Structural Change, Wage Inequality, and the Occupational Mix of Firms: Evidence from German Micro Data

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List of Abbreviations

BHP	Betriebs-Historik-Panel (in English: Establishment History Panel)
BeH	Beschäftigten-Historik (in English: Employee-History)
GDP	Gross Domestic Product
GP	Güterverzeichnis für Produktionsstatistiken (in English: Product Classification for Production Statistics)
GMM	Generalized Method of Moments
HS	Harmonized System (Classification of Traded Goods)
IAB	Institut für Arbeitsmarkt- und Berufsforschung der Bundesagentur für Arbeit (in English: Institute for Employment Research of the German Federal Employment Agency)
ISIC	International Standard Industrial Classification of All Economic Activities
MSE	Mean Squared Error
OECD	Organization for Economic Co-operation and Development
Prodcom	Production Communautaire (in English: Production of Industrial Goods)
OLS	Ordinary Least Squares

SITC	Standard International Trade Classification
Sypro	Systematik der Wirtschaftszweige für die Statistik im Produzierenden Gewerbe (in English: (Former) Classification of Economic Activities)
TFP	Total Factor Productivity
UN Comtrade	United Nations Commodity Trade Statistics
UNCTAD	United Nations Conference on Trade and Development
WI	Warenverzeichnis für die Industriestatistik (in English: (Former) Product Classification for Production Statistics)
WZ	Wirtschaftszweig (in English: Classification of Economic Activities)

Preface

This cumulative dissertation with the title "Structural Change, Wage Inequality, and the Occupational Mix of Firms: Evidence from German Micro Data" includes three self-contained papers. Two studies are single-authored and one paper has been written in cooperation with a co-author. Here, we split the work among us equally. The papers are included in this dissertation as follows:

- **Chapter 2:**
  Henze, P. (2014): Structural Change and Wage Inequality: Evidence from German Micro Data

- **Chapter 3:**
  Henze, P. (2015): Structural Change and Total Factor Productivity: Evidence from Germany

- **Chapter 4:**
  Boddin, D. & Henze, P. (2015): International Trade and the Occupational Mix in Manufacturing: Evidence from German Micro Data

Abstract

The purpose of this dissertation is to shed new light on the causes and consequences of structural change, both in terms of inter-sectoral reallocations of employment and intra-sectoral reallocations of employment. Its focus lies on Germany, which is among the industrialized nations that experienced substantial structural change over the last decades, i.e. a shift of employment toward services. The results of my empirical analyses show that structural change has a positive effect on the increasing wage gap in Germany that is comparable to the effect of international trade. Additionally, I show the importance of using detailed micro-level data to account for intra-sectoral changes of employment, i.e. the rising share of employment in service occupations within manufacturing. In a further step, I show that diverging sectoral growth rates of total factor productivity (TFP) are a driving force behind inter-sectoral changes of employment. My findings reveal a negative relationship between employment growth and TFP growth and thus confirm the theoretical predictions of Ngai & Pissarides (2007). In a final step, I focus on intra-sectoral reallocations of employment within the manufacturing sector and investigate the effects of three different channels of international trade on the occupational mix in manufacturing. Hence, I am able to investigate very precisely which employees benefit or suffer from the increasing exposure to international trade. The results provide diverse occupational effects from trade at the industry-level, while estimations at the establishment-level only show few significant effects.

Chapter 1

Introduction

1.1 Research Focus

Most developed economies experienced substantial structural change during the last decades, i.e. a shift of employment from manufacturing to services. In this dissertation, I shed new light on the causes and consequences of structural change. To do so, I have access to the "Establishment History Panel" (in German: Betriebs-Historik-Panel (BHP)) provided by the German Federal Employment Office, a detailed micro data set that covers the years from 1975 to 2010. Thus, I am able to analyze the German economy at a very detailed level to observe structural change over the last three decades very closely. In a first step, I investigate the effect of structural change on the wage gap in Germany. Second, I test the theory of Ngai & Pissarides (2007). The authors explain structural change as an inter-sectoral process that is caused by diverging growth rates of total factor productivity (TFP) between manufacturing and service industries. Finally, I focus on intra-sectoral reallocations of employment, most notably the occupational mix within the German manufacturing sector, and estimate how international trade affects the change of the occupational structure.

Recently, structural change regained new interest in the literature. A growing number of papers discusses the effects of structural change and the driving forces behind it. A very prominent work is the paper by Blum (2008) that analyzes the effects of structural change, international trade, and technological progress on the growing wage gap in the United States. Blum concludes that structural change accounts for more than 60% of the relative increase in wages of skilled workers between 1970 and 1996. He uses industry-level data and argues that, in manufacturing capital is complementary to low-skilled labor, but in services, it is complementary to high-skilled labor. Hence, structural change that goes hand in hand with capital accumulation in services increases the demand for high-skilled employees and therefore increases the wage gap.

In this dissertation, I use German data to investigate structural change and its effect on the wage gap in more detail. The German economy experienced significant structural change during the last decades. From 1975 to 2010, the share of employment in manufacturing decreased from 55% to 37%, whereas the employment share of services grew from 45% to 63%.[1] Moreover, the data for Germany highlight that it is of particular importance to account for intra-sectoral changes of employment, i.e. the increasing share of employment in service occupations within the manufacturing sector. If employment shares are derived on the basis of the actual occupations of the employees, the share of employment in manufacturing occupations declined from 48% to 30% and increased from 52% to 70% in service occupations. Hence, the related literature, such as Blum (2008) using industry-level data that do not allow to distinguish between the occupations within an industry

[1]Author's calculation based on the "Establishment History Panel".

underestimates structural change. The data for Germany also confirm the change in labor demand: The higher the required qualification level of an occupational group in services, the higher is its employment growth.

Moreover, Germany is one of the countries in which income inequality increased most over the last decades. For instance, the last OECD report on income inequality "Divided We Stand: Why Inequality Keeps Rising" (OECD (2011)) concludes that German income inequality has increased significantly. In the 1980s, inequality in Germany measured by the Gini coefficient was close to the levels of the Scandinavian countries and substantially below the OECD average, but in 2008, it was close to the OECD average. Furthermore, the authors conclude that the increasing income inequality in Germany is mainly driven by the widening wage gap. The gap between the 10% best paid and the 10% least paid employees increased by roughly 20% since the mid-1980s. The BHP confirms these findings. The data reveal that the wage gap in Germany increased by 26% between 1975 and 2010.

My findings in this dissertation show that structural change is an important determinant for the rising wage gap in Germany. Moreover, the estimations highlight that more aggregated (industry-level) data are not appropriate to identify the wage effect of structural change. Furthermore, I identify diverging growth rates of total factor productivity as a driving force behind inter-sectoral structural change and thus confirm the theory of Ngai & Pissarides (2007). Finally, I investigate how different channels of international trade affect the occupational mix of establishments within the German manufacturing sector and provide evidence of diverse occupational effects from trade at the industry-level while the findings at the establishment-level only show few significant effects.

1.2 Research Structure and Results

The general structure of this dissertation is as follows. In the second chapter, I analyze the effect of structural change on the wage gap. The third chapter focuses on the theory of Ngai & Pissarides (2007) who argue that diverging TFP growth rates between manufacturing and service industries are a driving force behind structural change. The fourth chapter addresses intra-sectoral employment changes. Here, I analyze the effect of different channels of international trade on the occupational mix of German manufacturing establishments. The final fifth chapter summarizes the main results and concludes.

Chapter 2 focuses on the effect of structural change on the growing wage gap in Germany. Motivated by the findings of Blum (2008) for the U.S., I use the "Establishment History Panel" to investigate the increasing wage gap as well as structural changes in the sectoral composition from 1975 to 2010 in detail. First, I provide an overview of a large body of theoretical explanations for structural change and show that structural change is an independent process beside technological progress and international trade affecting the wage gap. The data reveal that the German wage gap, measured as the difference between the upper and the lower quartile of real wages, increased continuously. Furthermore, employment in the German manufacturing sector declined steadily, whereas employment in services grew. In addition to the industry classification of each establishment, the BHP also provides information on the occupational status of the employees according to the Blossfeld classification of occupations (for further information see Blossfeld (1987) and Appendix A.1). This classification gives a detailed insight into the structure of employment within an establishment and thus accounts for intra-sectoral reallocations of employment. By accounting for intra-sectoral changes, i.e. the increasing employment in service occupations within manufacturing, structural change is even more significant. Finally, I match the BHP with trade data from the UN Comtrade database to estimate the effects of structural change, international trade, and technological progress on the wage gap. My results show a positive effect of structural change on the wage gap that is comparable to the effect of international trade. Furthermore, I provide evidence that the wage effect of structural change is mainly driven by the increase in employment of service occupations within the manufacturing sector. Finally, I aggregate the BHP and reveal that more aggregated data, which do not account for intra-sectoral changes would bias or ignore the wage effect of structural change.

In chapter 3, I refer to a particular theoretical explanation for the driving forces behind structural change and test the theory of Ngai & Pissarides (2007). The authors explain structural change as a technology-driven process caused by diverging sectoral growth rates of total factor productivity between manufacturing and service industries. Ngai & Pissarides (2007) argue that employment shares shift to industries with low TFP growth rates, i.e. to services, if the elasticity of substitution between final goods is below one. To test the theoretical predictions, I aggregate the BHP to the 2-digit level. Hence, I am able to match the core data set with sectoral data on TFP obtained from the EU KLEMS database. Furthermore, this level of aggregation ensures that industries differ significantly from each other such that the elasticity of substitution between final goods is below one. The results of my empirical analysis confirm the theoretical predictions of Ngai & Pissarides (2007), i.e. they show a negative relationship between employment growth and TFP growth.

Chapter 4 is joint work with Dominik Boddin. Here, we focus on intra-sectoral reallocations of employment, i.e. on changes of the employment structure within the German manufacturing sector. We exploit the information of the BHP on the occupational structure (according to the Blossfeld occupational groups) within each establishment and examine the impact of increasing international trade on the occupational mix. As the BHP does not provide any information on activities in international trade, we match the BHP with trade data from the UN Comtrade database. We develop an improved matching approach novel in the literature that accounts for the input and output structure of the manufacturing sector. Therefore, our approach of allocating commodity imports and exports to the industry classification of the BHP is much more precise than the "standard method" of using single correspondence tables. In our estimations, we simultaneously consider three channels of international trade: import intensity, i.e. imports of inputs and intermediate products, import competition, i.e. imported goods competing with final goods of domestic establishments, and export intensity, i.e. exports of goods produced by domestic establishments. We estimate the effect of increasing international trade on the employment of each occupational group included in the BHP, both at the industry-level and at the establishment-level. The results at the industry-level show that increasing imports decrease employment and rising exports increase employment. Moreover, the employees in rather unskilled occupations mainly suffer from job losses due to an increase in imports of intermediate and final goods. In contrast, the employees in these occupations benefit most from an increase in exports. Our findings at the establishment-level imply that the employment in only a few occupations is affected by changes in international trade.

Altogether, this dissertation presents new empirical evidence on structural change at the establishment-level and thus contributes to the recent empirical literature. By using the BHP, a unique micro data set, I highlight that structural change is an important determinant for the increasing wage gap in Germany, a fact that so far has been widely ignored by the literature. Furthermore, I confirm Ngai & Pissarides (2007) that diverging TFP growth rates are a driving force behind structural change. Finally, my results suggest that international trade only affects the employment of a few occupational groups.

Chapter 2

Structural Change and Wage Inequality: Evidence from German Micro Data

Summary:

This chapter measures the impact of structural change, international trade, and technological progress on the growing wage gap. I find a positive effect of the increasing importance of services on the rising wage gap in Germany that is comparable to the effect of international trade. To quantify the causal relationship between the structural change of the German economy and the wage premium, I use the "Establishment History Panel" (in German: Betriebs-Historik-Panel (BHP)), a detailed establishment-level data set provided by the German Federal Employment Office covering the period 1975-2010. This empirical work puts the focus on an important cause of the increasing wage gap, which has so far been widely ignored by the literature.

2.1 Introduction

There is a vast literature on growing wage inequality between different skill groups. Numerous studies identify an increasing wage gap between high-skilled and low-skilled workers throughout Europe, the United States, and most other OECD countries.[1] Blum (2008) argues that the wage premium has risen while the supply of skilled workers has increased at the same time. Thus, changes in labor supply cannot be an explanation for the empirical findings. The economic literature mainly states two arguments that explain the increasing demand for skilled workers: international trade and skill-biased technological change.

International trade affects the widening wage gap through two channels: First, as the Heckscher-Ohlin model predicts, relative demand for high-skilled workers increases if the relative price for goods using high-skilled labor intensively rises. This leads to an increasing wage gap between sectors because industries producing goods that use high-skilled labor intensively benefit from the rise in the relative prices. Second, relative demand for high-skilled workers rises because production stages using low-skilled labor intensively are increasingly outsourced to low-wage countries (Feenstra & Hanson (1999)). In contrast, skill-biased technological change increases relative demand for high-skilled workers within industries. Low-skilled workers are more and more replaced by a higher degree of automatization, and the ongoing computerization increases the required qualification of the remaining employees. Therefore, relative demand for high-skilled workers as well as the wage gap increase.

In this chapter, I focus on structural change as another possible determinant for the increasing demand for high-skilled workers, which is still widely unexplored in

[1]See for example Blum (2008), OECD (2008) and OECD (2011).

the literature. During the last decades, the wage gap increased not only in parallel to the increasing international trade and ongoing skill-biased technological change, but also while the economies of developed countries, such as Germany, experienced significant structural change. The sectoral reallocation of employment led to systematic changes in the composition of employment, i.e. a declining employment in manufacturing and a growing employment in the service sector.

