Who Gains? Who Loses?

An Empirical Analysis on Wages, Inequality, and Trade

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Contents

List of Tables

List of Figures

List of Abbreviations

2SLS	Two-Stage Least Squares
BLS	Bureau of Labor Statistics
BIBB	Bundesinstitut für Berufsbildung
CEPII	Centre d'Etudes Prospectives et d'Informations Internationales
EMU	European Monetary Union
EU	European Union
FDI	Foreign Direct Investment
GDP	Gross Domestic Product
HIC	High Income Country
IAB	German Institute for Employment Research
ILC	International Labor Comparison
ILO	International Labor Organization
IMF	International Monetary Fund
ITS	International Trade in Services Statistics
IV	Instrumental Variable
LIC	Low Income Country
LMIC	Lower Middle Income Country
MiDi	Micro Database Direct Investment
OECD	Organization for Economic Co-operation and Development
OLS	Ordinary Least Squares
UBS	United Bank of Switzerland

UK	United Kingdom
UMIC	Upper Middle Income Country
UNCTAD ...	United Nations Conference on Trade and Development
US	United States
USA	United States of America
USD	US Dollar
WDI	World Development Indicators

Chapter 1

Introduction

Literature on the determinants of wages, wage setting and the distribution of wages is vast. Katz and Autor (1999, p. 1) argue that "studies of the wage structure are as old as the economic profession". However, due to a lack of comprehensive, international comparable wage data many studies analyzing wage distributions focus either on a small number of countries, or on a small number of occupations (see e.g. Goos & Manning, 2007, and Gosling, Machin, & Meghir, 2000 for the UK, or Dustmann, Ludsteck, & Schönberg, 2009, and Spitz-Oener, 2006 for Germany). Wage inequality also plays an important role in the discussion of the effects of trade and foreign direct investment on income inequality (see e.g. Sachs & Shatz, 1996 for the United States, Haskel & Slaughter, 2001 for the United Kingdom, or Beyer, Rojas, & Vergara, 1999 for Chile). Furthermore, wages indicate labor costs are therefore a key variable in the international trade research.

In order to investigate these important issues, I rely on a unique set of data and make a novel contribution to the analysis of international wage patterns. Thus, this thesis contributes to the existing discourses in four different ways. First, ***Chapter 2*** introduces a comprehensive wage database which provides the basis for the empirical analysis in the following chapters. Second, I present new evidence on occupational wage distribution and the channels through which technological change affects wages in ***Chapter 3***. Third, the effects of trade and foreign direct investment on the degree of wage inequality are determined in ***Chapter 4***. Fourth, in ***Chapter 5*** of this thesis, I change the perspective of wages. While wages and wage distributions were of main interest in the previous chapters, wages now serve as measures of labor costs to analyze the determinants of service offshoring. Finally, ***Chapter 6*** summarizes the main findings of this thesis and concludes.

The next paragraphs give a more detailed overview of the following chapters, including major findings.

An Almost Ideal Wage Database

Since 1924, the International Labor Organization (ILO) has conducted an annual wage survey called *October Inquiry*, which contains detailed annual wage data for 161 occupations in over 130 countries. Although the wage data are freely available for research, they are rarely used. Freeman and Oostendorp (2000, 2001) adjusted and standardized the *October Inquiry* in an extensive research project, which I update. In ***Chapter 2*** of this thesis, I provide documentation about the several steps taken to transfer the data into a comparable and usable format. I describe the way I converted, standardized and imputed the data and present first results on developments in the wage structure between and within countries and occupations. ***Chapter 2*** is based on a working paper (see Harsch & Kleinert, 2011) which was updated for this thesis.

The standardization and imputation process leads to a comprehensive database which allows analyzing worldwide wage distribution based on comparable wage data for a large number of countries and occupations. To the best of my knowledge, the *October Inquiry* is the most comprehensive wage database in the world to date. The required standardization approach is extensive, but it does not change the structure of the data. Neither does the imputation which is necessary to fill in a large number of gaps in the *October Inquiry* database.

A first analysis of wage distributions shows decreasing wage spreads between countries and stable differences among occupations within countries over time. These falling differences between the countries seem to be mainly driven by decreasing differences in the wages of low skilled occupations. The wages of the high skilled workers, in contrast, still differ between countries. A more detailed analysis of occupational wage distributions is given in ***Chapter 3*** which is introduced in the following paragraph.

Evidence on Occupational Wage Distribution

The adjusted *October Inquiry* database provides a robust basis for the analysis of international wage patterns. In ***Chapter 3*** of this thesis, I present a comprehensive study on occupational wage distributions and wage inequality. I focus on the question whether and to what extent wages differ across and within occupations. Moreover, I analyze whether increasing wage spreads are affected by technological change. To motivate the empirical approach, I introduce a short theoretical model of wage setting and occupational wage differences following Firpo, Fortin, and Lemieux (2011). On the one hand, the model describes the theoretical mechanism of wage setting, while, on the other hand, the model gives an idea of the channels through which technological change affects wages.

In a first empirical analysis, I test the implications of the theoretical model for the member states of the OECD member states, the EU, the United States, and Germany. Proceeding like this is of interest for the empirical validity of the theoretical model. Moreover, I can give a more detailed introduction to the *October Inquiry* database and describe the development of wage inequality. The empirical findings verify mostly the implications of the theoretical model as I can show stable wage differences with respect to the skill level of workers. Nevertheless, a key finding is that even if workers carry out the same occupation, wages differ between industries. This is not fully consistent with the theory of Firpo et al. (2011).

In a second step, I focus on the analysis of German wage structures. Therefore, I refer to the "nuanced version" of the skill-biased technological change as a possible explanation for an increasing wage inequality. Autor, Levy, and Murnane (2003) argue that it is not predominantly the skill level that divides workers into "winners" or "losers" of technological change, but the series of tasks required by the occupation carried out. I use the introduction of computers as a measure for technological change. Following Spitz-Oener (2006), there are two hypotheses that can be tested empirically. First, computers substitute for workers that perform manual and cognitive routine tasks. Second, computers complement workers performing analytical and interactive activities.

I use a modified difference-in-difference estimation approach to test these hypotheses. Therefore, I identify a group that receives the treatment "introduction of computer technologies" during a particular time period measured on the occupational level. Results are compared to an "un-treated" control group. Both hypotheses are supported by the estimated results. I find evidence that the series of tasks workers perform in a particular occupation is the channel through which technological change affects wages, and not the skill level. Workers in occupations that are characterized by non-routine analytic tasks, for example researching, analyzing, evaluating, or planning, gain after the introductions of computers. Independently from the skill level, workers who perform routine cognitive tasks like calculating or bookkeeping experience a wage loss compared to the control group. However, I do not find evidence for the hypothesis formulated by Autor, Katz, and Kearney (2006) or Michaels, Natraj, and Reenen (2010) that primarily medium skilled workers lose.

Evidence on Trade, FDI, and Wage Inequality

However, it is certainly not only technological change that affects the degree of wage inequality. The effects of globalization on wage spreads and wage inequality are subject of numerous studies in the economic literature and are also central to many current public discussions. In ***Chapter 4*** of this thesis I focus on the question, whether trade and foreign direct investment (FDI) affect the degree of wage inequality. One shortcoming of previous studies is a lack of robust knowledge about the actual degree of wage inequality across countries for comparable occupations. Using the newly standardized *October Inquiry* database introduced in ***Chapter 2*** allows analyzing the effect of trade and FDI on the degree of wage inequality across countries in a more comprehensive way.

To provide the theoretical basis for the empirical analysis, I refer to Feenstra and Hanson (1995) who show theoretically that capital flows lead to increasing wages of high skilled workers in countries with different factor endowments. Under certain conditions, also low skilled workers can gain. In the empirical analysis, I look at the effects of trade and FDI on the degree of wage inequality in the OECD member states. I then compare the results for the full OECD sample to other country samples (e.g. EU member states, High Income Countries (HIC), or the entire country sample). To account for the endogeneity of trade, FDI, and wage inequality, I follow Frankel and Romer (1999) and generate a geographical component which is used as instrumental variable in the regression approach.

I find evidence that trade activity leads to a small but statistically significant increase in wage inequality in the OECD. In contrast, results are not clear-cut for the EU. Moreover, there are significant negative effects of trade on relative wages in non-manufacturing sectors in the OECD, presumably a sign of increasing inequality. Smaller effects with the same sign are observed for the EU, HIC, and the total number of countries in the dataset. In contrast, I do not observe an increasing wage inequality in manufacturing sectors. The results indicate that an increase in the trade volume leads to a significant increase in wage inequality. Surprisingly, using the analogous instrumental variable approach to determine the effect of FDI on wage inequality shows no statistically significant results. This is a puzzling result, which might be due to the fact that the data does not allow differentiating between vertical and horizontal foreign investment.

Determinants of Service Offshoring

The study presented in ***Chapter 5*** is based on a joint research project (see Biewen, Harsch, & Spies, 2012). We provide evidence on how German multinational firms restructured their service imports during the last decade. One of our main hypothesis is that cost pressures may have forced firms to offshore service tasks that were previously conducted in-house and therefore to become service importers.

Making use of new micro-level data on service imports of German multinationals from 2003 to 2008, we assess the determinants of service offshoring along the extensive (a firm's probability of becoming a services importer) and intensive margins (the level of sourcing services). We use cross-country and cross-sectoral occupational wage data from the *October Inquiry* database introduced in ***Chapter 2***. The fact that individual service transactions can be matched with sectoral wage information in each country allows us to study the impact of wages in much more detail than previously done in the literature.

In particular, we evaluate how internal frictions in terms of a lower sales level (per employee) and external frictions in terms of a reduced availability of credits co-determine the likelihood and the extent of sourcing services from abroad. By focusing on the analysis of the determinants of service imports of German multinationals, we complement existing studies that have either described the patterns of service trade and traders or that have investigated the determinants of manufacturing goods imports and exports (see e.g. Bernard, Jensen, Redding, & Schott, 2007 for the United States, Mayer & Ottaviano, 2008 for several European countries, or Eaton, Kortum, & Kramarz, 2004 for France).

First, we find that the probability of a firm becoming a service importer is decreasing if firms are already under cost pressure. In contrast, firms intensify existing linkages of service imports in times of a decrease in sales or sales per employee. Second, financial constraints, which play a major role for goods trade, do not seem to have any significant effect on service imports. These results support the hypothesis that the observed crisis-resilience of service trade stems from increased pressures to save on variable costs through offshoring (see e.g. Borchert & Mattoo, 2009). Moreover, a lower dependence on external finance also seems to stabilize trade in services.

Finally, ***Chapter 6*** summarizes the main findings of this thesis and gives an outlook on future areas of research in the fields of wage distribution, wage inequality, and effects of trade.

Chapter 2

An Almost Ideal Wage Database[1]

2.1 Introduction

The lack of comprehensive, international comparable wage data has been complained for a while and has made the analysis of wage growth and inequality for a larger sample of countries hardly possible. Freeman and Oostendorp (2000, 2001) have started a project of wage data harmonization making use of the *October Inquiry* database of the International Labor Organization (ILO). They made this rather unused data available for a wider group of researchers by cleaning, correcting, and normalizing the data in order to make the observations comparable across countries and occupations. Unfortunately, the data are still not widely used. Therefore, I try a new start in preparing the *October Inquiry* closely following the procedure of Freeman and Oostendorp (2000, 2001). In this chapter, I describe the steps taken to transfer the data into a comparable and usable format.

Moreover, I decided to provide four different STATA datasets based on the *October Inquiry* and make them available for other researchers because of three reasons.[2] First, working with international comparable wage data is an improvement for re-

[1]This chapter is based on a working paper, see Harsch and Kleinert (2011). The concept for this paper was developed jointly. The empirical analysis was carried out by the author of this thesis. Writing was shared between the authors.

[2]The datasets can be downloaded at the following webpage: http://www.wiwi.uni-tuebingen.de/lehrstuehle/volkswirtschaftslehre/international-macroeconomics-and-finance/research/wages-around-the-world.html

search. Second, harmonization of the *October Inquiry* database was really hard work and very time-consuming, therefore I want to prevent others from that work. Third, I believe that there is not one dataset suitable for the different questions researchers have with respect to wage data.

The first dataset I provide is a more or less raw dataset, corrected only for structural displacements and typos. The second dataset is corrected and cleaned for labeling mistakes. Moreover, I account for country-specific single events such as a currency reform. I describe the corrections to illustrate the changes I made, and to give everyone the chance to correct my work (and therefore the data), or to let me know about specific events not yet captured. Third, I use the corrected data to construct a dataset that reports standardized wages for every combination of country, year and occupation. Following Freeman and Oostendorp (2000, 2001), I chose men's average monthly wage as standard. I provide a standardized dataset that is reduced in observations by reporting only *one* wage for each country-year-occupation combination. In a fourth step, I enlarge the dataset by reducing the numerous missing observations. For this purpose, I impute the predicted values from a linear prediction. This greatly increases international comparability of the data because the wage data of many countries show gaps over time and across occupations.

In this chapter, I describe how I have transformed the ILO *October Inquiry* into a consistent database and give a short overview over the wage pattern around the world. In section 2.2, I introduce the *October Inquiry* dataset. I describe the challenges posed by the database and illustrate the correction procedure and the standardization process in section 2.2.1. In section 2.2.2, I briefly discuss international wage patterns and their evolution over time using the results from the standardization procedure. Section 2.3 gives some descriptive statistics of the standardized data. Section 2.4 contains the description of the data imputation. In section 2.5, I compare the *October Inquiry* to wage data provided by the Bureau of Labor Statistics (BLS) and the United Bank of Switzerland (UBS). Section 2.6 summarizes the work and gives an outlook on future work with the data.

2.2 Data

Since 1924, the International Labor Organization has conducted an *October Inquiry* to obtain data on wages and hours worked for a large number of countries and occupations all over the world. Every year, the ILO sends questionnaires to national governments asking for detailed information about wages, hours of work, and occupations. This leads to an annual wage survey which contains data covering up to 161 occupations[3] in 49 industries for more than 130 countries. As there are large gaps in the data, it is only usable from the beginning of the 1980s on, although a larger period of time is available. For my analysis, I choose the time period from 1983 until 2008. Although data coverage is rather high after 1980, the yearly country coverage is far from the maximum of 134 countries that report wages in the *October Inquiry*. Most countries reported wages between the middle of the 1980s and the turn of the millennium. Only five countries (Germany, Mauritius, Norway, Philippines, and Puerto Rico) report wages for all 26 years.

Theoretically, the approach of the ILO could result in an "ideal" database. Comparing wages for 161 occupations in 135 countries all over the world for a large period of time would promise an improvement in the analysis of wage growth and wage inequality. However, the *October Inquiry* database is far away from being useable for research purposes. The results of the survey are published without any correction or adjustment. Cleaning and correcting the data is very time-consuming. Moreover, as the reported wages differ, for instance, in reference time and in gender, wages are not comparable. To give a few examples: Germany reports hourly, daily, or monthly minimum wages as an average for both sexes. China reports average yearly or monthly wages for men, women and averages for both sexes. Canada reports hourly minimum, maximum or averaged wages for men, women, and/or both sexes. Table 2.4 shows the different reference time periods and the respective number of observations. As the data is at this time neither comparable across countries nor within countries, or occupations, "the survey is one of the least widely used sources of cross country data in the world" (Freeman & Oostendorp, 2000, p. 5).

[3] Theoretically there are 159 different occupations, but there are three kinds of occupation 139 *Government Executive Official*. I handle them as three different occupations.

As I am convinced that supplying comparable wage data for such a large number of countries yields an improvement for economic research, I transformed the *October Inquiry* into a usable and comparable form, which allows analyzing wage growth, wage gaps, and inequality in a comprehensive way. Yet, that required a comprehensive data correction and standardization procedure which is described in the following section.

2.2.1 Data Corrections and Standardization Process

As countries report the wage data in numerous ways, the *October Inquiry* wage observations are mostly not comparable. Neither within nor across countries, wages are reported consistently. Even within countries or for a particular occupation, wages are not comparable. Therefore, a considerably correction and standardization process is necessary.

Data Structure

The data is very unbalanced and the reported wages differ in various dimensions. First, wages differ in the time they refer to. Within six different reported reference time periods (hourly, daily, fortnightly, weekly, monthly, and yearly wages), there are several other structures: for example minimum, average, and median wages.[4] Germany, for instance, reports mostly monthly minimum wages from collective bargaining agreements, the United States report median wages for hours or years, the Netherlands maximum yearly wages, and India maximum daily wages. Altogether the database reports 33 different time periods. The time period is in some cases specific to a particular country-occupation combination. Germany, for example, reports daily wages for only three occupations (miner in coalmining industry, miner in other underground industry, underground helper) and thus for only 1.7% of all German wage data. For most other occupations, monthly wages are reported. On average, every country reports wages in four different time periods, in maximum in 16 periods, and in minimum one time period.

[4]I use the terms *time period* and *reference time period* interchangeably throughout my thesis. Both terms refer to the time period a wage is paid for.

Second, there is no regularity in reporting wages with respect to gender. There are three gender categories: men and women (averaged wages for both sexes), men, and women. Yet, if two countries report the minimum monthly wage of a cook in the year of 2003, these two wages are hard to compare if they differ in the reported gender, as the gender wage gap poses a systematic bias in the comparison. The raw data contains 134 countries of which 98 report wages in all three gender categories, 21 report in two, and 15 in only one gender category.

Third, countries do not report the data continuously from 1983 until 2008. Moreover, even if countries report wages for every year, wages were not necessarily reported for all 161 occupations. In fact, the database contains two types of gaps: time gaps and ”occupation” gaps. Table 2.1 gives a first impression of the unbalanced structure of the raw data. On average, every country reports a total number of 1,641 wage observations for 109 occupations in ten years. Each of the 161 occupations is reported 1,397 times on average. There are 13,024 observations per year, and 6,816 wages reported per reference time period. But, as Table 2.1 shows, the variations are large. Most countries report wages in the years 1987 and 1990, and least countries report in 2008. There are 96 countries which report wages in the most often used time period (*per month, average*). On average, 20 countries report wages for each of the 33 different time periods. These differences in reporting the data makes the comparison of the wages as they are released in the *October Inquiry* database impossible.

Data Corrections

The described differences in reporting wage observations complicate the comparison of the data a lot. Yet, the differences affect the data in a systematic way so that standardization can be achieved. Miss-codifications and single events such as currency reforms for which the data must be corrected are more challenging. Because the *October Inquiry* is published without any correction or adjustment, I perform an extensive cleaning procedure which is very time-consuming.

First, I identify unnatural growth in wages over time. For every country-occupation combination, I check wages in local currency that changed from one period to the following in an unnatural way and stayed on that level (what might result from a currency reform or a change in the reported time period) or return again on the former level in the next period (what could be result from an outlier, error or miss-coded data). I find large irregularities in the data. In some cases, the hourly wage is as high as a monthly wage in the same country and year, or a wage that is labeled as a monthly wage is ten times higher than in comparable occupations. That makes it necessary to analyze detailed wage growth for every country-occupation combination for the whole period of time, using information from the footnotes the ILO gives to almost every single wage observation.[5] I find a high need for adjustment and correction of such irregularities by relabeling and redefining payment periods, or adjusting for currency reforms. In some cases no correction is possible, thus I drop the observations or the country as a whole. The countries which were dropped are marked with dots in Tables 2.2 and 2.3 which give the whole number of observations by country for the several steps of the correction and standardization process.

The countries of the European Monetary Union (EMU) changed their currencies from national currencies to the Euro in the year 1999 or later. That makes comparison over time rather cumbersome. I therefore decide to convert the national currencies into Euros for all observation of EMU countries before 1999 using the Euro conversion rate. Thus, the standardized wage is a Euro wage even if it refers to a year before the introduction of the Euro. I proceed in the same way for all countries with currency reforms in the time period 1983-2008. Therefore, the standardized wages are in the current local currency of every country.

Although the reported wages are labeled correct with respect to time period and currency after the correction process, the data is far from being comparable within and across countries, or occupations. The wage data has to be transformed into a usable ”standard form” in order to create a wage structure that is based on comparable wages.

[5]Footnotes contain, for example, information whether data source or reported reference time period changed in a particular country, year, and occupation.

Standardization Process

After the correction and cleaning procedure, the database contains wage data for 26 years, 112 countries, and 161 occupations. Wages are listed in more than thirty different time dimensions, for men, for women, or averages for both sexes. Thus, the task is to normalize the data in order to create one single comparable standard wage. I follow Freeman and Oostendorp (2000) and choose the average monthly wage of a man as a standard form, which is the most common form reported. The standardization procedure assumes that all deviations from an observed average systematic effect are random for all observations.

I start the standardization by simplifying the reported time periods. I am aware of the risk of losing information, for example, if some occupations are systematically paid for a particular time period. But there is not enough variation in the data to keep the more than thirty time periods. Thus, I multiply a weekly wage with factor 4.33, a fortnightly wage with factor 2.16 and divide a yearly wage by twelve to transform the data into monthly wages.

The standardization process requires the reported time periods not to be specific to a particular country. If only a few countries report wages for a specific time period (for example *prevailing hourly wages*) or one country dominates a particular time period (only the United States report *median hourly wages*), the wages of these time periods can not be standardized independently from the country effect. I therefore merge these time periods with a closely related time period. As there are, for example, only few observations that are labeled *per hour worked, minimum.*, the observations are grouped to *per hour, minimum.*. That reduces the number of subcategories of time periods to 18. Table 2.4 shows the number of observations reported per time period for the raw and the cleaned data.

As mentioned above, I choose the most common form of the reported wage as the standard form: the average monthly wage of a man. Although the average monthly wage of a man is the most common form, it applies only to ten percent of the data. I nevertheless dare to undertake the standardization procedure that translates the wage of each country-year-occupation observation, which is reported for another time period and/or gender, to man's average monthly wages. Thus, controlling for country, year, and occupation effects allows to compute factors, that contain the deviation from any time period-gender combination to average monthly wages of men.

Suppose each wage observation W (in logs) is the sum of the (unobserved) log wage in standard form (monthly average (ma) for a man (men)), W^*, and an adjustment coefficient W^a. The adjustment coefficient contains the deviation of the observed log wage from the standard wage, W^*. The observed wage, W, can then be described as:

$$W_{j,t,o,td,s} = W^*_{j,t,o,ma,men} + W^a_{td,s} + v_{j,t,o,td,s}, \tag{2.1}$$

where j refers to the country ($j = 1, ..., 112$), t is the year ($t = 1983, ..., 2008$), o denotes the occupation ($o = 1, ..., 161$), td is the time period (for example *per hour, average.*, $td = 1, ..., 18$), s denotes the sex ($s = average, men, women$), and $v_{j,t,o,td,s}$ is an error term.

The vector of the adjustment coefficients, $W^a_{td,s}$, contains the conversion factors of any given time period-gender structure to average monthly wages for man for any given country-year-occupation observation. The adjustment coefficients can be calculated if the differences of the reported wages for a particular time period and gender to the standard wages are known, thereby controlling for country, year, and occupation effects. The difference between the time period and the gender for the reported wages and the standard wage can be derived from a regression framework that explains wages by the time period, gender, occupation, year, and country effects. I chose country-year pairs instead of average time effects over all countries and average country effects over all years.

The regression approach for the observed wage is given by equation (2.2) and estimated taking into account that the residuals are heteroscedastic (Wooldridge, 2001). I cluster around country-occupation pairs.

$$W_{jt,td,o,s} = D_{td}\alpha_{td} + D_s\alpha_s + D_o\alpha_o + D_{jt}\alpha_{jt} + v_{jt,td,o,s}, \tag{2.2}$$

where D_{td} is a row vector of eighteen time periods, with *per month, average* being the reference period. D_s is a row vector of the gender dummies, where *men* is chosen as reference. D_o denotes a row vector of 161 occupation dummies, taking *cook* as reference, which is the occupation with the most observations. Finally, D_{jt} contains 1184 country-year dummies. I chose the United States in 2006 as reference. The vectors α_{td}, α_s, α_o, α_{jt} give the systematic deviation of the observed wages from the standard wage, respectively. The results are presented in the following section.

2.2.2 Results and Interpretation of the Coefficients

The results of standardization process allow to transform the *October Inquiry* into a form that makes cross-country comparisons possible. Moreover, interpreting the estimated coefficients makes it possible to analyze the differences in wages explained by the time periods of payment and the gender wage gaps. In this section I present and discuss the results.

The regression estimates and the resulting adjustment coefficients of the different reported time periods are presented in Table 2.5. Column one gives the regression results and standard errors of equation (2.2), column two refers to the computed adjustment coefficients. As the regression equation is estimated in logs, I use the exponential function to compute adjustment coefficients of the reference period and the gender effect. These adjustment coefficients are used to convert the observed wages in their standard form, as they contain the difference of the observed from the standard wage. The adjustment coefficient is one, if the time has the standard form *per month, average*. If the observed wage is not of that standard form, it has to be multiplied with the adjustment coefficient to yield the average monthly wage. Equation (2.2) explains a great part of the variation in the data. The adjusted R^2 is 0.987. That confirms that the standardization procedure is not afflicted with large errors. The dummy variables have the correct sign and are of the right magnitude. The coefficients suggest that the adjustments are plausible. I find, for example, an adjustment coefficient that is lower than one for maximum monthly wages and higher than one for minimum monthly wages. If, for example, the minimum wage per hour applying to women in a particular country, year and occupation is converted to the standard monthly wage of a man, the observed wage must be multiplied by 188.757 for *Per hour. Minimum.* and 1.187 for women, which yields an adjustment coefficient of 224.055.

In the regression analysis, the time adjustment coefficient is based on an averaged effect over all countries. I am aware of the fact, that people in less developed countries might, for instance, work more than 20 days a month. As there is not enough variation in the data, it is not possible to estimate time coefficients depending on the development level of countries.[6]

The gender adjustment coefficients presented in Table 2.6 reveal that mens' wages are about 18 percent higher than those of women and about three percent higher than those of the average of men and women. In my analysis, the gender coefficient is also constant over time and across different groups of countries. In future work, I will have a closer look at the changes of the gender factor over time and between different country groups and for the whole sample. Moreover, there are possibly pronounced differences between countries that are expected to vary with the level of development.

Applying the appropriate adjustment factors to all observed wages yields standard wages for all country-year-occupation combinations. Many country-year- occupation combinations occur more than once in the data, because the countries report wages for more than one time period (e.g. *per month, average* and *per month, minimum.*) or because countries report wages for more than one gender for a particular year-occupation combination. I keep the standardized wage with the shortest way to average monthly wages for men, but take into account the precision of the estimated parameter. The other country-year-occupation observations are dropped. Thus, I end-up with a dataset that holds only one observation for each country-year-occupation combination. That reduces the number of observations in the dataset to 93,535, but leaves the number of countries and year-country-occupation combinations unchanged (see Table 2.7).

[6]The ILO also collects data about hours worked. It would possible to use that information when estimating adjustment coefficients for different groups. Unfortunately, there is a huge requirement of cleaning and correcting the data, too.

2.3 A First Glance: Some Descriptive Statistics

To give a first impression of the data, I present some summary statistics in this section. The data is still very unbalanced, as it contains many gaps in time and for particular occupations. In combination with the different dimensions of the data, presenting descriptive statistics is rather difficult.

First, Table 2.8 contains unweighted averages of annual growth rates, wage gaps (highest wage over lowest wage), and within country wage variation coefficients for the whole sample and a split for OECD and Non-OECD countries for 1986, 1996, and 2006. The annual growth rate of nominal wages falls from 12.2% on average between 1986 and 1996 to 6.8% between 1996 and 2006. In parts, this fall reflects declining inflation. This can be seen by contrasting the results from Table 2.8 with the first column of Table 2.9, that shows the average growth rates of three occupations in US Dollar.[7] These growth rates are far smaller, because denominating the wages in US Dollar controls partly for inflation in all countries except the United States. The differences in the average growth rates shown in Table 2.8 are also to some extend the result of changing composition of the sample over the years. Yet, the fall in the growth rates does not seem to be driven by outliers. The fall in the growth rats of nominal wages is apparent for both groups, OECD-countries and Non-OECD countries by a similar factor. The wage structure as a whole is robust against these changes in the sample. Neither the wage gap, i.e. the ratio of the largest over the smallest wage in each country, nor the variation coefficient changes much over time. Note that both measures are by construction not affected by inflation.

At this very aggregated level, wage income does not seem to have increased on average. The differences between the reported occupations within the countries have remained stable. The wage gap has increased slightly, whereas the variation coefficient has decreased. Moreover, splitting the countries between OECD and Non-OECD countries reveals no different pattern for the two groups. The growth rates' difference between the OECD and Non-OECD countries, however, seem to indicate decreasing differences between the countries.

[7] Classification are added with respect to the skill level (low skilled, medium skilled, high skilled) of an occupation which is taken from the German Institute for Employment Research.

As mentioned above, I also focus on the differences between occupations (see Table 2.9). Therefore, I chose three occupations with high data coverage as representative for three different skill levels. The low skilled *Waiter*, the medium skilled *Cook*, and the high skilled *General Physician* show very different patterns on the average for all countries. While the growth rate decreases for the *Waiter*, it increases for the high skilled *Physician*. The variation coefficients also reveals that the differences between the countries decrease for the low skilled *Waiter*, but increase for the high skilled *General Physician*. The wage gap gives the relation of highest wage over lowest wage within each occupation.

To analyze occupational wage differences across countries in a more comprehensive way, I regress occupation-dummies on the log standardized wage using three regression frameworks. The first includes all countries contained in the dataset[8], the second only OECD-countries, and the third Non-OECD-Countries. I use a simple regression approach analogous to the one presented in equation (2.2):

$$W_{o,jt_i} = D_o\alpha_o + D_{jt}\alpha_{jt} + v_{o,jt_i}, \tag{2.3}$$

with i=all countries, OECD, Non-OECD. Again, I control for country- and year-effects using the United States in the year 2006 as benchmark. Afterwards, I compare the results of the three samples with those based on equation (2.2). The results are presented in Tables 2.10 and 2.11.

Each coefficient has to be interpreted in relation to the benchmark occupation: the *Cook*. The interpretation of the coefficients is analogous to the adjustment coefficients presented above. The occupation coefficient is one for *Cook*, it is larger than one if the average wage of an occupation is lower than the wage of a Cook, and it is lower than one if the average wage of an occupation is higher than the wage of a *Cook*. I find, for instance, that the wage of a waiter is on average 19 percent lower than the wage of a *Cook*. But, in OECD-countries it is nine percent lower, and 23 percent lower in Non-OECD-countries. The wage of a salesperson in wholesale is on average seven percent higher than the wage of a *Cook*, 17 percent in OECD-

[8] I use the imputed dataset which is described below.

and about four percent in Non-OECD-countries. Looking at a salesperson in retail trade, I find that the wage is lower than the wage of a *Cook*. On average it is 12 percent lower, three percent in OECD- and 16 percent Non-OECD countries. The best-paid occupation is the airtransport pilot, whose wage is almost five times higher than that of a *Cook*. The worst paid occupation is a laborer in the spinning and weaving industry, with an average wage which is almost 30 percent lower, nine in OECD- and more than 50 percent in Non-OECD-Countries. A more comprehensive analysis of occupational wage spreads is presented in Chapter 3 of this thesis.

2.4 Imputation

The standardization process leads to a dataset that contains comparable wage data within and between countries and occupations. Yet, the data is unbalanced. There are gaps with respect to occupations, i.e. not all countries report wages for all occupation for every year, and with respect to time, i.e. not all countries report wages for every year. Often, countries report every other year, but for some countries no pattern can be found. I decided to fill in gaps in order to base the cross-section comparisons on a larger sample. To make sure that I do not impose a structure on the data, I fill in just small gaps and use only the within-country variation for the imputations. Therefore, the wage structure of each country has to be revised separately with respect to yearly and occupational wage gaps.

With respect to the occupations gaps, I impute only those missing wages for which I can compute the coefficients of the occupation dummies with sufficient precision. The coefficients result from a multivariate regression similar to the one employed in the standardization process. For imputation I regress the standardized log wage on occupation and time dummies for each country separately. Thus, I assume that the wage structure does not change much over time within a country and impute the missing wages by using the occupation dummy variables. They reflect the wage pattern averaged over all years. As the cook is the most reported occupation, I choose it as benchmark and compute the coefficients of the occupation dummies by using the exponential function. In some cases the wage of the cook is not reported for every year, I therefore have to choose the most often reported occupation as a benchmark instead. With respect to the yearly gaps, I decide to fill in only one-year gaps. Thus, if wage in the year before and in the year after the missing is known, I use linear projections to impute the missing wages. That increases the number of observations from 93,535 to 147,016. The imputation procedure does neither change the time structure of the data nor the wage pattern with respect to occupations. The occupation coefficients using the imputed data are shown in Columns (2), (3), and (4) in Tables 2.10 and 2.11. They have the same structure as the coefficients using the standardized data (see column (1)). Thus, the imputation process of the data does not change the structure of the reported wages.

The imputed dataset contains standardized wages for up to 161 occupations from 49 industries in 112 countries between 1983 and 2008. The data is now usable for many applications and relatively easy to adjust for others. The standard wage is given in local currencies and in US-Dollar. The originally reported wage data have also been kept in the dataset. Table 2.7 shows the change in the data that results from the four steps of modification that I have conducted.

2.5 Comparison to the Data from BLS and UBS

For an empirical analysis that involves wage data from many countries, two alternative data sources could be used: (i) the International Labor Comparison (ILC) by the Bureau of Labor Statistics (BLS) and (ii) prices and earning data provided by the United Bank of Switzerland (UBS). Each of the data sources has advantages and drawbacks. Unfortunately, they cannot be combined. In particular, using the data from the other sources to fill the gaps in the standardized *October Inquiry* data is hardly possible.

The International Labor Comparison program of the BLS provides measures of labor force, employment, unemployment, hourly compensation costs, productivity, and unit labor costs which are adjusted to a common conceptual framework for 36 countries. The earliest available year is 1996. For a breakdown by 40 manufacturing industries, data from 1975 to 2002 is also available for some years.[9] The data is balanced, cleared and adjusted since a direct comparison of national statistics across countries can be misleading as concepts and methods differ. Consistency is the great advantage of the data. It has been compiled to assess the performance of the U.S. labor market relative to foreign countries which explains the focus on all employees or production workers. But, the international BLS data does not provide a breakdown by education or occupation. That is certainly the main advantage of the *October Inquiry*. Moreover, it is impossible to calculate skill-specific labor compensation costs from the BLS data. For many purposes, however, skill or even occupation-specific wages are preferable. I cannot use the BLS information to augment the *October Inquiry* dataset because it is calculated starting with the wage sum (by industry or for the manufacturing sector) and dividing it by the number of employees. There is no way to recover occupation-specific wages from this approach.

The information in the ILO *October Inquiry* is much richer but the variety of gaps makes it rather difficult to use this database in cross-country studies at the industry or sector level. While all occupations can be uniquely related to a particular industry, the gaps prohibit even an unweighted aggregation to the sector level. Thus, industry studies must rely on comparing typical occupations. Such an approach also allows for an analysis that uses the differences in the skill level between the occupations.

The UBS *Prices and Earning Study* is published every three years and compares wages of particular "representative" employees in 73 (latest survey in 2009) cities in the world since 1971 (31 cities in 1971). The representative employees are from seven manufacturing and seven service industries. The data is comparable across countries for each employee, respectively but not across industries, because the representative employee varies purposely in age, sex, family status, and other characteristics that affect the workers income. For instance, the female factory worker is an unskilled or semi-skilled machine operator in a medium-sized company mainly in the textile industry, about 25 years old and single (United Bank of Switzerland, 2009, p. 35). The engineer, in contrast, is employed by an industrial firm in the electrical engineering sector, has a degree from an university or a technical college, and at least five

[9] See www.bls.gov/fls/compensation

years of working experience. He is about 35 years old, married and has two children (United Bank of Switzerland, 2009, p. 35). Thus, the labor compensation includes different elements in each sector which biases sector level cross-section studies.

