integration strategies over strategies of outsourcing. The same is true for the comparison between firms sourcing their inputs abroad and firms sourcing domestically, a finding that is independent of the "exporter premia" that are also well-documented in the literature.[6] While indicative of a productivity-dependent selection of firms, a result that features prominently in the AH model, these studies do not investigate whether (and how) this selection is governed by the headquarter intensity of the industry; hence they fall short of an empirical test of the AH model.

The second type of firm-level studies, namely Federico (2012), Defever & Toubal (2013), and Corcos et al. (2013), estimates decision models for the firm's choice between foreign integration and foreign outsourcing in the spirit of the AH model. The evidence reported in these studies seems contradictory. Investigating a cross-section of French firms Defever & Toubal (2013) find that firm productivity is negatively correlated with the prevalence of intra-firm trade, while this same correlation is positive in Federico (2012) (using a cross-section of Italian firms) and in Corcos et al. (2013) (using an extended cross-sectional sample

[5] Feenstra & Hanson (2005) test a variant of the hold-up model in relation to multinational operations in China's processing trade; see also Fernandes & Tang (2012). Costinot et al. (2011) find that industries in which non-routine activities loom large have higher shares of intra-firm trade. This is explained by non-routine activities often requiring ex-post "adaptation" on the part of the contractual partners (for example because problems arising ex post call for renegotiation), and by adaptation being less costly if carried out intra-firm.

[6] In Kohler & Smolka (2013), we use changes in sourcing strategies through time to show that firms select their sourcing strategy based on their productivity.

of the same French firm-level data source).[7] One is tempted to argue that all of these studies potentially lend empirical support to the AH model, provided only that the (unobservable) fixed cost ranking underlying their respective samples is of suitable (opposite) sign. We show that this reading of the firm-level empirical literature is misleading, because the AH model implies an ambiguous effect of productivity at the firm-level, independently of the fixed cost ranking.

The rest of this chapter is organized as follows. In Section 4.2 we reformulate the AH model and investigate the modularity properties of the firm's maximum profit function. Based on these properties, we derive firm-level predictions from the model. Section 4.3 introduces the Spanish firm-level data we use in order to test these predictions. It also looks at the prevalence of different sourcing strategies in our data, and how their use has changed over the past few years. In Section 4.4 we bring our novel firm-level predictions of the AH model to the data. We do so by drawing on a set of discrete choice models on alternative locations and ownership structures of sourcing. Section 4.5 concludes.

4.2 The hold-up model of global sourcing

4.2.1 Model assumptions

In the AH model, firms, interchangeably referred to as headquarters and headquarter firms, produce differentiated varieties of a final good by securing (and entering) a production relationship with an input supplier. Production relies on two types of intermediates, a headquarter service provided by the firm and a manufacturing component (henceforth simply called input) provided by the input supplier. Both intermediates are essential for the production of the final good, and both are highly customized. The headquarter service is produced domestically, while input suppliers may either be located (and produce) in the domestic or the foreign economy. Customization of intermediates for a specific variety of the final good has two consequences. First, due to impossible third party verification, the two agents cannot enter an enforceable contract about the exact quality of the intermediates to be delivered. And secondly, once produced both intermediates are entirely relationship-specific and have no use outside the production relationship. As a result, the two agents have to bargain about sharing the revenue generated from producing and selling the final good.

[7] Federico (2012) also looks at the choice between domestic integration and domestic outsourcing. Contrary to all three of the aforementioned studies, we also explore the choice between foreign sourcing and domestic sourcing conditional on the ownership structure of sourcing.

The model assumes ex-post Nash bargaining according to some underlying (i.e., exogenous) relative bargaining power as well as ex-post outside options of the two agents. Under an outsourcing relationship, either party has a zero ex-post outside option. Under integration, the headquarter acquires a property right that secures part of the revenue in case bargaining breaks down. Hence, integration affords the headquarter a positive ex-post outside option.[8] Once an agreement has been reached, the final good is produced, with revenue generated on monopolistically competitive markets, and shared according to the bargaining agreement.[9] In a preceding stage, the two agents decide about the quantity of intermediates to produce, based on expected revenue shares as well as the marginal costs prevailing in their respective locations. In the first stage of the game, anticipating decisions in all subsequent stages, the headquarter decides about whether to secure participation of a foreign or a domestic input supplier, and whether to rely on an outsourcing or an integrated production relationship.[10]

We use indices $h = d, f$ and $j = v, o$ to denote the two available locations (domestic and foreign) and ownership structures (vertical integration and outsourcing) of input supply. We refer to ℓ_h as the inverse unit cost of the input, with a value equal to ℓ_d if it is produced domestically, and ℓ_f if it is produced abroad. Following Antràs & Helpman (2004), we assume $\ell_d < \ell_f$, which implies a foreign cost advantage for the manufacturing component. Without loss of generality, we normalize the unit cost for the headquarter service to unity. The ex-post revenue share accruing to the headquarter is denoted by m_j, so that $1 - m_j$ accrues to the input supplier. The outside option deriving from the residual property right implies that $m_v > m_o$. Each combination of location and ownership structure of sourcing requires its own fixed cost F_{hj}, which is specific to the industry that a firm belongs to. We emphasize that the model does not take a stance on the differences in fixed costs across sourcing strategies, and that it even allows for "reversals" in fixed cost differences across industries.

In order to nail down the headquarter's choice of a sourcing strategy $\{h, j\}$, Antràs & Helpman (2004) make three further assumptions: i) a Cobb-Douglas technology for final goods production relying on the two intermediates, ii) a uniform and constant perceived

[8] Assuming a zero outside option for the outsourcing relationship is a mere normalization. What matters, in line with Grossman & Hart (1986), is that the headquarter enjoys a larger outside option with integration than with outsourcing.

[9] The underlying assumption is that the bargaining agreement as such can be contracted with perfect enforcement.

[10] Antràs & Helpman (2008) allow both intermediates to be composed of a continuum of tasks that falls into two ranges of contractible and non-contractible tasks, respectively. Schwarz & Suedekum (2013) similarly allow for a continuum of intermediates, modeled on an interval of variable length that is endogenously determined by the headquarter. Although the entire continuum of intermediates is assumed non-contractible, it falls into two subranges where the headquarter relies on outsourcing and integration, respectively, vis-à-vis multiple suppliers of intermediates. See also Antràs (2012) for a survey.

price elasticity of final goods demand, and iii) a zero ex ante outside option of the input supplier. Assumptions i) and ii) generate concavity of the revenue function. Assumption iii) ties down the participation constraint such that the return that the input supplier may expect from entering the production relationship is zero.[11]

4.2.2 Setup for decision making

We write $\Pi(\ell_h, m_j; \eta, \theta)$ for the headquarter's maximum operating profit, given the sourcing strategy $\{h, j\}$. In this expression, η denotes the industry-specific elasticity of final output with respect to the headquarter service, referred to as the headquarter intensity, and θ denotes the firm's total factor productivity.[12] The headquarter's operating profit is equal to its revenue share minus the cost of the headquarter service, plus a transfer payment from the supplier that just secures the supplier's participation. It is easy to show that this profit is equal to the total revenue from the production relationship minus the cost of both intermediates, minus the supplier's ex-ante outside option. Calling $\Pi(\ell_h, m_j; \eta, \theta)$ a maximum profit means that the levels of both intermediates have been chosen optimally, given monopolistic competition on goods markets as well as prices of the intermediates, and given the sourcing strategy.

The headquarter's choice of the sourcing strategy $\{h, j\}$ is then dictated by

$$\max_{h,j}\{\Pi(\ell_h, m_j; \eta, \theta) - F_{hj}\}. \tag{4.1}$$

In a long-run general equilibrium, maximum profits as given in (4.1) are approaching zero if there is free entry into this industry. Antràs & Helpman (2004) show that under the above assumptions we have

$$\Pi(\ell_h, m_j; \eta, \theta) = Z(\ell_h, m_j; \eta)\theta^{\varepsilon-1}, \tag{4.2}$$

where $\varepsilon > 1$ denotes the perceived price elasticity of demand for final goods (in absolute

[11] As with the zero ex-post outside option, this is a mere normalization that is not crucial for the results obtained.

[12] To avoid cluttered notation, we abstain from indexing firms and industries until we get to the point where it is necessary.

value) in a market environment of monopolistic competition, and where

$$
\begin{aligned}
Z(\ell_h, m_j; \eta) &:= Az(m_j; \eta)C(\ell_h, m_j; \eta), && (4.3)\\
z(m_j; \eta) &:= 1 - \frac{\varepsilon - 1}{\varepsilon}\Big[m_j\eta + (1 - m_j)(1 - \eta)\Big], && (4.4)\\
\text{and} \quad C(\ell_h, m_j; \eta) &:= \Big[m_j^\eta(\ell_h(1 - m_j))^{1-\eta}\Big]^{\varepsilon - 1}. && (4.5)
\end{aligned}
$$

In these definitions, A captures the size of the market.[13] The term $C(\ell_h, m_j; \eta)$ highlights the efficiency cost of the hold-up problem. This is best seen by realizing that $C(\ell_h, m_j; \eta)^{\varepsilon-1}$ is equal to the inverse minimum unit-cost function for the final good, dual to the assumed Cobb-Douglas technology, with the prices of the two inputs inflated by $1/m_j$ and $1/(1-m_j)$, respectively. Thus, the hold-up problem acts like an input tax that implies a lower than optimal overall input provision (and thus lower revenue) as well as a distorted input mix (unless $m_j = 0.5$). From $C(\ell_h, m_j; \eta)$, as well as from the definition of $z(m_j; \eta)$ in (4.4), it follows that there is a non-monotonic relationship between the headquarter's profit and its revenue share m_j.

The decision rule in (4.1) requires a discrete comparison of the operating profit for $\ell_h = \ell_d, \ell_f$ and $m_j = m_o, m_v$. To describe this comparison, we introduce the following definitions:

$$
\begin{aligned}
\Delta_\ell\Pi(m_j; \eta, \theta) &:= \Pi(\ell_f, m_j; \eta, \theta) - \Pi(\ell_d, m_j; \eta, \theta), && (4.6)\\
\Delta_m\Pi(\ell_h; \eta, \theta) &:= \Pi(\ell_h, m_v; \eta, \theta) - \Pi(\ell_h, m_o; \eta, \theta), && (4.7)\\
\Delta_\ell F_j &:= F_{fj} - F_{dj}, && (4.8)\\
\text{and} \quad \Delta_m F_h &:= F_{hv} - F_{ho}. && (4.9)
\end{aligned}
$$

The term $\Delta_\ell\Pi(m_j; \eta, \theta)$ gives the difference in operating profits across the two locations of sourcing, conditional on sourcing under the ownership structure j. Under the above assumption that $\ell_d < \ell_f$, this difference is strictly positive. It is therefore a measure for the *location advantage of foreign sourcing.* Similarly, the term $\Delta_m\Pi(\ell_h; \eta, \theta)$ gives the difference in operating profits across the two ownership structures of sourcing, conditional on sourcing in location h. If this difference is positive, there is a *strategic advantage of integration*; if it is negative, there is a *strategic advantage of outsourcing.* Definitions analogous to (4.6) and (4.7) hold for $\Delta_\ell Z(m_j; \eta)$ and $\Delta_m Z(\ell_h; \eta)$. If positive, the term $\Delta_\ell F_j$ measures the industry-specific *fixed cost disadvantage of foreign sourcing.* A fixed cost disadvantage of *domestic*

[13]More specifically, if B denotes the entire expenditure falling on differentiated varieties of the good in question, the term A may be written as $B[(\varepsilon - 1)/\varepsilon]^{\varepsilon-1}$. Remember that the unit cost of the headquarter service has been normalized to unity.

sourcing is easily accommodated by $\Delta_\ell F_j < 0$. Similar statements apply to the term $\Delta_m F_h$. If $\Delta_m F_h > 0$, we speak of a *fixed cost disadvantage of integration*; if $\Delta_m F_h < 0$, we have a fixed cost disadvantage of *outsourcing*.

4.2.3 Firm-level predictions

We aim at firm-level predictions going beyond the cut-offs in productivity that separate firms with different sourcing strategies, as described in detail in Antràs & Helpman (2004). We therefore introduce a second dimension of firm heterogeneity that concerns the fixed costs of sourcing and that is independent of the firm's productivity. More specifically, we assume that when sourcing in location h firm i faces a fixed cost disadvantage of integration equal to $\Delta_m F_h + \mu_{i,h}$. Thus, in addition to $\Delta_m F_h$, which is common to all firms in the same industry, there is a firm-specific element $\mu_{i,h}$ that adds to the fixed cost difference across the two ownership structures of sourcing. By complete analogy, the firm-specific fixed cost disadvantage of foreign sourcing is equal to $\Delta_\ell F_j + \mu_{i,j}$ when sourcing under ownership structure j.

It is straightforward to translate the above setup into simple decision rules for a firm's input sourcing. We define a binary variable $V_{i,h}$, such that $V_{i,h} = 1$ if the firm i decides to integrate its input supply, conditional upon sourcing in location h, and $V_{i,h} = 0$ otherwise. Likewise, a variable $V_{i,j}$ describes firm i's choice of the sourcing location, conditional upon its ownership structure j. Foreign sourcing implies $V_{i,j} = 1$, and domestic sourcing implies $V_{i,j} = 0$. Then, the decision rule for firm i choosing the ownership structure of its sourcing, conditional on sourcing in location h, emerges as

$$V_{i,h} = \begin{cases} 1 & \text{if } \Delta_m \Pi(\ell_h; \eta, \theta_i) - (\Delta_m F_h + \mu_{i,h}) \geq 0 \\ 0 & \text{otherwise.} \end{cases} \tag{4.10}$$

A similar representation exists with respect to the firm's decision rule for the location of sourcing, given the ownership structure j. Given a firm's productivity θ_i, there exists a unique threshold value $\tilde{\mu}_{i,h}$ which makes the firm indifferent between integration and outsourcing in location h. The same applies to $\tilde{\mu}_{i,j}$, which denotes the threshold value for the location of sourcing, given the ownership structure j. If $\mu_{i,h} < \tilde{\mu}_{i,h}$, then according to (4.10) firm i chooses integration if sourcing in h; if $\mu_{i,h} > \tilde{\mu}_{i,h}$, it chooses outsourcing. Analogously, if $\mu_{i,j} < \tilde{\mu}_{i,j}$, then firm i prefers foreign sourcing if in ownership structure j, and if $\mu_{i,j} > \tilde{\mu}_{i,j}$ it will source domestically.

We now derive firm-level predictions on the location advantage of foreign sourcing and the strategic advantage of integration or outsourcing, respectively. In doing so, we exploit certain *modularity properties* of the maximum profit function $\Pi(\ell_h, m_j; \eta, \theta)$ as defined in (4.2) through (4.5). These properties describe the responsiveness of $\Delta_\ell \Pi(m_j; \eta, \theta)$ and $\Delta_m \Pi(\ell_h; \eta, \theta)$, respectively, to changes in η and θ.[14]

Definition 1. **(a)** *The function $H(g,q)$ is called supermodular with respect to g and q, if for any two values $g_1 > g_0$ and $q_1 > q_0$ the following is true: $\Delta_g H(q_1) > \Delta_g H(q_0)$, where $\Delta_g H(q) := H(g_1, q) - H(g_0, q)$.* **(b)** *The function $H(g,q)$ is called submodular, if $-H(g,q)$ is supermodular with respect to g and q.* **(c)** *If $H(g,q)$ is twice differentiable, then it is called supermodular, if $\partial^2 H/(\partial g \partial q) > 0$, and vice versa for submodularity.*

Proposition 1 **(location of sourcing, conditional on the ownership structure** j**).** **(a)** *A higher productivity of the firm strengthens the location advantage of foreign sourcing.* **(b)** *Within a very large and plausible parameter subspace of $\{m_j, \eta\}$, a higher headquarter intensity of the industry weakens the location advantage of foreign sourcing.* **(c)** *In this same parameter subspace, a higher headquarter intensity of the industry weakens the positive interaction between the location advantage of foreign sourcing and the firm's productivity (as described in part a).*

Proof. Part (a) of the proposition follows from $\Delta_\ell \Pi(m_j; \eta, \theta) = \Delta_\ell Z(m_j; \eta)\theta^{\varepsilon-1}$ and $\varepsilon > 1$. Part (c) is equivalent to the profit function $\Pi(\cdot)$ being submodular in ℓ and η. In Appendix A we show that submodularity obtains for a large and plausible parameter subspace of m_j and η. This will also prove part (b) of the proposition. □

Part (a) of Proposition 1 is familiar from existing literature. It tells us that a firm's productivity is a leverage for the location advantage of foreign sourcing. Figure 4.1 illustrates this leverage effect by plotting the location advantage of foreign sourcing as an increasing function of $\Theta_i := \theta_i^{\varepsilon-1}$, which is a positive monotonic transformation of firm i's productivity. The plot is linear with a slope equal to $\Delta_\ell Z(m_j; \eta_0)$, and it holds for an industry with a certain headquarter intensity η_0. If we depict the industry-specific fixed cost difference across sourcing locations on the vertical axis, the plot is a demarkation line for domestic and foreign sourcing. In the figure, we compare the case of a fixed cost disadvantage of foreign sourcing, $\Delta_{\ell 0} F_j > 0$, with the case of a fixed cost disadvantage of domestic sourcing, $\Delta_{\ell 1} F_j < 0$. The threshold values for the firm-specific fixed cost differences $\tilde{\mu}_{i,j}$ are found as vertical arrows between the industry-specific fixed cost differences and the demarkation line. Positive

[14] We propose a "modularity view" on firm-level sourcing decisions in Kohler & Smolka (2011). Mrázowá & Neary (2013) point out more generally that *modularity properties* lie at the heart of the selection effects discussed in modern trade literature focusing on firm heterogeneity.

(negative) threshold values are represented by upward (downward) arrows. For instance, for an industry-specific fixed cost disadvantage of foreign sourcing equal to $\Delta_{\ell 0} F_j > 0$ a firm positioned at Θ_i will face a negative threshold value $\tilde{\mu}_{i,j}$ for foreign sourcing, indicated by the downward arrow, while for $\Delta_{\ell 1} F_j < 0$ it will face a positive threshold, indicated by the upward arrow. A more productive firm positioned at $\Theta_{i'}$ will face positive threshold values for $\Delta_{\ell 0} F_j$ as well as $\Delta_{\ell 1} F_j$, but the threshold will be higher in absolute value for $\Delta_{\ell 1} F_j$.

<<Figure 4.1 about here>>

The key point is that, irrespective of the sign and magnitude of the fixed cost difference across sourcing locations, a firm with a higher productivity faces a lower algebraic threshold value $\tilde{\mu}_{i,j}$. In the empirical section below, we shall translate this relationship into a probability model for $V_{i,j}$, and the upshot will be that, other things equal, a more productive firm is more likely to choose foreign sourcing, whatever the fixed cost difference $\Delta_\ell F_j$.

Parts (b) and (c) of Proposition 1 are novel to the literature and essentially rely on the same submodularity property of the profit function; see the proof. In Figure 4.1, this property appears as a counter-clock-wise rotation of the demarkation line caused by any *decrease* in the headquarter intensity. Part (b) of Proposition 1 means that, other things equal, firms belonging to an industry with a higher headquarter intensity face threshold values for their respective fixed cost differences that are lower in algebraic value. Again, this holds true independently of the industry-specific fixed cost difference across sourcing locations.

Intuitively, a foreign cost advantage for the input should become less compelling for foreign sourcing, if the headquarter intensity η increases, since this means the foreign input becomes less important for the production relationship. However, Proposition 1 states that the relevant submodularity property does not hold for the entire parameter space. In Appendix A, we demonstrate the ambiguity and we show by means of numerical simulations that submodularity does hold for a very large and plausible parameter subspace. Part (c) of Proposition 1 implies an interaction between the firm's productivity and the industry's headquarter intensity in a firm's decision about its sourcing strategy. The positive relationship between the firm's productivity and the likelihood of it choosing foreign sourcing becomes stronger, if it belongs to an industry with a lower headquarter intensity.

Proposition 2 (**ownership structure of sourcing, conditional on location** h). **(a)** *Industries with a headquarter intensity above a threshold value* $\tilde{\eta}(m_o, m_v)$ *feature a strategic advantage of integration; industries with a headquarter intensity below* $\tilde{\eta}(m_o, m_v)$ *feature a strategic advantage of outsourcing.* **(b)** *A higher productivity of the firm strengthens any* *strategic advantage of sourcing, whether this advantage lies with integration or with outsourcing.* **(c)** *Within a large and plausible parameter subspace of* $\{m_j, \eta\}$*, a higher headquarter intensity of the industry strengthens any strategic advantage of integration, while it weakens any strategic advantage of outsourcing.* **(d)** *In this same parameter subspace, a higher headquarter intensity of the industry strengthens any positive interaction between a strategic advantage of integration and the firm's productivity (as described in part b), while it weakens any positive interaction between a strategic advantage of outsourcing and the firm's productivity (as described in part b).*

Proof. Part (a) of the proposition follows from Antràs (2003). In terms of the present notation, his Proposition 1 and Lemma 3 state that $Z(\ell_h, m_v; \eta, \theta) / Z(\ell_h, m_o; \eta, \theta)$ is monotonically increasing in η, with a unique threshold level η^* implicitly defined through $Z(\ell_h, m_v; \eta^*, \theta) / Z(\ell_h, m_o; \eta^*, \theta) = 1$. In view of our Proposition 2, we may write $\eta^* = \tilde{\eta}(m_o, m_v)$. Moreover, we have $\Delta_m Z(\ell_h; \eta, \theta_i) < 0$ for all $\eta < \tilde{\eta}(m_o, m_v)$ and vice versa for all $\eta > \tilde{\eta}(m_o, m_v)$. Part (b) derives readily from the fact that $\Delta_m \Pi(\ell_h; \eta, \theta) = \Delta_m Z(\ell_h; \eta)\theta^{\varepsilon - 1}$. Part (d) is equivalent to the profit function $\Pi(\cdot)$ being supermodular in m and η. In Appendix A we show that supermodularity obtains within a large and plausible parameter subspace of $\{m_j, \eta\}$. This will also prove part (c) of the proposition. □

<<Figure 4.2 about here>>

Part (a) of Proposition 2 is the familiar Antràs effect. Integration offers a higher ex-post revenue share for the headquarter. But for a low enough headquarter intensity the revenue share effect is dominated by the adverse incentive effect that integration exerts on the input supplier. Intuitively, the threshold $\tilde{\eta}(m_o, m_v)$ is higher for a higher value of m_o and lower for a higher value of m_v. Importantly, the Antràs effect interacts with the firm's productivity, as stated in part (b) of Proposition 2. Figure 4.2 illustrates Proposition 2, with demarkation lines familiar from Figure 4.1. The bottom part of the figure depicts a demarkation line for an industry with low headquarter intensity $\eta_1 < \tilde{\eta}(m_o, m_v)$, with the strategic advantage lying with outsourcing. If this is paired with a fixed cost disadvantage of integration, $\Delta_{m0} F_h > 0$, then a firm with a productivity measured at Θ_i faces a negative threshold $\tilde{\mu}_{i,h} < 0$, indicated by a downward arrow. A firm with a higher productivity measured at $\Theta_{i'}$ similarly faces a negative threshold $\tilde{\mu}_{i',h} > 0$, which is even higher in absolute value. The reason is that the strategic advantage of outsourcing is magnified by a high productivity. With a fixed cost disadvantage of outsourcing, $\Delta_{m1} F_h < 0$, firm i faces a positive threshold $\tilde{\mu}_{i,h} > 0$, measured by the upward arrow. For firm i' the threshold is still negative, but has become smaller in magnitude. Thus, whatever the industry-specific fixed cost difference $\Delta_m F_h$, the firm-specific threshold value $\tilde{\mu}_{i,h}$ is increasing in the firm's productivity. In terms of the probability model developed below, a more productive firm in an industry with $\eta < \tilde{\eta}(m_o, m_v)$ is less likely to choose integration, irrespective of the fixed cost difference across ownership structures. This statement is reversed for any industry with $\eta > \tilde{\eta}(m_o, m_v)$, such as η_2 in Figure 4.2.

The supermodularity between m and η that we claim in parts (c) and (d) of Proposition 2 implies a counter-clockwise rotation of the demarkation line caused by an *increase* in the industry's headquarter intensity. Repeating the above exercise of identifying threshold values $\tilde{\mu}_{i,h}$ and $\tilde{\mu}_{i',h}$, this has two implications. i) The relationship between the likelihood of integration and a firm's productivity must include a positive interaction between the productivity of the firm and the headquarter intensity of the industry. ii) Other things equal, the likelihood of integration is increasing in the headquarter intensity of the industry that the firm belongs to. Again, all of this this holds true irrespective of the sign and magnitude of the industry-specific fixed cost differences across ownership structures.

4.3 Firm-level data

4.3.1 Source

Our firm-level data are drawn from the "Encuesta Sobre Estrategias Empresariales" (ESEE), an annual survey of roughly 2,000 manufacturing firms in Spain. It is arranged by the "Sociedad Estatal de Participaciones Industriales", a public foundation based in Madrid.[15] To date the ESEE covers a representative panel of Spanish manufacturing firms for the years 1990-2011. Its panel structure allows us to track manufacturing firms in Spain over time. The initial selection of surveyed firms (in 1990) followed a two-way sampling procedure. Questionnaires were sent out to all firms that employed more than 200 workers and to a subset of firms that employed between 10 and 200 workers. Firms in this latter subset were selected through a stratified, proportional and systematic sampling (with a random seed). Later, special efforts have been made in order to keep the sample representative with respect to the population of reference. The survey distinguishes 20 different industries and four different size groups for firms that employ between 10 and 200 individuals. Industries are defined according to sets of products at the NACE-2009 level.[16]

[15] Detailed information on the foundation's history and activities are available at `http://www.fundacionsepi.es/`.

[16] Table B.1 in Appendix B gives a list of manufacturing industries considered in the survey. Prior to 2009, firms have been classified into industries according to the older NACE-1993 classification. We have used

A central feature of our data is that from 2006 onwards they include information on the global sourcing activities of firms along the two dimensions of sourcing, location and ownership structure. The two relevant questions in the survey, pivotal for the quality of the data, read as follows:[17]

1. *Of the total amount of purchases of goods and services that you incorporate (transform) in the production process, indicate – according to the type of supplier – the percentage that these represent in the total amount of purchases of your firm in* [year].
   (a) *Spanish suppliers that belong to your group of companies or that participate in your firm's joint capital.* [yes/no] / [if yes, then percentage rate]
   (b) *Other suppliers located in Spain.* [yes/no]/[if yes, then percentage rate]
2. *For the year* [year]*, indicate whether you imported goods and services that you incorporate (transform) in the production process, and the percentage that theses imports – according to the type of supplier – represent in the total value of your imports.* [yes/no]
   (a) *From suppliers that belong to your group of companies and/or from foreign firms that participate in your firm's joint capital.* [yes/no]/[if yes, then percentage rate]
   (b) *From other foreign firms.* [yes/no]/[if yes, then percentage rate]

We use answers to question 1.(a) to construct a dummy variable for domestic integration (abbreviated DI) that takes on the value one if the firm answers "yes", and zero if it answers "no". We proceed accordingly for domestic outsourcing (question 1.(b): DO), foreign integration (question 2.(a): FI), and foreign outsourcing (question 2.(b): FO). We can then characterize observations by defining a tuple of variables $\Omega = \langle DI, DO, FI, FO\rangle$. For example, we attach $\Omega = \langle 1, 0, 1, 0\rangle$ to any observation that reports to source inputs from both a foreign and a domestic integrated supplier (but not from another independent supplier in Spain or abroad). Sometimes it shall prove convenient to refer to Ω as a set of tuples. An example is: $\Omega = \{\langle 1, 0, 1, 0\rangle, \langle 0, 0, 1, 0\rangle\}$, which we write shorthand as $\Omega = \{\langle \cdot, 0, 1, 0\rangle\}$.

concordance information provided by the SEPI foundation, in order to take care of this change in industrial classification. More information on the survey and its sampling properties are available in English from SEPI's website at `http://www.fundacionsepi.es/esee/en/epresentacion.asp`.

[17] The survey questionnaire is distributed in Spanish and available for download at `http://www.fundacionsepi.es/esee/sp/svariables/indice.asp`.

4.3.2 Firm productivity

A pivotal variable in our empirical analysis is a firm's productivity level. Firm-level estimates of total factor productivity (TFP) are often plagued by biases originating from endogenous selection into markets, simultaneous choice of input factors, omitted firms' input and output prices, and endogenous product mixes. We apply the Olley & Pakes (1996) estimation algorithm, henceforth called OPA, in order to estimate industry-specific production functions. From these estimates we recover each firm's TFP level as a firm-specific, time-variant variable. The OPA takes care of the selection bias as well as the simultaneity bias.

We employ the ESEE firm-level data from 2000-2011 in applying the OPA, using annual information on each firm's real output, real investment, real capital stock, real purchases, labor employment, and exit decisions. *Real output* is the total production value plus other operating income (i.e., income from rent and leasing, industrial property, commissions, and certain services), expressed in terms of prices of the year 2000. We deflate production values and other types of operating revenue by using firm-level information on goods price variations from the ESEE, coupled with an industry-level price index from the INE for years with missing data. Using goods price variations at the level of individual firms is important to avoid estimation biases due to firm-specific mark-up pricing, firm-specific demand shocks, or firm-specific market access; see Klette & Griliches (1996) and De Loecker (2007). *Real investment* is the total investment value in real estate, construction, and equipment, deflated with an industry-level price index from the Spanish National Statistics Institute (INE). The *real capital stock* is the reported value of real estate, construction, and equipment, deflated with an industry-level price index from the INE. We use a firm-level price index, coupled with industry-level data from INE, to compute *real purchases*, defined as the total expenditure on intermediate inputs and external services. *Labor employment* is measured by effectively worked hours, which reduces the possibility of measurement bias relative to standard measures used in the literature. *Exit decisions* of firms are also reported in the data, which allows us to distinguish between firms shutting down production and firms staying in the market, but exiting the ESEE panel.

4.3.3 Prevalence of sourcing activities

Table 4.1 reports the prevalence of certain sourcing activities for two different years, 2006 and 2011, separately for small firms (with at most 200 employees) and large firms (with more than 200 employees). We define sourcing activities in a mutually inclusive way, so that a firm may count for more than one sourcing activity due to multiple ways of sourcing.

The first four rows from above distinguish among four sourcing activities: domestic sourcing ($\Omega = \{\langle 1,1,\cdot,\cdot\rangle, \langle 1,0,\cdot,\cdot\rangle, \langle 0,1,\cdot,\cdot\rangle\}$), foreign sourcing ($\Omega = \{\langle \cdot,\cdot,1,1\rangle, \langle \cdot,\cdot,1,0\rangle, \langle \cdot,\cdot,0,1\rangle\}$), outsourcing ($\Omega = \{\langle \cdot,1,\cdot,1\rangle, \langle \cdot,1,\cdot,0\rangle, \langle \cdot,0,\cdot,1\rangle\}$), and integration ($\Omega = \{\langle 1,\cdot,1,\cdot\rangle, \langle 1,\cdot,0,\cdot\rangle$, $\langle 0,\cdot,1,\cdot\rangle\}$). There is a fifth group that we refer to as non-sourcing firms ($\Omega = \langle 0,0,0,0\rangle$). These firms report zero volumes for input sourcing in the survey questionnaire.[18] We find that domestic sourcing is more common than foreign. More than 90% of firms source domestically, with just marginally higher values for large than for small firms. For foreign sourcing, the difference is much larger: for small firms we observe shares of 33.7% and 41% in 2006 and 2011, for large firms the corresponding figures are 65.9% and 76%, respectively. While the shares increase for all four types of sourcing, with a corresponding fall in the non-sourcing category, the increase over time is clearly strongest for foreign sourcing, and more so for large firms than for small firms.

<<Table 4.1 about here>>

In the bottom part of Table 4.1, we look at all combinations of the two sourcing dimensions (location and ownership structure). We see that domestic outsourcing ($\Omega = \{\langle \cdot,1,\cdot,\cdot\rangle\}$) is by far the most widely used sourcing strategy (roughly 90% of firms). Domestic integration ($\Omega = \{\langle 1,\cdot,\cdot,\cdot\rangle\}$) is a less common phenomenon, observed in 10% of the small and 30% of the large firms in 2011. Even wider gaps are observed for foreign integration ($\Omega = \{\langle \cdot,\cdot,1,\cdot\rangle\}$) and foreign outsourcing ($\Omega = \{\langle \cdot,\cdot,\cdot,1\rangle\}$): 5% and 40.2% for small, and 34.1% and 70.1% for large firms, respectively. Looking at changes through time, we find the strongest increases for large firms, with 8.8% for foreign outsourcing and 9.3 for foreign integration. Interestingly, small firms show a very modest increase of 1% in foreign integration, and large firms even show a decrease in domestic integration.

4.4 Empirical model

We now turn to a firm-level analysis of firms' sourcing behavior in the spirit of the AH model. The purpose of this section is to develop and apply a test of Propositions 1 and 2 with our firm-level data. Either proposition identifies the productivity of the firm as a key determinant of the firm's sourcing decision (along with the headquarter intensity of the industry to which the firm belongs). We will first study the relationship between firm productivity and the location of sourcing, conditional on the ownership structure of sourcing (Proposition 1).

[18] See Kohler & Smolka (2011) for a discussion of the incidence of non-sourcing firms.

Parts (a) and (c) of Proposition 1 imply that a higher productivity encourages firms to source their inputs offshore (rather than domestically), but that this productivity effect is the weaker the larger the headquarter intensity of the corresponding industry. We will then inspect the role of firm productivity for the ownership structure of sourcing, conditional on the location of sourcing (Proposition 2). Parts (a), (b), and (d) of Proposition 2 imply that the likelihood of a firm to engage in vertical integration (rather than outsourcing) may be increasing or decreasing in the productivity of the firm, depending on the corresponding industry's headquarter intensity: in industries with high headquarter intensities (above the threshold $\tilde{\eta}$), the productivity effect is positive and increasing in the headquarter intensity, but it is negative in industries with low headquarter intensities (below the threshold $\tilde{\eta}$) and decreasing (in absolute value) in the headquarter intensity.

4.4.1 The location of sourcing

Let firms be indexed by $i = 1, \ldots, I$, and let industries by indexed by $s = 1, \ldots, S$, with $S = 20$. Let the set of firms belonging to industry s be given by $\mathcal{I}_s$. We write $D_{i,j}(m_j; \eta_s, \theta_i) := \Delta_\ell \Pi(m_j; \eta_s, \theta_i) - \Delta_\ell F_{s,j} + \mu_{i,j}, i \in \mathcal{I}_s$, for firm i's total profit difference between foreign sourcing and domestic sourcing, conditional on the ownership structure $j = v, o$ of sourcing. We assume that this total profit difference can be approximated by the following linear expression:

$$D_{i,j}(m_j; \eta_s, \theta_i) = \beta_1 \cdot \theta_i + \beta_2 \cdot (\theta_i \times \eta_s) + \beta_3 \cdot \eta_s - \Delta_\ell F_{s,j} + \mu_{i,j}, \; i \in \mathcal{I}_s. \tag{4.11}$$

This parametrization satisfies part (a) of Proposition 1 as long as $\frac{\partial D_{i,j}(m_j;\eta_s,\theta_i)}{\partial \theta_i} = \beta_1 + \beta_2 \cdot \eta_s > 0$ for all values of η_s. Parts (b) and (c) require that $\frac{\partial D_{i,j}(m_j;\eta_s,\theta_i)}{\partial \eta_s} = \beta_2 \cdot \theta_i + \beta_3 < 0$ for all values of θ_i and $\frac{\partial^2 D_{i,j}(m_j;\eta_s,\theta_i)}{\partial \theta_i \partial \eta_s} = \beta_2 < 0$, respectively.

A number of empirical challenges arise in our setup. First, the profit difference $D_{i,j}(m_j; \eta_s, \theta_i)$ is a latent variable that is not observed by the econometrician. In the estimation, we will therefore revert to an observable binary variable $\tilde{V}_{i,j}$ (to be described below) that mirrors the decision variable $V_{i,j}$ as defined above in the AH model. Recall that $V_{i,j}$ is equal to one if $D_{i,j}(m_j; \eta_s, \theta_i) \geq 0$, and equal to zero otherwise. Second, and relatedly, we have seen in the previous section that in our data multiple ways of sourcing are the rule rather than the exception, and that sourcing strategies appear to be complementary to one another (rather than mutually exclusive). We must therefore find and impose suitable sample restrictions that lead to an empirical model which closely resembles the firm's decision problem as it is framed in the AH model. We must do so separately for the two ownership structures of sourcing. Third, the industry-specific headquarter intensity of production is not directly observed. Antràs (2003) argues that headquarter firms engage in cost sharing with their suppliers through capital investments (rather than labor investments). A high capital intensity thus comes with high levels of cost sharing, reflected in high values of the parameter $\eta_s \in \mathbb{R}$. Hence we follow Antràs (2003), Yeaple (2006), and Nunn & Trefler (2008), among others, in that we proxy an industry's headquarter intensity by its (logged) capital intensity, computed as the weighted average over all firms active in the industry (pooled from 2000 to 2011). The industries featuring the lowest headquarter intensity are "Leather & Footwear" ($\eta_s = 3.91$), "Furniture" (4.07), and "Textile & Wearing Apparel" (4.19). The industries featuring the highest headquarter intensity are "Beverages" (5.90), "Ferrous Metals & Non-Ferrous Metals" (5.21), and "Mineral (Non-Metal) Products" (5.08). The average headquarter intensity across industries is equal to $\bar{\eta}_s = 4.64$, with a standard deviation of $\sigma_\eta = 0.47$. Finally, in addition to the factors discussed in the AH model, there are a number of other factors (both at the industry level and at the firm level) that could exert a potentially important influence on the firm's preferred location of sourcing. We must therefore look for an empirical strategy that takes care of these other (confounding) factors, with the aim of obtaining consistent and unbiased estimates of our parameters of interest $\boldsymbol{\beta} = (\beta_1, \beta_2, \beta_3)$.

Recall that our data allow us to track individual firms over time. Individual observations are thus of dimension it (rather than just i), where $t = 1, \ldots, T$ is an index for years. We write Ω_{it} for the sourcing tuple of individual observations. Let Ω_j denote the set of admissible tuples Ω when studying the location choice of sourcing and conditioning on the ownership structure j of sourcing. As a baseline specification, we then write:

$$\tilde{V}_{it,j} = \beta_1 \cdot \theta_{it} + \beta_2 \cdot (\theta_{it} \times \eta_s) + \gamma_{s,j} + \gamma_{t,j} + \mu_{it,j}, \; i \in \mathcal{I}_s, \Omega_{it} \in \Omega_j, \tag{4.12}$$

where the firm's productivity θ_{it} is a time-varying variable, and where the industry's headquarter intensity η_s is a time-invariant variable whose value is dictated by technology. Three comments on this equation are in order. First, $\gamma_{s,j}$ is an industry fixed effect capturing (i) the main effect of the headquarter intensity, $\beta_3 \cdot \eta_s$, and (ii) the (unobservable) industry-specific fixed cost difference between foreign and domestic sourcing, $\Delta_\ell F_{s,j}$. Under standard assumptions on the distribution of $\mu_{it,j}$, this means that controlling for the fixed cost difference through industry fixed effects implies that the parameter β_3 is not identified, and that therefore a test of part (b) of Proposition 1 is not within reach of our model.[19] Second, $\gamma_{t,j}$ is

[19]We see no way to circumvent this problem at the firm-level. We shall later provide some tentative evidence on the relation between the industry's headquarter intensity and the prevalence of foreign sourcing at the industry-level.

a year fixed effect absorbing the influence of year-specific global shocks affecting all firms in Spain in exactly the same way. Third, we assume that $\mu_{it,j}$ is an independently distributed random variable with $E[\mu_{it,j}|\cdot] = 0$, which implies that (4.12) is the linear probability model (LPM):[20]

$$E[\tilde{V}_{it,j}|\cdot] = \Pr(\tilde{V}_{it,j} = 1|\cdot) = \beta_1 \cdot \theta_{it} + \beta_2 \cdot (\theta_{it} \times \eta_s) + \gamma_{s,j} + \gamma_{t,j},\ i \in \mathcal{I}_s, \Omega_{it} \in \Omega_j. \quad (4.13)$$

The restriction to observations that satisfy $\Omega_{it} \in \Omega_j$ is crucial. It reflects the fact that we condition on the ownership structure j of sourcing, and that in this setup we are interested purely in the firm's choice of the location of sourcing. Our choice of restrictions is largely dictated by the data. For example, we never exclude firms that rely on domestic outsourcing ($\Omega_{it} = \langle \cdot, 1, \cdot, \cdot \rangle$), since we would otherwise be left with an almost empty set of firms due to the large incidence of this sourcing strategy (cf. Table 4.1). When conditioning on vertical integration ($j = v$), we impose $\Omega_v = \{\langle 1, 1, 0, 0 \rangle, \langle 1, 1, 1, 0 \rangle\}$. In words, we exclude all firms that do not rely on vertical integration and domestic outsourcing at home, as well as all firms that do rely on outsourcing abroad.[21] When conditioning on outsourcing ($j = o$), we impose $\Omega_o = \{\langle 0, 1, 0, 0 \rangle, \langle 0, 1, 0, 1 \rangle\}$, and thus exclude all firms that pursue foreign integration or domestic integration (or both), as well as all firms that do not rely on domestic outsourcing.