The closest related literature is represented by Blum (2008), who investigates the effects of structural change, international trade, and technological progress on the growing wage gap in the United States. By using aggregated industry-level data, he confirms that the rise of the skill premium occurs in parallel to the change of the sectoral composition between 1970 and 1996. In manufacturing, the employment level as well as capital accumulation declined, whereas they increased significantly in the service sector. Blum (2008) argues that capital is relatively complementary to low-skilled labor in manufacturing, but complementary to high-skilled labor in services. Therefore, structural change in the U.S. economy causes a change in labor demand, which leads to an increasing wage premium of high-skilled workers. Blum concludes that structural change accounts for 60% of the relative increase in wages of skilled workers between 1970 and 1996.

This chapter of the dissertation investigates the effect of changes in the sectoral composition of the German economy on the widening wage gap and puts focus on structural change as an important cause for the growing wage gap. For this purpose, I have access to a very detailed micro data set, the "Establishment History Panel". On the basis of this data set, I am able to analyze the impact of structural change on the wage gap much more precisely than other empirical studies using aggregated industry-level data, such as Blum (2008). First, by using industry-level data, it is only possible to examine inter-sectoral changes of employment. If there is merely information about the employment at the industry-level, the respective analysis has to assume that all employees within an industry perform tasks that belong to this sector.[2] Thus, only changes in the total employment of each industry can be observed. In this chapter, I highlight that it is not sufficient to analyze structural change solely by considering an inter-sectoral reallocation of employment. The data set I use provides evidence that besides inter-sectoral employment changes, there is a significant process of intra-sectoral transformation, i.e. in addition to the increasing employment in the service sector, there is an increasing share of employment in service occupations within the manufacturing sector.[3] Therefore, all empirical investigations based on aggregated industry-level data underestimate structural change because they ignore any intra-sectoral changes. Second, by using industry-level data, the impact of structural change on the growing wage gap is very likely to be biased since it is not possible to control for a wide range of effects at the establishment-level, which also affect the wage structure. For example, it is not observable if some industries have experienced market concentration, i.e. if there is a decreasing number of establishments that have become larger over the last decades. The economic literature points out that larger firms tend to pay higher wages to high-skilled workers.[4] Therefore, a market concentration would foster the wage gap. In addition, industry-level data do not provide any information on the establishment structure. For example, a higher share of high-skilled employees or a growing share of female employees also increases the wage gap. Thus, industry-level

[2]For example, it has to be assumed that all employees of the industry "Manufacture of electric motors" perform occupations to produce electric motors and therefore, they can be assigned to the manufacturing sector. This implies that there are no employees within this industry that do industry-unrelated tasks, such as administration or complementary services.

[3]Following the example from before, there is an increasing share of employees within the industry "Manufacture of electric motors" that perform service tasks.

[4]See Oi & Idson (1999) for a review of the empirical literature.

data may link wage effects to structural change that are in fact caused by other factors, which would lead to an overestimation of the wage effect of structural change.

The main contribution of this chapter to the literature is thereby the analysis of a rather unheeded cause for the increasing wage gap by estimating the effect of structural change with a very detailed and unique establishment-level data set. With this data set at hand, I have insight into the German economy and observe structural change over the last three decades very closely. Therefore, I am able to determine inter-sectoral movements as well as intra-sectoral changes of employment on the basis of the occupational structure within establishments. This leads to a very precise identification of the true extent of structural change in contrast to empirical analyses using industry-level data. Furthermore, the micro data set allows me to control for a wide range of additional variables at the establishment-level that also affect the wage gap, such as the share of high-skilled employees, the share of female employees, and the plant size. In addition, I am able to control for the large establishment and industry heterogeneity within Germany by using industry and establishment fixed-effects. Therefore, to my knowledge, this chapter provides the first analysis that accounts for this additional, important information that other studies, such as Blum (2008) and OECD (2011)[5] disregard, and allows for a very precise identification of another determinant for the rising wage gap in Germany.

[5]Blum (2008) analyzes the impact of wage inequality in the U.S. by constructing a multi-sector general equilibrium model and decomposing the effects of structural change, international trade, and technological progress on the wage premium. For the empirical analysis, Blum (2008) uses sectoral data at the 2-digit level from 1970 to 1996. In contrast to this, the OECD explains the rise in income inequality with international trade, technological progress and changes in labor market institutions by using a fixed-effects model with data at the macro-level for all OECD countries from the early 1980s to 2008.

I focus my empirical analysis on Germany by using the "Establishment History Panel" (in German: Betriebs-Historik-Panel (BHP)), a detailed establishment-level data set provided by the German Federal Employment Office, covering the period 1975-2010. In contrast to other studies, such as OECD (2011), which consider all kinds of income[6] to analyze the increasing income inequality, I focus on wages since the wage gap is the driving force behind the increasing income inequality in Germany (OECD (2011)). The BHP contains valuable information on the general employment structure (e.g. the number of employees), the structure of employees by educational and vocational qualifications, the structure of employees by Blossfeld occupational groups[7], the wage structure, and activities in research and development. To control for the effect of international trade, I include sectoral data on exports and imports for Germany.

The data show that the German economy has significantly changed in the last three decades and thus confirm the findings of Blum (2008) for the United States. In the 1975-2010 period, the wage gap, calculated as the difference between the upper and the lower quartile of the wage distribution, increased by almost 26%. At the same time, the share of employment decreased in the manufacturing sector and increased in the service sector. Due to the information on the structure of employees by Blossfeld occupational groups, it is possible to distinguish between the tasks of the employees within an establishment and account for intra-industry changes. On the basis of this information, structural change is even more striking. Moreover, the data show that the rise of employment in services has not led to an equal increase in the employment of all service occupations. It can be shown that the higher the required qualification level of an occupational group, the higher

[6]For example wages, capital income, etc.

[7]For further information, see Appendix A.1 and Blossfeld (1987).

was its growth in employment. Therefore, structural change contributes to the increasing relative demand for high-skilled workers and the increasing wage gap in a similar way as skill-biased technological change.

The empirical analysis is conducted as follows. The dependent variable, the wage gap, is measured as the difference between the upper and the lower quartile of the wage distribution in a respective establishment. The independent variables, which I am particularly interested in, are the structural composition of an establishment, international trade, and technological progress. I estimate the impact of these variables on the German wage gap by using a fixed-effects model, which includes various control variables at the establishment-level.

The results show that structural change has a significant positive effect on the wage gap. In addition, the effect of structural change on the wage gap is much higher within the manufacturing sector. If the estimated coefficients are standardized, i.e. corrected for different levels of aggregations, the effect of structural change decreases but is still positive, significant, and comparable with the effect of international trade. I also estimate the regression model with more aggregated data and show that the wage effect of structural change would be biased and/or ignored if industry-level data were used. Various robustness checks confirm my results.

The rest of this chapter is structured as follows. In the next section, I give a brief overview of the causes for the increasing wage inequality mainly discussed in the literature. Furthermore, I introduce structural change as another determinant for the rise of the wage gap and summarize some theoretical approaches that explain the driving forces behind structural change. Section 3 contains a detailed description of the data set I use. In Section 4, I present some stylized facts about wage inequality, employment changes and capital accumulation in Germany. Sections 5 and 6 introduce the empirical model and present the empirical findings and robustness checks. Section 7 summarizes and concludes.

2.2 Theoretical Background

Blum (2008) argues that the theoretical literature mainly explains the growing wage inequality by the increase in international trade and the ongoing skill-biased technological change.

In general, international trade is supposed to affect the widening wage gap through two channels. First, according to the Heckscher-Ohlin model, relative demand for high-skilled workers increases if the relative prices of tradable goods using high-skilled labor intensively increase. In accordance with the Stolper-Samuelson theorem, the decline of relative prices for goods using low-skilled labor intensively leads to a decline in the wages of low-skilled workers, whereas the wages of the high-skilled workers increase. Empirical studies show that this mechanism holds for the 1970s in the U.S. (Leamer (2001)), but not for more recent periods. Berman et al. (1994) find no evidence for a significant effect of changes in international trade on labor demand in U.S. manufacturing in the 1980s. Moreover, the Stolper-Samuelson theorem predicts a decline in the relative wages of high-skilled workers in unskilled-labor abundant countries as a consequence of international trade. But, in the course of the increase in international trade, wage inequality rises in both, developed and developing countries (Goldberg & Pavcnik (2007)). Second, relative demand for high-skilled workers rises through outsourcing of production stages that use low-skilled labor intensively. In the mid-1980s, multinational enterprises began to unbundle their production processes by creating global supply chains (Baldwin (2006) and Grossman & Rossi Hansberg (2008)), because trade costs decreased substantially due to advances in transportation and communication technologies

(Freund & Weinhold (2002)). Therefore, the outsourcing of production stages using low-skilled labor intensively to countries with much lower wages became profitable for an increasing number of firms in developed countries. Hence, the relative demand for low-skilled workers in the industrialized countries declined. The empirical findings for the relationship between outsourcing and wages of low-skilled workers are very heterogeneous. Baumgarten, Geishecker & Görg (2013) investigate the effects of outsourcing in Germany and conclude that the effects strongly depend on the extent to which the respective task of a worker can be relocated abroad. The ease of relocating a worker's job is not necessarily correlated with the qualification level.[8] Taking cross-industry movements of workers into account, low- and medium skilled employees experience significant wage declines due to the relocation of their jobs. Again, this depends very much on the "offshorability" of the respective job. Other studies, e.g. Feenstra & Hanson (1999), estimate a significant outsourcing effect, accounting for 15% to 24% of the rise in the demand for high-skilled workers in the U.S. between 1970 and 1996.

A second explanation for the increasing wage gap in most industrialized countries is skill-biased technological change. The shift of the relative demand toward skilled workers occurs in particular within rather than between industries, in contrast to what the traditional trade theory predicts. Similar to the outsourcing effect, but in contrast to the Heckscher-Ohlin effect, skill-biased technological change increases the relative demand for high-skilled workers within industries. Labor saving technological progress replaces low-skilled labor by a higher degree of automatization, and the ongoing computerization raises the required qualification of the

[8]For example, it is easy to relocate the high-skilled job of an IT specialist since this task does not necessarily require physical closeness. It is possible to communicate online and send labor in progress via email/firm intranet. In contrast, it is not possible to relocate the low-skilled job of a hairdresser or cabdriver because physical closeness is inevitable for these jobs.

employees.[9] Numerous empirical studies support this effect. Berman et al. (1994) show for the U.S. that two-thirds of the employment changes of high-skilled workers and more than half of the wage changes happen within an industry. Berman et al. (1998) confirm the importance of this effect for developed countries, including Germany. Feenstra & Hanson (1999) find evidence that skill-biased technological change, in particular the increasing computerization, accounts for 8% to 36% of the wage gap within industries in the U.S. between 1979 and 1990.

This chapter focuses on structural change as another possible cause for the increasing wage gap that is widely unexplored in the literature by now. The theoretical literature explains structural change as a process at the industry-level behind a balanced growth path at the aggregate level of the economy that is in line with the Kaldor facts (Kaldor (1963)).[10] Clark (1940) and Kuznets (1966) describe structural change by looking at the continuous decline of agriculture in terms of output and employment coming along with long run increases in income per capita. Nowadays, these Kuznet facts, i.e. structural reallocations of employment at the industry-level, describe the increasing importance of services (Kongsamut et al. (2001) and Alvarez-Cuadrado & Long (2011)). Recently, the literature developed several multi-sector growth models that allow for the process of structural change and still guarantee a balanced growth path, i.e. combine the Kaldor facts with the Kuznets facts. These models can be classified into two groups concerning the assumption of the driving force behind structural change: preference-driven and

[9] For a review, see for example Berman et al. (1994), Berman et al. (1998), Blum (2008).

[10] The literature on economic growth traditionally features models that assume a trajectory where the growth of output, the capital-labor ratio, the return to capital, and the factor income shares are (roughly) constant over all sectors. In the last decades, these Kaldor facts (Kaldor (1963)) determine the literature and, therefore models on economic growth assume restrictions on preferences and technology to be in line with these Kaldor facts (Alvarez-Cuadrado & Long (2011)).

technology-driven structural change (Alvarez-Cuadrado & Long (2011)).

In the first category, structural change is the result of different income elasticities of demand across goods (Kongsamut et al. (2001)).[11] As the economy grows and income rises, the demand of consumers changes. If income per capita rises, demand (and therefore resources and production) shifts from products with low demand elasticity, such as food, to products with high demand elasticity, such as services or luxury goods (Kongsamut et al. (2001) and Foellmi & Zweimüller (2008)). This leads to a decline of agriculture and manufacturing and an expansion of the service sector as it can be seen in the data.

The second category of models argues that technological differences across sectors are the driving forces behind structural change. They can be classified into two different mechanisms: First, Ngai & Pissarides (2007) assume that structural change is the result of diverging TFP growth rates between manufacturing and service sectors. Second, Acemoglu & Guerrieri (2008) suppose that differences in the elasticity of output to capital and therefore different factor proportions across sectors cause structural change. If sectoral TFP diverges or capital accumulates, these differences lead to unbalanced growth between industries and therefore to changes in the sectoral composition. Alvarez-Cuadrado & Long (2011) recently developed another model of structural change. By assuming sectoral differences in the elasticity of substitution between capital and labor, the authors examine another source for technology-driven structural change. Due to different degrees of "flexibility", i.e. different elasticities of substitution between capital and labor across sectors, the sectoral composition of output changes systematically if relative prices of factors of production change.[12]

[11] There is a vast literature about the assumption of non-homotheticity as a driving force behind structural change. See for example Echeverria (1997) and Gollin, Parente & Rogerson (2007).