The adjusted ILO *October Inquiry* dataset, in contrast, allows for a comparison across sectors. In addition, it includes much more occupations and is conducted every year. Therefore, there are many questions for which the corrected and adjusted ILO *October Inquiry* is the best available dataset. A very appealing feature of the *October Inquiry* is that occupations of different skill levels are included. Beyond that, several occupations, such as the laborer, the stenographer-typist or the computer programmer, are reported for different sectors and some occupations, such as the teacher, are reported for different skill-levels (first, second, third level) which allows to disentangle sector, occupation and skill-level effects.

2.6 Summary

The *October Inquiry* is not a commonly used database. The correction process applied in this paper is extensive and time-consuming. Data for almost every country had to be corrected and imputed separately. I adjusted the data with respect to single events like currency reforms, typos, outliers, and mislabeled observations. As wages are reported for numerous different time periods, I had to reduce the number of time periods. The required standardization approach is complex, but it does not change the structure of the data. Neither does the imputation.

The standardization and imputation process yields a comprehensive database that allows analyzing worldwide wage distributions based on comparable wage data for a large number of countries and occupations. To the best of my knowledge, the *October Inquiry* is the most comprehensive wage database in the world. Moreover, the estimated adjustment factors needed to standardize the data can be interpreted as occupational and gender wage gaps. I find that on average wages differ about 18 percent between men and women, and about three percent between men and the averaged wage of men and women. This approach assumes that the wage gap is independent from the level of development of the different countries. Therefore, one should keep this in mind when working with the data.

A first glance at the data shows decreasing differences between the countries and stable differences among the occupations within the countries. The falling differences between the countries seem to be driven by falling differences in the wages of low skilled occupations. The wages of the high skilled, in contrast, still differ between the countries. In Chapter 3 of this thesis, I present a comprehensive study on occupational wage distributions and wage inequality.

2.7 Appendix for Chapter 2

Table 2.1: **Unbalanced Data: Number of Observations**

This Table gives the minimum, maximum, and average number of observations by country, year, occupation, time period, and several combinations of the variables.

Dimension	**Observations**		
	Minimum	Average	Maximum
Country	3	1,641	13,481
	(*France*)		(*Korea*)
Year	4,100	8,651	13,024
	(*1983*)		(*2006*)
Occupation	460	1,397	2,492
	(*Railway steam-engine fireman*)		(*Cook*)
Time Period	2	6,816	62,766
	(*Per Week (Minimum)*)		(*Per Month (Average)*)
Year-Country-Combinations	23	53	66
	(*2008*)		(*1987/1990*)
Country-Year-Combinations	1	10	26
	(*Croatia, Djibouti, etc.*)		(*Germany, Norway, etc.*)
Occupation-Country -Combinations	42	109	122
	(*Coalmining engineer*)		(*Cook/Construction Carpenter*)
Country-Occupation-Combinations	1	111	161
	(*France*)		(*United Kingdom, Romania*)
Time Period-Country-Combinations	1	20	96
	(*Several times*)		(*Per Month, average*)
Country-Time Period -Combinations	1	4	16
	(*Several Countries*)		(*Guyana, Saint Lucia*)

Table 2.2: **Observations by Country (I)**

Country	Cleaned Data	Standardized Data	Imputed Data	Country	Cleaned Data	Standardized Data	Imputed Data
Algeria	1,110	1,019	2,812	Ethiopia	47	47	58
Angola	.	.	.	Falkland Islands (Malvinas)	.	.	.
Antigua and Barbuda	1,411	483	904	Fiji	.	.	.
Argentina	474	474	1,150	Finland	7,342	2,670	3,384
Australia	3,466	1,825	2,718	France	.	.	.
Austria	5,250	2,655	3,000	French Polynesia	326	326	360
Azerbaijan	827	470	676	Gabon	406	247	776
Bahamas	502	334	927	Germany	3,990	3,990	4,134
Bahrain	1,462	991	2,622	Gibraltar	429	246	468
Bangladesh	1,985	1,201	1,960	Grenada	406	343	420
Barbados	1,223	675	949	Guam	200	110	450
Belarus	2,199	658	715	Guatemala	407	217	596
Belgium	874	848	1,188	Guyana	933	869	2,227
Belize	1,913	1,135	1,365	Honduras	2,546	1,425	1,950
Benin	766	413	1,125	Hong Kong	1,639	830	1,534
Bermuda	410	359	1,059	Hungary	3,432	1,782	2,086
Bolivia	2,328	1,254	1,898	Iceland	809	325	1,274
Botswana	152	152	184	India	2,584	1,324	1,761
Brazil	957	383	1,206	Indonesia	832	415	1,302
Brunei Darussalam	.	.	.	Ireland	30	30	30
Bulgaria	508	233	122	Isle of Man	.	.	.
Burkina Faso	775	677	1,276	Italy	3,479	3,479	3,672
Burundi	585	567	810	Japan	1,384	939	1,248
Cameroon	524	524	1,190	Jordan	3,106	1,868	2,907
Canada	2,365	1,249	1,860	Kazakhstan	838	347	351
Cape Verde	161	159	160	Kenya	254	157	176
Central African Republic	723	723	1,276	Korea	13,445	3,247	3,792
Chad	913	732	1,122	Kuwait	372	128	128
Chile	579	441	720	Kyrgyzstan	550	216	396
China	1,593	976	1,834	Latvia	3,372	1,195	1,480
Colombia	223	223	417	Lesotho	204	194	230
Comoros	987	786	1,404	Liberia	59	54	86
Costa Rica	3,185	1,661	2,415	Lithuania	1,136	363	705
Croatia	119	119	119	Luxembourg	456	165	267
Cuba	2,543	1,199	1,460	Madagascar	1,221	841	1,264
Cyprus	7,798	2,348	2,852	Malawi	934	676	1,350
Czech Republic	2,931	1,768	2,208	Malaysia	583	251	1,106
Czechoslovakia	875	834	1,120	Maldives	66	36	36
Côte d'Ivoire	992	787	1,738	Mali	.	.	.
Denmark	1,804	1,010	1,770	Mauritius	3,649	1,987	2,964
Djibouti	48	48	48	Mexico	4,008	1,707	2,717
Egypt	916	678	1,624	Mongolia	44	44	44
El Salvador	.	.	.	Mozambique	350	350	444
Eritrea	366	279	375	Myanmar	.	.	.
Estonia	1,119	525	705	Namibia	66	50	105

Table 2.3: **Observations by Country (II)**

Tables 2.2 and 2.3 give the number of observations by country for the cleaned data, the standardized data, and the imputed data.

Country	Cleaned Data	Standardized Data	Imputed Data
Nepal	114	108	170
Netherlands	700	386	408
Netherlands Antilles	533	301	576
New Caledonia	65	65	65
Nicaragua	565	565	1,000
Nigeria	.	.	.
Norway	1,089	758	1,482
Pakistan	1,379	773	1,106
Papua New Guinea	480	418	882
Peru	2,442	1,042	2,160
Philippines	960	842	2,520
Poland	2,450	1,057	1,771
Portugal	7,580	1,590	3,312
Puerto Rico	216	192	1,104
Romania	8,365	3,253	3,381
Russian Federation	1,482	623	1,342
Rwanda	845	845	1,008
Saint Kitts and Nevis	.	.	.
Saint Lucia	.	.	.
Saint Pierre and Miquelon	.	.	.
Saint Vincent and the Grenadines	.	.	.
San Marino	293	293	404
Senegal	73	73	73
Serbia and Montenegro	159	159	159
Seychelles	.	.	.
Sierra Leone	.	.	.
Singapore	3,838	2,060	3,473
Slovakia	4,336	1,670	2,041
Slovenia	366	303	728
Sudan	.	.	.
Suriname	.		.
Sweden	2,247	1,192	1,898
Thailand	3,521	1,008	1,400
Togo	216	213	336
Trinidad and Tobago	758	680	1,304
Tunisia	.		.
Turkey	277	153	330
Ukraine	152	152	300
United Kingdom	7,371	1,914	3,864
United States	3,468	2,501	3,850
Uruguay	853	489	572
Venezuela	1,133	975	1,540
Virgin Islands (US)	.	.	.
Zambia	.	.	.

Table 2.4: **Number of Observations by Time Period**

This Table gives number of observations by time period for the raw and the cleaned data. Cleaned Data: yearly wages divided through 12, weekly wages multiplied with factor 4.33, fortnightly wages with factor 2.16.

Time Period	Observations		Time Period	Observations	
	Raw Data	Cleaned Data		Raw Data	Cleaned Data
Per hour			**Per fortnight**		
Per hour.	7,701	6,069	Per fortnight.	320	
Per hour. Adjusted.		4,444	Per fortnight. Average.	195	
Per hour. Average.	9,568	6,708	Per fortnight. Maximum.	14	
Per hour. Maximum.	1,279	795	Per fortnight. Minimum.	303	
Per hour. Median.	1,513		Per fortnight. Prevailing.	9	
Per hour. Min-Max.	204		**Per month**		
Per hour. Minimum.	6,992	5,412	Per month.	58,263	49,406
Per hour. Prevailing.	747		Per month. Adjusted.		25,827
Per hour paid for.	7,209	3,111	Per month. Average.	64,338	54,249
Per hour paid for.	16		Per month. Maximum.	2,948	1,085
Per hour paid for. Maximum.	10		Per month. Median.	1,460	
Per hour paid for. Minimum.	10		Per month. Min-Max.	107	
Per hour worked.	3,251	3,092	Per month. Minimum.	19,216	13,038
Per hour worked. Maximum.	38		Per month. Prevailing.	2,255	1,440
Per hour worked. Minimum.	38		**Per year**		
Per day			Per year.	371	
Per day.	1,116	804	Per year. Average.	1,199	
Per day. Adjusted.		426	Per year. Maximum.	674	
Per day. Average.	2,205	1,707	Per year. Median.	824	
Per day. Maximum.	1,790	812	Per year. Minimum.	794	
Per day. Median.	32		Per year. Prevailing.	169	
Per day. Minimum.	6,193	4,302			
Per day. Prevailing.	113				
Per week					
Per week.	12,492				
Per week. Average.	3,15				
Per week. Maximum.	172				
Per week. Median.	2,573				
Per week. Min-Max.	13				
Per week. Minimum.	2,442				
Per week. Prevailing.	141				

Table 2.5: **Time Periods Regression Results and Adjustment Coefficients**

The results presented in this Table are based on regression equation (2.2). Column 1 gives the regression results, column two gives the computed adjustment coefficients. The adjustment coefficients are used to convert the observed wages in their standard form, as they contain the difference of the observed from the standard wage. The adjustment coefficient is one, if the time has the chosen standard form *Per Month. Average.* If the observed wage is not of that standard form, it has to be multiplied with the adjustment coefficient to yield the average monthly wage.
***. **. * = significance at the 1%. 5%. 10%-level. Standard errors are given in parentheses.

Dependent Variable: Log Wage		
Time	Regression Coefficient	Adjustment Coefficient
Per hour.	-4.911***	135.744
	(0.020)	
Per hour. Adjusted.	-5.039***	154.327
	(0.024)	
Per hour. Average.	-5.183***	178.242
	(0.017)	
Per hour. Maximum.	-5.054***	156.571
	(0.025)	
Per hour. Minimum.	-5.240***	188.757
	(0.019)	
Per hour paid for.	-5.130***	169.098
	(0.024)	
Per hour worked.	-4.916***	136.483
	(0.019)	
Per day.	-2.423***	11.285
	(0.050)	
Per day. Adjusted.	-3.047***	21.056
	(0.051)	
Per day. Average.	-3.211***	24.802
	(0.038)	
Per day. Maximum.	-3.527***	34.024
	(0.044)	
Per day. Minimum.	-4.008***	55.029
	(0.037)	
Per month.	0.169***	0.844
	(0.005)	
Per month. Adjusted.	0.060***	0.942
	(0.017)	
Per month. Maximum.	0.234***	0.792
	(0.030)	
Per month. Minimum.	-0.116***	1.123
	(0.016)	
Per month. Prevailing.	-0.030	0.971
	(0.027)	
Constant	7.792***	
	(0.041)	
N	182,786	
R-squared	0.987	

Table 2.6: **Gender Regression Results and Adjustment Coefficients**

The results presented in this Table are based on regression equation (2.2). Column 1 gives the regression results, column two gives the computed adjustment coefficients. The adjustment coefficients are used to convert the observed wages in their standard form, as they contain the difference of the observed from the standard wage. The adjustment coefficient is one, if the time has the chosen standard form *Men*. If the observed wage is not of that standard form, it has to be multiplied with the adjustment coefficient to yield the average monthly wage.
***. **. * = significance at the 1%. 5%. 10%-level. Standard errors are given in parentheses.

Dependent Variable: Log Wage		
Sex	Regression Coefficient	Adjustment Coefficient
Men and Women	-0.030***	1.031
	(0.006)	
Women	-0,172***	1,187
	(0.004)	
Constant	7.792***	
	(0.041)	
N	182,786	
R-squared	0.987	

Table 2.7: **Construction of the Datasets**

This Table gives the total number of observations, the number of country-year-occupation combinations, and the number of countries for each of the datasets (raw data, cleaned data, standardized data, and imputed data).

Data Set	Observations	Country-Year-Occupation	Number of Countries
Raw Data	224,570	109,651	134
Cleaned Data	182,786	93,535	112
Standardized Data	93,535	93,535	112
Imputed Data	147,016	147,016	112

Table 2.8: **Descriptive Statistics**

In this Table, I present some descriptive statistics. The growth rate is the unweighted average of wage-ratios in t over in $t-1$ for all occupations within a country (in percent). The wage gap is the highest wage over the lowest wage within a country. The variation coefficients is defined as the relation of standard deviation and mean within each country.

	Growth Rate			Wage Gap			Variation Coefficient		
Year	Mean	Min.	Max.	Mean	Min.	Max.	Mean	Min.	Max.
Whole sample, varying number of countries									
1986	.	.	.	15.54	1.05	59.46	0.66	0.04	1.48
1996	12.15	-2.93	64.62	12.24	1.92	74.58	0.52	0.18	1.30
2006	6.84	-1.85	34.54	14.29	1.16	66.34	0.58	0.05	1.13
OECD countries, varying number of countries									
1986	.	.	.	8.97	1.70	15.07	0.48	0.14	1.07
1996	5.99	2.51	16.78	6.08	1.92	15.02	0.37	0.18	0.60
2006	3.65	-1.85	23.54	7.08	2.11	13.26	0.45	0.22	0.70
Non-OECD countries, varying number of countries									
1986	.	.	.	18.80	1.05	59.46	0.74	0.04	1.48
1996	19.13	-2.93	64.62	17.30	2.71	74.58	0.64	0.25	1.30
2006	10.60	-1.09	34.54	22.57	1.16	66.35	0.74	0.05	1.13

Table 2.9: **Descriptive Statistics: Occupational Wage Gap**

This Table gives descriptive statistics for three occupations: the low skilled waiter, the medium skilled cook, and the high skilled general physician. The growth rate is the unweighted average of wage-ratios in t over in $t-1$ for all occupations within a country (in percent). The wage gap is the highest wage over the lowest wage within a country. The variation coefficients is defined as the relation of standard deviation and mean within each country.

	Growth Rate			Wage Gap	Variation Coefficient
Year	Mean	Min.	Max.	Mean	Mean
Occupation: Low skilled, Medium Skilled, High Skilled					
Low skilled (Waiter)					
1986	.	.	.	77.49	1.09
1996	4.79	-5.47	11.90	48.89	1.00
2006	3.06	-0.81	10.23	39.14	1.00
Medium Skilled (Cook)					
1986	.	.	.	95.49	0.97
1996	5.93	-5.65	13.53	45.59	1.02
2006	3.01	-8.77	9.77	40.94	0.97
High Skilled (General Physician)					
1986	.	.	.	49.17	0.85
1996	3.34	-9.66	11.45	72.24	1.09
2006	4.27	-7.76	15.90	135.20	0.97

Table 2.10: **Coefficients for Low Skill and High Skill Occupations**

Tables 2.10 and 2.11 give the wage spread between occupation based on different samples. All coefficients are relative to occupation *Cook*.

Occupation	Cleaned Data	Imputed Data	OECD	Non-OECD	Occupation	Cleaned Data	Imputed Data	OECD	Non-OECD
Low Skilled					**High Skilled**				
Deep-sea fisherman	1.023	1.018	0.955	1.045	Accountant	0.382	0.385	0.471	0.352
Dockworker	0.867	0.905	0.777	0.974	Air traffic controller	0.397	0.419	0.385	0.431
Field crop farm worker	1.322	1.385	1.131	1.549	Air transport pilot	0.229	0.209	0.258	0.187
Forestry worker	1.157	1.207	1.071	1.277	Aircraft engine mechanic	0.516	0.510	0.602	0.463
Inshore (coastal) maritime fisherman	1.054	1.028	0.966	1.056	Auxiliary nurse	0.924	0.949	0.849	1.006
Labourer (construction)	1.171	1.239	0.973	1.394	Book-keeping machine operator	0.628	0.683	0.717	0.678
Labourer (printing)	1.145	1.202	0.963	1.332	Chemical engineer	0.440	0.403	0.427	0.384
Labourer (manufacturing)	1.108	1.159	0.964	1.265	Chemistry technician	0.662	0.656	0.619	0.668
Labourer (manufacturing. chemical)	1.189	1.225	0.999	1.357	Coalmining engineer	0.485	0.470	0.495	0.431
Labourer (Iron and steel)	1.039	1.102	0.924	1.215	Computer programmer (insurance)	0.453	0.463	0.495	0.442
Labourer (manufacture of machinery)	1.145	1.220	1.031	1.341	Computer programmer (public administration)	0.529	0.562	0.520	0.580
Labourer (Spinning. weaving. finishing textile)	1.307	1.390	1.090	1.573	Dentist (general)	0.469	0.472	0.421	0.484
Labourer (electric light and power)	1.038	1.116	0.933	1.206	Electronics engineering technician	0.660	0.686	0.609	0.727
Logger	1.196	1.233	1.019	1.375	Fire-fighter	0.851	0.890	0.737	0.973
Office clerk	0.888	0.943	0.821	1.005	First-level education teacher	0.664	0.718	0.617	0.768
Packer (Slaughtering)	1.147	1.164	1.006	1.254	Flight operations officer	0.420	0.406	0.399	0.400
Packer (manufacturing. chemical)	1.084	1.182	0.914	1.346	Forest supervisor	0.821	0.830	0.758	0.863
Plantation worker	1.348	1.389	1.051	1.575	General physician	0.378	0.381	0.352	0.390
Postman	0.953	1.003	0.847	1.073	Government executive official: a)	0.472	0.453	0.483	0.441
Railway vehicle loader	1.052	1.110	0.961	1.175	Government executive official: b)	0.435	0.446	0.476	0.438
Room attendant or chambermaid	1.216	1.305	1.177	1.369	Government executive official: c)	0.527	0.582	0.527	0.604
Telephone switchboard operator	0.811	0.871	0.820	0.895	Journalist	0.526	0.536	0.522	0.541
Ticket seller (cash desk cashier)	0.847	0.891	0.788	0.946	Kindergarten teacher	0.845	0.858	0.736	0.925
Tree feller and bucker	1.222	1.232	0.991	1.373	Mathematics teacher (second level)	0.560	0.594	0.547	0.618
Underground helper. loader	0.849	0.868	0.754	0.939	Mathematics teacher (third level)	0.444	0.459	0.445	0.466
Waiter	1.174	1.230	1.094	1.300	Petroleum and natural gas engineer	0.349	0.328	0.400	0.286
					Power distribution and transmission e	0.389	0.382	0.447	0.358
					Power-generating machinery operator	0.655	0.674	0.653	0.675
					Refuse collector	1.150	1.179	0.997	1.285
					Ship's chief engineer	0.489	0.453	0.468	0.434
					Supervisor or general foreman	0.621	0.636	0.563	0.668
					Teacher (language. literature) (second level)	0.560	0.589	0.544	0.612
					Teacher (language. literature) (third level)	0.447	0.465	0.439	0.479

All estimations relative to occupation *Cook*; all estimations include country-year and occupation dummies.
Cleaned Data: Estimated on basis of regression $W_{td,s,o,jt} = D_{td}\alpha_{td} + D_s\alpha_s + D_o\alpha_o + D_{jt}\alpha_{jt} + v_{td,s,o,jt}$;
Imputed Data: Estimated on basis of regression $W_{o,jt} = D_o\alpha_o + D_{jt}\alpha_{jt} + v_{o,jt}$
OECD, Non-OECD: Estimated on basis of imputed data; based on regression $W_{o,jt} = D_o\alpha_o + D_{jt}\alpha_{jt} + v_{o,jt}$

Table 2.11: **Coefficients for Medium Skill Occupations**

Sample	Cleaned Data	Imputed Data	OECD	Non-OECD	Occupation	Cleaned Data	Imputed Data	OECD	Non-OECD
Medium Skilled					Medium Skilled				
Able seaman	0.891	0.921	0.792	1.003	Medical X-ray technician	0.697	0.729	0.685	0.747
Aircraft accident fire-fighter	0.725	0.760	0.642	0.813	Metal melter	0.791	0.847	0.775	0.879
Aircraft cabin attendant	0.502	0.528	0.555	0.511	Metalworking machine setter	0.908	0.911	0.828	0.954
Aircraft loader	0.901	0.939	0.816	1.004	Miner (Coalmining)	0.710	0.724	0.662	0.754
Airline ground receptionist	0.633	0.643	0.718	0.613	Miner (Other mining and quarrying)	0.795	0.809	0.703	0.873
Ambulance driver	0.915	0.989	0.886	1.069	Mixing- & blending-machine operator (chem.)	0.836	0.848	0.744	0.907
Automobile mechanic (Passenger transport)	0.895	0.913	0.813	0.960	Mixing- & blending-machine operator (other chem.)	0.872	0.887	0.788	0.939
Automobile mechanic (Repair of motor vehicles)	0.924	0.925	0.869	0.948	Motor bus driver	0.879	0.933	0.828	0.989
Baker (ovenman)	1.075	1.111	0.928	1.223	Occupational health nurse	0.651	0.728	0.674	0.746
Bank teller	0.673	0.710	0.727	0.708	Office clerk (Printing. publishing)	0.831	0.886	0.753	0.961
Bench moulder (metal)	0.877	0.928	0.836	0.978	Office clerk (Electric light and power)	0.702	0.753	0.685	0.792
Blast furnaceman (ore smelting)	0.784	0.822	0.755	0.850	Paper-making-machine operator	0.892	0.926	0.774	1.026
Book-keeper	0.820	0.875	0.760	0.940	Petroleum and natural gas extraction	0.489	0.478	0.511	0.458
Bookbinder (machine)	0.967	0.983	0.821	1.073	Physiotherapist	0.708	0.723	0.754	0.694
Bricklayer (construction)	0.917	0.960	0.832	1.021	Plantation supervisor	0.906	0.942	0.862	0.981
Building electrician	0.842	0.844	0.746	0.891	Plasterer	0.909	0.972	0.827	1.045
Building painter	0.928	0.969	0.833	1.043	Plumber	0.879	0.913	0.775	0.983
Bus conductor	1.014	1.067	0.854	1.187	Plywood press operator	1.046	1.075	0.888	1.189
Butcher	1.019	1.036	0.904	1.109	Post office counter clerk	0.795	0.863	0.797	0.884
Cabinetmaker	1.047	1.095	0.957	1.166	Printing pressman	0.834	0.848	0.741	0.905
Card- & tape-punching-machine op. (insurance)	0.775	0.799	0.775	0.809	Professional nurse (general)	0.668	0.718	0.669	0.736
Card- & tape-punching-machine op. (publ. admin.)	0.874	0.907	0.803	0.960	Quarryman	0.928	0.970	0.808	1.082
Cash desk cashier	1.038	1.058	1.020	1.083	Railway engine-driver	0.665	0.699	0.639	0.722
Cement finisher	0.927	0.955	0.805	1.042	Railway passenger train guard	0.769	0.792	0.769	0.765
Clerk of works	0.612	0.643	0.646	0.635	Railway services supervisor	0.629	0.615	0.605	0.587
Clicker cutter (machine)	1.170	1.224	1.070	1.301	Railway signalman	0.833	0.888	0.742	0.979
Cloth weaver (machine)	1.126	1.139	1.006	1.209	Railway steam-engine fireman	0.822	0.845	0.723	0.891
Construction carpenter	0.912	0.920	0.808	0.978	Reinforced concreter	0.925	0.950	0.813	1.020
Constructional steel erector	0.868	0.908	0.793	0.964	Road transport services supervisor	0.717	0.703	0.656	0.723
Controlman	0.595	0.575	0.585	0.546	Salesperson (Wholesale trade)	0.930	0.936	0.856	0.965
Cook	1.000	1.000	1.000	1.000	Salesperson (Retail trade)	1.125	1.125	1.021	1.178
Dairy product processor	0.977	1.005	0.881	1.072	Sawmill sawyer	1.070	1.120	0.931	1.234
Derrickman	0.691	0.722	0.674	0.739	Sewing-machine operator	1.229	1.250	1.109	1.329
Electric power lineman	0.699	0.732	0.679	0.752	Ship plater	0.862	0.898	0.818	0.932
Electronic equipment assembler	0.999	1.054	0.917	1.138	Ship's steward (passenger)	0.866	0.883	0.861	0.894
Electronics draughtsman	0.733	0.747	0.675	0.784	Shoe sewer (machine)	1.178	1.233	1.093	1.300
Electronics fitter	0.882	0.999	0.786	1.138	Stenographer-typist (banks)	0.639	0.664	0.743	0.635
Farm supervisor	0.863	0.862	0.869	0.839	Stenographer-typist (insurance)	0.740	0.751	0.792	0.734
Furniture upholsterer	1.048	1.076	0.965	1.129	Stenographer-typist (publ. admin.)	0.844	0.869	0.860	0.879
Garment cutter	1.093	1.097	0.989	1.148	Stenographer-typist (printing. publishing)	0.807	0.834	0.839	0.838
Grain miller	0.938	0.956	0.887	0.991	Stenographer-typist (wholesale trade)	0.850	0.886	0.893	0.875
Hand compositor	0.880	0.901	0.756	0.988	Stock records clerk	0.852	0.899	0.867	0.913
Hot-roller (steel)	0.802	0.835	0.767	0.862	Supervisor or general foreman	0.525	0.497	0.529	0.468
Hotel receptionist	0.972	1.043	1.004	1.065	Tanner	1.072	1.105	0.947	1.184
Insurance agent	0.585	0.615	0.602	0.617	Technical education teacher (second level)	0.584	0.637	0.555	0.678
Laster	1.169	1.241	1.112	1.300	Thread and yarn spinner	1.135	1.162	1.022	1.242
Leather goods maker	1.234	1.267	1.084	1.257	Urban motor truck driver	0.952	0.992	0.958	0.991
Long-distance motor truck driver	0.876	0.885	0.859	0.882	Veneer cutter	1.066	1.102	0.915	1.213
Loom fixer. tuner	1.035	1.091	0.932	1.174	Welder	0.905	0.928	0.832	0.978
Machine compositor	0.835	0.840	0.737	0.896	Wood grinder	0.899	0.912	0.745	1.041
Machinery fitter-assembler	0.891	0.899	0.834	0.923	Wooden furniture finisher	1.092	1.125	0.959	1.213

All estimations relative to occupation *Cook*; all estimations include country-year and occupation dummies.
Cleaned Data: Estimated on basis of regression $W_{td,s,o,jt} = D_{td}\alpha_{td} + D_s\alpha_s + D_o\alpha_o + D_{jt}\alpha_{jt} + v_{td,s,o,jt}$;
Imputed Data: Estimated on basis of regression $W_{o,jt} = D_o\alpha_o + D_{jt}\alpha_{jt} + v_{o,jt}$
OECD, Non-OECD: Estimated on basis of imputed data; based on regression $W_{o,jt} = D_o\alpha_o + D_{jt}\alpha_{jt} + v_{o,jt}$

Chapter 3

Evidence on Occupational Wage Distribution

3.1 Introduction

A large amount of research has dealt with the determinants of wages, wage setting and the distribution of wages. Katz and Autor (1999, p. 1) argue that "studies of the wage structure are as old as the economic profession".[1] Nevertheless, during the last decade, new explanations for changes in wage inequality based on a more nuanced view of skill-biased technological change were proposed.

Goos and Manning (2007) show that since the middle of the 1970s, the United Kingdom has been characterized by a job polarization with an increase in employment shares in the highest- and lowest-wage occupations. This observation is not consistent with the well-known idea of technological change as one of the main reasons for a skill-bias on the labor market with increasing shares of high skilled and decreasing shares of low skilled work. Therefore, Goos and Manning (2007) argue

[1]Katz and Autor (1999) summarize three main determining factors of differences in wages: First, wages are determined by competitive factors, such as costs of training, probability of success, or steadiness of work. Second, there are differences in individual innate abilities that may initiate wage spreads. Third, institutional factors like regulated wages, entry barriers, or restricted labor mobility affect wages ("Laws of Europe"). Moreover, shifts in demand across occupations may cause wage differentials. But if supply is highly elastic, advantages and disadvantages of different employments equalize in the long run, as long as there are no regulatory barriers.

that the more nuanced view of the technological change and the "routinization" hypothesis are better explanations of job polarization. The key idea is that the introduction of information technologies such as computers has not only decreased the relative demand for un- or less skilled labor. Moreover, the return to *routine tasks* decreased in general, as they can now be operated by computers.

This hypothesis of a nuanced version of the skill-biased technological change was introduced in the literature by Autor et al. (2003). They present a general equilibrium model and show empirically that the use of computer technology leads to a decrease in the demand for work that requires routine manual or clerical skills, and increases demand for workers with nonroutine cognitive or interpersonal skills. The main feature is that Autor et al. (2003) describe work as a series of tasks. As the "task content of work" is typically measured at the occupational level, occupations play a major role in the analysis of wage distributions. Autor et al. (2006) analyze the U.S. labor market and describe the polarization of wages. They argue that since the late 1980s, employment is polarized into high-wage and low-wage jobs, while middle-wage work suffers. While upper-tail inequality (measured as the *50-90 wage gap*) increased during the 1990s, lower-tail inequality (*50-10 wage gap*) decreased since the late 1980s (Autor, Katz, & Kearney, 2008).

Gosling et al. (2000) present similar results for the United Kingdom, whereas Dustmann et al. (2009) analyze wage inequality in Germany. Their results are also consistent with the hypothesis of polarization of work, as they show that wage inequality in Germany increased in the 1980s mostly at the top of the wage distribution, while the rise in lower tail wage inequality occurred in the 1990s, one decade later than in the United States. Michaels et al. (2010) show for the OECD that industries with faster growth of information and communication technologies faced a greater increase in relative demand for highly educated workers, while the relative demand for middle educated workers decreased. Although it seems intuitive that different occupations with different skill requirements are one possible channel for changes in wage distributions, the role of occupations in these changes has not been systematically analyzed (Firpo et al., 2011).

Due to a lack of comparable international wage data, there are still important issues concerning international wage structures and occupational wage distributions which have not yet been analyzed. Although a broad number of micro-level datasets have become available, the empirical analysis of wage distribution focusses either on a small number of countries or on a small number of occupations. Therefore, until recently, only little attention was paid to international occupational wage distributions and the effects of occupations on wage inequality across countries. Making use of the newly standardized and imputed *October Inquiry* database provided by the International Labor Organization (see Freeman & Oostendorp, 2000, 2001; Harsch & Kleinert, 2011) allows to analyze international wage structures and occupational wage distribution in a comprehensive way.

This Chapter is organized as follows. In Section 3.2, I introduce a simple theoretical model of wage setting following Firpo et al. (2011) which can be used to analyze the channels through which technological change affects wages. Section 3.3 contains the introduction of the data that is used in the empirical analysis. In Section 3.4, I test whether the assumptions of the theoretical model can be verified. Therefore, I determine wage spreads in the OECD and the EU that are due to differences in skill levels and analyze wage spreads that occur in the same occupation across different industries. The results are compared to the occupational wage distributions in the United States and Germany. Section 3.5 focusses on the question if the nuanced version of the skill-biased technological change is also observable for Germany using the *October Inquiry* database. Section 3.6 concludes and gives an outlook on further work based on the *October Inquiry* database.

3.2 Theory of Wage Settings

To give a brief introduction to the theoretical mechanism of wage setting in occupations, I follow Firpo et al. (2011) who refer to Welch (1969) and develop a intuitive theoretical framework which captures occupational wage differences and allows to analyze the channels through which technological change affects wages.[2]

Following Firpo et al. (2011), the wage setting process can be described as given in equation (3.1):

$$w_{it} = \theta_t + \sum_{k=1}^{K} r_{kt} S_{ik} + u_{it}, \tag{3.1}$$

where w_{it} is the wage of worker i at time t, S_{ik} are skill components of worker i (for $k = 1, ..., K$), r_{kt} are the returns to each skill component k, and θ_t is a base payment a worker earns with no regard of his or her skills. u_{it} is an idiosyncratic error term. However, the model assumes that individuals that are characterized through the same bundle of skill earn the same returns to skill, no matter which occupation they choose. Therefore, the key criticism is that this framework does not capture the case of workers that may be indeed characterized by the same skills, but are allocated to different occupations or tasks. The hypothesis of Rosen (1983), who argues that returns to skill will equalize across occupations if there is enough heterogeneity is not plausible. Firpo et al. (2011) state that the hypothesis of equalization of wages across occupations only holds if skills can be unbundled and efficiently allocated across occupations. But, using a theoretical multisector model of earnings, Heckman and Scheinkman (1987) show that workers cannot unbundle their skills. Moreover, they present empirical evidence that rejects the hypothesis of equal pricing of skills in subsectors of the United States.

Thus, it seems reasonable and intuitive to assume that skills have different impacts in different occupations: Being good at mathematics is important for an accountant, but less important for a lawyer. Consequently, returns to the skill "being good at mathematics" are supposed to differ between both occupations. There-

[2]For a full Ricardian model of labor market interactions see e.g. Acemoglu and Autor (2011), who explain why wages in the middle fell more than wages at the top or the bottom of the wages distribution. Therefore, they operationalize the supply and demand for skills and assume that there are two distinct skill groups which perform two different and imperfectly substitutable tasks.

fore, Firpo et al. (2011) allow returns to skills to vary across occupations o (for $o = 1, ..., O$):

$$w_{iot} = \theta_{ot} + \sum_{k=1}^{K} r_{okt} S_{ik} + u_{iot}, \tag{3.2}$$

where w_{iot} is the wage of worker i in occupation o at time t, r_{okt} are the returns to each skill component k in occupation o, and θ_{ot} is the base payment a worker earns in occupation o with no regard of his or her skills. Again, u_{iot} is an idiosyncratic error term.

This is a simple and quite general model, which on the one hand allows to explain wage differences of identical skilled workers in different occupations and, on the other hand, captures the effect of technological change on wages. If someone is a really good speaker, he or she will earn a higher return on communications skills when working as a teacher or politician, as he or she would earn as therapist of deaf people. Somebody who has distinctive skills in writing expects a higher return on this skill in occupations where writing is essential (e.g. authors, deskman, editor). Prior to the invention of automation technology, the returns to manual skills were high for workers in particular occupations. With greater use of robots or other information technologies, the return to manual skills decreased in occupations where these returns were previously high. This impact of technological change on the return to skills in different occupations can be determined by analyzing the changes in the *return to skill* parameter r_{okt}. The main disadvantage of the model is the fact that is does not allow to draw conclusions on the allocation of workers into particular occupations.