We define $\tilde{V}_{it,v}$ to take on the value one if $\Omega_{it} \in \{\langle 1, 1, 1, 0 \rangle\}$, and zero if $\Omega_{it} \in \{\langle 1, 1, 0, 0 \rangle\}$. This leads to a model that explains which firms are more likely to choose foreign integration among the set of firms relying on both domestic integration and domestic outsourcing (but not on foreign outsourcing). Similarly, we define $\tilde{V}_{it,o}$ to take on the value one if $\Omega_{it} \in \{\langle 0, 1, 0, 1 \rangle\}$, and zero if $\Omega_{it} \in \{\langle 0, 1, 0, 0 \rangle\}$. This, in turn, leads to a model that explains which firms are more likely to choose foreign outsourcing among the set of firms relying on domestic outsourcing alone (and not on any strategy of vertical integration). Due to the definitions

[20] We revert to the LPM instead of the non-linear Probit model, because the interaction effect, $\frac{\partial^2 \Pr(\tilde{V}_{it,j}=1|\cdot)}{\partial\theta_{it}\partial\eta_s}$, is not identified in the Probit model with industry fixed effects. To see this, notice that in the Probit model the analogue to (4.13) is $\Pr(\tilde{V}_{it,j} = 1|\cdot) = \Phi(\beta_1 \cdot \theta_{it} + \beta_2 \cdot (\theta_{it} \times \eta_s) + \gamma_{s,j} + \gamma_{t,j})$, where Φ is the standard normal cumulative distribution function. Straightforward differentiation yields:

$$\frac{\partial^2 \Pr(\tilde{V}_{it,j} = 1|\cdot)}{\partial\theta_{it}\partial\eta_s} = \Phi'(\cdot)\beta_2 + \Phi''(\cdot) \times \left(\beta_1 \frac{\partial\gamma_{s,j}}{\partial\eta_s} + \beta_1\beta_2\theta_{it} + \beta_2\eta_s \frac{\partial\gamma_{s,j}}{\partial\eta_s} + \beta_2^2\theta_{it,j}\eta_s\right).$$

Since the industry fixed effect absorbs the main effect of the industry's headquarter intensity, the derivative $\frac{\partial\gamma_{s,j}}{\partial\eta_s}$ is not identified (and neither is the interaction effect).

[21] Instead of excluding firms that do not rely on domestic outsourcing, we could impose $\Omega_o = \{\langle 1, ., 0, 0 \rangle, \langle 1, ., 0, 1 \rangle\}$ and then control for the firm's domestic outsourcing status through a dummy variable DO_{it}. It turns out that with this alternative approach the results reported in this chapter do not change in any significant way.

of $\tilde{V}_{it,v}$ and $\tilde{V}_{it,o}$ as well as the fact that Ω_v and Ω_o are disjunct sets, we are thus testing Proposition 1 in two independent ways.

The model given by equations (4.12) and (4.13) assumes that the fixed cost difference between foreign and domestic sourcing is specific to the industry (and thus captured by $\gamma_{s,j}$). In light of the revolutionary improvements in transport and communication technology seen over the past decades, it seems plausible that over the recent past the fixed costs of foreign sourcing have decreased by more than the fixed costs of domestic sourcing, so that the difference $\Delta_\ell F_{s,j}$ has decreased over time (for either ownership structure). To the extent that this development has affected all industries in Spain in the same way, this is captured by the year fixed effects, $\gamma_{t,j}$. It is however easy to imagine that some industries (e.g. those intensive in complex capital goods) have benefitted more from this development than other industries. This leads us to expect that changes in the fixed cost difference between foreign and domestic sourcing do not apply equally to all industries, but, rather, that they are specific to the industry. We allow for this possibility by extending the model to include industry-and-year fixed effects $\gamma_{st,j}$ (rather than just industry effects $\gamma_{s,j}$ and year effects $\gamma_{t,j}$).

Our model uses two sources of variation in the data to identify the parameters β_1 and β_2. The first is variation *across* firm-year pairs *within* industries, and the second is variation *across* industries. This approach has the advantage that the variation in the variables of interest is large. Under the given set of assumptions, the OLS estimator is asymptotically consistent. However, if there is an omitted firm-specific variable that is correlated with the other covariates, the assumptions on the error term are violated and the estimates suffer from omitted variables bias due to unobserved heterogeneity. A more satisfying approach could therefore be to exploit the *within-firm* variation in the data over time, along with the variation *across* industries. This would allow us to control for any time-invariant firm-specific variable that influences the firm's decision in favor of one or the other sourcing strategy.[22] However, because of the sample restrictions employed, there is very little within-firm variation in the dependent variable that could be exploited for identification purposes.[23] We therefore follow an alternative route in order to reduce the risk of omitted variables bias. In particular, we augment the model by a number of explanatory variables at the firm-level that could explain

[22] A way to get rid of these variables is to within-transform the data and compute all variables relative to the firm-specific mean value over time. The so-called within-group estimator (or fixed effects estimator) is asymptotically consistent, whether the (time-invariant) firm-specific variables are correlated with the other covariates or not.

[23] Although we use data for six years (2006 to 2011), over that period the average number of years in which we observe a firm is three.

the firm's decision to engage in foreign sourcing. These variables are a firm's age, capital intensity, skill intensity, employment, export status, and ownership status (measuring other firms' capital in the reporting firm's joint capital).[24]

<<Table 4.2 about here>>

Table 4.2 reports the estimated parameters of interest in (4.12) and (4.13), along with the corresponding heteroskedasticity-robust standard errors.[25] The estimates show, first, whether (and how) the decision to engage in foreign sourcing is governed by the productivity of the firm; they show, second, whether the correspondence between foreign sourcing and productivity (if any) is stronger in some industries than in others, depending on the headquarter intensity of the industry. Columns (I) to (III) condition on the firm relying on vertical integration ($j = v$); columns (IV) to (VI) condition on the firm relying on outsourcing ($j = o$). In either case, the first column reports the estimates of the baseline specification, as spelled out in (4.12) and (4.13); in the second column, we augment the model by industry-and-year fixed effects; in the third column, we extend the model to include the above-mentioned firm-specific control variables.

In all the specifications employed, we obtain a positive estimate for β_1 and a negative estimate for β_2. When conditioning on vertical integration, we obtain estimates of β_1 in the interval between +0.20 and +0.28, and estimates of β_2 between -0.03 and -0.05. The same intervals when conditioning on outsourcing lie between +0.47 and +0.55 for β_1 and between -0.04 and -0.10 for β_2. In the model with industry-and-year fixed effects and firm-level controls, either parameter is statistically significant at high levels of confidence. To facilitate the interpretation of our results, we use the estimates in columns (III) and (VI) to plot in Figure 4.3 the productivity effect on the probability of foreign sourcing as a function of the industry's headquarter intensity (in the range of sample values): $\frac{\partial \widehat{\Pr(\tilde{V}_{it,j}=1|\cdot)}}{\partial \theta_{it,j}} = \widehat{\beta}_1 + \widehat{\beta}_2 \cdot \eta_s$. We also include the corresponding 90 percent confidence interval in this figure. The figure shows that there is a statistically significant positive productivity effect on the probability of foreign sourcing in all industries of our sample[26], and that this effect is the smaller, the larger the headquarter intensity of the industry. This holds true irrespective of the ownership structure of sourcing that we condition on (vertical integration in the left panel and outsourcing in the right panel). This is notable support for parts (a) and (c) of Proposition 1.

[24]See Table B.2 in Appendix B for a precise definition of these variables.

[25]The errors in the LPM are by construction heteroskedastic.

[26]The industry with the highest headquarter intensity ("Beverages") is the only exception, where the productivity effect is essentially zero.

<<Figure 4.3 about here>>

How important, quantitatively, is the productivity effect? In the "average" industry with $\eta_s = \bar{\eta}_s$, a unit-increase in log productivity (i.e., a doubling of productivity) increases the probability of a firm to engage in foreign sourcing by roughly 5.5%-points when conditioning on vertical integration ($j = v$), and by 11.1%-points when conditioning on outsourcing ($j = o$). The effects are significantly larger in industries with lower headquarter intensities, and smaller in industries with higher headquarter intensities, as suggested by the AH model. Overall, the productivity effect is large enough to be economically relevant, also because on average across firms the predicted probability of foreign sourcing is as low as 3% under vertical integration and roughly 28% under outsourcing.[27]

Regarding the firm-level control variables, we find that firm size and export status are significantly correlated with foreign sourcing, irrespective of the ownership structure of sourcing. Larger firms and exporting firms are more likely to source their inputs from abroad. When conditioning on outsourcing ($j = o$), we also find a positive role for the firm's age, capital intensity, and skill intensity for its probability to engage in foreign sourcing. The ownership situation of the firm, i.e., whether and how other firms participate in the reporting firm's joint capital, does not seem to exert a relevant influence on the firm's decision to source its inputs abroad.

4.4.2 The ownership structure of sourcing

We now analyze how firms choose the ownership structure for their sourcing. We write $D_{i,h}(\ell_h; \eta_s, \theta_i) := \Delta_m \Pi(\ell_h; \eta_s, \theta_i) - \Delta_m F_{s,h} + \mu_{i,h}, i \in \mathcal{I}_s$, for firm i's total profit difference between vertical integration and outsourcing, conditional on the sourcing location $h = f, d$ of sourcing. We assume that this total profit difference can be approximated by the following linear expression:

$$D_{i,h}(\ell_h; \eta_s, \theta_i) = \delta_1 \cdot \theta_i + \delta_2 \cdot (\theta_i \times \eta_s) + \delta_3 \cdot \eta_s - \Delta_m F_{s,h} + \mu_{i,h},\ i \in \mathcal{I}_s. \tag{4.14}$$

Parts (a) and (b) of Proposition 2 require that $\frac{\partial D_{i,h}(\ell_h;\eta_s,\theta_i)}{\partial \theta_i} = \delta_1 + \delta_2 \cdot \eta_s$ is positive for all values of $\eta_s > \tilde{\eta}_s$, and negative for all values of $\eta_s < \tilde{\eta}_s$. Part (c) is true for $\frac{\partial D_{i,h}(\ell_h;\eta_s,\theta_i)}{\partial \eta_s} =$

[27] One of the drawbacks of the LPM is that predicted success probabilities can lie outside the unit interval. It turns out that in our application the predicted probability of foreign sourcing is below zero for as much as 130 out of 618 observations in column (III) (when $j = v$). On average across these observations, however, it is equal to -0.02 and thus only sightly below zero. In column (VI) (when $j = o$), there are only 354 observations (out of 8,388) that feature predicted probabilities of foreign sourcing above one (26) or below zero (328).

$\delta_2 \cdot \theta_i + \delta_3 > 0$ for all values of θ_{it}, while part (d) is true for $\frac{\partial^2 D_{i,h}(\ell_h;\eta_s,\theta_i)}{\partial\theta_i\partial\eta_s} = \delta_2 > 0$.

We face the same empirical challenges as above, and we deal with them in a completely analogous way. Let $\tilde{V}_{i,h}$ be an observable binary variable that mirrors the decision variable $V_{i,h}$ which is equal to one if $D_{i,h}(\ell_h;\eta_s,\theta_i) \geq 0$, and equal to zero otherwise. Let Ω_h denote the set of admissible tuples Ω when studying the ownership structure of sourcing and conditioning on the location h of sourcing. We thus write:

$$\tilde{V}_{it,h} = \delta_1 \cdot \theta_{it} + \delta_2 \cdot (\theta_{it} \times \eta_s) + \gamma_{s,h} + \gamma_{t,h} + \mu_{it,h},\ i \in \mathcal{I}_s, \Omega_{it} \in \Omega_h, \tag{4.15}$$

where $\mu_{it,h}$ is an independently distributed random variable with zero conditional mean, $E[\mu_{it,h}|\cdot] = 0$, so that:

$$E[\tilde{V}_{it,h}|\cdot] = \Pr(\tilde{V}_{it,h} = 1|\cdot) = \delta_1 \cdot \theta_{it} + \delta_2 \cdot (\theta_{it} \times \eta_s) + \gamma_{s,h} + \gamma_{t,h},\ i \in \mathcal{I}_s, \Omega_{it} \in \Omega_h. \tag{4.16}$$

The industry fixed effect, $\gamma_{s,h}$, absorbs the fixed cost difference between vertical integration and outsourcing, $\Delta_m F_{s,h}$, as well as the main effect of the industry's headquarter intensity, which is why the parameter δ_3 is not identified in this model. Hence, we cannot test part (c) of Proposition 2.[28] For domestic sourcing ($h = d$), we impose $\Omega_d = \{\langle 0,1,0,0\rangle, \langle 1,1,0,0\rangle\}$ as a sample restriction. The variable $\tilde{V}_{it,d}$ is set to one if $\Omega_{it} \in \{\langle 1,1,0,0\rangle\}$ and to zero if $\Omega_{it} \in \{\langle 0,1,0,0\rangle\}$. The model thus explains which firms among the set of domestic outsourcing firms (not involved in any type of foreign sourcing) choose to additionally source from an integrated domestic supplier. For foreign sourcing ($h = f$), we proceed similarly. We impose $\Omega_f = \{\langle \cdot,1,0,1\rangle, \langle \cdot,1,1,1\rangle\}$ and set $\tilde{V}_{it,f}$ to one if $\Omega_{it} \in \{\langle \cdot,1,1,1\rangle\}$ and to zero if $\Omega_{it} \in \{\langle \cdot,1,0,1\rangle\}$. A problem with this model could be collinearity between the foreign integration dummy (FI_{it}) and the domestic integration dummy (DI_{it}). We have checked for (and ruled out) this possibility, by including the domestic integration dummy (DI_{it}) as explanatory variable in the regression equation, and, alternatively, by conditioning on the domestic integration dummy, such that $\Omega_f = \{\langle 1,1,0,1\rangle, \langle 1,1,1,1\rangle\}$. Our results are robust to these modifications.[29] Therefore, and because Ω_f and Ω_d are disjunct sets, our approach amounts to two independent tests of Proposition 2.

<<Table 4.3 about here>>

In Table 4.3, we report estimates of the parameters δ_1 and δ_2, as given in equations (4.15)

[28]We shall later provide some tentative evidence on the relation between the industry's headquarter intensity and the prevalence of vertical integration at the industry-level.

[29]Whether or not we condition on domestic outsourcing is not important for the results obtained either.

and (4.16). The table is structured in the same way as Table 4.2. In columns (I) to (III), we restrict the sourcing location to the domestic economy ($h = d$); in columns (IV) to (VI), we condition on the firm sourcing in the foreign economy ($h = f$). In either case, we start with the baseline specification in the first column; we then include industry-and-year fixed effects in the second column; and we finally control for a number of firm-level variables in the third column.

Our estimates paint a remarkably consistent picture of the role of firm productivity for the ownership structure of sourcing, and how this role depends on the headquarter intensity of the industry to which the firm belongs. For either sourcing location, we find a negative and highly significant estimate for δ_1 and a positive and highly significant estimate for δ_2 (throughout all the specifications employed). When conditioning on the domestic economy ($h = d$), we find point estimates that lie between -0.603 and -0.436 for δ_1, and between $+0.102$ and $+0.151$ for δ_2. When conditioning on the foreign economy ($h = f$), the point estimates range from -0.724 to -0.514 for δ_1, and from $+0.118$ to $+0.188$ for δ_2. This means that the effect of productivity on the firm's ownership decision is ambiguous: in industries with low headquarter intensities ($\eta_s < \tilde{\eta}_s$), the firms with high productivity are deterred from vertical integration, while in industries with high headquarter intensities ($\eta_s > \tilde{\eta}_s$), they are attracted by it.

In Figure 4.4, we use the estimates in columns (III) and (VI) to plot the productivity effect on the probability of vertical integration as a function of the industry's headquarter intensity, by complete analogy to Figure 4.3: $\frac{\partial \widehat{\Pr(\tilde{V}_{it,h}=1|\cdot)}}{\partial \theta_{it,h}} = \widehat{\delta_1} + \widehat{\delta_2} \cdot \eta_s$. We see that, irrespective of the location of sourcing (domestic in the left panel and foreign in the right panel), there is a statistically significant negative productivity effect on the probability of vertical integration in industries with sufficiently low headquarter intensities. This same productivity effect is positive in industries with sufficiently high headquarter intensities. This is strong support for parts (a), (b), and (d) of Proposition 2.[30]

The productivity of the firm can make a huge difference for the firm's decision to vertically integrate its supplier, especially in industries with high headquarter intensities. For example, in the "Beverages" industry, a doubling of the firm's productivity increases the firm's likelihood to vertically integrate the supplier by more than 15%-points (in either sourcing location). In the "average" industry with $\eta_s = \bar{\eta}_s$, the productivity effect is positive albeit small

[30]On average across firms, the predicted probability of vertical integration is equal to 5% when $h = d$ and equal to 9% when $h = f$. In column (III) ($h = d$), the predicted probability of vertical integration is below zero for 1,372 out of 5,795 observation and equals -0.02 on average across these observations. In column (VI) ($h = f$), it is below zero for 727 out of 4,774 observations and equals -0.05 on average across these observations.

(but still statistically different from zero). In both sourcing locations, the threshold value separating industries that are headquarter-intensive from those that are component-intensive is found in the vicinity of $\eta_s = 4.3$.[31]

<<Figure 4.4 about here>>

Our estimates more generally suggest that the ownership decision in the domestic economy is governed by the same variables (and in similar ways) as the ownership decision in the foreign economy. Large firms as well as skill-intensive firms have significantly higher probabilities of vertical integration both at home and abroad. The same applies to firms whose joint capital is (partly) under the control of other firms.[32] The export status of the firm enters the regression equation with a positive sign, but it is only statistically significant in the case of the foreign economy. Firms operating an integrated production structure at home are more likely to do so in the foreign economy as well.

4.4.3 Industry-level relationships

As we have shown above, estimating the main effect of the industry's headquarter intensity on a firm's probability to engage in foreign sourcing or in vertical integration is not within reach of our firm-level analysis. However, we can study the prevalence of both foreign sourcing and intra-firm sourcing at the industry-level in relation to the headquarter intensity of the industry. We have argued in the introduction that knowledge of the fixed cost ranking of alternative locations and organizational forms of sourcing is crucial for an industry-level test of the model. Having said that, there are two industry-level predictions of the model that are robust across all possible fixed cost configurations.[33] More specifically, the AH model implies that the prevalence of foreign sourcing and of intra-firm sourcing (as fractions of firms in a given industry) are respectively weakly decreasing and weakly increasing in the headquarter intensity of the industry. Intuitively, the economic mechanisms behind these relationships are not any different from those discussed in Section 4.2. Formally, they follow straightforwardly from the analysis presented in Antràs & Helpman (2004). If our data, when aggregated to the industry level, were to contradict these relationships, the validity of the AH model would have been in doubt.

[31] In the AH model, if the ex-post outside option under vertical integration is different in the domestic economy from what it is in the foreign economy, so that $m_{v,d} > m_{v,f}$, we have $\tilde{\eta}_d \neq \tilde{\eta}_f$.

[32] Our results (both on the location as well as on the ownership structure of sourcing) are qualitatively similar if we exclude such firms from the estimation.

[33] These predictions do however require that the fixed costs be the same across industries. Moreover, they hinge upon a certain shape of the productivity distribution of firms, such as Pareto, as assumed in Antràs & Helpman (2004).

<<Figures 4.5 and 4.6 about here>>

We find the opposite. In Figure 4.5, we plot the share of firms choosing foreign sourcing in a given industry against the headquarter intensity of the industry (both averaged across the years 2006-2011). We find a negative association between the two variables, both under vertical integration (left panel) as well as under outsourcing (right panel).[34] We do the same in Figure 4.6 for the share of firms choosing vertical integration in a given industry. We find a positive association between this share and the industry's headquarter intensity, both in the domestic economy (left panel) as well as in the foreign economy (right panel). This is some tentative evidence supporting the notion that higher headquarter intensities tend to favor the domestic economy as the preferred location of sourcing, and the integrated input production as the preferred ownership structure of sourcing. The firm-level analogue to these industry-level relationships are given in part (b) of Proposition 1 and in part (c) of Proposition 2, respectively.

4.5 Conclusion

Recently developed models of international trade study the global sourcing activities of firms through the lens of the property rights theory of the firm. In this chapter, we have developed an empirical strategy towards a firm-level test of one such model, namely the hold-up model of global sourcing by Antràs & Helpman (2004). Drawing on recent work by Mrázowá & Neary (2013), we have reframed this model in terms of its properties of supermodularity and submodularity, respectively, between a firm's productivity and the key characteristics of a sourcing strategy relating to the location and the ownership structure of sourcing. We have derived firm-level predictions that can be brought to suitably rich firm-level data sets. A merit of our approach is that these predictions do not depend upon (unobserved) fixed cost differences across alternative sourcing strategies.

We have applied our firm-level test to a unique data set for Spanish manufacturing firms. The Spanish data allow us to identify sourcing activities of firms that correspond very closely to those featured in the AH model. We bring our novel firm-level predictions to the data by drawing on a series of discrete choice models of sourcing. These models are set up to explain a firm's location of sourcing, conditional on the ownership structure of sourcing (vertical integration *versus* outsourcing), as well as a firm's ownership structure of sourcing,

[34] We employ the same sample restrictions in this subsection as in the preceding two subsections.

conditional on the location of sourcing (domestic *versus* foreign). In all relevant dimensions, our empirical findings are consistent with the hold-up model of global sourcing.

The first finding is that highly productive firms are more likely to choose foreign sourcing (under either ownership structure). The reason for this is that foreign sourcing is associated with a location advantage that becomes strengthened by the firm's productivity. Since the location advantage of foreign sourcing tends to be large when the foreign input is very important, the productivity effect is stronger in industries with lower headquarter intensities. The second finding of our empirical analysis is that it is not generally the case that highly productive firms are more likely to choose vertical integration. Rather, this relationship holds true only in industries featuring a strategic advantage of vertical integration (so-called headquarter-intensive industries). In industries featuring a strategic advantage of outsourcing (so-called component-intensive industries), the highly productive firms are less likely to choose vertical integration. The reason for this is that any strategic advantage (whether with integration or with outsourcing) is strengthened by the firm's productivity.

Figures and tables

Figure 4.1. The location advantage of foreign sourcing

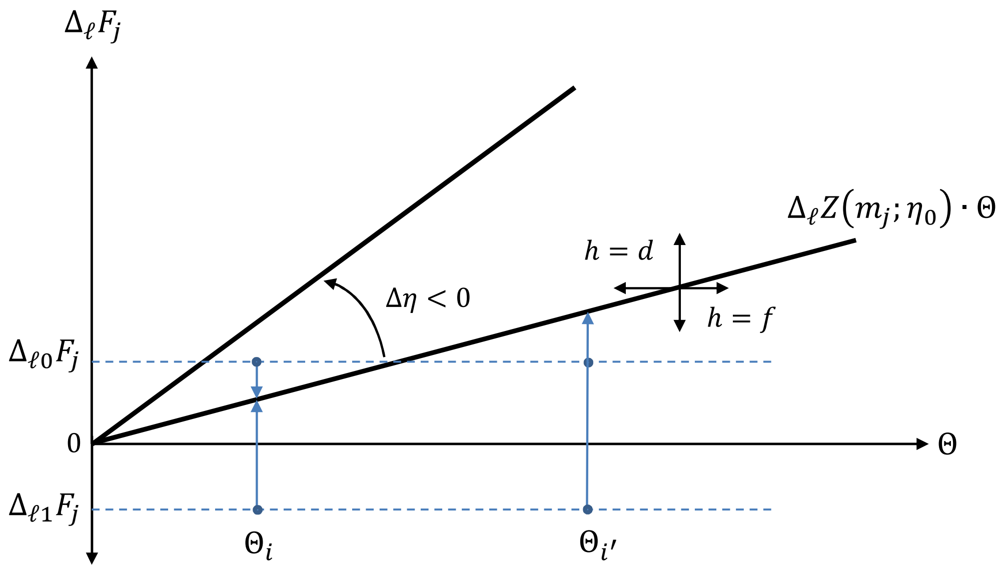


Figure 4.2. The strategic advantage of integration or of outsourcing

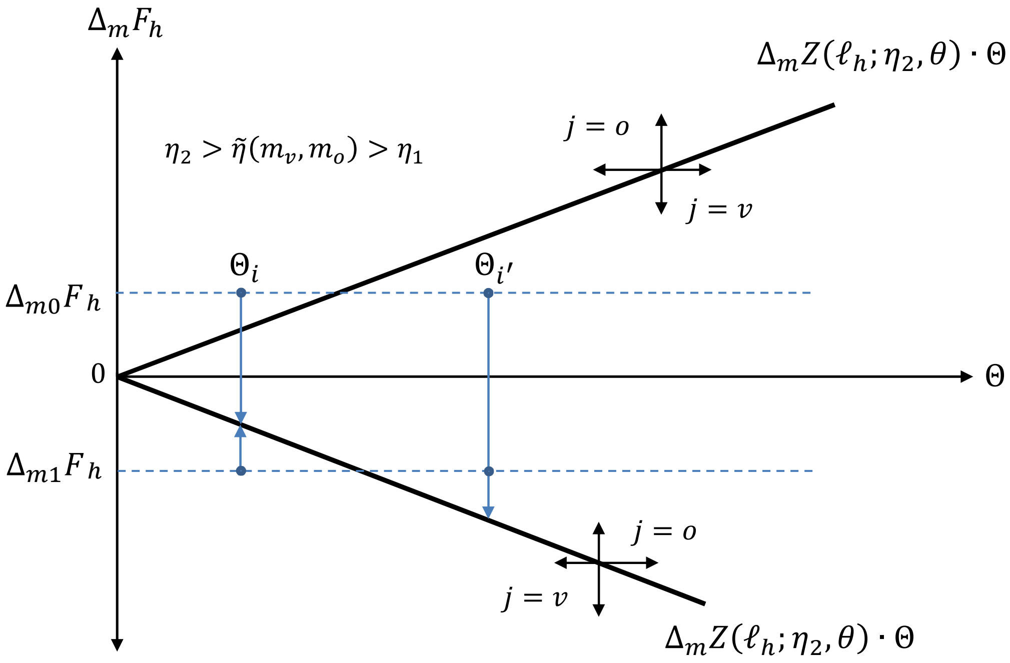


Figure 4.3. The marginal effect of productivity on the probability of foreign sourcing (conditional on the ownership structure of sourcing)

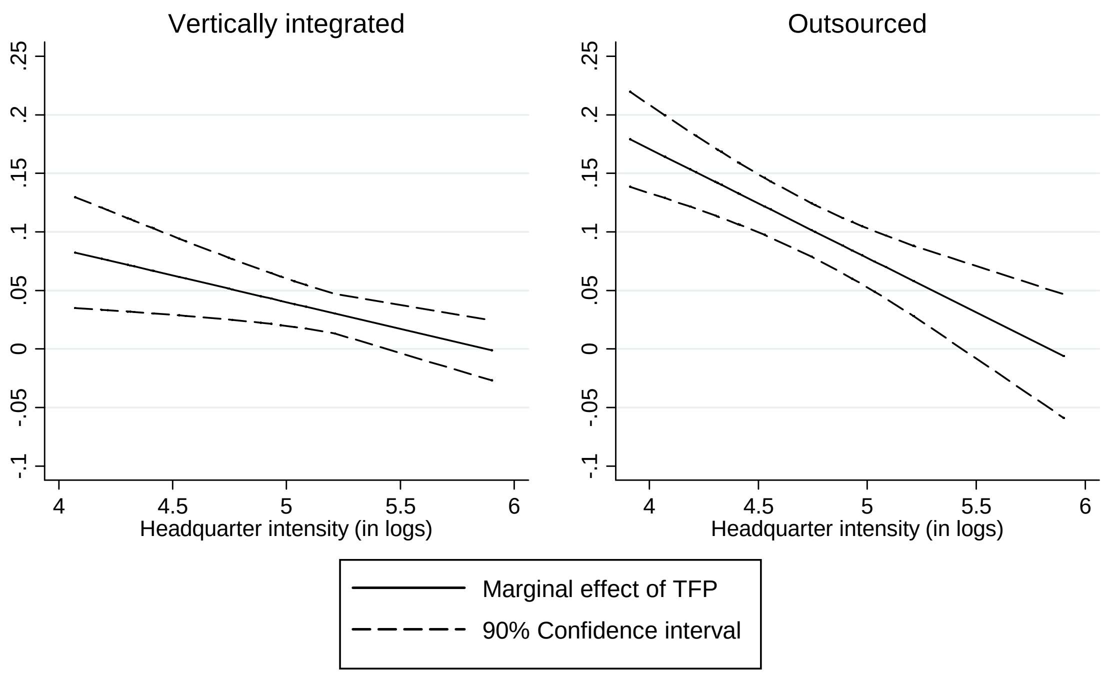


Figure 4.4. The marginal effect of productivity on the probability of vertical integration (conditional on the location of sourcing)

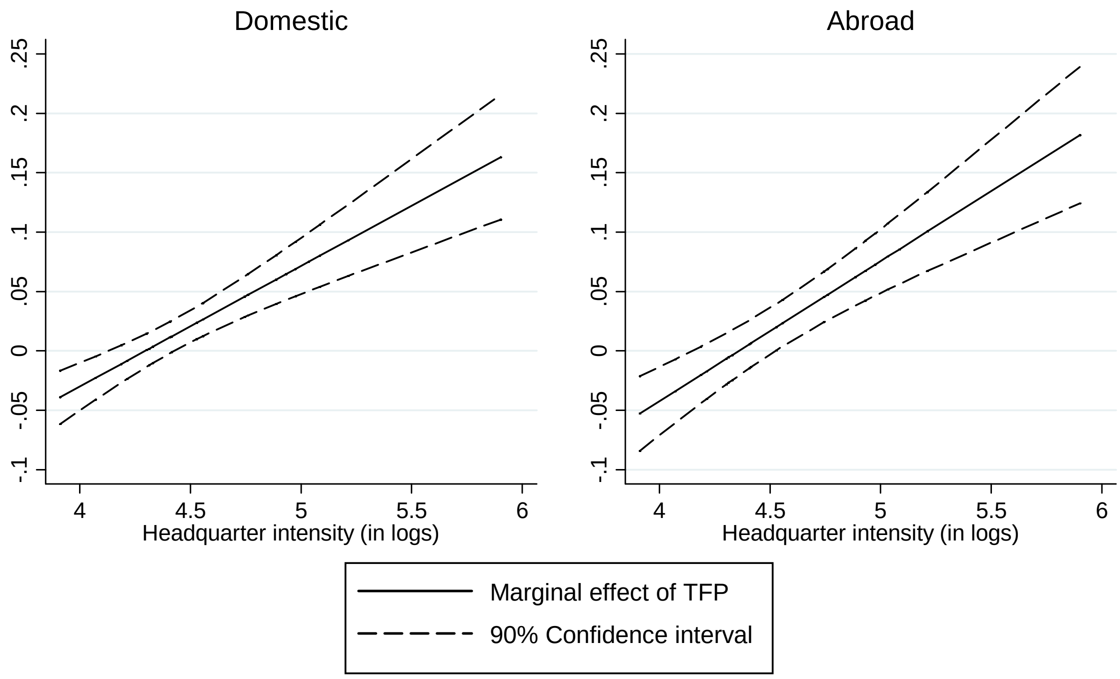


Figure 4.5. Share of foreign sourcing firms plotted against headquarter intensity, by industry (conditional on the ownership structure of sourcing)

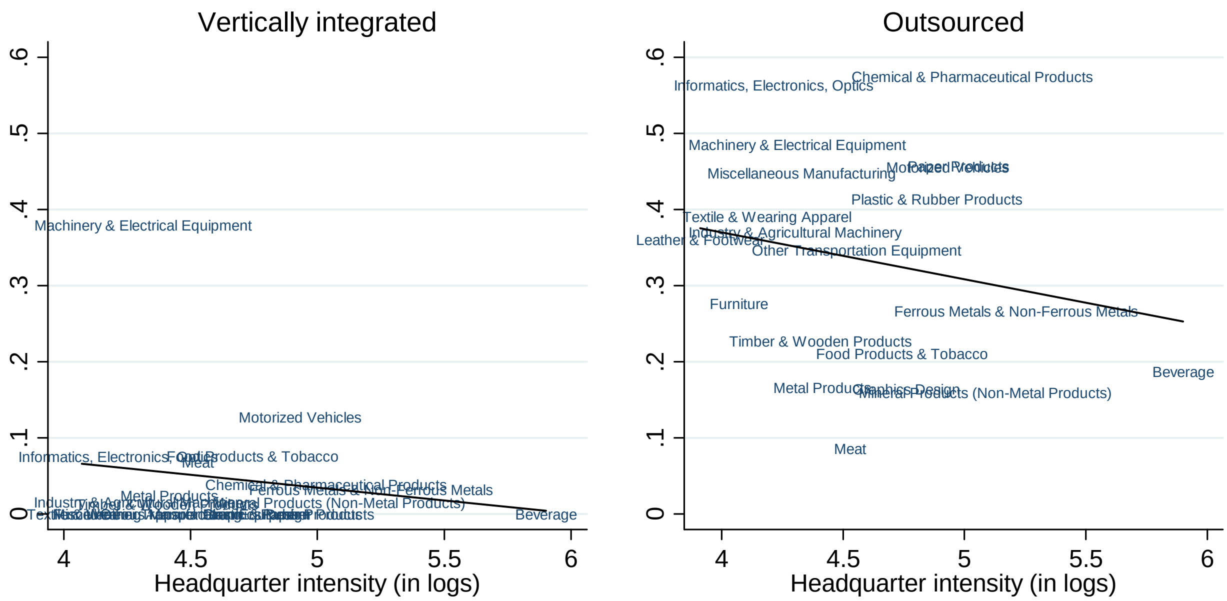


Figure 4.6. Share of integrating firms plotted against headquarter intensity, by industry (conditional on the location of sourcing)

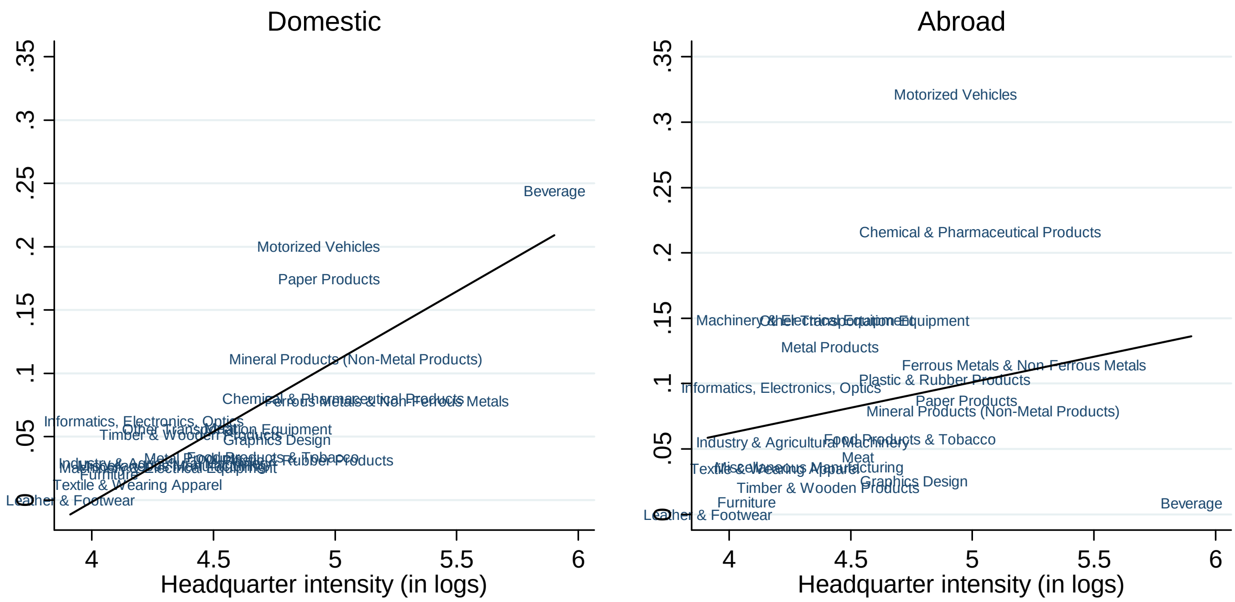


Table 4.1. Sourcing decisions of Spanish firms (2006/2011)

	Small firms			*Large firms*		
	2006	*2011*	*Δ 2006/2011*	*2006*	*2011*	*Δ 2006/2011*
	(I)	(II)	(III)	(IV)	(V)	(VI)
Domestic sourcing: Ω={‹1,1,.,.›,‹1,0,.,.›,‹0,1,.,.›}	91.6	94.6	+3.0	92.4	95.8	+3.4
Foreign sourcing: Ω={‹.,.,1,1›,‹.,.,1,0›,‹.,.,0,1›}	33.7	41.0	+7.3	65.9	76.0	+10.1
Outsourcing: Ω={‹.,1,.,1›,‹.,1,.,0›,‹.,0,.,1›}	92.0	94.6	+2.6	93.1	96.6	+3.6
Integration: Ω={‹1,.,1,.›,‹1,.,0,.›,‹0,.,1,.›}	13.0	14.5	+1.5	49.3	55.2	+5.9
Non-sourcing: Ω={‹0,0,0,0›}	6.9	4.5	-2.4	3.2	1.3	-1.9
Domestic outsourcing: Ω={‹.,1,.,.›}	90.4	93.6	+3.2	88.8	93.5	+4.7
Domestic integration: Ω={‹1,.,.,.›}	10.2	10.9	+0.7	35.6	33.6	-2.0
Foreign outsourcing: Ω={‹.,.,.,1›}	32.6	40.2	+7.6	61.3	70.1	+8.8
Foreign integration: Ω={‹.,.,1,.›}	4.0	5.0	+1.0	24.8	34.1	+9.3

Columns (I), (II), (IV), and (V) give the percentages of firms that pursue the respective sourcing strategies. All percentages are of the total number of firms in the respective size category. Columns (III) and (VI) give the percentage point changes from 2006 to 2011.