[12] If the aggregated capital-labor ratio increases, the more flexible sector can substitute the rela-

In summary, there is a large body of literature explaining possible causes for structural change and the transmission channels through that the mechanisms work. In the following, I will not refer to a particular model that analyzes the causes for structural change, but take structural change as an independent process beside technological progress and international trade affecting the wage gap.

The sectoral reallocation of employment that has taken place in Germany since 1975 has led to an expansion of the employment in the service sector and a decline of the employment in the manufacturing sector. Moreover, the data show that the increasing service employment has not led to a uniform rise of employment in all service occupations. The rise of service employment has especially strengthened the demand for high-skilled workers. These findings are in line with Blum (2008). He argues that structural change leads to a change in labor demand, since capital is relatively complementary to low-skilled labor in manufacturing but relatively complementary to high-skilled labor in services. Therefore, there is an additional skill-bias of structural change similar to the effect of technological change.

Table 2.1 confirms the change in labor demand by comparing the employment growth of occupational groups related to service tasks between 1975 and 2010.[13] The different occupational groups are classified according to the Blossfeld classification of occupations[14] and describe the tasks done by the employees. Table 2.1 shows that occupational groups requiring the highest qualification levels experienced the highest employment growth rates. While the employment in unskilled

tively more expensive input (labor) by the relatively cheaper input (capital) more easily. Hence, this sector is able to reduce the average costs of its inputs to a higher degree and will grow relatively to less flexible sectors. Therefore, differences in the sectoral elasticity of substitution between capital and labor cause a change in the sectoral composition of output.

[13] The growth of an occupational group is calculated as the percentage change of the total number of full-time employees classified within this group.

[14] For further information, see Appendix A.1 and Blossfeld (1987).

Table 2.1: Employment Growth of occupational Groups, 1975-2010
(According to the Blossfeld Classification of Occupations)

Services	**Growth**	**Administration**	**Growth**
Unskilled services	70.78%	Unskilled commercial and administrative occupations	34.02%
Skilled services	145.99%	Skilled commercial and administrative occupations	84.55%
Semiprofessions	343.22%	Managers	101.01%
Professions	388.20%		

Source: Establishment History Panel, author's computation.

service occupations grew only by 71%, the employment in skilled service occupations grew more than twice as much and the employment in semiprofessions and professions even by 343% and 388%, respectively. The same holds for administrative services. The employment in unskilled administrative occupations increased by 34%, but the employment of managers grew by more than 100%. In summary, these findings show that the higher the required qualification level of an occupational group, the higher is its employment growth. This confirms that structural change contributes to the increasing relative demand for high-skilled workers and thus to the increasing wage gap.

2.3 Data

The empirical analysis is based on the "Establishment History Panel" (in German: Betriebs-Historik-Panel (BHP)) provided by the Research Data Center of the German Federal Employment Office.[15] The BHP is a unique data set covering the period 1975-2010 for establishments in West Germany and 1991-2010 for East Germany. It includes a 50% sample of all establishments in Germany with at least one employee subject to social insurance contributions before June 30th of the respective year.[16] The data base of the BHP is the Employee-History (in German: Beschäftigten-Historik (BeH)) of the IAB. By aggregating the individual data of the BeH to the establishment-level and assigning establishment numbers ("artificial establishment number"), it is possible to create a panel data set for the entire time period. Based on the information of the Employee-History, the BHP provides detailed information on the general employment structure, e.g. the total number of full-time and part-time employees and the share of female employees, the composition of employment regarding employees' educational and vocational qualifications, the occupational status and age structure, the wage structure of full-time employees[17], and R&D activities. In addition to these variables, the data set contains information about establishment characteristics, e.g. the artificial establishment number, the date of first and last appearance, the district code, and

[15] The data has been made available in fall 2011. For my research, I have access to the data via on-site use at the Research Data Center of the German Federal Employment Agency at the Institute for Employment Research (in German: Institut für Arbeitsmarkt- und Berufsforschung (IAB)) and via remote data access.

[16] Since 1999, establishments with at least one part-time employee are also included in the panel.

[17] The wages reported in the BHP are based on the regulations for the German social security notification. Employers have to report the employees' gross wage subject to social security contributions in a given year. Hence, the wages are reported up to the upper earnings limit for social security contributions (in German: Beitragsbemessungsgrenze) in the respective year. This can lead to an underestimation of the wage gap since the upper quartile of the reported wages is cut off at this threshold, i.e. all employees earning more than the upper earnings limit for social security contributions are included with an wage equal to the upper earnings limit.

This censoring problem of the BHP cannot be solved by the imputation of wages above the upper earnings limit for social security contributions (Gartner (2005)). The BHP does not contain information about individual wages necessary for the imputation but only provides information on average wages paid in the wage quartiles of a respective establishment.

the 3-digit classification of economic activities.[18]

To account for the increase in international trade, I include sectoral export and import data for Germany in the data set. I use data obtained from the United Nations Commodity Trade Statistics database (UN Comtrade database) at the 2-digit level for German manufacturing trade from 1978 to 2010[19] and total trade in services from the database of the United Nations Conference on Trade and Development (UNCTAD) for the 1980-2010 period. To control for further effects on the wage gap,[20] I use data at the macro-level provided by the German Federal Statistical Office on German GDP and information on the level of education.[21]

2.4 Stylized Facts

According to the recent OECD report "Divided We Stand: Why Inequality Keeps Rising" (OECD (2011)), income inequality in Germany rose significantly in the last decades. Here, income inequality includes all kinds of earnings, e.g. wages and capital income.

Figure 2.1 shows that German income inequality increased continuously and faster than the OECD average since the end of the 1980s until 2008. While German inequality was close to the levels of the Scandinavian countries and substantially

[18]For further information see Eberle (2011) and Gruhl et al. (2012).

[19]The 3-digit classification of economic activities 93 that is included in the BHP is defined as "Industrial Classification of Economic Activities for the Statistical Office of the Federal Employment Agency, 1993 Edition". The first two digits are based on the ISIC, Rev.3 classification ("International Standard Industrial Classification of All Economic Activities") that contains 60 industries. In contrast, the data on manufacturing trade from the UN Comtrade database are classified according to the "Standard International Trade Classification, Revision 2" (SITC, Rev.2) and contain 63 commodities. To match the trade data with the BHP, I generate a correspondence table on the basis of Arip et al. (2010) at the 2-digit level.

[20]To measure the effect of international trade and other control variables, I follow OECD (2011).

[21]Both control variables at the macro-level are only included in estimations without year fixed-effects since they would otherwise be omitted because of collinearity.

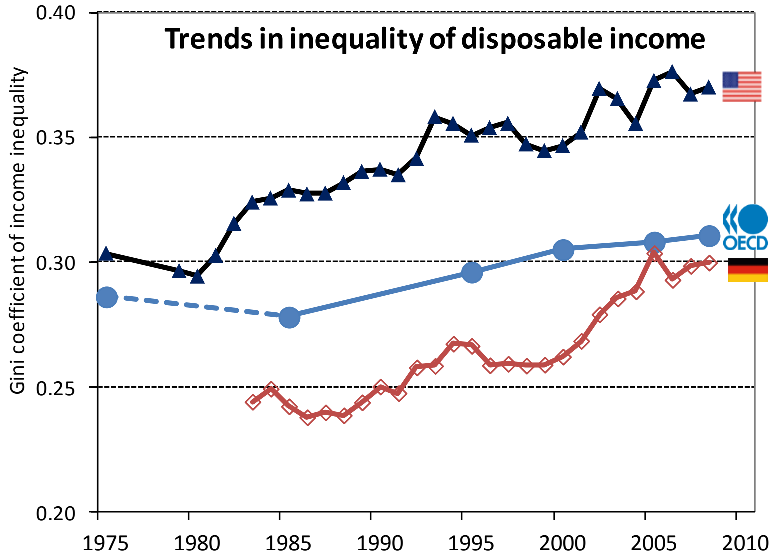

Figure 2.1:
Income Inequality in Germany measured by the Gini Coefficient
(**Source:** OECD (2011a))

below the OECD average in the mid-1980s, it was almost equal to the OECD average in 2008. In addition, the wage gap, measured as the wage ratio of the top 10% of the working population over the bottom 10%, rose from 6:1 in the 1990s to 8:1 in 2008 (OECD (2011)).[22] Like in the United States (Blum (2008)), the rise in income inequality occurred at the same time as the sectoral composition of the German economy changed from manufacturing toward services. By using the BHP, it is possible to examine the wages and the structure of the German economy between 1975 and 2010 in detail.

Figure 2.2 confirms the findings of the OECD report concerning the wage gap in Germany. The wage gap, calculated as the difference between the upper and the

[22]The authors conclude that the rise in income inequality in Germany is mainly driven by the increasing wage gap.

Figure 2.2:
Wage Gap in Germany
Source: Establishment History Panel, author's computation.

lower quartile of real wages, increased continuously.[23] The upper graph of Figure 2.2 shows the wage gap in Germany over all establishments and industries. In 1975, the average wage of employees in the upper quartile was Euro 9.65 larger than the average wage of employees in the lower quartile. Until 2010, the wage gap increased by 26% to Euro 12.14. The lower graph illustrates the increasing wage inequality by separating the manufacturing from the service sector. It shows that the wage gap increased in parallel in both sectors, but the difference between the wage inequality within the manufacturing and within the service sector did not rise.

[23]The wage gap is calculated as the difference between the upper and the lower quartile of real gross daily wages of an establishment's full-time employee. For that purpose, I calculate the wage gap as the average difference over all establishments in a given year. To ensure sufficient observations for the calculation of differences in wage quartiles within an establishment, I only include establishments with at least eight employees.

However, the wage gap between the sectors differs to a great degree. On average, the wage gap within the service sector was 21% larger than within manufacturing. Hence, a growing service sector leads immediately to a larger overall wage gap.

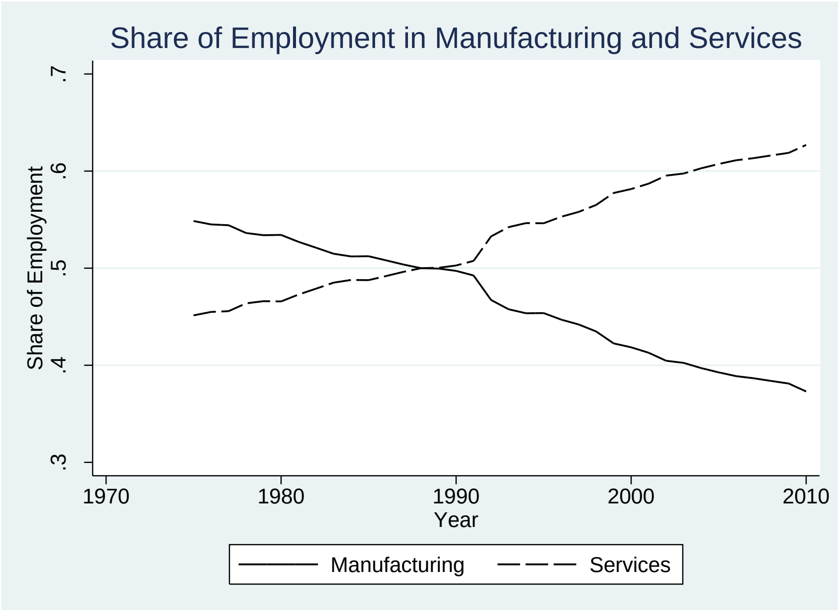

Figure 2.3:
Share of Employment in Manufacturing and Service Industries
Source: Establishment History Panel, author's computation.

Figure 2.3 shows the employment in the manufacturing and service sector in Germany between 1975 and 2010.[24] It supports the point made by Blum (2008) that the wage gap grew with changes in the sectoral composition. To calculate the share of employment, all establishments are classified into manufacturing or services on the basis of the 3-digit classification of economic activities included in the BHP.[25] The data show that the share of employment in manufacturing de-

[24]The descriptive statistics include the effects of the German reunification in 1991. In the empirical analysis, I will control for any effects that are caused by this event.
[25]Here, all employees within an establishment are assigned to the same sector. For further information on the classification of industries see Appendix A.2.

clined steadily whereas the share of employment in services rose. In 1975, 55% of all workers were employed in manufacturing and 45% worked in services. Within 36 years, the sectoral employment shares more than reversed. In 2010, 63% of all employees worked in the service sector and 37% were employed in the manufacturing sector. Hence, Figure 2.3 reflects the inter-sectoral reallocation of employment that is defined as structural change according to empirical analyses on the basis of industry-level data such as Blum (2008).