The presented wage setting model implies several assumptions about the wage setting process and wage distributions. First, the model shows that returns to skill differ between different skills and therefore, wages differ between occupations with different skill requirements. Second, the wage a worker earns in a particular occupation consists of two components, a base payment and the returns to skill. Therefore, wages should not differ within the same occupation in general. But, the model makes no clear assumptions concerning wage differences within the same occupation across countries. Third, as the theoretical model predicts that the returns to skill are equal in the same occupation, wages are not supposed to differ within the same occupation across industries. These three assumptions can be easily verified by empirical analysis presented in section 3.4. Moreover, the model gives an idea of the channels through which technological change affects wages. Therefore, I analyze the effect of computer introduction on wages in Germany referring to Spitz-Oener (2006) in section 3.5.

3.3 Data

For the empirical analysis I use the *October Inquiry* database provided by the International Labor Organization, which is – to the best of my knowledge – the most far-ranging wage database in the world. There is no other database that contains such a large number of international comparable wage data for such a large time period. Freeman and Oostendorp (2000, 2001) as well as Harsch and Kleinert (2011) transformed the unadjusted, uncorrected, and therefore rather unused *October Inquiry* into a usable form which allows analyzing wage growth and inequality in a comprehensive way. The corrected, standardized, and imputed *October Inquiry* database provides a robust basis for the analysis of the structure of worldwide wages.The total number of wage observations by country as well as the number of observations by industry and occupation can be found in the appendix (see Tables 3.1, 3.2, and 3.3).

As there are still gaps in the data that could not be filled in through imputation, these gaps may cause a bias. Hence, keeping only countries which report wages every year would reduce the sample size a lot. Therefore, I use two different samples in the empirical analysis and compare the results: The unbalanced whole sample with a varying number of countries and a reduced sample, which only contains countries which report wages for at least 15 years (hereinafter referred to as *Whole Sample* and *Reduced Sample*).[3]

[3]**OECD member states** that report wages in at least 15 years: Australia, Austria, Belgium, Canada, Denmark, Finland, Germany, Iceland, Italy, Japan, Mexico, Norway, Portugal, United Kingdom, United States. **EU member states** that report wages in at least 15 years: Belgium, Denmark, Germany, Italy, Portugal, United Kingdom.

But, there are also some disadvantages that restrict the analysis of wage distributions: First, the number of occupations and the descriptions of the particular skill requirements are constant over time. The data does not contain information on the change of tasks that are required in a particular occupation. There are also no "new" occupations occurring over time, for example new IT-jobs. Second, there is no information on the number of employees in each occupation. This restricts the analysis of wage inequality as wages can not be weighted due to the number of employees. Moreover, data on the number of employees can hardly be taken from other data sources, because there is either no such a detailed data available or industry classifications differ a lot. Third, wages are averaged wages for each occupation. There is no information on wage distribution within occupations for different aged workers. But, keeping in mind the restrictions of the data, it is still a considerable improvement working with the *October Inquiry* database.

I introduce a skill variable which distinguishes three groups. Occupations are classified into unskilled, medium skilled, or high skilled occupations, following the classification of the German Institute for Employment Research (IAB). Workers in unskilled occupations have no postsecondary education. The workers in medium-skilled occupations completed an apprenticeship or a high school degree (which is called *Abitur* in Germany). Workers in high skilled occupations have graduated from a university or a college. Table 3.4 gives the total number of observations and the share of each skill level for the OECD, the EU, the United States and Germany. The share of each skill group is quite similar in the reported country samples (20% high skilled, 65% medium skilled, and 15% low skilled workers), because these countries report wages for almost all of the maximum of 161 occupations contained in the *October Inquiry*.

Several authors argue that it is not only the skill level that affects wage distribution and wage inequality, but the task content of jobs (for example Autor et al., 2003, who describe work as a series of tasks). As the task content of work is typically measured at the occupational level, I follow Spitz-Oener (2006) and classify each of the 161 occupations reported in the *October Inquiry* into five task groups (see Table 3.5). Table 3.6 gives the total number of observations by task as well as the share of each skill level, respectively. As Germany, the United States, and the member states of the EU and the OECD report wages for almost the maximum of 161 occupations and the classification of tasks and the skill level do not differ between countries, the share of each task and each skill level are quite similar in these countries. For example, about seven percent of all workers are working in an occupation that requires non-routine analytic tasks. All workers performing these kind of occupations are high skilled. Almost 19% of all workers are occupied in a job that is characterized by non-routine interactive tasks, 44% of them are high skilled, and 56% of them are medium skilled. The largest share of workers, about 45%, perform occupations with routine manual task requirements. Six percent of these workers are high skilled, 69% are medium skilled, and 25% are low skilled.

To analyze the effect of technological change on wages with regard to the hypothesis of a more "nuanced view of technological change" (see e.g. Goos & Manning, 2007) in the case of Germany, I use cross-sectional data of the year 2006 from the "Qualification and Career Survey" which is a survey of employees carried out by the German Federal Institute for Vocational Training (Bundesinstitut für Berufsbildung, BIBB). The database contains information on 20,000 individuals, which are classified according to their occupation. The dataset contains, for example, information on the introduction of computers, new machines, or whether the actual job is thought to be a "new occupation".

I follow Spitz-Oener (2006) and generate a dummy variable for computer use as measure for technological change indicating whether or not the majority of employees in each occupation stated that computers were introduced during the past two years (2004-2006). As there are more than 20,000 individuals in the database and each occupation occurs more than once, I summarize the answers to the questions over each occupation. If the majority of employees in an occupations states that computers were firstly introduced during the past two years, the dummy variable is 1, and 0 otherwise.

Unfortunately, the *October Inquiry* and the "Qualification and Career Survey" have no common occupation identifier. Therefore, I use the International Standard Classification of Occupations (ISCO-88) to merge both datasets. As control variables, I introduce information on prices of computer software and hardware taken from the Federal Statistical Office of Germany.

In the following section 3.4, I focus on the analysis of wage distributions in the member states of the OECD and the EU. The results are compared to the occupational wage distributions in the United States and Germany. To give a first introduction, I present the mean and median wages (given in US Dollar) as well as the log wages for both groups of countries, the United States, and Germany (see Figure 3.1). The curves of the mean and the median wages follow a similar development. As wages are given in US-Dollar, there might be a bias because of exchange rate fluctuations. Thus, I also present the wage structure using the log mean and log median wage (see also Figure 3.1).

3.4 Trends in Occupational Wage Distribution

The theoretical model presented in Section 3.2 implies several assumptions concerning wage distributions. In this section, I will empirically analyze whether these assumptions can be verified. The first part of the empirical analysis refers to the assumption that wages do not differ within the same occupation in general because skill requirements do not differ within the same occupation. However, the model makes no clear assumptions concerning wage differences within the same occupation across countries. Base payments and returns to skill may differ between countries. Thus, I determine differences in payment within the same occupations across countries.

The second assumption is very intuitive: Skills that are needed to carry out an occupation differ between occupations as well as the occupational returns to skills, respectively. Therefore, wages are supposed to differ with regard to different occupational skill requirements. In a first step, I analyze wage distributions across different skill levels. In a second step, I follow Spitz-Oener (2006) and use a narrower skill definition based on the idea of work as a series of tasks.

Third, the theoretical model assumes that the returns to skill are equal in the same occupation within a country. As each occupation requires a special bundle of skills, there are wage differences between occupations, but there should be no differences within occupations. To test whether this assumption is supported by the data, I choose occupations that are reported for several industries and determine whether there are differences in payment within occupations across industries.

The goal of this section is to analyze whether the assumptions of the theoretical model are right and there is only heterogeneity between occupation - or if there is also heterogeneity within occupations. All results are given for the member states of the OECD and the EU, as well as for the United States and Germany.

3.4.1 Wage Spreads within Occupations

The theoretical predictions presented in Section 3.2 show that even if workers embody the same bundle of skills, their income may differ because they choose different occupations that require different series of tasks. Therefore, returns to skill may differ between occupations, but should be equal within an occupation. However, do two workers that carry out the same occupation really earn the same wage? In the year 2006, a cook in Australia earned an average monthly wage of 2,133 US Dollar, while in the same year a cook in Canada earned 1,597 US-Dollar, in Germany 2,360 US-Dollar, and in the United States 1,893 US-Dollar. This is the case, although occupation - and therefore under assumption the required bundle of skills - is identical and these countries can be assumed to be quite similar with respect to income. The theoretical model contains two variables, which can explain country-specific variation. First, the occupational basement payments may differ between countries. Second, it seems intuitive that returns to skill may vary across countries with respect to country specific preferences and skill requirements.

To determine wage differences in the same occupation across countries, I focus on the occupation-specific ratio of wages, hereinafter referred to as *occupational wage spread*. This approach reflects, on the one hand, the wage inequality across countries as well as trends in payment of occupations, and, on the other hand, the nominal different costs of labor for production process. I follow Freeman and Oostendorp (2000) and compute the relation between the minimum wage (respectively the median wage) and the maximum wage that is paid for each occupation in the OECD and the EU, measured in US-Dollar. This is not a common measure of wage inequality, but it is very intuitive and quite easy to interpret. The smaller the ratio, the higher are differences in payment between the country with the minimum or median wage for the considered occupation and the highest wage country. For example, the least wage for a cook in the year 1995 in the EU was paid in Portugal (544 US-Dollar), the highest wage was paid in Luxembourg (2,330 US-Dollar). Thus, the wage spread of a cook in the year 1995 in the EU is 0.23. This ratio is computed for each occupation in each year. The results given in Table 3.7 are presented as five-year-averages for the OECD and the EU. First, I give averages over all occupations in the OECD and the EU. Second, I differentiate between occupations within the same skill level. Third, I distinguish between occupations in manufacturing and non-manufacturing sectors. The first and the last year of the sample are left out as data coverage in quite low in these two years.

I find considerable wage spreads within occupations, which are larger in the OECD than in the EU. In the OECD as well as in the EU, wage spreads are increasing since the beginning of the 1980s. Differentiating between the skill level and sectors does not change the results a lot. In the OECD, the wage spread decreases from around 0.2 in the 1980s to around 0.1 in the years after the millennium. That means that the difference between the worst and the best paid worker in the same occupation across the member states of the OECD increased from 80% to 90% during the last two decades. In contrast, the relation of the median and the maximum wage only changed around 5%. The results in the EU vary less strongly. On average, the worst paid worker in a particular occupation earned 30% of the wage of the best paid worker in the 1980s. This ratio decreased to 24% in the middle of the first decade of the new century. Differences in manufacturing sectors are slightly, but consequently larger than differences in non-manufacturing sectors in both, the OECD and the EU. This leads to the conclusion that either returns to skill or base payments vary between countries.

3.4.2 Wage Spreads by Skill Level

A worker's skill level is positively associated with educational attainment, and is also reflected by her or his occupation. Each skill level is characterized by a bundle of skills that is required to carry out a particular occupation. As shown before, the returns to skills differ with respect to occupational skill requirements, and thus, wages differ. In the following section, I determine in a first step the degree of wage dispersion that is affected by the skill level. In a second step, I use a more nuanced view of the skill level and focus on occupational task requirements.

The standard deviation of log wages is quite a useful measure of wage distribution.[4] Figure 3.2 displays the evolution of the standard deviations of log wages for unskilled, medium skilled, and high skilled workers. The results are almost constant for each skill level in Germany. The standard deviation of the log wage of high skilled workers in the OECD, the EU and Germany varies slightly around 0.4, whereas the result of around 0.25 hardly differs between medium and unskilled workers. There is a lot more variation in the United States, which might support the hypotheses of the polarization of work (see e.g. Autor et al., 2006).

To show whether the skill level affects wages in different countries in a different way, I use a simple approach and regress the skill level on the log wage (in US Dollar) using time and year fixed effects:

$$lnw_{ojt} = \alpha + \beta_1 skill_o + u_{jt} + \eta_{ojt}, \tag{3.3}$$

where the dependent variable lnw_{ojt} is the log wage that is paid in occupation o in country j at time t, $skill_o$ is the skill level that is needed to carry out occupation o, which is constant over time and does not differ between countries. u_{jt} contains country- and year fixed effects which are represented by combined dummy variables, and η_{ojt} is an error term.

I choose the log wage level of medium skilled workers which is scaled to 1.0 as a benchmark. The scaled coefficients are computed by using the exponential function

[4] The standard deviation is sensitive to extreme outliers. However, Harsch and Kleinert (2011) have cleaned the data and dropped extreme outliers.

of the estimated coefficients. The wage distribution between low skilled and high skilled workers is represented by the scaled coefficients and can be interpreted in relation to those of medium skilled workers. The differences in payment resulting through different skill levels reflect the degree of inequality in the wage structure. Results are presented in Table 3.8. All estimations are significant at the 1% level. The results are robust to the inclusion of several control variables, for example, unemployment by skill level, GPD growth, or exchange rates. The first column gives the estimations results, the second column contains the computed wage dispersion between the different skill levels, respectively.

Results are quite similar for the OECD and the EU, as well as for the United States and Germany. Low skilled workers earn on average about 15 percent less than medium skilled workers, whereas high skilled workers earn about 60 percent more than medium skilled workers. As Germany is a member of the EU, and both, the United States and Germany, are members of the OECD, I test whether the results for the OECD and EU are driven by these countries. Excluding Germany slightly changes the results for the EU: While the scaled coefficient for low skilled workers stays almost unchanged (0.849), the scaled coefficient for high skilled workers decreases (1.533). Thus, wages differences between medium and high skilled workers are driven by Germany. Running the approach for the OECD without Germany does only change the scaled coefficient of high skilled workers (1.510). Excluding both, the United States and Germany from the OECD countries leads to the same result. The scaled coefficient for low skilled workers does not change (0.839), while the scaled coefficient for high skilled workers decreases (1.492). It can therefore be concluded that Germany drives wage inequality with regard to the relation of medium to high skilled workers. The same applies to the OECD for the United States and Germany.

The results are consistent with the assumptions of the theoretical model presented in Section 2. There is a large wage heterogeneity between the different skill levels, which can be explained by different returns to the bundle of skills that is required to carry out an occupation.

However, several authors argue that it is not only the skill level that affects wage distribution and wage inequality, but the task content of jobs (for example Autor et al. (2003), who describe work as a series of tasks). Therefore, I compute the standard deviation of the log wage for each task group as a measure of wage distribution (see Table 3.5 for a presentation of the task groups). The results for the member states of the OECD and the EU, as well as the United States and Germany are presented in Figure 3.4. Again, the evolution of the standard deviations of log wages is quite stable in the OECD and the EU. It is remarkable that Germany is characterized by a almost constant wage distribution, while there is a large wage heterogeneity in the United States. The results for the OECD are robust to the exclusion of Germany and the United States. This is also valid for the exclusion of Germany from the sample of the EU.

Using task classification instead of the skill level allows a more nuanced view of wage the distribution. The development of the standard deviation of log wages supports the assumption of the theoretical model that wages are determined by the bundle of skill that is required to carry out an occupation, as there is hardly any change in the wage distribution within the task groups. With the exception of the United States, wage distribution within the five task groups is more or less constant.

I use a fixed effects approach to determine the effect of the different task classifications on the log wage distribution (in US-Dollar). The estimation equation is quite similar to the one presented in equation (3.3), as I change only the explanatory variable "skill level" into "task classification" of occupation o. I choose the log wage level of workers who perform *Nonroutine Analytic* as a benchmark. Again, the benchmark is scaled to 1.0. The wage distribution between the five different task classifications is represented by the scaled coefficients, which can be interpreted in relation to the wage level of the *Nonroutine Analytic* task group.

Again, the scaled coefficients are computed by using exponential function of the estimated coefficients. The differences in payment resulting through different task requirements reflect the wage distribution within each country or country group. Results are presented in Table 3.9. All estimations are significant at the 1% level. The first column gives the estimation results, the second column contains the computed wage dispersion between the different task groups, respectively. The results are also robust to the inclusion of several control variables, for example, unemployment by skill level, exchange rates, or GDP growth. Determining the wage spread within task groups allows to draw a more complex picture about wage distributions within countries or groups of countries. The spread between workers occupied in jobs with different task requirements is considerable larger than the spread between different skill levels. For example, workers in jobs that require routine manual tasks earn on average about 50% of the wage of workers in jobs with nonroutine analytic tasks requirements. The largest spreads can be found in the United States. The results for the EU and the OECD are robust to the exclusion of Germany, as the scaled coefficients change for less than one percent. Excluding also the United States from the OECD-sample leads only to a small change in the result for *Nonroutine Interactive* tasks.

The results are consistent with the assumptions of the theoretical model. Wages differ with respect to the tasks required to carry out an occupation. There is a large heterogeneity between the different task groups, which can be explained by different returns to the bundle of skills that is required to carry out an occupation.

3.4.3 Occupational Wage Spreads across Industries

The theoretical model presented in section 2 allows to explain, why wages differ across occupations, even if workers are skilled equal. The descriptive analysis of occupational wage spreads as given in the previous section shows that wages in the same occupation differ across countries. I focus on the question, whether there are differences in wages in the same occupation across different industries.

Therefore, I focus on occupations, which are reported for several industries, and analyze whether there is a wage gap in the same occupation between industries in the OECD, the EU, the United States, and Germany. There are two occupations in the dataset, which are reported for several industries: *Stenographer-Typist* and *Laborer*. The stenographer-typist is reported for five different industries, the laborer for eight industries. I analyze the relationship between the wage level and the industry by regressing occupation-industry-dummies on the log dollar wage, controlling for country- and year-effects. The results of the regression are labeled as coefficients.

For both of the two occupations, I chose the industry with the highest averaged wage in the OECD as benchmark: *Banks* is benchmark industry for *Stenographer-Typist*, and *Electric light and power* for *Laborer*. The wage level of both benchmark industries is scaled as 1.0, the results for the other industries can be interpreted in relation to the benchmark and are hereinafter referred to as *scaled coefficients*. All estimations are significant at the 1%-level. The results are robust to the inclusion of several other control variables.

The first column of Table 3.10 gives the regression results, the second column gives the exponential function of the coefficient and shows the scaled coefficient of the wage level of each industry compared to the benchmark industry. I find significant differences in the wage level for the different industries. Thus, a stenograph-typist in *Wholesale trade* is on average paid worst in the OECD, the EU, and Germany. He or she earns at least 15% less than a stenograph-typist who works in a bank. In contrast, a stenograph-typist in the United States earns most in the sector *Wholesale trade*. The differences in payment for a laborer are not as large as for a typist, but, there are also significant differences. The industry with the lowest wage for a laborer is *Spinning, weaving and finishing textile* in the OECD, the EU, and the United States. In Germany, a laborer in *Iron and Steel Basic Industries* earns the least.

The results show, that there is wage inequality within the same occupation across industries. Again, there are two variables in the theoretical model given in equation (3.1) which may explain this variation in wages in the same occupation. First, it is possible that the base payment θ_{ot} a worker earns in occupation o varies between industries. Therefore, the variable θ_{ot} should be rewritten with an industry index i: θ_{o_it}. Second, even if the same bundle of skills is needed to pursue a particular occupation, the returns to skill r_{kt} may differ between industries and lead to differences in wages.

3.5 Polarization of Work

The previous section shows that there is wage heterogeneity between and within occupations. While Germany is characterized by a remarkable stable wage distribution over time, there is large wage heterogeneity in the United States (see Figure 3.4). One possible explanation for an increasing wage inequality is the "nuanced version" of the skill-biased technological change which was introduced by Autor et al. (2003), who describe work as a series of tasks. They argue that it is not predominantly the skill level that divides workers into "winners" or "losers" of technological change, but the task content of the occupation they perform. This leads to the hypotheses that computers substitute for workers that perform manual and cognitive routine tasks but complement workers performing analytical and interactive activities (Spitz-Oener, 2006). Dustmann et al. (2009) follow this line of argument and show that wage inequality in Germany increased in the 1980s mostly at the top of the wage distribution, while rise in lower tail wage inequality occurred in the 1990s, one decade later than in the United States.

The findings of Dustmann et al. (2009) are not supported by the analysis presented in the previous section. I find a quite stable wage distribution within and across the task groups over time. But shouldn't Germany have experienced similar changes in skill demand compared to those in the United States? Did similar changes in skill requirements in Germany, and the United States not lead to similar changes in the structure of wages? To answer these questions, I will take a closer look at the German wage structure.

Spitz-Oener (2006) uses detail task measures to show that the German labor market has passed through similar changes in skill requirements compared to those in the United States. She finds evidence that there has been a strong decline in demand for manual and cognitive routine tasks, while a sharp increase in the demand for nonroutine cognitive tasks is observable. Following the argumentation of Spitz-Oener (2006), there are two hypotheses on the effect of the introduction of computer technologies as a measure of technological change that can be tested empirically. First, computer technologies are a substitute for routine manual and routine cognitive activities. Therefore, wages of workers who perform routine manual and routine cognitive tasks are supposed to decrease with an increasing use of computers. Second, using computers is complementary to analytic and interactive occupational tasks. This should result in increasing wages for workers performing these activities. These hypotheses are also consistent with the theoretical model presented in section 3.2. If the demand for particular skills is de- or increasing with the introduction of computer technologies, the returns to these skills are supposed to be directly affected.

To test these hypotheses, I use a difference-in-difference as basic estimation approach, which is a well-known way to estimate causal relationships. In a first step, a group that receives some sort of treatment is identified. Here, the treated group contains occupations in which computer technologies were introduced in the years 2004-2006.[5]

In a second step, after identifying the treated "computer group", I compare the differences in log wages after and before the intervention for the treated group to the same difference for the unaffected control group. The estimation approach is described by the following equation:

$$lnW_{ot} = \beta_1 + \beta_2 COMP_o + \beta_3 P_t + \beta_4 COMP_o * P_t + \beta_5 X_t + \epsilon_{ot}, \qquad (3.4)$$

where lnW_{ot} is the log wage that is paid in occupation o in year t. $COMP_o$ is a dummy variables indicating whether computers were introduced (1) or not (0) in occupation o, P_t is a binary variable taking value 1 if time period is 2005-2008, and taking value 0 otherwise (time period 2002-2004). $COMP_o * P_t$ is an interaction term which represents the actual treatment variable. X_t is a vector of control variables (like software or hardware prices, GDP per capita, or unemployment rates), and ϵ_{ot} is an error term.

[5]There is the risk of a bias because the fact that computer technologies were not introduced during these years does not necessarily mean that computers have been not used at all. In fact, it is possible that computers were introduced several years ago. However, I am interested in the direct effect of the introduction of computer technologies, therefore it is not necessary to differentiate if computers are used not at all or if computers were introduced several years ago. In both cases no direct change of wages should be observable (under the assumption that the effect is not lagged for more than two years).

In a next step, I also include occupation dummies and industry dummies to control whether the results are driven by particular occupations or industries.

I run the estimation approach separately for each task group (see Table 3.5 for a detailed description of the task groups). The results are presented in Tables 3.11 and 3.12. The high r-squared in columns (2)-(4) of both tables indicates that the inclusion of occupation dummies in equation (3.4) might cause a bias due to multicollinearity, whereas including industry dummies does not affect the results. But, as I am interested in the effect of technological change on the wage of workers performing different tasks, I need to absorb the wage effects driven by particular occupations. Therefore, I modify equation (3.4) in the following way:

$$lnW_{ot} = \beta_1 + \beta_2 P_t + \beta_3 COMP_o * P_t + \beta_5 X + \eta_o + \epsilon_{ot}, \tag{3.5}$$

where η_o are occupation fixed effects which substitute for the dummy variable $COMP_o$. It is not possible to run the regression including both, the dummy variable $COMP_o$ and fixed effects η_o. Again, the interaction term $COMP_o * P_t$ is of main interest as it represents the treatment effect. The estimation results are given in Tables 3.11 and 3.12 in columns (5) and (6). Neither the sign nor the size of the estimated coefficients of the treatment effect $COMP_o * P_t$ changes, but the significance of the results varies (the same applies to the other control variables). Thus, the fixed effects estimation based on equation (3.5) seems to be the most suitable approach.

The results presented in columns (5) and (6) at the upper part of Table 3.11 support the hypothesis of increasing wages of workers who perform non-routine analytic tasks. Compared to the control group their wages increase about five percent after the introduction of computer technologies. In contrast, workers who perform routine cognitive tasks (like calculating or bookkeeping) experience a wage loss of more than six percent compared to the control group where no computers were introduced in the relevant time period (see lower part of Table 3.11). Thus, also the second hypothesis is supported. Both results are significant at the 5%-level and are robust to the inclusion or exclusion of control variables as well as the in- and exclusion of industry dummy variables. In contrast, I do not observe any significant effect of computer introduction on the wage of workers who perform non-routine interactive, routine manual, or non-routine manual tasks.

To support the theory that the task content of work and not the skill level is the channel for the wage effect of technological change, I re-estimate equations (3.4) and (3.5) separately for each skill level.[6] The results given in Table 3.13 show no significant effect of computer introduction on the wage level. These findings support the hypothesis that it is not the skill level that affects the degree of an increase or decrease of wages due to technological change.

Based on these results, I generate 15 interaction groups of the skill level and the task groups to analyze if the observed results are driven by one special group (for example low skilled workers that perform routine cognitive tasks). As data coverage is quite low in some cases, it is not possible to run the regression based on equation (3.5) for each of the 15 interaction groups. There are, for example, no low skilled workers that perform non-routine analytic tasks. Therefore, Table 3.14 only contains results for four combinations: Low skilled workers performing non-routine manual tasks, and high skilled workers that perform non-routine analytic, non-routine interactive, or routine manual tasks. The interesting result is that workers performing manual tasks experience a five percent wage loss compared to the control group – no matter if they are low skilled performing non-routine manual tasks or if they are high skilled performing routine manual tasks. In contrast, wages of high skilled workers performing non-routine analytic, or non-routine interactive tasks are increasing after the introduction of computers. Results are significant at the 1%-, 5%-, and 10%-level and are robust to the in- and exclusion of control variables. However, data coverage is still quite low.

Bringing these results together with theoretical model presented in section 3.2, it becomes evident that each occupation requires a special bundle of skills to perform the series of tasks required for the particular job. I can show that the task content

[6]Based on the estimation results presented in Tables 3.11 and 3.12, it would be sufficient to run only regressions based on equation (3.5). However, to show that the estimated coefficients of $COMP_o * P_t$ are also robust to the different estimation approaches in this case, I present the results based on equation (3.4) for each skill level, too.

of work is the channel through which technological change (measured by the introduction of computer technologies) affects wages. My results support the hypotheses that computer technologies are a substitute for (non-)routine manual and routine cognitive activities, and are complementary to analytic and interactive occupational tasks. Hence, wages of workers performing manual tasks decrease after the introduction of computer technologies no matter if workers are low skilled or high skilled. In contrast, wages of workers in occupations that are characterized by non-routine analytic or non-routine interactive tasks increase. However, I do not find evidence for the hypothesis that primarily medium skilled workers lose (see e.g. Autor et al., 2006, Michaels et al., 2010).

3.6 Summary

A large amount of research has dealt with the determinants of wages, wage setting and the distribution of wages. Due to a lack of comparable international wage data, there are still many questions about international wage structures and occupational wage distributions which have not yet been analyzed. Making use of the newly standardized and imputed *October Inquiry* database provided by the International Labor Organization (see Freeman & Oostendorp, 2000, 2001; Harsch & Kleinert, 2011) allows to analyze international wage structures and occupational wage distribution in a comprehensive way.

To give a brief introduction to the theoretical mechanism of wage setting in occupations, I introduce a intuitive theoretical model of wage setting following Firpo et al. (2011) which captures occupational wage differences. Moreover, the model allows to analyze the channels through which technological change affects wages.

There are several assumptions in the theoretical model which I test empirically for the member states of the OECD, the EU, the United States, and Germany. First, the model assumes that wages do not differ within the same occupation in general because skill requirements do not differ within the same occupation. However, the model makes no clear assumptions concerning wage differences within the same occupation across countries. I find considerable wage spreads within occupations, which are larger in the OECD than in the EU. In the OECD as well as in the EU, wage spreads are increasing since the beginning of the 1980s. This leads to the conclusion that either returns to skill or base payments vary between countries.

Second, I test the very intuitive assumption that the required skills differ between occupations as well as the occupational returns to skills, respectively. Therefore, wages are supposed to differ with regard to different occupational skill requirements. I find evidence that low skilled workers earn on average about 15 percent less than medium skilled workers, whereas high skilled workers earn about 60 percent more than medium skilled workers. The results are consistent with the assumptions of the theoretical model, as there is a large wage heterogeneity between the different skill levels, which can be explained by different returns to the bundle of skills that is required to carry out an occupation. However, several authors argue that it is not only the skill level that affects wage distribution and wage inequality, but the task content of jobs. I follow Spitz-Oener (2006) and classify each of the 161 occupations reported in the *October Inquiry* into five task groups. I can show that the spread between workers occupied in jobs with different task requirements is considerable larger than the spread between different skill levels. For example, workers in jobs that require routine manual tasks earn on average about 50% of the wage of workers in jobs with nonroutine analytic tasks requirements. The largest spreads can be found in the United States.

Third, the theoretical model assumes that the returns to skill are equal in the same occupation within a country. Therefore, there should be no wage differences within the same occupation. To test whether this assumption is supported by the data, I choose two occupations that are reported for several industries and determine whether there are differences in payment within occupations across industries. I find significant differences in the wage level for the different industries. A stenograph-typist in *Wholesale trade* sector is on average paid worst in the OECD, the EU, and Germany. He or she earns at least 15% less than a stenograph-typist working for a bank. The differences in payment for a laborer are not as large as for a typist, however, there are also significant differences.

Moreover, the model gives an idea of the channels through which technological change affects wages. Therefore, I analyze the effect of technological change on wages in Germany. One possible explanation for an increasing wage inequality is a nuanced version of the skill-biased technological change which was introduced by Autor et al. (2003). They argue that it is not predominantly the skill level that divides workers into "winners" or "losers" of technological change, but the series of task required by the occupation they perform. I use the introduction of computers as a measure for technological change. Following Spitz-Oener (2006), there are two hypotheses that can be tested empirically. First, computers substitute for workers that perform manual and cognitive routine tasks. Second, computers complement workers performing analytical and interactive activities. I use a difference-in-difference estimation approach test these hypotheses. Therefore, I identify a group that receives treatment (the introduction of computer technologies) during a particular time period (2004-2006). Results are compared to an "un-treated" control group. Both hypotheses are supported by my results. I find evidence that it is not the skill level that predominantly is the channel through which technological change affects wages, but the series of task workers perform in a particular occupations. Workers in occupations that are characterized by non-routine analytic tasks, for example researching, analyzing, evaluating, or planning, gain after the introductions of computers. Independently from the skill level, workers who perform routine cognitive tasks like calculating or bookkeeping experience a wage loss compared to the control group. These results are also in line with the theoretical model presented in section 3.2. However, the results do not support the hypothesis formulated by Autor et al. (2006) or Michaels et al. (2010) that primarily medium skilled workers lose.

3.7 Appendix for Chapter 3

Figures

Figure 3.1: **Evolution of Mean and Median Wages (in US Dollar)**

Figure 3.1 shows the evolution of mean and median wages and mean and median log wages over time for the OECD, the EU, Germany, and the United States.

Source: Own calculations, data from *October Inquiry*.

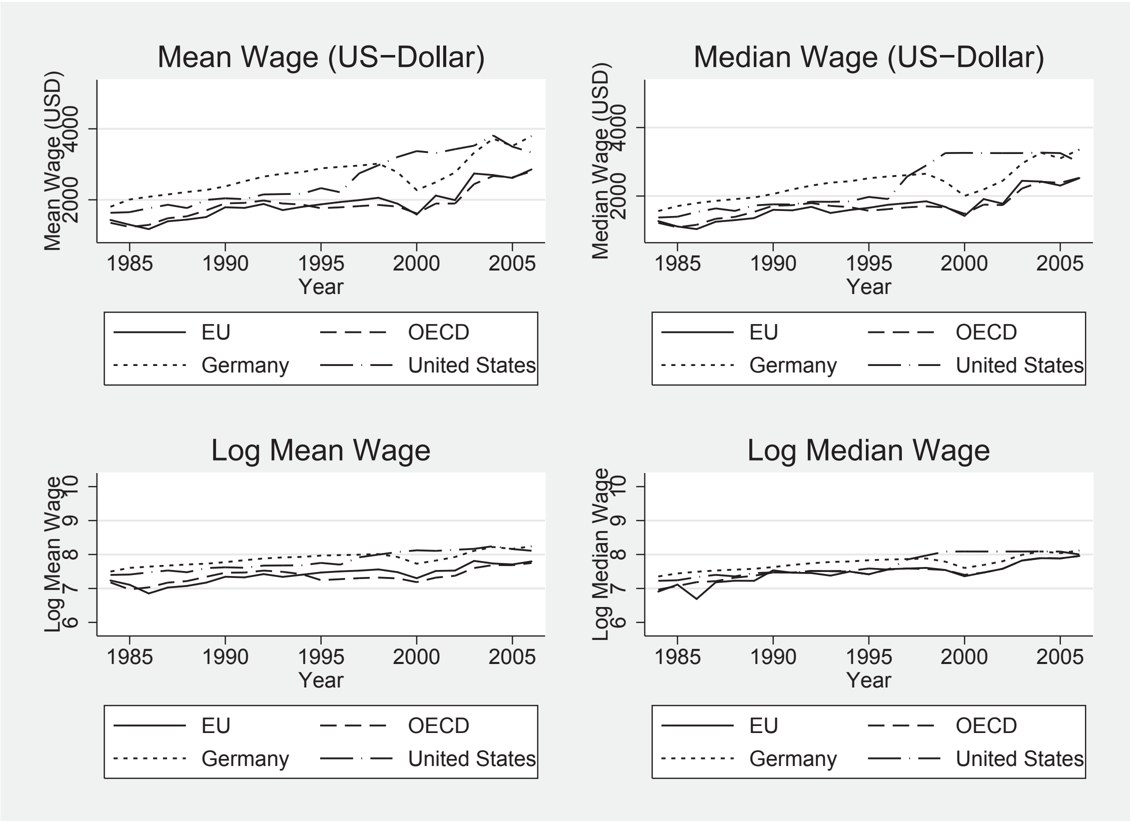


Figure 3.2: **Standard Deviation of Log Wages by Skill Level (I)**

Figure 3.2 shows the evolution of standard deviation of log wages over time for the OECD, the EU, Germany, and the United States. Classification of the skill level are taken from the German Institute for Employment Research (IAB). Unskilled workers have no postsecondary education, medium-skilled workers completed an apprenticeship or a high school degree, and workers in high skilled occupations have graduated from a university or a college.

Source: Own calculations, data from *October Inquiry*.