Table 4.2. Linear probability model for foreign sourcing, conditional on the ownership structure of sourcing (pooled regressions 2006-2011)

	Ownership structure: Vertically integrated			*Ownership structure: Outsourced*		
	Estimation sample: $\Omega_{it} \in \{\langle 1,1,1,0\rangle, \langle 1,1,0,0\rangle\}$			*Estimation sample:* $\Omega_{it} \in \{\langle 0,1,0,1\rangle, \langle 0,1,0,0\rangle\}$		
	Dep. var. equal to one if $\Omega_{it} \in \{\langle 1,1,1,0\rangle\}$*, zero otherwise*			*Dep. var. equal to one if* $\Omega_{it} \in \{\langle 0,1,0,1\rangle\}$*, zero otherwise*		
VARIABLES	(I)	(II)	(III)	(IV)	(V)	(VI)
Total factor productivity	0.203	0.279**	0.268**	0.475***	0.478***	0.543***
	(0.125)	(0.129)	(0.114)	(0.145)	(0.146)	(0.118)
Total factor productivity X	-0.031	-0.045*	-0.046**	-0.048	-0.048	-0.093***
Headquarter intensity	(0.023)	(0.024)	(0.021)	(0.030)	(0.030)	(0.025)
Firm-level controls						
Age			0.000			0.001*
			(0.000)			(0.000)
Capital intensity			0.003			0.033***
			(0.007)			(0.005)
Skill intensity			-0.008			0.147***
			(0.022)			(0.033)
Employment			0.030***			0.055***
			(0.007)			(0.007)
Export dummy			0.032**			0.189***
			(0.014)			(0.013)
Ownership			-0.001			0.010
			(0.004)			(0.006)
Observations	645	645	618	8,492	8,492	8,388
R-squared	0.112	0.167	0.227	0.134	0.140	0.223
Industry FE	YES	COLLINEAR	COLLINEAR	YES	COLLINEAR	COLLINEAR
Year FE	YES	COLLINEAR	COLLINEAR	YES	COLLINEAR	COLLINEAR
Industry-and-year FE	NO	YES	YES	NO	YES	YES
Firm-level controls	NO	NO	YES	NO	NO	YES

The table reports estimated coefficients (robust standard errors in parenthesis) of a linear probability model (LPM) that explains the likelihood of a firm to source inputs from a foreign supplier, conditional on the ownership structure of sourcing. Columns (I) to (III) look at foreign sourcing conditional on operating a vertically integrated production structure, restricting the sample to observations that report strictly positive sourcing from a domestic integrated as well as outsourced supplier, but zero sourcing from a foreign outsourced supplier. Columns (IV) to (VI) look at foreign sourcing conditional on operating an outsourced production structure, restricting the sample to observations that report zero sourcing from both domestic and foreign integrated suppliers, but strictly positive sourcing from domestic outsourced suppliers. Total factor productivity is a time-varying, firm-specific variable estimated with the Olley & Pakes (1996) algorithm. Headquarter intensity is a time-constant, industry-specific variable, measured as the average capital intensity of all firms in the respective industry. Both variables are given in logs. For a detailed description of all variables (including the firm-level controls), see Table B.2 in Appendix B. *,**,*** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 4.3. Linear probability model for vertical integration, conditional on the location of sourcing (pooled regressions 2006-2011)

	Sourcing location: Domestic economy			*Sourcing location: Foreign economy*		
	Estimation sample: $\Omega_{it} \in \{\langle 1,1,0,0\rangle,\langle 0,1,0,0\rangle\}$			*Estimation sample:* $\Omega_{it} \in \{\langle \cdot,1,1,1\rangle,\langle \cdot,1,0,1\rangle\}$		
	Dep. var. equal to one if $\Omega_{it} \in \{\langle 1,1,0,0\rangle\}$*, zero otherwise*			*Dep. var. equal to one if* $\Omega_{it} \in \{\langle \cdot,1,1,1\rangle\}$*, zero otherwise*		
VARIABLES	(I)	(II)	(III)	(IV)	(V)	(VI)
Total factor productivity	-0.603***	-0.602***	-0.436***	-0.674***	-0.724***	-0.514***
	(0.104)	(0.103)	(0.093)	(0.121)	(0.112)	(0.109)
Total factor productivity X Headquarter intensity	0.151***	0.151***	0.102***	0.176***	0.188***	0.118***
	(0.023)	(0.023)	(0.021)	(0.027)	(0.025)	(0.024)
Firm-level controls						
Age			-0.001***			-0.000*
			(0.000)			(0.000)
Capital intensity			0.001			0.004
			(0.003)			(0.004)
Skill intensity			0.032*			0.106***
			(0.018)			(0.020)
Employment			0.018***			0.045***
			(0.004)			(0.005)
Export dummy			0.005			0.026***
			(0.007)			(0.007)
Ownership			0.090***			0.059***
			(0.007)			(0.005)
DI dummy			COLLINEAR			0.038*
						(0.023)
Observations	5,878	5,878	5,795	4,875	4,875	4,774
R-squared	0.103	0.114	0.248	0.114	0.124	0.261
Industry FE	YES	COLLINEAR	COLLINEAR	YES	COLLINEAR	COLLINEAR
Year FE	YES	COLLINEAR	COLLINEAR	YES	COLLINEAR	COLLINEAR
Industry-and-year FE	NO	YES	YES	NO	YES	YES
Firm-level controls	NO	NO	YES	NO	NO	YES

The table reports estimated coefficients (robust standard errors in parenthesis) of a linear probability model (LPM) that explains the likelihood of a firm to operate a vertically integrated production structure, conditional on the location of sourcing. Columns (I) to (III) look at vertical integration in the domestic economy, restricting the sample to observations that report zero sourcing from abroad and positive sourcing from domestic independent suppliers. Columns (IV) to (VI) look at vertical integration in the foreign economy, restricting the sample to observations that report positive sourcing from foreign independent suppliers (as well as domestic independent suppliers). Total factor productivity is a time-varying, firm-specific variable estimated with the Olley & Pakes (1996) algorithm. Headquarter intensity is a time-constant, industry-specific variable, measured as the average capital intensity of all firms in the respective industry. Both variables are given in logs. For a detailed description of all variables (including the firm-level controls), see Table B.2 in Appendix B. *,**,*** denote significance at the 10%, 5%, and 1% levels, respectively.

Appendices

A Proofs

Proof of Proposition 1, parts (b) and (c)

Statements (b) and (c) of Proposition 1 require that the maximum profit function $\Pi(\ell, m; \eta, \theta)$, as defined in (4.2) to (4.5), be submodular with respect to ℓ and η, according to Definition (1). Although the proposition uses discrete comparisons, as defined in (4.6) to (4.9), since $\Pi(\ell, m; \eta, \theta)$ is twice differentiable we may treat ℓ and m as continuous variables. The proof thus requires demonstrating that $\partial^2\Pi(\ell, m; \eta, \theta)/\,\partial\ell\partial\eta < 0$, which is equivalent to $\partial^2 Z(\ell, m; \eta)/\,\partial\ell\partial\eta < 0$. This is, in turn, equivalent to $\partial^2 Z(\ell, m; \eta)/\,\partial\eta\partial\ell < 0$ (Young's theorem). In what follows, we simplify by writing Z instead of $Z(\ell, m; \eta)$, and similarly for z.

It proves convenient to work with $\ln Z$. We generally have

$$\frac{\partial \ln Z}{\partial \eta} = \frac{1}{Z}\frac{\partial Z}{\partial \eta}, \text{ hence } \frac{\partial Z}{\partial \eta} = Z\frac{\partial \ln Z}{\partial \eta}, \tag{A.1}$$

and therefore

$$\frac{\partial^2 Z}{\partial\eta\partial\ell} = Z\frac{\partial^2 \ln Z}{\partial\eta\partial\ell} + \frac{\partial Z}{\partial \ell}\frac{\partial \ln Z}{\partial \eta}. \tag{A.2}$$

Remember that $Z = AzC$, with $z = 1 - \left[(\varepsilon - 1)/\varepsilon\right]\left[m\eta + (1-m)(1-\eta)\right]$ and $C = [m^\eta(\ell(1-m))^{1-\eta}]^{\varepsilon-1}$. Thus, $\ln Z = \ln A + \ln z + \ln C$.

Evaluating the different terms in (A.2) in turn, we first note that $z > 0$, whence $Z > 0$. Secondly, we have

$$\frac{\partial^2 \ln Z}{\partial\eta\partial\ell} = \frac{\partial^2 \ln C}{\partial\eta\partial\ell} = \frac{\partial^2 \ln C}{\partial\ell\partial\eta} = -(\varepsilon-1)\frac{1}{\ell} < 0. \tag{A.3}$$

This inequality is related to the location advantage that we have discussed in Section 4.2. The location advantage of *foreign* sourcing derives from the assumption that $\ell_f > \ell_d$, coupled with the input cost effect $\partial Z/\partial\ell > 0$, which simply means that lower input costs raise profits. Remember that ℓ denotes the inverse input cost. In view of Young's theorem, the inequality in (A.3) states that the input cost effect on log-profits falls as the headquarter intensity rises. Thus, the first product on the right-hand side of (A.2) is negative, which works in favor of $\Pi(\ell, m; \eta, \theta)$ being submodular with respect to ℓ and η. Intuitively, a higher headquarter intensity makes the manufacturing component less important for the production relationship, which dampens the input cost effect. Note that the dampening effect on log-profits is increasing in magnitude, as the perceived demand elasticity ε increases.

Having established submodularity of log-profits does not prove Proposition 1, which implies submodularity of the profit function. Towards this end, we must now look at the second term in (A.2). We first write the input cost effect as

$$\frac{\partial Z}{\partial \ell} = \frac{\partial \ln Z}{\partial \ln \ell}\frac{Z}{\ell} = \frac{\partial \ln C}{\partial \ln \ell}\frac{Z}{\ell} = (\varepsilon - 1)(1-\eta)\frac{Z}{\ell} > 0. \tag{A.4}$$

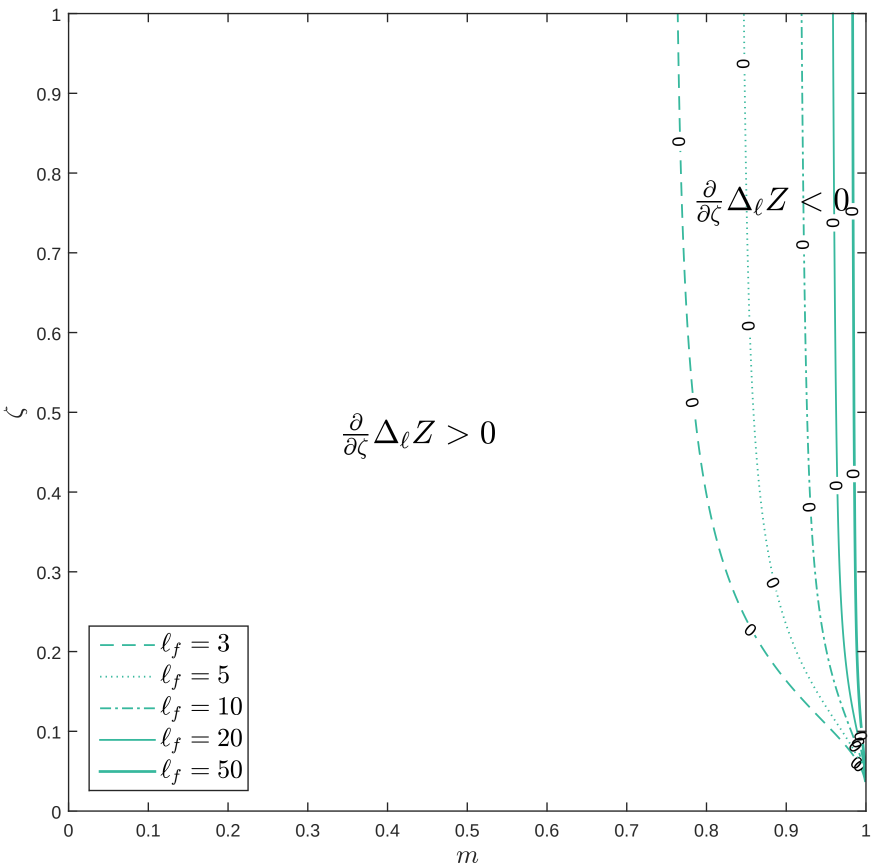
The sufficient condition for submodularity thus emerges as $\partial \ln Z/\partial \eta < 0$. However, the sign of $\partial \ln Z/\partial \eta$ is ambiguous. To see this, we write

$$\begin{aligned} \frac{\partial \ln Z}{\partial \eta} &= \frac{\partial \ln C}{\partial \eta} + \frac{\partial \ln z}{\partial \eta} \\ &= (\varepsilon - 1)[\ln m - \ln(1-m) - \ln \ell] + \frac{\varepsilon - 1}{\varepsilon}\frac{1-2m}{z}. \end{aligned} \tag{A.5}$$

The derivative $\partial \ln C/\partial \eta$ in (A.5) gives the direct cost effect of a small increase in the headquarter intensity. It is easy to see that this is negative for large enough values of ℓ. More importantly, for given ℓ it approaches a value of plus infinity, if we let m converge to the value of 1. Obviously, the second term in (A.5) involves no strong enough counter effect of an increase in m. The ambiguous sign of $\partial \ln Z/\partial \eta$ reflects a core feature of the AH model: In the presence of the hold-up problem, optimization requires aligning η and m, i.e., bringing the ex post revenue share for the headquarter in line with the importance of the headquarter service for the production relationship. In (A.5), it therefore turns out that, given some initial value of η, a further increase in η increases profits by increasing $\ln Z$ in (A.5), provided that the value of m is large enough. The opposite obtains for a low enough value of m.

This limiting behavior of (A.5) along with (A.4) leads to potential violations of submodularity, because the first term in (A.2) remains unaffected by variations in m. We therefore revert to a numerical simulation to demonstrate that, assuming a reasonable value of ε, submodularity obtains for a very large subspace. For this purpose, we define $\zeta := 1 - \eta$ and set $\varepsilon = 6$ (following Bergstrand et al. (2013)), $A = 1$, and $\ell_d = 1$. Moreover, rather than evaluating $\frac{\partial^2 Z}{\partial \eta \partial \ell}$, we look at $\frac{\partial}{\partial \eta}\Delta_\ell Z$ (in line with the model). Figure A.1 plots isoclines for $\frac{\partial}{\partial \eta}\Delta_\ell Z = 0$, thus separating the parameter space into subspaces where Z is submodular and supermodular, respectively, with respect to η and ℓ for different values of ℓ_f. Notice that submodularity of Z with respect to η and ℓ requires that $\frac{\partial}{\partial \eta}\Delta_\ell Z > 0$, because due to the definition of ζ we have $\operatorname{sign}\left(\frac{\partial}{\partial \eta}\Delta_\ell Z\right) = \operatorname{sign}\left(-\frac{\partial}{\partial \zeta}\Delta_\ell Z\right)$.

Figure A.1. Modularity properties of Z, Proposition 1, parts (b) and (c)



Proof of Proposition 2, parts (c) and (d)

We proceed in complete analogy to the proof of Proposition 1 above, treating m and η as continuous variables and making use of Young's theorem. We need to show that $\partial^2\Pi(\ell, m; \eta, \theta)/\partial m\partial\eta < 0$, which is equivalent to $\partial^2 Z(\ell, m; \eta)/\partial\eta\partial m < 0$. As above, we work with $\ln Z$. We have

$$\frac{\partial^2 Z}{\partial\eta\partial m} = Z\frac{\partial^2 \ln Z}{\partial\eta\partial m} + \frac{\partial Z}{\partial m}\frac{\partial \ln Z}{\partial\eta}, \tag{A.6}$$

whereby $Z > 0$. Again, we consider each term on the right hand side in turn. From (A.5), we have

$$\begin{aligned}
\frac{\partial^2 \ln Z}{\partial\eta\partial m} &= \frac{\varepsilon - 1}{m - m^2} + \frac{\varepsilon - 1}{\varepsilon}\left[\frac{-2}{z} - \frac{1 - 2m}{z^2}(\alpha - 2\alpha\eta)\right] \\
&= \frac{\varepsilon - 1}{m - m^2} + \frac{\alpha}{z^2}\left[-(1 - 2m)(\alpha - 2\alpha\eta) - 2z\right], \\
&= \frac{\varepsilon - 1}{m - m^2} + \frac{\alpha^2 - 2\alpha}{z^2}
\end{aligned} \tag{A.7}$$

This cross-derivative is strictly positive. To see this, recall that α, m, and η lie strictly between zero and 1. Moreover, note that the first term on the right-hand side of the final equation (call it x) is strictly negative, and the second term (call it y) is strictly positive. For any given value of α, the values of m and η that minimize the denominator in x and thus maximize the (absolute) value of the function x are $m = 1/2$ and $\eta = 1/2$. In turn, for any given value of α the value of m that minimizes the value of the function y is $m = 1/2$. Hence, it suffices to show that

$$\frac{4\alpha}{1-\alpha} + \frac{\alpha^2 - 2\alpha}{(1-\alpha/2)^2} > 0. \tag{A.8}$$

Straightforward manipulation of this expression yields $2\alpha - \alpha^2 > 0$, which is always true. This demonstrates supermodularity of log-profits.

As with submodularity in Proposition 1, the supermodularity implied by Proposition 2 relates to profits, not log-profits. Hence, we must also look at the second term in (A.6). We have explored the properties of $\partial \ln Z/\partial\eta$ above: It is positive for large enough values of m and negative for small enough values of m. As regards the derivative $\partial Z/\partial m$, we may write $\partial Z/\partial m = A\left[C\frac{\partial z}{\partial m} + z\frac{\partial C}{\partial m}\right]$. Again, we look at each of these two terms in turn. We have

$$\frac{\partial z}{\partial m} = \frac{\varepsilon - 1}{\varepsilon}(1-2\eta), \tag{A.9}$$

This captures the strategic implication of a variation in m. The cost channel is described by

$$\begin{aligned}\frac{\partial C}{\partial m} &= C\left[(\varepsilon-1)\eta m^{-1} - (\varepsilon-1)(1-\eta)(1-m)^{-1}\right] \\ &= C(\varepsilon-1)\left[\eta\left(\frac{1}{m-m^2}\right) - \frac{1}{1-m}\right]\end{aligned} \tag{A.10}$$

Putting things together, we have

$$\begin{aligned}\frac{\partial Z}{\partial m} &= AC\left[\frac{\varepsilon-1}{\varepsilon}(1-2\eta) + z(\varepsilon-1)\left(\frac{\eta}{m-m^2} - \frac{1}{1-m}\right)\right] \\ &= AC(\varepsilon-1)\left(\frac{1-2\eta}{\varepsilon} + \frac{z}{1-m}\frac{\eta-m}{m}\right)\end{aligned} \tag{A.11}$$

Unlike the term $\partial Z/\partial \ell$ in the previous proof, this term is ambiguous, again reflecting the hold-up problem that is at the core of the model. The term becomes negative for a sufficiently high value of m, depending on the industry's headquarter intensity η. Considering that high values of m also tend to generate positive values of $\partial \ln Z/\partial\eta$, this works against the kind of supermodularity presently at stake. However, it is not necessarily true that low values of m work for supermodularity. They tend to generate a negative value of $\partial \ln Z/\partial\eta$, but a sufficiently low value of η might still render a positive value of $\partial Z/\partial m$, which then again works against supermodularity.

We must thus conclude that extreme values for m and η may lead to potential violations of supermodularity, because the unambiguously positive sign of the first term in (A.6) may be offset by a negative sign of the second term. As with Proposition 1, the statements (c) and (d) of Proposition 2 are true only for certain ranges of parameter values. We explore this issue further by means of numerical simulation. As before, we use $\zeta := 1-\eta$. Assuming $\varepsilon = 6$ as well as $A = 1$, Figure A.2 depicts isoclines for $\partial^2 Z/\partial\zeta\partial m = \partial^2 Z/\partial\eta\partial m = 0$ separating the parameter space into an inner subspace of supermodularity ($\partial^2 Z/\partial\eta\partial m > 0$ or, equivalently $\partial^2 Z/\partial\zeta\partial m < 0$) and outer subspaces of submodularity ($\partial^2 Z/\partial\eta\partial m < 0$ or, equivalently $\partial^2 Z/\partial\zeta\partial m > 0$), respectively. To look at these results through the lens of our theoretical model, we must, however, inspect the term $\frac{\partial}{\partial\eta}\Delta_m Z$ (instead of the cross-partial derivative $\partial^2 Z/\partial\zeta\partial m$ as such). This is what we do in Figure A.3, where we assume that $m_0 = 1/2$. In this figure we see that supermodularity of Z with respect to m and η ($\frac{\partial}{\partial\eta}\Delta_m Z > 0$ or, equivalently, $\frac{\partial}{\partial\zeta}\Delta_m Z < 0$) obtains within a large and plausible parameter subspace of $\{m_v, \eta\}$.

Figure A.2. Sign of $\partial^2 Z/\partial\zeta\partial m$

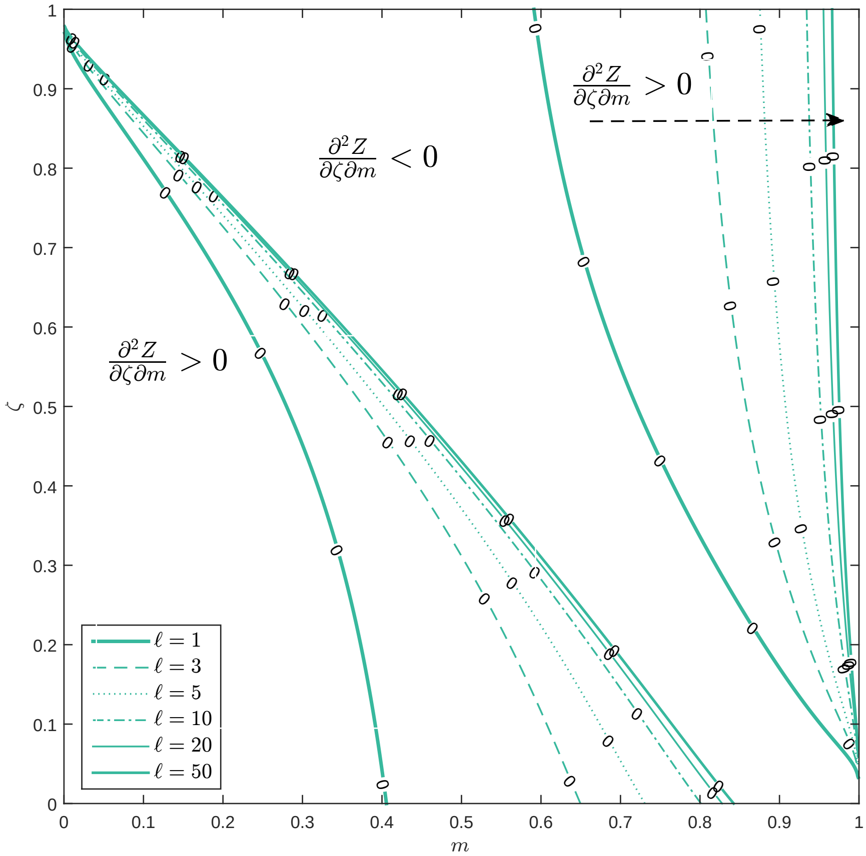
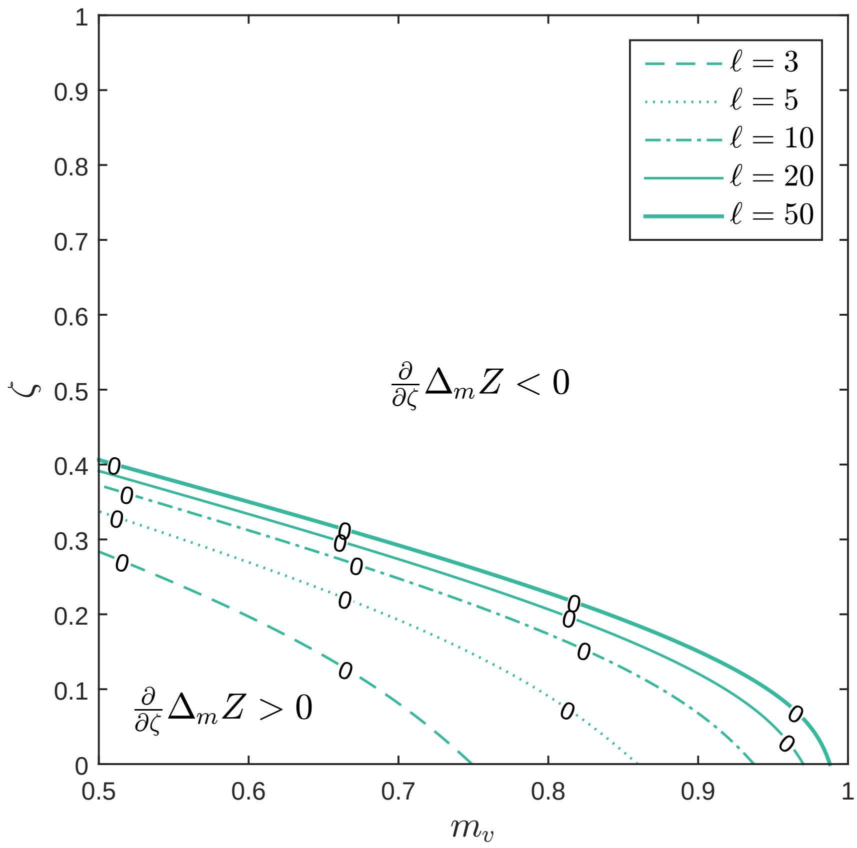


Figure A.3. Modularity properties of Z, Proposition 2, parts (c) and (d)



B Data appendix

Table B.1. List of industries

CNAE-09 Classification	Industry
101	Meat
102-109, 120	Food Products and Tobacco
110	Beverages
131-133, 139, 141-143	Textile
151-152	Leather & Footwear
261-262	Timber & Wooden Products
171-172	Paper Products
181-182	Graphics Design
201-206, 211-212	Chemical & Pharmaceutical Products
221-222	Plastic & Rubber Products
231-237, 239	Mineral Products (Non-Metal Products)
241-245	Ferrous Metals & Non-Ferrour Metals
251-257, 259	Metal Products
281-284, 289	Industry & Agricultural Machinery
261-268	Informatics, Electronics, Optics
271-275, 279	General & Electric Machinery
291-293	Motorized Vehicles
301-304, 309	Other Transportation Equipment
310	Furniture Industry
321-325, 329	Miscellaneous Manufacturing

Table B.2. Definition of firm-specific variables

Variable	Definition
Total factor productivity	Log of total factor productivity obtained from production function estimates à la Olley & Pakes (1996)
Age	Age of the firm in years
Capital intensity	Ratio of capital assets to the average number of workers during the year (expressed in thousands of Euros per worker)
Skill intensity	Number of graduate workers (university and three-year degrees) over the total number of workers as of December 31st
Employment	Log of the average number of workers during the year
Export dummy	Equal to one if the firm repots positive export values, zero otherwise
Ownership	Proportion of other firm's capital in the reporting firms's joint capital: equal to zero for 0%; one for $0-25\%$; two for $25-50\%$; three for $>50\%$

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Chapter 5

Facts and figures on a recent migration boom to Spain

This chapter is based on joint work with Nina Neubecker (previously unpublished).

5.1 Introduction

Thanks to its strong economic growth over the past twenty years and its liberal immigration policy, today Spain ranks among the world's major countries of immigration. From 1995 to 2010, the stock of foreign-born individuals in Spain has risen by 5.3 million people. This is the second largest increase observed in any country in the world.[1] From 2000 to 2008, Spain experienced the highest growth rate of the foreign-born population recorded in any OECD country over such a short period of time after World War II; see OECD (2010).

In this chapter, we use publicly available migration data, in order to identify some of the characteristic traits of this unique migration episode. We provide answers to questions such as: When did migration start to pick up momentum? How strongly was migration affected by the Global Financial Crisis in 2007/08? What countries did migrants come from, and where in Spain did they settle? Has the settlement pattern changed over time, and how does it compare to the settlement pattern of natives? These are interesting questions that can inspire future theoretical and empirical work on migration.

In Section 5.2, we give some information on the institutional background in Spain over the relevant period of time, and we briefly discuss the data source. Section 5.3 explores our

[1] The United States received 14.3 million people over the same period. Italy ranks third (2.7), followed by the United Kingdom (2.3), Canada (2.2), and Germany (1.8); see the World Development Indicators 2010, The World Bank.

migration data, in order to derive stylized facts on the recent migration boom to Spain.

5.2 Institutional background and data source

According to Ortega Pérez (2003), it was not until the 1990s that migration became a vital policy issue in Spain. Before, European legislation had prompted the socialist government to approve the rather 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 migration as a "structural phenomenon" and grants foreigners important rights such as access to education and legal counsel. This 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 quite a controversial debate, and the rights it granted to undocumented migrants were partly withdrawn by the conservative party after winning the absolute majority in the general elections of March 2000; see *Ley Orgánica 8/2000.* More recently, the socialist government initiated measures to fight undocumented migration and to better integrate documented migrants; see OECD (2006, 214). For example, in 2005, an unprecedented regularization process took place and a well-endowed integration fund was introduced. The latest reform of the *"Law on the Rights and Freedoms of Aliens in Spain and their Social Integration"* provides migrants, whether legally or illegally residing in Spain, with rights of assembly, demonstration, unionisation and strike; see OECD (2010) and *Ley Orgánica 2/2009.* In addition, it facilitates sanctions against people housing visa overstayers.

We use data on migration flows and stocks 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 is that they include both documented and undocumented migrants registering at Spanish municipalities (*municipios*). Spanish legislation requires all individuals residing in Spain to register at the local Municipal Register. Through registration, local authorities keep record of the individual's name, surname, sex, usual domicile, nationality, passport number, as well as the place and date of birth.[3] Most importantly, migrants are strongly incentivized to register, given that the *Law on the Rights and Freedoms of Aliens in Spain and their Social Integration* in 2000 (*Ley Orgánica 4/2000, artículo 12*) entitles all foreigners with or without

[2]See Chapters 6 and 7 for more detailed information on the data.

[3]For further information, see INE at `http://www.ine.es/en/metodologia/t20/t203024566_en.htm`, accessed on 08/19/2011.

legal residence permits to free medical care under the same conditions as Spanish nationals. Foreigners with valid residence permits have furthermore access to free legal support and public assistance in housing issues under the same conditions as Spanish nationals; see articles 1.10 and 1.16 of *Ley Orgánica 8/2000* and articles 13 and 20 of *Ley Orgánica 4/2000*. These rights are only conditional on having registered at the Municipal Register. Since the registry data is confidential and must not be communicated to the Ministry of Internal Affairs, registration is essentially costless; see article 18 of the *Ley Reguladora de las Bases del Régimen Local* and its amendment in 1996.

5.3 Stylized facts

From 1997 to 2009, a total of 5,960,312 migrants registered at Spanish municipalities. By migrants 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 migrant population and the number of new migrants per year. This suggests that Spanish migration is more of a permanent nature, rather than just temporary. The inflow peaked in 2007 at 915 thousand migrants, a number that is 26 times the inflow in 1997. Beginning in 2007, the Global Financial 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 migrants in 2008 and 2009, relative to the pre-crisis years. We may summarize these findings as follows.

Stylized fact 1. *From 1997 to 2007, continuous and considerable increases in annual migrant inflows have boosted the foreign-born population in Spain. The Global Financial Crisis marks a preliminary end to the Spanish migration boom.*

Aggregate numbers on migrant stocks and flows hide important cross-country variation. The following statistics paint a more differentiated picture of the Spanish migration experience. More precisely, we portray changes at the *intensive margin* as well as 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 5.1 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 migrants in Spain, which is roughly half of the overall migration to Spain.[4] Leaving aside the year 2009, we see a steady and significant increase in the migrant population of people with Romanian, Moroccan, Bolivian, and British nationality. In contrast, the number of migrants born in Ecuador (Colombia) stagnates around 450 (250) thousand people since 2004 (2003). The development of migrant inflows over time is more heterogenous across origin countries than that of migrant stocks. The general upward trend in the number of new migrants 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 explained by time-variant source country characteristics or time-variant bilateral factors. In contrast, the joint decrease in the number of new migrants in 2009 can be attributed to the Global Financial Crisis. This time-specific shock has, at least in principle, a uniform impact on all migration flows to Spain.

<< Figure 5.1 about here >>

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

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

We next take a closer look at the regional distribution of foreign-born individuals in Spain. A first observation is that migrants are not evenly distributed across provinces. The four major provinces of destination account for 50% of all new migrants between 1997 and 2009. These provinces are Madrid (22.2%), Barcelona (13.6%), Alicante (7.4%), and Valencia

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

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

(5.6%). They also represent the most populous locations in general. Our primary interest therefore lies with the distribution of migrants across provinces relative to that of natives.

Figure 5.2 depicts concentration curves for each of the six major countries of origin. Each subfigure plots the cumulative proportion of Spanish nationals (ordinate) against the cumulative proportion of foreign nationals (abscissa), separately for the years 1999 and 2009. The units of geographical reference are provinces of destination, sorted in descending order based on the share of migrants in the total province's population; see Duncan & Duncan (1955, 210-211) for the same approach.[6] The 45-degree line is a benchmark indicating no difference in the spatial concentration between migrants and natives. Two patterns stand out. First, all concentration curves deviate from the 45-degree line to a significant extent. Hence, there is what we may call clustering of migrants. The spatial diffusion of each of the groups of migrants differs from that of natives both at the beginning and the end of the Spanish migration boom. These differences are more pronounced for some countries of origin than for others. For example, in 1999, approximately 70% of all migrants from Ecuador resided in provinces hosting 20% of all Spaniards, while the same number for Moroccan and Colombian migrants is 50%. Second, each country's concentration curve for the year 1999 lies strictly to the right of the corresponding curve for the year 2009. Thus, the geographic distribution of the major migrant populations has become more similar to that of natives over time, although there are again relevant differences across countries of origin. This convergence may be the result of changes in new migrants' location choices, but they may also be due to internal migration moves.[7]

<< Figure 5.2 about here >>

This trend can also be seen by tracking indexes of spatial diffusion over time. The index of dissimilarity reads as $D = 0.5\sum_1^k |x_i - y_i|$, where x_i is the share of a certain migrant group residing in province i, y_i is the corresponding share for Spanish nationals, and k is the total number of provinces in Spain; see Duncan & Duncan (1955). Graphically speaking, D measures the maximum vertical distance between a given migrant group's concentration curve as in Figure 5.2 and the 45-degree line. Alternatively, D gives the minimum share of migrants who have to move to another province in order to replicate the spatial distribution

[6] We do not follow Duncan & Duncan (1955) in labeling the curve "segregation curve" because we study spatial concentration of migrants 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).

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

of Spanish nationals. Thus, D can only take on values in the closed unit interval, with higher numbers indicating stronger dissimilarity in location choices between migrants and natives. The left panel of Figure 5.3 depicts the index of dissimilarity for the four major countries of origin from 1997 to 2009. For these countries, the index takes on values between 0.2 and 0.6. For Ecuadorian and Romanian migrants, 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] This is summarized as follows.

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

<< Figure 5.3 about here >>

The index of dissimilarity proves useful in detecting differences in location choices between natives and migrants. 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 migrants than of natives is located in each group's single most attractive province of destination. The right panel of Figure 5.3 therefore shows the development of the "migration Herfindahl-Hirschman Index" (henceforth HHI) for different ethnic groups over time. It allows us to assess differences in spatial concentration across groups of migrants and natives, and to track these differences over time.[9] Following Conway & Rork (2010, 768), we calculate this index as the total sum of the squared shares of migrants in each province in total migrants in Spain, separately for the different ethnic groups in Spain. In our case of $n = 52$ destination provinces, it ranges 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 migrant group is independent of the spatial distribution of natives in Spain, we also compute the HHI for Spanish nationals as a reference group. For Spanish nationals, 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 migrant groups, the HHI is above that of the reference group, indicating stronger spatial concentration of migrants relative to natives. 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; 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 migrant groups both in terms of the order of magnitude and the development over time.

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

most concentrated groups of migrants are people with Ecuadorian and Romanian nationality. We also see a time trend similar to that of the index of dissimilarity. We summarize these findings as follows.

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

The analysis presented so far provides valuable information on migrants' tendency to cluster in space. However, it cannot identify migrants' preferred provinces of destination. Figure 5.4 illustrates differences in the spatial distribution of each of the four major migrant groups and the group of natives in the year 1999. The darker the color of a certain province, the larger is the share of migrants settled in this province relative to the corresponding share of natives.

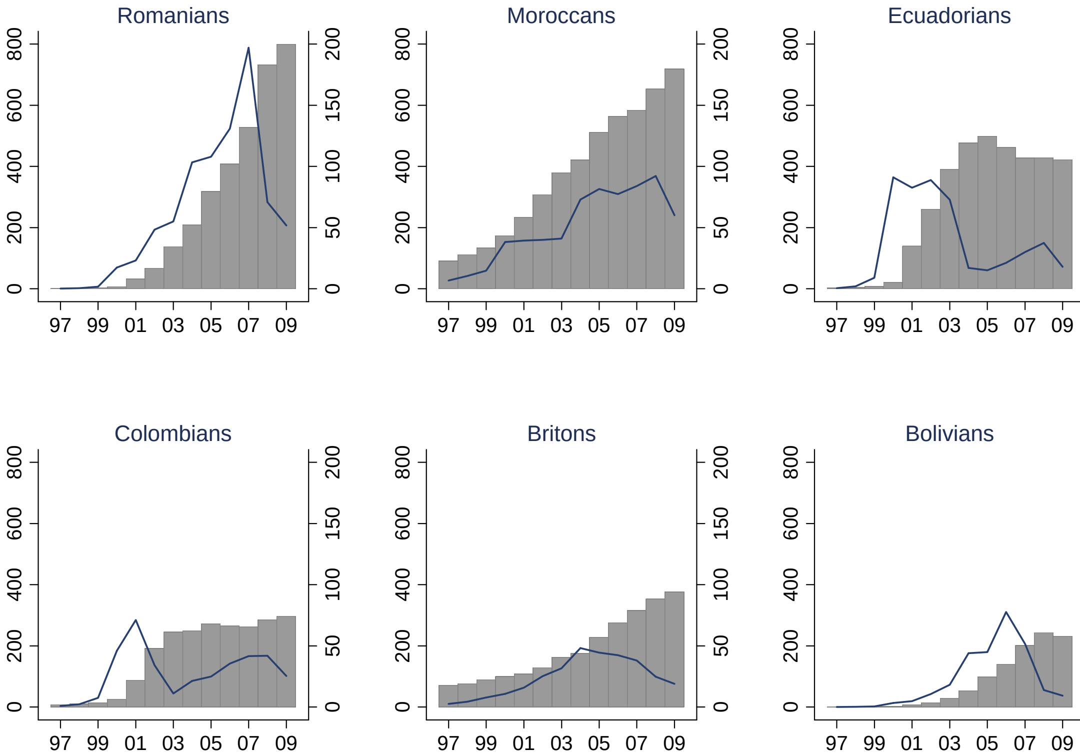
<< Figure 5.4 about here >>

The maps show that migrants from all four countries were more strongly attracted by the province of Madrid than were natives. For Ecuador, the difference in the population shares in Madrid was almost 50.0 percentage points. This is an extremely large number. For Romania (31.6), Colombia (26.0), and Morocco (4.6) the corresponding differences are smaller but still significant. We see relevant cross-country heterogeneity in the settlement of migrants. For example, a relatively large share of migrants from Morocco targeted provinces in the North-East (Barcelona and Girona) and in the South-East (Murcia) of Spain, whereas Romanians were underrepresented (relative to natives) in the provinces of Barcelona and Murcia. Migrants from Colombia, in contrast to those from Ecuador, had disproportionately large representations in the North of Spain, especially in the provinces of Cantabria, La Rioja, Navarra, and Álava. Such differences are not trivial to explain and require further investigation. We sum these observations up as

Stylized fact 5. *The major migrant groups had disproportionately large, some of them extremely large, representations in the province of Madrid. There is significant cross-country heterogeneity in the settlement pattern in Spain, even for countries with a supposedly similar cultural background.*

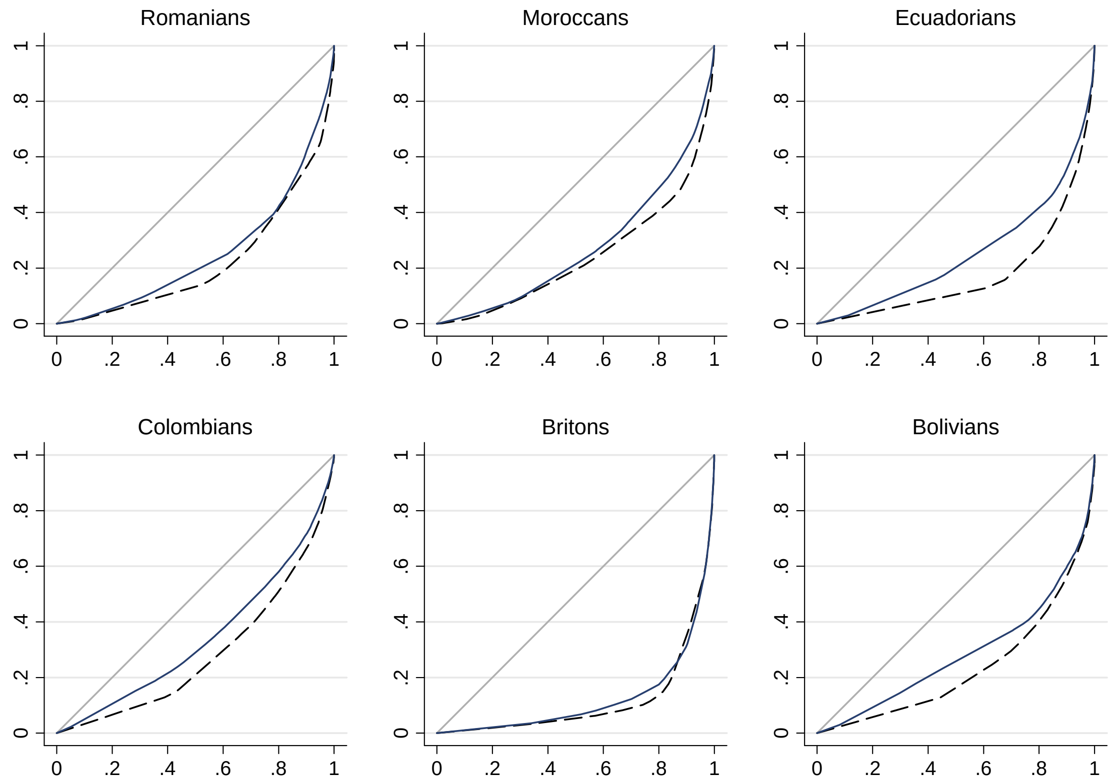
Figures

Figure 5.1. Migration stocks and inflows in thousands, Spain 1997 to 2009.†



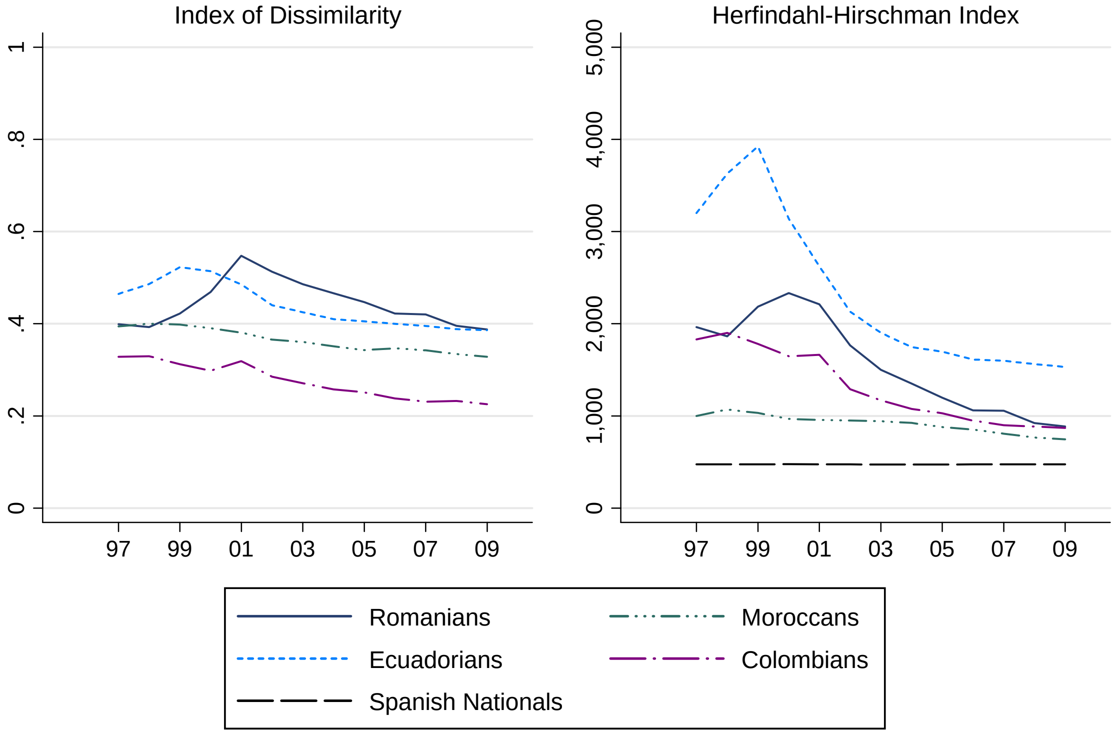
† This figure shows migrant stocks in Spain (bars; left ordinate) and inflows to Spain (lines; right ordinate) by nationality for the six major origin countries over the period 1997-2009. Numbers are given in thousands ('000s). *Source:* Authors' tabulations using data from INE.