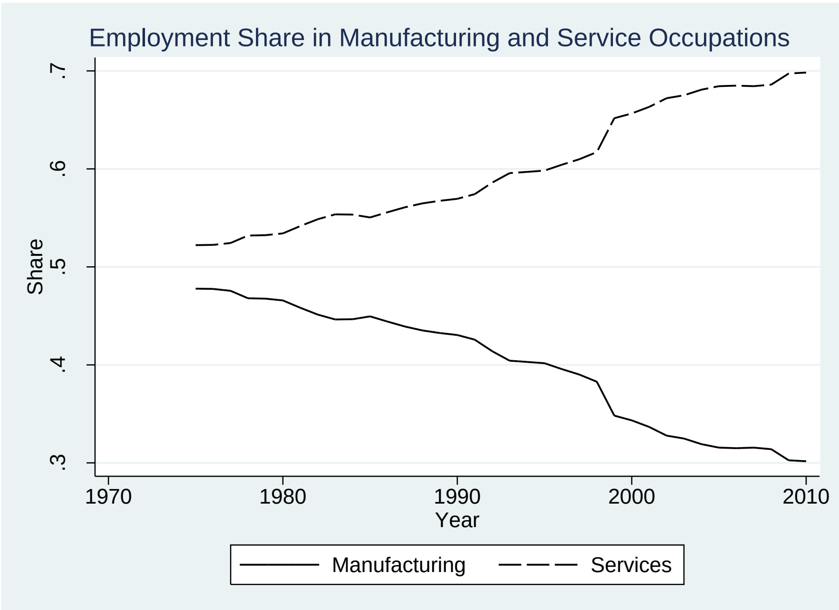

Figure 2.4:
Share of Employment in Manufacturing and Service Occupations
Source: Establishment History Panel, author's computation.

Figure 2.4 also illustrates the share of employment related to the two sectors. Here, I focus on the employment according to the Blossfeld classification of occupations. While the previous measurement assigns all employees of a respective establishment to the sector in which the establishment is classified,[26] this classification

[26]For example, if an establishment is classified as "Manufacturer of electric motors", i.e. it is

provides information about the structure of employment within an establishment and therefore accounts for intra-sectoral reallocations of employment. Together with the employment notification, the employer reports the task done by an employee at the 3-digit level from the classification of occupations (Hethey-Maier & Seth (2010)).[27] These data are used to recode the information according to the Blossfeld classification of occupations (Blossfeld (1987)). This classification aggregates the tasks into 12 groups on the basis to which economic sector the respective occupation is related. In addition, the classification also distinguishes between the respective qualification level.[28] With this classification included in the BHP, it is possible to determine the structural composition of the economy more precisely since there is an increasing number of establishments in the manufacturing sector producing services (Kelle (2013)).[29] The data reflect this shift. With the information about the employment structure within the establishments, the employment in services, i.e. in service occupations, is much larger for the whole period. In 1975, the employment in manufacturing occupations accounted for 48% and in service occupations for 52% of the total employment. As before, the share of employment in services increased continuously and the share of the employment in manufacturing decreased. In 2010, service occupations accounted for 70% of the employment share. Figure 2.4 highlights that structural change is even more significant if intra-sectoral changes are included. There is an increasing number of manufacturers that produce services and therefore hire a growing share of employees performing service tasks. Since most of the growing employment in service occupations refers

assigned to an industry within the manufacturing sector, all employees of this establishment are classified as employees in the manufacturing sector.

[27] See "Klassifikation der Berufe - KldB75".

[28] For further information, see Appendix A.1 and Blossfeld (1987).

[29] E.g. advertising, data processing, assembly and maintenance services.

to high-skilled labor, this leads to an increasing wage gap.

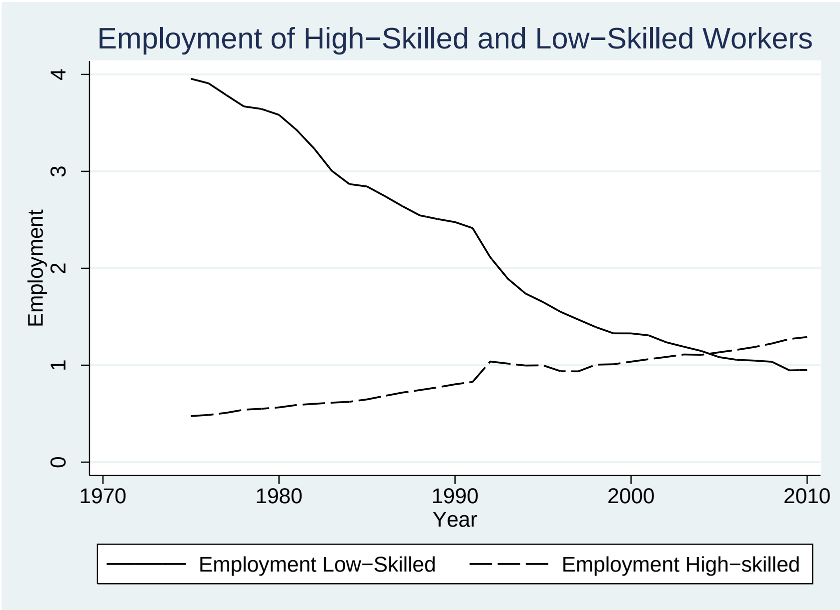

Figure 2.5:
Average Employment of high-skilled and low-skilled Workers
Source: Establishment History Panel, author's computation.

Figure 2.5 shows the employment levels in Germany for high-skilled and low-skilled workers.[30] The employment is calculated as the average number of employees per establishment in a given year. The rise in employment of high-skilled employees and the steep decline in the employment of low-skilled workers confirms the on-going change in the employment structure. In 1975, an establishment on average employed 0.5 high-skilled workers and 4 low-skilled workers. In the last decades, this changed fundamentally. In 2010, an establishment employed 1.3 high-skilled and 0.9 low-skilled workers on average. The persistent change in the employment

[30] High-skilled employees are defined as employees with a degree from a specialized college of higher education (in German: Fachhochschule) or a university degree. Low-skilled employees do not have an upper secondary school leaving certificate or a vocational qualification.

reflects the transition of the German economy, both in terms of structural change and skill-biased technological change.

Figure 2.6 illustrates capital accumulation in Germany in manufacturing and services between 1975 and 2010. Until 1990, capital accumulated equally in the manufacturing and the service sector, but in the 1990s, the investments in the service sector grew more rapidly. Between 1993 and 2001, capital accumulated by almost 25% in the service sector and declined by 16% in manufacturing. These findings describe the structural change in the German economy, which are very similar to the movements Blum (2008) finds for the United States. Blum argues that, in manufacturing capital is complementary to low-skilled labor, but in services, it is complementary to high-skilled labor. Hence, capital accumulation in services causes an increase in the demand for high-skilled employees and thus an increase in the wage premium.

In summary, the sectoral composition of the German economy changed considerably. The employment in the manufacturing sector declined significantly, whereas the employment in the service sector grew. This is supported by the data in terms of the sectoral employment, the demand for high-skilled and low-skilled employees and the capital accumulation in the two sectors. Furthermore, the BHP supports the findings of the OECD (2011) and many other studies concerning the increasing wage inequality in Germany. In the 1975 to 2010 period, the wage gap between the upper quartile and the lower quartile increased by 26%. Moreover, the wage gap within the service sector was much larger than within the manufacturing sector. Therefore, the rise of the service sector directly increased the overall wage gap. In addition, structural change increased the relative demand for high-skilled workers, which also led to an increasing wage gap. In the following, I will introduce the empirical model I use to calculate the effects of structural change, international

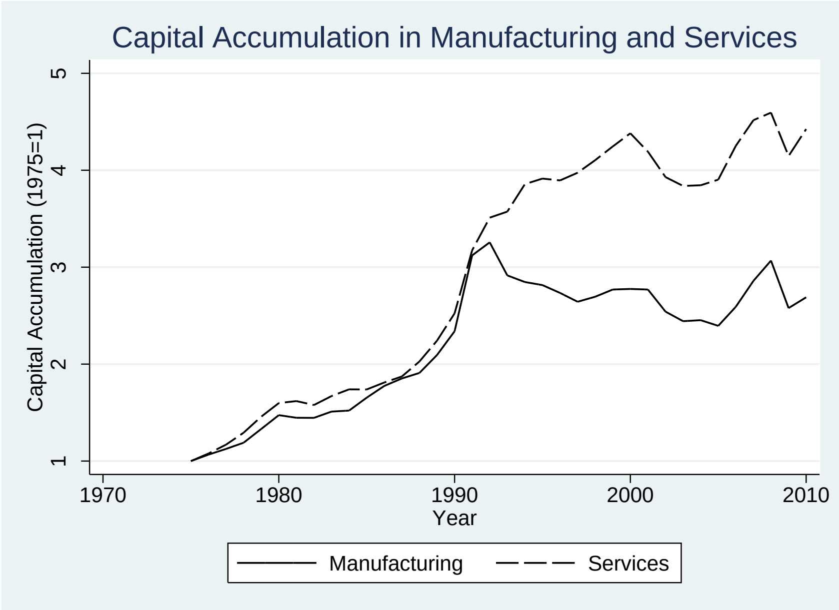

Figure 2.6:
Capital Accumulation in Manufacturing and Services
Source: German Federal Statistical Office, author's computation.

trade, and technological progress on the wage gap in Germany.

2.5 Empirical Strategy

To identify the wage effects of structural change, international trade, and technological progress, I estimate a fixed-effects regression model.[31] To evaluate the effect of structural change in Germany, I implement an appropriate proxy, the share of employees with tasks in services or administration (see equation (2.3)). In order to calculate the effect of changes in the sectoral composition in Germany, I use the

[31] I follow the empirical model of the OECD (2011) study. That study uses macro data for all OECD countries (OECD (2011), Chapter 2) from the early 1980s to 2008 and estimates the income effects of international trade, technological progress and changes in labor market institutions and policies.

"Establishment History Panel" together with the additional data sets mentioned above. Altogether, it is a detailed panel data set covering the years 1980-2010 in Germany.[32] To account for the substantial establishment heterogeneity, I use the respective establishment as the panel variable and thus I am able to control for all establishment-specific effects.[33] The estimated fixed-effects equation looks as follows:

$$\Delta w_{jit} = \alpha + \beta_1 Struc_{jit} + \beta_2 Trade_{it} + \beta_3 Tech_{jit} + \gamma' X_{jit} + \nu_j + \lambda_i + \eta_t + \epsilon_{jit}. \quad (2.1)$$

The dependent variable, Δw_{jit}, is the wage gap within establishment j in industry i at time t. It is calculated as the difference between the upper and the lower quartile of the wage distribution among full-time employees in an establishment:[34]

$$\Delta w_{jit} = w_{jit}^{Q.75} - w_{jit}^{Q.25} \quad (2.2)$$

The first explanatory variable, $Struc_{jit}$, measures the structural composition within an establishment. It is constructed as the share of employees with an occupational status "services" (E_{jit}^{serv}) or "administration" (E_{jit}^{admin}) according to the Blossfeld

[32] Because the data for trade in services are only available from 1980 to 2010, I have to skip the 1975-1979 period of the BHP.

[33] Each establishment is represented by its respective artificial establishment number. This number is randomly generated to make the data anonymous, but it allows for the identification of the same establishment in different years. Therefore, it is possible to merge the yearly data of the BHP to create a panel data set. Afterwards, I am able to control for all establishment-specific effects using the "areg" command in Stata. This is equivalent with creating a dummy variable for each establishment and adding them into the regression.

[34] The BHP only provides information on the average wage of the employees in the respective wage quartile. Therefore, precisely, the wage gap is calculated as the difference between the average wage of an employee in the upper quartile and the average wage of an employee in the lower quartile.
Moreover, all estimations include establishments with at least eight employees to ensure sufficient observations within an establishment to calculate meaningful differences in wage quartiles, employment shares, etc.

classification over the total employment of the respective establishment E_{jit}:

$$Struc_{jit} = \frac{E_{jit}^{serv} + E_{jit}^{admin}}{E_{jit}} \tag{2.3}$$

$Trade_{it}$ are exports from Germany. It is an indicator that controls for the openness of the German economy to international trade. $Tech_{jit}$ is a proxy for technological progress and is measured by the number of engineers and scientists in an establishment. This information is included in the BHP to account for research and development activities. X_{jit} is a vector of control variables accounting for further influences at the establishment-level that may also have an effect on the wage gap, e.g. the size of the establishment,[35] the share of female employees, and the share of high-skilled employees. For regressions without year fixed-effects, I include a second vector of control variables accounting for effects at the macro-level, e.g. German GDP, a dummy variable controlling for German reunification in 1991, and the education level of the German population.[36]

Equation (2.1) is estimated by a fixed-effects model with establishment-specific fixed-effects, ν_j, as well as with industry-specific effects, λ_i, to capture sector-specific variation and year-specific effects, η_t, to control for common global shocks and business cycle effects. ϵ_{jit} is the error term. All variables are transformed into logarithms such that the estimated coefficients can be interpreted as elasticities.

To check for the robustness of the proxies for international trade, I estimate all regressions with both German export and import data. In addition, equation (2.1) is estimated by pooled-OLS[37], fixed-effects and random-effects as well on the basis of various different specifications.

[35] The size of an establishment is measured by the total number of full-time employees.

[36] The overall education level is measured as the percentage share of German citizens with post-secondary education.

[37] To estimate a pooled-OLS model, all fixed-effects are excluded.