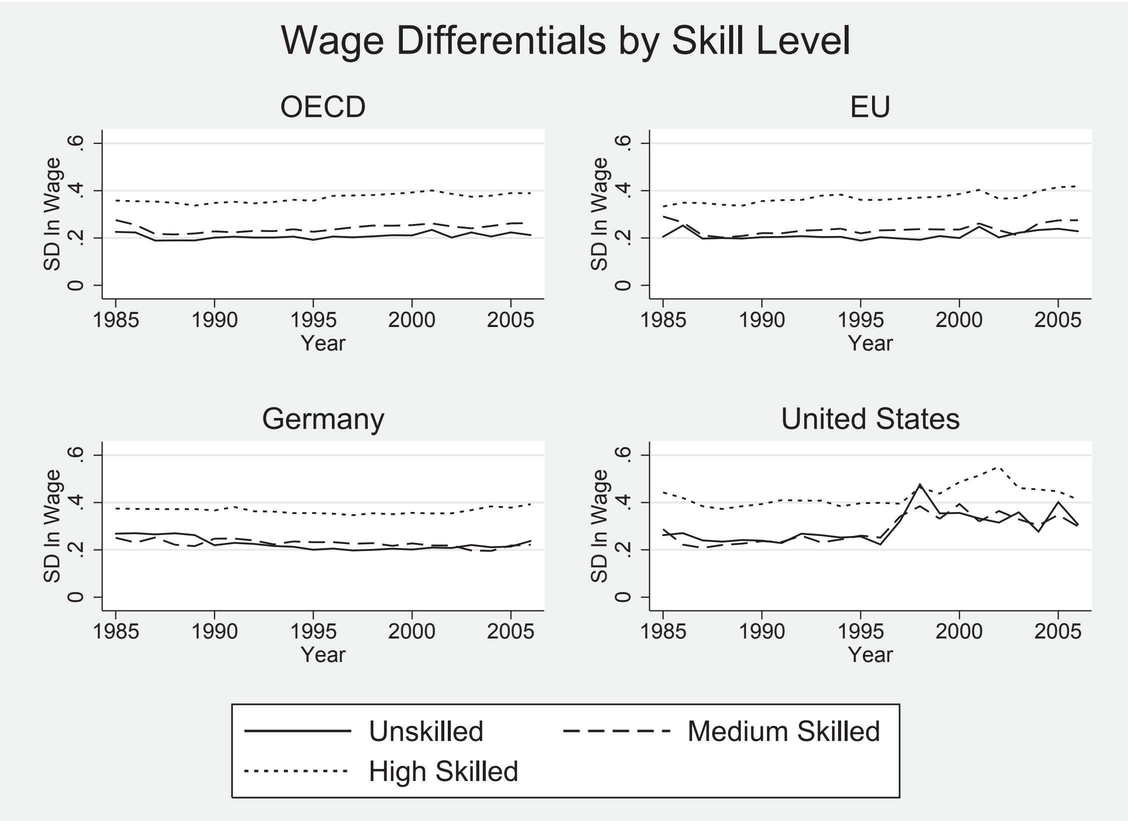


Figure 3.3: **Standard Deviation of Log Wages by Skill Level (II)**

Figure 3.3 shows the evolution of standard deviation of log wages over time for High Income, Upper Middle Income, Lower Middle Income, and Low Income countries following the World Bank Classifications. Classification of the skill level are taken from the German Institute for Employment Research (IAB). Unskilled workers have no postsecondary education, medium-skilled workers completed an apprenticeship or a high school degree, and workers in high skilled occupations have graduated from a university or a college.

Source: Own calculations, data from *October Inquiry*.

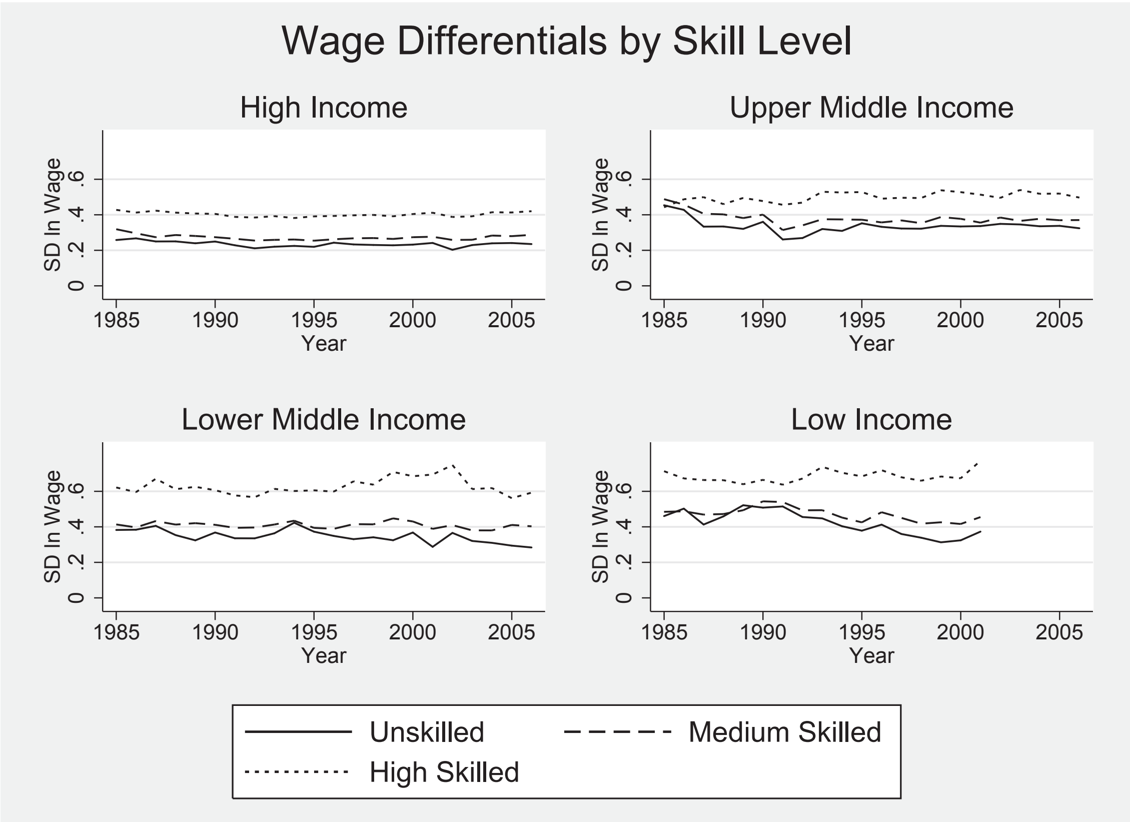
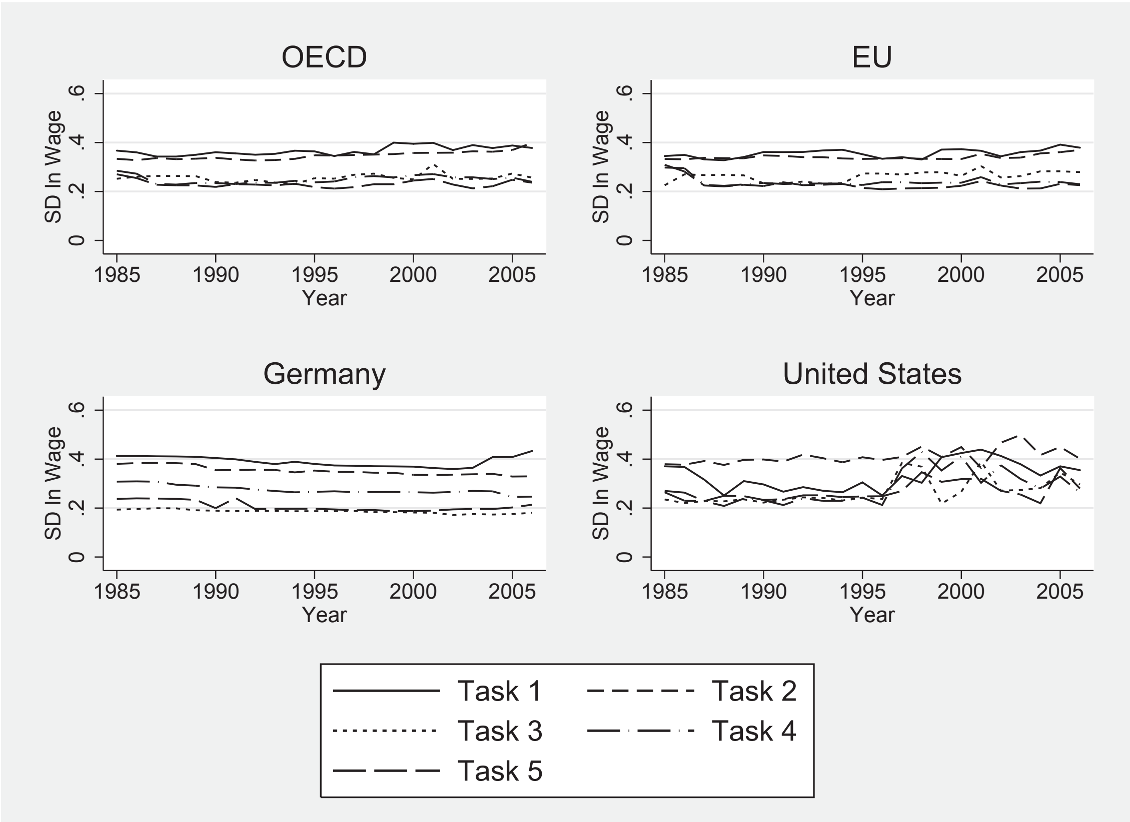


Figure 3.4: **Standard Deviation of Log Wages by Task Groups**

Figure 3.4 shows the evolution of standard deviation of log wages for the OECD, the EU, Germany, and the United States. Occupations are classified with respect to particular task requirements into five task groups following Spitz-Oener (2006): Task 1: Nonroutine Analytic; Task 2: Nonroutine Interactive; Task 3: Routine Cognitive; Task 4: Routine manual; Task 5: Nonroutine manual. Source: Own calculations, data from *October Inquiry*.



Data and Results

Data Coverage and Descriptive Statistics

Table 3.1: **Country Coverage and Number of Observations**

This Table gives the total number of observations by country for the years 1983-2008.

Country	Observations	Country	Observations	Country	Observations
Algeria	2,812	Egypt	1,624	Mexico	2,717
Argentina	1,150	Eritrea	375	Mongolia	44
Australia	2,718	Estonia	705	Mozambique	444
Austria	3,000	Ethiopia	58	Namibia	105
Azerbaijan	676	Finland	3,384	Nepal	170
Bahamas	927	French Polynesia	360	Netherlands	408
Bahrain	2,622	Gabon	776	Netherlands Antilles	576
Bangladesh	1,960	Germany	4,134	New Caledonia	65
Barbados	949	Gibraltar	468	Nicaragua	1,000
Belarus	715	Grenada	420	Norway	1,482
Belgium	1,188	Guam	450	Pakistan	1,106
Belize	1,365	Guatemala	596	Papua New Guinea	882
Benin	1,125	Guyana	2,227	Peru	2,160
Bermuda	1,059	Honduras	1,950	Philippines	2,520
Bolivia	1,898	Hong Kong	1,534	Poland	1,771
Botswana	184	Hungary	2,086	Portugal	3,312
Brazil	1,206	Iceland	1,274	Puerto Rico	1,104
Bulgaria	122	India	1,761	Romania	3,381
Burkina Faso	1,276	Indonesia	1,302	Russian Federation	1,342
Burundi	810	Ireland	30	Rwanda	1,008
Cameroon	1,190	Italy	3,672	San Marino	404
Canada	1,860	Japan	1,248	Senegal	73
Cape Verde	160	Jordan	2,907	Serbia and Montenegro	159
Central African Republic	1,276	Kazakhstan	351	Singapore	3,473
Chad	1,122	Kenya	176	Slovakia	2,041
Chile	720	Korea	3,792	Slovenia	728
China	1,834	Kuwait	128	Sweden	1,898
Colombia	417	Kyrgyzstan	396	Thailand	1,400
Comoros	1,404	Latvia	1,480	Togo	336
Costa Rica	2,415	Lesotho	230	Trinidad and Tobago	1,304
Croatia	119	Liberia	86	Turkey	330
Cuba	1,460	Lithuania	705	Ukraine	300
Cyprus	2,852	Luxembourg	267	United Kingdom	3,864
Czech Republic	2,208	Madagascar	1,264	United States	3,850
Czechoslovakia	1,120	Malawi	1,350	Uruguay	572
Côte d'Ivoire	1,738	Malaysia	1,106	Venezuela	1,540
Denmark	1,770	Maldives	36		
Djibouti	48	Mauritius	2,964		

Table 3.2: **Industries, Occupations and Number of Observations (I)**

Industry	Occupation	Observations	Industry	Occupation	Observations
Agricultural production (field crops)	Farm supervisor	784	Freight transport by road	Urban motor truck driver	987
	Field crop farm worker	906		Long-distance motor truck driver	923
Air transport	Air transport pilot	941	Grain mill products	Grain miller	985
	Flight operations officer	879	Insurance	Computer programmer	933
	Airline ground receptionist	984		Stenographer-typist	948
	Aircraft cabin attendant	917		Card- and tape-punching- machine operator	862
	Aircraft engine mechanic 1,007			Insurance agent	994
	Aircraft loader	886	Iron and steel basic industries	Occupational health nurse	539
Banks	Accountant	1,054		Blast furnaceman (ore smelting)	729
	Stenographer-typist	1,010		Hot-roller (steel)	659
	Bank teller	1,115		Metal melter	686
	Book-keeping machine operator	932		Labourer	771
Coalmining	Coalmining engineer	468	Logging	Logger	696
	Miner	568		Tree feller and bucker	585
	Underground helper, loader	504	Manufacture of bakery products	Baker (ovenman)	1,144
Communication	Post office counter clerk	979	Manufacture of dairy products	Dairy product processor	1,013
	Postman	1,015	Manufacture of electronic equipment	Electronics draughtsman	753
	Telephone switchboard operator	1,010		Electronics engineering technician	888
Construction	Building electrician	1,206		Electronics fitter	800
	Plumber	1,206		Electronic equipment assembler	844
	Constructional steel erector	1,166	Manufacture of footwear	Clicker cutter (machine)	967
	Building painter	1,148		Laster	884
	Bricklayer (construction)	1,178		Shoe sewer (machine)	976
	Reinforced concreter	1,051	Manufacture of industrial chemicals	Chemical engineer	950
	Cement finisher	1,041		Chemistry technician	972
	Construction carpenter	1,184		Supervisor or general foreman	990
	Plasterer	1,031		Mixing- and blending-machine operator	969
	Labourer	1,157		Labourer	971
Petroleum/natural gas production	Petroleum and natural gas engineer	642	Manufacture of leather (products)	Tanner	878
	Petroleum and natural gas extraction	647		Leather goods maker	893
	Supervisor or general foreman	683	Manufacture of machinery	Bench moulder (metal)	825
	Derrickman	612		Machinery fitter-assembler	912
Deep-sea/coastal fishing	Inshore (coastal) maritime fisherman	478		Labourer	856
	Deep-sea fisherman	504	Manufacture of metal products	Metalworking machine setter	967
Education services	Mathematics teacher (third level)	1,038		Welder	1,041
	Teacher in languages and literature	999	Manufacture of other chemical products	Mixing- and blending-machine operator	864
	Teacher in languages and literature	1,040		Packer	841
	Mathematics teacher (second level)	1,011		Labourer	895
	Technical education teacher (second level)	1,001	Manufacture of pulp, paper and paperboard	Wood grinder	700
	First-level education teacher	1,031		Paper-making-machine operator	810
	Kindergarten teacher	1,074	Manufacture of wearing apparel	Garment cutter	1,061
Electric light and power	Power distribution and transmission	1,016		Sewing-machine operator	1,088
	Office clerk	1,004	Manufacture of wooden furniture and fixtures	Furniture upholsterer	998
	Electric power lineman	1,020		Cabinetmaker	1,049
	Power-generating machinery operator	1,035		Wooden furniture finisher	1,021
	Labourer	1,011	Maritime transport	Ship's chief engineer	779
Engineering/architectural services	Clerk of works	808		Ship's steward (passenger)	706
Forestry	Forest supervisor	726		Able seaman	840
	Forestry worker	753			

Table 3.3: **Industries, Occupations and Number of Observations (II)**

Industry	Occupation	Observations
Medical and dental services	General physician	1,092
	Dentist (general)	1,022
	Professional nurse (general)	1,097
	Auxiliary nurse	1,045
	Physiotherapist	1,007
	Medical X-ray technician	995
	Ambulance driver	943
Other mining and quarrying	Miner	763
	Quarryman	814
Passenger transport by road	Road transport services supervisor	910
	Bus conductor	880
	Automobile mechanic	1,057
	Motor bus driver	1,078
Petroleum refineries	Controlman	736
Plantations	Plantation supervisor	586
	Plantation worker	678
Printing, publishing, allied industries	Journalist	999
	Stenographer-typist	1,000
	Office clerk	1,094
	Hand compositor	1,046
	Machine compositor	994
	Printing pressman	1,137
	Bookbinder (machine)	1,072
	Labourer	1,037
Public administration	Computer programmer	896
	Government executive official: a)	888
	Government executive official: b)	687
	Government executive official: c)	726
	Stenographer-typist	903
	Card- and tape-punching- machine operator	790
	Office clerk	962
	Fire-fighter	897
Railway transport	Ticket seller (cash desk cashier)	735
	Railway services supervisor	726
	Railway passenger train guard	640
	Railway vehicle loader	618
	Railway engine-driver	787
	Railway steam-engine fireman	428
	Railway signalman	701
Repair of motor vehicles	Automobile mechanic	1,145
Restaurants and hotels	Room attendant or chambermaid	1,092
	Hotel receptionist	1,134
	Cook	1,147
	Waiter	1,124
Retail trade (grocery)	Book-keeper	1,087
	Cash desk cashier	1,139
	Salesperson	1,140
Sanitary services	Refuse collector	902
Sawmills, planing and other wood mills	Sawmill sawyer	963
	Veneer cutter	829
	Plywood press operator	787
Shipbuilding and repairing	Ship plater	688
Slaughtering, preparing and preserving meat	Butcher	1,043
	Packer	1,024
Spinning, weaving and finishing textiles	Thread and yarn spinner	931
	Loom fixer, tuner	850
	Cloth weaver (machine)	971
	Labourer	1,033
Supporting services to air transport	Air traffic controller	899
	Aircraft accident fire-fighter	722
Supporting services to maritime transport	Dockworker	895
Wholesale trade (grocery)	Stenographer-typist	937
	Stock records clerk	1,107
	Salesperson	1,102

Table 3.4: **Number of Observations by Skill Level**

This Table gives the total number of observations by skill level for the OECD, the EU, Germany, and the United States for the years 1983-2008. Classification of the skill level are taken from the German Institute for Employment Research (IAB). Unskilled workers have no postsecondary education, medium-skilled workers completed an apprenticeship or a high school degree, and workers in high skilled occupations have graduated from a university or a college.

OECD	Observations	Percentage	**EU**	Observations	Percentage
High Skilled	5,692	19.57%	High Skilled	3,477	19.56%
Medium Skilled	18,996	65.30%	Medium Skilled	11,509	64.75%
Low Skilled	4,403	15.14%	Low Skilled	2,788	15.69%
Germany	Observations	Percentage	**United States**	Observations	Percentage
High Skilled	726	20.75%	High Skilled	704	20.78%
Medium Skilled	2,222	63.52%	Medium Skilled	2,200	64.94%
Low Skilled	550	15.72%	Low Skilled	484	14.29%

Table 3.5: **Task Classification**

This Table gives the classification of five task groups following Spitz-Oener (2006).

Classification	**Tasks**
Non-routine analytic	researching, analyzing, evaluating and planning, making plans, constructions, designing, sketching, working out rules/prescriptions, using and interpreting rules
Non-routine interactive	negotiating, lobbying, coordinating, organizing, teaching or training, selling, buying, advising customers, advertising, entertaining or presenting, employ or manage personnel
Routine cognitive	calculating, bookkeeping, correcting of texts/data, measuring of length/weight/temperature
Routine manual	operating or controlling machines, equip machines
Non-routine manual	repairing or renovation houses/apartments/machines/vehicles, restoring of art/monuments, serving or accommodating

Table 3.6: **Number of Observations by Task and by Skill Level**

This Table gives the number of observations by task classification (see Spitz-Oener, 2006) and skill level. The country samples contain only occupations which are reported in at least 20 years.

			Percentage of Skill Level within Task Group		
Tasks	**Observations**	**Percentage**	**High Skilled**	**Medium Skilled**	**Low Skilled**
OECD					
Non-routine analytic	1,974	6.79%	100.00%	0.00	0.00
Non-routine interactive	5,395	18.55%	44.34%	55.66%	0.00
Routine cognitive	2,990	10.28%	11.27%	77.83%	10.90%
Routine manual	12,909	44.37%	6.23%	69.24%	24.53%
Non-routine manual	5,823	20.02%	3.18%	81.20%	15.63%
EU					
Non-routine analytic	1,193	6.71	100.00%	0.00	0.00
Non-routine interactive	3,311	18.63%	44.76%	55.24%	0.00
Routine cognitive	1,914	10.77%	12.12%	77.48%	10.40%
Routine manual	8,056	45.32%	5.71%	68.73%	25.56%
Non-routine manual	3,300	18.57%	3.33%	80.61%	16.06%
Germany					
Non-routine analytic	264	7.55%	100.00%	0.00	0.00
Non-routine interactive	682	19.50%	45.16%	54.84%	0.00
Routine cognitive	374	10.69%	11.76%	76.47%	11.76%
Routine manual	1,518	43.40%	5.80%	68.12%	26.09%
Non-routine manual	660	18.87%	3.33%	80.00%	16.67%
United States					
Non-routine analytic	264	7.79%	100.00%	0.00	0.00
Non-routine interactive	616	18.18%	46.43%	53.57%	0.00
Routine cognitive	374	11.04%	11.76%	76.47%	11.76%
Routine manual	1,474	43.51%	5.97%	71.64%	22.39%
Non-routine manual	660	19.48%	3.33%	80.00%	16.67%

Table 3.7: **Wage Spread within Occupations**

I split the sample into OECD member countries, and EU member countries and compute the relation between the minimum wage (respectively the median wage) and the maximum wage that is paid for each occupation (in US-Dollar). The smaller the ratio, the higher are differences in payment between the country with the minimum or median wage for the considered occupation and the highest wage country. This ratio is computed for each occupation in each year. Table 3.7 gives five-year-averages for all occupations in the OECD and the EU, for occupations within the same skill level, and occupations in manufacturing and non-manufacturing sectors.

	OECD					EU				
Time Period	1984-1988	1989-1993	1994-1998	1999-2003	2004-2007	1984-1988	1989-1993	1994-1998	1999-2003	2004-2007
Average										
Min/Max	0.192	0.202	0.120	0.112	0.098	0.295	0.223	0.294	0.260	0.237
Median/Max	0.624	0.648	0.635	0.540	0.548	0.642	0.666	0.684	0.645	0.587
High skilled										
Min/Max	0.188	0.224	0.131	0.122	0.106	0.279	0.241	0.311	0.272	0.259
Median/Max	0.597	0.656	0.616	0.523	0.538	0.599	0.667	0.648	0.621	0.605
Medium Skilled										
Min/Max	0.190	0.196	0.116	0.109	0.093	0.293	0.216	0.288	0.255	0.224
Median/Max	0.630	0.654	0.644	0.546	0.544	0.647	0.666	0.688	0.646	0.572
Low Skilled										
Min/Max	0.205	0.201	0.120	0.112	0.107	0.322	0.227	0.296	0.268	0.259
Median/Max	0.632	0.615	0.622	0.538	0.576	0.673	0.665	0.713	0.674	0.624
Manufacturing Sectors										
Min/Max	0.185	0.183	0.104	0.101	0.088	0.296	0.203	0.275	0.238	0.222
Median/Max	0.638	0.645	0.645	0.550	0.566	0.657	0.665	0.694	0.653	0.600
Non-Manufacturing Sectors										
Min/Max	0.200	0.224	0.138	0.126	0.110	0.293	0.246	0.317	0.287	0.255
Median/Max	0.607	0.652	0.623	0.529	0.528	0.624	0.667	0.672	0.636	0.573

Table 3.8: **Wage Spread by Skill Level**

The results presented in this Table are based on a fixed effect regression approach. I split the sample into OECD member countries, EU member countries, Germany, and the United States. The dependent variable is the log wage, respectively. All estimations include skill level dummies, country- and year fixed effects and several control variables (e.g. unemployment, GDP per Capita, exchange rates). The log wage of medium skilled workers is chosen as benchmark for wage spread and is scaled to 1.0. The wage spreads are computed as exponential function of the estimated coefficients and have to be interpreted in relation to the benchmark.
***. **. * = significance at the 1%. 5%. 10%-level. Standard errors are given in parentheses.

OECD			**EU**		
Dependent Variable: Log Wage					
	Coefficient	Wage Spread		Coefficient	Wage Spread
Low Skilled	-0.175***	0.839	Low Skilled	-0.166***	0.847
	(0.005)			(0.006)	
High Skilled	0.428***	1.534	High Skilled	0.444***	1.559
	(0.004)			(0.005)	
Constant	7.990***		Constant	6.419	
	(0.014)			(0.025)	
R-squared	0.821		R-squared	0.805	
N	40,833		N	22,213	
United States			**Germany**		
	Coefficient	Wage Spread		Coefficient	Wage Spread
Low Skilled	-0.170***	0.844	Low Skilled	-0.175***	0.839
	(0.015)			(0.012)	
High Skilled	0.506***	1.659	High Skilled	0.517***	1.677
	(0.013)			(0.011)	
Constant	7.176***		Constant	7.320	
	(0.027)			(0.022)	
R-squared	0.554		R-squared	0.600	
N	3,850		N	4,134	

Table 3.9: **Wage Spread by Task Classification**

The results presented in this Table are based on a fixed effect regression approach. I split the sample into OECD member countries, EU member countries, Germany, and the United States. The dependent variable is the log wage, respectively. All estimations include task classification dummies, country- and year fixed effects and several control variables (e.g. unemployment, GDP per Capita, exchange rates). See Table 3.5 and Spitz-Oener (2006) for details of task classifications. The log wage of workers who perform *Nonroutine Analytic* tasks is chosen as benchmark for wage spread and is scaled to 1.0. The wage spreads are computed as exponential function of the estimated coefficients and have to be interpreted in relation to the benchmark.
***. **. * = significance at the 1%. 5%. 10%-level. Standard errors are given in parentheses.

OECD			**EU**		
Dependent Variable: Log Wage					
	Coefficient	Wage Spread		Coefficient	Wage Spread
Nonroutine Interactive	-0.380***	0.684	Nonroutine Interactive	-0.345***	0.708
	(0.008)			(0.010)	
Routine Cognitive	-0.610***	0.543	Routine Cognitive	-0.548***	0.578
	(0.009)			(0.011)	
Routine manual	-0.716***	0.489	Routine manual	-0.690***	0.502
	(0.008)			(0.009)	
Nonroutine manual	-0.647***	0.524	Nonroutine manual	-0.641***	0.527
	(0.008)			(0.010)	
Constant	8.643***		Constant	7.137***	
	(0.016)			(0.030)	
R-squared	0.809		R-squared	0.786	
N	32,553		N	19,753	
United States			**Germany**		
	Coefficient	Wage Spread		Coefficient	Wage Spread
Nonroutine Interactive	-0.312***	0.732	Nonroutine Interactive	-0.248***	0.780
	(0.022)			(0.019)	
Routine Cognitive	-0.751***	0.472	Routine Cognitive	-0.488***	0.614
	(0.023)			(0.021)	
Routine manual	-0.775***	0.461	Routine manual	-0.677***	0.508
	(0.020)			(0.017)	
Nonroutine manual	-0.654***	0.520	Nonroutine manual	-0.660***	0.517
	(0.021)			(0.019)	
Constant	8.230***		Constant	8.104***	
	(0.031)			(0.027)	
R-squared	0.591		R-squared	0.575	
N	3,850		N	4,134	

Table 3.10: **Wage Spread across Industries**

Results are based on a fixed effect regression approach. Dependent variable is the log wage, respectively. All estimations include industry-occupation dummies, country- and year fixed effects and several control variables. The log wage of workers in industry *Banks* (for stenographer-typist) and *Electric light and power* (for laborer) are chosen as benchmark (scaled to 1.0), respectively. ***. **. * = significance at the 1%. 5%. 10%-level. Standard errors in parentheses.

Industry	**OECD**		**EU**		**United States**		**Germany**	
Occupation: Stenographer-Typist	Coefficient	Wage Spread	Coefficient	Wage Spread	Coefficient	Wage Spread	Coefficient	Wage Spread
Insurance	-0.083***	0.920	-0.097***	0.908	-0.018***	0.982	-0.152***	0.859
	(0.020)		(0.023)		(0.062)		(0.012)	
Public Administration	-0.146***	0.864	-0.175***	0.839	0.052***	1.053	-0.063***	0.939
	(0.021)		(0.026)		(0.062)		(0.012)	
Printing, publishing and allied industries	-0.108***	0.897	-0.150***	0.861	0.021***	1.021	-0.072***	0.930
	(0.020)		(0.024)		(0.062)		(0.012)	
Wholesale trade (grocery)	-0.185***	0.831	-0.278***	0.757	0.141***	1.152	-0.306***	0.736
	(0.020)		(0.023)		(0.062)		(0.012)	
R-squared	0.911		0.901		0.714		0.979	
N	1,439		796		125		130	
Occupation: Laborer	Coefficient	Wage Spread	Coefficient	Wage Spread	Coefficient	Wage Spread	Coefficient	Wage Spread
Iron and steel basic industries	-0.009***	0.992	-0.115***	0.891	0.021***	1.021	-0.509***	0.601
	(0.021)		(0.025)		(0.063)		(0.014)	
Spinning, weaving and finishing textile	-0.179***	0.836	-0.203***	0.817	-0.087***	0.917	-0.488***	0.614
	(0.020)		(0.024)		(0.063)		(0.014)	
Printing, publishing and allied industries	-0.055***	0.947	-0.058***	0.944	0.005***	1.005	-0.169***	0.844
	(0.020)		(0.024)		(0.063)		(0.014)	
Manufacture of industrial chemicals	-0.053***	0.948	-0.078***	0.925	-0.078***	0.925	-0.304***	0.738
	(0.021)		(0.025)		(0.063)		(0.014)	
Manufacture of other chemical products	-0.098***	0.906	-0.089***	0.915	-0.151***	0.860	-0.304***	0.738
	(0.021)		(0.026)		(0.063)		(0.014)	
Manufacture of machinery (except electrical)	-0.117***	0.890	-0.185***	0.831	-0.050***	0.951	-0.422***	0.656
	(0.020)		(0.024)		(0.063)		(0.014)	
Construction	-0.065***	0.937	-0.082***	0.921	-0.024***	0.977	-0.215***	0.807
	(0.020)		(0.024)		(0.063)		(0.014)	
R-squared	0.922		0.917		0.714		0.977	
N	2,530		1,316		200		208	

Table 3.11: **Technical Changes and Wage Inequality by Task (I)**

The results presented in columns (1)-(4) of Table 3.11 are based on a difference-in-difference (DID) estimation approach, while columns (5)-(6) include occupation fixed-effects (FE). $COMP_o$ is a dummy variables indicating whether computers where introduced (1) or not (0) in occupation o in the years 2004 until 2006, P_t is a binary variable taking value 1 if time period is 2005-2008, and taking value 0 otherwise. $COMP_o * P_t$ is an interaction term which represents the actual treatment variable. ***. **. * = significance at the 1%, 5%, 10%-level. Standard errors in parentheses.

Estimation	(DID)	(DID)	(DID)	(DID)	(FE)	(FE)
Dependent Variable: Log Wage						
Task 1: Non-routine analytic						
$COMP_o * P_t$	0.057	0.057**	0.057**	0.057	0.057**	0.057**
	(0.215)	(0.024)	(0.024)	(0.147)	(0.024)	(0.024)
P_t	-0.082	-0.082	-0.082	-0.082	-0.082	-0.082
	(0.829)	(0.091)	(0.091)	(0.565)	(0.091)	(0.091)
$COMP_o$	-0.186	0.077**	0.351***	0.077		
	(0.176)	(0.030)	(0.030)	(0.187)		
Controls	✓	✓	✓	✓	✓	✓
Occupation Dummies		✓	✓			
Industry Dummies			✓	✓		✓
Occupation Fixed Effects					✓	✓
Constant	9.303	9.214***	8.940***	9.214*	9.241***	9.241***
	(6.951)	(0.762)	(0.762)	(4.737)	(0.762)	(0.762)
Observations	72	72	72	72	72	72
R-squared	0.046	0.990	0.990	0.620	0.499	0.499
Task 2: Non-routine interactive						
$COMP_o * P_t$	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
	(0.105)	(0.009)	(0.009)	(0.067)	(0.009)	(0.009)
P_t	-0.088	-0.088**	-0.088**	-0.088	-0.088**	-0.088**
	(0.409)	(0.036)	(0.036)	(0.261)	(0.036)	(0.036)
$COMP_o$	-0.179**	-0.426***	-0.426***	0.157**		
	(0.086)	(0.018)	(0.018)	(0.074)		
Controls	✓	✓	✓	✓	✓	✓
Occupation Dummies		✓	✓			
Industry Dummies			✓	✓		✓
Occupation Fixed Effects					✓	✓
Constant	9.108***	8.956***	8.956***	8.373***	9.044***	9.044***
	(3.432)	(0.304)	(0.304)	(2.189)	(0.304)	(0.304)
Observations	186	186	186	186	186	186
R-squared	0.078	0.994	0.994	0.659	0.578	0.578
Task 3: Routine cognitive						
$COMP_o * P_t$	-0.064	-0.064**	-0.064**	-0.064	-0.064**	-0.064**
	(0.090)	(0.030)	(0.030)	(0.043)	(0.030)	(0.030)
P_t	0.058	0.058	0.058	0.058	0.058	0.058
	(0.288)	(0.095)	(0.095)	(0.137)	(0.095)	(0.095)
$COMP_o$	-0.148**	-0.273***	-0.322***	-0.179***		
	(0.073)	(0.037)	(0.037)	(0.037)		
Controls	✓	✓	✓	✓	✓	✓
Occupation Dummies		✓	✓			
Industry Dummies			✓	✓		✓
Occupation Fixed Effects					✓	✓
Constant	8.139***	8.372***	8.584***	8.441***	8.018***	8.018***
	(2.343)	(0.773)	(0.774)	(1.117)	(0.773)	(0.773)
Observations	102	102	102	102	102	102
R-squared	0.202	0.927	0.927	0.834	0.284	0.284

Table 3.12: **Technical Changes and Wage Inequality by Task (II)**

The results presented in columns (1)-(4) of Table 3.12 are based on a difference-in-difference (DID) estimation approach, while columns (5)-(6) include occupation fixed-effects (FE). $COMP_o$ is a dummy variables indicating whether computers where introduced (1) or not (0) in occupation o in the years 2004 until 2006, P_t is a binary variable taking value 1 if time period is 2005-2008, and taking value 0 otherwise. $COMP_o * P_t$ is an interaction term which represents the actual treatment variable. ***. **. * = significance at the 1%, 5%, 10%-level. Standard errors in parentheses.