Figure 5.2. Concentration curves for foreign nationals in Spain, 1999 and 2009.†



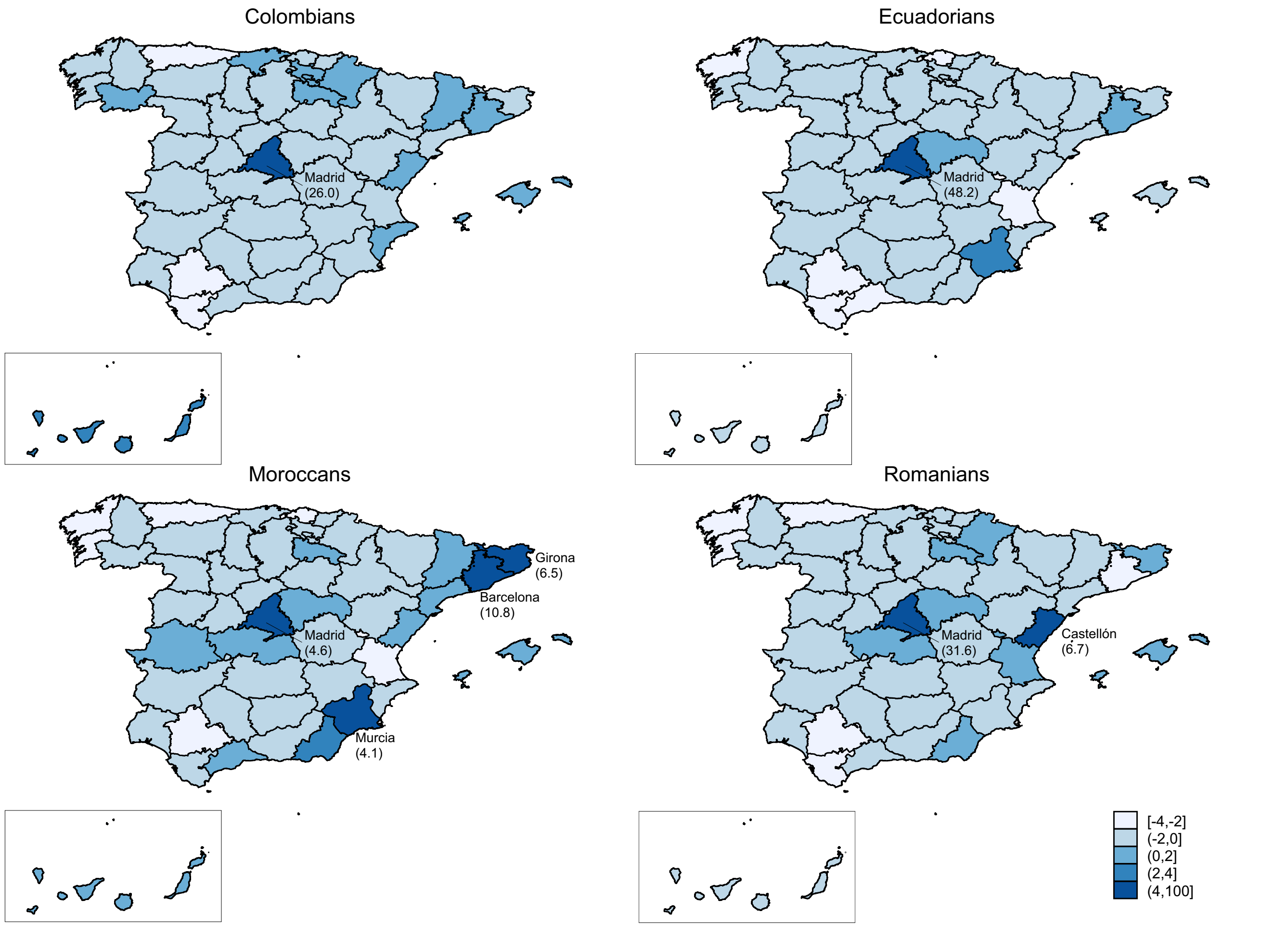
† This figure shows concentration curves for foreign nationals in Spain for the years 1999 (dashed curves) and 2009 (solid curves). Each subfigure plots the cumulative proportion of Spanish people (ordinate) against the cumulative proportion of foreign nationals (abscissa). The units of geographical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

Figure 5.3. Spatial clustering of migrant groups in Spain, 1997 to 2009.[†]



[†] This figure shows the index of dissimilarity (left panel) and the Herfindahl-Hirschman index (right panel) for the stock of selected ethnic groups in Spain over the period 1997-2009. Both indexes use Spanish provinces as units of geographical reference. For definitions of the indexes, see the text. *Source:* Authors' tabulations using data from INE.

Figure 5.4. Comparison of the spatial distribution of major migrant groups in Spain and natives, 1999.†



† This figure illustrates differences in the spatial distribution of natives and major migrant 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 migrants living in a certain province and the corresponding share for natives. Dark colors represent strong concentration of migrants relative to natives. Light colors represent strong concentration of natives relative to migrants. The provinces Las Palmas and Santa Cruz de Tenerife are grouped together as Islas Canarias. *Source:* Authors' tabulations using data from INE.

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Chapter 6

Networks and selection in international migration to Spain

This chapter is based on joint work with Nina Neubecker and Anne Steinbacher. A discussion paper of this chapter is available as DIW Discussion Paper No. 1306. An earlier draft appeared as University of Tübingen Working Papers in Economics and Finance No. 35 and as IAW Discussion Paper No. 83.

6.1 Introduction

An established body of literature argues that already settled migrants, often simply called a migrant network, alleviate the burden of migration for prospective newcomers, for example through informal job referrals among co-national peers (Munshi, 2003).[1] In this paper, 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 destinations 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 has increased dramatically over the past few years, starting out from 4.9% in 2000 and approaching 14.1% in 2008 (OECD, 2010, 240).

[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 paper 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 generalizes the standard multinomial logit (MNL) model described in McFadden (1984, 1411-1415), which assumes that, conditional on observables, any two migration destinations are equally substitutable for one another. This assumption is largely at odds with the fact that destinations located in the same *territorial entity* (e.g. a sovereign state or a country subdivision with independent legislative authority) are similar in many respects that are difficult or impossible to observe. They share the same legal and political framework; they have a common cultural background; and they engage in similar economic activities. Our NMNL framework allows for such similarities in the multi-level hierarchy of territorial entities, featuring the highest degree of substitutability across destinations that are located in the same region of a given country, and the lowest one across destinations that are located in different countries. In doing so, our model introduces unobserved heterogeneity into the migration function that challenges previous identification strategies based on aggregate cross-sectional migration data.

Previous attempts to model cross-destination substitutability in migration are furthermore challenged by 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 & 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*). Therefore, as a general rule, destinations in regions with a pronounced political and cultural autonomy should appear as close substitutes, relative to destinations in other regions. Our NMNL framework allows us to model this issue 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 requires a careful interpretation of the network 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 that are

[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 & Koppelman (2001) could be used to closely approximate our three-level NMNL, but its estimation is not feasible with our data.

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 is 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.

Our estimates reveal robustly positive network effects on the scale of migration. The effects are of considerable size, although smaller than those reported in the received literature. Since individual migration moves are independent of the effect they have on others' migration decisions our results have important policy implications. In a dynamic model of labor migration, network effects indicate a welfare loss in the laissez-faire transition path equilibrium (Carrington et al., 1996; Chau, 1997). From the perspective of a social planner who wants to maximize world welfare, they call for migration subsidies that accelerate the speed of migration. Our estimates also attest to strong negative effects of migrant networks on the skill structure of migration, defined as the ratio of high-skilled to low-skilled migrants. This finding accords with the idea that high-skilled individuals have lower effective migration costs than low-skilled individuals (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 estimates strongly reject a uniform degree of substitutability across alternative destinations, working against the standard MNL model in our application to the Spanish case. We find pronounced heterogeneity in the estimated network coefficients across destinations, an observation that has (to the best of our knowledge) received no attention at all in the literature. We use the structural interpretation of our network coefficients in order to exploit this heterogeneity and compute elasticity values for the network effect. The estimated elasticity is lowest for the destinations located in the region of Extremadura, slightly exceeding a

[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 (Neubecker & Smolka, 2013).

value of 0.1. It is highest for the destinations located in the region of Cataluña, lying in the vicinity of 0.55. We can conclude from our results that the ease with which one destination can be substituted for another one is highest in the region of Cataluña, arguably the region with the highest degree of political and cultural autonomy in Spain.

Our paper is related to recent estimates of network effects based on aggregate migration data. Beine et al. (2011) 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 that already host 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.[5] Similar results are obtained by Beine & Salomone (2013) who study potential gender differences in network effects. The paper by Beine et al. (2012) disentangles what the authors call local and national network externalities, saying that local migrant networks facilitate the assimilation of migrants in the host society, while nation-wide migrant networks help overcome the legal entry barriers to migration. However, all of these papers derive the estimated migration functions from a standard MNL model that assumes a uniform degree of cross-destination substitutability.[6]

Our paper is also related to a number of macro-level studies that are more generally concerned with the determinants of international migration.[7] In this literature, migrant networks robustly rank among the most important factors shaping migration, but the estimated migration functions often lack an explicit micro-foundation (Clark et al., 2007; Lewer & den Berg, 2008; Pedersen et al., 2008; Mayda, 2010). Two recent papers, Bertoli & Fernández-Huertas Moraga (2013) and Ortega & Peri (2013), develop micro-founded random utility migration models in order to estimate the determinants of migration. In both papers, the standard MNL assumption of a uniform degree of cross-destination substitutability is relaxed. Bertoli & Fernández-Huertas Moraga (2013) use the same Spanish data source as we do in this paper. They argue that the Common Correlated Effects (CCE) estimator, a panel estimator

[5]See Grogger & Hanson (2011, 53) for complementary evidence. Mckenzie & Rapoport (2010) find positive self-selection on education from Mexican migrants to the U.S. 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.

[6]While revising this paper, we became aware of research by Bertoli & Fernández-Huertas Moraga (2012). They use the same migration data as Beine et al. (2011) in order to estimate network effects in migration, relaxing the assumption of a uniform degree of substitutability across alternative destinations. 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 our paper); see Appendix A for details.

[7]For the location choice of migrants within borders, see Bartel (1989), Zavodny (1997, 1999), Chiswick & Miller (2004), Card & Lewis (2007), 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 & Genicot (2010).

proposed by Pesaran (2006), yields 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 our paper), assuming, contrary to our model, that there is a single similarity parameter for all nests.[8] Ortega & 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.[9] Their model, best understood as a two-level NMNL model with a single similarity parameter for all nests, allows for a higher degree of substitutability across destinations that are located outside the individual's country of origin. However, neither Bertoli & Fernández-Huertas Moraga (2013) nor Ortega & Peri (2013) identify the effects of migrant networks on the scale and skill structure of migration, as we do in this paper.

The remainder of this paper is organized as follows. Section 6.2 characterizes individual decision making in a three-level NMNL model. From this model, we derive estimable equations 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.

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[10]: first to which country to migrate (including the country of origin), second which region to move to within the chosen

[8] 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 (Wen & Koppelman, 2001). Bertoli et al. (2013) employ the CNL model in order to study the effect of the recent economic crisis in Europe on migration to Germany.

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

[10] 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 (Domencich & McFadden, 1975).

country, and third which province to pick within the preferred region.[11] 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.[12] 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. (2011, 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 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 $U_{ij} \equiv U_{ij}^o - e_{ij}^o = Y_j - C_{ij}$ and $\xi_{ij} \equiv Y_j - c_{ij} + \theta \ln(1 + M_{ij})$.

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

[12] 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.

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:

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

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

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

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

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

see McFadden (1978, 80-81) and McFadden (1981, 226-230).[13]

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 two parameters govern the degree of substitutability across alternative destinations; 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:

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

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 $\kappa_r = \lambda_z = 1 \; \forall r, z$. This rules out any correlation among the random utilities. 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[14]:

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

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

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

[13] We show in Appendix B how to derive (6.8).

[14] 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 Appendix A how to compute $P_i^o(j^o = j) = \partial \ln H_i(\cdot)/\partial U_{ij}$.

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 expected 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 inclusive values Φ_{ir}, Ω_{iz}, and Ψ_i. It is therefore responsive to the attractiveness of all provinces $k = 1, \ldots, J$, whether in the same region r (or the same country z) as province j or not. It is in this sense that we refer to the inclusive values as "multilateral resistance" terms.[15] For example, consider the elasticity of the ij-specific migration rate, m_{ij}/m_i, with respect to Y_k, the utility-relevant characteristics of province k, where $j \in A_{zr}, r \in A_z$, and $k \in A_{y\ell}, \ell \in A_y$. Straightforward though cumbersome differentiation yields[16]:

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

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]

[15] 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 (Anderson & van Wincoop, 2003). Anderson (2011) sketches a general equilibrium migration model with multilateral resistance. See also Hanson (2010, 4373-4375) for a discussion.

[16] We show in Appendix D how to compute this elasticity.

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

Given that $0 < \kappa_r, \lambda_z \leq 1$, this elasticity is positive for $k = j$ and negative for all other provinces $k \neq j$.

Any change in the conditions in some province $k \neq j$ induces *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 value) for any change in the conditions in other provinces in the same region, $I(\ell, r) = I(y, z) = 1$. The fact that these substitution effects are strongest within regions and weakest across countries is due to the similarity of provinces located in the same region (and in 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 in the same country.

The flexible structure of cross-destination substitutability in our 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):

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

where the multilateral resistance term Ψ_i 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).[18] 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

[18]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 $k \neq i, j$.

assumption is not violated. In our more general NMNL modeling framework, the relative odds become:

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

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 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).[19] 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 $j \in A_{zr}, r \in A_z$:

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

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-destination substitutability (and thus larger network coefficients) in regions that put a lot of emphasis on their political and cultural autonomy.

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

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):

$$U_{ij}^o = Y_j - \gamma^s C_{ij} + e_{ij}^o, \tag{6.22}$$

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:

$$\begin{aligned} \ln\left(\frac{m_{ij}^h}{m_{ij}^l}\right) &= \frac{\theta\gamma^*}{\lambda_z\kappa_r}\ln(1+M_{ij}) + \ln\left(\frac{m_i^h}{m_i^l}\right) - \gamma^* c_{iz} - \frac{\gamma^*}{\lambda_z}c_{ir} - \frac{\gamma^*}{\lambda_z\kappa_r}c_{ij} \\ & -\Psi_i^* - (1-\lambda_z)\Omega_{iz}^* - (1-\kappa_r)\Phi_{ir}^*, \end{aligned} \tag{6.23}$$

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.[20]

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,

[20]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. (2011).

the model for the skill structure of migration is estimated at the level of regions in Spain.[21] For both models, our benchmark estimates are based on a sample comprising the 55 most important countries of origin listed in Table E.1 in Appendix E. These are all countries with at least 630 migrants in Spain in the year 1996. All migration data come from the Spanish Instituto Nacional de Estadística (INE). The full internet sources of our data are listed in Table E.2 in Appendix E.

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.[22] 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 already 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 documented 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.[23] Each registrant must provide his or her name, surname, sex, usual domicile, nationality, passport number, as well as the place and date of birth.[24] Since this information is confidential and must not be communicated to other administrative units, the probability of forced repatriation is plausibly independent of registration.

We identify the model from the within-cluster variation across provinces in the data.

[21]Spain is divided into 52 provinces which 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.

[22]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 assume that in every period individuals left in the home country draw new realizations of the random utility variables $e^o_{i1}, \ldots, e^o_{iJ}$, an assumption too strong to be plausible.

[23]As part of its austerity measures in 2012, the Spanish government has—with some exceptions—restricted this access to health care for undocumented migrants from September 2012 onwards.

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

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).[25] 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-destination 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 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, which is part of French national territory[26]; 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 those related to 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

[25]When zero values inflate the dependent variable, the FE estimator delivers inconsistent estimates (Santos Silva & 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.

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

migrants (i.e., migrants from Ecuador) but also by a network of migrants from other Latin American countries (Neubecker & Smolka, 2013). 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 with a set of world region-and-province fixed effects.[27]

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 available from DataInvex Statistics on Foreign Investments in Spain and detailed by the country of the last owner and by the region of destination in Spain.[28] Due to limited data availability, we have to use FDI flows for the year 1997. We think that endogeneity is unlikely, however, because the decision to engage in FDI is often made some time before the actual investments are carried out.

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 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

[27]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.

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

called internal migration).[29]

Because it indicates a large historical network, internal migration can be expected to correlate positively with the migrant network in 1996.[30] 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.[31] 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, 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. We therefore simplify the structure of our model to a two-level NMNL model in which the regions of destination (indexed here by j) are the final migration destinations within the primary nest of Spain. Equation (6.23) then becomes:

$$\ln\left(\frac{m_{ij}^h}{m_{ij}^l}\right) = \frac{\theta\gamma^*}{\lambda_z}\ln(1+M_{ij}) + \ln\left(\frac{m_i^h}{m_i^l}\right) - \gamma^* c_{iz} - \frac{\gamma^*}{\lambda_z}c_{ij} - \Psi_i^* - (1-\lambda_z)\Omega_{iz}^*. \tag{6.24}$$

The dependent variable 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

[29]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.

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

[31]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.

November 2006 and February 2007.[32] Migrants report, *inter alia*, 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.[33] Importantly, this definition is independent of the individual's legal status, so the data again include documented and undocumented migrants. We aggregate the 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, absorbing, among other things, the multilateral resistance terms Ψ_i^* and Ω_{iz}^*, 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. We control for the geographical distance between the country of origin i and the region of destination j, using the STATA module GEODIST by Picard (2010) in combining geographical data on the countries of origin from Mayer & Zignago (2006) and on the regions of destination from the Spanish Wikipedia/GeoHack webpage. We control for a common language through an indicator variable that 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

[32]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 both the survey and the sampling can be found in Reher & Requena (2009) as well as in INE (2007).

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

origin, and zero otherwise. The information on native languages in Spain are taken from a number of recent survey studies.[34] Language information on the countries of origin come from Mayer & 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 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.

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. 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 migration model. We also discuss the results of several robustness checks.[35]

<<Figures 6.1(a) and 6.1(b) about here>>

6.4.1 Results for the scale of migration

In this subsection 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

[34] See Table E.2 in Appendix E for a list of surveys.

[35] The detailed results of these robustness checks are available from the authors upon request.

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.[36]

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.[37] 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. 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 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.

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.

<<Tables 6.1 and 6.2 about here>>

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

[37]This estimate of the average network coefficient is virtually identical to the local network externality estimated by Beine et al. (2012).

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 (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.

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. In all the specifications employed, it exceeds the critical value of 10, 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, which implies 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).[38] 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,

[38]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.

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 uniform degree of cross-destination substitutability featured in the standard MNL model is too restrictive to be plausible in the Spanish case.

<<Table 6.3 about here>>

The estimated network coefficients can be used to compute both the network elasticity of migration as well as the cross-elasticities of the network defined as:

$$\begin{aligned}\frac{\partial \ln(m_{ij})}{\partial \ln(1+M_{ik})} &= \theta\left[\frac{I(j,k)}{\lambda_z\kappa_r} - \left(\frac{m_{ik}}{m_i}\right)\right.\\ &\left.-\frac{I(\ell,r)}{\lambda_z\kappa_r}(1-\kappa_r)\left(\frac{m_{ik}}{m_{ir}}\right) - \frac{I(y,z)}{\lambda_z}(1-\lambda_z)\left(\frac{m_{ik}}{m_{iz}}\right)\right]. \qquad (6.25)\end{aligned}$$

The network elasticity ($j = k$) is a function of the network parameter θ, the similarity parameters κ_r and λ_z, and 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 prevail even if the true network *coefficient*, η_{zr}, was known with certainty.[39] 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 results reported in Table 6.3 in order 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, while 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 0.195 (= 0.155/0.795).

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,

[39] Schmidheiny & Brülhart (2011) discuss a related type of uncertainty in a two-level NMNL model. They show that the Poisson model and the standard MNL model are the polar cases of a two-level NMNL model with two nests, one being a degenerate nest with a single alternative, and the other one featuring many alternatives with a single similarity parameter $\lambda \in (0, 1)$. When λ is unknown, the elasticities of the Poisson model and of the standard MNL model can thus serve as boundary values for the true elasticities.

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 same 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 a minor 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.[40]

<<Figures 6.2(a) and 6.2(b) about here>>

We have also computed the cross-elasticities of the network based on (6.25), 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 that ranges between 0.0 and -0.05. For the provinces in the region of Cataluña, the same cross-elasticity lies between -0.22 and -0.27. In Figures F.6.1(a) and F.6.1(b) in Appendix F, 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 not specific to any region of destination in Spain, they are lower (in absolute value) than the cross-elasticities depicted in Figure 6.2(b), and they are characterized by a higher uncertainty about their true values.

Robustness analysis

We have conducted two types of robustness checks. Both of them seem to indicate, if anything, 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

[40]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 similarity parameter κ_r for the region of Extremadura is only compatible with a larger network parameter θ.

measurement errors in our migration data. The migration data that we have considered above covers the period 1997-2006. 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 G 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.[41]

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.[42,43] 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 (6.24). The full data matrix would contain 935 pairs of 55 countries of origin and 17 regions of destination. However, for some observations we lack the information on the migrant skill ratio (the dependent variable) due to the limited sample size of the NIS. The FE estimator is therefore applied to 241 observations with non-missing values for the migrant skill ratio. 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 accords with 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.

<<Tables 6.4 and 6.5 about here>>

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

[42]Sample selection based on explanatory variables is a type of exogenous sample selection.

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

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:

$$\frac{\partial \ln(m_{ij}^h/m_{ij}^l)}{\partial \ln(1+M_{ij})} = \theta\gamma^* \left[\frac{1}{\lambda_z} - \left(\frac{m_{ij}}{m_i}\right) - \frac{1-\lambda_z}{\lambda_z}\left(\frac{m_{ij}}{m_{iz}}\right)\right], \tag{6.26}$$

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.[44] Then, because 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 that the corresponding elasticity lies between -0.621 and -0.584.

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 that could be due to the large number of missing values for the migrant skill ratio. We have found contrary evidence, using a Heckman (1976)-style procedure similar to the one proposed by Wooldridge (1995, 123-124).[45] This procedure is described in detail in Appendix H. Second, following the methodology proposed by Grogger & Hanson (2011, 53-54), we have excluded the possibility that individuals group regions of destination 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

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

[45] Technically, the 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 & Scott (1948).

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. The starting point is to use equations (6.10) and (6.11) in order to compute the probability $P_i^o(j^o \in A_{zr}) = P_i^o(j^o \in A_{zr}|r \in A_z)P_i^o(r \in A_z)$, separately for each skill group. It is easy to show that this alternative migration function depends, among other things, on the number of provinces in each regional nest and on 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. 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.[46]

6.5 Conclusion

In this paper, we have documented strong positive network effects on the scale of migration and a strong negative effect on the ratio of high-skilled to low-skilled migrants. Both types of effects are robust across alternative estimators, estimation samples, and sets of control variables. Our identification strategy is based on a three-level NMNL model that allows for varying degrees of substitutability across alternative migration destinations. The ease with which one destination in Spain can be substituted by another one depends on whether the two destinations are located in the same region or not; in case they are, it also depends on the degree of political and cultural autonomy of that region. Our approach is corroborated by the significant degree of heterogeneity in the estimated network elasticity across regions.

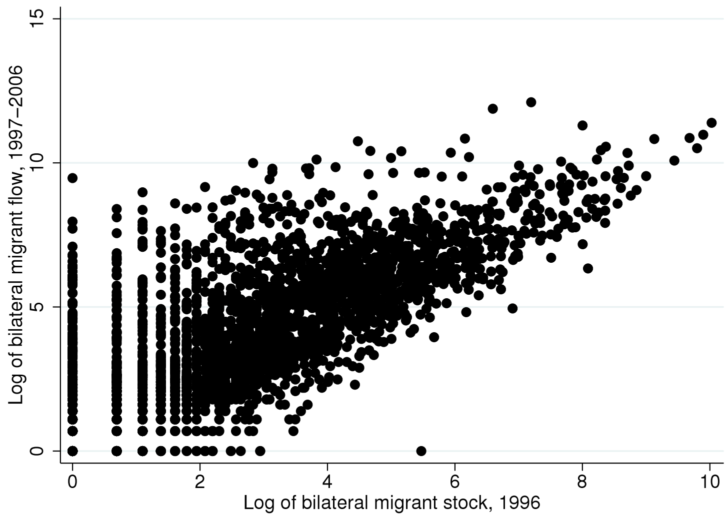
Our findings add to the understanding of the recent migration phenomenon in Spain. This migration has gained momentum through Spain's strong economic growth in the years before the Global Financial Crisis. It has changed the size and composition of the country's

[46]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.

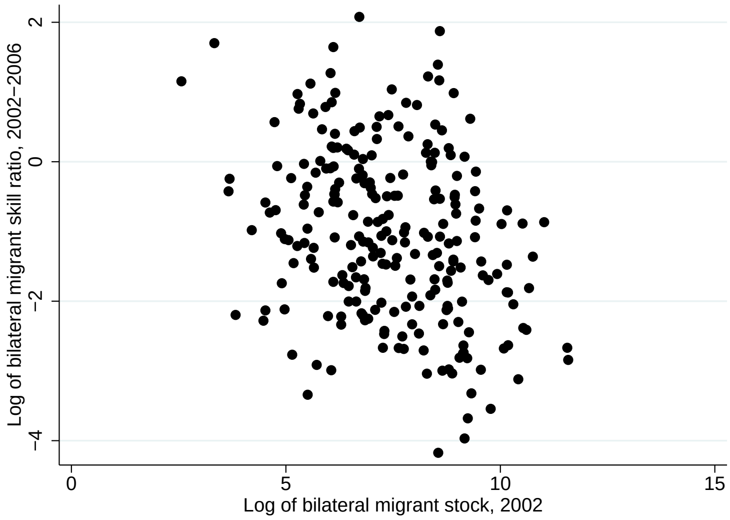
population and labor supply, with potentially important effects on a number of key macroeconomic variables such as wages, unemployment, and production, as well as on the national welfare state. The recent economic recession in Spain is reflected in a sharp decline in new migration and a significant amount of return migration in the very short run. The analysis of the structural relationships among past migration, future migration, and the labor market outcomes involves non-trivial dynamics. Attempts to study these dynamics seem to appear as a challenging yet promising avenue for future research.

Figures and tables

Figure 6.1. Migrant networks and the scale and skill structure of migration

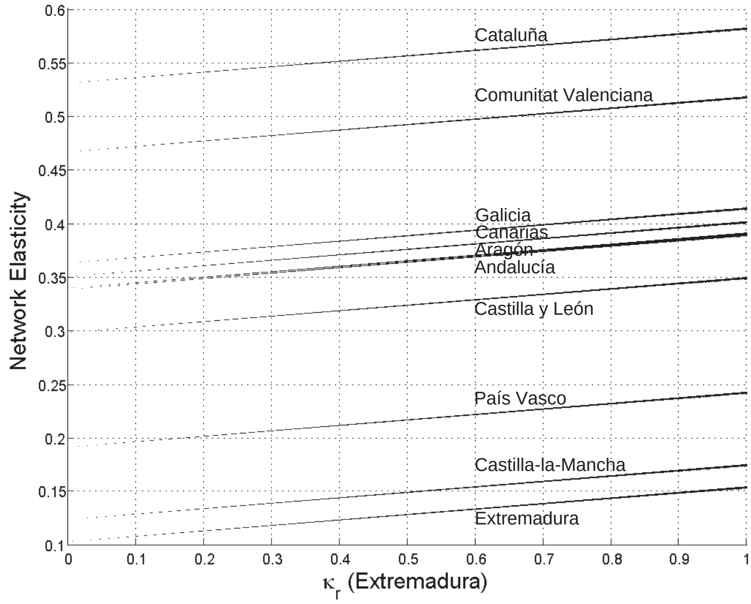


(a) $\ln(m_{ij})$ plotted against $\ln(1{+}M_{ij})$, provincial level

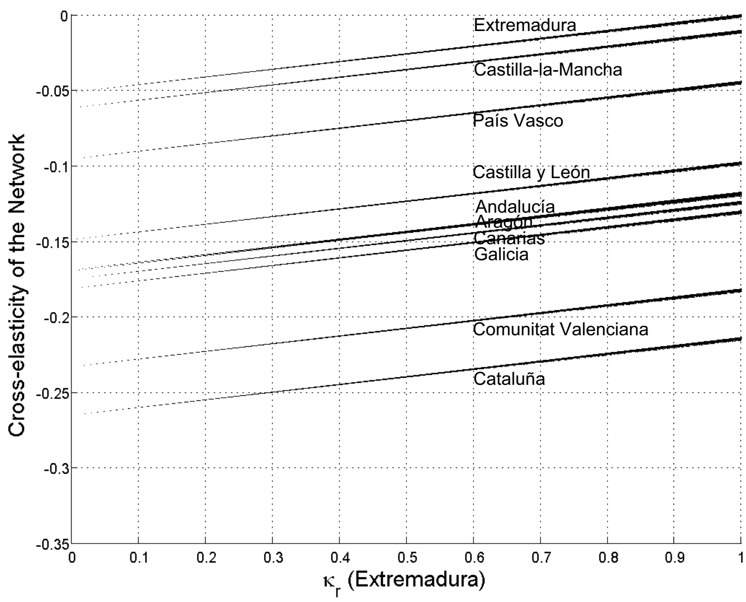


(b) $\ln(m^h_{ij}/m^l_{ij})$ plotted against $\ln(1{+}M_{ij})$, regional level

Figure 6.2. Counterfactual network elasticities and cross-elasticities



(a) Network elasticities



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

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 Region-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.

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 Region-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.

Table 6.3. Estimated network coefficients, by region†

Region r	Estimate of η_{zr}	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.

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 Region-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. 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 Region-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.

Appendices

A Comparison with Bertoli & Fernández-Huertas Moraga (2012)

We show that our three-level NMNL model is more general than the migration model estimated in the paper "Visa Policies, Networks and the Cliff at the Border" by Bertoli, Simone, and Jesús Fernández-Huertas Moraga, IZA Discussion Paper No. 7094 (2012) (henceforth

BFM, 2012). The response probability generating function in BFM (2012) can be written as:

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

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).[47] These assumptions imply that equation (A.1) becomes:

$$H_i = \sum_z \left(\sum_{j \in A_z} \exp[U_{ij}/\lambda] \right)^{\lambda}, \tag{A.2}$$

where the number and composition of nests is chosen arbitrarily by the authors. Equation (A.2) gives rise to a two-level NMNL model with a single similarity parameter for all nests. The pattern of cross-elasticities generated by equation (A.2) is thus more restrictive than the one generated by our three-level NMNL model with heterogeneous similarity parameters across nests.

B Derivation of $P_i^o(j^o = j)$

We show that

$$P_i^o(j^o = j) = \frac{\exp[U_{ij}]}{H_i(\cdot)} \frac{\partial H_i(\cdot)}{\partial \exp[U_{ij}]}. \tag{B.1}$$

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

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

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

Since $F_i(e_{i1}^o,\dots,e_{iJ}^o) = \exp[-H_i(\exp[-e_{i1}^o],\dots,\exp[-e_{iJ}^o])]$ is a joint cumulative distribution function, (B.2) can be written as:

$$P_i^o(j^o=1) = \int_{-\infty}^{\infty}\left(\int_{-\infty}^{U_{i1}-U_{i2}+e_{i1}^o}\cdots\left(\int_{-\infty}^{U_{i1}-U_{iJ}+e_{i1}^o} f(e_{i1}^o,\dots,e_{iJ}^o)de_{iJ}^o\right)\dots de_{i2}^o\right)de_{i1}^o, \tag{B.3}$$

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

$$f(e_{i1}^o,\dots,e_{iJ}^o) = \frac{\partial^J F(e_{i1}^o,\dots,e_{iJ}^o)}{\partial e_{i1}^o\dots\partial e_{iJ}^o} \tag{B.4}$$

(B.3) can be written as:

$$\begin{aligned} P_i^o(j^o=1) &= \int_{-\infty}^{\infty}\left(\int_{-\infty}^{U_{i1}-U_{i2}+e_{i1}^o}\cdots\left(\int_{-\infty}^{U_{i1}-U_{iJ}+e_{i1}^o} \frac{\partial^J F(e_{i1}^o,\dots,e_{iJ}^o)}{\partial e_{i1}^o\dots\partial e_{iJ}^o}de_{iJ}^o\right)\dots de_{i2}^o\right)de_{i1}^o \\ &= \int_{-\infty}^{\infty}\frac{\partial F(e_{i1}^o, U_{i1}-U_{i2}+e_{i1}^o,\dots,U_{i1}-U_{iJ}+e_{i1}^o)}{\partial e_{i1}^o}de_{i1}^o \\ &= \int_{-\infty}^{\infty}\frac{\partial\left(\exp\left[-H_i\left(e^{-e_{i1}^o}, e^{U_{i2}-U_{i1}-e_{i1}^o},\dots,e^{U_{iJ}-U_{i1}-e_{i1}^o}\right)\right]\right)}{\partial e_{i1}^o}de_{i1}^o \\ &= \int_{-\infty}^{\infty} e^{-e_{i1}^o}\frac{\partial H_i(e^{-e_{i1}^o}, e^{U_{i2}-U_{i1}-e_{i1}^o},\dots,e^{U_{iJ}-U_{i1}-e_{i1}^o})}{\partial e^{-e_{i1}^o}}\times \\ &\quad \times\exp\left[-H_i\left(e^{-e_{i1}^o}, e^{U_{i2}-U_{i1}-e_{i1}^o},\dots,e^{U_{iJ}-U_{i1}-e_{i1}^o}\right)\right]de_{i1}^o, \end{aligned} \tag{B.5}$$

where

$$\frac{\partial H_i(e^{-e_{i1}^o}, e^{U_{i2}-U_{i1}-e_{i1}^o},\dots,e^{U_{iJ}-U_{i1}-e_{i1}^o})}{\partial e^{-e_{i1}^o}} = \sum_j\left(e^{U_{ij}-U_{i1}}\frac{\partial H_i(\cdot)}{\partial e^{U_{ij}-U_{i1}-e_{i1}^o}}\right). \tag{B.6}$$

Recall that H_i is linearly homogeneous. Hence,

$$H_i\left(e^{-e_{i1}^o}, e^{U_{i2}-U_{i1}-e_{i1}^o},\dots,e^{U_{iJ}-U_{i1}-e_{i1}^o}\right) = e^{-e_{i1}^o-U_{i1}}H_i\left(e^{U_{i1}}, e^{U_{i2}},\dots,e^{U_{iJ}}\right) \tag{B.7}$$

and
$$\frac{\partial H_i(e^{-e^o_{i1}}, e^{U_{i2}-U_{i1}-e^o_{i1}}, \ldots, e^{U_{iJ}-U_{i1}-e^o_{i1}})}{\partial e^{-e^o_{i1}}} = \frac{\partial H_i(e^{U_{i1}}, e^{U_{i2}}, \ldots, e^{U_{iJ}})}{\partial e^{U_{i1}}}. \tag{B.8}$$

Thus, (B.5) can be written as:

$$\begin{aligned}
P^o_i(j^o = 1) &= \int_{-\infty}^{\infty} e^{-e^o_{i1}} \frac{\partial H_i(e^{U_{i1}}, e^{U_{i2}}, \ldots, e^{U_{iJ}})}{\partial e^{U_{i1}}} \exp\left[-e^{-e^o_{i1}-U_{i1}} H_i\left(e^{U_{i1}}, e^{U_{i2}}, \ldots, e^{U_{iJ}}\right)\right] de^o_{i1} \\
&= \frac{\partial H_i(\cdot)}{\partial \exp[U_{i1}]} \int_{-\infty}^{\infty} e^{-e^o_{i1}} \exp\left[-e^{-e^o_{i1}-U_{i1}} H_i\left(e^{U_{i1}}, e^{U_{i2}}, \ldots, e^{U_{iJ}}\right)\right] de^o_{i1} \\
&= \frac{\partial H_i(\cdot)}{\partial \exp[U_{i1}]} \int_{-\infty}^{\infty} e^{-\zeta+U_{i1}-\ln H_i(\cdot)} \exp\left[-e^{-\zeta}\right] d\zeta \\
&= \frac{\partial H_i(\cdot)}{\partial \exp[U_{i1}]} \frac{\exp[U_{i1}]}{H_i(\cdot)},
\end{aligned} \tag{B.9}$$

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.