2.6 Results

2.6.1 Results from the Baseline Model

Table 2.2: The Effects of Structural Change, International Trade and Technological Progress on the Wage Gap in Germany; 1980-2010

Variables	Fixed-Effects Regression				
	(1)	(2)	(3)	(4)	(5)
Structural Change					
Struc	0.4839***	0.4849***	0.4778***	0.4851***	0.4781***
	(0.0096)	(0.0093)	(0.0093)	(0.0097)	(0.0094)
International trade					
Exports		0.0177***	0.0174***		
		(0.0034)	(0.0034)		
Imports				0.0339***	0.0332***
				(0.0027)	(0.0029)
Technological Progress					
R&D			0.0153***		0.0151***
			(0.0014)		(0.0014)
Other Controls	Yes	Yes	Yes	Yes	Yes
Establishment Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.7244	0.7243	0.7257	0.7243	0.7257
Root MSE	0.3496	0.3497	0.3497	0.3497	0.3497
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000
No. of Obs.	1.87 Mill.	1.87 Mill.	1.87 Mill.	1.87 Mill.	1.87 Mill.

Dep. Variable: Wage gap ($Q_{0.75}$-$Q_{0.25}$).

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.
All variables are logarithms, such that the coefficients can be interpreted as elasticities.

Table 2.2 shows the results from the baseline regression model represented by equation (2.1). Here, the estimations include all control variables as well as establishment, industry and year fixed-effects.[38] First, without controlling for international trade and technological progress, column 1 of Table 2.2 shows that the structural composition has a positive and significant effect on the wage gap in Germany. The coefficient of structural change, β_1, suggests that a 10% increase in the share of employees with occupations in services or administration leads to a 4.8% increase in the difference between the upper and the lower wage quartile. This supports the argument that structural change leads to an increase in the relative demand for high-skilled workers and therefore to an increasing wage gap. Taking international trade into account, column 2 shows that the coefficient of the structural composition remains almost constant. The coefficient of international trade, β_2, is also positive and significant but much smaller than β_1. A 10% increase in exports leads to a 0.2% increase in the wage gap. Column 3 includes the effect of technological progress. The estimation shows that the impact of technological advances on the wage gap is positive and significant, too. If R&D activities increase by 10%, wage inequality increases by 0.2%. When including the effect of technological change, the coefficients β_1 and β_2 remain almost constant. Columns 4 and 5 serve as robustness checks by estimating the specifications of columns 2 and 3 with German import data. As the estimations show, the coefficient of German imports is higher than the coefficient of German exports but it is still much smaller than the coefficient of structural change. All other coefficients remain roughly constant, i.e. the results are not sensitive to changes of the measurement of international trade.

To summarize, the results show that structural change, international trade, and technological progress have a positive and significant effect on the increasing wage

[38] I also estimate equation (2.1) with an interaction effect including time- and industry fixed-effects ($\lambda_i \times \eta_t$) to control for time-variant industry fixed-effects. The results remain constant. All non-reported results can be obtained upon request.

gap in Germany. Moreover, the coefficients on changes in the structural composition of employment are considerably larger than the coefficients on international trade and technological progress. These findings hold for various specifications of the estimated equation (2.1).

After having identified the substantial effect of structural change on the wage gap in Germany, I split the data set into sub-periods and sectors to investigate the driving forces behind the overall effect more closely. To check whether the wage effect of structural change varies in the course of time, I subdivide the data set into three periods and estimate them separately. In addition, I estimate equation (2.1) only with establishments in manufacturing or services, respectively.

Table 2.3: Fixed-Effects Estimation within Sub-Periods and Sectors

	Overall Effect	Effects within Sub-Periods			Effects Within Sectors	
		1980-1989	1990-1999	2000-2010	Manufacturing	Services
	(1)	(2)	(3)	(4)	(5)	(6)
Structural Change						
Struc	0.4778***	0.3916***	0.4760***	0.4439***	0.7846***	0.1731***
	(0.0093)	(0.0238)	(0.0173)	(0.0183)	(0.0131)	(0.0133)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Establishment Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.7257	0.7502	0.7771	0.7864	0.7702	0.6924
Root MSE	0.3497	0.2765	0.3160	0.3311	0.3126	0.3691
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
No. of Obs.	1.87 Mill.	419.335	733.532	731.762	690.722	1.18 Mill.

Dep. Variable: Wage gap ($Q_{0.75}$-$Q_{0.25}$).

Notes: Robust standard errors in parentheses,
*** p<0.01, ** p<0.05, * p<0.1.
All variables are logarithms, such that the coefficients can be interpreted as elasticities.

The results are reported in Table 2.3. Column 1 repeats the result of Table 2.2, column 3. Here, only the coefficient of the structural composition is reported. To check whether this effect varies over time, I subdivide the data set into three periods: 1980-1989, 1990-1999 and 2000-2010. The results are reported in columns 2 to 4. The estimated coefficients show that the effect of structural change on the wage gap differs in the course of time. Between 1990 and 1999, a 10% increase in the share of employees with occupations in services or administration leads to a 4.8% increase in the wage gap. This effect is 22% larger than in the first sub-period. Between the second and the third sub-period, the coefficient decreases somewhat but remains almost constant. This suggests that most of the wage effect of structural change occurred after 1990.[39]

Moreover, to check if the effect arises mainly within the manufacturing or within the service sector, I separately estimate equation (2.1) only with establishments that are classified either in the manufacturing or in the service sector. Columns 5 and 6 report the results. The outcome shows that the wage effect is mainly driven by changes in the composition of employment within the manufacturing sector. The estimated coefficient for establishments within the manufacturing sector is more than four times larger than the coefficient for service establishments only. Furthermore, I estimate equation (2.1) for each 3-digit industry separately. The results are reported in Table A.2, Appendix A.2 and confirm the findings above.

[39] In order to check if it is sufficient to use a dummy variable to control for the effects of the German reunification in 1991, I additionally estimate equation (2.1) for West Germany separately. Thus, I am able to test if the effects estimated so far might be driven by the integration of the East German economy despite using the reunification dummy. The results are reported in Table A.6, Appendix A.3. The estimated coefficients are slightly smaller than in Table 2.3 but they confirm the findings above and provide evidence that the effect of structural change on the increasing wage gap is not mainly driven by the transformation of the East German economy after 1991. Thus, the results show that it is sufficient to use a dummy variable to control for the German reunification as before.

The industry-specific regressions clearly show that the effect of structural change on the wage gap is much higher within manufacturing industries than within service industries. In service industries, the estimated coefficients are smaller and often, they are insignificant. These results provide further evidence that an important part of structural change fostering the wage gap occurs within the manufacturing sector. There is an increasing number of manufacturers producing services using high-skilled labor intensively.

Next, I estimate equation (2.1) and then use the estimated coefficients to derive standardized coefficients because the variables included in the regression analysis are measured at different levels. For instance, the share of employees with tasks in services is measured at the establishment-level but the trade data are only available at the industry-level. Therefore, the variances of the independent variables differ considerably and thus, the sizes of the unstandardized coefficients are not comparable. The estimated coefficients so far show that the effects of structural change, international trade, and technological progress contribute to the increasing wage gap in Germany. But it is not possible to conclude from the unstandardized coefficients that the effect of structural change is many times higher compared to the effects of international trade and technological progress. To check which of the independent variables have a greater effect on the dependent variable, I derive beta coefficients that account for differences in the variances of the independent variables.[40] The beta coefficients can be interpreted as a change in the standard deviation of the dependent variable due to a one standard deviation change in the respective independent variable.

[40]Standardized (beta) coefficients are derived by multiplying the primary, unstandardized coefficient by the ratio of the standard deviations of the respective independent variable and the dependent variable: $\beta_i^* = \beta_i \frac{S_{x_i}}{S_y}$.

Table 2.4: Derivation of standardized Coefficients

Variables	Pooled-OLS		Fixed-Effects	
		Standardized		Standardized
	(1)	(2)	(3)	(4)
Structural Change				
Struc	0.7126***	0.2341	0.4779***	0.1723
	(0.0044)		(0.0094)	
International trade				
Exports	0.0302***	0.2494	0.0175***	0.4006
	(0.0046)		(0.0034)	
Technological Progress				
R&D	0.0488***	0.0658	0.0153***	0.0145
	(0.0008)		(0.0014)	
Other Controls	Yes	Yes	Yes	Yes
Establishment Fixed-Effects	No	No	Yes	Yes
Industry Fixed-Effects	No	No	Yes	Yes
Year Fixed-Effects	No	No	Yes	Yes
No. of Obs.	1.87 Mill.	1.87 Mill.	1.87 Mill.	1.87 Mill.

Dep. Variable: Wage gap ($Q_{0.75}$-$Q_{0.25}$).

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. All unstandardized variables are logarithms, such that the coefficients can be interpreted as elasticities.

The results are reported in Table 2.4. The beta coefficients show that the effect of international trade on the wage gap is much more important than the unstandardized coefficients would suggest. In addition, the effect of structural composition is still important but much smaller than the unstandardized coefficients would indicate. First, I estimate a pooled-OLS model. The calculated beta coefficient shows that a one standard deviation increase in the share of employees performing service tasks results in a 0.23 standard deviation increase in the wage gap. Concerning the effect of international trade, the beta coefficient suggests that a one standard deviation increase in exports results in a 0.25 standard deviation increase in the wage gap. Hence, the effect of international trade is now comparable to the effect of the structural composition. The effect of technological progress is much smaller compared to international trade and the structural composition. A one standard deviation change in R&D activities results in a 0.07 standard deviation increase in the wage gap. Columns 3 and 4 show the results of the fixed-effects regression. Again, a comparison of the unstandardized coefficients would mislead to the interpretation that the effect of structural change on the wage gap is much larger than the effect of international trade. Now, the effect of international trade becomes even larger than the effect of structural change.

In summary, the results highlight the importance of accounting for differences in the variances of variables measured at different levels. After taking this into account, the effect of structural change is still significant and meaningful. But now, it is comparable to the effect of international trade that is now, on the other hand, in line with the literature (see for example OECD (2011)).[41]

Finally, I estimate equation (2.1) with more aggregated data. In order to check whether the detailed establishment-level data of the BHP provide additional information on the effect of structural change on the wage gap, I aggregate the micro data to the industry- and to the macro-level. Hence, I am able to highlight that it is crucial to use micro data in contrast to other studies that only use sectoral (Blum (2008)) or macro data (OECD (2011)). For the calculation at the industry-level, all variables are aggregated to the 3-digit level (according to the classification of economic activities 93 that is included in the BHP) and to the 2-digit level (according to the ISIC classification of the trade data from the UN Comtrade database):

[41] I also estimate the beta coefficients with data on imports instead of exports which confirms the robustness of the results.

$$\Delta w_{it} = \alpha + \beta_1 Struc_{it} + \beta_2 Trade_{it} + \beta_3 Tech_{it} + \epsilon_{it}.^{42} \tag{2.4}$$

The estimated equation at the macro-level is as follows:

$$\Delta w_{t} = \alpha + \beta_1 Struc_{t} + \beta_2 Trade_{t} + \beta_3 Tech_{t} + \epsilon_{t}.^{43} \tag{2.5}$$

Table 2.5: Estimations with more aggregated Data

	Establishment-Level (1)	Industry-Level (3-digit) (2)	Industry-Level (2-digit) (3)	Macro-Level (4)
Structural Change				
Struc	0.4867***	0.7542**	0.7844**	0.3048
	(0.0047)	(0.3195)	(0.4179)	(4.9547)
Other Controls	No	No	No	No
Establishment Fixed-Effects	No	No	No	No
Industry Fixed-Effects	No	No	No	No
Year Fixed-Effects	No	No	No	No
Adj. R^2	0.7003	0.7949	0.8850	0.0419
Root MSE	0.4034	0.1241	0.0953	0.9341
Prob > F	0.0000	0.0121	0.1842	0.2538
No. of Obs.	5.3 Mill.	6418	1728	31

Dep. Variable: Wage gap ($Q_{0.75}$-$Q_{0.25}$).

Notes: Robust standard errors in parentheses,
*** p<0.01, ** p<0.05, * p<0.1.
All variables are logarithms, such that the coefficients can be interpreted as elasticities.

[42] The variables are derived in the same way as in equation (2.5), but they are calculated for each industry i.

[43] Here, Δw_t is the average wage gap over all establishments, $j = 1, ..., n$, in a given year t: $\Delta w_t = \frac{1}{n}\sum_{j=1}^{n} \Delta w_j$ and $Struc_t$ is calculated as the average share of employees with an occupational status "services" or "administration" according to the Blossfeld classification over all establishments in a given year: $Struc_t = \frac{1}{n}\sum_{j=1}^{n} Struc_j$. $Tech_t$ is derived equally. $Trade_t$ is measured as total exports or imports over all industries, $i = 1, ..., k$, in the respective year: $Trade_t = \sum_{i=1}^{k} Trade_i$.
In this specification no control variables or fixed-effects are included in the estimation.

Table 2.5 presents the results. Column 1 shows the findings for the effect of the structural composition at the establishment-level. In this specification, I use the baseline specification as reported in Table 2.2, column 3 but without including control variables and fixed-effects. The estimation suggests that a 10% increase in the share of employees with tasks in services or administration leads to a 4.9% increase in the wage gap. By aggregating the micro data to the 3-digit industry-level in column 2 (according to equation (2.4)), the coefficient β_1 remains positive and significant at the 5%-level and is even larger than at the establishment-level. With information at the 3-digit industry-level, a 10% increase in the share of employees with occupations in services or administration leads to a 7.5% increase in the difference between the upper and the lower wage quartile. However, the standard error increases significantly which leads to a less precise estimation. In addition, the F-statistic of the estimation shows that the regression model is not significant at the 1%-level any more. This points out that the explanatory value of the regression model as a whole declines in comparison to the regression at the establishment-level. Column 3 presents the results of the regression at the 2-digit level. The estimated coefficient β_1 remains almost constant compared to the regression at the 3-digit level, but now, the standard error increases again and the F-statistic shows that the regression model has lost all its explanatory power. Thus, the effect of structural change on the growing wage gap cannot be determined any more. Column 4 shows the results of the regression at the macro-level. Here, all variables are aggregated according to equation (2.5). Now, the coefficient β_1 is still positive but insignificant. Furthermore, according to the F-statistic, the model has no explanatory power.