Estimation	(DID)	(DID)	(DID)	(DID)	(FE)	(FE)
Dependent Variable: Log Wage						
Task 4: Routine manual						
$COMP_o * P_t$	-0.004	-0.004	-0.004	-0.004	-0.004	-0.004
	(0.064)	(0.015)	(0.015)	(0.032)	(0.015)	(0.015)
P_t	-0.042	-0.042	-0.042	-0.042	-0.042	-0.042
	(0.209)	(0.050)	(0.050)	(0.104)	(0.050)	(0.050)
$COMP_o$	0.134**	0.784***	0.002	0.035		
	(0.052)	(0.036)	(0.036)	(0.030)		
Controls	✓	✓	✓	✓	✓	✓
Occupation Dummies		✓	✓			
Industry Dummies			✓	✓		✓
Occupation Fixed Effects					✓	✓
Constant	8.083***	7.833***	8.214***	8.182***	8.110***	8.110***
	-1.76	-0.421	-0.423	-0.873	-0.421	-0.421
Observations	414	414	414	414	414	414
R-squared	0.061	0.955	0.955	0.789	0.278	0.278
Task 5: Non-routine manual						
$COMP_o * P_t$	-0.018	-0.018	-0.018	-0.018	-0.018	-0.018
	(0.081)	(0.033)	(0.033)	(0.042)	(0.033)	(0.033)
P_t	0.007	0.007	0.007	0.007	0.007	0.007
	(0.265)	(0.106)	(0.106)	(0.137)	(0.106)	(0.106)
$COMP_o$	0.095	-0.135**	-0.080	0.009		
	(0.066)	(0.052)	(0.052)	(0.039)		
Controls	✓	✓	✓	✓	✓	✓
Occupation Dummies		✓	✓			
Industry Dummies			✓	✓		✓
Occupation Fixed Effects					✓	✓
Constant	7.983***	8.109***	8.058***	7.970***	8.002***	8.002***
	(2.226)	(0.890)	(0.891)	(1.151)	(0.889)	(0.889)
Observations	180	180	180	180	180	180
R-squared	0.05	0.873	0.873	0.766	0.159	0.159

Table 3.13: **Technical Changes and Wage Inequality by Skill Level**

The results are based on a difference-in-difference (DID) or fixed-effects estimation approach, where $COMP_o$ is a dummy variables indicating whether computers where introduced (1) or not (0) in occupation o in the years 2004 until 2006, P_t is a binary variable taking value 1 if time period is 2005-2008, and taking value 0 otherwise. $COMP_o * P_t$ is an interaction term which represents the actual treatment variable.
***. **. * = significance at the 1%. 5%. 10%-level. Standard errors in parentheses.

Estimation	(DID)	(DID)	(DID)	(DID)	(FE)	(FE)
Dependent Variable: Log Wage						
High Skilled						
$COMP_o * P_t$	0.014	0.014	0.014	0.014	0.014	0.014
	(0.105)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
P_t	-0.088	-0.088**	-0.088**	-0.088	-0.088**	-0.088**
	(0.421)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
$COMP_o$	-0.226***	-0.516***	-0.712***	-0.355***		
	(0.086)	(0.020)	(0.020)	(0.077)		
Controls	✓	✓	✓	✓	✓	✓
Occupation Dummies		✓	✓			
Industry Dummies			✓	✓		✓
Occupation Fixed Effects					✓	✓
Constant	9.229***	9.145***	8.489***	8.489***	9.140***	9.140***
	(3.524)	(0.343)	(0.343)	(2.855)	(0.343)	(0.343)
Observations	198	198	198	198	198	198
R-squared	0.097	0.993	0.993	0.455	0.495	0.495
Medium Skilled						
$COMP_o * P_t$	-0.008	-0.008	-0.008	-0.008	-0.008	-0.008
	(0.042)	(0.013)	(0.013)	(0.024)	(0.013)	(0.013)
P_t	-0.015	-0.015	-0.015	-0.015	-0.015	-0.015
	(0.159)	(0.047)	(0.047)	(0.089)	(0.047)	(0.047)
$COMP_o$	0.041	-0.137***	0.094**	0.072***		
	(0.035)	(0.040)	(0.040)	(0.025)		
Controls	✓	✓	✓	✓	✓	✓
Occupation Dummies		✓	✓			
Industry Dummies			✓	✓		✓
Occupation Fixed Effects					✓	✓
Constant	8.064***	8.115***	7.884***	7.905***	8.077***	8.077***
	(1.336)	(0.398)	(0.400)	(0.748)	(0.397)	(0.397)
Observations	606	606	606	606	606	606
R-squared	0.025	0.928	0.928	0.718	0.215	0.215
Low Skilled						
$COMP_o * P_t$	-0.008	-0.008	-0.008	-0.008	-0.008	-0.008
	(0.091)	(0.020)	(0.020)	(0.032)	(0.020)	(0.020)
P_t	-0.072	-0.072	-0.072	-0.072	-0.072	-0.072
	(0.296)	(0.066)	(0.066)	(0.105)	(0.066)	(0.066)
$COMP_o$	0.272***	0.787***	0.787***	0.152***		
	(0.074)	(0.030)	(0.030)	(0.037)		
Controls	✓	✓	✓	✓	✓	✓
Occupation Dummies		✓	✓			
Industry Dummies			✓	✓		✓
Occupation Fixed Effects					✓	✓
Constant	8.341***	8.232***	8.232***	8.232***	8.395***	8.395***
	(2.491)	(0.553)	(0.553)	(0.885)	(0.552)	(0.552)
Observations	150	150	150	150	150	150
R-squared	0.232	0.968	0.968	0.916	0.407	0.407

Table 3.14: **Technical Changes and Wage Inequality by Skill and Task**

The results presented in Table 3.14 are based on a fixed-effects estimation approach, where $COMP_o * P_t$ represents the treatment variable with $COMP_o$ as a dummy variables indicating whether computers where introduced (1) or not (0) in occupation o in the years 2004 until 2006. P_t is a binary variable taking value 1 if time period is 2005-2008, and taking value 0 otherwise. Task (1): Non-routine analytic; Task (2): Non-routine interactive; Task (3): Routine cognitive; Task (4): Routine manual; Task (5): Non-routine manual.
***. **. * = significance at the 1%. 5%. 10%-level. Standard errors in parentheses.

Dependent Variable: Log Wage				
	Low Skilled Task (5)	High Skilled Task (1)	High Skilled Task (2)	High Skilled Task (4)
$COMP_o * P_t$	-0.054*	0.057**	0.009*	-0.052***
	(0.031)	(0.024)	(0.006)	(0.016)
P_t	0.012	-0.082	-0.114***	-0.001
	(0.099)	(0.091)	(0.024)	(0.067)
Occupation Fixed Effects	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Constant	7.625***	9.241***	9.315***	8.350***
	(0.834)	(0.762)	(0.184)	(0.562)
Observations	30	72	84	24
R-squared	0.506	0.509	0.794	0.770

Chapter 4

Evidence on Trade, FDI, and Wage Inequality

4.1 Introduction

The relationship between trade, foreign direct investment (FDI) and wage inequality has been subject to intense scrutiny in the economic literature. Due to a lack of comparable wage data, many questions concerning the relation of wage inequality, trade, and FDI are unacknowledged. Mostly, empirical findings are only limited to a few countries or occupations. Sachs and Shatz (1996), for example, analyze the effect of trade with developing countries on wage inequality in the United States. Haskel and Slaughter (2001) use UK data to determine the impact of international trade and technical development on changes in the skill premium, while Hanson and Harrison (1999) analyze whether the increased wage inequality was associated with Mexico's sweeping trade reform in 1985. Beyer et al. (1999) study the empirically link between trade liberalization and wage inequality in Chile, and Attanasio, Goldberg, and Pavcnik (2004) focus on the effects of the tariff reductions in the 1980s and 1990s in Colombia on the wage distribution.

But little is known about the actual empirical degree of wage inequality across countries and particular occupations. Moreover, Bernanke (2007) states that the available empirical research on the influence of trade on wage inequality dates from the 1980s and 1990s and does not address later developments.

This lack of internationally comparable wage data has been deplored for years and has constrained the empirical analysis of wage inequality. This is the case although the International Labor Organization (ILO) has conducted their *October Inquiry* to obtain data on international wages, which leads to an annual wage survey containing data for 161 occupations in 49 industries for more than 130 countries. The ILO *October Inquiry* is the most far-ranging survey of wages around the world. But as it is published without correction or adjustment, it is rarely used. Freeman and Oostendorp (2000, 2001) started a novel project making use of the *October Inquiry*, which was comprehensively updated by Harsch and Kleinert (2011).[1]

This chapter examines the question whether trade activity and FDI affect the degree of wage inequality across countries. Making use of the *October Inquiry* allows to analyze wage inequality in a novel and comprehensive way. This is not only of interest for academic research purposes, but also for the public discussion about the effects of outsourcing and trade activity on employment and wages. First, section 4.2 describes the data. Section 4.3 gives a theoretical overview of predictions of foreign activities on wage inequality. Following Feenstra and Hanson (1995), I show theoretically that capital flows can lead to increasing wages of high skilled workers in countries with different factor endowments. Under certain conditions, also low skilled workers can gain. In the empirical analysis, which is presented in section 4.4, I analyze the effect of trade and FDI on the degree of wage inequality in the OECD. I follow Frankel and Romer (1999) and generate an instrumental variable that consists of geographical components, data on bilateral trade and bilateral capital flows, respectively. This approach controls for endogeneity of trade and FDI with respect to wage inequality. All results are given for the member states of the OECD, and are compared to several other country samples. Section 4.5 concludes.

The main conclusions of this chapter are as follows. First, I find evidence that trade activity leads to an increase of wage inequality in the OECD. In contrast,

[1] The standardization process of the *October Inquiry* database is also described in Chapter 2 of this thesis.

results are not clear-cut for the EU. Second, there are significant negative effects of trade on the degree of wage inequality in non-manufacturing sectors in the OECD. The same but smaller effects are observed for the EU, High Income Countries, and the total number of countries in the dataset. In contrast, I do not observe an increasing wage inequality in manufacturing sectors. Third, I do not find any significant effect of foreign investment activities on wage inequality.

4.2 Data

This section describes the data used in the present study. First, I briefly describe the *October Inquiry* wage database (see Chapter 2 of this thesis or Harsch & Kleinert, 2011 for a detailed description). After that I give an overview of the explanatory variables used in this paper.

4.2.1 October Inquiry

The standardized and imputed *October Inquiry* database contains standardized wages for up to 161 occupations from 49 industries in 112 countries between 1983 and 2008. The standardized wage is given in current local currency and in US-Dollar. But there are still gaps in the data which could not be filled in through imputation. These gaps may cause a bias. Hence, keeping only countries which report wages every year would reduce the sample size a lot. Therefore, I use two different samples in the empirical analysis and compare the results: The unbalanced whole sample with a varying number of countries and a reduced sample, which only contains countries which report wages for at least 15 years (hereinafter referred to as *Whole Sample* and *Reduced Sample*).[2] The main part of the empirical analysis focusses on the degree of wage inequality in a sample of OECD member states

[2] OECD member states that report wages in at least 15 years: Australia, Austria, Belgium, Canada, Denmark, Finland, Germany, Iceland, Italy, Japan, Mexico, Norway, Portugal, United Kingdom, United States.
EU member states that report wages in at least 15 years: Belgium, Denmark, Germany, Italy, Portugal, United Kingdom.

which is compared to other country samples (e.g. European Union, High Income Countries, Upper Middle Income Countries).

To give a more detailed impression of the data, I present some descriptive statistics (see Table 4.1). On average, every country reports 1,313 wage observations. The country with the lowest number of observations is Ireland (30 observations), while Germany is the country with most observations (4,134). On average, 49 countries report wages in each year. A maximum of 59 countries reports wages in the year 1995, a minimum of 22 countries reports wages in 2008. This is also reflected by the total number of observations by year (6,925 in 1995, 2,319 in 2008). In each year, the total number of the 161 occupations is reported by at least six countries. As a total average, every occupation is reported by 37 countries in each year. The maximum number of 57 countries reports wages for *Building electrician* and *Construction carpenter* in the year 1995. The least reported occupations are the *Railway steam-engine fireman* and the *Coalmining engineer*, which are on average reported by 18 countries each year. Data coverage is quite low in the first and the last year of the dataset. The total number of countries reporting as well as the number of industries and occupations can be found in the Appendix of Chapter 3 (see Tables 3.1, 3.2, 3.3).

4.2.2 Explanatory Variables

As this paper aims to analyze the impact of trade and foreign investment on wage inequality, several explanatory variables are necessary. These variables are introduced in this section.

I use information on GDP, imports, exports, foreign investment (all given in US Dollar), and labor force taken from the World Bank's *World Development Indicators (WDI)*. The *WDI* is a rich and widely used database containing information on the development of most economies in the world. The database contains the most current and accurate global development data, and it also includes national, regional and global estimates.

I follow Freeman and Oostendorp (2000) and compute the well-known measure that gives an approximation of a country's trade activity:

$$T_{i,j} = \frac{Export_{i,j} + Import_{i,j}}{GDP_{i,j}},$$

where $T_{i,j}$ is a measure of the amount of trade of country i in year j. This trade measure will be used in the empirical analysis to determine whether trade affects wage inequality. To analyze the effect of FDI on wage inequality, I choose FDI inflows, and FDI outflows as a percentage of GDP also taken from the *WDI*. Unfortunately, the data does not allow to differentiate between the motivation of foreign investment which can be divided into two different types: vertical and horizontal foreign investment.[3] But, as the aim of this paper is to analyze the entire effect of trade activity and foreign investment on wage inequality, it is not necessary to differentiate between the two types of foreign investment.

Hence, to estimate the effect of trade and FDI on wage inequality, it is necessary to add several control variables. To control for endogeneity of trade and FDI with respect to wage inequality, I follow Frankel and Romer (1999) and generate an instrumental variable that consists of bilateral trade data and bilateral geographical components. They argue that only geographical characteristics are robust to endogeneity problems that occur in the analysis of the effects of trade on wage inequality. Therefore, I use annual measures of bilateral trade which are taken from the OECD's *STAN Database for Industrial Analysis*. As bilateral FDI data is hardly available, I use data on outstanding amounts of bilateral bank assets as approximation of capital flows taken from the Bank for International Settlements (BIS). Moreover, I use data from the *Centre d'Études Prospectives et d'Informations Internationales* (*CEPII*) which has built two datasets providing data on (bilateral) geographical elements and variables. I merge both datasets to yield a single database which contains information on geographical elements of each country as well as bilateral data, for example, distance measures, dummy variables indicating whether two countries are contiguous, share a common language, have had a common colonizer after 1945, have had

[3]While vertical foreign investment is motivated by cost advantages in production, horizontal foreign investment has the aim to develop foreign markets.

a colonial relationship after 1945, or are/were the same country. The process of generating the instrumental variables is described in section 4.4. The fact that not all explanatory variables are available for a large period of time reduces the panel to the years 1988-2008.

Moreover, I add several classifications, for example whether a country is a member of the OECD, or the European Union. The countries are also classified into High (HIC), Upper Middle (UMIC), Lower Middle (LMIC), and Low Income (LIC) countries following the World Bank classifications. As wages are supposed to differ between the skill level that is needed to carry out an occupation, I classify the reported occupations into low skilled, medium skilled, or high skilled occupations, following the classification of the German Institute for Employment Research (IAB). A more detailed description of the skill level classification can be found in section 3.3.

4.3 Theoretical Background

There is a large amount of research on the effects of trade and capital flows on wages and wage inequality. Borjas, Freeman, and Katz (1991), for example, show that during the 1980s trade competition led to a fall in relative employment and wages of unskilled workers in the United States. Yet, these results are not supported by the research of Bound and Johnson (1992), as well as Berman, Bound, and Griliches (1994). They argue that it is not predominantly trade that causes the negative wage effects, but technological change such as the use of computers. Bivens (2007) argues that although the results that were published in the 1990s differ a lot, most of them indicate that trade could account for 10 to 40 % of the relative wage inequality in the 1980s. The question is whether these findings are still prevalent today. Krugman (2008, p. 2) suggests that there has been "a transformation of the nature of world trade", for instance a shift to outsourcing of services. Moreover, the distributional effects of trade may be considerably larger today than they were in the early 1990s. Blinder (2006) calls this phenomena a *Second Industrial Revolution*. This view goes along with Bivens (2007), who finds that, by 2006, trade flows between the United

States and its poorer trading partners increased inequality in relative earnings by almost 7%.

Two of the most important theoretical studies on the impact of trade and capital flows on relative wages were published by Feenstra and Hanson (1995, 1996). They argue that technology may be an important factor, but that "the trade-versus-technology debate obscures a more fundamental question about how firms respond to import competition and how these responses, in turn, are transmitted to the labor market" (Feenstra & Hanson, 1996, p. 240). Similar to the Hecksher-Ohlin model, the primary aim of the model is to explain the rise of relative wages for skilled workers in both countries, the United States as well as Mexico. The relative wage is defined as the relation of the wages of high skilled and low skilled workers. As the research of Feenstra and Hanson (1995) is one of the most well-known trade-wage-models, I will briefly present their model to give an idea of the theoretical mechanism and the effects of trade and capital flows on relative wages. A more detailed presentation of the model can be found in the Appendix (see section 4.6). According to the model, the impact of foreign activities on the degree of wage inequality is not clear-cut. On the one hand, the model shows that the demand for high skilled labor in both countries increases with the volume of foreign activities and, hence, also the wage increases. On the other hand, Feenstra and Hanson (1995) argue, this does not necessarily mean that low skilled workers lose in real terms. Instead, under certain conditions it is possible that all workers gain.

Determining the Equilibrium

There is just a single manufactured final good Y that consists of a continuum of intermediate inputs, which are labeled $z \epsilon [0, 1]$. For each unit of z, an amount of $a_L(z)$ of unskilled and $a_h(z)$ of skilled labor is used in the production process. The total factor input of unskilled and skilled labor for each unit z is denoted by $L(z)$ and $H(z)$. By assumption, the ratio of $a_H(z)/a_L(z)$ is increasing in z, which indicates an increasing input of high skilled labor.

Each country has a factor endowment of unskilled labor L_i, skilled labor H_i, and capital K_i. Factor prices differ by assumption in the North and in the South and are labeled w_i for low skilled labor, q_i for high skilled labor, and r_i for capital. The rate of return of capital is supposed to be higher in the South ($r_N < r_S$), as there is a shortage of capital in the South that leads to higher capital costs/returns. The ratio of wages for skilled and unskilled workers ($q_N/w_N < q_S/w_S$) is lower in the North (hereafter referred to as *relative wage*). Thus, a smaller wage ratio in the North also implies lower wage spread. Moreover, different wage ratios in the North and the South also imply that the relative costs of production using high skilled labor are lower in the North.

The relation between labor supply and relative wages can be described in the following way: $L_i(q_i/w_i) \leq 0$ and $H_i(q_i/w_i) \geq 0$. Hence, labor supply of unskilled workers depends negatively and labor supply of high skilled workers depends positively on the relative wage. One explanation for this might be that with a rising relative wage more unskilled workers are motivated to become skilled. There might also be other effects on labor supply which are not specified at this point.

The described differences in relative wages and returns to capital lead to one single point, labeled z^*, at which the minimum costs of production in the North (c_N) and the South (c_S) are equalized:

$$c_S(w_S, q_S, r_S; z^*) = c_N(w_N, q_N, r_N; z^*). \tag{4.1}$$

Graphically, this point is shown in Figure 4.1. For the following analysis, it is not necessary to determine the absolute slopes of the northern and southern cost functions. By assumption, inputs z are produced in both countries. As the relative wage in the North is lower than in the South, the North has a cost advantage if the fraction of high skilled labor in the production process of z increases. The factor prices of each input z equal the minimum of the unit-costs across the countries. Therefore, all production activities will take place in the South if $z < z^*$ and in the North if $z^* < z$ for financial reasons.

Equations (4.1) , (4.12), and (4.13) describe the equilibrium of the model. Below, world expenditure is normalized to $E = 1$ and therefore, all factor prices can be interpreted as shares of world factor income. Wages for both types of labor only depend on functions of z^*, while z^* is determined by the intersection of the minimum cost functions of North and South. In a next step, I show what happens if capital flows from the North to the South.

The Effect of Capital Flows

As capital in the South is by assumption scarcer than in the North, the return to capital must be higher ($r_N < r_S$). Thus, it follows that $(r_S - r_N)dK > 0$, where dK is the amount of capital that flows from North to South. To analyze the impact of Southern capital growth, the critical point z^* is initially assumed to be fixed. Thus, wages for unskilled and skilled workers are constant (see equations (4.9) and (4.10)). Therefore, the first impact of capital flows from North to South is to lower the return to capital (equation (4.15)) in South and to raise it in North. Capital flows from North to South lead to a relative increase in the costs of capital in the North because returns to capital are increasing, while capital costs in the South are decreasing in relative terms. As a result, the cost functions of both countries change and the critical value shifts from z^* to z', as shown in Figure 4.2.

The activities in the range $[z^*, z']$ now rather take place in the South than in the North, as cost advantages are shifting. These activities are more skill intensive than the former activities that took place in the South. Moreover, the range of activities that now take place in the North is smaller, $[z', 1]$, but still more skill-intensive than all production activities taking place in the South. If wages are still assumed to be fixed, the relative demand for skilled labor increases in the South as well as in the North. If the relative demand for labor (given in equation (4.16)) is differentiated after the critical value z^* in North and South, the relations are positive as the ratio of skilled/unskilled labor at point z^* outranges the average for the South and is lower than the average for the North. Thus, relative demand is a negative function of the relative wage in both countries.

In summary, capital flows from the North to the South will lead to an increase in the critical value of z^*. As a result, the relative demand for skilled labor increases in both countries, in the North as well as in the South. The increase in z^* at fixed factor prices leads to a concentration in more high skilled production activities. Therefore, the relative demand for high skilled labor increases. As a main result, the relative wage (q_i/w_i) in both countries increases and high skilled workers in both countries gain. Moreover, Feenstra and Hanson (1995) show, that the increase in relative wages is robust to a change in factor prices. Thus, the gap between the wages of unskilled and high skilled workers increases. This is a very intuitive first result that explains theoretically why high skilled workers gain, while unskilled workers may lose.

But, Feenstra and Hanson (1995) argue that this does not necessarily mean that one of the types of labor loses in real terms. As the payments to labor are defined as a fraction of total factor payments, an increase of the critical value z^* leads to increasing payments to labor in the South, while payments to labor are declining in the North. Thus, Southern labor benefits from the capital flow. As the relative wage of high skilled workers rises, Southern high skilled workers will gain by an increasing share of total factor payments. On the other hand, unskilled workers in the North are faced with a declining share of total factor payments. But although this conclusion seems intuitive, Feenstra and Hanson (1995) argue that all workers can gain from the capital flow. Therefore, the real return to the production factors and the change in the price index, which is denoted by π, have to be determined.

In a world with only one final good Y, total expenditure is given by $E = \pi Y$. As mentioned before, total expenditure is normalized to one, $E = 1$. Hence, it can be shown that the increase in total output Y due to the capital flow is given by:

$$\hat{Y} = (r_S - r_N)dk > 0. \tag{4.2}$$

The price index π falls by the corresponding amount:

$$\hat{\pi} = -\hat{Y} = -(r_S - r_N)dk < 0. \tag{4.3}$$

It is important to mention, that this decreasing price index is related only to the initial difference in the return to capital. This change is not related to the extent of change of the critical value z^*.

In an extreme case, where z^* does not change because of a discontinuity in the cost function, the point of discontinuity z^* satisfies the conditions, where Southern costs are below the Northern costs for $z < z^*$, and above the Northern costs for $z > z^*$. This case is illustrated by Figure 4.3. Feenstra and Hanson (1995) show that a small capital flow from the North to the South will lead to a downward shift of the minimum-cost function to the left of the critical value z^*, and to an upward shift to the right of z^* (see 4.3). The critical value z^* is not affected. Hence, labor demand equations given in (4.12) and (4.13) do not change. The new minimum-cost profile must correspond to the described reduced price-index π, so that in consequence the real returns, which are given by w_i/π for low skilled and q_i/π for high skilled workers, are increasing. Thus, following the argumentation of Feenstra and Hanson (1995), all workers can gain. In former research, it was more or less consensual that with leaving capital, the marginal product of labor is decreasing and therefore real wages are supposed to fall. Therefore, in the following section, I use an empirical approach to analyze whether Feenstra and Hanson (1995) are right and all workers can gain - or if wage inequality rises with an increase in foreign activities.

4.4 Wage Inequality, Trade, and Foreign Investment

The theoretical model of Feenstra and Hanson (1995) shows that capital flows between countries with different factor endowments can lead to an increase in wages for high skilled workers in both countries. Under certain conditions, also low skilled workers can gain. At this point, it is necessary to state that the empirical estimation of the effects of foreign activities on relative wages differs from the theoretical model presented in the previous section. The idea of the model is to show, that capital flows will induce a shift in the factor-intensities in production and therefore affect the relative wages. This theoretical model offers some guidance to analyze empirically the effects of foreign activities on relative wages and the degree of wage inequality.

Thus, the empirical part of this chapter is organized as follows. First, I compute relative wages as measures of wage inequality. Second, I test whether trade flows affect the degree of wage inequality. Third, I analyze the relationship between FDI and the degree of wage inequality. Therefore, I use three different approaches of computing a relative wage.

First, the relative wage is computed as the ratio of the averaged wage of low skilled workers relative to the averaged wage of high skilled workers in each country and year. This ratio does not account for sectoral differences, but gives a good impression of a country's average wage spread. Hence, there is only one particular relative wage for each country and year, which has to be treated as a macro variable. The lower the ratio, the higher is the inequality between low skilled and high skilled workers. Second, Feenstra and Hanson (1995) define the relative wage as the relation of the wages of workers in manufacturing and non-manufacturing industries. I proceed in a slightly different way, as I classify the 49 industries that are reported in the *October Inquiry* database into manufacturing and non-manufacturing industries. But as there are also high skilled workers in manufacturing sectors, for example engineers, I generate a combined variable that contains information on the characteristics of the industry and the particular skill level required to carry out a particular occupation. Thus, there is one relative wage ratio for manufacturing as well as for non-manufacturing industries in each country and year that captures the wage spread between low and high skilled workers, respectively. The lower the particular relative wage ratio, the higher is the wage inequality between low skilled and high skilled workers in manufacturing and in non-manufacturing sectors. Third, I follow Freeman and Oostendorp (2000, 2001) and compute an inequality measure which is defined as the ratio of the lowest wage and the highest wage that is paid in each country and year (hereafter referred to as *Min/Max*).[4]

In the following analysis, I use all three types of relative wages and compare the results.[5] Table 4.4 gives five-year averages of the relative wages for the whole sample, the OECD countries, and the EU. The left hand side of the table contains the results for the unbalanced sample. The right hand side gives the results for

[4]See Table 4.3 for a more detailed description.

[5]I use the terms *relative wage* and *relative wage ratio* interchangeably throughout my thesis. Both terms refer to ratio of the averaged wages of low skilled workers relative to the averaged wages of high skilled workers.

the reduced sample, which contains only countries that report wages for at least 15 years, respectively. The differences in the results of the two samples are quite small. The lower the coefficient, the larger is the degree of wage inequality. I find that the average wage spread between high skilled and low skilled workers, which is given in the first rows of the table, is slightly increasing in the OECD and considerably increasing in the EU. These findings are in line with the results for manufacturing and non-manufacturing sectors. The bottom rows of the table show the spread between the lowest and the highest wage. Thus, wage inequality has been increasing during the sample period. The presented results are really close to the wage spreads presented in Freeman and Oostendorp (2000).[6]

4.4.1 The Effect of Trade on Wage Inequality

Typically, regressions of income on the ratio of exports or imports to GDP find a moderate positive relationship (Frankel & Romer, 1999). Thus, following this argumentation, wage inequality is supposed to decrease with increasing trade activity if wages for all workers rise with increasing trade shares. The theoretical model predicted that at least high skilled workers gain, which would indicate an increasing wage inequality if wages of low skilled workers stay constant or decrease. If all workers gain by the same extent, there should be no effect observable as wage inequality is not supposed to rise.

Frankel and Romer (1999) describe the difficulties in estimating the effect of trade on income. They argue that there might be a problem of endogeneity, because, for example, income in a country is high for reasons that have nothing to do with trade, and trade is increasing because of higher income. Moreover, if measures of a country's trade policy are used in the regression analysis, a bias is likely to occur because these policies may also affect income. The same endogeneity problem may arise in the analysis of trade effects on relative wages, as wage inequality may be high because of reasons that are independent from trade, but exports are increasing because of low wages for low skilled workers. Moreover, the way a government deals

[6]Moreover, Table 4.5 in the Appendix yields the results for country groups following the World Bank Classification.

with trade may also have an effect on the way a government handles wage inequality. Thus, policy variables can hardly be used to identify the impact of trade.

Because a country's geographical characteristics are not affected by income or policies, and geographical characteristics are supposed to have no effect on income, except for the impact on trade, they can be used to obtain instrumental variables. Hence, I instrument a country's trade activity with a constructed geographical component of bilateral trade, relying on a very similar approach to that proposed by Frankel and Romer (1999). Afterwards, I compare the results to those of an OLS estimation, controlling for the validity of the instrumental variable estimation.

The estimation procedure of the geographical component is quite standard in empirical literature, and is based on the following estimation equation [7]:

$$\begin{aligned} ln(T_{ij}/GDP_i) \;=\;& a_0 + a_1 lnD_{ij} + a_2 lnN_i + a_3 lnA_i + a_4 lnN_j \\ & + a_5 lnA_j + a_6(L_i + L_j) + a_7 lnB_{ij} + a_8 B_{ij} lnD_{ij} \\ & + a_9 B_{ij} lnN_{it} + a_{10} B_{ij} lnA_i + a_{11} B_{ij} lnN_j \\ & + a_{12} B_{ij} lnA_j + a_{13} B_{ij}(L_i + L_j) + e_{ij}, \end{aligned} \tag{4.4}$$

where $ln(T_{ij}/GDP_i)$ is the log of bilateral trade (exports and imports) between countries i and j in relation to the GDP of country i. D_{ij} is the log distance between i and j, measured as log of the distance between countries' capital cities. lnN_i and lnN_j are the log populations of both countries, lnA_i and lnA_j are the log areas of both countries. L_i and L_j are dummy variables containing information whether a country is landlocked, B_{ij} is a dummy for a common border between countries i and j. All other variables are interaction terms with the border-dummy B_{ij}. e_{ij} is the error term.

First, as the values of GDP, trade, and population change from one year to another, I estimate equation (4.4) separately for each year of the sample. In a second step, I use the estimated results to calculate annual fitted values of trade between countries i and j relative to GDP of country i. Third, these fitted values are exponentiated and aggregated over all countries j for each country i and year.

[7] See e.g. Frankel and Romer (1999) for a detailed presentation.

Hence, the geographical component of a country equals the sum of the estimated geographic components of its bilateral trade with each other country in each year of the sample.

Frankel and Romer (1999) show that the generated geographical component is now usable to instrument a country's trade activity. The trade share is treated as endogenous, and the constructed geographical component of trade is used as an instrument. I use a two-stage instrumental variable regression estimation (IV), also including country- and year-fixed effects, as well as several control variables (for example GDP per capita, unemployment rate, and exchange rate). Following Frankel and Romer (1999), I include the log of population as an explanatory variable to get an approximation of the within-country trade.

The constructed geographical instrument and the instrumented trade measure are highly positive correlated (around 0.809 in each of the subsamples). Moreover, the first stage regression has reasonable explanatory power, and the coefficient of the constructed geographical component is positive, as expected, and highly statistically significant. As the $F-$statistic is considerably larger than the rule of thumb value of 10, the geographical component does not seem to be a weak instrument.

I present the results for the OECD in Table 4.6 for each type of relative wage. The left hand side of the table shows the results using the unbalanced sample, the right hand side using the reduced sample. However, the differences in the results of the two samples are quite small. The IV estimates are compared to OLS estimates, based on a fixed effects estimation using country- and year fixed effects and the analogous explanatory variables. The estimated coefficients of the trade share are robust to the exclusion of the control variables, as the sign does not change and the estimated coefficients of trade stay almost unchanged. Moreover, the estimated coefficient of trade differs between the OLS and IV estimation, which is a strong evidence for the endogeneity of trade. The almost unchanged standard errors indicate there was no loss in efficiency due to the instrumental variable estimation. This result is also supported by the Hausman test.

I find small significant negative effects of trade on relative wages in the OECD. The lower the relative wage ratio, the higher the wage inequality. Therefore, a negative estimated coefficient of trade share indicates increasing wage inequality. Using the reduced sample, I find evidence that an increasing trade share decreases the relative wage and thus increases wage inequality significantly by 0.5 percent. The strongest negative effect of trade on wage inequality is observed for relative wages in non-manufacturing sectors, where trade increases the wage spread by one percent. But still, the effect is quite small. Moreover, trade affects the *Min/Max* ratio significantly negative, as the ratio decreases by about 0.8 percent.

The results for all types of relative wages for the total number of countries, the EU, and High Income Countries (HIC) are given in Table (4.7). I run both approaches, the IV estimation and the OLS, and compare the results, respectively. Again, a negative coefficient indicates that wage inequality is rising with increasing trade activity. Hence, using the IV approach, I find a slightly significant negative relationship between trade and relative wages in the EU. Compared to the OECD, the effect is quite small. However, I do not find any significant effect of trade on relative wages in manufacturing sectors, neither in the entire sample, nor in the EU or in HIC. Instead, using the IV approach, I find that trade affects relative wages in non-manufacturing sectors significantly negative in all of the three country samples. However, I find no evidence that trade has a negative effect on the ratio of minimum and maximum wages. Thus, results are not as clear-cut as for the OECD.

In summary, I find evidence that the trade share has a small but significant negative effect on relative wages in the OECD. Thus, the gap between the average wages of low skilled and high skilled workers is rising with increasing trade flows. Moreover, I can show that this negative effect in the OECD is driven by increasing wage inequality in non-manufacturing sectors, which is a little puzzling. The results for the whole number of countries, the EU, and HIC are not clear-cut. The hypothesis that all workers can gain is not verified by the empirical analysis.

4.4.2 The Effect of Foreign Investment on Wage Inequality

In a next step, I focus on the effect of FDI flows on relative wages and wage inequality, which are a good approximation for the theoretically relevant capital flows. Again, I proceed in two steps. First, following the idea of Frankel and Romer (1999), I construct a geographical component that can be used as an instrument for the ratio of total FDI to GDP, as there might be a problem of endogeneity in the analysis of the effect of FDI on wage inequality. Second, I estimate the effect of FDI share on wage inequality using a instrumental variable approach, and compare the results to an OLS estimation. Results are given for the OECD using the unbalanced and the reduced sample, as well as for the whole number of countries, the members of the EU, and High Income Countries.

First of all, I will briefly address to the suspected endogeneity problem. Wage inequality in a country may be high for reasons that have nothing to do with income, and foreign investment can be increasing because of increasing wage spreads. Moreover, the way a country is dealing with foreign investment activities might also reflect the domestic policy and therefore affect income and wage inequality, which leads to an endogeneity problem, too. Therefore, I generate a geographical instrument to account for endogeneity, again following Frankel and Romer (1999).

The argumentation is analogous to the previous section: Because a country's geographical characteristics are not affected by income or policies, and geographical characteristics are supposed to have no effect on income, except for a supposed impact on foreign investment, they can be used to obtain an instrumental variable. The estimation strategy of generating the instrumental variable is given by the following equation:

$$\begin{aligned} ln(Capital_{ij}/GDP_i) &= a_0 + a_1 lnD_{ij} + a_2 lnN_i + a_3 lnA_i + a_4 lnN_j \\ &\quad + a_5 lnA_j + a_6(L_i + L_j) + a_7 lnB_{ij} + a_8 B_{ij} lnD_{ij} \\ &\quad + a_9 B_{ij} lnN_{it} + a_{10} B_{ij} lnA_i + a_{11} B_{ij} lnN_j \\ &\quad + a_{12} B_{ij} lnA_j + a_{13} B_{ij}(L_i + L_j) + e_{ij}. \end{aligned} \tag{4.5}$$

$ln(Capital_{ij}/GDP_i)$ reflects bilateral capital flows between countries i and j in relation to GDP of country i. I use outstanding amounts of bilateral bank assets as approximation of capital flows, because there is no data on bilateral FDI for such a large number of countries and such a long time period. All other variables were already specified in the previous section.