C Derivation of $\partial \ln H_i(\cdot)/\partial U_{ij}$

Since
$$\ln H_i(\cdot) = \ln \sum_z \left(\sum_{r \in A_z} \left(\sum_{j \in A_{zr}} \exp[U_{ij}/(\kappa_r \lambda_z)] \right)^{\kappa_r} \right)^{\lambda_z} \tag{C.1}$$

we have
$$\frac{\partial \ln H_i(\cdot)}{\partial U_{ij}} = H_i(\cdot)^{-1} \exp[U_{ij}/(\kappa_r \lambda_z)] QX, \tag{C.2}$$

where

$$\begin{aligned}
Q &= \left(\sum_{j \in A_{zr}} \exp[U_{ij}/(\kappa_r \lambda_z)] \right)^{\kappa_r - 1} \\
&= (\exp[(-c_{iz} - c_{ir})/(\kappa_r \lambda_z)])^{\kappa_r - 1} \left(\sum_{j \in A_{zr}} \exp[\xi_{ij}/(\kappa_r \lambda_z)] \right)^{\kappa_r - 1}
\end{aligned} \tag{C.3}$$

and

$$X = \left(\sum_{r\in A_z}\left(\sum_{j\in A_{zr}} \exp[U_{ij}/(\kappa_r\lambda_z)]\right)^{\kappa_r}\right)^{\lambda_z-1} \tag{C.4}$$

$$= (\exp[-c_{iz}/\lambda_z])^{\lambda_z-1}\left(\sum_{r\in A_i}(\exp[-c_{ir}/\lambda_z])\left(\sum_{j\in A_{zr}} \exp[\xi_{ij}/(\kappa_r\lambda_z)]\right)^{\kappa_r}\right)^{\lambda_z-1}.$$

By defining $\Phi_{ir} = \ln\sum_{k\in A_{zr}}\exp[\xi_{ik}/(\kappa_r\lambda_z)]$, $\Omega_{iz} = \ln\sum_{\ell\in A_z}\exp[\Phi_{i\ell}\kappa_\ell - c_{i\ell}/\lambda_z]$ and $\Psi_i = \ln\sum_z \exp[\Omega_{iz}\lambda_z - c_{iz}]$, equation (C.2) can be written as:

$$\frac{\partial \ln H_i(\cdot)}{\partial U_{ij}} = \frac{\exp[\xi_{ij}/(\kappa_r\lambda_z) - c_{ir}/\lambda_z - c_{iz}]}{H_i(\cdot)\exp[(1-\kappa_r)\Phi_{ir} + (1-\lambda_z)\Omega_{iz}]}$$

$$= \frac{\exp[\xi_{ij}/(\kappa_r\lambda_z) - c_{ir}/\lambda_z - c_{iz}]}{\exp[\Psi_i + (1-\kappa_r)\Phi_{ir} + (1-\lambda_z)\Omega_{iz}]}, \tag{C.5}$$

which gives $P_i^o(j^o = j)$, where $j \in A_{zr}, r\in A_z$; see equations (6.8) and (6.16).

D Derivation of $\partial \ln(m_{ij}/m_i)/\partial \ln Y_k$

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

$$\ln\left(\frac{m_{ij}}{m_i}\right) = \xi_{ij}/(\lambda_z\kappa_r) - c_{ir}/\lambda_z - c_{iz} - \Psi_i - (1-\kappa_r)\Phi_{ir} - (1-\lambda_z)\Omega_{iz} \tag{D.1}$$

we have

$$\frac{\partial \ln(m_{ij}/m_i)}{\partial \ln Y_k} = \frac{Y_k}{\lambda_z\kappa_r} - \frac{\exp[\Omega_{iz}\lambda_z - c_{iz}]\lambda_z}{\exp[\Psi_i]}\frac{\partial\Omega_{iz}}{\partial\ln Y_k} - (1-\kappa_r)\frac{\partial\Phi_{ir}}{\partial\ln Y_k}$$

$$-(1-\lambda_z)\frac{\partial\Omega_{iz}}{\partial\ln Y_k}$$

$$= \frac{Y_k}{\lambda_z\kappa_r} - \frac{m_{iz}\lambda_z}{m_i}\frac{\partial\Omega_{iz}}{\partial\ln Y_k} - (1-\kappa_r)\frac{\partial\Phi_{ir}}{\partial\ln Y_k} - (1-\lambda_z)\frac{\partial\Omega_{iz}}{\partial\ln Y_k}. \tag{D.2}$$

Since

$$\frac{\partial\Phi_{ir}}{\partial\ln Y_k} = \frac{\exp[\xi_{ik}/(\lambda_z\kappa_r)]}{\sum_{k\in A_{zr}}\exp[\xi_{ik}/(\lambda_z\kappa_r)]}\frac{Y_k}{\lambda_z\kappa_r} = \frac{m_{ik}}{m_{ir}}\frac{Y_k}{\lambda_z\kappa_r} \tag{D.3}$$

and

$$\frac{\partial \Omega_{iz}}{\partial \ln Y_k} = \frac{\exp[\Phi_{ir}\kappa_r - c_{ir}/\lambda_z]\kappa_r}{\sum_{\ell \in A_z} \exp[\Phi_{i\ell}\kappa_\ell - c_{i\ell}/\lambda_z]} \frac{\partial \Phi_{ir}}{\partial \ln Y_k} = \frac{m_{ir}\kappa_r}{m_{iz}} \frac{\partial \Phi_{ir}}{\partial \ln Y_k} \tag{D.4}$$

equation (D.2) can be written as:

$$\frac{\partial \ln (m_{ij}/m_i)}{\partial \ln Y_k} = Y_k \left(\frac{1}{\lambda_z \kappa_r} - \frac{m_{ik}}{m_i} - \frac{(1-\kappa_r)}{\lambda_z \kappa_r} \frac{m_{ik}}{m_{ir}} - \frac{(1-\lambda_z)}{\lambda_z} \frac{m_{ik}}{m_{iz}} \right). \tag{D.5}$$

E Data appendix

Table E.1. List of the 55 countries considered in the empirical analysis, 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	Ireland
Bosnia and Herzegowina	Venezuela	& SOUTHEAST 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 E.2. Data sources

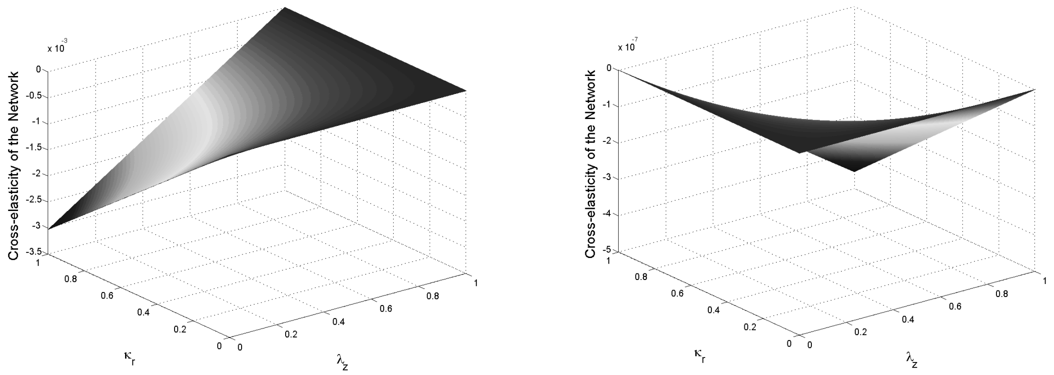
Variable	Definition	Data Sources
Migrant Flow m_{ij}	Migrants who registered at municipalities in Spain between January 1, 1997 (or January 1, 2002), and December 31, 2006, by province of destination (or region of destination) and by country of origin. Migrants are defined as individuals whose last country 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 Skill Ratio m^h_{ij}/m^l_{ij}	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
Migrant Network M_{ij}	Number of settled migrants as of May 1, 1996 (or January 1, 2002), 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	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)

Table E.2. Data sources *(continued)*

Variable	Definition	Data Sources
Indicator for Common Lanuage	This 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).

F Counterfactual cross-elasticities of the migrant network

Figure F.1. Counterfactual cross-elasticities of the migrant network



(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 $k \in A_{y\ell}$, $z \neq y$

G 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:

$$\ln(\tilde{m}_{ij}) = \eta_{zr} \ln(\tilde{M}_{ij}). \tag{G.1}$$

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:

$$\ln((1 - y_{ij})m_{ij}) = \eta_{zr} \ln((1 + x_{ij})M_{ij}), \tag{G.2}$$

which can be rewritten as:

$$\ln(m_{ij}) = \eta_{zr} \ln(M_{ij}) + \eta_{zr} \ln(1 + x_{ij}) - \ln(1 - y_{ij}). \tag{G.3}$$

The last two terms in equation (G.3), 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:

$$v_{ij} = v_{ir}, \quad v = \{x, y\}. \tag{G.4}$$

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 $j, k \in A_{zr}$.

H 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:

$$y_{ij} = \mu_i + \mathbf{x}_{ij}\boldsymbol{\beta} + u_{ij}, \qquad j = 1, \ldots, J, \tag{H.1}$$

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

$$h_{ij}^{*} = \boldsymbol{\delta}_{j0} + \mathbf{x}_{i1}\boldsymbol{\delta}_{j1} + \cdots + \mathbf{x}_{iJ}\boldsymbol{\delta}_{jJ} + v_{ij}, \tag{H.2}$$

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, $p = 1, 2, \ldots, J$.[48] 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:

$$E(u_{ij}|\mu_i, \mathbf{x}_i, \mathbf{v}_i) = 0, \qquad j = 1, \ldots, J. \tag{H.3}$$

Under (H.3), there is no sample selection bias. An alternative that implies sample selection bias is:

$$E(u_{ij}|\mu_i, \mathbf{x}_i, \mathbf{v}_i) = E(u_{ij}|v_{ij}) = \rho v_{ij}, \qquad j = 1, \ldots, J, \tag{H.4}$$

where $\rho \neq 0$ is some unknown scalar. Under the alternative (H.4) we have:

$$E(y_{ij}|\mu_i, \mathbf{x}_i, \mathbf{s}_i) = \mu_i + \mathbf{x}_{ij}\boldsymbol{\beta} + \rho E(v_{ij}|\mu_i, \mathbf{x}_i, \mathbf{s}_i) = \mu_i + \mathbf{x}_{ij}\boldsymbol{\beta} + \rho E(v_{ij}|\mathbf{x}_i, \mathbf{s}_i). \tag{H.5}$$

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,

$$E(v_{ij}|\mathbf{x}_i, s_{ij} = 1) = E(v_{ij}|\mathbf{x}_i, v_{ij} > -\mathbf{x}_i\boldsymbol{\delta}_j) = (1 + \mathbf{x}_i\boldsymbol{\delta}_j)/2. \tag{H.6}$$

and

$$E(y_{ij}|\mu_i, \mathbf{x}_i, s_{ij} = 1) = \rho^{*} + \mu_i + \mathbf{x}_{ij}\boldsymbol{\beta} + \rho^{*}\mathbf{x}_i\boldsymbol{\delta}_j, \tag{H.7}$$

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 (H.2), using linear probability models for the full data matrix. We then estimate equation (H.7) in an FE framework (within-transformed data), using only observations with $s_{ij} = 1$. We finally test $H_0 : \rho = 0$, using the t-statistic for ρ^{*}.

[48]In the following, $\mathbf{x}_{ij}$ includes one element more than in equation (H.1), despite the fact that we use the same notation for convenience. We thus assume that there is exactly one exclusion restriction in equation (H.1). 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.

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Chapter 7

Co-national and cross-national pulls in international migration to Spain

This chapter is based on joint work with Nina Neubecker. It was published as an article in October 2013 in the International Review of Economics & Finance, 28, 51-61. An earlier draft appeared as University of Tübingen Working Papers in Economics and Finance No. 46.

7.1 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 & Jakubek, 2013), and by building up certain ethnic-specific institutions in the host country.[1] We argue that whatever the precise support channel, the migrants who

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

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) of the migrant population at destination are significant determinants of migration flows. Apart

[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.

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 & 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 & 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 7.2 describes the settlement patterns of migrants from different nationalities in Spain. Section 7.3 presents our estimation approach, the data used for estimation, and the estimation results. Section 7.4 concludes.

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[3] Grogger & Hanson (2011), Beine et al. (2011a,b), and the analysis presented in Chapter 6 find that migrant networks also 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.

7.2 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 E.2 in Appendix E to Chapter 6.

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.

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 7.1 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 corresponding 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

[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).

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 7.1 about here>>

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 7.2 plots the country-pair-specific "index of dissimilarity" à la Duncan & 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 $D = 0.5 \sum_1^{\mathrm{N}} |x_j - y_j|$ 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 & 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 7.2 about here>>

The linear best fit in Figure 7.2 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.

7.3 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.

7.3.1 Empirical model and data

Consider a large number of origin countries (indexed by i or $\ell = 1, \ldots, I$) and a large number of destinations at the sub-country level (indexed by j or $k = 1, \ldots, J$).[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 $o = 1, \ldots, m_i$.

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:

$$U_{ij}^o = V_{ij} + e_{ij}^o, \tag{7.1}$$

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:

$$j^o = \text{argmax}(U_{i1}^o, \ldots, U_{iJ}^o), \quad j^o \in \{1, \ldots, J\}. \tag{7.2}$$

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

$$\begin{aligned} P_i^o(j^o = j) &= \Pr(U_{ij}^o > U_{ik}^o \quad \forall k \in \{1, \ldots, J\} : k \neq j) \\ &= \Pr(e_{ik}^o - e_{ij}^o < V_{ij} - V_{ik} \quad \forall k \in \{1, \ldots, J\} : k \neq j). \end{aligned} \tag{7.3}$$

This probability depends on the distribution assumed for the stochastic taste variables, $e_{i1}^o, \ldots, e_{iJ}^o$. 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

$$\lim_{g_{ij} \to \infty} H_i(\mathbf{g}_i) = +\infty \quad \text{for} \quad j = 1, \ldots, J. \tag{7.4}$$

[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.

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

$$F_i(e^o_{i1}, \ldots, e^o_{iJ}) = \exp\left[-H_i\left(\exp[-e^o_{i1}], \ldots, \exp[-e^o_{iJ}]\right)\right] \tag{7.5}$$

is a multivariate extreme value distribution function and that, if $(e^o_{i1}, \ldots, e^o_{iJ})$ is distributed F_i, (7.3) can be written as:

$$P^o_i(j^o = j) = \frac{\exp[V_{ij}]}{H_i(\exp\left[V_{i1}\right], \ldots, \exp\left[V_{iJ}\right])} \frac{\partial H_i(\exp\left[V_{i1}\right], \ldots, \exp\left[V_{iJ}\right])}{\partial \exp[V_{ij}]}; \tag{7.6}$$

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

$$H_i(\exp\left[V_{i1}\right], \ldots, \exp\left[V_{iJ}\right]) = \sum_{j=1}^{J} \exp[V_{ij}], \tag{7.7}$$

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

$$P^o_i(j^o = j) = \frac{\exp[V_{ij}]}{\sum_{j=1}^{J} \exp[V_{ij}]} \tag{7.8}$$

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

$$\ln\left(m_{ij}\right) = V_{ij} - \ln \sum_{j=1}^{J} \exp[V_{ij}] + \ln\left(m_i\right), \tag{7.9}$$

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 & van Wincoop, 2003). Differentiating equation (7.9) with respect to V_{ik} yields

$$\frac{\partial \ln\left(m_{ij}\right)}{\partial V_{ik}} = \begin{cases} 1 - \frac{\exp[V_{ij}]}{\sum_{j=1}^{J} \exp[V_{ij}]} = 1 - m_{ij}/m_i \geq 0 \quad \text{for} \quad k = j, \\ -\frac{\exp[V_{ik}]}{\sum_{j=1}^{J} \exp[V_{ij}]} = -m_{ik}/m_i \leq 0 \quad \text{for} \quad k \neq j. \end{cases} \tag{7.10}$$

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 (7.9), we assume that the log number of migrants from country i to destination j can be approximated linearly by the following expression:

$$\ln(m_{ij}) = \beta_0 \ln(M_{ij}) + \beta_1 \ln\left(\sum_{\ell \neq i} \eta_{i\ell} M_{\ell j}\right) + \lambda \cdot \mathbf{X}_{ij} + \varepsilon_{ij}, \tag{7.11}$$

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 (7.11) 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 (7.11), 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 (7.11) 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 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

[8] These countries are listed in Table E.1 in Appendix E to Chapter 6.

[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.

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 & Peri (2013) and our three-level NMNL model in 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]

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

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

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.

7.3.2 Estimation results

Table 7.1 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]

<<Table 7.1 about here>>

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 (7.11); 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 (7.10). 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

[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.

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 $\ell \neq i$:

$$\frac{\partial \ln(m_{ij})}{\partial \ln(M_{\ell j})} \cong \beta_1 \times \frac{\eta_{i\ell} M_{\ell j}}{\sum_{\ell \neq i} \eta_{i\ell} M_{\ell j}}. \tag{7.12}$$

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 $\frac{\eta_{i\ell} \mathrm{M}_{\ell j}}{\sum_{\ell \neq i} \eta_{i\ell} \mathrm{M}_{\ell j}} \leq 1$, 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 7.3 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 7.3 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 7.3 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 7.3 about here>>

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 & 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.

7.3.3 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 7.1 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 nation-

[13] This comparison follows the “rule of thumb” suggested by Staiger & 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).

alities. 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 7.2 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. 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 A.1 in Appendix A. 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.

<<Table 7.2 about here>>

7.4 Conclusion

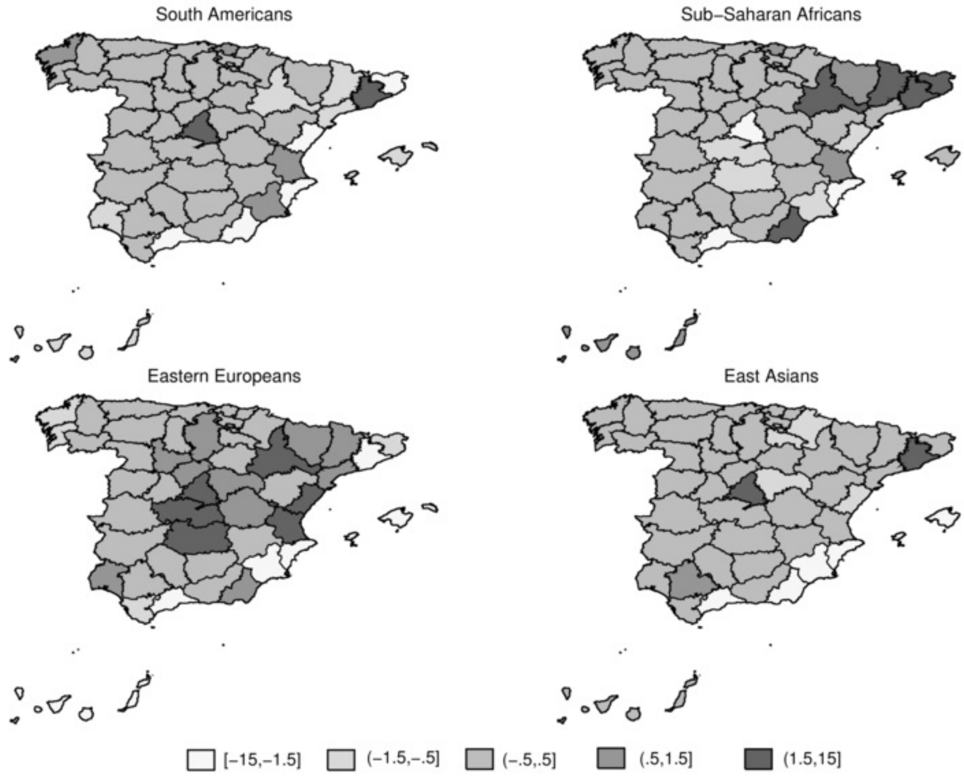
We expand the perspective of the attraction of a migrant pool from co-national migrants to co-national migrants together with migrants from adjacent nationalities. We find that cross-national links are relevant predictors of international migration flows, both independently and in conjunction with co-national 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.

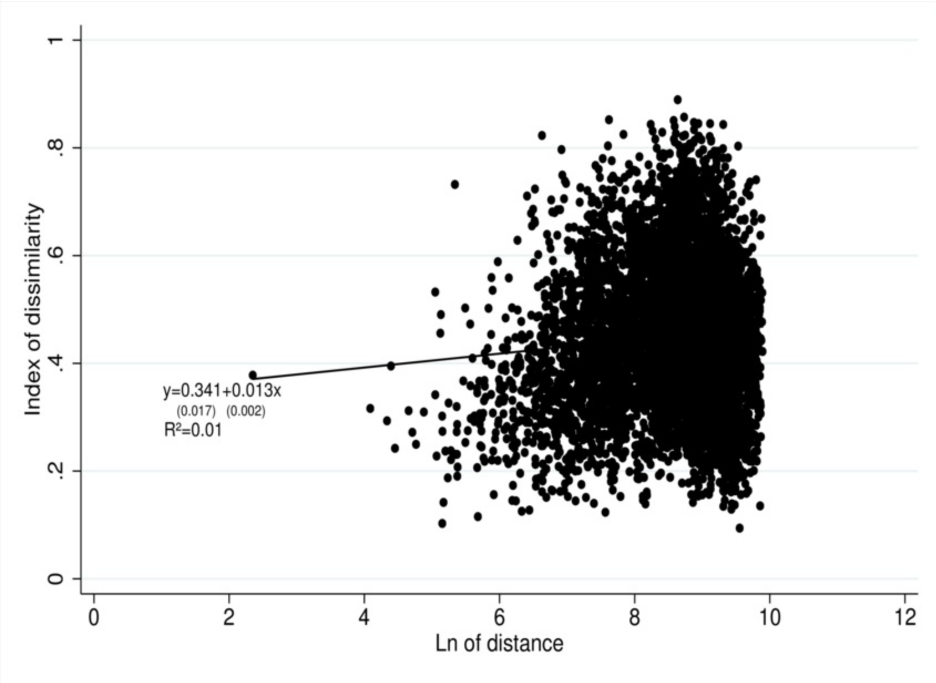
Figures and tables

Figure 7.1. Differences in the geographical concentration of migrant populations in Spain, 2009†



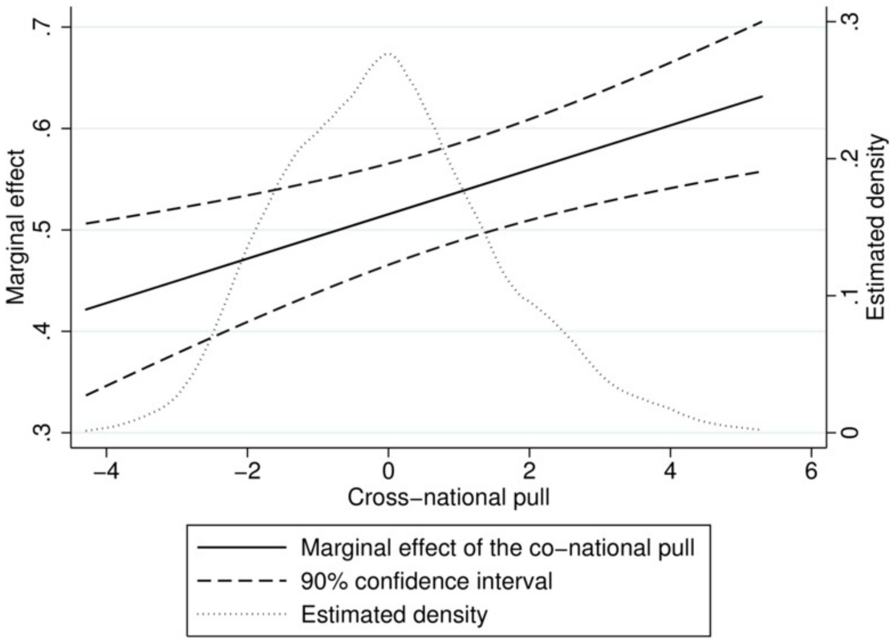
† This figure illustrates differences in the geographical distributions of migrants in Spain from four different world regions relative to the distribution of all migrants in Spain in the year 2009 (in each case excluding migrants from the world region under consideration). For example, we compare the 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.

Figure 7.2. Index of dissimilarity of migrant populations in Spain and distance between countries of origin, 2009†



† This figure plots the country-pair-specific index of dissimilarity à la Duncan & Duncan (1955) for any two migrant populations settled in Spain in the year 2009 against the log of the distance (measured in kilometers) between the countries of origin considered. Larger values of the index of dissimilarity indicate stronger dissimilarity in the geographical distributions of two migrant populations. *Source*: Authors' tabulations using data from INE and CEPII.

Figure 7.3. Marginal effect of the co-national pull†



† This figure shows the marginal effect of the co-national pull along with its 90% confidence interval for relevant values of the cross-national pull. It is based on the estimation results from column (f) of Table 7.1. The figure also shows the estimated density of the cross-national pull.

Table 7.1. 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 7.3 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.

Table 7.2. 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 7.3 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.

Appendix

A Further robustness checks

Table A.1. 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 7.3 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.

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Chapter 8

Individual attitudes towards trade: Stolper-Samuelson revisited

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8.1 Introduction

Low- and middle-income countries such as China, India, Russia, and Brazil have (re-)entered the stage of the world economy. These economies, home to a substantial portion of world population, show high degrees of trade openness and have recently boasted enormous output growth; see Freeman (2009, p. 63).[1] The rapid integration of emerging markets into the global economy promises substantial gains from trade. Yet, these gains seem endangered by anti-free trade campaigns motivated by globalization fears. Can we explain this tension by the well-known Stolper-Samuelson arguments? From a neoclassical point of view, the new global economic architecture implies that developed economies like the United States or Europe import low-skilled labor from developing countries like China, indirectly, through the factors embodied in traded goods. This will result in changes of relative wages or unemployment, making the scarce factors worse off and benefitting the abundant factors. In this sense,

[1] In the year prior to the Global Financial Crisis, China's economy has grown in real terms by 13.0%, followed by those of India (9.1%), Russia (8.1%), and Brazil (5.3%); the degrees of trade openness (measured as the sum of the value of imports and exports over total output) for these economies range between 25% (Brazil) and 75% (China) in 2007; all four countries together comprise nearly 2.8 billion people in 2007, which was then as much as about 42% of total world population; all data come from the World Development Indicators (2007).

economic theory fuels the public debate on the potential link between "globalization" and contemporaneous increases in wage inequality in many advanced countries. This is despite the fact that it has turned out difficult to empirically disentangle the effects of globalization on wage inequality from those originating in skill-biased technological change; see Feenstra & Hanson (2003), Lawrence (2008), and Krugman (2008).

This paper takes an altogether different perspective on this discussion. It draws attention to how people *expect* international trade to affect their income situations. Looking through the lens of the Stolper-Samuelson theorem, we ask whether the distributional predictions of free trade are shaping individuals' attitudes towards protection. We find a characteristic pattern which is consistent with endowment-based views of comparative advantage highlighted by the Heckscher-Ohlin (H-O) model. Given that individual attitudes towards trade co-determine trade policy outcomes, this potentially has wider implications in a political economy context; see Rodrik (1995). It also sheds light on the rising demand for protection in developed countries; see Scheve & Slaughter (2007). Since unskilled labor makes the bulk of the labor force in *all* countries[2] , but is intensively used in the comparative disadvantage sector only in *advanced* countries, the Western world would seem prone to a new wave of protectionism.[3]

Empirical identification of Stolper-Samuelson effects on the formation of individual trade attitudes comes from the variation in factor ownership (at the individual level), factor abundance (at the country level), and the interaction of the two. Influential work by O'Rourke & Sinnott (2001) and Mayda & Rodrik (2005) consults rich internationally comparable survey data from the International Social Survey Program (ISSP, 1995).[4] The bottom line of these studies is that high-skilled individuals are more likely to be pro-trade than low-skilled individuals, but only in countries with high incomes per capita. This result has been interpreted as support for the H-O model; see also Scheve & Slaughter (2006), O'Rourke (2006),

[2]In fact, there is not a single OECD economy with a majority of people having attained tertiary education, the level of education which is typically seen as essential in qualifying for a high-skilled job. The OECD average of people with tertiary education in 2007 is 28% for the population aged 25-64; see OECD (2009, p. 29f.).

[3]Gallup's annual World Affairs poll reports that, in January 2000, 35 percent of the American adult population believed that trade is a *"threat to the economy from foreign imports"*. This number has almost steadily increased over the years, reaching a critical level of 52 percent in February 2008, an all time high since September 1992; see `http://www.gallup.com/poll/115240/Americans-Negative-Positive-Foreign-Trade.aspx`. A similar trend can be found in Western Europe, but not in China or India; see Pew GAP (2007, p. 1).

[4]Recent years have seen a surge in empirical research on individual trade policy preferences. For example, evidence from purely national surveys comes from Scheve & Slaughter (2001), Hoffman (2009), Ehrlich & Maestas (2010), and Blonigen (2011) for the United States and from Wolfe & Mendelsohn (2005) for Canada. Beaulieu et al. (2005) document cross-country evidence from Latin America.

and Mayda et al. (2007). Yet, for this interpretation to be more plausible, we would have to observe that high-skilled individuals are significantly less pro-trade than low-skilled individuals in a significant share of developing countries. With few exceptions, however, the literature documents a non-negative effect of being high-skilled on pro-trade attitudes across all countries.

This paper paints a more distinct and thus more convincing picture of the role of the H-O model in shaping free trade attitudes. Using the 2007 wave of the Pew Global Attitudes Project (GAP), we find statistically significant and economically large Stolper-Samuelson effects, with high-skilled individuals being more pro-trade than low-skilled individuals in high-skilled labor abundant countries, and vice versa in a significant share of low-skilled labor abundant countries. Our findings can be attributed to the fact that our novel survey data combine a number of desirable features which are, at least in their entirety, absent in the existing literature. First, they contain a rather extensive set of individual attributes, such as gender, aspects of culture, and, most importantly, income. Accounting for this set in the empirical model is important in order to obtain consistent and unbiased estimates, given that such characteristics correlate with the type of labor individuals supply on factor markets.[5] Second, the data allow us to employ a direct and reliable measure of a country's relative factor abundance. Employing such a measure in the empirical model facilitates an unambiguous interpretation of the results obtained.[6] And finally, the survey incorporates a large set of countries from both ends of the world income distribution. This is essential for having sufficient identifying variation in explanatory variables.[7]

In this paper, we also identify and address a weakness on the methodological side in the literature. In particular, we show that the interaction effect between individual factor ownership and a country's relative factor abundance is not identified in a non-linear model with country fixed effects.[8] As a straightforward remedy to this shortcoming, we apply,

[5]For example, Hainmueller & Hiscox (2006) and Mansfield & Mutz (2009) argue that high-skilled individuals are more likely to favor free trade due to a general "enlightenment" that comes with a better educational background. In this paper, we explicitly capture individuals' economic awareness and their inclinations towards nationalist ideas and carry out baseline estimations of the effects of various aspects of individual enlightenment.

[6]O'Rourke & Sinnott (2001) and Mayda & Rodrik (2005) use GDP per capita as a proxy variable for a country's relative endowment with high-skilled labor. Mayda & Rodrik (2001) pursue a similar strategy as we do here.

[7]Arguably, the blind spot in O'Rourke & Sinnott (2001) and Mayda & Rodrik (2005) is that labor-abundant, low-income countries are scarce in the ISSP survey data. Mayda & Rodrik (2005) also employ the World Values Survey (WVS) data collected between 1995 and 1997 and covering 40 countries from all stages of development. However, the WVS does not allow to control for individual income, which is paramount in the estimation. The same holds true for Hainmueller & Hiscox (2006) who additionally use the 2003 wave of the Pew GAP data including 44 countries.

[8]Our argument is related, but not identical, to that raised by Ai & Norton (2003) who stress the by

inter alia, the simple linear probability model (LPM). In contrast to the widely used Probit framework, our approach does allow for a specification with fixed country effects on the formation of trade policy preferences. These capture potentially important "fundamentals" such as a country's political system, but also feedback effects from existing trade policies and previous trade exposure.

The remainder of this paper is organized as follows. Section 8.2 presents our empirical strategy, starting out with a condensed Stolper-Samuelson view on free trade preferences and proceeding with a discussion of the econometric model and our survey data. Section 8.3 turns to a detailed presentation of our regression results. The final section concludes the paper.

8.2 Empirical strategy

This section presents our empirical approach to studying Stolper-Samuelson effects on free trade preferences. The first subsection explains how the distributional effects of trade liberalization in the H-O model translate into different individual attitudes towards trade. In the second subsection, we set up a simple random utility framework to discuss the relevant econometric issues that arise in our context. In so doing, we slightly modify the existing modeling approach along several dimensions. The final subsection presents our survey data in some detail. It also looks at whether and how trade preferences correlate with governments' policies and countries' stages of development.

8.2.1 A Stolper-Samuelson view on free trade preferences

The distributional effects of trade policy interventions in an H-O setting with two factors of production and two goods can be appropriately discussed by recalling the Stolper-Samuelson theorem; see Stolper & Samuelson (1941). In its general version the theorem states that protection of domestic import-competing industries will raise the real reward of the scarce factor and lower the real return to the abundant factor.[9] This result emerges from the differentiated zero profit conditions, which in terms of proportional changes are given by

$$\hat{p}_\ell = \theta_{\ell L}\hat{w}_L + \theta_{\ell H}\hat{w}_H \qquad \text{for} \quad \ell = 1, 2, \tag{8.1}$$

now well-known difficulties of computing and interpreting interaction effects in non-linear models such as the Probit or the Logit model.

[9] The notion of a "general" version of the theorem was introduced by Bhagwati (1959); see also Deardorff (1993).

where a 'hat' indicates a percentage change, the $\theta_{\ell j}$'s are the cost shares of high- and low-skilled labor (with $j = H, L$), the p_ℓ's are goods prices, and the w_j's are factor prices.[10]

Protection, for example through an import tariff, increases the domestic relative price of the imported good.[11] From equation (8.1), goods price changes are a cost-share weighted average of factor price changes. This implies that the $\hat{p}_\ell$'s lie in between the $\hat{w}_j$'s. Let p_1 denote the price of the imported commodity with $\hat{p}_1 > 0$ through the imposition of a tariff. The price of the factor which is intensively used in the import-competing sector, say low-skilled labor (i.e. $\theta_{1L} > \theta_{2L}$), rises disproportionately compared to the commodity price. By the same logic, high-skilled labor experiences a real income loss, $\hat{w}_L > \hat{p}_1 > \hat{p}_2 > \hat{w}_H$. If we further impose the assumptions necessary to establish the Heckscher-Ohlin theorem – identical technologies and preferences across countries and no factor intensity reversals – it follows that protection harms the country's abundant factor because it is intensively employed in the export industry.

Hypothesis 1. *In human-capital-abundant economies, high-skilled individuals favor free trade, while low-skilled individuals oppose free trade. In labor-abundant economies, this conflict of interests is reversed.*

One of the captivating features of the Stolper-Samuelson logic is that it reflects changes in a country's factor supply, because inputs are embodied in traded goods. As stated by Deardorff (1993, p. 7):

> *"The Stolper-Samuelson Theorem [...] states what might appear obvious to many outside of economics. In its simple form [...] it says that protection helps the scarce factor, or, equivalently, that free trade hurts the scarce factor. [...] [Many politicians and others in the public at large] say that of course trade lowers wages in the United States, since it makes American labor compete with foreign labor that may be paid only a fraction as much."*

In a wider sense, Hypothesis 1 therefore draws on how people *expect* international trade to affect their incomes. Consequently, any empirical test of this hypothesis is informative as to the extent to which individuals are sensitive towards how an integrated world economy may affect the relative scarcity of their factors, compared to an autarky situation.

[10]In what follows, the terms 'high-skilled labor' and 'human capital' are used interchangeably. Analogously for 'low-skilled labor' and 'labor'.

[11]Metzler (1949) shows that the imposition of an import tariff raises the domestic relative price of the imported good only if the elasticity of foreign demand for domestic exports is greater than the domestic marginal propensity to consume the exported good. The restriction to the small economy case precludes any terms-of-trade effects and is therefore sufficient to obtain this result.

Hypothesis 1 also implies that whether an individual opposes or favors protection depends entirely on the *direction*, but not the *magnitude*, of the predicted utility change. The prediction for an individual's free trade preference is solely determined by whether the factor is relatively scarce or abundant compared to the rest of the world, essentially because individuals are confronted with a binary choice; see Balistreri (1997).

To see why the *degree* of relative scarcity of the two factors may also be decisive for preference formation, we incorporate country-pair-specific trading costs. If trade costs are prohibitively high for some country pairs, each country will only trade with a subset of the other countries. As a result, comparative advantage is no longer defined globally; see Deardorff (2004). We do not inspect the trade pattern of individual countries here. But it is clear that, other things equal, the probability that a certain factor in a given country is used intensively in the comparative advantage sector is the higher, the higher the relative abundance of this factor in that country. We obtain the following prediction.

Hypothesis 2. *A high-skilled individual is more likely to favor free trade, the higher a country's human-capital-to-labor ratio. The reverse holds true for a low-skilled individual.*

Importantly, both hypotheses are independent of whether or not tariffs are prohibitively high. This is because there is no role for the magnitude of an individual's trade-policy induced utility change and because the direction of the goods price change does not depend on the degree of protection.

8.2.2 Econometric model

The fundamental idea in our regression analysis is that trade policy interventions in the form of import tariffs (or the withdrawal thereof) have effects on an individual's utility level due to changes in personal earnings, both in expectation terms. We provide a combined test of Hypotheses 1 and 2 and closely follow previous studies in estimating the *interaction effect* between individual skill and a country's degree of human capital abundance.

For this purpose, we set up the following random utility framework. Let the expected utility change of individual i in country c when moving towards free trade ($E[\Delta U_{ic}|_{\text{Free Trade}}]$) be a linear function of the expected income change à la Heckscher-Ohlin ($E[\Delta w_{ic}|_{\text{H-O}}]$), which depends on individual skill h_{ic} and the residence country's degree of human capital abundance h_c. Let the effect of other individual attributes such as age, income, or education and that of other country characteristics such as the political system, the stage of development, or the actual trade policies be summarized in $A_{ic}(.)$ and $B_c(.)$, respectively. Decomposing $A_{ic}(.)$ into a function of observables $a_{ic} \equiv a(X_{ic1}, \ldots, X_{icL})$ and an unobservable random component μ_{ic}, and analogously for $B_c(.)$ with $b_c \equiv b(Z_{c1}, \ldots, Z_{cK})$ and σ_c, we have

$$E[\Delta U_{ic}|_{\text{Free Trade}}] = E[\Delta w_{ic}|_{\text{H-O}}](h_{ic}, h_c) + a_{ic} + b_c + \mu_{ic} + \sigma_c. \tag{8.2}$$

We aim for an estimable equation of (8.2). An individual's expected income change is unobserved. Our analysis must therefore take the link between such expectations and individual trade policy preferences as given. Assuming that this link exists, we ask whether parameter estimates on the arguments of $E[\Delta w_{ic}|_{\text{H-O}}](h_{ic}, h_c)$ can be interpreted as reflecting a Stolper-Samuelson data generating process. Hence, we rewrite equation (8.2) as

$$E[\Delta U_{ic}|_{\text{Free Trade}}] = \gamma_0 + \gamma_1 \cdot h_{ic} + \gamma_2 \cdot h_{ic} \times h_c + \gamma_c + \alpha \mathbf{X}'_{ic} + \mu_{ic}, \tag{8.3}$$

where γ_1 and γ_2 are the parameters of interest, $\gamma_c \equiv \gamma(h_c, b_c, \sigma_c)$ is a fixed effect absorbing both observed and unobserved heterogeneity at the country level, $\alpha = (\alpha_1 \ldots \alpha_L)$ is a row vector of parameters to be estimated, and $\mathbf{X}'_{ic} = (X_{ic1} \ldots X_{icL})'$ is a column vector of individual-specific explanatory variables.