These results indicate that the establishment-level data provide important information in comparison to the results at the industry-level or the macro-level.

The estimation of the impact of structural change on the increasing wage gap at a more aggregated level would bias and/or ignore the distributional effects of the structural reallocation.

The previous approach highlights the importance of using establishment-level data by including the same variables as in equation (2.1) but aggregated to different levels. Next, I compare the wage effect of structural change at the establishment-level with the wage effect if intra-industry changes are ignored. As mentioned above, the structural reallocation of labor is much more significant after accounting for intra-sectoral changes. Hence, I calculate the structural composition at the establishment-level according to the occupations the employees perform. Now, I estimate equation (2.1) on the basis of the industry classification of the respective establishment. Here, I follow empirical studies at the industry-level (such as Blum (2008)) that have no information about the structural composition of occupations but only have information about the employment at the industry-level. Therefore, these studies can only examine inter-sectoral changes. I also distinguish if industry-level studies have access to further control variables such as the average plant size, the average share of female employees or the average share of high-skilled employees.

The results are reported in Table 2.6. Column 1 shows the effect of structural change on the wage gap as reported in Table 2.2, column 3. Here, the structural composition is calculated according to the occupations within an establishment. Furthermore, all control variables are derived at the establishment-level. The estimated coefficient accounts for inter-industry and intra-industry employment changes and is positive and significant. Next, I estimate the wage effects if only inter-sectoral employment changes can be observed. For that purpose, I assume that all employees of an industry perform occupations that are related to this

Table 2.6: Including versus Excluding intra-sectoral Employment Changes

	Intra-sectoral changes & inter-sectoral changes	Only inter-sectoral changes			
		Industry-Level (3-digit)		Industry-Level (2-digit)	
	(1)	(2)	(3)	(4)	(5)
Structural Change					
Struc	0.4778***	0.1979	0.5875***	-0.0261	0.1206
	(0.0093)	(0.1551)	(0.1377)	(0.1208)	(0.1157)
Control Variables	Yes	Yes	No	Yes	No
Establishment Fixed-Effects	Yes	No	No	No	No
Industry Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes
Prob > F	0.0000	0.0000	0.0000	0.0012	0.0012
No. of Obs.	1.87 Mill.	6418	6418	1728	1728

Dep. Variable: Wage gap ($Q_{0.75}$-$Q_{0.25}$).

Notes: Robust standard errors in parentheses,
*** p<0.01, ** p<0.05, * p<0.1.
All variables are logarithms, such that the coefficients can be interpreted as elasticities.

industry.[44] Columns 2 and 3 present the results for the estimations at the 3-digit industry-level. First, column 2 includes control variables at the industry-level. The estimated wage effect of structural change is still positive, but now it is no longer significant. If the control variables are excluded, column 3 shows that the effect again becomes significant. Hence, if only inter-sectoral changes are considered, it is either not possible to identify an effect of structural change on the wage gap or the data link wage effects to structural change that are in fact caused by other factors not included in the regression. Columns 4 and 5 show the regressions at the 2-digit

[44] First, I classify the employees according to the 3-digit industry classification of economic activities 93 included in the BHP. In a further step, I classify the employees on the basis of the 2-digit ISIC classification of the trade data from the UN Comtrade database.

industry-level. Here, it is not possible to identify an effect of structural change on the wage gap.

In summary, I obtain strong empirical evidence that structural change is an important determinant for the increasing wage inequality in Germany. The effects of international trade and technological progress are also positive and significant which is in line with the literature on income inequality (e.g. OECD (2011) and Feenstra & Hanson (1999)). Moreover, if I account for differences in the variances of the variables by using standardized coefficients, the effect of structural change on the wage gap is comparable to the positive effect of international trade. By splitting the data set into sectors, the estimations provide evidence that the overall wage effect of structural change is significantly larger within the manufacturing sector. The comparison with estimations of more aggregated data highlight that the detailed establishment-level data set of the BHP provides important information about the effects of structural change on the wage gap. If the impact of structural change on the wage gap is estimated at a more aggregated level, the wage effect would be biased or even ignored. Finally, the results clearly show that it is very important to account for intra-industry changes and control for further effects such as the plant size or the share of high-skilled employees.

2.6.2 Robustness Checks

In order to check if my results are robust, I estimate my baseline model in various specifications and by different estimation models. The output tables are reported in the Appendix A.3, Table A.3 to A.6.

First, I estimate equation (2.1) by a pooled-ordinary least square (pooled-OLS) regression model. The results are reported in Table A.3, Appendix A.3. Without controlling for the structural composition of establishments, column 1 suggests that international trade and technological progress have a positive and significant impact on the wage gap. Taking the structural composition into account, column 2 shows that the coefficients on international trade and technological progress remain almost constant. Thus, structural change has an additional effect on the wage distribution that was hidden in the error term before. The coefficient of structural change is positive, significant, and much larger than the coefficients on international trade and technological progress. Column 3 presents the results with an alternative proxy for international trade without controlling for the structural composition. This specification estimates equation (2.1) with imports to Germany instead of exports from Germany. Column 4 includes the additional impact of structural change. Both columns provide a robustness check concerning the selection of an indicator for international trade. The results confirm the findings of columns 1 and 2. Second, columns 5 to 12 of Table A.3 repeat the estimation strategy form before by using a fixed-effects and a random-effects model respectively. For each model, equation (2.1) is estimated both with and without $Struc_{jit}$ and with both proxies for international trade. The results confirm the estimations of my baseline model concerning the effects of structural change, international trade, and technological progress.

Furthermore, I estimate a fixed-effects specification of equation (2.1) with clustered standard errors for each industry. The results are reported in Table A.4, Appendix A.3. The coefficients serve as an additional robustness check and confirm the findings for structural change and technological progress. Now, however, the coefficients on exports are insignificant.

Next, I also run a fixed-effects regression that controls for regional heterogeneity by including dummies for 16 federal states within Germany. The results, together with selected coefficients of control variables, are reported in Table A.5, Appendix A.3. To compare the results, columns 1 and 2 of Table A.5 repeat the estimated coefficients of the fixed-effects estimation of Table A.4. Columns 3 and 4 show the results of the same fixed-effects regression but supplemented with regional fixed-effects. All findings confirm the previous results. In addition, the coefficients of control variables show that the wage gap increases if an establishment becomes larger, if the share of high-skilled employees increases, and if the share of female employment grows. All these effects are in line with the literature.

Finally, I estimate equation (2.1) with establishments in West Germany only. By excluding the establishments in East Germany, I am able to check if the effects I derived so far might be driven by the integration of the East German economy in the course of the German reunification. The results are reported in Table A.6, Appendix A.3 and show that the estimated coefficients are slightly smaller than in Table 2.3 but confirm all previous findings. This provides evidence that the process of German reunification after 1991 does not drive the results.

2.7 Conclusion

This chapter examines the impact of structural change, international trade, and technological progress on the increasing wage gap in Germany and thus puts the focus on an additional cause for the increasing wage inequality, which so far has not been explored by the literature.

I use German data and provide evidence that the increasing employment in service occupations leads to an additional skill-bias and therefore changes the labor demand. Taking the employment growth rates in service occupations into account, the calculations show that the employment did not grew equally in all occupations but that occupational groups requiring the highest qualification levels experienced the highest employment growth rates. Hence, structural change in Germany works similarly to the effect of skill-biased technological change. The stylized facts show that the wage gap in Germany continuously increased, which is in line with the findings of many other studies (e.g. OECD (2011)). In 2010, the difference between the upper and the lower quartile of the wage distribution was 26% larger than in 1975. In addition, the wage gap within the service sector was roughly 21% larger over the whole period. Therefore, an increasing service sector immediately leads to a larger overall wage gap. Simultaneously, the structural composition of the German economy changed considerably. Taking the occupations of employees within an establishment into account, the employment share of services increased from 52% to 70%, whereas the employment in manufacturing declined from 48% to 30%. This structural change is also reflected in the employment of high-skilled and low-skilled employees and in terms of capital accumulation in services and in the manufacturing sector.

In the empirical analysis, I estimate the effects of the structural composition, international trade, and technological progress on the wage gap in Germany for the 1980-2010 period. I obtain strong evidence that the structural composition is an important determinant for the growing wage gap in Germany. The effect of the respective coefficient is positive, significant, and comparable to the effect of international trade. In addition, I show that the effect of structural change cannot easily be identified by using more aggregated data or by excluding intra-sectoral changes of employment.

Chapter 3

Structural Change and Total Factor Productivity: Evidence from Germany

Summary:

This chapter uses a long time series of German employment data to test the theory of Ngai & Pissarides (2007). The theory suggests that the shift of employment shares from manufacturing to services is due to divergent growth rates of total factor productivity (TFP) in the two sectors. To test the theoretical predictions, I use the "Establishment History Panel" together with sectoral data on total factor productivity. The results confirm the theoretical predictions, i.e. they show a negative relationship between employment growth and TFP growth.

3.1 Introduction

During the last decades, most developed economies experienced a substantial structural change. Economic growth took place at very different rates across industries. Employment in manufacturing steadily declined, whereas employment in the service sector grew continuously. Several recent multi-sector growth models are able to explain the driving forces behind structural change. The models can be classified into two groups regarding their explanations: technology-driven and preference-driven structural change. The most prominent paper of the first group is the one by Ngai & Pissarides (2007), which explains structural change by divergent total factor productivity (TFP) growth rates between manufacturing and service industries. Exemplary for the second group is the paper by Kongsamut et al. (2001), who show that non-homothetic preferences can be a driving force behind structural change.[1]

The current chapter focuses on the first strand of literature by testing the theory of Ngai & Pissarides (2007) with German labor market data and data on German TFP from 1980 to 2009. To the best of my knowledge, this is the first analysis to test this theory. The results confirm the theoretical predictions of Ngai & Pissarides (2007) and thus identify diverging sectoral growth rates of TFP as one of the driving forces behind structural change.

In particular, this chapter is the first empirical study that tests the employment effects of diverging TFP growth rates over a very long time period. This is especially important for two reasons: First, employment movements are not expected to occur immediately if TFP growth rates start to diverge. Firms observe changes in TFP

[1] A recent review of the literature on structural change that is dating back to the 19$^{\text{th}}$ century is provided by Matsuyama (2008).

ex post and therefore the reaction is, by nature, lagged. If only cross-section data are used, the effects will be underestimated, because it is not possible to account for delayed effects. Second, as the data show, there are periods where TFP growth rates between manufacturing industries and services did not diverge significantly. If only a short time period is considered that focuses on these years, the results will be misleading. Hence, it is of particular importance to analyze a long time period to identify the employment effects of diverging sectoral TFP growth rates accurately.

Ngai & Pissarides (2007) focus on total factor productivity and show that employment shares shift to industries with low TFP growth rates if the elasticity of substitution across final goods is sufficiently low, i.e. below one. The mechanism that Ngai & Pissarides (2007) describe goes back to Baumol (1967), who developed a model with two sectors that differ in their respective productivity growth: First, there is a technologically "progressive" sector in which innovations and economies of scale are achieved and thus lead to high productivity gains.[2] Therefore, it is possible to decrease the overall costs of production or to offset other increasing costs of production, e.g. increasing wages. Second, there is a "stagnant" sector that, by its nature, experiences relatively smaller productivity increases because labor is the only input and "product" quality is directly related to the amount of labor that is used. The manufacturing sector represents the former, "progressive" sector, where technological progress, e.g. the increasing automatization, improves the quality of products and/or decreases the costs of production. The latter category, the "stagnant" sector, is the service sector. Hence, production costs and prices of the "stagnant" industry rise relative to those of the "progressive" sector. This phe-

[2] Görg, Hanley & Strobl (2005) provide empirical evidence that international outsourcing of inputs is another source that is able to promote TFP of manufacturing firms.

nomenon is commonly known as "Baumol's cost disease". Finally, Baumol assumed that the output shares of the two sectors are fairly constant.[3] Thus, the share of production inputs, such as labor used in the "stagnant" sector has to rise continuously to compensate the relative productivity deficit. Ngai & Pissarides (2007) introduce this mechanism into a neoclassical growth model. In line with Baumol (1967), they assume a "progressive" manufacturing sector and a "stagnant" service sector in terms of total factor productivity growth. Furthermore, they assume that structural change is a process at a rather aggregated industry-level. At this level, industries and their final products differ significantly from each other such that the elasticity of substitution between final goods is sufficiently low (below one). This assumption corresponds to the constant output share assumption of the two sectors that Baumol (1967) stated. Because the elasticity of substitution between the sectors is below one, demand reacts disproportionately little to price increases in services and therefore an increasing share of workers has to work in the service sector to compensate the relative productivity losses and to satisfy the demand of consumers.