Again, equation (4.5) is estimated separately for each year of the sample. The estimated results are used to calculate annual fitted values of the outstanding amounts of bilateral bank assets between country i and j relative to GDP of country i. In a next step, the fitted values are exponentiated and aggregated over j for each country i and each year of the sample.

I use an instrumental variable regression approach to estimate the effect of total FDI (inflows and outflows) in percent of GDP on relative wages in the OECD. The share of FDI on GDP is treated as endogenous, while the constructed geographical component is used as an instrument. Moreover, I include country- and year-fixed effects, as well as several control variables (for example GDP growth per capita, unemployment rates, exchange rates). I compare the results of the IV-estimation to an OLS fixed effects approach, including country- and year-fixed effects, as well the analogous control variables.

The constructed geographical instrument and the share of total FDI are highly correlated (around 0.663 in each of the subsamples). The first stage regression has obvious explanatory power, and the coefficient of the constructed geographical component is highly statistically significant. Moreover, the $F-$statistic is clearly larger than the rule of thumb value of 10, so that the geographical component is not a weak instrument.

The results for the OECD are presented in Table 4.8. Using the IV-estimation, I do not find any significant effect of FDI on relative wages. However, there are only small significant positive effects of FDI on relative wages observable using the OLS regression approach. But, as the Hausman test shows that using a instrumental variable estimation is the right specification, the results of the OLS are not valid. Overall, results are not clear-cut.

In addition, I run the same approach for the total number of countries, the EU, and High Income Countries (HIC). Results are given in Table 4.9. I do not find any statistically significant effect of FDI on relative wages. Using the OLS regression approach, I find a small positive effect of FDI on relative wages in High Income Countries. But the results do not persist when the instrumental variable estimation is used. However, the regression results show that there is mostly no statistically significant relationship between the share of FDI and wage inequality measured as relative wages.

This is a surprising result, which might be due to the fact that the data does not allow to differentiate between vertical and horizontal foreign investment. As vertical foreign investment is motivated by cost advantages in production, a negative effect on relative wages in the domestic market seems intuitive. However, given the aggregated nature of the data on FDI, it is not possible to determine the effects of vertical and horizontal foreign investment at this point.

4.5 Summary

This chapter was motivated by the question whether trade and foreign investment activities have a significant effect on relative wages and the degree of wage inequality. To get an idea of how capital flows and foreign investment affect relative wages, I used a theoretical model following Feenstra and Hanson (1995). They show that capital flows between two countries with different factor endowments can lead to a higher demand of high skilled labor and therefore to an increase in wages of high skilled workers. Feenstra and Hanson (1995) argue that an increasing demand for high skilled labor does not necessarily mean that unskilled workers will lose. Instead, it is possible that all workers gain.

However, the lack of international comparable wage data has constrained the empirical analysis of wage inequality for years. The novel and standardized *October Inquiry* is a large wage database which allows to analyze wage inequality for a large period of time, and for a large set of countries in a comprehensive way. Therefore, I computed three different types of relative wages as measures for wage inequality and combined the *October Inquiry* database with data from several other datasources like the *WDI*, the OECD *STAN* database, or the *CEPII* data.

Thus, in the empirical section, I determined the effect of trade and FDI on wage inequality. Frankel and Romer (1999) describe the endogeneity problem that may occur when estimating the effect of trade on income, because income in a country might be high for reasons that have nothing to do with trade, and trade can be high because of higher income. Moreover, measures of a country's trade policy may lead to a bias because these policies may also affect income. As a country's geographical characteristics are not affected by income or policies, and geographical characteristics are supposed to have no effect on income, except for their impact on trade, Frankel and Romer (1999) argue that they can be used to obtain instrumental variables. Therefore, I generated a geographical component which can be used as instrumental variable. I find evidence that trade activity leads to an increasing degree of wage inequality in the OECD. In contrast, results are not clear-cut for the EU. Moreover, there are significant negative effects of trade on relative wages in non-manufacturing sectors in the OECD, what indicates increasing inequality. The same but smaller effects are observed for the EU, High Income Countries, and the total number of countries in the dataset. In contrast, I do not observe an increasing wage inequality in manufacturing sectors.

The results show that an increasing trade volume leads to a significant increase in wage inequality. This effect can be explained in two directions. First, a trade driven increase in the demand for high skilled labor leads to increasing wages and therefore to increasing relative wage spreads. Second, a decrease in the demand for low skilled labor yields in consequence to lower wages. To analyze which direction dominates the increasing wage inequality, a more detailed diversification of skill groups and wages would be necessary.

Surprisingly, using the analogous instrumental variable approach to determine the effect of FDI on wage inequality shows no significant results. This is a puzzling result, which might be due to the fact that the data does not allow to differentiate between vertical and horizontal foreign investment.

4.6 Appendix for Chapter 4

Figures

Figure 4.1: **Composition of Production**

Source: Own presentation based on Feenstra and Hanson (1995)

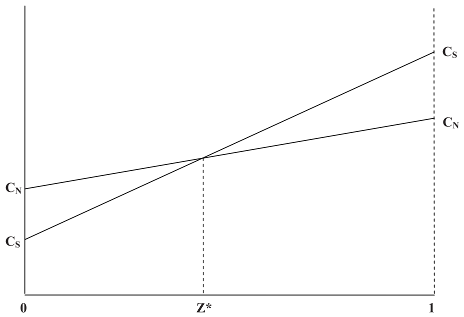


Figure 4.2: **Composition of Production after Capital Flow**

Source: Feenstra and Hanson (1995)

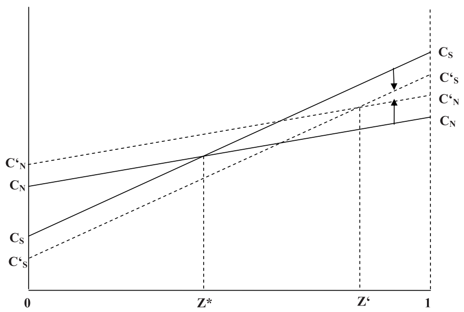
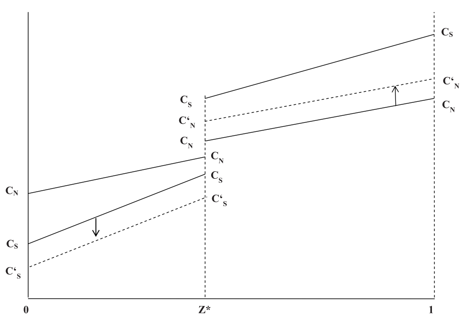


Figure 4.3: **Composition of Production with Discontinuity**

Source: Feenstra and Hanson (1995)



Theoretical Background

In addition to the theoretical model of Feenstra and Hanson (1995) described in section 4.3, I present a more detailed description of important parts of their model here.

Production Function

The production process of each unit of input $x(z)$ is described by the following Cobb-Douglas production function:

$$x(z) = A_i \left(min \left\{ \frac{L(z)}{a_L(z)}, \frac{H(z)}{a_H(z)} \right\} \right)^{\theta} (K(z))^{1-\theta}, \tag{4.6}$$

with $K(z)$ as further input factor capital and A_i as a constant neutral technological factor that differs between North (N) and South (S), with $i = N, S$. The production of the final good Y follows the function:

$$lnY = \int_0^1 \alpha(z) lnx(z)dz, with \int_0^1 .\alpha(z)dz = 1, \tag{4.7}$$

with $\alpha(z)$ as the share of expenditure for each input z. The assembly of the final good is - by assumption - costless.

Minimum Cost Function

The minimum cost function of producing one unit of input $x(z)$ is described by the following equation (4.8):

$$c(w_i, q_i, r_i; z) = B_i[w_i a_L(z) + q_i a_H(z)]^{\theta} r_i^{1-\theta}. \tag{4.8}$$

B_i is defined as $B_i = \theta^{-\theta}(1-\theta)^{-(1-\theta)} A_i^{-1}$, where θ shows the fraction of the input factors labor and capital. If wages are fixed, the minimum cost function is a continuous function of input z.

Derivation of Critical Value z^*

Analytically the dividing point z^* can be determined by deriving the total demand for each factor, assuming full employment. Therefore, the cost function (4.8) is differentiated for each input factor with respect to its particular factor price. Moreover, the function is integrated over all industries that produce in each country. This leads to the full employment conditions that are given in equations (4.9) and (4.10) for unskilled and high skilled labor in the South.

$$L_S(q_S/q_S) = \int_0^{z^*} B_s\theta \frac{r_S}{w_S a_L(z) + q_S a_H(z)}^{1-\theta} a_L(z) x_S dz, \tag{4.9}$$

$$H_S(q_S/q_S) = \int_0^{z^*} B_s\theta \frac{r_S}{w_S a_L(z) + q_S a_H(z)}^{1-\theta} a_H(z) x_S dz. \tag{4.10}$$

Analogous conditions could be written for production in the North. As the range of the production activities differs because of differences in factor prices, production takes place in the North in the interval $[z^*, 1]$.

In a next step, the demand for an input z from the South is determined:

$$x_S(z) = \alpha(z)E/c_S(z), z\epsilon[0, z^*], \tag{4.11}$$

where E is the world expenditure on the final good Y, which is the sum of factor payments in both countries, and $\alpha(z)$ is the share of expenditure for each input z. Combining with the cost function (4.8) and input demand (4.11), the labor demand function given in equations (4.9) and (4.10) can be rewritten as follows:

$$L_S(q_S/q_S) = \int_0^{z^*} B_s\theta \frac{A_L(z)\alpha(z)E}{w_S a_L(z) + q_S a_H(z)} dz, \tag{4.12}$$

$$H_S(q_S/q_S) = \int_0^{z^*} B_s\theta \frac{A_H(z)\alpha(z)E}{w_S a_L(z) + q_S a_H(z)} dz. \tag{4.13}$$

Capital Demand

The demand for capital is derived by utilizing the production function given in equation (4.6) and dividing national income of South into the share of labor (θ), and the share of capital $(1-\theta)$. National income can be described as follows:

$$w_S L_S + q_S H_S + r_S K_S \tag{4.14}$$

Therefore, the equation of national income leads to the following capital demand:

$$r_S K_S = [w_S L_S + q_S H_S](1-\theta)/\theta \tag{4.15}$$

Increase in the Relative Demand of Skilled Labor

Analytically, this increasing demand of skilled labor in both countries can be shown by defining the relative demand for skilled labor in the South as relation of the demand of high skilled and unskilled labor ((4.13)/(4.12)):

$$D_s(q_s/w_s; z^*) = \frac{\int_0^{z*}\left(\frac{a_H(z)\alpha(z)E}{w_S a_L(z)+q_S a_H(z)}\right)}{\int_0^{z*}\left(\frac{a_L(z)\alpha(z)E}{w_L a_L(z)+q_L a_L(z)}\right)} \tag{4.16}$$

The skilled labor demand is analogous in the Northern country, except the range of the integral $[z^*, 1]$ and the use of northern factor prices. If $z*$ is only produced in one country i, the amount of unskilled labor used in production can be described as follows:

$$L_i(z^*) = \theta a_L(z^*)\alpha(z^*)E\ [w_i a_L(z^*) + q_i a_H(z^*)] \tag{4.17}$$

Effect of Southern Capital Growth

To fully determine the effects of Southern capital growth on relative wages, production function and full employment conditions have to be combined. Therefore, the prices of the intermediate goods are defined as follows:

$$p_i(z) = min\{c_S(w_S, q_S, r_S; z), c_N(w_N, q_N, r_N; z)\}. \tag{4.18}$$

Because markets are competitive, the value of industry production is maximized in each country by given factor endowments:

$$E_i(L_i, H_i, K_i) =^{max}_{x_i(z)} \int_0^1 p_i(z)x_i(z)dz. \tag{4.19}$$

Production of northern inputs $x_S(z)$ equals zero for $z \epsilon [0, z^*)$, while production of southern inputs $x_N(z)$ equals zero for $z \epsilon (z^*, 1]$.

As the function given in equation (4.19) as well as the production function (4.6) are concave, the resulting industry-value functions $E_i(L_i, H_i, K_i)$ are concave functions of factor endowments. The derivatives of the industry-value functions equal the factor prices. Thus, the downward sloping relative demand for skilled labor follows from the isoquants of $E_i(L_i, H_i, K_i)$.

Changes in Factor Prices

Summing up factor demands given in equations (4.12) and (4.13) allows to analyze the structure of changes in factor prices more comprehensively for the South and the analogous for the North:

$$w_S L_S + q_S H_S = \theta \int_0^{z^*} \alpha(z) dz, \tag{4.20}$$

$$w_N L_N + q_N H_N = \theta \int_{z^*}^{1} \alpha(z) dz. \tag{4.21}$$

Data and Results

Data Coverage and Descriptive Statistics

Table 4.1: **Description of the *October Inquiry* Dataset (ILO)**

This Table describes *October Inquiry* Dataset as prepared by Harsch and Kleinert (2011) and introduced in Chapter 2 of this thesis.

Dimension	**Observations**		
	Minimum	**Average**	**Maximum**
Observations by country	30	1,313	4,134
	(*Ireland*)		(*Germany*)
Year-country-combinations	22	49	59
	(*2008*)		(*1995*)
Observations by year	2,319	5,654	6,925
	(*2008*)		(*1995*)
Occupation-country-combinations	36	77	100
	(*Railway steam-engine fireman*)		(*several occupations*)
Observations by occupation	428	913	1,206
	(*Railway steam-engine fireman*)		(*Building electrician*)
Year-occupation-combinations	161	161	161
Year-industry-combinations	49	49	49

Table 4.2: **List of Variables**

This Table lists the variables used in this chapter, their definition and sources.

Variable Name	Description	Source
Area	area of a country in sq.km	CEPII, www.cepii.fr/anglaisgraph/bdd/distances.htm
Boarder	dummy that indicates if two countries have a common boarder	CEPII, www.cepii.fr/anglaisgraph/bdd/distances.htm
Common Language	dummy that indicates if two countries have a common official language	CEPII, www.cepii.fr/anglaisgraph/bdd/distances.htm
Distance	distance between capital cities in km	CEPII, www.cepii.fr/anglaisgraph/bdd/distances.htm
GDP	nominal GDP in billions of current USD	World Development Indicators, World Bank
Imports	bilateral imports of manufactured goods in billions of current USD	STAN database, Source OECD
Landlocked	dummy that indicates if a country is completely surrounded by other countries	CEPII, www.cepii.fr/anglaisgraph/bdd/distances.htm
Population	population of a country	CEPII, www.cepii.fr/anglaisgraph/bdd/distances.htm

Relative Wages and wage Inequality

Table 4.3: **Relative Wages as Measures for Wage Inequality**

Table 4.3 gives three different relative wages which are used as measures of wage inequality. The lower the coefficient, the larger is the degree of wage inequality, respectively. Descriptive statistics are given in Tables 4.4 and 4.5.

Relative wages as measures for wage inequality:

(1): $RW_{it}=\frac{\varnothing WageLowSkilled}{\varnothing WageHighSkilled}$

(2): $RW_{it\_manu}=\frac{\varnothing WageLowSkilled}{\varnothing WageHighSkilled}$

(3): $Min/Max_{it}=\frac{LowestWage}{HighestWage}$

where i is country, t is the particular year, and $manu$ indicates whether the sector is *manufacturing*.

Table 4.4: **Relative Wages for all Countries, the OECD, and the EU**

Table 4.4 gives five-year averages of the relative wages for the whole sample, the OECD countries, and the EU. The left hand side of the table contains the results for the unbalanced sample. The right hand side gives the results for the reduced sample, which contains only countries that report wages for at least 15 years, respectively. The lower the coefficient, the larger is the degree of wage inequality, respectively.

	Time Period									
	1984-1988	1989-1993	1994-1998	1999-2003	2004-2007	1984-1988	1989-1993	1994-1998	1999-2003	2004-2007
	Whole Sample					**Reduced Sample**				
	Relative Wage: Low Skilled/High Skilled									
World	0.490	0.481	0.475	0.489	0.483	0.575	0.536	0.504	0.498	0.475
OECD	0.586	0.588	0.555	0.547	0.518	0.569	0.578	0.554	0.558	0.529
EU	0.627	0.604	0.578	0.572	0.506	0.620	0.600	0.584	0.578	0.527
	Relative Wage: Low Skilled/High Skilled Manufacturing Industries									
World	0.528	0.500	0.495	0.507	0.494	0.696	0.616	0.581	0.552	0.500
OECD	0.645	0.652	0.585	0.572	0.540	0.630	0.649	0.597	0.603	0.569
EU	0.699	0.676	0.654	0.656	0.557	0.710	0.678	0.668	0.685	0.616
	Relative Wage: Low Skilled/High Skilled Non-Manufacturing Industries									
World	0.478	0.493	0.490	0.496	0.494	0.520	0.522	0.498	0.498	0.479
OECD	0.572	0.567	0.553	0.546	0.519	0.568	0.561	0.550	0.548	0.522
EU	0.593	0.564	0.540	0.532	0.489	0.593	0.564	0.545	0.525	0.483
	Wage Inequality: Lowest Wage/Highest Wage									
World	0.116	0.118	0.116	0.121	0.126	0.148	0.158	0.146	0.139	0.135
OECD	0.194	0.211	0.197	0.186	0.170	0.200	0.213	0.208	0.198	0.183
EU	0.227	0.230	0.204	0.194	0.146	0.230	0.227	0.207	0.190	0.167

Table 4.5: **Relative Wages for HIC, UMIC, LMIC and LIC**

Table 4.5 gives five-year averages of the relative wages for High Income (HIC), Upper Middle Income (UMIC), Lower Middle Income (LMIC), and Low Income Countries (LIC). The left hand side of the table contains the results for the unbalanced sample. The right hand side gives the results for the reduced sample, which contains only countries that report wages for at least 15 years. The lower the coefficient, the larger is the degree of wage inequality, respectively.

	Time Period									
	1984-1988	1989-1993	1994-1998	1999-2003	2004-2007	1984-1988	1989-1993	1994-1998	1999-2003	2004-2007
	Whole Sample					**Reduced Sample**				
	Relative Wage: Low Skilled/High Skilled									
HIC	0.538	0.546	0.526	0.526	0.494	0.519	0.528	0.522	0.526	0.498
UMIC	0.638	0.518	0.534	0.496	0.495	0.973	0.603	0.552	0.476	0.467
LMIC	0.409	0.444	0.439	0.437	0.435	0.417	0.450	0.402	0.420	0.407
LIC	0.272	0.319	0.327	0.370	0.475	0.407	0.554	0.400	0.352	
	Relative Wage: Low Skilled/High Skilled Manufacturing Industries									
HIC	0.573	0.587	0.565	0.570	0.531	0.577	0.593	0.572	0.581	0.546
UMIC	0.708	0.514	0.525	0.480	0.491	.	0.624	0.565	0.501	0.486
LMIC	0.358	0.389	0.368	0.398	0.406	0.402	0.415	0.366	0.372	0.370
LIC	0.369	0.407	0.480	0.500	0.552	.	.	.	.	.
	Relative Wage: Low Skilled/High Skilled Non-Manufacturing Industries									
HIC	0.542	0.541	0.529	0.527	0.501	0.523	0.518	0.522	0.525	0.499
UMIC	0.510	0.510	0.501	0.469	0.497	0.651	0.586	0.515	0.451	0.439
LMIC	0.472	0.516	0.513	0.495	0.479	0.431	0.507	0.441	0.471	0.448
LIC	0.294	0.337	0.339	0.410	0.445	0.263	0.396	0.234	0.227	
	Wage Inequality: Lowest Wage/Highest Wage									
HIC	0.152	0.172	0.164	0.165	0.153	0.168	0.181	0.170	0.166	0.156
UMIC	0.117	0.120	0.111	0.108	0.109	0.089	0.135	0.145	0.111	0.100
LMIC	0.082	0.073	0.078	0.053	0.067	0.090	0.080	0.068	0.065	0.073
LIC	0.052	0.036	0.055	0.059	.	0.197	0.036	0.054	0.039	.

Effect of Trade on Relative Wages

Table 4.6: **Effect of Trade on Relative Wages in the OECD**

The results presented in this Table are based on a IV estimation, compared to the results of an OLS estimation. Dependent variable is the relative wage, respectively. Estimations include country- and year fixed effects and several control variables (e.g. unemployment, GDP per Capita, exchange rates). Using the IV estimation, trade is treated as endogenous and instrumented with a geographical component (see equation 4.4). I split the sample into the unbalanced "whole sample", and the reduced sample (OECD member states reporting wages in at least 15 years).
***. **. * = significance at the 1%. 5%. 10%-level. Standard errors are given in parentheses.

	Whole Sample				Reduced Sample			
Dependent Variable: Relative Wage in the OECD								
Estimation	(OLS)	(OLS)	(IV)	(IV)	(OLS)	(OLS)	(IV)	(IV)
Trade Share	-0.003***	-0.002***	-0.005***	-0.005***	-0.002	-0.001	-0.007**	-0.005**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
ln Population	-0.031	-0.053	0.012	-0.009	-0.082	-0.104	0.023	-0.027
	(0.057)	(0.058)	(0.059)	(0.061)	(0.071)	(0.070)	(0.077)	(0.076)
Controls	-	✓	-	✓	-	✓	-	✓
Constant	1.055	1.413	0.343	0.688	1.920	2.241*	0.155	0.950
	(0.949)	(0.974)	(0.991)	(1.017)	(1.188)	(1.186)	(1.300)	(1.278)
Observations	300	300	300	300	241	241	241	241
R-squared	0.041	0.061	0.024	0.044	0.023	0.095	0.002	0.083
Dependent Variable: Relative Wage Manufacturing in the OECD								
Trade Share	-0.001	-0.001	-0.000	-0.000	0.005	0.004	0.005	0.005
	(0.005)	(0.002)	(0.002)	(0.002)	(0.005)	(0.004)	(0.005)	(0.005)
ln Population	0.042	-0.037	0.025	-0.053	-0.101	-0.220*	-0.105	-0.243*
	(0.100)	(0.100)	(0.103)	(0.103)	(0.135)	(0.133)	(0.146)	(0.142)
Controls	-	✓	-	✓	-	✓	-	✓
Constant	-0.146	1.168	0.130	1.422	2.283	4.258*	2.343	4.637*
	(1.679)	(1.687)	(1.732)	(1.739)	(2.287)	(2.260)	(2.473)	(2.415)
Observations	279	279	279	279	220	220	220	220
R-squared	0.002	0.060	0.005	0.097	0.005	0.097	0.048	0.081
	Whole Sample				Reduced Sample			
Dependent Variable: Relative Wage Non-Manufacturing in the OECD								
Estimation	(OLS)	(OLS)	(IV)	(IV)	(OLS)	(OLS)	(IV)	(IV)
Trade Share	-0.003***	-0.003***	-0.006***	-0.006***	-0.004*	-0.003	-0.010***	-0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
ln Population	-0.121**	-0.106*	-0.057	-0.042	-0.127*	-0.104	0.003	0.007
	(0.058)	(0.060)	(0.061)	(0.063)	(0.066)	(0.067)	(0.073)	(0.073)
Controls	-	✓	-	✓	-	✓	-	✓
Constant	2.571***	2.307**	1.497	1.250	2.672**	2.263**	0.492	0.402
	(0.974)	(1.007)	(1.028)	(1.060)	(1.106)	(1.133)	(1.221)	(1.231)
Observations	297	297	297	297	241	241	241	241
R-squared	0.071	0.077	0.035	0.044	0.084	0.108	0.048	0.081
Dependent Variable: Min/Max in the OECD								
Trade Share	-0.002***	-0.002**	-0.004***	-0.003***	-0.002	-0.002	-0.008***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
ln Population	-0.164***	-0.145***	-0.131***	-0.112**	-0.161***	-0.114*	-0.045	-0.026
	(0.047)	(0.047)	(0.049)	(0.049)	(0.060)	(0.060)	(0.066)	(0.064)
Controls	-	✓	-	✓	-	✓	-	✓
Constant	2.936***	2.584***	2.380***	2.044**	2.900***	2.076**	0.960	0.609
	(0.790)	(0.794)	(0.824)	(0.827)	(1.006)	(0.996)	(1.110)	(1.079)
Observations	300	300	300	300	241	241	241	241
R-squared	0.098	0.154	0.084	0.141	0.096	0.179	0.063	0.159

Table 4.7: **Effect of Trade on Relative Wages (World, EU, HIC)**

The results presented in this Table are based on a IV estimation, compared to the results of an OLS estimation. Dependent variable is the relative wage, respectively. All estimations include country- and year fixed effects and several control variables (e.g. unemployment, GDP per Capita, exchange rates). Using the IV estimation, trade is treated as endogenous and instrumented with a constructed geographical component.

***, **, * = significance at the 1%, 5%, 10%-level. Standard errors are given in parentheses.

	World		**EU**		**HIC**	
Dependent Variable: Relative Wage						
Estimation	(OLS)	(IV)	(OLS)	(IV)	(OLS)	(IV)
Trade Share	-0.001	-0.002*	-0.003	-0.009*	-0.001	-0.001
	(0.001)	(0.001)	(0.004)	(0.005)	(0.001)	(0.001)
Ln Population	-0.070	-0.046	-0.114	0.205	-0.103*	-0.076
	(0.053)	(0.054)	(0.257)	(0.301)	(0.060)	(0.062)
Controls	✓	✓	✓	✓	✓	✓
Constant	1.695*	1.298	2.489	-3.004	2.208**	1.752*
	(0.888)	(0.906)	(4.443)	(5.201)	(1.007)	(1.028)
Observations	283	283	90	90	252	252
R-squared	0.047	0.044	0.158	0.134	0.086	0.083
Dependent Variable: Relative Wage in Manufacturing Sectors						
Estimation	(OLS)	(IV)	(OLS)	(IV)	(OLS)	(IV)
Trade Share	-0.002	-0.002	-0.006	0.000	-0.002	-0.001
	(0.002)	(0.002)	(0.004)	(0.005)	(0.002)	(0.002)
Ln Population	0.083	0.068	0.775**	0.435	0.060	0.040
	(0.104)	(0.106)	(0.302)	(0.353)	(0.125)	(0.127)
Controls	✓	✓	✓	✓	✓	✓
Constant	-0.823	-0.572	-12.79**	-6.933	-0.460	-0.130
	(1.761)	(1.795)	(5.219)	(6.094)	(2.095)	(2.134)
Observations	262	262	90	90	231	231
R-squared	0.019	0.019	0.121	0.100	0.068	0.068
Dependent Variable: Relative Wage in Non-Manufacturing Sectors						
Estimation	(OLS)	(IV)	(OLS)	(IV)	(OLS)	(IV)
Trade Share	-0.001	-0.002**	-0.001	-0.012**	-0.000	-0.002*
	(0.001)	(0.001)	(0.005)	(0.006)	(0.001)	(0.001)
Ln Population	-0.157***	-0.122**	-0.548	0.070	-0.180***	-0.138**
	(0.050)	(0.051)	(0.342)	(0.407)	(0.056)	(0.057)
Controls	✓	✓	✓	✓	✓	✓
Constant	3.159***	2.573***	9.932*	-0.696	3.519***	2.813***
	(0.839)	(0.858)	(5.906)	(7.021)	(0.933)	(0.955)
Observations	283	283	90	90	252	252
R-squared	0.101	0.094	0.221	0.173	0.114	0.106
Dependent Variable: Min/Max						
Estimation	(OLS)	(IV)	(OLS)	(IV)	(OLS)	(IV)
Trade Share	-0.000	-0.001	0.001	-0.004	0.000	-0.001
	(0.001)	(0.001)	(0.004)	(0.005)	(0.001)	(0.001)
Ln Population	-0.142***	-0.116**	-0.471*	-0.176	-0.189***	-0.153***
	(0.044)	(0.045)	(0.275)	(0.321)	(0.050)	(0.051)
Controls	✓	✓	✓	✓	✓	✓
Constant	2.550***	2.110***	8.274*	3.184	3.298***	2.701***
	(0.742)	(0.759)	(4.747)	(5.537)	(0.826)	(0.846)
Observations	283	283	90	90	252	252
R-squared	0.177	0.173	0.264	0.248	0.192	0.185

Effect of FDI on Relative Wages

Table 4.8: **Effect of FDI on Relative Wages in the OECD**

The results presented in this Table are based on a IV estimation, compared to the results of an OLS estimation. Dependent variable is the relative wage, respectively. Estimations include country- and year fixed effects and several control variables (e.g. unemployment, GDP per Capita, exchange rates). Using the IV estimation, FDI share is treated as endogenous and instrumented with a geographical component (see equation 4.5). I split the sample into the unbalanced "whole sample", and the reduced sample (OECD member states reporting wages in at least 15 years).
***. **. * = significance at the 1%. 5%. 10%-level. Standard errors are given in parentheses.

	Whole Sample				Reduced Sample			
Dependent Variable: Relative Wage in the OECD								
Estimation	(OLS)	(OLS)	(IV)	(IV)	(OLS)	(OLS)	(IV)	(IV)
FDI (% of GDP)	0.000	0.000	0.000	0.000	0.001***	0.001***	-0.006	-0.005
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)	(0.006)
ln Population	-0.065	-0.062	-0.065	-0.062	-0.122**	-0.115**	0.213	0.192
	(0.047)	(0.049)	(0.047)	(0.049)	(0.048)	(0.050)	(0.388)	(0.362)
Controls	No	✓	No	✓	No	✓	No	✓
Constant	1.628**	1.555*	1.631**	1.554*	2.592***	2.444***	-3.038	-2.694
	(0.797)	(0.820)	(0.797)	(0.820)	(0.815)	(0.844)	(6.526)	(6.063)
Observations	317	317	317	317	260	260	260	260
R-squared	0.006	0.024	0.006	0.025	0.041	0.095		
Dependent Variable: Relative Wage in Manufacturing Sectors in the OECD								
FDI (% of GDP)	0.000	0.000	-0.001	-0.001	0.001	0.001**	0.018	0.017
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.018)	(0.016)
ln Population	0.015	-0.022	0.016	-0.021	-0.054	-0.109	-0.964	-1.000
	(0.084)	(0.085)	(0.084)	(0.085)	(0.094)	(0.097)	(0.998)	(0.942)
Controls	No	✓	No	✓	No	✓	No	✓
Constant	0.311	0.918	0.289	0.910	1.493	2.410	16.930	17.450
	(1.418)	(1.441)	(1.420)	(1.445)	(1.600)	(1.663)	(16.930)	(15.930)
Observations	293	293	293	293	236	236	236	236
R-squared	0.000	0.041		0.037	0.012	0.058		
	Whole Sample				Reduced Sample			
Dependent Variable: Relative Wage Non-Manufacturing in the OECD								
Estimation	(OLS)	(OLS)	(IV)	(IV)	(OLS)	(OLS)	(IV)	(IV)
FDI (% of GDP)	-0.000	-0.000	0.000	0.000	0.000	0.000	-0.015	-0.014
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.015)	(0.013)
ln Population	-0.137***	-0.117**	-0.138***	-0.118**	-0.154***	-0.119**	0.654	0.676
	(0.049)	(0.050)	(0.049)	(0.051)	(0.046)	(0.048)	(0.814)	(0.773)
Controls	No	✓	No	✓	No	✓	No	✓
Constant	2.832***	2.487***	2.857***	2.501***	3.142***	2.520***	-10.44	-10.79
	(0.821)	(0.849)	(0.824)	(0.852)	(0.776)	(0.814)	(13.68)	(12.94)
Observations	314	314	314	314	260	260	260	260
R-squared	0.027	0.037	0.0204	0.030	0.045	0.073		
Dependent Variable: Min/Max in the OECD								
FDI (% of GDP)	0.000	0.000	0.000	0.000	0.000	0.000	-0.010	-0.007
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.010)	(0.008)
ln Population	-0.191***	-0.162***	-0.192***	-0.162***	-0.192***	-0.149***	0.320	0.284
	(0.039)	(0.039)	(0.039)	(0.039)	(0.041)	(0.041)	(0.530)	(0.444)
Controls	No	✓	No	✓	No	✓	No	✓
Constant	3.396***	2.876***	3.401***	2.877***	3.424***	2.682***	-5.174	-4.566
	(0.646)	(0.649)	(0.647)	(0.649)	(0.689)	(0.697)	(8.909)	(7.432)
Observations	317	317	317	317	260	260	260	260
R-squared	0.078	0.139	0.0775	0.1386	0.086	0.177		

Table 4.9: **Effect of FDI on Relative Wages (World, EU, HIC)**

The results presented in this Table are based on a IV estimation, compared to the results of an OLS estimation. Dependent variable is the relative wage, respectively. Estimations include country- and year fixed effects and several control variables (e.g. unemployment, GDP per Capita, exchange rates). Using the IV estimation, FDI share is treated as endogenous and instrumented with a geographical component (see equation 4.5). I use the reduced sample (countries reporting wages in at least 15 years).

***. **. * = significance at the 1%. 5%. 10%-level. Standard errors are given in parentheses.

	World		**EU**		**HIC**	
Dependent Variable: Relative Wage						
Estimation	(OLS)	(IV)	(OLS)	(IV)	(OLS)	(IV)
FDI (% of GDP)	0.000	-0.004	-0.000	-0.023	0.001***	-0.005
	(0.000)	(0.004)	(0.001)	(0.040)	(0.000)	(0.007)
ln Population	-0.073**	0.033	-0.311*	1.388	-0.073**	0.203
	(0.030)	(0.102)	(0.171)	(3.051)	(0.036)	(0.287)
Controls	✓	✓	✓	✓	✓	✓
Constant	1.726***	-0.012	5.934**	-23.220	1.717***	-2.823
	(0.500)	(1.684)	(2.953)	(52.36)	(0.601)	(4.712)
Observations	351	351	97	97	279	279
R-squared	0.200		0.175		0.076	
Dependent Variable: Relative Wage in Manufacturing Sectors						
Estimation	(OLS)	(IV)	(OLS)	(IV)	(OLS)	(IV)
FDI (% of GDP)	0.000	0.008	-0.001	0.024	0.001*	0.012
	(0.001)	(0.009)	(0.001)	(0.043)	(0.000)	(0.012)
ln Population	-0.073	-0.248	0.469**	-1.351	-0.061	-0.534
	(0.069)	(0.208)	(0.198)	(3.292)	(0.068)	(0.513)
Controls	✓	✓	✓	✓	✓	✓
Constant	1.812	4.719	-7.391**	23.84	1.566	9.393
	(1.160)	(3.461)	(3.418)	(56.50)	(1.139)	(8.493)
Observations	327	327	97	97	255	255
R-squared	0.097		0.260		0.056	
	World		**EU**		**HIC**	
Dependent Variable: Relative Wage in Non-Manufacturing Sectors						
Estimation	(OLS)	(IV)	(OLS)	(IV)	(OLS)	(IV)
FDI (% of GDP)	-0.000	-0.009	0.000	-0.035	0.000	-0.013
	(0.000)	(0.006)	(0.001)	(0.061)	(0.000)	(0.011)
ln Population	-0.044	0.162	-0.637***	1.983	-0.048	0.497
	(0.028)	(0.148)	(0.216)	(4.637)	(0.035)	(0.497)
Controls	✓	✓	✓	✓	✓	✓
Constant	1.235***	-2.148	11.48***	-33.47	1.306**	-7.639
	(0.462)	(2.450)	(3.738)	(79.58)	(0.577)	(8.167)
Observations	351	351	97	97	279	279
R-squared	0.175		0.204		0.069	
Dependent Variable: Min/Max						
Estimation	(OLS)	(IV)	(OLS)	(IV)	(OLS)	(IV)
FDI (% of GDP)	0.000	-0.006	-0.000	-0.013	0.000	-0.007
	(0.000)	(0.004)	(0.001)	(0.024)	(0.000)	(0.007)
ln Population	-0.045**	0.082	-0.396**	0.534	-0.081***	0.218
	(0.019)	(0.094)	(0.172)	(1.837)	(0.030)	(0.289)
Controls	✓	✓	✓	✓	✓	✓
Constant	0.881***	-1.208	6.976**	-8.981	1.492***	-3.404
	(0.319)	(1.555)	(2.979)	(31.52)	(0.491)	(4.749)
Observations	351	351	97	97	279	279
R-squared	0.139		0.252		0.164	

Chapter 5

Determinants of Service Offshoring[1]

5.1 Introduction

The 2007-2008 financial crisis and the subsequent recession had an unprecedented impact on global economic integration. In 2009, worldwide FDI inflows fell by 39% (UNCTAD, 2010), and the volume of world trade contracted by over 12% and therefore by more than world GDP International Monetary Fund (2010). In contrast to the general collapse of cross-border activities, trade in services proved to be relatively resilient throughout the crisis. German manufacturing goods experienced a decrease in imports of 16.5%, while the contraction of commercial service imports of 7.7% appears modest (see Figure 5.1)[2]. This becomes even more apparent if one abstracts from the trade-related service categories like transport services (see Figure 5.2) which leads to the hypothesis that the determinants of trade in goods and trade in services differ.