The left-hand side of equation (8.3), the expected utility change as such, is an unobservable latent variable. Following existing literature, we construct an individual-specific pro-trade dummy variable from our survey data which serves as an indicator for the sign of the expected change in utility, $Y_{ic} \stackrel{\text{def}}{=} 1(E[\Delta U_{ic}|_{\text{Free Trade}}] > 0)$. If we additionally impose $\mu_{ic} \sim \text{Normal}(0, 1)$, we arrive at the familiar Probit framework, where an individual's probability of being in favor of free trade, conditional on all explanatory variables, reads as $\Pr(Y_{ic} = 1|\cdot) = \Phi(\gamma_0 + \gamma_1 \cdot h_{ic} + \gamma_2 \cdot h_{ic} \times h_c + \gamma_c + \alpha \mathbf{X}'_{ic})$, with Φ being the cumulative distribution function of the standard normal distribution. The main interest in our application is with the effect of individual skill on the probability of being pro-trade,

$$\frac{\Delta \Pr(Y_{ic} = 1|\cdot)}{\Delta h_{ic}} = \Phi'(\cdot)[\gamma_1 + \gamma_2 h_c], \tag{8.4}$$

and how this effect varies with a country's degree of human capital abundance (interaction effect),

$$\frac{\Delta^2 \Pr(Y_{ic} = 1|\cdot)}{\Delta h_{ic} \Delta h_c} = \Phi'(\cdot)\gamma_2 + \Phi''(\cdot)[\gamma_1 \frac{\Delta \gamma_c}{\Delta h_c} + \gamma_1 \gamma_2 h_{ic} + \gamma_2 h_c \frac{\Delta \gamma_c}{\Delta h_c} + \gamma_2^2 h_{ic} h_c]. \tag{8.5}$$

Given the non-linearity of the model, equations (8.4) and (8.5) both depend on all explanatory variables and parameters through $\Phi'(\cdot)$ and $\Phi''(\cdot)$. As Ai & Norton (2003) discuss, computing and interpreting interaction effects in non-linear models is thus less trivial than it is in a linear least squares framework.[12] There is another issue involved, however, which has to do with the model's specification with country fixed effects as given in equation (8.3). In fact, the interaction effect, given by equation (8.5), is not identified in the model, because the derivative (or difference) $\Delta\gamma_c/\Delta h_c$ is not identified. The reason is that the country fixed effect absorbs the main effect of a country's human capital abundance on individual trade attitudes. Hence, the results reported in the existing literature need to be interpreted with care. Notice that our concern equally applies to a wider set of non-linear models with interaction terms and fixed effects.

We consider two simple and straightforward ways to circumvent this problem. The first assumes the probability of being in favor of free trade, conditional on all explanatory variables, to be equal to the right-hand side of equation (8.3), $\Pr(Y_{ic} = 1|\cdot) = \gamma_0 + \gamma_1 \cdot h_{ic} + \gamma_2 \cdot h_{ic} \times h_c + \gamma_c + \alpha\mathbf{X}'_{ic}$. This is the linear probability model (LPM), which comes at the cost that predictions may lie outside the unit interval. Still, this is our preferred specification since it explicitly estimates all fixed country effects. Then, $\Delta\Pr(Y_{ic} = 1|\cdot)/\Delta h_{ic} = \gamma_1 + \gamma_2 h_c$ and $\Delta^2 \Pr(Y_{ic} = 1|\cdot)/(\Delta h_{ic}\Delta h_c) = \gamma_2$. Our second approach keeps the underlying latent variable model and takes care of all arguments of $\gamma(h_c, b_c, \sigma_c)$. The model is then specified as

$$E[\Delta U_{ic}|_{\text{Free Trade}}] = \gamma_0 + \gamma_1 \cdot h_{ic} + \gamma_2 \cdot h_{ic} \times h_c + \gamma_3 \cdot h_c + \alpha\mathbf{X}'_{ic} + \beta\mathbf{Z}'_c + \eta_{ic}, \tag{8.3'}$$

where $\eta_{ic} = \mu_{ic} + \sigma_c$ with $\eta_{ic} \sim \text{Normal}(0,1)$, $\beta = (\beta_1 \dots \beta_K)$ is a row vector of additional parameters to be estimated, and $\mathbf{Z}'_c = (Z_{c1} \dots Z_{cK})'$ is a column vector of country-specific explanatory variables. The effect of individual skill is as in equation (8.4), whereas the interaction effect now becomes

$$\frac{\Delta^2 \Pr(Y_{ic} = 1|\cdot)}{\Delta h_{ic}\Delta h_c} = \Phi'(\cdot)\gamma_2 + \Phi''(\cdot)[\gamma_1\gamma_3 + \gamma_1\gamma_2 h_{ic} + \gamma_2\gamma_3 h_c + \gamma_2^2 h_{ic} h_c]. \tag{8.5'}$$

In this model, the interaction effect is identified, given that the parameter γ_3 is identified.

In both econometric models, the LPM and the modified Probit model, the effect of being high-skilled on an individual's attitude towards free trade is a function of the economy's human capital abundance. Hypothesis 1 suggests that high-skilled individuals exhibit more protectionist attitudes than low-skilled individuals in labor-abundant countries, and vice

[12] In fact, many authors have interpreted the marginal effect of the interaction term as the interaction effect; see Ai & Norton (2003).

versa in human-capital-abundant countries. Hence, we expect that

$$\left.\frac{\Delta \Pr(Y_{ic}=1|\cdot)}{\Delta h_{ic}}\right|_{h_c<h_c^*} < 0 < \left.\frac{\Delta \Pr(Y_{ic}=1|\cdot)}{\Delta h_{ic}}\right|_{h_c>h_c^*}, \tag{8.6}$$

where h_c^* is the estimated threshold value which separates human-capital-abundant countries from labor-abundant countries. Furthermore, Hypothesis 2 states that a high-skilled individual's probability of favoring free trade is the higher, the higher his or her country's degree of human capital abundance. A positive cross-derivative,

$$\frac{\Delta^2 \Pr(Y_{ic}=1|\cdot)}{\Delta h_{ic}\Delta h_c} > 0, \tag{8.7}$$

would support this idea.

8.2.3 Data

We analyze the 2007 wave of the Pew Global Attitudes Project (GAP), an extensive internationally comparable survey data set with detailed information on the characteristics of more than 40,000 individuals worldwide. These characteristics include, but are not limited to, a respondent's age, gender, real income, employment status, and religiousness.[13] The data comprise some 47 countries, 26 of which are developing and newly industrialized countries from Latin America, Asia, the Middle East, and Africa.[14] For a combined test of Hypotheses 1 and 2, the country coverage of the survey data is particularly important. Suppose there are two regions, *America* and *Europe*. *America* consists of human-capital-abundant *North* and labor-abundant *South*, and similarly for Europe with *West* and *East*. Given that transaction costs are prohibitive for trade between *America* and *Europe*, there is only intra-regional trade. In this world, the logic of comparative advantage predicts that high-skilled individuals in *North America* and *Western Europe* are equally affirmative towards free trade. In case the estimation sample is biased towards human-capital-abundant economies, the data could therefore lead the researcher to erroneously reject Stolper-Samuelson effects on preference formation.

We deduce an individual's preference towards trade policy by exploiting answers to the following question: *"What do you think about the growing trade and business ties between [respondent's country] and other countries – do you think it is a very good thing, somewhat good thing, somewhat bad thing or a very bad thing for our country?"* Notice that this question

[13] For summary statistics and coding information of these variables, see Table A.1 in Appendix A.

[14] For further information on the GAP survey data, see also `http://pewglobal.org/`.

does not make the trade *policy* argument explicit. Yet, a respondent's skeptical view on his or her country's engagement in international trade can be plausibly associated only with the desire of a reduction in trade flows. Since the government is the political institution to pursue a pertinent policy, we argue that the relevant trade policy issue is sufficiently attached to the survey question.

We drop all individuals who have refused to answer this question, about 5% of the entire sample, and construct a pro-trade dummy variable Y_{ic} which takes on the value one if the respondent's answer is *"very good"* or *"somewhat good"* and zero otherwise. We stick to this binary coding throughout the text since it eliminates any culturally driven inclinations towards extreme or moderate responses. These cannot be accounted for by country fixed effects since they come with country-specific dispersions of trade opinions instead of mean shifts.[15]

The two pivotal variables in our analysis are those capturing an individual's skill level h_{ic} and a country's degree of human capital abundance h_c. We proxy the former by an individual's educational background, measured through an ordered six-valued variable of educational attainment.[16] We assume that a higher formal education is associated with a higher probability of being employed in a job with high skill requirements.[17] Existing literature on individual trade policy preferences mostly proxies a country's degree of human capital abundance h_c by its GDP per capita. However, GDP per capita is positively correlated with the quality of schooling across countries and the extent to which countries participate in intra-industry trade; see Hainmueller & Hiscox (2006) and Beaulieu et al. (2011), respectively. Both relations may alter the effect of individual skill on trade policy preferences and can thus exacerbate identification. Therefore, we exploit the fact that each national survey sample is representative for the country's population as a whole. More precisely, we measure h_c by each country's weighted average of the individual skill variable[18], which is a direct measure

[15] We have also applied alternative dummy definitions. In particular, we have assigned non-respondents to either the pro-trade or the anti-trade group of people. All qualitative results reported in this paper are insensitive to this type of recoding.

[16] Strictly hierarchical classes are (0) no formal education or incomplete primary education, (1) complete primary education, (2) incomplete secondary education (technical/vocational), (3) complete secondary education (technical/vocational) / incomplete secondary education (university-preparatory) / complete secondary education (university-preparatory), (4) some university education (without degree), (5) university education (with degree). There is some cross-country heterogeneity in the survey categories of educational attainment. More information on how we map country-specific groups of educational attainment into the above hierarchical structure is available upon request.

[17] An alternative, more flexible model specification uses dummy variables for the different educational categories. This pays attention to the fact that differences in educational attainment reflect an ordinal instead of a cardinal scale. The estimates (not reported) do not alter any of the conclusions drawn in this paper.

[18] Employing the median instead of the mean yields virtually identical results.

of human capital abundance.[19]

<< Figures 8.1(a) and 8.1(b) about here >>

Rodrik (1995) points out that individual trade policy preferences are an input in the political decision process and will therefore co-determine actual trade policies. Our survey data allow for a rough inspection of this claim. Combining information from Global Trade Alert (GTA) and the GAP survey, Figure 8.1(a) plots the plain count of protectionist policy measures between May 01, 2009, and October 31, 2010, against average trade opinions in 2007 for the cross-section of 47 countries.[20]

The figure suggests a significant relationship between voting bodies' preferences and implemented trade policies. Countries in which people hold more trade-skeptical views tend to have governments which are more inclined towards protectionist policies. The linear prediction shows that a one-point increase in the four-valued ordered trade opinion variable is associated with a reduction by 50 protectionist policy measures in the considered time span. This is more than double the median number of registered policy measures.[21]

Figure 8.1(b) unveils an important link between a country's stage of development and people's attitudes towards trade. Rich countries are on average more trade-skeptical than poor countries. Pure country-average income differences account for as much as one-fifth of the variation in average trade opinions. For example, there is very high acceptance of international trade in extremely poor African countries, but also in emerging Asian and East-Asian markets such as China, India, and Malaysia. Individuals in Arab and Latin American countries are significantly less pro-trade, while the evidence from European Union member countries is mixed. Finally, on average, U.S. citizens hold the least positive opinions towards international trade.

[19]Sampling weights correct for deviations from random sampling.

[20]GTA is a recently established academic initiative for monitoring state policies that may detrimentally affect global trade integration in one way or the other. It is coordinated by the Centre for Economic Policy Research (CEPR), London, UK. See Table A.3 in Appendix A for a definition of protectionist policy measures and http://www.globaltradealert.org for more information on this data source.

[21]The evidence also suggests that this relationship becomes tighter, the more democratic a political regime is. To see this, we regress the count of protectionist policy measures on the main and interaction terms of the average trade opinion and the country's democracy index (from the Economist Intelligence Unit). Results show that the link between voter attitudes and policies is strongest in the most democratic countries such as Sweden, and practically non-existent in authoritarian regimes such as China.

8.3 Regression results

In the first subsection, we present Probit estimates of a naïve model of free trade preferences, where non-linearities in the effect of individual skill on trade attitudes are not taken into account.[22] Subsection constitutes the core of our regression analysis and reports estimates of equations (8.3) and (8.3') in the LPM and the Probit model, respectively. In Subsection 8.3.3, we show that the relevance of the factor endowments model is independent of other factors such as individual economic awareness and openness towards foreign cultures and ideas. Finally, in Subsection 8.3.4, address the rather general concern that individuals' policy preferences are not driven solely by economic self-interest.

8.3.1 Naïve Probit model

The main motivation for our naïve regression model is to make two sources of endogeneity visible which existing literature has not been able to address simultaneously. The first concerns the fact that the estimation sample's country composition exerts a significant influence on estimated coefficients of individual skill. The second source of endogeneity is omitted variable bias when not controlling for individual income. For our purposes, we split the sample of 47 countries into two subsamples. The first covers the top 50% of countries by their GDP per capita ("higher-income countries"), the second all remaining countries ("lower-income countries"). Table 8.1 reports estimation results of the naïve model in a Probit framework.

Columns (1) to (4) are based on the sample with higher-income countries and report marginal effects for the average individual in the estimation sample. First and foremost, we find a positive and robustly significant effect of individual skill on free trade preferences. The probability of being pro-trade increases by more than one-and-a-half percentage points for each discrete "jump" to the next higher level of educational attainment. This effect is significant in both a statistical and an economic sense, given that we distinguish among six education groups. Apart from individual skill, the column (1) model explains trade attitudes by an individual's age, gender, and a comprehensive set of country fixed effects. Our results are in line with those reported in related literature. Specifically, we find that older and female people hold more skeptical views towards trade.

[22]Throughout our analysis, we estimate heteroskedastic robust standard errors to immunize inference against misspecification; see White (1980). Given our assumptions in Subsection 8.2.2, stochastic and non-stochastic country effects (σ_c and b_c) induce correlation among individual observations within country clusters. Whenever we introduce country fixed effects, however, the γ_c's capture any such type of within-country correlation. At any rate, inference based on cluster robust standard errors may be misleading if the number of clusters is small as in our case (< 50); see Cameron & Miller (2010).

<< Table 8.1 about here >>

In columns (2) to (4) we successively control for individual income, religiousness, and employment status, in addition to the other covariates. For our sample of higher-income countries, the skill effect is marginally reduced when controlling for *Income* in column (2). An increase in income by one percent raises the predicted probability of being pro-trade by more than one-and-a-half percentage points. Being tied to religious beliefs is associated with more protectionist attitudes, but the effect is quantitatively small and not statistically different from zero.[23] The opposite holds true for employed people, who feature a predicted probability of favoring free trade which is two percentage points higher than that of their unemployed peers.

Columns (5) to (8) report regression results for the sample of lower-income countries. The picture is quite different from that based on higher-income countries. Most importantly, the marginal effect of individual skill loses a great deal of its strength, even if we do not control for income; see column (5). Once we do control for it in columns (6) to (8), it vanishes completely. Furthermore, we find an enhanced role for individual income with a marginal effect equal to three percentage points. In turn, other individual attributes such as religiousness, gender, and employment status are no significant predictors of free trade preferences.

These results uncover two important points. The first is that estimated coefficients of *Skill* are upward biased if the estimation sample mostly comprises rich human capital abundant countries (*sampling bias*). The second states that individual income is positively correlated with both individual skill and free trade preferences and, if omitted from the model, results in overestimation of the skill effect (*omitted variable bias*).

8.3.2 Heckscher-Ohlin model

The preliminary analysis in the previous subsection suggests that the effect of individual skill on free trade preferences correlates with country characteristics. Although the results are in line with the Stolper-Samuelson logic, they do not serve as a test of Hypotheses 1 and 2. This test is the purpose of this subsection, exploiting the full country coverage of our sample. We first turn to estimation of equation (8.3) in a linear probability model.[24] Results are reported

[23] A drawback is that the variable is binary and does not distinguish among different religious groups; see Daniels (2005) for the effect of religious affiliation on people's attitudes towards a number of international policy issues. Lewer & Van den Berg (2007) estimate a gravity equation in order to study the role of religion for bilateral trade flows.

[24] Throughout most of our regression analysis, the linear models predict probabilities of being pro-trade outside the closed unit interval for about half a percent of all estimation sample observations. Whenever

in columns (1) to (4) of Table 8.2.

Throughout all specifications employed, the estimated coefficient of individual skill has a negative sign while that of the interaction term is positive. The estimation outcome is robust (in a qualitative sense) to controlling for individual income and including other individual-level covariates such as religiousness and employment status. Our estimates suggest that the effect of individual skill is an increasing function of a country's degree of human capital abundance. In accordance with Hypotheses 1 and 2, high-skilled individuals are more likely to favor free trade than low-skilled individuals, but only if they live in countries with sufficiently high relative levels of human capital. By contrast, in labor-abundant economies it is the low-skilled people who are more inclined towards free trade, other things equal. Our evidence substantially strengthens the findings in Mayda & Rodrik (2005), Scheve & Slaughter (2006), and O'Rourke (2006), because it is based on a correctly identified interaction effect, explicit endowment information, and a novel extensive data set.

<< Table 8.2 about here >>

To fully grasp the quantitative implications, we plot the marginal effect of individual skill on the probability of being pro-trade against a country's relative endowment with human capital. Figure 8.2(a) visualizes

$$\frac{\Delta \widehat{\Pr(Y_{ic} = 1|\cdot)}}{\Delta h_{ic}} = \hat{\gamma}_1 + \hat{\gamma}_2 \cdot h_c \tag{8.8}$$

as well as the 90% confidence intervals for the regression that corresponds to column (4) in Table 8.2. The marginal effect of individual skill has a positive sign for countries with a weighted mean of individual skill above $h_c^* = 2.1$ and a negative sign for countries below this threshold. For example, in Morocco and Tanzania, individuals with the highest skill level (university eduction with degree) feature a predicted probability of opposing free trade which is almost seven percentage points higher than that of an individual with the lowest skill level (no formal or incomplete primary education), other things equal. In the U.S., on the other end of the distribution of human capital abundance, the skill effect runs into the opposite direction: going from the lowest to the highest skill level increases an individual's predicted probability of being in favor of free trade by twelve percentage points. In countries with degrees of human capital abundance close to the threshold h_c^*, the model predicts a zero-effect on individual trade preferences for a given change in individual skill.

outside the unit interval, predictions exceed one, but only by a marginal amount.

Importantly, we again find that omitting *Income* from the model implies a significant bias in estimated coefficients.[25] First, quantitative differences in the impact of *Skill* across countries are magnified when we control for *Income* in column (2), compared to estimates in column (1). This finding strengthens Hypothesis 2. Second, in column (1) only three out of our 47 countries have a predicted effect of skill that is negative, where all of these countries are on the African continent. In contrast, the subsequent models imply a much higher threshold value h_c^*. Therefore, the number of countries with a predicted marginal effect below zero increases, with 13 countries out of 47 (more than a fourth of all countries) featuring a negative impact of *Skill* on the likelihood of supporting free trade, including both African, Middle-Eastern as well as Asian economies. This result is vital for our treatment of the H-O model since it implies that Hypothesis 1 is supported by the data as well.[26]

<< Figures 8.2(a) and 8.2(b) about here >>

Next, we evaluate the robustness of the above findings in a Probit framework. Since the Probit model does not allow us to include country fixed effects, two threats to valid inference arise. First, omitted variables at the country level (contributing to b_c) could render parameter estimates inconsistent. Second, stochastic and (unobserved components of) non-stochastic country effects (σ_c and b_c) in the error term cast doubt on the validity of ordinary and heteroskedastic robust standard errors alike. We tackle these problems by assigning each country to one of eight world regions and controlling for effects common to all countries located in the same world region; see Table A.2 in Appendix A. Furthermore, we include an extensive set of country-level control variables.[27]

Columns (5) to (8) of Table 8.2 report marginal and interaction effects, computed from parameter estimates of variants of equation (8.3') and evaluated at estimation sample averages of all covariates.[28] The model again reveals a non-linearity in the relationship between

[25]Results from Table 8.1 seem to suggest that the impact of income on free trade preferences varies across countries as well. However, in a robustness check to Table 8.2 where we include an interaction term of *Income* with *GDP per capita*, we find contrary evidence in the sense that this latter interaction effect is insignificant.

[26]If we exclude individuals that are self-employed from the estimation sample, Hypothesis 1 is reinforced further. This is reassuring because for self-employed individuals we would expect the impact of trade to be driven by other factors than individual skill.

[27]These variables refer to both the country's stage of development (*GDP per capita*, *Country Mean of Skill*), institutions (*Electoral Process*, *Political Pluralism and Participation*, *Functioning of Government*, *Freedom of Speech and Belief*, *Associational and Organizational Rights*, *Rule of Law*, *Personal Autonomy and Individual Rights*), economic indicators (*Trade Openness*, *Labor Force Share*). See Table A.3 in Appendix A for coding and data sources.

[28]To facilitate comparison to columns (1) to (4), in columns (5) to (8) the marginal effect of *Skill* is evaluated at $h_c = 0$ and at estimation sample averages of all other covariates. Similarly, reported marginal effects of *Country Mean of Skill* are evaluated at $h_{ic} = 0$ when interacted with *Skill*.

individual skill and free trade preferences consistent with the distributional predictions of free trade in the H-O model. In human-capital-abundant countries high-skilled individuals hold on average less protectionist attitudes than low-skilled individuals, and vice versa in labor-abundant countries.

Such differences across countries can conveniently be identified through inspection of Figure 8.2(b), which shows

$$\frac{\Delta \widehat{\Pr(Y_{ic}=1|\cdot)}}{\Delta h_{ic}} = \Phi'(\hat{\gamma}_0 + \hat{\gamma}_1 \cdot \bar{h}_{ic} + \hat{\gamma}_2 \cdot \bar{h}_{ic} \times h_c + \hat{\gamma}_3 \cdot h_c + \hat{\alpha}\bar{\mathbf{X}}'_{ic} + \hat{\beta}\bar{\mathbf{Z}}'_c)[\hat{\gamma}_1 + \hat{\gamma}_2 \cdot h_c], \quad (8.8')$$

for regression results of columns (8), where $\hat{\alpha}\bar{\mathbf{X}}'_{ic} = \hat{\alpha}_1 \cdot \bar{X}_{ic1} + \cdots + \hat{\alpha}_L \cdot \bar{X}_{icL}$ and $\hat{\beta}\bar{\mathbf{Z}}'_c = \hat{\beta}_1 \cdot \bar{Z}_{c1} + \cdots + \hat{\beta}_K \cdot \bar{Z}_{cK}$. In equation (8.8') 'bars' indicate estimation sample averages and bold letters represent vectors. The figure shows that the marginal effect of individual skill on free trade preferences increases with a country's relative endowment with human capital. The range of relative endowments (*Country Mean of Skill*) with a negative predicted marginal effect of individual skill is however somewhat reduced compared to the LPM. We suggest that this highlights the importance of unobserved country effects, which are only partly captured by the world region fixed effects and country-level variables. Overall, the data strongly support both Hypothesis 1 and Hypothesis 2, irrespective of the econometric model used.

Our country-specific variables also carry some interesting implications. Estimation results (not reported) show most such country characteristics to be significant predictors of individual attitudes towards trade.[29] For example, better functioning governments and better associational and organizational rights are associated with more favorable views on trade. The opposite holds true for higher degrees of political pluralism and participation as well as personal autonomy and individual rights. Further research is needed to better understand why free trade preferences respond differently to different aspects of the institutional architecture in which states and countries are embedded. An interesting step into this direction can be found in Ehrlich (2007).

8.3.3 Conditioning on aspects of individual enlightenment

Hainmueller & Hiscox (2006) argue that education is not a "clean" device for factor ownership, because it could *(i)* spur people's awareness of the aggregate gains from trade and *(ii)* make individuals less amenable to nationalist ideas; see also Mayda & Rodrik (2005).[30] Our model

[29] Regression results for the full set of country-level control variables are available on request from the authors.

[30] The first aspect is a particularly serious concern in our application, because the question on trade

could therefore suffer from omitted variable bias. However, this bias would apply equally to all countries: our previous estimation results may *overstate* the positive effect of skill in human-capital-abundant countries such as the United States and, by the same token, *understate* the negative effect of skill in labor-abundant countries such as Tanzania. These considerations reinforce rather than contradict our Stolper-Samuelson interpretation, because they imply that we may have underestimated the set of countries with a negative skill effect.

In our regressions in Table 8.3 we return to the linear probability framework and condition on aspects of both people's economic awareness and their openness towards foreign cultures and habits. Individual-specific controls are not applicable for Canada, the Czech Republic, France, Germany, the Slovak Republic, Sweden, the United Kingdom and the United States. We therefore first reproduce our previous estimation results on the restricted sample for which all of the additional control variables are available.[31] The variation in the effect of *Skill* across countries is reduced somewhat compared to estimates in Table 8.2, but the estimated threshold value separating human capital abundant countries from labor abundant countries even increases slightly.

<< Table 8.3 about here >>

In column (2), we add a four-valued ordered proxy variable to capture an individual's economic understanding, which could make individuals responsive to the aggregate gains from trade (*Economic Awareness*). The survey design confronts respondents with a statement which, we believe, calls for an affirmative reply of a person with some training in economics: *"Most people are better off in a free market economy, even though some people are rich and some are poor."*[32] The statement nicely encapsulates a basic principle of economics: that *"free markets are usually a good way to organize economic activity"* but that they *"can nonetheless leave sizable disparities in economic well-being."* (Mankiw, 2008, pp. 8 & 12)[33] *Economic Awareness* enters the model with a significant and positive coefficient, as expected. Going from the answer category with the lowest value (*"completely disagree"* (0)) to that with

preferences does not address the distributional consequences of international trade within the respondent's country, but rather the implications for the country at large.

[31] To exclude the possibility that changes in estimated coefficients reflect mere changes in sample composition, we employ exactly the same estimation sample in all specifications.

[32] The questionnaire allows for four different answer categories, from "*completely disagree*" (0) to "*completely agree*" (3).

[33] Moreover, the question does not refer to issues such as international trade, trade liberalization, or globalization, at least not explicitly. Answers to this question are thus not subject to what has been dubbed justification bias in the literature on opinion polls. This type of bias would arise if individuals were partly using their answers as a means of ex post justification for their (positive or negative) preferences towards trade; see Malchow-Møller et al. (2009).

the highest value (*"completely agree"* (3)) increases an individual's probability of favoring free trade by four-and-a-half percentage points.

Column (3) inspects the role of information in attitude formation and the possibility that highly educated individuals are more likely to be exposed to relevant information on the (aggregate) economic effects of trade policies. We include a measure of an individual's exposure to international news (*Informed*).[34] The variable is indeed positively correlated with an individual's skill level (correlation coefficient equal to 0.06). Yet, our regression results suggest that exposure to information does not exert any significant impact on trade policy preferences.

Material self-interest may be less important for trade attitudes than perceptions of the effects of trade on the economy as a whole; see Mansfield & Mutz (2009). A more general treatment of this concern is delegated to Subsection 8.3.4. Here we ask whether the extent to which individuals hold sociotropic views makes a difference for perceptions of international trade. An individual's affirmation of the following statement may yield informative insights in this regard: *"Protecting the environment should be given priority, even if it causes slower economic growth and some loss of jobs."*.[35] The underlying question posits a trade-off between environmental protection and economic growth and the availability of jobs, the latter securing personal income. The positive and significant coefficient of *Sociotropic Views* in column (4) is consistent with the interpretation that a tendency towards environmental protection reveals sociotropic attitudes.

We next turn to aspects of nationalist dispositions. Column (5) controls for fears that increasing globalization may crowd out local traditions. We exploit survey information on whether individuals agreed or not with the following statement: *"It's good that American ideas and customs are spreading around the world."*[36] The negative and significant coefficient of *Fears of Cultural Spill-Overs* shows that pro-trade views go hand in hand with openness towards foreign cultures and habits. Column (6) incorporates feelings of national superiority through a four-valued ordered variable constructed from individual responses towards the

[34]This variable is based on the following survey question: *"Which of the following two statements best describes you: 'I follow INTERNATIONAL news closely ONLY when something important is happening.' OR 'I follow INTERNATIONAL news closely most of the time, whether or not something important is happening'?"*. The indicator *Informed* is coded (1) for individuals who choose the second statement.

[35]The variable *Sociotropic Views* takes on integer values from 0 (*"completely disagree"*) to 3 (*"completely agree"*).

[36]The dichotomous variable *Fears of Cultural Spill-Overs* is coded (1) if respondents take a positive stance on spreading American ideas and customs, and (0) for negative views. Obviously, answers to this question are heavily loaded by the explicit reference to the United States. Our data show that anti-American sentiments are popular in both developing and developed countries. That said, we argue that our indicator variable also captures fears of the cultural impact of globalization in general, and we expect the purely American-specific element to be independent of individual trade policy preferences.

following statement (*Nationalism*): *"Our people are not perfect, but our culture is superior to others."*[37] "Nationalist" people are, surprisingly, more likely to be pro-trade. While this finding conflicts with the intuition that nationalist sentiments should foster preferences for isolationist policies, feelings of national superiority may mitigate worries that the domestic economy is not able to cope with foreign competition.

The model in column (7) takes a closer look at the extent to which individuals are afraid of negative economy-wide effects from international competition. The binary variable *Fears of International Competition* is based on the following survey question: *"Turning to China, overall do you think that China's growing economy is a good thing or a bad thing for our country?"* Though economic growth of one country may in principle be good or bad for another country, we expect people who perceive another country's growth as a threat rather than an opportunity to be more likely to retain protectionist attitudes. Indeed, individuals who fear negative repercussions from China's growing economy (*Fears of International Competition* coded (1)) have a significantly lower probability of favoring free trade by as much as seven percentage points.

Finally, column (8) gives results from the most encompassing model which conditions on all aspects of individual enlightenment simultaneously. Various aspects of individual enlightenment exist, and most of them are significantly linked to individual trade policy preferences. However, our main focus is on parameter estimates for *Skill* and its interaction with *Country Mean of Skill*, which do not change significantly relative to the baseline specification in column (1). To put results into perspective, we conclude that controlling for individual income is more important for the identification of Stolper-Samuelson effects than is conditioning on individual's economic awareness, aspects of culture, or the like.

8.3.4 Economic self-interest versus social values and identity

Whether social values and identity or pure material self-interest are dominant in shaping individual political behavior is an ongoing scientific debate. The literature as it currently stands takes the view that both factors are potentially important, depending on how clear-cut the policy alternatives and implications are and how long the time horizon is to which these apply; see e.g. Chong et al. (2001), Ehrlich et al. (2010), and Hunt et al. (2010). In this paper, the assumption that individuals prefer a certain policy choice over another if it brings about a greater (expected) *personal* income is pivotal. In this subsection, we exploit the idea that in individual decision making the weight put on material self-interest is larger

[37] Again, the survey allows for four different answers, ranging from *"completely disagree"* (0) to *"completely agree"* (3).

for some individuals than for others. The absence of economic and financial concerns may signal that material self-interest is less influential because it erodes the need for individuals to base their decisions on mere pocketbook considerations. This should also affect the extent to which Hypotheses 1 and 2 are borne out by the data.

Our strategy is to divide the entire sample into two groups, the first of which includes only individuals who express economic and/or financial concerns and the second all the remaining individuals. This distinction is based on answers to the following question in the GAP survey: *"What do you think is the most important problem facing you and your family today?"* The questionnaire allows for a maximum of three answers and is open in the sense that pollers do not present or read out a list with possible answers to individuals. We identify responses referring to problems which are relevant from a very economic/financial perspective. Individuals whose answers fall into at least one such category are classified as *"economically/financially concerned"*.[38] One might be tempted to expect the skill distribution to draw a sharp line between the two groups of individuals, but the evidence proves contrary. For example, close to one sixth of individuals who express economic and/or financial concerns have exposure to at least some university education, as opposed to 23 percent for the other group. We run the same regressions separately on each of the two subsamples, estimating the effect of *Skill* and its interaction with *Country Mean of Skill* and bringing in different sets of control variables; see Table 8.4.

<< Table 8.4 about here >>

We find the estimates based on the sample with *"economically/financially concerned"* individuals to neatly reflect the Stolper-Samuelson logic; see columns (1) to (4). The quantitative implications are similar to those in the previous subsection, at least for models in which we use the same set of control variables as in our benchmark regressions. Column (4) applies a specification similar to that in column (8) of Table 8.3, controlling for all aspects of individual enlightenment. In this model, the predicted negative skill effect extends to a larger set of countries, as compared to Table 8.3. This set now includes labor-abundant China, for example. Estimates on the subsample with individuals who do not express economic and/or

[38]In the survey, each of the answers is assigned to one of the following categories: *"Economic/financial problems"*, *"Health"*, *"Education and children"*, *"Housing"*, *"Social relations"*, *"Work"*, *"Transportation"*, *"Crime"*, *"Problems related to government"*, *"Terrorism and war"*, *"Other"*. Each category comprises two to six pre-specified subcategories plus a "residual" group for answers which do not fit into any one of the given subcategories. We categorize the following subcategories as indicating economic or financial concerns: *"Low wages"*, *"Unemployment"*, *"Poverty"*, *"Other economic/financial problems"*, and *"Lack of good jobs"*. Answers to the survey question are again not applicable for a relevant subset of countries in the GAP. We are left with roughly 17,000 individual observations with economic and/or financial concerns and 12,000 without.

financial concerns, while similar with respect to all control variables, yield complementary insights; see columns (5) to (8). In particular, the data do not confirm Hypothesis 1 as there is no country in the sample for which a given positive change in *Skill* entails a significant decline in individual support for free trade.

The factor endowments model thus may have significant explanatory power in understanding trade attitudes of individuals whose concerns about their personal financial situation loom large in their preference structures. However, with other factors such as social values and identity gaining relative importance in individual decision making, this explanatory power seems to be reduced.

8.4 Conclusion

Motivated by the incidence of the growing North-South share in world trade and the rising demand for protection in high-income countries, this paper contributes to the empirical literature on individual attitudes towards trade. Using a wide cross section of 47 countries from all over the world, we focus on the interplay between individual factor ownership and countries' relative factor endowments. The linear probability model can be used to straightforwardly examine how this interplay is shaping free trade preferences. We argue that our approach has important advantages over the commonly applied Probit model.

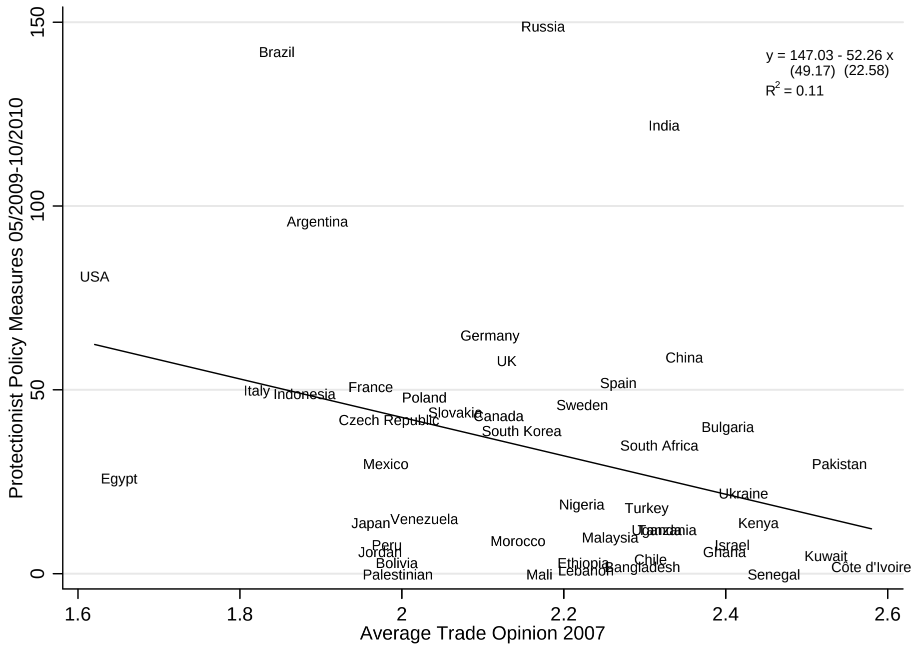
Our evidence suggests that the H-O model, one of the most influential models in the theory of international trade, has a significant stake in explaining the formation of trade policy preference at the individual level. Stolper-Samuelson-type distributional effects of trade policy interventions account for a significant share of the heterogeneity of free trade preferences across individuals and countries both in statistical and economic terms. In the United States, being high-skilled increases an individual's predicted probability of favoring free trade by up to twelve percentage points. In Ethiopia, the effect amounts to eight percentage points, but in exactly the opposite direction. Our results derive from a novel survey data set, and they are robust to conditioning on aspects of individual enlightenment.

The empirical support for the factor endowments model may appear puzzling, given that the neoclassical assumptions are often blamed to be patently false. In fact, economists have long struggled with bringing the Heckscher-Ohlin model to actual trading data in a meaningful way. That said, our empirical analysis does prove that an individual's revealed preference towards trade policy includes an element which is responsive to the relative abundance of his or her production factor in the domestic economy. This element turns out to shape attitudes towards trade policies in a way that exactly mirrors the predictions of the H-O model.

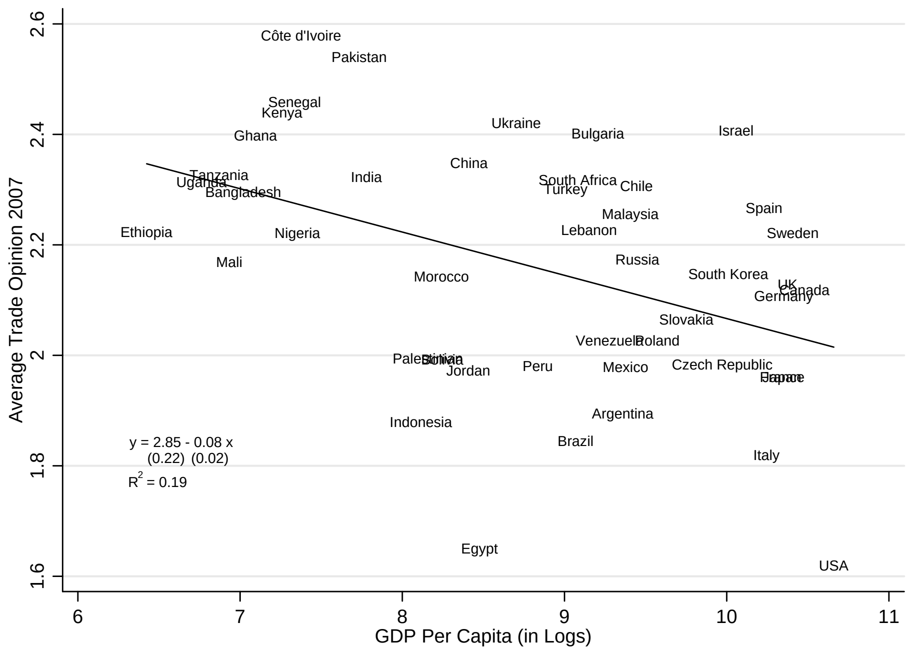
This result becomes elucidating if interpreted against the notion of factors being embodied in traded goods and services. Broadly speaking, it tells us that people are sensitive towards how an integrated world economy may affect the relative scarcity of their factors, compared to an autarky situation.