The current chapter is based on a very detailed establishment-level data set, the "Establishment History Panel" (in German: Betriebs-Historik-Panel (BHP)), covering all establishments in West Germany over the time span from 1975 to 2010 and all establishments in East Germany from 1991 onwards. The data set provides a detailed insight into the German economy over a long time period and is therefore ideally suited to investigate long-term structural changes in employment

[3]Baumol (1967) argued that the output of the "stagnant" industry tends to decline and perhaps, finally, vanishes because the demand for these products, i.e. services, is rather elastic. However, Baumol analyzed the effects if the relative output of the two sectors maintains despite changes in the relative costs and prices. Government subsidies or a sufficiently price inelastic demand for services may lead to fairly constant output shares according to Baumol.

shares. Among other things, it provides information on the classification of economic activities and on the employment structure of each establishment. Because the BHP contains no information on total factor productivity, I have to match the BHP with sectoral data on TFP from the EU KLEMS Growth and Productivity Accounts. The EU KLEMS database provides data on TFP for Germany from 1975 to 2010 at the 2-digit industry-level. Hence, I aggregate the BHP to the 2-digit level and therefore, both data sets can be matched accurately. The empirical analysis at the 2-digit level is in accordance with the theory of Ngai & Pissarides (2007), since the authors assume rather aggregated industries. As Baumol, Blackman & Wolff (1985) show, this level of aggregation ensures that industries differ sufficiently from each other such that the elasticity of substitution between final goods is below one. Hence, the 2-digit industry-level is very appropriate to test the theoretical predictions of Ngai & Pissarides (2007).

The empirical evidence on the link between TFP growth rates and employment shifts is, however, scarce. There is only a very small body of loosely related empirical literature that analyzes earlier time periods: Baumol, Blackman & Wolff (1985) use sectoral data for the U.S. between 1947 and 1976 and provide evidence consistent with the theoretical model if 2-digit industry-level data are used. They show that the output shares of the "progressive" and "stagnant" sector remained fairly constant in the postwar period. In addition, they find increasing relative prices for the "stagnant" sector. Therefore, the share of total expenditures on services and their share of the labor force rose significantly. Ngai & Pissarides (2007) conclude that this level of aggregation satisfies the key assumption of a sufficiently low elasticity of substitution. In addition, Kravis, Heston & Summers (1983) use cross-sectional UN data for 34 countries in 1975 and show that this assumption can be considered as valid. Furthermore, they show that relative price changes between services and manufacturing depict differences in TFP growth rates. Finally, the closest related study by Falvey & Gemmell (1996) also provides evidence in favor of the theory by Ngai & Pissarides (2007). Using a cross-section of 60 countries in 1980, the authors estimate a small (negative) price elasticity for services. Falvey & Gemmell (1996) also find a positive relationship between employment growth and the increase in relative prices for services if 2-digit industries are observed.[4]

The data for Germany show that total factor productivity growth rates between manufacturing and services only started to diverge in the mid-1990s. Before, TFP grew equally in both sectors. Furthermore, the data show that the employment in manufacturing steadily decreased, whereas it increased in services. All manufacturing industries at the 2-digit level lost employment shares. In contrast, almost all service sectors grew.

In my empirical analysis, I analyze the data set mentioned above by using a fixed-effects regression model. The dependent variable, the industry-specific employment growth, is explained by differences in lagged TFP growth rates. The results of my regression analysis support the theoretical predictions, i.e. they show that industries with increasing TFP experience decreasing employment growth, as the theory would imply. These results are confirmed by various robustness checks.

The rest of this chapter is organized as follows. In the next section, I describe the data in more detail and present some stylized facts on German sectoral TFP growth as well as on sectoral employment changes. Section 3 introduces my baseline model and presents the regression results. Section 4 presents various robustness checks to confirm my findings. In section 5, I summarize the main results and conclude.

[4]An earlier paper by Madison (1980) also confirms this correlation by using historical data for 16 OECD countries between 1870 and 1987.

3.2 Data and Stylized Facts

My empirical analysis builds on two data sets: First, the "Establishment History Panel" (in German: Betriebs-Historik-Panel (BHP)) provided by the Research Data Center of the German Federal Employment Office[5] and second, the "EU KLEMS Growth and Productivity Accounts".

The "Establishment History Panel" is a very detailed data set at the establishment-level that covers all establishments in West Germany between 1975 and 2010. Establishments from East Germany are included from 1991 onwards. It provides a detailed insight into German establishments over a long time period. For example, the BHP contains information on establishment characteristics[6], the general employment structure[7], the structure of employees by educational and vocational qualifications or by occupational status.[8] Since the TFP data from the EU KLEMS database are only available at the 2-digit industry-level, I aggregate the BHP according to the industry classification of each establishment to accurately match the two data sets. Hence, I have to assume that all employees of an establishment classified as a manufacturer are engaged in manufacturing activities.[9] The aggregated data are particularly favorable to test the underlying theory of Ngai &

[5]For my research, I have access to the data via on-site use at the Research Data Center of the German Federal Employment Agency at the Institute for Employment Research (in German: Institut für Arbeitsmarkt- und Berufsforschung (IAB)) and via remote data access.

[6]Such as the industry classification of each establishment.

[7]For example the total number of full-time employees.

[8]For further information about the BHP see Eberle (2011), Gruhl et al. (2012) and Hethey-Maier & Seth (2010).

[9]All control variables are derived in the same way.
The aggregated data only allow for the analysis of inter-sectoral changes which is in line with Ngai & Pissarides (2007). Intra-sectoral movements, i.e. the increasing share of employment in service occupations within manufacturing industries, cannot be observed here. For empirical analyses concerning intra-sectoral employment changes see Henze (2014) and Boddin & Henze (2015).

Pissarides (2007), because the authors postulate the crucial assumption of a sufficiently low (below one) elasticity of substitution across final goods. Therefore, final products have to be sufficiently different across industries. Among others, Baumol, Blackman & Wolff (1985) show that this assumption is ensured at the 2-digit level.

The EU KLEMS Growth and Productivity Accounts provide industry-level information on production, inputs, and productivity for 25 European countries, the U.S. and Japan. The measures are included in the data set from 1970 onwards.[10] For the empirical analysis, I use data on total factor productivity in Germany. The EU KLEMS Accounts provide data on total factor productivity for Germany for the 1975 to 2010 period at the 2-digit industry-level.[11] However, I have to eliminate the 1975 to 1979 period as well as the most recent year 2010 due to missing information on total factor productivities in various industries. Finally, I am able to analyze the effects of diverging TFP growth rates on the industry-specific employment growth for the 1980 to 2009 period.

Figure 3.1 shows total factor productivity growth in Germany between 1980 and 2009. Here, I calculate TFP growth as the average annual TFP growth in all manufacturing as well as in all service industries. As mentioned before, Ngai & Pissarides (2007) assume higher total factor productivity growth for the "progressive" manufacturing sector than for "stagnant" services. However, the data show that TFP grew equally in the manufacturing sector and services until the mid-1990s. Between 1980 and 1996, TFP grew approximately by 17% in both sectors. But, after 1996, TFP growth in the manufacturing sector significantly exceeded TFP

[10] The statistics are available at the website of the EU KLEMS project. For further information see http://www.euklems.net/ and O'Mahony & Timmer (2009) as well as Gouma & Timmer (2012).

[11] The data set covers 34 industries at the 2-digit ISIC Revision 4 classification. Since some industries of the EU KLEMS data set cover more than one of the 2-digit industries of the BHP, I have to assign the same TFP growth rates to these industries (see Tables 3.1 and 3.3).

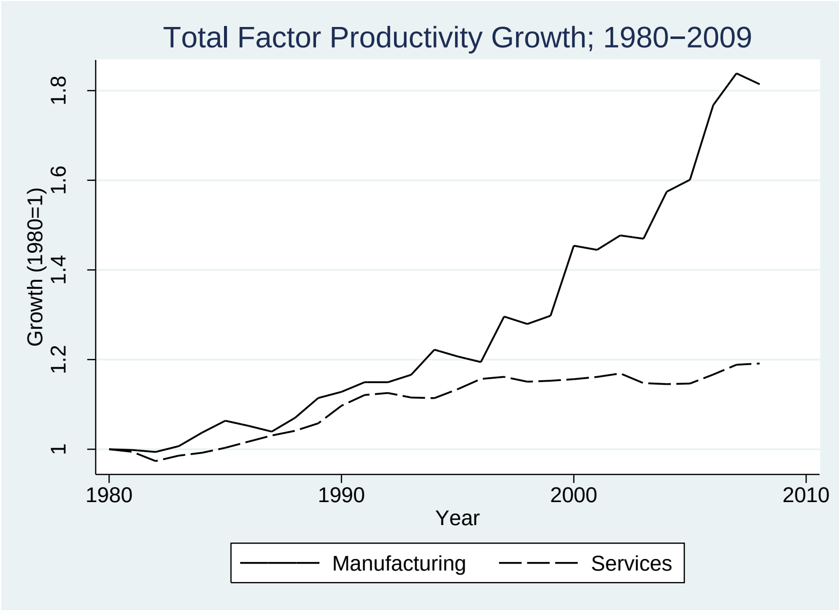

Figure 3.1:
Total Factor Productivity Growth in Manufacturing and Services
Source: EU KLEMS database, author's computation.

growth in the service sector. Between 1996 and 2009, TFP grew by more than 50% within manufacturing industries, whereas it remained constant within the service sector. For this period, the data confirm the assumption that TFP increased faster within manufacturing industries than within the service sector. Therefore, the manufacturing sector can be defined as the "progressive" sector while the service sector is "stagnant", which is in line with the theoretical assumptions.

Table 3.1 shows TFP growth within the manufacturing and the service sector in more detail. It presents the average annual TFP growth rate of each industry at the 2-digit level between 1980 and 2009. The data show that total factor productivity within manufacturing industries grew substantially faster than within service industries. Almost all manufacturing industries experienced positive TFP growth. The highest TFP growth rates occurred in the industries "coke and refined

Table 3.1: Average annual Growth of Total Factor Productivity by Industry; 1980-2009

Industry Code	Industry	TFP Growth
	Manufacturing	
10-14	Mining and quarrying	0.91%
15-16	Food products, beverages and tobacco	-0.56%
17-19	Textiles, wearing apparel, leather and related products	2.66%
20-22	Wood and paper products; printing and reproduction of recorded media	1.35%
23	Coke and refined petroleum products	5.51%
24	Chemicals and chemical products	3.52%
25-26	Rubber and plastics products, and other non-metallic mineral products	2.06%
27-28	Basic metals and fabricated metal products, except machinery & equipment	1.98%
29	Machinery and equipment n.e.c.	1.03%
30-33	Electrical and optical equipment	4.30%
34-35	Transport equipment	1.13%
36-37	Other manufacturing; repair and installation of machinery and equipment	1.85%
40-41	Electricity, gas and water supply	-0.10%
45	Construction	-0.09%
	Services	
50	Wholesale and retail trade and repair of motor vehicles and motorcycles	2.27%
51	Wholesale trade, except of motor vehicles and motorcycles	2.44%
52	Retail trade, except of motor vehicles and motorcycles	0.49%
55	Accommodation and food service activities	-0.90%
60-63	Transport and storage	2.11%
64	Postal and courier activities	0.37%
65-67	Financial and insurance activities	0.27%
70	Real estate activities	1.33%
72	IT and other information services	-0.02%
73-74	Professional, scientific, technical, administrative and support services	-1.78%
75	Public administration and defense; compulsory social security	0.98%
80	Education	-0.66%
85	Health and social work	0.73%
92	Arts, entertainment, recreation	-1.15%
93	Other service activities	0.64%

Source: EU KLEMS database, author's computation.

petroleum products" and "electrical and optical equipment". Here, the average annual TFP growth rates between 1980 and 2009 were 5.51% and 4.30%, respectively. By contrast, TFP growth within service industries was substantially lower. The data reveal that one third of all service industries was characterized by negative average annual TFP growth and only four industries generated an average growth of more than one percent. Only "wholesale industries" and "transport and storage" achieved average annual growth rates above 2%.

Table 3.2: Average annual Growth of Total Factor Productivity within Sub-Periods

	Overall	**1980-1989**	**1990-1999**	**2000-2009**
	(1)	(2)	(3)	(4)
Manufacturing	1.84%	0.78%	1.41%	3.34%
Services	0.63%	0.68%	0.90%	0.41%

Source: EU KLEMS database, author's computation.