[1]This chapter is based on a joint research project, see Biewen, Harsch and Spies (2012). The concept for this paper was developed jointly. The empirical analysis was mainly carried out by Biewen and Spies. Writing was shared between the authors.

[2]Note that this calculation is derived from World Bank data. Using the micro-level *ITS* data, we calculate a 10% drop of service imports. The difference may result from the fact that publicly reported aggregate statistics usually include the earnings and expenditures of the state, positions related to goods trade, import sales tax, and ancillary services in transit trade in addition to the service transactions of firms. Furthermore, it contains estimates (e.g. for transactions below the reporting limit of €12,500) and collective reports which are excluded from the *ITS* data. Finally, we adjust for negative reports that may occur if incorrect payments or cancelations were carried out.

Borchert and Mattoo (2009, 2012) give three possible explanations for the apparent different behavior of trade in services. First, they state that the demand for services is less cyclical compared to the demand for goods. Second, trade in services is argued to be less dependent on external finance and therefore less susceptible to changes in interest rates or credit conditions. Amiti and Weinstein (2009), Feenstra, Li, and Yu (2011), and Chor and Manova (2010) demonstrate that credit conditions act as financial frictions which affect trade in manufactured goods, in particular for sectors which require extensive external financing. Third, Borchert and Mattoo (2009, 2012) justify the crisis-resilience of cross-border service trade with the cost pressures firms have to cope with. These constraints may have forced firms to offshore and thus to import services that were formerly conducted in-house. Following this line of argumentation, the financial and real frictions to which firms are exposed affect trade in goods and trade in services differently.

These arguments are in contrast to the recently increasing literature on trade in services that relies on heterogeneous firm models developed for trade in manufacturing goods. Supporting the applicability of trade-in-goods-models, Breinlich and Criscuolo (2011) find that only a small fraction of UK firms are engaged in trade in services. These service trading firms are larger and more productive than non-traders, using more capital intensive production processes. The authors also report important differences between traders and non-traders in terms of firm size, productivity and other characteristics. Although pure service exporters are smaller than pure good exporters, they are more productive and employ higher skilled labor. Kelle and Kleinert (2010) describe trade in services and its large increase during the past decade using German data. First, they argue that service trade is not limited to firms which are classified as service firms, but that firms from all industries export and import services. Second, confirming the reasoning of Breinlich and Criscuolo (2011), they report that the service trade of German firms is dominated by only few large multinationals, which serve many countries. Using Italian firm level data, Federico and Tosti (2011) confirm that trade in services is highly concentrated among the top exporters and importers. Challenging the applicability of the trade-in-goods-models, Conti, Turco, and Maggioni (2010) find that a higher level of productivity and a higher skill intensity affect the performances of service traders only if the geographical distance to their trading partners is large. Instead, the authors explain the success of service traders with their experience in the national market and with their belonging to national as well as international networks.[3]

As micro-level data on service trade has only recently become available, the few existing studies have remained inconclusive about the factors which determine trade in services and whether they differ from the factors which determine trade in goods. Moreover, research mainly stresses the export side of trade in services.[4] By focusing on the analysis of the determinants of service imports of German multinationals, we complement the few existing studies that have either described the patterns of service trade and traders – but have mostly focussed on the export side – or that have investigated the determinants of manufacturing goods imports and exports (see e.g. Bernard et al., 2007 for the United States, Mayer & Ottaviano, 2008 for several European countries, Eaton et al., 2004 for France, Castellani, Serti, & Tomasi, 2010 for Italy, or Halpern, Koren, & Szeidl, 2005 for Hungary). This field of research has so far received little attention in the economic literature. Therefore, we aim at contributing a new perspective of trade in services as we analyze the factors that determine service imports of German multinational firms using micro-level data. We proceed as follows: first, we investigate the factors that affect the probability of a firm to become a service importer, that means to offshore services which were formally produced in-house (extensive margin). We test whether external or internal frictions, like disruptions in external liquidity or internal cost pressures, have induced multinational firms offshore their service activities during the last decade. Second, we analyze the effect of external and internal frictions on the level of cross-border service activities (intensive margin).

Following previous research, we employ a two-stage Heckman selection model to assess through which channels the extensive and intensive margins of service offshoring are affected. We benefit from the fact that the German International Trade

[3]See also Kelle, Kleinert, Raff, and Toubal (2012) who describe the patterns of service trade and traders for Germany, Walter and Dell'mour (2010) for Austria, or Temouri, Vogel, and Wagner (2010) who use a sample of German, French and UK firms.

[4]Breinlich and Criscuolo (2011) and Federico and Tosti (2011) investigate service exporters and importers.

in Services Statistics (*ITS*) and the Micro Database Direct Investment (*MiDi*), both provided by the Deutsche Bundesbank, have a common firm identifier. We use the merged dataset to study the following determinants: first, we employ proxy measures for the availability of external finance and the presence of internal cost pressure closely following the arguments of Borchert and Mattoo (2009). We construct internal cost pressure measures from the *MiDi* and the external financial frictions' proxy from the Beck, Demirguc-Kunt, and Levine (1999) financial structure database. External liquidity constraints are supposed to play a major role for trade in goods but may be less relevant for trade in services. Cost pressures may have forced firms to offshore service tasks that were previously conducted in-house.
Second, we use cross-country and cross-sectoral occupational wage data, as newly collected and prepared by Harsch and Kleinert (2011) and introduced in Chapter 2 of this thesis. The fact that individual service transactions can be matched with sectoral wage information in each country allows us to study the impact of wages in much more detail than previously done in the literature. Third, we take advantage of ownership information available in the *MiDi*. Earlier studies have reported a higher resilience of foreign-owned firms to cyclical fluctuations (see e.g. Altomonte & Ottaviano, 2009) which might therefore feel less pressure to outsource service activities. In addition to the propensity and intensity of service offshoring, we study whether firms have restructured their service activities and adopted organizational forms that allow them to save on (wage) costs.

This chapter is organized as follows: Section 5.2 contains the description of the merged *MiDi-ITS* data along with the explanatory variables. After explaining the methodology in Section 5.3, results are presented in Section 5.4. We find evidence that a firm which is faced with a decline in sales and sales per employee (labor productivity) is less likely to start importing services. In contrast, firms that are already service importers intensify these linkages in times of cost pressures. Credit constraints do not seem to have an impact on service imports. Section 5.5 concludes.

5.2 Data

This section describes the combined *MiDi-ITS* data used for our empirical analysis. After presenting the Micro Database Direct Investment (*MiDi*) and the International Trade in Services Statistics (*ITS*), we briefly lay out which explanatory variables we use.

Micro Database Direct Investment (*MiDi*)

The Micro Database Direct Investment (*MiDi*) is provided by the Deutsche Bundesbank and covers all international capital links from and to Germany (see Hügelschäffer, Kromer, & Lipponer, 2009). The data set is available for research purposes as a panel data set, currently covering the time period 1996-2009. For the empirical estimations we restrict the sample to the years for which the explanatory variables are available. Therefore, our sample reduces the to the years 2003-2008.

The *MiDi* contains comprehensive information on balance sheets of foreign affiliates as well as the turnover and the number of employees. Whereas the information regarding the foreign affiliates is very detailed, information on the German investor reduces to a few key variables, such as the balance sheet total, the turnover, the number of employees, the industry (*3/4*-digit NACE Rev. 1), and the legal form. Because some of these variables are only available from 2002 on, we exclude all previous years.[5]

As reporting thresholds in terms of ownership shares have changed over time for indirect, or second-tier investments, we limit our sample in this study to direct, or first-tier investments (see Hügelschäffer et al., 2009 for a detailed description).

German International Trade in Services Statistics (*ITS*)

The *ITS* comprises information on all service transactions between German residents and non-residents that surpass the threshold of €12,500. Like the *MiDi*, the *ITS* is provided by the Deutsche Bundesbank. The data set is available for research purposes for the years 2001 until 2010. In its original version, the *ITS* also includes

[5]For further information on this database see Hügelschäffer et al. (2009) and Statist. Sonderveröffentlichung 10: Foreign Direct Investment Stock Statistics (2011).

reports from public authorities and private transfers, which we remove in order to focus on firms' transactions. Again, we use the panel from the year 2003 to 2008.

While the *ITS* reports detailed service trade information at the level of the individual transaction, the firm-level information is limited to the service type and the industry. Thanks to a common firm identifier, some firm-level information can be retrieved from the *MiDi*. Before matching the *ITS* with the *MiDi*, we have made a few adjustments. First, we have aggregated the individual transactions for each year starting with the year 2002. Second, we have dropped all firm-country-service type-year combinations for which the import value is negative or equals zero.[6] Third, we have assigned each service type to a sector (see Table 5.1). Afterwards, we match the two datasets on several dimensions – the firm, the sector, the year and the country.[7] By doing this, we implicitly assume that, if a multinational parent imports a particular service (e.g. transport) from country A and has an affiliate in country A which operates in a sector similar to the imported service type (e.g. transport), the transaction takes place between the parent and its affiliate. This will allow us to broadly approximate intra-firm trade when we investigate the mode choice of international sourcing.[8]

As we have firm-level information only for multinational firms, our sample consists of German firms that own at least one affiliate abroad. This introduces a selection bias. In 2008, the last year in our sample, out of 28,476 service importers only 2,701 firms also own at least one affiliate abroad. On average, these multinationals import more than three and a half times as much as their domestic counterparts. Consequently, their joint import value accounts for about 59% of total service imports (see Table 5.4).[9] When interpreting our results, we will therefore keep in mind that the selectivity concern affects more the extensive than the intensive margin of trade.

[6]Negative values may arise in the case of corrected or canceled payments.

[7]See Kelle et al. (2012) for a more detailed description of the matching process.

[8]Note that this procedure contains the risk of overestimating intra-firm trade. When interpreting the results, we will keep in mind that they are based on a lower bound for the international sourcing of services from independent suppliers.

[9]Altomonte, Mauro, Ottaviano, Rungi, and Vicard (2012) show very similar results for France. While multinational business groups represent only 10% of the trading firms, they account for almost 65% of exports and 62% of imports.

Explanatory Variables

Our main variables of interest are measures of cost pressure and liquidity constraints. By employing these variables, we aim at testing Borchert and Mattoo (2012)'s argument that services trade reacts different to these internal and external frictions than goods trade.

We assume that firms are exposed to cost pressure if they experience a decrease in their sales or in their sales per employee from one year to another. We calculate changes in sales and in sales per employee between the years t and $t-1$ as

$$\Delta x_{it} = \frac{x_{it} - x_{it-1}}{0.5\,(x_{it} + x_{it-1})}, \tag{5.1}$$

where Δx_{it} is the mid-point growth rate of firm-level sales ($sales_{it}$) or sales per employee ($prod_{it}$) of firm i. In contrast to conventional growth rates, mid-point growth rates bear the advantage of keeping observations which are 0 in $t-1$ (earlier applications include Davis & Haltiwanger, 1992 and Buono, Fadinger, & Berger, 2008).[10]

We use information on external liquidity constraints from the 2010 update of the financial structure database from Beck et al. (1999). Liquidity constraints are likely to have an impact on the imports of goods, whose production require substantial pre-finance of the employed intermediate inputs. Borchert and Mattoo (2009) argue that liquidity constraints may have a lower effect on services imports, which bind less financial resources in their production. Whereas Chor and Manova (2010) use the interbank lending rate to measure the impact of credit constraints on the crisis-related reduction of US imports, we appeal to the variable "claims on the private sector by deposit money banks and other financial institutions over GDP". In order to arrive at the level of aggregated loans in the trade partner country, we multiply the measure again with GDP. We then calculate the mid-point growth rate as outlined above and obtain a measure of the evolution of each country's credit conditions over time.

[10]Note that growth rates can only be calculated for firms which are present in the sample for at least two years and which do not report zero sales in two consecutive years.

We complement our set of explanatory variables with other variables that have been suggested in previous literature. Given the lack of detailed information on inputs into the production of services, we use labor productivity, defined as sales per employee, as our productivity measure. Additionally, we take advantage of information on the foreign ownership status of the investing firms. Altomonte and Ottaviano (2009) argue that global supply chains had a non-neutral effect on the trade collapse during the financial crisis. On the one hand, large multinationals are financed by globally operating financial institutions which were particularly hit by the crisis. Through this channel, foreign ownership may have a negative impact on the intensive margin of service imports. On the other hand, large multinationals may be more resilient to financial crises as they can alleviate liquidity shortages of affiliates. We include a dummy variable and test whether and which foreign ownership has an impact on a firm's service imports, in particular when experiencing internal cost pressures.

To assess whether low wage costs in a country have induced firms to newly engage in or to increase their service offshoring, we use comprehensive data on sector-specific cross-country wages recently compiled by Harsch and Kleinert (2011) and introduced in Chapter 2 of this thesis. The data is based on the International Labor Organization's October Inquiry which was in its raw version hardly used in the past. The by now cleaned, standardized and imputed data set contains wages for up to 161 occupations from 49 industries in 112 countries between 1983 and 2008. As the dataset is still highly unbalanced and does not include wage information on the same occupations for every country in each year, we cannot take the median or mean wage across all occupations belonging to a certain sector. Instead, we select one "representative" occupation per sector that shows the greatest country and year coverage within our sample (see Table 5.2). The chosen occupations are all low-skilled.

We estimate the probability and the level of service offshoring as gravity-type equations in section 5.4. For this purpose, we take bilateral great-circle distances between the most populated cities from *CEPII*.[11] GDP is again taken from the World

[11]See Section 4.2 for a more detailed description of the *CEPII* data.

Bank's *World Development Indicators (WDI)*. After estimating the determinants of service offshoring, we assess the mode choice of global sourcing (in-house versus arms-length service imports) by controlling additionally for the experience a firm has in a certain market. We assume that a firm has experience in a certain market if its ultimate owner originates from the country from which the firm imports.

As firms cannot choose freely between intra-firm and arms-length trade, we estimate the probability that a firm has previously established an affiliate in the sector it wants to import from controlling for "diversity". This variable draws on evidence from Kelle et al. (2012) and Breinlich and Criscuolo (2011) and captures the range of sectors and countries in which a firm owns affiliates. Higher diversity supposedly helps firms to surpass the barrier of having also an affiliate in the import sector. The descriptive statistics of all explanatory variables are summarized in Table 5.3.

5.3 Methodology

The main purpose of this chapter is to evaluate the importance of internal versus external frictions in determining the service offshoring of multinational firms. We distinguish between the intensive margin (the import value) and the extensive margin (the probability of service offshoring).

To investigate whether internal and external frictions induce new firms to import services or change the value a multinational firm imports of an existing service type and from an existing market, we adopt a two-stage estimation approach. A Heckman selection model allows us to model the service offshoring of multinational firms as a two-stage process.

In the first stage, we estimate the probability of being a service importer by employing a simple probit model. For this purpose, we inflate our data set to include all firm-country-service type combinations for which we have information on the explanatory variables. This strategy implicitly supposes that there is a (potentially small) fixed cost that turns importing services profitable for some but not for all firm-country-service type combinations.[12] Hence, we use the information contained in the zeros to model the selection into importing services. Therefore, we estimate the extensive margin of offshoring using the selection equation

$$z^*_{ikjt,\text{off}} = \alpha_1 Z'_{\text{off}} + \alpha_2 \Delta x_{it} + \alpha_3 \Delta credit_{jt} + e_{ikjt,\text{off}}, \tag{5.2}$$

where

$$z_{ikjt,\text{off}} = \begin{cases} 1 & \text{if } z^*_{ikjt,\text{off}} > 0 \\ 0 & \text{otherwise}, \end{cases} \tag{5.3}$$

where i denotes a firm importing service type k from country j, and t denotes a particular year. Z'_{off} is a vector of various explanatory variables of the service offshoring propensity, such as the labor productivity of the investing firm, the country- and sector-specific wages, GDPs and distances, and a foreign ownership dummy. Δx_{it} is the mid-point growth rate of firm-level sales $\Delta sales_{it}$ or sales per employee $\Delta prod_{it}$ as calculated in equation (5.1). $\Delta credit_{jt}$ applies this same formula to changes in the availability of credit at the country-level. $e_{ikjt,\text{off}}$ is the error term.

In the second stage, we estimate the change in the level of service imports conditioning on the multinational firm being a service importer. We estimate the intensive margin of offshoring as

$$y_{ikjt,\text{off}} = \beta_1 Y'_{\text{off}} + \beta_2 \Delta x_{it} + \beta_3 \Delta credit_{jt} + \beta_4 mills_{ikjt,\text{off}} + u_{ikjt,\text{off}}. \tag{5.4}$$

The dependent variable is the import intensity $y_{ikjt,\text{off}}$ which is regressed on a vector of explanatory variables Y'_{off}, the mid-point growth rate Δx_{it}, the change in the availability of credit $\Delta credit_{jt}$, and the inverse Mills ratio $mills_{ikjt,\text{off}}$ that has been calculated from equation (5.2).

Consistent estimation requires either exclusion restrictions or a sufficiently non-linear Mills ratio. The existing literature provides little guidance on valuable exclusion restrictions. Therefore, $Z'_{\text{off}} = Y'_{\text{off}}$, and model identification is based only upon the non-linearity in the functional form.

[12] Note that the low reporting limit of €12,500 allows us to treat zero observations as non-profitable strategies.

In additional to the determinants of service offshoring, we estimate the choice of a multinational service importer to source either through an affiliated supplier (intra-firm trade) or through an independent supplier (arms-length trade) making use of the methodology described above. Because we know in which country and in which sector the foreign affiliates of German investors operate, we can broadly sort service import transactions into the two sourcing modes: a multinational firm is said to engage in arms-length trade if it imports a service type from a country in which it does not possess an affiliate that operates in the sector to which the service type has been assigned. Similarly, it engages in intra-firm trade if it imports a service type from a country where it runs also an affiliate operating in the same sector. The admittedly broad categories – country and sector – form the criteria along which we sort service transactions into sourcing modes.[13]

We apply the Heckman-type selection model as outlined in equations (5.2)-(5.4) also to the mode choice of service sourcing. As setting up a foreign affiliate involves fixed costs, firms cannot freely choose between sourcing a service from an affiliated or from an independent supplier. Instead, the probability of sourcing a particular service in-house or at arms length depends on the pre-existence of an affiliate active in the sector in which the service is generated. In a first step, we therefore estimate the likelihood that a multinational firm has an affiliate in service sector k. In a second step, we estimate the probability of outsourcing $y_{ikjt,\text{out}}$, given that the firm has an affiliate in the sector from which it sources the service. Thus, the decision to source from an independent supplier is driven by variations in firm and country characteristics,

$$y_{ikjt,\text{out}} = (\beta_1 Y'_{\text{out}} + \beta_2 \Delta x_{it} + \beta_3 \Delta credit_{jt} + \beta_4 mills_{ikjt,\text{out}} + u_{ikjt,\text{out}} > 0)\,, \quad (5.5)$$

where Y'_{out} is a again the vector of other explanatory variables, Δx_{it} the mid-point growth rate, $\Delta credit_{jt}$ the change in the availability of credit, $mills_{ikjt,\text{out}}$ the inverse Mills ratio from the first step and $u_{ikjt,\text{out}}$ the error term.

[13]In 2008, out of the 2,701 multinational service importers, only 266 were classified as intra-firm traders using the above definition. These imported, on average, an over six times greater value than arms length traders (see Table 5.5).

5.4 Results

This section presents the results of estimating the determinants of service offshoring (5.4.1) and the determinants of the mode choice of sourcing these services (5.4.2) as well as robustness checks (5.4.3).

5.4.1 Determinants of Service Offshoring

In the first stage of the Heckman procedure, we estimate the probability of a multinational firm to become a service importer (extensive margin). As the number of zeros exceeds the number of ones by far in the inflated data set, we observe service imports only for 0.4% of all firm-country-service type combinations. Because the high ratio of zeros results in extremely low marginal effects and increases the computation time substantially, we randomly draw a 5% sample of all zeros. In the second stage, we estimate the offshoring intensity (intensive margin).

Extensive Margin

The results of the first stage estimation are given in the upper part of Table 5.6. They show that more productive firms are more likely to import services. This is in line with the vast evidence on trade in goods. Firms tend to source from nearby countries with a high GDP but low wages in the sector supplying the respective service. These results are highly significant at the 1%-level after controlling for unobserved heterogeneity at the country-, sector- and service-type-level. Firms with a foreign ultimate beneficial owner are more likely to import services than firms with a German ultimate beneficial owner. All these results are very robust to the inclusion of additional variables.

Turning to our main variables of interest, we include internal cost pressure measures as explanatory variables (see Columns (2)-(7)). Both, the growth rate of sales and the growth rate of sales per employee (labor productivity) exhibit a positive impact on the probability of service offshoring. Or, to put it differently, if firms experience a decline in sales or labor productivity, the likelihood that they will import services from abroad decreases. On the one hand, this result challenges the hypothesis that firms react to cost pressures by sourcing from (potentially low wage cost) foreign countries. On the other hand, entering a new market involves fixed costs, and even though the fixed costs of sourcing services may be lower than the fixed costs of sourcing goods, it seems plausible that the probability of starting to import a new service type from an existing market or an existing service type from a new market decreases if a firm is already under cost pressure. The effect is higher for foreign owned firms, as the positive interaction effect indicates.

Second, we test the external finance channel measured as the mid-point growth rate of credits. In line with the argument of Borchert and Mattoo (2009), we find no evidence that external credit constraints are of importance for services trade.

Taken together, these results indicate that internal cost pressures are the important factors which determine a firm's decision to become a service importer. In times of a decrease in the growth rate of sales or the growth rate of sales per employee a firm is less likely to become a services importer.

Intensive Margin

Next, we investigate the determinants of the level of service imports (intensive margin). The results are given in the lower part of Table 5.6. From the baseline model (Column 1), it becomes evident that a multinational firm's labor productivity increases its service imports. A higher wage in the sector and country from where the imports originate decreases it. This fits again the hypothesis that firms offshore service activities to save on wage costs. The gravity variables, GDP and distance, have the expected sign and are mostly significant. Multinationals that have a foreign ultimate owner import less services than domestically owned firms. Hence, whereas foreign ownership increases the likelihood of service offshoring (as indicated by the positive coefficient in the upper part of Table 5.6), it decreases its level (as indicated by the negative coefficient in the lower part of Table 5.6).

From Column (2) on, we again add firm-level measures of cost pressure. Columns (2)-(4) show that a decrease in sales between t and $t-1$ significantly increases the level of service imports. This effect is stronger for domestically than for foreign-owned firms. The inclusion of a decrease in labor productivity, as measured by a negative change in sales per employee, from Column (5) on, exhibits a similar, but even stronger impact than the decrease in sales on service offshoring. This finding contrasts with the negative impact of cost pressure in terms of a decrease in sales and a decrease in productivity on the offshoring probability which we received for the first stage. Hence, while high internal cost pressures seem to prevent firms from starting the import of services from abroad, they intensify already existing linkages. Reasoning in terms of Borchert and Mattoo (2009), a reduced sales or productivity level puts pressure on the firm to save production costs and eventually intensifies the import of services from foreign producers. The higher coefficient of the productivity drop variable furthermore indicates that a reduced sales level becomes specially problematic for firms if it is generated by an equal amount of employees, i.e. if the firm is not instantaneously able to adjust its workforce. Likewise, the interaction effect is higher and more significant. A decrease in productivity harms domestically owned multinational firms more than foreign owned multinationals which seem to be better able to absorb increased cost pressures.

To match the approach of studies that have investigated the collapse of manufacturing trade, we also test for the impact of external liquidity constraints in Columns (3) and (6). As for the extensive margin, we do not find any evidence that deteriorated credit conditions lower service trade in a similar way as they affected trade in goods during the recent crisis.

5.4.2 Determinants of Service Sourcing Modes

In addition to the determinants of service offshoring, we estimate the choice of a multinational service importer to source either through an affiliated supplier (intra-firm trade) or through an independent supplier (arms-length trade) making also use of Heckman-type selection model. As we know from the data in which country and in which sector the foreign affiliates of German investors operate, we can broadly sort service import transactions into the two sourcing modes. First, a multinational firm is said to engage in arms-length trade if it imports a service type from a country in which it does not possess an affiliate that operates in the sector to which the service type has been assigned. Second, a multinational firm engages in intra-firm trade if it imports a service type from a country where it runs also an affiliate operating in the same sector. The results of estimating a two-stage Heckman-type selection model are summarized in Table 5.7.

In a first step, we estimate the likelihood that a multinational firm has an affiliate in sector k which is supplying the respective service type. Column (1) suggests that the probability of having an affiliate in sector k is not driven by the labor productivity of the multinational firm despite a fixed cost entry barrier. Being diverse in the sense of owning affiliates in a wide range of sectors and countries helps firms to overcome this entry barrier instead, and makes it more likely that a multinational firm buys or establishes an additional affiliate in sector k. Wages have the expected negative effect on the dependent variable except for the specification in which we control for credit constraints in the outcome equation.

In contrast to the missing link between productivity and owning an affiliate in sector k in the first stage, productivity is found to negatively impact the decision to source from an independent supplier in the second stage. Wages have a marginally significant effect which becomes insignificant when we control for a country's credit constraints (Columns (4) and (7)) in the first stage. Wages exercise their negative impact rather through the intensive margin where their coefficient becomes significant at the 1% level. Foreign ownership is not significant in any of the specifications. As expected, experience in a foreign market (defined as the nationality of the ultimate owner) is positively associated with the likelihood of sourcing through independent suppliers.

In Columns (2)-(7), we introduce again the cost pressure variables. A positive growth rate of sales and labor productivity increases the probability of arms length importing and accordingly, a negative growth rate decreases it. Hence, *ceteris paribus*, given a certain sales and productivity level of the firm, a decrease in these measures induces firms to sort into intra-firm trading. In the case of productivity, this effect is stronger for domestic firms as indicated by the negative interaction effect. Furthermore, credit constraints do not play any role here.

5.4.3 Robustness Checks

In Section 5.4.1, we estimated the service offshoring intensity on the entire sample, i.e. we pooled all different service types together. The descriptive statistics presented in Figure 5.2 indicate, however, that trade-related services, like transport, business and personnel services, respond very heterogeneously to cyclical fluctuations. In order to test whether there are also important differences with respect to the responsiveness of service types to changes in the presence of external finance and internal cost pressures, we repeat the estimations for a sample from which we exclude transport services. Trade in transport services is directly linked to trade in manufactured goods, and hence, their inclusion might bias the responsiveness of service traders to these frictions in the direction of goods traders. Table 5.8 reports the results of this exercise. The results of the first stage of the Heckman approach differ only slightly from the results presented on the entire sample. Signs do not change. The probability of offshoring increases with labor productivity, but the effect is smaller compared to the results including transport services. The offshoring probability decreases with higher wage costs in the sector and country from where the imports are sourced. These results are highly significant at the 1%-level. GDP and distance have the expected sign and are also significant. Both cost pressure measures, the growth rate of sales and the growth rate of sales per employee (labor productivity), again exhibit a positive impact on the probability of service offshoring. This indicates that firms rather import services in times of positive growth rates. Although the coefficient of external liquidity remains insignificant, the sign changes from positive to negative.

The results of the second stage of the Heckman estimation show that the intensity of service offshoring is less responsive to labor productivity when trade in goods-related services are excluded (lower part of Table 5.8). It is more responsive to foreign ownership. The finding that foreign-owned investors offshore less in this reduced sample underlines the particular role of transport services. The size of wage coefficient remains similar in both samples.

Again, labor productivity has a positive but slightly smaller effect on the offshoring intensity whereas wage costs affect it negatively. The effect of other variables is similar regarding coefficient signs and significance but some larger – excepting for credit constraints – than in the entire sample.

Service offshoring also proves to be more responsive to sales or productivity drops when limiting the sample to business services. The higher coefficient strengthens therefore the hypothesis that firms which experience cost pressures offshore more rather than less services and this reaction helps explaining the absence of a collapse in service trade in times of recession. Again, changes in the availability of external finance do not influence service trade.

5.5 Summary

The financial crisis in the years 2007-2008 and the resulting recession had a huge impact on global economic integration. In contrast to the general decrease of cross-border activities, trade in services proved to be relatively resilient throughout the crisis which leads to the hypothesis that the determinants of trade in goods and trade in services differ. However, service imports have – compared to trade in goods and service exports – received little attention in economic research. Beyond that, as micro-level data on service trade has only recently become available, most research has so far focussed on international service trade at the macro-level.

In this study, we analyze the factors that determine service imports using German micro data. Moreover, using the *October Inquiry* database introduced in ***Chapter 2*** allows to match individual service transactions with sectoral wage information in each country to study the impact of wages in detail. We use a two-step Heckman selection model to investigate the adjustments of German multinationals along the extensive margin (the probability to become a services importer) and the intensive margin (the offshore intensity) of service imports.

In the first stage, we estimate the probability of a firm becoming a services importer. Our results are mostly in line with the vast evidence on trade in goods.

We show that more productive firms are more likely to import services. Moreover, these service importing firms source from nearby countries with a high GDP and low wages in the sector which supplies the respective service. Firms with a foreign ultimate beneficial owner are also more likely to import services than firms with a German ultimate beneficial owner.

Our main focus is on the effect of external and internal frictions on service trade. First, we show that – in contrast to trade in goods – credit constraints as measures of external frictions do not seem to have any impact on service trade. This is also in line with the arguments of Borchert and Mattoo (2009) who show that trade in services less dependent on external finance and therefore less susceptible to changes in interest rates or credit conditions. Second, we include the change of growth rate of sales and the change of growth rate of sales per employee (labor productivity) as measures of internal frictions which have a positive impact on the probability of service offshoring. Accordingly, the probability that firms will import service from abroad decreases if firms are already under cost pressure. This result seems plausible as entering a new market always causes fixed costs, even though fixed costs of sourcing services are probably lower than fixed costs of sourcing goods.

In the second stage we estimate the offshore intensity (intensive margin). Again, we show that firms offshore services to nearby countries to save on wage costs. While foreign ownership increases the likelihood of service offshoring, it decreases its level. We do not observe any effect of credit conditions on the intensity of offshoring, too.

We find evidence that both a decrease in sales and a decrease in labor productivity significantly increase the level of service imports. While internal cost pressures do not force firms to start importing services from abroad, they intensify already existing service import relations. This effect is stronger for domestically than for foreign owned firms. Our results are robust to the exclusion of transport service which is directly linked to trade in goods.

Additionally, we determine the factors which influence the mode of service imports again using a two-step Heckman selection model. First, we estimate the probability that a firm owns an affiliate in the sector that supplies the respective services.

While labor productivity seems to have no impact on the likelihood of having an affiliate, owning already affiliates in a wide range of sectors increases it. Second, we determine the outsourcing probability through arm's length trade. In contrast to first stage, productivity is found to have a negative impact on the decision to source from an independent supplier on the intensive margin. While the effect of wages was only slightly significant at the first stage, the second stage results show the negative impact of wages which are highly significant.

In summary, we provide evidence on the determinants of service imports which have yet received little attention in economic research. Our findings indicate that firm which are already faced with a decline in sales and sales per employee (labor productivity) are less likely to become a service importer for the first time. A possible explanation are fixed costs that occur when entering a new market. In contrast, firms that are already service importers intensify these linkages in times of cost pressures. Credit constraints which play an important role in trade in goods do not seem to have no impact on service imports.
These findings support the hypotheses that the observed crisis-resilience of service trade can be explained by the intensification of already existing service import linkages in times of cost pressures. A lower dependence on external finance might also affect the less pronounced crisis susceptibility.

5.6 Appendix for Chapter 5

Evolution of Service Imports

Figure 5.1: **German Imports of Goods and Services**

Figure 5.1 shows the evolution of German imports of goods and services. Import values are given in billion €. Source: own calculations, data from World Bank (2011).