Figures and tables

Figure 8.1. Trade policy preferences and protection/GDP per capita

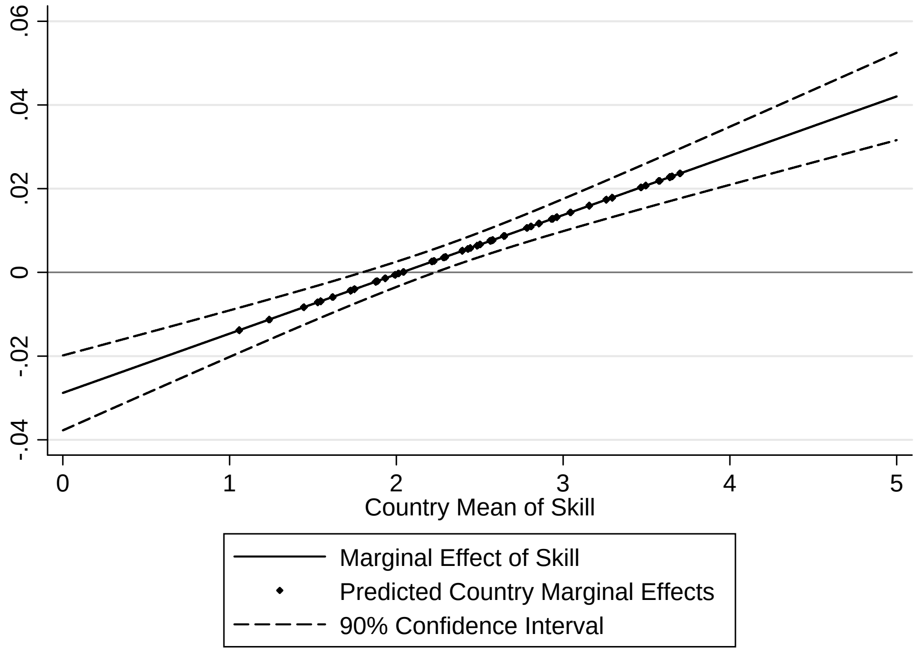


(a) Protectionist policy measures

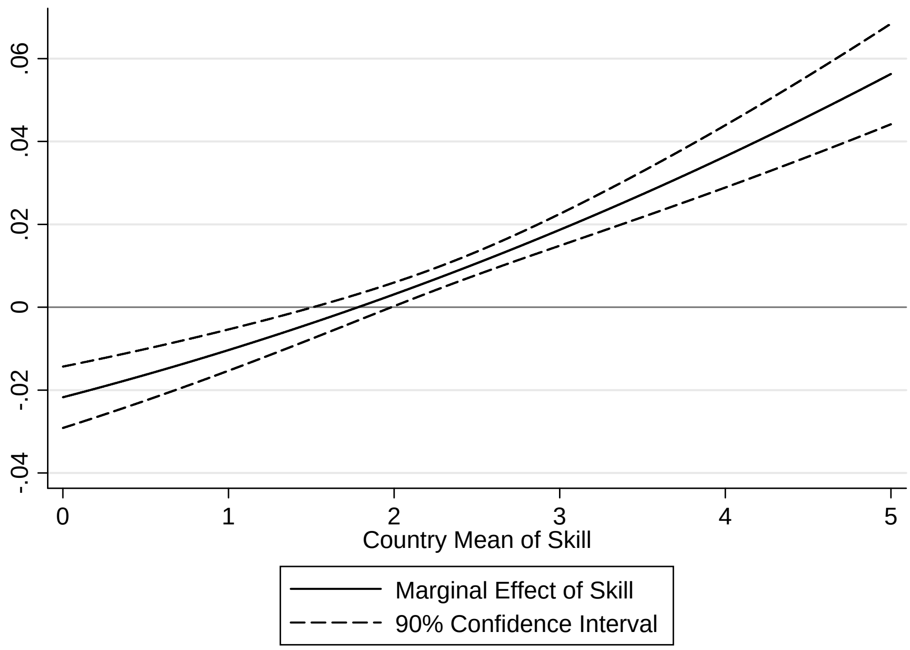


(b) GDP per capita

Figure 8.2. The marginal effect of skill as a function of human capital abundance



(a) Linear probability model



(b) Probit model

Table 8.1. Naïve Probit model[†]

	Dependent Variable: Individual-Specific Pro-Trade Dummy							
	Higher-Income Countries				*Lower-Income Countries*			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Skill	0.017***	0.016***	0.016***	0.015***	0.006***	-0.001	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Income		0.017***	0.016***	0.016***		0.029***	0.029***	0.030***
		(0.005)	(0.005)	(0.005)		(0.003)	(0.003)	(0.003)
Religious			-0.005	-0.005			-0.001	-0.003
			(0.008)	(0.008)			(0.006)	(0.006)
Unemployed				-0.020**				0.006
				(0.008)				(0.007)
Age	-0.001***	-0.001***	-0.001***	-0.001***	-0.000	-0.000*	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.019***	0.017**	0.015**	0.015**	0.001	0.002	0.002	0.001
	(0.006)	(0.007)	(0.007)	(0.007)	(0.004)	(0.005)	(0.005)	(0.005)
Observations	15,208	13,055	13,011	13,011	23,129	20,207	20,051	19,431
Countries	24	23	23	23	23	23	23	22
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.064	0.062	0.063	0.063	0.087	0.089	0.090	0.093

[†] The table gives the marginal effects, evaluated at estimation sample averages, for each explanatory variable on the probability of being pro-trade in a Probit model. For a description of individual-specific variables see the text and Table A.1 in Appendix A. Heteroskedastic robust standard errors are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table 8.2. Heckscher-Ohlin model†

	Dependent Variable: Individual-Specific Pro-Trade Dummy							
	Linear Probability Model				*Probit Model*			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Skill	-0.018***	-0.027***	-0.028***	-0.029***	-0.018***	-0.021***	-0.021***	-0.022***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)
Skill × *Country Mean of Skill*	0.012***	0.014***	0.014***	0.014***	0.013***	0.013***	0.013***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Country Mean of Skill					-0.039***	-0.038***	-0.039***	-0.042***
					(0.006)	(0.007)	(0.007)	(0.007)
Income		0.026***	0.026***	0.026***		0.011***	0.011***	0.011***
		(0.003)	(0.003)	(0.003)		(0.002)	(0.002)	(0.002)
Religious			-0.004	-0.006			-0.007	-0.008*
			(0.005)	(0.005)			(0.005)	(0.005)
Unemployed				-0.008				-0.022***
				(0.005)				(0.005)
Age	-0.000***	-0.001***	-0.001***	-0.001***	-0.000*	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.009**	0.008*	0.007	0.006	0.010***	0.009**	0.007	0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	38,337	33,262	33,062	32,442	37,111	32,545	32,354	31,734
Countries	47	46	46	45	45	45	45	44
Country Fixed Effects	Yes	Yes	Yes	Yes	No	No	No	No
World Region Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Country-level Control Variables	No	No	No	No	Yes	Yes	Yes	Yes
R^2	0.066	0.066	0.066	0.068	–	–	–	–
Pseudo-R^2	–	–	–	–	0.052	0.050	0.051	0.053

† Columns (1) to (4) give the marginal effects for each explanatory variable on the probability of being pro-trade in a linear probability model. Columns (5) to (8) give the marginal effects, evaluated at estimation sample averages, for each explanatory variable on the probability of being pro-trade in a Probit model. The first row for the Probit model evaluates the marginal effect of *Skill* at $h_c = 0$ and at estimation sample averages of all other covariates. Similarly, reported marginal effects of *Country Mean of Skill* are evaluated at $h_{ic} = 0$ when interacted with *Skill*. For a descriptions of variables see the text and Tables A.1 and A.3 in Appendix A. World region fixed effects refer to world regions as in Table A.2 in Appendix A. Heteroskedastic robust standard errors are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table 8.3. Conditioning on aspects of individual enlightenment (LPM)†

	Dependent Variable: Individual-Specific Pro-Trade Dummy							
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Skill	-0.018***	-0.018***	-0.018***	-0.018***	-0.018***	-0.018***	-0.019***	-0.018***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Skill ×	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***
Country Mean of Skill	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Income	0.022***	0.022***	0.022***	0.022***	0.022***	0.022***	0.021***	0.021***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Economic Awareness		0.015***						0.012***
		(0.003)						(0.003)
Informed			-0.005					-0.004
			(0.005)					(0.005)
Sociotropic Views				0.010***				0.007**
				(0.003)				(0.003)
Fears of					-0.025***			-0.021***
Cultural Spill-Overs					(0.005)			(0.005)
Nationalism						0.007**		0.006*
						(0.003)		(0.003)
Fears of							-0.074***	-0.072***
Internt'l Competition							(0.007)	(0.007)
Age	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.002	0.003	0.003	0.002	0.003	0.003	0.001	0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Observations	22,378	22,378	22,378	22,378	22,378	22,378	22,378	22,378
Countries	38	38	38	38	38	38	38	38
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.070	0.071	0.070	0.070	0.071	0.070	0.077	0.080

† The table gives the marginal effects for each explanatory variable on the probability of being pro-trade in a linear probability model. For a description of individual-specific variables see the text and Table A.1 in Appendix A. Heteroskedastic robust standard errors are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table 8.4. Economic self-interest versus social values and identity (LPM)†

	Dependent Variable: Individual-Specific Pro-Trade Dummy							
	"Economically/Financially Concerned"				*"Economically/Financially Unconcerned"*			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Skill	-0.017**	-0.015**	-0.015**	-0.022***	-0.011	-0.013	-0.013	-0.013
	(0.007)	(0.007)	(0.007)	(0.009)	(0.008)	(0.008)	(0.009)	(0.010)
Skill ×	0.008**	0.007**	0.007**	0.009**	0.007**	0.008**	0.008**	0.007*
Country Mean of Skill	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
Income	0.022***	0.023***	0.024***	0.023***	0.018***	0.017***	0.017***	0.015**
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Religious		-0.000	-0.001	-0.000		-0.012	-0.012	-0.016*
		(0.007)	(0.007)	(0.008)		(0.008)	(0.008)	(0.010)
Unemployed			0.003	0.007			-0.008	-0.008
			(0.007)	(0.008)			(0.008)	(0.009)
Age	-0.000**	-0.000**	-0.000**	-0.001**	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male	0.002	0.002	0.002	0.006	0.005	0.005	0.003	-0.003
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Observations	17,136	16,655	16,538	12,575	12,303	12,160	12,094	9,272
Countries	38	37	37	37	38	37	37	37
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additional Controls	No	No	No	Yes	No	No	No	Yes
R^2	0.057	0.059	0.059	0.081	0.068	0.069	0.070	0.093

† The table gives the marginal effects for each explanatory variable on the probability of being pro-trade in a linear probability model. Additional controls are *Economic Awareness*, *Informed*, *Sociotropic Views*, *Fears of Cultural Spill-Overs*, *Nationalism* and *Fears of Internt'l Competition*. For a description of individual-specific variables see the text and Table A.1 in Appendix A. Heteroskedastic robust standard errors are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Appendix

A Data

Table A.1. Summary statistics for individual-level variables†

Variable	Observations	Arithmetic Mean	Standard Deviation	Minimum	Maximum
Pro-Trade Dummy	38,684	0.86	0.34	0	1
Skill	40,637	2.50	1.56	0	5
Income[b]	35,131	6.16	1.60	-0.55	9.81
Religious[c]	39,826	0.62	0.49	0	1
Unemployed[d]	40,515	0.34	0.47	0	1
Age[e]	40,614	39.57	15.55	18	97
Male[f]	40,826	0.49	0.50	0	1
Economic Awareness	33,978	1.86	0.92	0	3
Informed	38,842	0.54	0.50	0	1
Sociotropic Views	34,713	2.02	0.90	0	3
Fears of Cultural Spill-Overs	35,712	0.70	0.46	0	1
Nationalism	34,807	2.03	0.86	0	3
Fears of International Competition	30,987	0.28	0.45	0	1

† Summary statistics are not corrected for deviations from random sampling. Variables not described in the text are coded as follows: [b] *Income* is measured by log of monthly real income. Survey respondents sort themselves into income groups, based on (country-specific) lists of incomes. As a general rule, we compute individual income as the middle value of the income interval chosen by the individual, adjusted by PPP conversion factors from the World Development Indicators, expressed in logs, and, if necessary, converted to a monthly basis. More detailed information on this procedure is available upon request. [c] *Religious* is based on the following survey item: *"Which one of these comes closest to your opinion, number 1 or number 2?"*; coded (1) *"Number 2 – It is necessary to believe in God in order to be moral and have good values"*/NA/refused, (0) *"Number 1 – It is not necessary to believe in God in order to be moral and have good values"*. [d] *Unemployed* is coded (1) unemployed/not employed, (0) employed. [e] *Age* is the respondent's age in years. [f] *Male* is coded (1) male, (0) female.

Table A.2. Country-level information†

World Region	Country	Obs.	Country Mean of *Pro-Trade Dummy*	GDP Per Capita (in Logs)	Country Mean of *Skill*
Asia	*China*	2,998	0.96	8.41	2.01
	Pakistan	1,728	0.95	7.74	1.69
	Malaysia	670	0.95	9.41	2.47
	India	1,988	0.92	7.78	3.65
	Bangladesh	986	0.91	7.02	1.63
	South Korea	681	0.90	10.01	3.70
	Indonesia	949	0.75	8.12	2.26
	Japan	683	0.80	10.34	3.34
Eastern Europe	*Bulgaria*	461	0.95	9.21	2.95
	Ukraine	478	0.94	8.70	3.48
	Russia	941	0.87	9.45	2.95
	Slovakia	440	0.85	9.75	3.06
	Poland	468	0.83	9.57	2.49
	Czech Republic	446	0.80	9.97	2.94
Middle East	*Kuwait*	481	0.95		3.61
	Israel	865	0.93	10.06	3.60
	Lebanon	972	0.85	9.15	2.58
	Turkey	830	0.85	9.01	1.97
	Jordan	974	0.74	8.41	1.74
	Palestinian	771	0.72	8.16	2.83
Northern Africa	*Morocco*	864	0.80	8.24	1.16
	Egypt	957	0.63	8.48	1.74
North America	*Canada*	485	0.85	10.48	3.48
	USA	964	0.63	10.66	3.66
Rest of Africa	*Senegal*	694	0.96	7.34	1.45
	Ghana	662	0.95	7.10	2.37
	Kenya	981	0.95	7.26	1.95
	Cte d'Ivoire	700	0.95	7.38	2.64
	South Africa	949	0.91	9.08	2.48
	Ethiopia	686	0.90	6.42	2.06
	Tanzania	650	0.89	6.87	1.29
	Nigeria	1,107	0.87	7.35	2.67
	Mali	695	0.86	6.93	1.90
	Uganda	1,063	0.86	6.76	1.58
South America	*Chile*	769	0.91	9.44	2.54
	Peru	774	0.84	8.84	2.31
	Bolivia	791	0.84	8.25	2.59
	Venezuela	790	0.80	9.28	2.82
	Mexico	796	0.80	9.38	2.25
	Argentina	700	0.78	9.36	2.10
	Brazil	958	0.74	9.07	2.61
Western Europe	*Sweden*	471	0.91	10.41	3.71
	Spain	456	0.91	10.23	2.49
	Germany	495	0.86	10.35	3.16
	UK	467	0.84	10.38	3.29
	France	500	0.79	10.34	2.96
	Italy	450	0.77	10.25	2.84

† In each world region, countries are ranked according to the country mean of *Pro-Trade Dummy*. Sampling weights correct for deviations from random sampling. GDP data for Kuwait is not available. See the text and Tables A.1 and A.3 for coding information on all variables.

Table A.3. Coding information and data sources for country-level data[†]

Variable	Description and Coding
GDP Per Capita[a]	GDP per capita (in logs) as of 2006 in international dollars, calculated based on PPP conversion factors.
Country Mean of Skill[b]	Country average of *Skill*. Sampling weights correct for deviations from random sampling.
Electoral Process[c]	Variable takes on integer values from 0 to 12; higher values correspond to better institutional quality.
Political Pluralism & Participation[c]	Variable takes on integer values from 0 to 16; higher values correspond to higher degrees of pluralism and participation.
Functioning of Government[c]	Variable takes on integer values from 0 to 12; higher values correspond to better functioning of governments.
Freedom of Speech & Belief[c]	Variable takes on integer values from 0 to 16; higher values correspond to higher degrees of freedom.
Associational & Organizational Rights[c]	Variable takes on integer values from 0 to 12; higher values correspond to stronger rights.
Rule of Law[c]	Variable takes on integer values from 0 to 16; higher values correspond to better qualities of judicial institutions.
Personal Autonomy & Individual Rights[c]	Variable takes on integer values from 0 to 16; higher values correspond to higher degrees of autonomy.
Trade Openness[d]	Exports plus imports over GDP.
Labor Force Share[a]	Share of labor force in total population as of 2006.
Protectionist Policy Measures[e]	Count of protectionist policy measures between May 01, 2009, and October 31, 2010. By definition, protectionist policy measures have been *"implemented and almost certainly discriminate against foreign commercial interests"* (red measures) or have been *"either implemented and may involve discrimination against foreign commercial interests"* or have been *announced/are under consideration and would (if implemented) almost certainly involve discrimination against foreign commercial interests"* (amber measures).

[†] Data sources: [a]World Development Indicators. [b]GAP survey data. [c]Freedom House; data as of 2007. [d]Penn World Tables. [e]Global Trade Alert.

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Chapter 9

Does factor abundance shape free traders? Theory and evidence

This chapter is based on joint work with Ina C. Jäkel (previously unpublished).

9.1 Introduction

The political economy of trade policy treats *observed* levels of protection as *equilibrium* levels of protection in the political market.[1] While the supply function of protection is strongly tied to the primitives of the political system, the demand for protection in some way derives from domestic preferences towards trade policy. These preferences quite possibly reflect the income effects of protection on domestic factor owners.[2] Identifying the relevant factor-price effects of trade policy can thus help understand the sorting of workers into groups of trade skeptics and free traders, as well as observed differences in the level of protection across countries and over time.

This paper shows that the factor-price effects of protection in the neoclassical trade model are reflected in how individuals perceive international trade and protection in a large number of countries. It is the first to confront the many-factor-many-good Heckscher-Ohlin-Vanek

[1] Examples are Goldberg & Maggi (1999) and Dutt & Mitra (2002), who test the predictions of the protection for sale model (Grossman & Helpman, 1994) and the median voter model (Mayer, 1984), respectively. For literature surveys, see Nelson (1988) and Rodrik (1995). Gawande & Krishna (2003) survey the empirical literature.

[2] Saying that mere "pocketbook" considerations are the only (or predominant) force in explaining preferences towards protection would seem odd, of course. But saying that they are completely irrelevant would surely seem equally odd. The fundamental question for economics is what model of the economy best describes preference formation at the level of factor owners.

(HOV) model with international survey data on public opinion.[3] Extending the literature in this direction seems important because the HOV model places no restriction on the number of factors or goods and is compatible with (technology-induced) imperfect factor mobility across industries.

Neoclassical trade theory draws attention to cross-country differences in (relative) factor endowments as a source of comparative advantage. In the two-factor-two-good Heckscher-Ohlin-Samuelson (HOS) model, a country's abundant factor gains from free trade at the expense of the country's scarce factor. This well-known proposition obtains by virtue of combining the Stolper-Samuelson theorem with the Heckscher-Ohlin theorem. In this paper, we derive a similar testable proposition in the more general HOV model with many factors and many goods, drawing upon the work of Ethier (1982, 1984) and Deardorff (1980, 1982). These and other authors have succeeded in generalizing many of the results of the HOS model to higher dimensions, although in a much weaker form. The novel proposition that we bring to the data states that a country's abundant factors *on average* gain from free trade, *relative* to the country's scarce factors.

Confronting the neoclassical trade model with international survey data is not trivial. The literature (e.g. Mayda & Rodrik (2005)) documents that the labor market skills of workers, interpreted as factors employed in production, correlate with individual trade policy preferences in a way that is roughly consistent with the Stolper-Samuelson logic in the HOS model. However, one may wonder about the correct interpretation of this result, because differences in labor market skills account in and of themselves for a large part of the heterogeneity in workers' attitudes towards trade. For example, high-skilled managers and professionals welcome globalization due to their advanced educational background as well as their private and professional network (Hainmueller & Hiscox, 2006; Mansfield & Mutz, 2009). A key challenge is therefore to disentangle the factor-price effects of protection due to comparative advantage from these other effects specific to workers' labor market skills. It is probably fair to say that neither the early studies in the literature (Scheve & Slaughter, 2001; O'Rourke & Sinnott, 2001; Mayda & Rodrik, 2005) nor their many follow-up papers have done so in an entirely convincing way.[4]

[3] Empirical work based on the HOV model has a long tradition in international economics, starting with Leamer (1980) and gaining renewed momentum with Trefler (1993, 1995). More recent contributions include Davis & Weinstein (2001), Debaere (2003), and Romalis (2004). Balistreri (1997) invokes the HOV model in order to examine Canadian attitudes towards the free trade agreement between Canada and the United States.

[4] Papers using cross-country survey data are, for example, Beaulieu et al. (2005), O'Rourke (2006), Scheve & Slaughter (2006), Mayda et al. (2007), and Jäkel & Smolka (2013). Hoffman (2009) and Blonigen (2011) report evidence on trade policy preferences for the United States.

We develop and apply a novel identification strategy to fill this gap in the literature. More specifically, we exploit the *within-factor variation* in factor abundance *across countries*.[5] This allows us to hold workers' labor market skills constant. Different from previous literature, our approach requires outside data on endowments, trade, and production, in order to predict each country's vector of the (technology-adjusted) *factor content of trade*. We find independent support for the neoclassical trade model in two different survey data sets, viz. the 2003 National Identity module from the International Social Survey Program (ISSP) and the 2007 survey of the Pew Global Attitudes Project (GAP). Owners of abundant factors (i.e., factors intensively employed in comparative advantage industries) are robustly associated with more positive attitudes towards trade than owners of scarce factors. Independently of this results, we also find that workers with advanced labor market skills are more pro-trade than workers with basic labor market skills. This last finding gives credit to Hainmueller & Hiscox (2006) and Mansfield & Mutz (2009) in that it suggests individual labor market skills to exert an independent influence on workers' perceptions of international trade and protection.

The remainder of this paper is in four sections. Section 9.2 analyzes trade policy, factor rewards, and individual utility in the HOV version of the neoclassical trade model. In Section 9.3, we introduce the data used in this chapter, and we discuss our empirical strategy and estimation. In Section 9.4, we present our estimation results. The final section concludes.

9.2 Theory

There are many countries, indexed by $c = 1, \ldots, C$; many production factors, indexed by $m = 1, \ldots M$; and many industries, indexed by $n = 1, \ldots, N$. Countries are open and small in the sense that they trade goods (but not factors) and take prices on world markets as given. Consumers have identical and homothetic preferences. Both goods and factor markets are perfectly competitive and factors are perfectly mobile across industries, though technology may be such that some factors are employed in a subset of industries only. The production technology is linearly homogeneous but need not be identical in all countries. Each individual living in country c is endowed with $\delta_c \in (0, 1)$ efficiency units of exactly one of the production factors. The parameter δ_c thus reflects the technology level of country c (allowed to differ across countries).[6] In the following, we refer to a country's endowment with some factor

[5] By the very nature of comparative advantage, a given production factor is abundant in some countries and scarce in others.

[6] Trefler (1993) allows for all factors to differ in their productivities in every country relative to a benchmark country. Alternatively, technology differences can be modeled via differences in unit input coefficients across countries; see Trefler (1995).

m as its *effective* endowment with that factor. Factor price equalization (FPE) in terms of effective factor prices is assumed to prevail under free trade.

In the analysis that follows, we derive policy-induced relative (rather than absolute) factor price changes across owners of different factors. Specifically, we compare the free trade equilibrium of some country c with a policy equilibrium in which domestic prices may differ from world market prices. We assume that the government consumes the entire tariff revenue from trade policy. This assumption allows us to abstract from the effects of trade policy other than those on factor rewards.[7] Relative factor price changes are therefore indicative of relative income changes.

Assume that all goods are produced in both the policy and the free trade equilibrium. Let $\mathbf{p}_c = (p_{1c}, \dots, p_{Nc})$ and $\mathbf{w}_c = (w_{1c}, \dots, w_{Mc})$ denote the vectors of goods and (effective) factor prices, respectively. We write $c(\mathbf{w}_c) = \mathbf{w}_c\mathbf{A}(\mathbf{w}_c)$ for the vector of minimum unit-cost functions where $\mathbf{A}$ is the $(M \times N)$ technology matrix with individual elements a_{mn} giving the (effective) amount of factor m needed to produce one unit of good n. The market structure implies zero profits in both equilibria. Hence, $\mathbf{p}_c^p = \mathbf{w}_c^p\mathbf{A}(\mathbf{w}_c^p)$ and $\mathbf{p}^f = \mathbf{w}^f\mathbf{A}(\mathbf{w}^f)$ in the policy equilibrium and the free trade equilibrium, respectively. Let $\mathbf{T}_c^f = (T_{1c}^f, \dots, T_{Nc}^f)$ denote the vector of net exports in the free trade equilibrium. Since we are interested in the income effects of trade protection (rather than trade promotion), in the remainder of this paper we assume that trade policy takes the form of import tariffs:

Assumption 1. $p_n^f - p_{nc}^p \leq 0 \ \forall n : T_{nc}^f < 0$ *and* $p_n^f - p_{nc}^p = 0 \ \forall n : T_{nc}^f > 0$.

It follows from Assumption 1 that $(\mathbf{p}^f - \mathbf{p}_c^p)(\mathbf{T}_c^f)^{\mathrm{T}} \geq 0$, which implies

$$[c(\mathbf{w}^f) - c(\mathbf{w}_c^p)](\mathbf{T}_c^f)^{\mathrm{T}} \geq 0 \tag{9.1}$$

due to zero profits. This inequality states that the cost of producing the vector of net exports is higher when evaluated at free trade factor prices.

Define $b(\mathbf{w}_c) \equiv c(\mathbf{w}_c)(\mathbf{T}_c^f)^{\mathrm{T}}$ as the cost of producing the vector of free trade net exports evaluated at some factor price vector $\mathbf{w}_c$. Assume that $b(\mathbf{w}_c)$ is continuous and differentiable over the relevant parameter space. By virtue of the mean value theorem, there exists some intermediate vector $\widetilde{\mathbf{w}}_c$ for which $b(\mathbf{w}^f) - b(\mathbf{w}_c^p) = (\mathbf{w}^f - \mathbf{w}_c^p)\,\mathrm{d}\,b(\widetilde{\mathbf{w}}_c)$. Noting the definitions of $b(\mathbf{w}_c)$ and $c(\mathbf{w}_c)$, we have

$$[c(\mathbf{w}^f) - c(\mathbf{w}_c^p)](\mathbf{T}_c^f)^{\mathrm{T}} = (\mathbf{w}^f - \mathbf{w}_c^p)[\mathbf{A}(\widetilde{\mathbf{w}}_c) + \widetilde{\mathbf{w}}_c\mathrm{d}\mathbf{A}(\widetilde{\mathbf{w}}_c)](\mathbf{T}_c^f)^{\mathrm{T}}, \tag{9.2}$$

[7] Alternatively, we could assume that the government redistributes any revenue from trade policy with a poll subsidy.

where cost minimization implies $\widetilde{\mathbf{w}}_c \mathrm{d}\mathbf{A}(\widetilde{\mathbf{w}}_c) = 0$. If the changes in goods prices are small enough, we may set $\widetilde{\mathbf{w}}_c = \mathbf{w}^f$, so that (9.2) becomes

$$[c(\mathbf{w}^f) - c(\mathbf{w}^p_c)](\mathbf{T}^f_c)^{\mathrm{T}} = (\mathbf{w}^f - \mathbf{w}^p_c)\mathbf{A}(\mathbf{w}^f_c)(\mathbf{T}^f_c)^{\mathrm{T}}. \tag{9.3}$$

Define $\mathbf{F}^{\mathrm{T}}_c \equiv \mathbf{A}(\mathbf{w}^f)(\mathbf{T}^f_c)^{\mathrm{T}}$ as the vector of country c's factor content of trade in the free trade equilibrium. The factor content of trade with some factor m, F_{mc}, is positive if the amount of that factor embodied in production exceeds the amount embodied in consumption. Define $\Delta_f \mathbf{w}_c \equiv \mathbf{w}^f - \mathbf{w}^p_c$ as the vector of factor price changes when switching from the policy equilibrium to the free trade equilibrium. Then, (9.3) can be written as

$$[c(\mathbf{w}^f) - c(\mathbf{w}^p_c)](\mathbf{T}^f_c)^{\mathrm{T}} = \Delta_f \mathbf{w}_c \mathbf{F}^{\mathrm{T}}_c \geq 0, \tag{9.4}$$

where the inequality derives from (9.1).

In the following, we normalize factor prices in country c to lie on the unit simplex, $\sum_m w^f_{mc} = \sum_m w^p_{mc} = 1$. Prices are thus measured in terms of a factor bundle containing one unit of each factor.

Proposition 1. *Comparing the free trade equilibrium with the policy equilibrium, factor price changes and the free-trade factor content of trade are positively correlated.*

Proof. A positive correlation between the two variables exists if $\mathrm{Cov}(\Delta_f \mathbf{w}_c, \mathbf{F}^{\mathrm{T}}_c) \geq 0$. By definition of the covariance, we have $\mathrm{Cov}(\Delta_f \mathbf{w}_c, \mathbf{F}^{\mathrm{T}}_c) = \Delta_f \mathbf{w}_c \mathbf{F}^{\mathrm{T}}_c - M\, \overline{\mathbf{F}}_c\, \overline{\Delta_f \mathbf{w}}_c$, where bars indicate vector means. We know from (9.4) that the first term is positive. Hence, if either of the two vectors has zero mean, we have $\mathrm{Cov}(\Delta_f \mathbf{w}_c, \mathbf{F}^{\mathrm{T}}_c) \geq 0$; see also Deardorff (1980). From the normalization of factor prices, $\sum_m \Delta_f w_{mc} = 0$ and thus $\overline{\Delta_f \mathbf{w}}_c = 0$. $\square$

Proposition 1 is the cornerstone of our analysis. It states that, when switching from the policy equilibrium to the free trade equilibrium, rewards of factors with an above-average factor content of trade (under free trade) tend to increase relative to those of other factors. These factor price changes are indirectly linked to the specific pattern of goods price changes. In this sense, Proposition 1 is closely related to the higher-dimensional version of the Stolper-Samuelson theorem in Ethier (1982, 1984).

The relationship between the factor content of trade and relative factor price changes is also explored in Deardorff & Staiger (1988) and Deardorff (2000). These authors show that *changes* in the factor content of trade between two trading equilibria are indicative of changes in relative factor prices. Proposition 1, to the contrary, relates factor price differences between the policy equilibrium and the free trade equilibrium to the *level* of the factor content of trade prevailing under free trade.

We now invoke the HOV theorem, which establishes the following link between factor endowments and the factor content of trade in the integrated world equilibrium:

$$\mathbf{F}_c = \delta_c \mathbf{V}_c - s_c \sum \delta_c \mathbf{V}_c, \tag{9.5}$$

where s_c is country c's share in world consumption and $\delta_c \mathbf{V}_c = (\delta_c V_{1c}, \ldots, \delta_c V_{Mc})$ denotes the vector of effective factor endowments of country c.[8] We refer to the right-hand side in (9.5) as the predicted factor content of trade.

Let $U(\mathbf{p}, w_{mc})$ be the indirect utility of the owner of factor m, and let $\Delta_f U_{mc} \equiv U(\mathbf{p}^f, w^f_{mc}) - U(\mathbf{p}^p_c, w^p_{mc})$ be the corresponding utility difference when switching from the policy equilibrium to the free trade equilibrium. Let $\mathcal{M}_c = \{m : F_{mc} > \overline{\mathbf{F}}_c\}$ denote the set of factors with an above-average predicted factor content of trade in country c. Using the HOV theorem in equation (9.5) along with Proposition 1 yields the following corollary:

Corollary 1. *Comparing the free trade equilibrium with the policy equilibrium, on average owners of factors with an above-average predicted factor content of trade gain relative to owners of other factors:* $\overline{\Delta_f U}_{mc} \geq \overline{\Delta_f U}_{m'c}$, *where* $m \in \mathcal{M}_c$ *and* $m' \notin \mathcal{M}_c$.

Proof. The inequality can be rewritten as

$$\overline{U}(\mathbf{p}^f, w^f_{mc}) - \overline{U}(\mathbf{p}^p_c, w^p_{mc}) \geq \overline{U}(\mathbf{p}^f, w^f_{m'c}) - \overline{U}(\mathbf{p}^p_c, w^p_{m'c}).$$

Due to homothetic preferences, the indirect utility function $U(\mathbf{p}, w)$ is homogeneous of degree one in w. Hence, the inequality can be written as $\tilde{U}(\mathbf{p}^f)\left(\overline{w}^f_{mc} - \overline{w}^f_{m'c}\right) \geq \tilde{U}(\mathbf{p}^p_c)\,(\overline{w}^p_{mc} - \overline{w}^p_{m'c})$. Due to Assumption 1, we have $\tilde{U}(\mathbf{p}^f) \geq \tilde{U}(\mathbf{p}^p_c)$. To prove Corollary 1, it is thus sufficient to show that $\overline{\Delta_f w}_{mc} \geq \overline{\Delta_f w}_{m'c}$. This follows from the fact that $\mathrm{Cov}(\Delta_f \mathbf{w}_c, \mathbf{F}^{\mathrm{T}}_c) \geq 0$ (Proposition 1), because $m \in \mathcal{M}_c$ and $m' \notin \mathcal{M}_c$, where by definition of $\mathcal{M}_c$ the m-factors have an above-average predicted factor content of trade, whereas the m'-factors have a below-average predicted factor content of trade. □

We use Corollary 1 to derive testable predictions on how free trade preferences are supposed to vary in a cross-section of individual factor owners. If a country's factor content of trade with some factor m is positive, the factor is said to be in abundant supply in that country. Our first prediction relates to this common notion of factor abundance.

[8] Helpman & Krugman (1985) show that the HOV equation is actually implied by many models. Trefler & Zhu (2010) characterize the class of models for which this is true.

Prediction 1. *Assume that in quantities the predicted factor content of trade in country c is balanced under free trade: $\overline{\mathbf{F}}_c = 0$. Then, the owners of the abundant factors in that country ($m : F_{mc} \geq 0$) will on average hold more positive views towards free trade than the owners of the scarce factors ($m' : F_{m'c} < 0$).*

In principle, Prediction 1 could be applied to a cross-section of individual factor owners in a single country. This would however lead to an identification problem, because factor ownership affects free trade preferences in and of itself. In an empirical application of Prediction 1, it is therefore paramount to exploit the cross-country variation in the data, where the same factor can be abundant in one country but scarce in another one. This can be done without further ado by assuming that the free-trade predicted factor content of trade is balanced in all countries we are looking at.

A problem with Prediction 1 could be that the predicted factor content of trade is not balanced ($\overline{\mathbf{F}}_c \neq 0$), since this could lead to a misclassification of factors. If for example the average predicted factor content of trade is positive, we would erroneously assign a factor m with $0 < F_{mc} < \overline{\mathbf{F}}_c$ to the set of factors that are relatively better off in the free trade equilibrium: $\mathcal{M}_c = \{m : F_{mc} > \overline{\mathbf{F}}_c\}$. In order to get around this problem, we derive a prediction that exploits the full variation in the predicted factor content of trade.

Prediction 2. *Consider a given country c. The larger the predicted factor content of trade for some factor m, the more likely it is that this factor belongs to the set of factors that are relatively better off in the free trade equilibrium: $\mathcal{M}_c = \{m : F_{mc} > \overline{\mathbf{F}}_c\}$. Hence, the larger the predicted factor content of trade for some factor m, the more likely it is that the individual factor owner will hold more positive views towards free trade.*

Importantly, Prediction 2 applies to the cross-factor variation in the predicted factor content of trade *in a given country c*. The first and second moments of the distribution of $\overline{\mathbf{F}}_c$ can be vastly different across countries. A test of Prediction 2 in a framework that exploits the variation across both individuals and countries thus requires a careful empirical design.

9.3 Empirical approach

Corollary 1 sorts factor owners in each country into groups of winners and losers from free trade. Predictions 1 and 2 link this result to individual attitudes towards free trade. We next provide an empirical test of these two predictions. To this aim, we combine international survey data on public opinion and data on country and world endowments with different factors of production.[9]

9.3.1 International survey data

Our empirical analysis explores two large-scale, internationally comparable survey data sets, viz. the 2003 National Identity module from the International Social Survey Program (ISSP) and the 2007 wave of the Pew Global Attitudes Project (GAP). The two data sources exhibit relevant differences in terms of content, framing of survey questions, and country coverage. Confronting our predictions with two different datasets allows us to establish the generality of our results and proves that findings are not driven by the features of a particular dataset. Tables A.4 and A.5 in Appendix A provide summary statistics by country for the ISSP and the GAP, respectively.

Our sample from the 2003 National Identity module of the ISSP includes information on roughly 27,000 individuals from 28 countries, the majority of which are located in Europe with middle and high incomes per capita.[10] In the survey, respondents are asked for their opinion on the use of protectionist measures:

> "How much do you agree or disagree with the following statement? [Respondent's country] should limit the import of foreign products in order to protect its national economy."

We construct an individual-specific pro-trade indicator variable taking on the value one for individuals who hold positive views towards free trade (answer categories "disagree strongly" and "disagree") and zero for those with neutral or negative views (answer categories "neither agree nor disagree", "agree", and "agree strongly"). The binary coding mutes country-specific tendencies towards extreme or moderate responses (extreme-response bias).[11]

The 2007 wave of the GAP constitutes our second survey data source. The estimation sample includes information on 19,000 individuals from 28 countries. It offers a salient coverage of economies at different stages of development, including developing countries in Latin America, Asia, the Middle East, and Africa. We exploit individual answers to the following question:

[9] The construction of the data presented in Subsection 9.3.2 is described in more detail in Appendix A.

[10] For both the ISSP and the GAP, we restrict the sample to countries with information on endowments and to individuals for which all basic survey items of interest have non-missing values.

[11] Calculating an index of extreme response as in Van Herk et al. (2004), we indeed find that some countries exhibit a significantly higher share of extreme responses across survey items than do others. Cross-country differences in the tendency to agree rather than disagree with certain statements (acquiescence-bias) are absorbed into country fixed effects in the empirical model.

> "What do you think about the growing trade and business ties between [respondent's country] and other countries? Do you think it is a very good thing, somewhat good thing, somewhat bad thing or a very bad thing for your country?"

Again, we construct an indicator variable for being pro-trade coded one for individuals who answered "very good thing" or "somewhat good thing" and zero otherwise (answer categories "very bad thing" or "somewhat bad thing").[12]

The framing of the survey question in the ISSP favors a skeptical view towards free trade since the domestic economy is meant to be protected by imposing import restrictions. In terms of our pro-trade indicator, less than 50% of respondents in each country are pro-trade. This negative outlook on trade contrasts sharply with relatively favorable views in surveys with a more neutral framing, most notably the GAP. In the latter survey, a majority of individuals in all countries expresses favorable views towards trade, ranging from 60% in the United States to 95% in Bulgaria, Malaysia and Pakistan. The respective biases towards negative and positive attitudes raise concerns about measurement error, with consequences for regression results provided that the framing has a nonuniform impact across individuals. In fact, Hiscox (2006) shows that people with a poor educational background are particularly sensitive to issue framing. In our identification strategy we accommodate this concern by including skill specific indicators, which pick up such skill-related effects on attitude formation.

9.3.2 Factor ownership, factor abundance, and the factor content of trade

The ISSP reports individuals' occupations corresponding to the four-digit level of the ISCO-88 classification of the ILO ($\sim$ 500 occupations). At the one-digit level, these occupations are aggregated into nine major groups based on the similarity of skills required to fulfill the tasks and duties of the jobs. We treat each major ISCO-88 occupation as a unique factor of production ($M = 9$). The GAP allows for a distinction among six strictly hierarchical levels of educational attainment. We classify individuals with primary education (or less) as low-skilled labor, those with secondary education as medium-skilled labor, and those with tertiary education as high-skilled labor ($M = 3$). From the HOV equation in (9.5), the factor content of trade for any factor m only depends on the effective country and world endowments of that specific factor (as well as on the consumption share). The logic of Predictions 1 and

[12]We again find differences in extreme-response bias across countries. For example, individuals from African countries are more likely to give extreme responses than people from Europe.

2 is therefore insensitive to the presence of additional (unobserved) input factors.[13]

Country-specific information on endowments with each skill category are obtained from the ILO. Raw endowments V_{mc} are alternatively measured in terms of occupational positions (ISCO-88) or educational attainment (ISCED-76/ISCED-97). We aggregate education levels in the ISCED-76/ISCED-97 classification into broader educational groups to accommodate our three skill levels in the GAP. In consequence, the factor definitions in the endowment data are consistent with those in our survey data. In order to derive a country's effective endowment with each factor, we construct the country-specific technology parameter $\delta_c \in (0,1)$ on the basis of GDP per capita information from the WDI.[14] Finally, we use trade and GDP data from the WDI to compute countries' consumption shares in world output s_c.

The predicted factor content of trade for country c and factor m, F_{mc}, is given by the m-th element of the vector $\delta_c \mathbf{V}_c - s_c \sum_c \delta_c \mathbf{V}_c$. Differences in country size imply that F_{mc} is not directly comparable across countries. In particular, a large country will tend to have larger endowments of its abundant factors and a larger consumption share s_c than a small country. Hence, for factors that are scarce or abundant in both countries, we expect F_{mc} to be larger (in absolute value) in the large country. We therefore normalize the predicted factor content of trade for each factor by the country's overall effective labor endowment, $\widetilde{F}_{mc} = F_{mc}/(\sum_m \delta_c V_{mc})$. The scaling corrects for country size and makes the magnitude of F_{mc} for some specific factor m comparable across countries.[15]

<<Figures 9.1 and 9.2 about here>>

Figures 9.1 and 9.2 explore the plausibility of the obtained factor abundance profiles across countries in our two samples. The nine occupations of the ISCO-88 classification can be linked to four broad skill levels. The three top-major occupations – "Legislators, senior officials and managers", "Professionals" and "Technicians and associate professionals" – correspond to the two highest skill levels. Figure 9.1(a) to 9.1(c) show that these occupations tend to be more abundant in countries at a high stage of development. The group "Elementary occupations" coincides with the lowest skill level. In line with expectations, this type of

[13] Furthermore, even for an insufficient disaggregation of production factors into distinct skill levels, the inequality in (9.4) still correctly predicts the (weighted) average wage change for the combined broader skill groups. For two factors m' and m'' that are incorrectly treated as a single production factor m, the predicted wage change satisfies $\Delta_f w_m = \Delta_f w_{m'} \frac{F_{m'}}{F_m} + \Delta_f w_{m''} \frac{F_{m''}}{F_m}$.