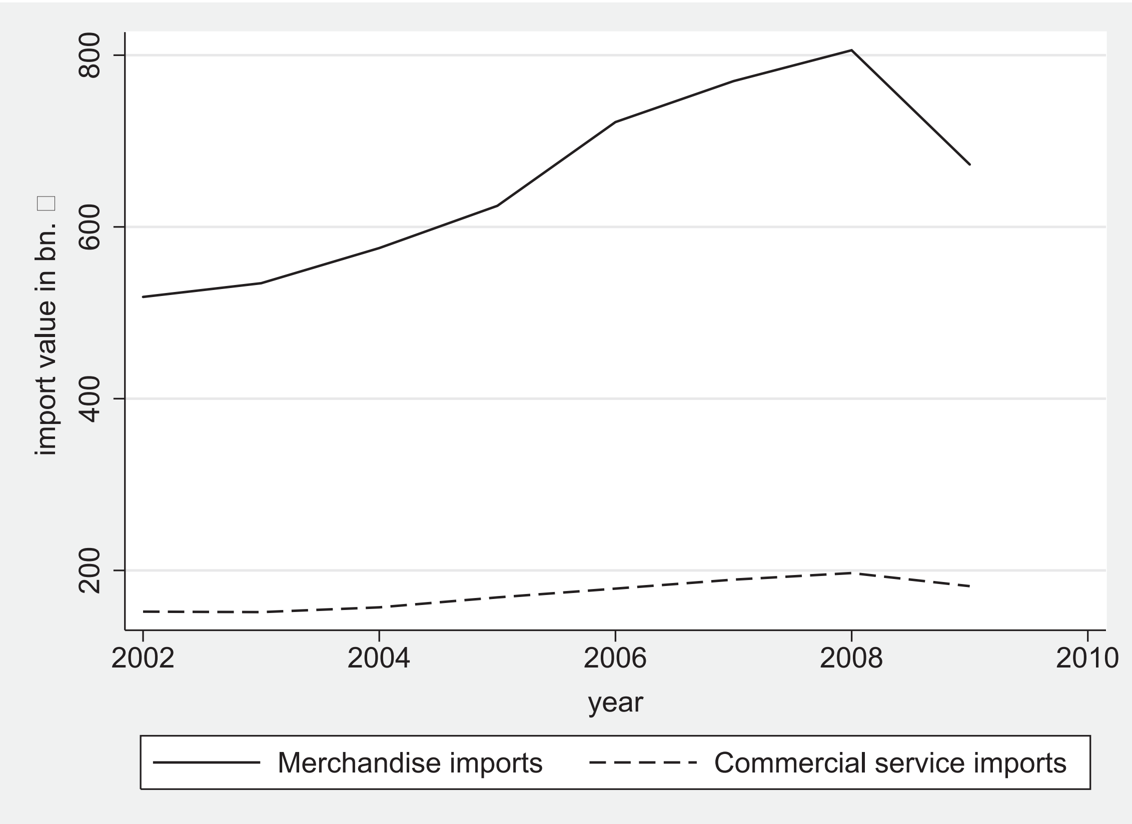
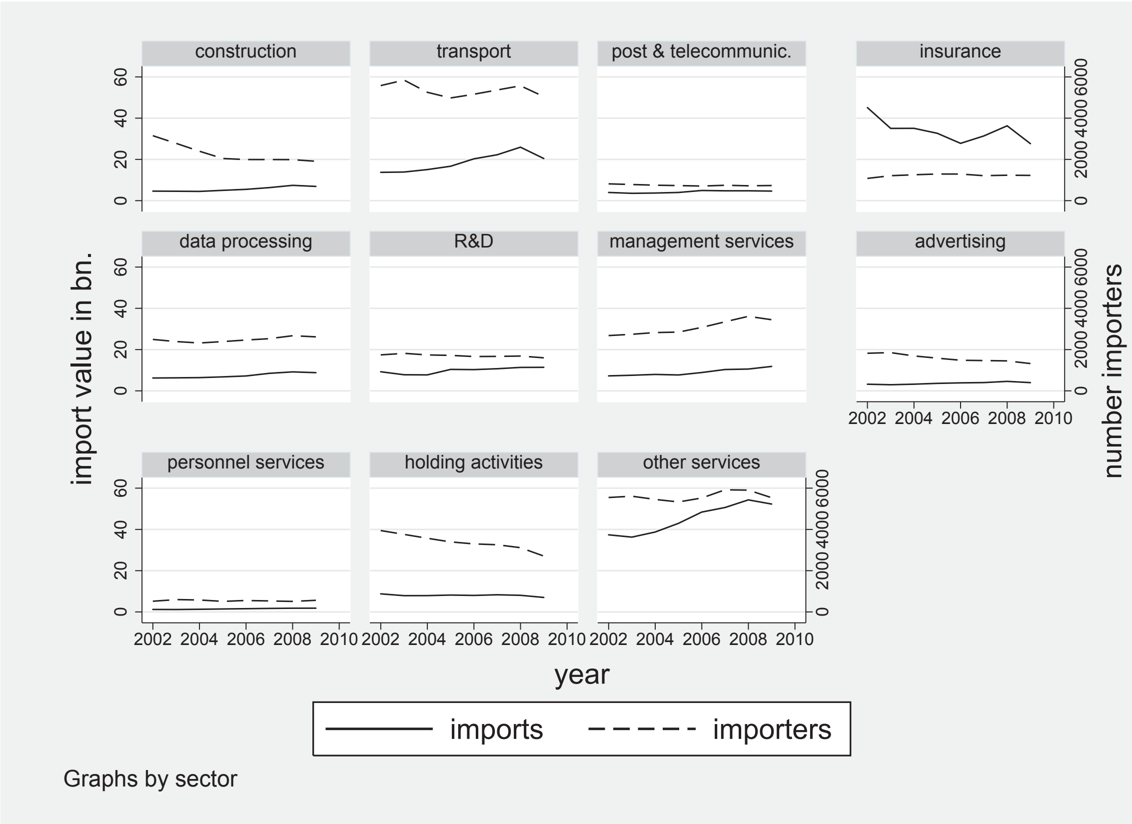


Figure 5.2: **German Service Imports by Services Type**

Figure 5.2 shows the evolution of German service imports by service type. Import values are given in billion €. Source: own calculations, data from ITS (2011).



Sectoral Classification of Services

Table 5.1: ***MiDi-ITS*** **match**

Table 5.1 shows the sectoral classifications of services of the German International Trade in Services Statistics (*ITS*) and the Micro Database Direct Investment (*MiDi*), both provided by the Deutsche Bundesbank.

Sector	***MiDi*** (NACE Rev. 1)	***ITS*** (kza)
Construction	4500: Construction	570, 580: Construction, Installation, Reparation
Transport	6000: Land Transport, Pipelines 6100: Water Transport 6200: Air Transport 6300: Supporting & Auxiliary Transport Activities, Travel Agencies	20: Air Transport 210, 220: Water Transport 230, 240: Land Transport, Rail & Road 300: Seaports 310, 320: Airports, Inland Harbor, Ocean Traffic & Road Transport
Post & Telecommunication	6400: Post & Telecommunications	518: Communication Services (Satellite, Telephone, Wire) 591: Post & Courier Services
Insurance	6600: Insurance & Pension Funding, ex. Social Security	400-461: Life, Pension & Re-insurance
Data Processing	7200: Computer & Related Activities	513: Electronic Data Processing
R&D	7300: Research & Development	501: Artistic Copyrights 502: Patents, Licenses & Inventions 511: R&D Activities
Management Services	7411: Legal Advice 7412: Accounting, Bookkeeping & Auditing Activities, Tax Consultancy 7413: Market Research, Public Opinion Polling 7414: Business & Management Consultancy	516: Entrepreneurship, Management, Organization, Administration, Market Research 519: Other Entrepreneurial Activities
Advertising	7440: Advertising	540: Advertising & Fair Costs
Personnel Services	7450: Labor Recruitment & Provision of Personnel	517: Personnel Leasing 521: Non-self-employed Work
Holding Activities	7490: Management Activities of Holding Companies	523: Commission for Intermediation in Goods & Services Deals 530: Subsidies to Subsidiaries

Table 5.2: **Representative Occupations by Industry**

Table 5.2 gives the "representative" occupations taken from *October Inquiry* database (provided by Harsch & Kleinert, 2011) on the sector level which show the greatest country and year coverage within the sample. The chosen occupations are all low-skilled.

Occupation	**Codeoccupation**	**Industry**	**Codeindustry**	**Isic88**	**Sector_import**
Farm supervisor	1	Agricultural production (field crops)	AA	11	100
Miner	12	Coalmining	BA	101	1000
Supervisor or general foreman	16	Crude petroleum and natural gas production	BB	111	1100
Miner	18	Other mining and quarrying	BC	141	1400
Baker (ovenman)	24	Manufacture of bakery products	CH	1541	1500
Cloth weaver (machine)	27	Spinning, weaving and finishing textiles	DA	171	1700
Sewing-machine operator	30	Manufacture of wearing apparel (except footwear)	DB	181	1800
Shoe sewer (machine)	35	Manufacture of footwear	DD	192	1900
Sawmill sawyer	36	Sawmills, planing and other wood mills	EA	201	2000
Paper-making-machine operator (wet end)	43	Manufacture of pulp, paper and paperboard	FA	211	2100
Printing pressman	49	Printing, publishing and allied industries	FB	22	2200
Controlman	60	Petroleum refineries	GC	232	2300
Mixing- and blending-machine operator	55	Manufacture of industrial chemicals	GA	241	2400
Blast furnaceman (ore smelting)	62	Iron and steel basic industries	IA	271	2700
Welder	67	Manufacture of metal products (except machinery and equipment)	JA	28	2800
Machinery fitter-assembler	69	Manufacture of machinery (except electrical)	JB	29	2900
Electronic equipment assembler	74	Manufacture of electronic equipment, machinery and supplies	JC	31	3100
Ship plater	75	Shipbuilding and repairing	JD	351	3510
Wooden furniture finisher	41	Manufacture of wooden furniture and fixtures	EB	361	3600
Electric power lineman	78	Electric light and power	KA	401	4000
Building electrician	81	Construction	LA	45	4500
Automobile mechanic	161	Repair of motor vehicles	PF	502	5000
Salesperson	93	Wholesale trade (grocery)	MA	512	5100
Salesperson	96	Retail trade (grocery)	MB	522	5200
Cook	98	Restaurants and hotels	MC	55	5500
Automobile mechanic	110	Passenger transport by road	NB	6021	6000
Aircraft accident fire-fighter	125	Supporting services to air transport	NG	6303	6300
Post office counter clerk	126	Communication	NH	64	6400
Bank teller	131	Banks	OA	651	6500
Insurance agent	136	Insurance	OB	660	6600
Clerk of works	137	Engineering and architectural services	OC	742	7420
Stenographer-typist	142	Public administration	PA	75	7500
Technical education teacher (second level)	151	Education services	PC	80	8000
Professional nurse (general)	156	Medical and dental services	PD	851	8500

Descriptive Statistics

Table 5.3: **Descriptive Statistics of the Explanatory Variables by Mode**

Table 5.3 gives the descriptive statistics of the explanatory variables, where i denotes a firm importing service type k from country j, and t denotes a particular year.

	mode	$wage_{kjt}$	$prod_{it}$	gdp_{jt}	$distance_j$	$foreign_{it}$
no service trade	mean	1,089	1,570	516,678	5,385	0.485
	sd	1,155	10,854	1464,640	4,256	0.499
	N	31,737	31,737	31,737	31,737	31,737
service trade intra-firm	mean	1,665	7,043	1190,226	3,826	0.479
	sd	1,338	124,236	2411,860	4,156	0.499
	N	7,737	7,959	7,959	7,959	7,959
service trade extra-firm	mean	1,712	9,718	1529,858	3,187	0.564
	sd	1,210	152,852	2692,503	3,710	0.496
	N	10,579	10,579	10,579	10,579	10,579
total	mean	1,311	4,151	836,503	4,676	0.501
	sd	1,232	86,287	1996,462	4,214	0.500
	N	50,275	50,275	50,275	50,275	50,275
	mode	$\Delta prod_{it}$	$\Delta sales_{it}$	$\Delta credit_{jt}$	$diverse_{it}$	$exper_{ikjt}$
no service trade	mean	0.021	-0.005	0.134	0	0
	sd	0.586	0.643	0.111	0	0
	N	30,454	31,737	29,856	0	0
service trade intra-firm	mean	0.038	0.019	0.113	1.747	0.109
	sd	0.397	0.403	0.089	0.905	0.312
	N	7,940	7,959	7,642	7,959	7,959
service trade extra-firm	mean	0.079	0.068	0.109	1.554	0.210
	sd	0.423	0.428	0.083	0.727	0.408
	N	10,502	10,579	10,152	10,579	10,579
total	mean	0.036	0.014	0.125	1.636	0.167
	sd	0.528	0.571	0.103	0.814	0.373
	N	48,896	50,275	47,650	18,538	18,538

Table 5.4: **Service Imports by Firm Type**

Table 5.4 gives the number of firms, the import values and the averaged import value are given in million € (years 2002-2008). Source: Own calculations, data from *ITS* and *MiDi*.

year		**no FDI, service imports**	**FDI, service imports**	**total**
2002	number of firms	26,600	2,781	29,381
	import value	51,325	89,549	140,874
	av. import value	0.435	2.003	0.866
2003	number of firms	26,737	2,651	29,388
	import value	51,649	75,430	127,080
	av. import value	0.415	1.601	0.741
2004	number of firms	25,287	2,568	27,855
	import value	56,232	75,437	131,669
	av. import value	0.470	1.629	0.794
2005	number of firms	24,287	2,544	26,831
	import value	58,952	80,554	139,506
	av. import value	0.494	1.683	0.835
2006	number of firms	24,607	2,614	27,221
	import value	63,320	83,507	146,827
	av. import value	0.522	1.695	0.861
2007	number of firms	25,412	2,638	28,050
	import value	68,919	90,102	159,022
	av. import value	0.548	1.827	0.909
2008	number of firms	25,775	2,701	28,476
	import value	72,188	102,190	174,378
	av. import value	0.558	2.035	0.971

Table 5.5: **Service Imports by Mode**

Table 5.5 gives the number of firms,the import values and the averaged import value are given in million € (years 2002-2008) by ***intra-firm trade*** and ***extra-firm trade***. Source: Own calculations, data from *ITS* and *MiDi*.

year		**intra-firm trade**	**extra-firm trade**	**total**
2002	number of firms	280	2,501	2,781
	import value	71,771	17,778	89,549
	av. import value	4.882	0.592	2.003
2003	number. of firms	289	2,362	2,651
	import value	57,164	18,265	75,430
	av. import value	3.735	0.574	1.601
2004	number of firms	281	2,287	2,568
	import value	52,857	22,580	75,437
	av. import value	3.505	0.723	1.629
2005	number of firms	264	2,280	2,544
	import value	56,097	24,457	80,554
	av. import value	3.620	0.756	1.683
2006	number of firms	287	2,327	2,614
	import value	57,739	25,767	83,507
	av. import value	3.534	0.784	1.695
2007	number of firms	283	2,355	2,638
	import value	65,904	24,198	90,102
	av. import value	4.088	0.729	1.827
2008	number of firms	266	2,435	2,701
	import value	75,572	26,617	102,190
	av. import value	4.848	0.769	2.035

Estimation Results

Table 5.6: **Determinants of Service Offshoring (Heckman Twostep)**

The upper part of the table reports 1st stage results on the extensive margin of service trade. Results are obtained for a 5% random sample of all zero observations. The lower part reports 2nd stage results on the intensive margin conditional on the probability of offshoring. i denotes a firm in sector k in country j and in year t. All estimations contain country, sector, service type and year dummies.

***p<0.01, ** p<0.05, * p<0.1. Robust t-statistics are given in parentheses.

1st stage results: offshoring probability (marginal effects)							
Explanatory Variables	Basic	$\Delta sales_{it}$			$\Delta prod_{it}$		
$prod_{it}$	0.043***	0.043***	0.043***	0.043***	0.048***	0.048***	0.048***
	(33.42)	(32.87)	(32.91)	(32.27)	(35.27)	(35.33)	(34.45)
$wage_{kjt}$	-0.022***	-0.022***	-0.022***	-0.025***	-0.025***	-0.025***	-0.027***
	(-3.62)	(-3.63)	(-3.63)	(-3.79)	(-3.98)	(-3.97)	(-4.06)
gdp_{jt}	0.106***	0.106***	0.106***	0.148***	0.107***	0.108***	0.145***
	(2.80)	(2.80)	(2.81)	(3.09)	(2.80)	(2.83)	(2.97)
$distance_j$	-0.051***	-0.051***	-0.051***	-0.056***	-0.051***	-0.052***	-0.056***
	(-7.68)	(-7.70)	(-7.72)	(-7.31)	(-7.66)	(-7.69)	(-7.19)
$foreign_{ikt}$	0.021***	0.022***	0.021***	0.023***	0.022***	0.021***	0.024***
	(4.92)	(5.09)	(4.95)	(5.26)	(5.04)	(4.84)	(5.27)
$\Delta sales_{ikjt}$		0.018***	0.010**	0.018***			
		(6.92)	(2.16)	(6.67)			
$foreign_{ikt} * \Delta sales_{ikjt}$			0.014**				
			(2.51)				
$\Delta prod_{ikjt}$					0.015***	0.005	0.015***
					(5.18)	(1.01)	(5.13)
$foreign_{ikt} * \Delta prod_{ikjt}$						0.017***	
						(2.94)	
$\Delta credit_{jt}$				-0.045			-0.038
				(-1.43)			(-1.17)
2nd stage results: offshoring intensity							
$prod_{it}$	0.520***	0.525***	0.526***	0.525***	0.545***	0.546***	0.545***
	(28.18)	(28.40)	(28.42)	(28.5)	(28.70)	(28.73)	(28.39)
$wage_{kjt}$	-0.318***	-0.319***	-0.319***	-0.412***	-0.327***	-0.326***	-0.417***
	(-4.05)	(-4.08)	(-4.08)	(-5.06)	(-4.17)	(-4.17)	(-5.12)
gdp_{jt}	1.264**	1.241**	1.241**	0.877	1.302***	1.317***	0.945
	(2.54)	(2.50)	(2.50)	(1.50)	(2.62)	(2.65)	(1.62)
$distance_j$	-0.250***	-0.244***	-0.244***	-0.190**	-0.249***	-0.251***	-0.198**
	(-3.02)	(-2.96)	(-2.96)	(-2.08)	(-3.01)	(-3.04)	(-2.16)
$foreign_{ikt}$	-0.201***	-0.209***	-0.220***	-0.201***	-0.220***	-0.238***	-0.211***
	(-4.00)	(-4.16)	(-4.36)	(-3.91)	(-4.38)	(-4.71)	(-4.12)
$\Delta sales_{ikjt}$		-0.113***	-0.260***	-0.109***			
		(-2.83)	(-3.84)	(-2.70)			
$foreign_{ikt} * \Delta sales_{ikjt}$			0.221***				
			(2.67)				
$\Delta prod_{ikjt}$					-0.266***	-0.455***	-0.275***
					(-6.45)	(-7.09)	(-6.55)
$foreign_{ikt} * \Delta prod_{ikjt}$						0.314***	
						(3.84)	
$\Delta credit_{jt}$				0.262			0.307
				(0.64)			(0.75)
mills (*lambda*)	0.732***	0.695***	0.688***	0.658***	0.661***	0.668***	0.626***
	(6.81)	(6.52)	(6.46)	(6.16)	(6.40)	(6.48)	(6.03)
N	50,275	50,275	50,275	47,650	48,896	48,896	46,335

Table 5.7: **Mode Choice of Service Outsourcing**

The upper parte of the Table contains the 1st stage results on the probability of a firm having an affiliate in the sector. The lower part reports outsourcing probability through arm's length trade. All estimations contain country, sector and year dummies.

***p<0.01, ** p<0.05, * p<0.1. Robust t-statistics in parentheses.

1st stage results: probability of having an affiliate in the sector (marginal effects)							
	basic	$\Delta sales_{it}$			$\Delta prod_{it}$		
$prod_{it}$	0.003	0.004	0.004	0.004	0.003	0.003	0.003
	(1.13)	(1.30)	(1.30)	(1.28)	(1.27)	(1.27)	(1.25)
$wage_{kjt}$	-0.005*	-0.005*	-0.005*	0.002	-0.006*	-0.006*	0.002
	(-1.81)	(-1.80)	(-1.80)	(0.78)	(-1.85)	(-1.85)	(0.72)
$diverse_{it}$	0.138***	0.138***	0.138***	0.137***	0.139***	0.139***	0.137***
	(38.93)	(38.71)	(38.70)	(37.81)	(38.81)	(38.78)	(37.91)
2nd stage results: outsourcing probability through arm's length (marginal effects)							
$prod_{ikjt}$	-0.013***	-0.014***	-0.014***	-0.014***	-0.016***	-0.016***	-0.015***
	(-5.46)	(-5.90)	(-5.89)	(-5.52)	(-6.50)	(-6.30)	(-6.12)
$wage_{kjt}$	-0.029***	-0.028***	-0.028***	-0.031***	-0.028***	-0.028***	-0.031***
	(-2.90)	(-2.69)	(-2.69)	(-2.89)	(-2.66)	(-2.70)	(-2.86)
$foreign_{ikt}$	-0.011	-0.010	-0.010	-0.013	-0.014	-0.011	-0.017
	(-1.07)	(-0.96)	(-0.93)	(-1.17)	(-1.31)	(-0.99)	(-1.54)
$experience_{ikjt}$	0.057***	0.058***	0.058***	0.061***	0.065***	0.064***	0.068***
	(5.84)	(5.89)	(5.89)	(6.20)	(6.44)	(6.32)	(6.74)
$\Delta sales_{ikjt}$		0.028***	0.031***	0.028***			
		(4.53)	(2.70)	(4.39)			
$foreign_{ikt} * \Delta sales_{ikjt}$			-0.005				
			(-0.37)				
$\Delta prod_{ikjt}$					0.037***	0.062***	0.036***
					(5.29)	(5.76)	(5.09)
$foreign_{ikt} * \Delta prod_{ikjt}$						-0.041***	
						(-3.03)	
$\Delta credit_{jt}$				0.074			0.079
				(1.35)			(1.42)
ρ	0.833	0.820	0.819	0.813	0.811	0.808	0.803
N	18,632	18,632	18,632	17,885	18,536	18,000	17,791

Table 5.8: **Determinants of Service Offshoring Excluding Transport (Heckman Twostep)**

The upper part of the table reports 1st stage results on the extensive margin of service trade excluding transport services. The lower part reports 2nd stage results on the intensive margin conditional on the probability of offshoring. i denotes a firm in sector k in country j and in year t. All estimations contain country, sector, service type and year dummies.

***p<0.01, ** p<0.05, * p<0.1. Robust t-statistics are given in parentheses.

1st stage results: offshoring probability (marginal effects)							
Explanatory Variables	Basic		$\Delta sales_{it}$			$\Delta prod_{it}$	
$prod_{it}$	0.028***	0.027***	0.027***	0.028***	0.033***	0.033***	0.033***
	(19.83)	(19.56)	(19.58)	(19.51)	(22.28)	(22.34)	(21.94)
$wage_{kjt}$	-0.018***	-0.018***	-0.018***	-0.021***	-0.021***	-0.021***	-0.023***
	(-2.92)	(-2.94)	(-2.93)	(-3.14)	(-3.35)	(-3.34)	(-3.45)
gdp_{jt}	0.090**	0.090**	0.090**	0.114**	0.098**	0.099**	0.123**
	(2.31)	(2.32)	(2.32)	(2.18)	(2.48)	(2.49)	(2.30)
$distance_j$	-0.041***	-0.041***	-0.041***	-0.045***	-0.043***	-0.043***	-0.047***
	(-6.26)	(-6.28)	(-6.30)	(-5.57)	(-6.39)	(-6.43)	(-5.66)
$foreign_{ikt}$	0.019***	0.019***	0.019***	0.020***	0.019***	0.018***	0.020***
	(4.20)	(4.30)	(4.19)	(4.18)	(4.18)	(4.02)	(4.12)
$\Delta sales_{it}$		0.010***	0.001	0.009***			
		(6.63)	(0.20)	(3.43)			
$foreign_{ikt} * \Delta sales_{it}$			0.014**				
			(2.54)				
$\Delta prod_{ikjt}$					0.015***	-0.001	0.008***
					(2.94)	(-0.31)	(2.81)
$foreign_{it} * \Delta prod_{it}$						0.016***	
						(2.77)	
$\Delta credit_{jt}$				0.014			0.019
				(0.39)			(0.53)
2nd stage results: offshoring intensity							
$prod_{ikjt}$	0.474***	0.486***	0.489***	0.489***	0.520***	0.525***	0.525***
	(20.73)	(21.08)	(21.18)	(21.01)	(21.62)	(21.78)	(21.61)
$wage_{kjt}$	-0.318***	-0.320***	-0.320***	-0.436***	-0.332***	-0.331***	-0.444***
	(-3.57)	(-3.60)	(-3.60)	(-4.70)	(-3.74)	(-3.73)	(-4.79)
gdp_{jt}	1.401**	1.365**	1.366**	0.777	1.390**	1.410**	0.821
	(2.20)	(2.14)	(2.15)	(1.02)	(2.18)	(2.22)	(1.07)
$distance_j$	-0.313***	-0.305***	-0.306***	-0.213*	-0.299***	-0.304***	-0.215*
	(-3.06)	(-2.99)	(-2.99)	(-1.83)	(-2.93)	(-2.98)	(-1.82)
$foreign_{ikt}$	-0.347***	-0.365***	-0.369***	-0.369***	-0.389***	-0.404***	-0.392***
	(-5.28)	(-5.55)	(-5.61)	(-5.51)	(-5.93)	(-6.11)	(-5.88)
$\Delta sales_{ikjt}$		-0.163***	-0.375***	-0.169***			
		(-3.48)	(-4.94)	(-3.55)			
$foreign_{it} * \Delta sales_{it}$			0.338***				
			(3.54)				
$\Delta prod_{ikjt}$					-0.294***	-0.543***	-0.314***
					(-6.15)	(-7.60)	(-6.48)
$foreign_{it} * \Delta prod_{it}$						0.437***	
						(4.71)	
$\Delta credit_{jt}$				0.081			0.114
				(0.14)			(0.20)
mills (*lambda*)	1.103***	1.064***	1.063***	1.005***	0.990***	1.014***	0.943***
	(8.77)	(8.51)	(8.50)	(8.07)	(8.21)	(8.42)	(7.83)
N	34,844	34,844	34,844	32,978	33,800	33,800	31,987

Chapter 6

Concluding Remarks and Outlook

This thesis contributed to a deeper understanding of international wage distributions and the effect of technological change, trade, and FDI on wage inequality. The empirical analyses in ***Chapters 3 and 4*** are based on the *October Inquiry* wage database, as newly adjusted by Harsch and Kleinert (2001) and introduced in ***Chapter 2***. In ***Chapter 5***, I analyzed the determinants and the level of service offshoring, using the *October Inquiry* wage data as suite of explanatory variables. This final chapter summarizes the main findings of this thesis and gives an outlook on future research.

An Almost Ideal Wage Database

Chapter 2 introduced the *October Inquiry* database which is provided by the International Labor Organization (ILO) and freely available for research purposes. To the best of my knowledge, the *October Inquiry* wage database is the most comprehensive data source of wages at the occupational level in the world to date. However, the data are published without any correction or adjustment and are therefore rarely used.

I closely followed the approach of Freeman and Oostendorp (2000, 2001) in adjusting and standardizing the data. I thoroughly cleaned and corrected the data in order to make them comparable across countries and occupations. Moreover, wages reported in the *October Inquiry* differed with regard to the reported payment period and gender. These differences made the comparison of the wage data impossible.

Therefore, I normalized the reported wages to obtain one single comparable standard wage for each year-country-occupation combination. I chose the most common form of the reported wages as standard (a male average monthly wage) and used a regression approach to estimate the differences between the reported wages and the standard wages. This approach led to standardized wages for every country-year-occupation combination which are easily comparable. The standardization approach was rather complex and imputation was necessary to fill in a large number of missing values in the *October Inquiry* database. However, neither standardizing nor imputation changed the structure of the data.

Unfortunately, there are still gaps in the data that could not be filled in through imputation what makes it rather difficult to use this database in cross-country studies at the industry or sector level. While each occupation can be related to a particular industry, the gaps prevent even an unweighted aggregation to the sector level. Thus, industry studies such as the study presented in Chapter 5 should rely on comparing typical occupations.

Another disadvantage of the data one should keep in mind is that the presented approach assumes that the differences in payment periods and gender are constant across countries and over time. This is a strong assumption, which is due to the fact that there is not enough variation in the data to estimate the adjustment coefficients separately for several country groups. Therefore, the standardization process should be repeated - if possible – for smaller groups of countries or different periods of time.

Unfortunately, the latest available year of the *October Inquiry* database is 2008. It would be very interesting to analyze the effect of the financial crisis and the subsequent recession on the degree of wage inequality. Therefore, the standardized *October Inquiry* database should be updated as soon as more recent data is provided by the International Labor Organization.

Nevertheless, the *October Inquiry* database provides a very robust basis for the analysis of worldwide wage distributions and the degree of wage inequality that is, for example, affected by technological change or trade. As the described adjustment and standardization approach is complex and very time-consuming, I decided to make the data available for other researchers and provide different STATA datasets based on the *October Inquiry*.[1]

Evidence on Occupational Wage Distribution

In ***Chapter 3*** of this thesis, I presented a comprehensive study on occupational wage distributions and wage inequality based on the *October Inquiry* database. To motivate the empirical approach, I introduced a short theoretical model of wage setting and occupational wage differences following Firpo et al. (2011). On the one hand, the model describes the theoretical mechanism of wage setting, while on the other hand, the model gives an idea of the channels through which technological change affects wages.

In a first empirical analysis, I tested the assumptions of the theoretical model for the member states of the OECD, the EU, the United States, and Germany. Proceeding in such a manner was not only of interest for the empirical validity of the theoretical model. Furthermore, I gave a more detailed introduction to the *October Inquiry* database and described the development of wage inequality. I found a large wage heterogeneity between the skill level groups, which is consistent with the theoretical model and can be explained by different returns to the bundle of skills that is required to carry out an occupation. However, one major finding is that even if workers carry out the same occupation, wages differ between industries. This results is not fully consistent with the theory of Firpo et al. (2011) who do not explain wage differences within the same occupation.

In a second step, I analyzed German wage structures in more detail. Thus, I referred to the ”nuanced version” of the skill-biased technological change which is a possible explanation for an increase in wage inequality. Autor et al. (2003) show that technological change does not predominantly affect wages of workers with regard to their skill level. Instead, the tasks required to carry out a particular occupation are the channel through which technological change affects wages. Therefore, I used the introduction of computers in particular occupations as a measure for technological

[1]The datasets can be downloaded at the following webpage: http://www.wiwi.uni-tuebingen.de/lehrstuehle/volkswirtschaftslehre/international-macroeconomics-and-finance/research/wages-around-the-world.html

change. Following Spitz-Oener (2006), I tested two hypotheses concerning the effect of the introduction of computers empirically: First, computers substitute workers that perform manual and cognitive routine tasks. Second, computers complement workers that perform analytical and interactive activities.

I used a slightly modified difference-in-difference estimation approach to test these hypotheses. Measured at the occupational level, I identified the treated group characterized by the "introduction of computer technologies" during a particular time period. Both hypotheses were supported by the estimated results. I found evidence that the task content of work is the channel through which technological change affects wages. Workers in occupations that are characterized by non-routine analytic tasks – for example researching, analyzing, evaluating, or planning – gain after the introductions of computers. Independently from the skill level, workers who perform routine cognitive tasks like calculating or bookkeeping experience a wage loss. In contrast to the arguments of Autor et al. (2006) or Michaels et al. (2010), I did not find evidence for the hypothesis that primarily medium skilled workers lose.

Evidence on Trade, FDI, and Wage Inequality

The effects of globalization and international interdependencies on wages are subject of various studies in the economic literature and are also central to many current public discussions. I made a contribution to this debate by focusing on the question whether – and to what extent – trade and foreign direct investment (FDI) affect the degree of wage inequality in different countries in ***Chapter 4*** of this thesis. While previous empirical studies were mostly based on only a small number of countries or occupations, using the *October Inquiry* database allowed to determine the effect of trade and FDI on the degree of wage inequality across countries in a more comprehensive way.

I followed Feenstra and Hanson (1995) to provide a theoretical motivation for the empirical analyses. They show that capital flows between two countries with different factor endowments lead to increasing wages of high skilled workers in both countries. Under certain conditions, it is possible that also low skilled workers gain.

Therefore, in the empirical analysis, I determined the effect of trade and FDI on the degree of wage inequality measured as relative wages in the OECD. To account for the endogeneity of trade, FDI, and wage inequality, I referred to Frankel and Romer (1999) and generated a geographical component which was used as an instrumental variable.

I found evidence that increasing trade flows lead to a small but significant increase in wage inequality in the OECD. This result indicates an increasing spread between wages of low skilled workers and wages of high skilled workers. Either wages of low skilled workers were decreasing, or wages of high skilled workers were increasing, or wages developed in both directions simultaneously. In future research, these effects should be analyzed in a more differentiated way to ultimately determine the skill group that drives the observed effects.

Moreover, I found significant negative effects of trade on relative wages in non-manufacturing sectors in the OECD. This result presumably indicates increasing wage inequality. In contrast, I did not observe any significant effect in manufacturing sectors. This is puzzling, as I had expected to observe negative effects in manufacturing sectors but not in non-manufacturing sectors. One possible explanation might be an increasing share of trade in services (see ***Chapter 5***).
As a comparison, I applied the described approach for the sample of EU member countries, High Income Countries (HIC), and the entire sample. I found a negative and slightly significant relationship between trade and relative wages in the EU. Compared to the OECD, the observed effect is quite small. However, I did not find any significant effect of trade on the degree of wage inequality in manufacturing sectors, neither in the entire sample, nor in the EU or in HIC. Instead, I observed a small but significant negative effect of trade on relative wages in non-manufacturing sectors in each of the three country samples.

Future research should replicate the presented approach in more sophisticated ways. Indicating whether the export receiving country is an advanced or less advanced country would allow to meet the assumptions of the theoretical model of Feenstra and Hanson (1995) more accurately.

Using the analogous instrumental variable approach to determine the effect of FDI on wage inequality did not show any significant results. This is also a little puzzling but might be explained by two aspects. First, I used outstanding amounts of bilateral bank assets as approximation of capital flows, because there is – to the best of my knowledge – no data on bilateral FDI for such a large number of countries and such a long time period. Second, the data did therefore not allow differentiating between vertical and horizontal foreign direct investment. However, if bilateral FDI data were available, it would be possible to differentiate between the recipient countries and therefore to assume that FDI in high-income countries is horizontal, whereas FDI in less advanced countries with lower wages is supposed to be vertical. Using such an approach could produce interesting insights.

Determinants of Service Offshoring

Chapter 5 of this thesis was based on a joint research project (see Biewen et al., 2012). While trade in goods collapsed during the financial crisis of 2007 and 2008 and the subsequent recession, trade in services proved to be relatively resilient. These observations lead to the hypothesis that the determinants of trade in goods and trade in services differ. Using German micro-level data, we analyzed the factors that determine service imports, which so far have received little attention in economic research. Matching individual service transactions with sectoral wage information in each country from the *October Inquiry* database allowed us to study the impact of wages in much more detail than previous research has been able to do.

In the first stage of a two-step Heckman selection model, we estimated the probability of German multinational firms to become a services importer, i.e. to import services that were formerly produced in-house (extensive margin). In the second stage, we determined the offshore intensity (intensive margin).

Determining the extensive margin, we found that compared to non-traders, firms that become a services importer are more productive and are more likely to have a foreign ultimate beneficial owner. These firms import services from nearby countries with high levels of GDP and low wages in the sector, which supplies the respective service. These findings are mostly in line with the vast evidence on trade in goods.

Our main focus was on the effect of external and internal frictions on service trade. First, we included the change of growth rate of sales and the change of growth rate of sales per employee (labor productivity) as measures of internal frictions. We found a positive relationship between both growth rates and the probability of service offshoring. Consequently, the probability that firms will start to import service from abroad decreases if firms are already under cost pressure. This result is plausible as entering a new market always causes fixed costs, even though fixed costs of sourcing services are probably lower than fixed costs of sourcing goods.

Second, we showed that – in contrast to trade in goods – credit constraints as proxies of external frictions do not have any impact on service trade. This is also in line with the arguments of Borchert and Mattoo (2009) who show that trade in services dependent less on external finance. Therefore, trade in services is less sensitive to changes in interest rates or credit conditions.

At the second stage of the two-step Heckman selection model we estimated the offshore intensity (intensive margin). Again, we showed that firms offshore services to nearby countries to save on wage costs. While foreign ownership increases the likelihood of becoming a services importer, it decreases its extent. Credit constraints again seem to have no effect on the intensity of offshoring.

We found evidence that both a decrease in sales and a decrease in labor productivity significantly increase the level of service imports. While internal cost pressures do not force firms to start importing services from abroad, they intensify already existing service import relations. We observed a stronger effect for domestically owned firms than for foreign owned firms. Our results are robust to the exclusion of transport services, which are directly linked to trade in goods.

Additionally, we determined the factors influencing the mode of service imports again using a two-step Heckman selection model. At the first stage, we estimated the probability that a firm owns an affiliate in the sector supplying the particular services. While labor productivity seems to have no impact on the likelihood of having an affiliate, owning already affiliates in a wide range of sectors increases it. At the second stage, we determined the outsourcing probability through arm's length trade. In contrast to the first stage, productivity is found to have a negative impact on the decision to source from an independent supplier on the intensive margin. While the effect of wages was only slightly significant at the first stage, the second stage results show the negative impact of wages, which are highly significant.

Our study provides evidence on the determinants of service imports, which so far have received only little attention in economic research. We showed that firms that already face a decline in sales and sales per employee (labor productivity) are less likely to become a service importer for the first time. In contrast, firm that are already service importers intensify these relations in times of cost pressures. Unlike the vast empirical evidence on trade in goods, external financial frictions seem to have no impact on service imports.

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