[14] Trefler (1995) employs the HOV equation to estimate the technology parameter. The correlation coefficient between the estimated parameter and a country's observable GDP per capita is close to 0.9. We normalize δ_c to unity for the country with the highest GDP per capita.

[15] In the ISSP, endowment data for one of the production factors is not applicable for Japan and the United Kingdom. Their overall effective endowment can therefore not be calculated and we set $\widetilde{F}_{mc}$ to missing for all factors in these two countries.

labor is abundant in developing countries such as the Philippines and Uruguay, but scarce in the highly developed economies of Europe and Northern America; see Figure 9.1(i). The remaining five occupations are related to an intermediate skill level. For these occupations, the relationship between factor abundance and GDP per capita is less clear-cut. Some occupations, such as “Clerks”, are relatively abundant in developed countries. Interestingly, “Craft and related trade workers” and “Plant and machine operators” reveal an inverse U-shaped relationship between GDP per capita and factor abundance.

Turning to the GAP, Figure 9.2 shows that the pattern found in our sample is again consistent with higher skill levels being more abundant in developed countries. Importantly, bundling low-skilled labor and medium-skilled labor into a single skill category would give a distorted picture of factor abundance: while the former is abundant in developing countries, the latter is often scarce in the same set of countries.

We may ask how these abundance profiles compare to those obtained in a simple model with only high-skilled and low-skilled labor and two industries. Allowing for more than two factors gives a more nuanced picture of factor abundance across countries. In particular, our data reveal that only the abundance of factors at the extreme end of the skill spectrum is consistently linked to the level of development of countries. To the contrary, intermediate skill levels reveal a much less predictable pattern across countries. Moreover, allowing for many factors also gives a more distinct profile of endowment structures within a given country. For example, it allows a country to be scarce in *all* types of labor (while being abundant in other, unobserved factors). According to our computations for the GAP, this is indeed the case for some countries.

Denote by $\mathcal{I}_c$ the set of individuals living in country c. Define v_i as a function taking on the value m if individual i's labor market skills correspond to factor m. For each individual i, we construct an indicator variable equal to one if the factor content of trade is positive:

$$FA_i \equiv FA(v_i, \mathbf{F}_c) = \begin{cases} 1, & \text{if } F_{mc} > 0, i \in \mathcal{I}_c, v_i = m \\ 0, & \text{if } F_{mc} \leq 0, i \in \mathcal{I}_c, v_i = m. \end{cases} \tag{9.6}$$

From Prediction 1, the group of individuals with $FA_i = 1$ will on average gain from free trade, relative to the group of individuals with $FA_i = 0$. For each individual i, the continuous variable $\widetilde{F}_i$ reflects the abundance of her production factor:

$$\widetilde{F}_i \equiv \widetilde{F}(v_i, \mathbf{F}_c) = \widetilde{F}_{mc}, \quad \text{if } i \in \mathcal{I}_c, v_i = m \tag{9.7}$$

From Prediction 2, individuals with a higher factor content of trade, $\widetilde{F}_i$, are more likely to fall into the group of factors with an above-average factor content of trade. Hence, they will have higher probabilities of being pro trade.

9.3.3 Estimation

Let $\Delta_f U_i$ denote individual i's change in utility when switching from the policy equilibrium to the free trade equilibrium. We assume that this change can be approximated by the following linear expression:

$$\Delta_f U_i = \beta \cdot f(v_i, \mathbf{F}_c) + \gamma_c + \eta_m + \lambda \cdot \mathbf{X}_i + \varepsilon_i, \quad i \in \mathcal{I}_c, v_i = m \tag{9.8}$$

where $f(v_i, \mathbf{F}_c)$ is a measure for the abundance of individual i's production factor. The term γ_c is a country fixed effect and η_m is a fixed effect for the individual's skill level.[16] The vector $\lambda = (\lambda_1 \dots \lambda_S)$ is a vector of parameters, $\mathbf{X}_i = (X_{i1} \dots X_{iS})^{\mathrm{T}}$ is a vector of observable attributes (such as age, gender, or income), and ε_i is a random term capturing the impact of unobservable attributes (such as intelligence, social values, or political identity).

We assume that our pro-trade dummy variable, denoted by y_i, is equal to one if the individual gains from free trade ($\Delta_f U_i > 0$). Hence, the probability of being pro-trade, conditional on the explanatory variables, can be written as:

$$\Pr(y_i = 1|\cdot) = \Pr(\Delta_f U_i > 0|\cdot) = \Phi(\beta \cdot f(v_i, \mathbf{F}_c) + \gamma_c + \eta_m + \lambda \cdot \mathbf{X}_i), \quad i \in \mathcal{I}_c, v_i = m \tag{9.9}$$

where the last equality requires that the random component is drawn independently from a standard normal distribution, $\varepsilon_i \sim N(0, 1)$.

We implement two tests of the Heckscher-Ohlin Vanek model of preference formation. The first test relates to Prediction 1 and uses FA_i as a measure of factor abundance. The second test builds on Prediction 2 and introduces the normalized factor content of trade, $\widetilde{F}_i$, into the model. We test both predictions against the null hypothesis that factor abundance is no significant predictor of individual attitudes towards trade ($H_0 : \beta = 0$). Since Prediction 1 relies on more restrictive assumptions than Prediction 2, the risk of committing a Type-II error is larger with the first test than with the second test.

The two predictions derived from our theoretical model relate to within-country differences in attitudes towards trade across factors. A careful design of the empirical model

[16] This set of dummy variables represents either the nine different occupational positions in the ISSP or the six different levels of educational attainment in the GAP. All of our results are robust to employing a full set of 509 occupation fixed effects at the four-digit level of ISCO-88 in the ISSP.

nevertheless allows to make use of the cross-country variation in the data. Consider two individuals from different countries but with the same value of $\widetilde{F}_i$. For simplicity, let us first assume that $\overline{\mathbf{F}}_c$ is the same in all countries. *Ceteris paribus*, the two individuals are then predicted to be equally affirmative towards free trade. Comparisons are less straightforward when $\overline{\mathbf{F}}_c$ differs across countries. For given $\widetilde{F}_i$, individuals in countries with a higher $\overline{\mathbf{F}}_c$ are less likely pro trade. We introduce country fixed effects γ_c in order to account for such differences in the probability of being pro trade across countries.

The cross-country dimension of the sample allows us to control for all effects common to a given skill group via η_m. Our empirical model in (9.8) then constitutes a test of the pure arithmetics of the factor abundance logic for preference formation. In particular, higher skill levels are associated with more positive views towards globalization in general (Hainmueller & Hiscox, 2006) and with less sensitivity towards issue framing (Hiscox, 2006). Moreover, psychological factors such as loss aversion feed into opposition towards free trade (Kemp, 2007), and presumably all the more so for low skilled workers. All of these confounding factors are absorbed into η_m. When η_m is dropped from the specification, β is upwards (downwards) biased in a sample where countries abundant in higher (lower) skill levels prevail. This bias results from a positive (negative) correlation between $f(v_i, \mathbf{F}_c)$ and ε_i.

9.4 Results

We now report our estimation results that provide tests of Predictions 1 and 2.

9.4.1 Empirical test of Predictions 1 and 2

Table 9.1 reports estimation results for the test of Prediction 1, which employs FA_i as a measure of factor abundance.[17] For both the ISSP and the GAP, we employ three different specifications. The first controls for country fixed effects and a limited set of standard individual-level control variables; see columns (1) and (4). In the second specification, we introduce the fixed effects for skill levels in both samples as well as an individual's years of formal education in the case of the ISSP; see columns (2) and (5). In the third specification, we add an extensive set of individual-specific control variables, including income, nationalist attitudes, and openness towards foreign cultures; see columns (3) and (6).[18] This last spec-

[17]Throughout the paper, we report the estimated marginal effects on the probability of being pro-trade (evaluated at the sample means of all regressors), instead of estimated coefficients. The estimated standard errors are robust to arbitrary forms of heteroskedasticity.

[18]The set of variables is largely identical to that used in Mayda & Rodrik (2005) for the ISSP and Jäkel & Smolka (2013) for the GAP; Tables A.2 and A.3 provide a comprehensive description of all variables.

ification significantly reduces the sample size in terms of both the number of observations and the number of countries due to missing data. To establish comparability between different specifications, we also report results for the second specification applied to this limited sample; see columns (2') and (5').

We find a robustly positive effect of factor abundance on individual free trade attitudes in both datasets and in all specifications that include η_m and thereby control for effects of individuals' skills that are unrelated to factor abundance. In the parsimonious specification without fixed effects for skill groups, however, we obtain an upward-biased estimate in the ISSP (3.3%-points) and a downward-biased estimate in the GAP (-0.9%-points). The difference in the direction of the bias when η_m is omitted neatly reflects our expectations, since the ISSP predominantly covers developed economies. In the specifications with fixed effects for skill levels, the estimated impact of FA_i is similar across the two survey data sources: being endowed with the country's abundant factor increases an individual's probability of being pro-trade by 1 to 3%-points.

<<Table 9.1 about here>>

While results in Table 9.1 yield support for Prediction 1, statistical significance varies somewhat across specifications. Deviations from the assumption of balanced factor content trade imply measurement error in the mapping of individuals to the set of factors that gain in relative terms from free trade. We therefore turn to an empirical test of Prediction 2, which discards the assumption that trade is balanced in factor content terms.

Results for the estimation of equation (9.9), where factor abundance is now measured by $\widetilde{F}_i$, are reported in Table 9.2. Specifications otherwise mirror those of Table 9.1. Table 9.2 substantiates the evidence for the factor abundance logic of trade policy preference formation. Once we include fixed effects for skill levels in the specification, the estimated effect of $\widetilde{F}_i$ is robustly positive in both survey data sets. The larger is the normalized factor content of trade, the more likely a factor is sufficiently abundant such that it gains from free trade, and hence the larger is the probability that the factor owner is a free trader. Moreover, compared to Table 9.1, results are fortified also in terms of statistical significance. Going beyond the traditional notion of factor abundance as deployed in Prediction 1 helps to identify the contribution of the HOV model in explaining individual preferences.

To gauge the quantitative implications, consider a one standard deviation increase in the normalized factor content of trade. Based on column (3), the ISSP predicts an increase in the probability of being a free trader of 2%-points for a one standard deviation increase in $\widetilde{F}_i$. Similarly, in the GAP an increase in $\widetilde{F}_i$ by one standard deviation implies a 1.5%-points higher probability of being pro-trade. The effect of factor abundance on preferences is therefore meaningful, particularly when judged against the overall low percentage of individuals voicing a pro-trade view of 25% in the ISSP.

<<Table 9.2 about here>>

The evidence in Tables 9.1 and 9.2 also illustrates that an individual's skill is a relevant predictor of trade policy preferences. We can interpret the estimated η_m's as the pure skill effects, which affect individuals' preferences independent on their country's endowments. In the ISSP, the fixed effects for occupational positions are jointly significant in all specifications. People working as *Legislators, senior officials and managers* (the reference category) or *Professionals* are more likely pro-trade than people in any of the other occupational positions. Interestingly, individuals employed as *Skilled agricultural and fishery workers* hold by far the most skeptical views towards free trade, with a predicted probability of being pro-trade 15%-points below that of the reference group. Although their skill level is higher, their probability of being pro-trade is even lower than that of individuals employed in *Elementary occupations*. We may attribute this finding to a high degree of industry-specificity, making workers particularly vulnerable to the impact of trade. To the contrary, *Service workers and shop and market sales workers* have moderate views on trade, despite the fact that these are occupational positions regarded as low-skilled. However, workers employed in the non-traded sector are plausibly less exposed to the disruptive effects of trade liberalization.

Apart from labor market skills, increasing an individual's exposure to education by one year increases her probability of being pro-trade by 1%-point. Hainmueller & Hiscox (2006) argue that the effect of education on pro-trade attitudes is larger in developed countries than in developing countries due to differences in the quality of educational systems. In unreported regressions, we find that an interaction between educational attainment and a country's GDP per capita (as a proxy for institutional quality) enters positively, confirming their priors. The effects of all other variables remain virtually unchanged.

The estimation results for the GAP strengthen the interpretation that the forces of factor abundance and pure skill effects coexist and jointly determine individuals' attitudes. In columns (5) and (5') of both tables, the fixed effects for educational attainment are jointly significant. Moreover, the highest levels of educational attainment (exposure to university education with or without degree) are associated with the most positive views towards free trade. When we add the whole set of individual-specific control variables in column (6), the set of fixed effects for skill levels is no longer jointly significant, but the estimated effect of factor abundance is unaltered. Factors such as individual income, nationalist attitudes, and openness towards foreign cultures are thus correlated with an individual's educational background, but not with the factor abundance status of her production factor.

9.5 Conclusion

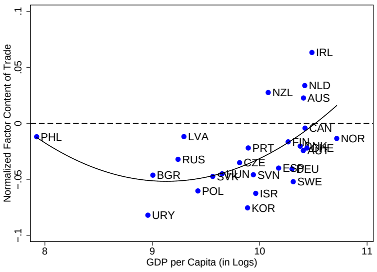
Trade theory can help identify the winners and losers of globalization. The implications of the neoclassical trade model with two goods and two factors are extreme. They have in fact provoked heated discussions among economists for decades. High-skilled individuals in high-skill abundant regions such as Europe or the United States gain from free trade in real absolute terms. Low-skilled individuals lose in real absolute terms. The opposite pattern applies to low-skill abundant countries such as China or India.

It is well-known that this proposition breaks down as soon as the model allows for more than two factors or goods. Building on Ethier (1982, 1984) and Deardorff (1980, 1982), we have shown in a rigorous way that with an arbitrary number of goods and factors it is still possible to identify groups of relative winners and losers. A country's abundant factors on average gain from free trade relative to the country's scarce factors (in real terms).

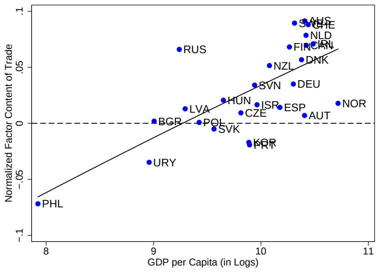
We have found strong empirical support for this novel proposition in two different international survey data sets on public opinion. The empirical strategy that we have developed in this paper neatly identifies the factor-price effects of protection due to comparative advantage, controlling for other effects specific to workers' labor market skills. This issue has troubled a number of earlier studies in the literature on individual trade policy preferences (e.g. Mayda & Rodrik (2005); Hainmueller & Hiscox (2006)).

Figures

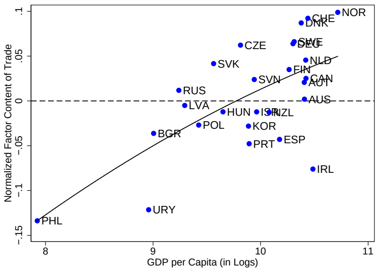
Figure 9.1. Factor content of trade and GDP per capita, ISSP



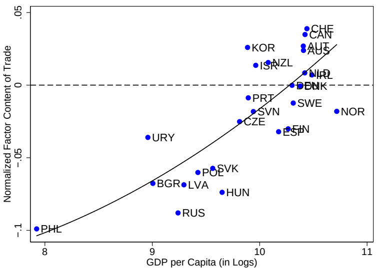
(a) Legislators, senior officials & managers



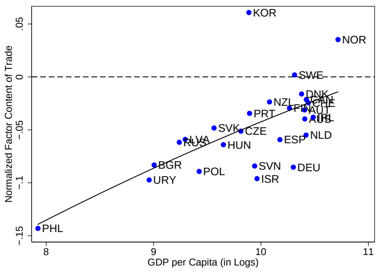
(b) Professionals



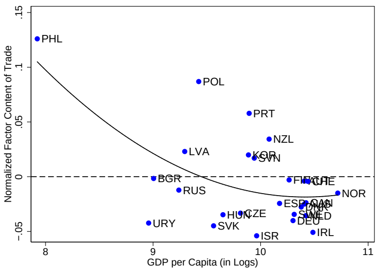
(c) Technicians & associate professionals



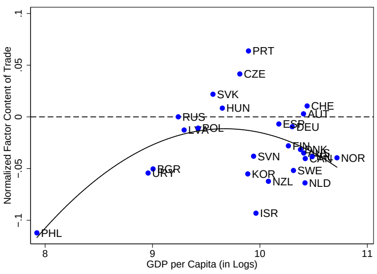
(d) Clerks



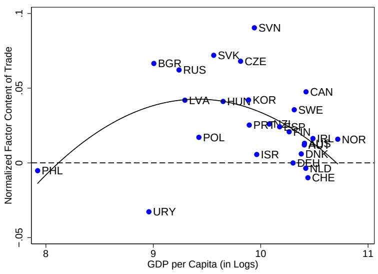
(e) Service workers & sales workers



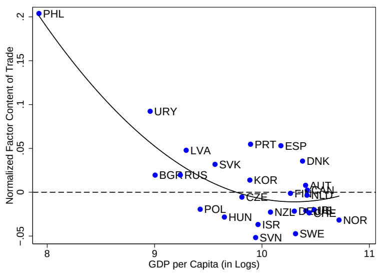
(f) Skilled agricultural workers



(g) Craft and related trade workers

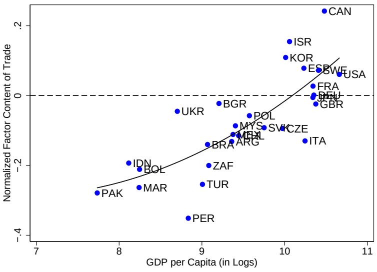


(h) Plant and machine operators

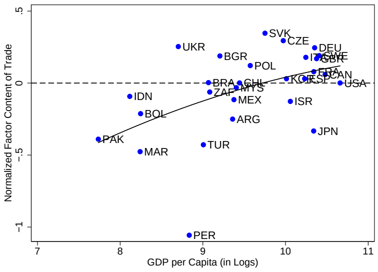


(i) Elementary occupations

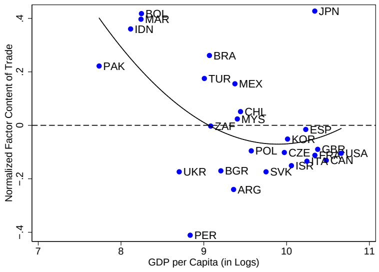
Figure 9.2. Factor content of trade and GDP per capita, GAP



(a) High-skilled workers



(b) Medium-skilled workers



(c) Low-skilled workers

Table 9.1. Test of Prediction 1 in a Probit framework[a]

	Dependent Variable: Individual-Specific Pro-Trade Dummy							
	ISSP 2003				GAP 2007			
	(1)	(2)	(2')	(3)	(4)	(5)	(5')	(6)
FA_i	0.033***	0.011	0.026**	0.028**	-0.009	0.014*	0.022*	0.021*
	(0.006)	(0.007)	(0.012)	(0.012)	(0.007)	(0.008)	(0.011)	(0.011)
Age_i	-0.002***	-0.001***	-0.000	0.000	-0.001***	-0.000*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Male_i$	0.076***	0.087***	0.087***	0.060***	0.022***	0.019***	0.023***	0.019**
	(0.006)	(0.006)	(0.010)	(0.011)	(0.005)	(0.005)	(0.008)	(0.008)
$Citizen_i$	-0.092***	-0.096***	-0.146***	-0.108**				
	(0.022)	(0.023)	(0.047)	(0.054)				
$Education\ (in\ years)_i$		0.010***	0.012***	0.008***				
		(0.001)	(0.002)	(0.002)				
$Income_i$				0.046***				0.017***
				(0.009)				(0.005)
Number of Observations	27,096	27,096	10,843	10,843	19,379	19,379	9,083	9,083
Number of Countries	28	28	26	26	28	28	20	20
Country Fixed Effects (γ_c)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects for Skill Levels (η_m)[b]	No	Yes	Yes	Yes	No	Yes	Yes	Yes
– Joint Significance[c]	–	278.3***	152.2***	64.6***	–	61.8***	14.5***	6.3
Additional Individual-Specific Controls[d]	No	No	No	Yes	No	No	No	Yes
Pseudo R^2	0.07	0.10	0.10	0.15	0.06	0.07	0.06	0.09
Log Pseudolikelihood	-14,153.43	-13,729.81	-5,911.02	-5,605.62	-7,807.78	-7,771.29	-3,545.26	-3,459.57

[a] The table gives the marginal effects for each explanatory variable on the probability of being pro trade, evaluated at the sample means. For the *FA* indicator variable, the table reports the effect of a discrete change from zero to one. Heteroskedasticity-robust standard errors are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

[b] Skill levels refer either to the nine different occupational positions (ISCO-88 classification at the one-digit level; ISSP) or to the six different levels of educational attainment (akin to ISCED-76/ISCED-97; GAP).

[c] Gives the χ^2 statistic for the test of joint significance of the fixed effects for skill levels.

[d] See Tables A.2 and A.3 in Appendix A for a description of all additional individual-specific control variables. Countries dropped in columns (2') and (3): Israel, United Kingdom. Countries dropped in columns (5') and (6): Canada, Czech Republic, France, Germany, Slovak Republic, Sweden, United Kingdom, United States.

Table 9.2. Test of Prediction 2 in a Probit framework[a]

	Dependent Variable: Individual-Specific Pro-Trade Dummy							
	ISSP 2003				GAP 2007			
	(1)	(2)	(2')	(3)	(4)	(5)	(5')	(6)
$\widetilde{F}_i$	0.378***	0.195***	0.346***	0.389***	-0.019	0.035**	0.057**	0.054**
	(0.061)	(0.076)	(0.125)	(0.128)	(0.014)	(0.017)	(0.025)	(0.025)
Age_i	-0.002***	-0.001***	-0.000	0.000	-0.001***	-0.000*	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Male_i$	0.076***	0.088***	0.087***	0.060***	0.022***	0.019***	0.024***	0.019**
	(0.006)	(0.007)	(0.011)	(0.011)	(0.005)	(0.005)	(0.008)	(0.008)
$Citizen_i$	-0.082***	-0.087***	-0.147***	-0.110**				
	(0.022)	(0.023)	(0.048)	(0.054)				
$Education\ (in\ years)_i$		0.010***	0.012***	0.008***				
		(0.001)	(0.002)	(0.002)				
$Income_i$				0.046***				0.016***
				(0.009)				(0.005)
Number of Observations	25,879	25,879	10,729	10,729	19,379	19,379	9,083	9,083
Number of Countries	26	26	25	25	28	28	20	20
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects for Skill Levels (η_m)[b]	No	Yes	Yes	Yes	No	Yes	Yes	Yes
– Joint significance[c]		261.36***	147.53***	62.03***	.	64.51***	16.58***	7.79
Additional Individual-Specific Controls[d]	No	No	No	Yes	No	No	No	Yes
Pseudo R^2	0.07	0.10	0.10	0.15	0.06	0.07	0.06	0.09
Log Pseudolikelihood	-13,512.18	-13,116.22	-5,850.43	-5,547.98	-7,807.8	-7,770.74	-3,544.55	-3,459.06

[a] The table gives the marginal effects for each explanatory variable on the probability of being pro trade, evaluated at the sample means. Heteroskedasticity-robust standard errors are given in parentheses. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

[b] Skill levels refer either to the nine different occupational positions (ISCO-88 classification at the one-digit level; ISSP) or to the six different levels of educational attainment (akin to ISCED-76/ISCED-97; GAP).

[c] Gives the χ^2 statistic for the test of joint significance of the fixed effects for skill levels.

[d] See Tables A.2 and A.3 in Appendix A for a description of all additional individual-specific control variables. Countries dropped in columns (2') and (3): Israel. Countries dropped in columns (5') and (6): Canada, Czech Republic, France, Germany, Slovak Republic, Sweden, United Kingdom, United States.

Appendix

A Data

All data used for the ISSP and the GAP pertain to the years 2003 and 2007, respectively, unless indicated otherwise.

Endowments. Data on country-specific endowments are taken from the ILO labor statistics. For countries for which ILO data are not available in the survey years, we take data from the closest applicable year and adjust for population growth from that year to the survey year, treating the endowment distributions as constant. Population data come from the World Development Indicators (WDI).

The ISSP sample uses data on the total economically active population by occupational position (nine occupations). The ILO data disaggregate labor into ten occupations in line with the major groups of the one-digit ISCO-88 classification.[19] We exclude "Armed forces", because its scope is independent of skill requirements. We drop countries for which data refer to the ISCO-68 classification, since it cannot be mapped with the ISCO-88 classification in any consistent way. We are left with 75 countries for the computation of world endowments, which account for roughly 75% of world GDP, 79% of world exports and 80% of world imports in 2003. We consider each of the nine occupational positions as a separate factor of production.

The GAP sample uses data on the total economically active population by levels of educational attainment (nine strictly hierarchical groups). The ILO data include information on educational attainment according to the International Standard Classification of Education (ISCED). We bring the older ISCED-76 classification in line with the recent ISCED-97 classification according to Table A.1. The 90 countries we use to compute world endowments account for 75% of world GDP, 80% of world exports and 84% of world imports in 2007. We map the information in the GAP survey with the ILO data according to Table A.1 and distinguish three labor inputs (high-skilled, medium-skilled, and low-skilled labor).

Technology. In order to compute technology parameters, we use WDI information on countries' GDP per capita. The country with the highest GDP per capita (Norway) provides the benchmark technology ($\delta_c = 1$).[20]. We define the country-specific efficiency parameter as the ratio of each country's GDP per capita relative to the GDP per capita of the benchmark economy.

[19] See `http://www.ilo.org/public/english/bureau/stat/isco/index.htm` (accessed on February 21, 2013) for details.

[20] Luxembourg and Qatar are excluded from these computations.

Factor content of trade. We compute the factor content of trade for each factor according to equation (9.5), given data on effective country and world endowments. Consumption shares are defined as $s_c = (Y_c - B_c)/Y_w$, where B_c represents country c's trade balance. Both GDP and trade data are from the WDI. World GDP, Y_w, is the sum of GDP over all countries for which endowment data are available.

Individual-level survey variables. Tables A.2 and A.3 give a comprehensive list of all individual-level survey variables that we employ in our regression analysis for the ISSP and the GAP, respectively. Whenever survey items allow for more than two ordered answer categories, we implement a binary coding for the corresponding variable, in order to mitigate the problem of extreme-response bias.

Table A.1. Harmonization of ISCED-76/ISCED-97 and GAP 2007 education data

ISCED-76		ISCED-97		GAP 2007		Production Factor (HOV)
X	No formal schooling	X	No schooling	0	No formal education; Incomplete primary education	Low-skilled labor
0	Education preceding the first level	0	Pre-primary education			
1	First level	1	Primary-education or first stage of basic education	1	Complete primary education	
2	Second level, first stage	2	Lower secondary education or second stage of basic education	2	Incomplete secondary education (technical/vocational)	Medium-skilled labor
3	Second level, second stage	3	Upper secondary education	3	Complete secondary education (technical/vocational); Incomplete secondary education (university-preparatory); Complete secondary education (university-preparatory)	
5	Third level, first stage (not equivalent to university qualification)	4	Post-secondary non-tertiary education	4	Some university education (without degree)	High-skilled labor
6	Third level, first stage (leading to university qualification)	5	First stage of tertiary education (not leading to research qualification)	5	University education (with degree)	
7	Third level, second stage (post-graduate)	6	Second stage of tertiary education (advanced research qualification)			

Table A.2. Coding of individual-level survey variables, ISSP 2003[a]

Variable	Description & Coding
Age	Respondent's age in years.
Male	Coded (1) male; (0) female.
Education (in years)	Respondent's education in years; upper bound at 20 years.
Income	Log of real income; calculated on the basis of income information in local currency and PPP conversion factors.
Citizen	Coded (1) citizen; (0) otherwise.
Unemployed	Coded (1) unemployed; (0) otherwise.
Social class	Subjective social class: six categories, higher values correspond to higher social classes.
Residence	Respondent's urban-rural self-assessment of the type of community: five categories, higher values correspond to more rural residences.
Product quality	"How much do you agree or disagree with the following statements? 'Free trade leads to better products becoming available in [respondent's country].' "; coded (1) "agree strongly", "agree"; (0) "neither agree nor disagree", "disagree", "disagree strongly".
Party affiliation	Respondent's party affiliation: categories (1) "far left" to (5) "far right".
Trade union	Trade union membership: coded (1) yes; (0) no.
Patriotism[a]	"How much do you agree or disagree with the following statements? 'I would rather be a citizen of [respondent's country] than of any other country in the world.' "; coded (1) "agree strongly", "agree"; (0) "neither agree nor disagree", "disagree", "disagree strongly".
Nationalism[a]	"How much do you agree or disagree with the following statements? 'Generally speaking, [respondent's country] is a better country than most other countries.' "; coded (1) "agree strongly", "agree"; (0) "neither agree nor disagree", "disagree", "disagree strongly".
National interests[a]	"How much do you agree or disagree with the following statements? '[Respondent's country] should follow its own interests, even if this leads to conflicts with other countries.' "; (1) "agree strongly", "agree"; (0) "neither agree nor disagree", "disagree", "disagree strongly".
Pride democracy[a]	"How proud are you of [respondent's country] in [...] the way democracy works"; coded (1) "very proud", "proud"; (0) "not very proud", "not proud at all".
Pride influence[a]	"How proud are you of [respondent's country] [in its] political influence in the world?"; coded (1) "very proud", "proud"; (0) "not very proud", "not proud at all".
Pride economy[a]	"How proud are you of [respondent's country] [in its] economic achievements?"; coded (1) "very proud", "proud"; (0) "not very proud", "not proud at all".
Pride social[a]	"How proud are you of [respondent's country] [in its] social security system?"; coded (1) "very proud", "proud"; (0) "not very proud", "not proud at all".

[a] Binary coding applied in order to mitigate problems of extreme-response bias.

Table A.3. Coding of individual-level survey variables, GAP 2007^a

Variable	Description & Coding
Male	Coded (1) male; (0) female.
Income	Log of monthly real income. Survey respondents sort themselves into income groups, based on (country-specific) lists of incomes. As a general rule, we compute individual income as the middle value of the income interval chosen by the individual, adjusted by PPP conversion factors from the World Development Indicators, expressed in logs, and, if necessary, converted to a monthly basis. More detailed information on this procedure is available upon request.
Unemployed	Coded (1) unemployed/not employed; (0) otherwise.
Religious	"Which one of these comes closest to your opinion, number 1 or number 2?"; coded (1) "Number 2 – It is necessary to believe in God in order to be moral and have good values"/NA/refused; (0) "Number 1 – It is not necessary to believe in God in order to be moral and have good values".
Economic awareness[a]	"Please tell me whether you completely agree, mostly agree, mostly disagree or completely disagree with the following statement. 'Most people are better off in a free market economy, even though some people are rich and some are poor' "; coded (0) "completely disagree", "disagree"; (1) "agree", "completely agree".
Informed	"Which of the following two statements best describes you: 'I follow INTERNATIONAL news closely ONLY when something important is happening' OR 'I follow INTERNATIONAL news closely most of the time, whether or not something important is happening'?"; coded (1) "Most of the time, whether or not something important is happening"; (0) "Only when something important is happening".
Sociotropic views[a]	"Please tell me whether you completely agree, mostly agree, mostly disagree or completely disagree with the following statement. 'Protecting the environment should be given priority, even if it causes slower economic growth and some loss of jobs.' "; coded (0)"completely disagree", "mostly disagree"; (1) "mostly agree", "completely agree".
Fears of cultural spill-overs	"I am going to read some phrases which have opposite meanings. Tell me which comes closer to describing your views."; coded (1) "It's bad that American ideas and customs are spreading around the world"; (0) "It's good that American ideas and customs are spreading around the world".
Nationalism[a]	"As I read another list of statements, for each one, please tell me whether you completely agree, mostly agree, mostly disagree or completely disagree with it. 'Our people are not perfect, but our culture is superior to others."; coded (0) "completely disagree", "mostly disagree"; (1) "mostly agree", "completely agree".
Fears of international competition	"Turning to China, overall do you think that China's growing economy is a good thing or a bad thing for our country?"; coded (1) "bad thing"; (0) "good thing".

[a] Binary coding applied in order to mitigate problems of extreme-response bias.

Table A.4. Descriptives on survey, technology, and endowment data, ISSP 2003[a]

Country	N	$\overline{y}_i$	δ_c	$\overline{FA}_i$	Factors with $F_{mc} > 0$[b]
Australia	2,098	0.14	0.73	0.68	1,2,3,4,8
Austria	954	0.23	0.73	0.71	2,3,4,7,8,9
Bulgaria	945	0.12	0.18	0.43	2,8,9
Canada	1,162	0.27	0.74	0.70	2,3,4,8,9
Czech Republic	1,183	0.26	0.40	0.59	2,3,7,8
Denmark	1,232	0.48	0.71	0.50	2,3,8,9
Finland	1,263	0.39	0.64	0.43	2,3,8
Germany	1,205	0.33	0.66	0.30	2,3
Hungary	970	0.14	0.34	0.47	2,7,8
Ireland	1,042	0.27	0.79	0.50	1,2,4,8
Israel	1,037	0.25	0.47	0.45	2,4,8
Japan	1,024	0.28	0.64	0.60	1,3,4,7
Latvia	981	0.16	0.24	0.37	2,6,8,9
Netherlands	1,714	0.40	0.74	0.67	1,2,3,4
New Zealand	996	0.21	0.53	0.64	1,2,4,6,8
Norway	1,383	0.36	1.00	0.58	2,3,5,8
Philippines	1,180	0.11	0.06	0.42	6,9
Poland	1,219	0.12	0.27	0.28	2,6,8
Portugal	1,394	0.19	0.44	0.54	6,7,8,9
Russia	2,212	0.21	0.23	0.77	2,3,7,8,9
Slovakia	1,152	0.10	0.32	0.62	3,7,8,9
Slovenia	1,056	0.28	0.46	0.42	2,3,6,8
South Korea	1,295	0.25	0.44	0.60	4,5,6,8,9
Spain	1,159	0.15	0.58	0.35	2,8,9
Sweden	1,102	0.35	0.67	0.65	2,3,5,8
Switzerland	1,021	0.43	0.76	0.64	2,3,4,7
United Kingdom	838	0.17	0.67	0.71	1,2,3,4,8
Uruguay	1,049	0.13	0.17	0.23	9

[a] The table reports the number of observations (N) as well as descriptive statistics for the pro-trade dummy variable, y_i; the technology index, δ_c; the indicator for factor abundance FA_i; and the factor content of trade, F_{mc}. Bars indicate country means. Chile, France, South Africa, and Venezuela participated in the ISSP 2003 but are excluded due to lack of ILO endowment data. The United States are excluded due to missing endowment data for some occupations. West Bank & Gaza is excluded due to missing trade data.

[b] Factors $m = 1, \ldots, 9$, are (1) "Legislators, senior officials and managers", (2) "Professionals", (3) "Technicians and associate professionals", (4) "Clerks", (5) "Service workers and shop and market sales workers", (6) "Skilled agricultural and fishery workers", (7) "Craft and related trade workers", (8) "Plant and machine operators and assemblers", and (9) "Elementary occupations".

Table A.5. Descriptives on survey, technology, and endowment data, GAP 2007[a]

Country	N	$\overline{y}_i$	δ_c	$\overline{FA}_i$	Factors with $F_{mc} > 0$[b]
Argentina	700	0.78	0.24	0.00	none
Bolivia	791	0.84	0.08	0.23	1
Brazil	958	0.74	0.18	0.85	1,2
Bulgaria	461	0.95	0.21	0.60	2
Canada	485	0.85	0.73	0.97	2,3
Chile	769	0.91	0.26	0.83	1,2
Czech Republic	446	0.80	0.44	0.72	2
France	500	0.79	0.64	0.83	2,3
Germany	495	0.86	0.65	1.00	2,3
Indonesia	949	0.75	0.07	0.34	1
Israel	865	0.93	0.48	0.49	3
Italy	450	0.77	0.58	0.67	2
Japan	683	0.80	0.64	0.06	1
Malaysia	670	0.95	0.25	0.24	1
Mexico	796	0.80	0.24	0.36	1
Morocco	864	0.80	0.08	0.71	1
Pakistan	1,728	0.95	0.05	0.47	1
Peru	774	0.84	0.14	0.00	none
Poland	468	0.83	0.30	0.60	2
Slovak Republic	440	0.85	0.35	0.69	2
South Africa	949	0.91	0.18	0.00	none
South Korea	681	0.90	0.46	0.94	2,3
Spain	456	0.91	0.57	0.67	2,3
Sweden	471	0.91	0.68	1.00	2,3
Turkey	830	0.85	0.17	0.56	1
Ukraine	478	0.94	0.12	0.64	2
United Kingdom	467	0.84	0.66	0.42	2
United States	964	0.63	0.88	0.97	2,3

[a] The table reports the number of observations (N) as well as descriptive statistics for the pro-trade dummy variable, y_i; the technology index, δ_c; the indicator for factor abundance, FA_i; and the factor content of trade, F_{mc}. Bars indicate country means. The following countries participated in the GAP 2007 but are excluded due to lack of ILO endowment data: Bangladesh, China, Côte d'Ivoire, Egypt, Ethiopia, Ghana, India, Jordan, Kenya, Lebanon, Mali, Nigeria, Russian Federation, Senegal, Uganda. Kuwait is excluded since its GDP per capita is not commensurate with its state of technology. Due to missing trade data, observations from West Bank & Gaza were also excluded from the sample.

[b] In the HOV model, factors $m = 1, 2, 3$, are (1) low-skilled labor, (2) medium-skilled labor, and (3) high-skilled labor; see Table A.1.

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Chapter 10

Summary and outlook

This thesis presents original research on three questions in international trade and migration. The first question asks which firms source their inputs intra-firm when engaging in offshoring, i.e., when moving the source of their formerly domestic input supply abroad. I present evidence based on Spanish firm-level data that supports recently developed models of global sourcing in the spirit of the property rights theory of the firm. An interesting avenue for future research could be to incorporate credit constraints into the hold-up model of global sourcing. Credit constraints have the potential to severely restrict the global sourcing activities of firms, and to hamper global economic integration. The Global Financial Crisis led to a drastic (and unforeseen) reduction in credit supply worldwide. This is a quasi-natural experiment, and it would be interesting to see how firms adjusted to this credit supply shock along the ownership dimension of sourcing as well as the locational dimension of sourcing.

The second question addressed in this thesis has to do with the determinants of international migration. I ask how a pool of existing migrants (a 'migrant network') influences the size and the skill composition of subsequent migration flows. Migrants feel attracted to destinations hosting other migrants that are culturally alike, for example because they receive assistance in finding jobs or housing. I show in this thesis that the network effect is strong among co-national migrants, that it biases the skill content of migration flows towards the low-skilled individuals, and that it is present even among migrants from 'adjacent' nationalities. Preliminary extensions of my work presented in this thesis point towards significant cross-country differences in the effect of migrant networks. I am concerned about how these differences can be reconciled with the characteristics of both the countries of origin and the countries of destination. The results of my research will lead to more informed statements about the structure of international migration flows.

The final question discussed in this thesis derives from the field studying the political economy of trade policy. The Global Financial Crisis has prompted governments to implement policies that can slow down (and be harmful to) the process of globalization; see the recent report "The gated globe" in The Economist, Oct 12th, 2013. In this thesis, I have asked whether public attitudes towards trade and globalization, an important ingredient in the government's decision problem, can be explained by standard economic theory. I show that comparative advantage in the neoclassical trade model can explain the formation of protectionist attitudes at the individual level. In future work, I plan to examine public attitudes towards China, a global player that has re-entered the stage of the world economy and that is transforming global production and consumption patterns in a profound way. I would like to understand which model of the economy best explains differences in attitudes towards China's growing economy, both across countries and across individuals.