Table 3.2 again presents aggregated average annual TFP growth rates in manufacturing and services but it distinguishes between different sub-periods. Column 1 shows the average annual TFP growth over the whole 1980 to 2009 period. Here, average TFP growth in manufacturing was approximately three times higher than in services. Columns 2 to 4 present the average TFP growth rates within each decade separately. Comparing the individual decades, column 2 highlights that TFP growth rates between manufacturing and services were more similar in the 1980s. Here, the average annual TFP growth rate was 0.78% in manufacturing and 0.68% in services. Afterwards, TFP grew much faster in the manufacturing sector than in services. In the 1990s, the average annual TFP growth in manufacturing was 50% higher than in services. In the last decade from 2000 to 2009, the average annual TFP growth rate in manufacturing exceeded the growth rate in services by more than a factor of eight. Hence, the findings of Table 3.2 confirm those of Figure 3.1. Especially for the last two decades the data show diverging TFP growth rates between the manufacturing sector and services.[12]

[12]In addition, Table B.1, Appendix B.1 provides evidence that the acceleration of diverging TFP

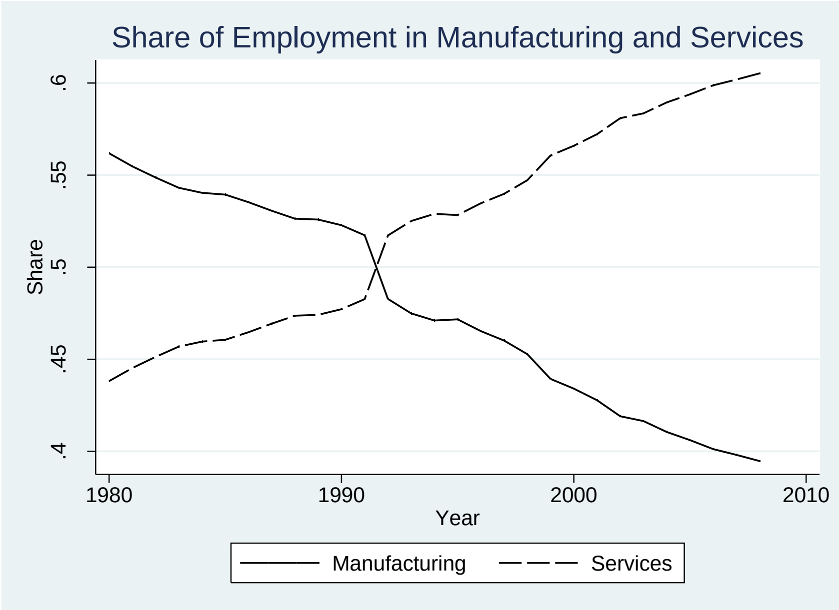

Figure 3.2:
Share of Employment in Manufacturing and Services; 1980-2009
Source: Establishment History Panel, author's computation.

Figure 3.2 shows the share of employees working either in establishments within the manufacturing sector or within services between 1980 and 2009. It supports the theoretical argument made by Ngai & Pissarides (2007) that employment shares shift to industries with a comparably low TFP growth rate, i.e. services. The share of employment in manufacturing and services is calculated on the basis of the 2-digit classification of economic activities included in the BHP. The data show that the share of employment in manufacturing declined steadily between 1980 and 2009, whereas the employment share in services increased. In 1980, 56% of all employees worked in establishments classified as manufacturers and 44% worked in the service sector. In 2009, 61% of all employees worked in the service sector

growth rates in the last two decades can also be observed if the 2-digit industries are considered separately.

and only 39% in manufacturing establishments.[13] Thus, employment shares more than reversed. Altogether, there is an increasing share of employees working in the service sector that, in addition, experienced low TFP growth.

Table 3.3 shows the shift of employment in more detail. It presents the industry-specific employment shares at the 2-digit level and compares industry sizes in 1980 and 2009. The data show that the employment share declined in each industry within the manufacturing sector between 1980 and 2009. The largest drop in employment shares occurred in the industries "textiles" (-82%), and "coke and refined petroleum products" (-63%). At the same time, these industries are among the sectors with the highest TFP growth rates. In contrast, employment in almost all service industries grew, in particular in "professional, scientific, technical & administrative services", where the employment share more than tripled and "arts, entertainment, recreation", where the employment share more than doubled in the 1980-2009 period. In accordance with the theoretical examination of Ngai & Pissarides (2007), these service industries are characterized by the lowest TFP growth rates of -1.78% and -1.15%, respectively.

In summary, the stylized facts support the hypothesis of technology-driven structural change. The data on sectoral TFP growth rates show that the manufacturing sector was characterized by higher sectoral TFP growth, especially from the mid-1990s onwards. The employment in manufacturing industries declined at the same time. In contrast, sectoral TFP growth rates were lower in services. Here, the employment shares increased.

[13]The break in the long-run trend in 1991 is caused by German reunification. Later, in the empirical analysis, I will control for any effects that are caused by this event.

Table 3.3: Industry-specific Shares of Employment

Industry Code	**Industry**	**Share of Employment**		Trend
		1980	**2009**	
	Manufacturing			
10-14	Mining and quarrying	1.55%	0.49%	↘
15-16	Food products, beverages and tobacco	3.16%	2.93%	↘
17-19	Textiles, wearing apparel, leather and related products	3.66%	0.66%	↘
20-22	Wood and paper products; printing & reproduction of rec. media	3.54%	2.65%	↘
23	Coke and refined petroleum products	0.29%	0.11%	↘
24	Chemicals and chemical products	2.94%	1.88%	↘
25-26	Rubber and plastics products, and other non-metallic products	3.71%	3.11%	↘
27-28	Basic metals and fabricated metal products	5.91%	4.26%	↘
29	Machinery and equipment n.e.c.	7.13%	5.61%	↘
30-33	Electrical and optical equipment	6.81%	5.49%	↘
34-35	Transport equipment	4.28%	3.85%	↘
36-37	Other manufacturing	1.64%	1.10%	↘
40-41	Electricity, gas and water supply	1.43%	1.28%	↘
45	Construction	9.84%	5.61%	↘
	$\sum$	55.89%	39.03%	
	Services			
50	Wholesale and retail trade of motor vehicles and motorcycles	1.79%	3.73%	↗
51	Wholesale trade, except of motor vehicles and motorcycles	5.63%	5.96%	↗
52	Retail trade, except of motor vehicles and motorcycles	5.75%	4.38%	↘
55	Accommodation and food service activities	1.19%	1.82%	↗
60-63	Transport and storage	4.55%	6.01%	↗
64	Postal and courier activities	0.69%	0.88%	↗
65-67	Financial and insurance activities	4.00%	3.75%	↘
70	Real estate activities	0.60%	0.82%	↗
72	IT and other information services	0.22%	1.81%	↗
73-74	Professional, scientific, technical & administrative services	3.93%	12.12%	↗
75	Public administration and defense; compulsory social security	7.02%	6.09%	↘
80	Education	1.43%	2.30%	↗
85	Health and social work	5.88%	8.51%	↗
92	Arts, entertainment, recreation	0.85%	1.91%	↗
93	Other service activities	0.39%	0.57%	↗
	$\sum$	43.92%	60.66%	

Source: Establishment History Panel, author's computation.

3.3 Baseline Model

3.3.1 Empirical Strategy

To check if the theoretical predictions can be confirmed by the data, I use a fixed-effects regression model to exploit the time series dimension of the panel data. To identify the employment effects of diverging TFP growth rates, I consider two important features of the transmission. First, employment movements due to diverging growth rates of total factor productivity occur with a lag because establishments observe TFP growth ex post and then adapt employment. Second, employment effects do not arise after differences in TFP growth rates in single years. Establishments do not adjust the employment if TFP growth rates deviate once, but only do so if the establishments identify a process of diverging TFP growth rates. To account for these characteristics, my baseline model estimates the employment effects of average past TFP growth rates. The estimated fixed-effects equation looks as follows:

$$\Delta E_{it} = \alpha + \beta_1 \Delta \widehat{TFP}_{it-k} + \delta' C_{it} + \lambda_i + \gamma_t + \epsilon_{it}, \qquad \text{with } k = 2, 3, 4 \qquad (3.1)$$

Equation (3.1) calculates the sectoral change of employment due to the average TFP growth rate in the previous two to four years. The dependent variable, ΔE_{it}, measures the annual employment growth in each industry i in year t. The first explanatory variable, $\Delta \widehat{TFP}_{it-k}$ is the average past TFP growth rate in industry i in the previous two to four years (k=2, 3, 4).[14] C_{it} is a vector of control variables at the 2-digit industry-level accounting for further influences that may have

[14]For example, the employment growth rate in the year 2000 is explained by the average TFP growth rate between 1998 and 1999 (for k=2) or between 1996 and 1999 (for k=4).

an effect on employment growth. I include the median of wages, the average establishment size within an industry, expenditures on R&D and the initial size of each industry[15] as control variables. I also add the overall workforce growth as a control variable as well as a dummy variable controlling for German reunification in 1991.[16] I estimate equation (3.1) with both industry-specific effects, λ_i, to capture unobserved sector-specific variation and year-specific effects, γ_t, to control for unobserved, time varying effects as well as business cycle effects. ϵ_{it} is the error term. Furthermore, to control for time-variant heterogeneity between the industries, I estimate equation (3.1) with an interaction effect including industry fixed-effects and a dummy variable that divides the sample into two sub-periods. In general, interaction effects control for time-variant industry fixed-effects by combining year and industry fixed-effects ($\gamma_t \times \lambda_i$). Here, I am not able to include an interaction term with both industry and year fixed-effects, because the number of variables would exceed the number of observations. Therefore, I divide the sample into two sub-periods according to the TFP growth between manufacturing and services. Table 3.2 shows that TFP growth rates between manufacturing and services mainly diverged after 2000. Hence, to capture the different characteristics between these two sub-periods, I create a dummy variable that is equal to zero before 2000 and equal to one afterwards. Then I include an interaction term between the dummy variable and the industry fixed-effects into the estimations that cover the whole time period. Hence, I am able to account for time-variant industry fixed-effects between the two sub-periods.[17] I estimate equation (3.1) over the whole time period

[15] The initial size of an industry is included both in terms of sectoral GDP as well as total employment.

[16] The dummy variable distinguishes between the period before and after German reunification, i.e. it is equal to zero before 1991 and equal to one afterwards.

[17] Robustness checks show that the results are not sensitive to changes in the chosen threshold between the two sub-periods.

and within sub-periods from 1980-1989, 1990-1999, and 2000-2009.

I include up to four lags in the regressions for two reasons: First, it is hardly possible to include more lags in the estimated regressions, especially when I analyze sub-periods. Each additional lag reduces the number of observations by roughly 50. Since the number of observations within sub-periods drops rapidly, no more lags can be included.[18] Second and most importantly, there is an extensive literature on the employment adjustment behavior of firms. For example, Jung (2014) provides empirical evidence for Germany that establishments adjust their employment, i.e. increase or decrease the number of employees, in the median within 1.8 years.[19] Because Jung (2014) uses a very similar data set (the IAB Establishment Panel)[20], it is appropriate to adopt his findings for my empirical analysis. Hence, it is sufficient to use up to four lags to capture the vast majority of employment adjustments due to differences in TFP growth rates.[21]

To confirm the theoretical predictions, I expect a negative β_1 coefficient. This would imply that employment shares decrease in sectors with higher TFP growth rates.

Finally, I check both employment and TFP growth on the stationarity with Fishers unit root test for panel data by applying the Augmented-Dickey-Fuller

[18] Later, in section 3.4.1, I additionally estimate another specification of the baseline model with up to five lags.
Furthermore, I include up to ten lags when the entire time period is analyzed since there is a sufficient number of observations for more lags in this case. This is done both for equation (3.1) and equation (3.2) in the following section. The results highlight that there is no long-term employment effect that was not captured before.

[19] The establishments adjust the employment due to cost changes, business cycles, etc.

[20] The IAB Establishment Panel is a representative annual survey of all German establishments. Jung (2014) investigates the period 1996 to 2010.

[21] Jung (2014) additionally points out that his results are in line with results from earlier studies for Germany. The bulk of empirical studies, such as Kölling (1998) and Yaman (2011) find out that employment adjustment in Germany occurs in the median within 0.7 to 7.7 years. The wide range is caused, among others, by different data sets, empirical methods and observation periods.

test. The results show that the null hypothesis that the series are non-stationary is clearly rejected, i.e. the variables are stationary (I(0)).

3.3.2 Results

Table 3.4: Lagged Employment Effects of average TFP Growth Rates (1980-2009)

Variables	Fixed-Effects Regression (1)	(2)	(3)
$\Delta\widehat{\text{TFP}}_{t-2}$	-0.0293*		
	(0.0164)		
$\Delta\widehat{\text{TFP}}_{t-3}$		-0.0533	
		(0.0409)	
$\Delta\widehat{\text{TFP}}_{t-4}$			-0.0467
			(0.0982)
Other Controls	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes
R^2	0.5132	0.5179	0.5245
Prob > F	0.0000	0.0000	0.0000
No. of Obs.	1304	1247	1190

Dep. Variable: Employment growth in year t: ΔE_{it}.

Notes: Clustered standard errors (by industry) in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 3.4 presents the results of the estimation. I first estimate equation (3.1) over the whole time period from 1980 to 2009. The first column shows the employment effect of the average TFP growth rate in the previous two years. The estimated coefficient β_1 is negative and significant, as the theory would suggest. The coefficient implies that the employment growth decreases by 0.03 percentage points if the average TFP growth rate in the two previous years increases by 1 percentage point. The result shows that establishments adjust their employment within two years, which confirms Jung (2014). Columns 2 and 3 illustrate that the estimated coefficients are still negative if the employment effects of the average TFP growth rates in the previous three or four years are estimated. Now, however, they are insignificant.[22]

Table 3.5: Lagged Employment Effects of average TFP Growth Rates (1980-1989)

Variables	Fixed-Effects Regression (1)	(2)	(3)
$\Delta\widehat{\text{TFP}}_{t-2}$	0.0706		
	(0.0576)		
$\Delta\widehat{\text{TFP}}_{t-3}$		-0.0008	
		(0.0722)	
$\Delta\widehat{\text{TFP}}_{t-4}$			0.1271
			(0.1439)
Other Controls	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes
R^2	0.4298	0.4366	0.3003
Prob > F	0.0000	0.0000	0.0000
No. of Obs.	413	364	315

Dep. Variable: Employment growth in year t: ΔE_{it}.

Notes: Clustered standard errors (by industry) in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table 3.5 shows the findings for the first sub-period between 1980 and 1989. As Figure 3.1 highlights, TFP growth rates started to diverge in the mid-1990s only.

[22]Since the entire time period provides sufficient observations for more lags, I also estimate equation (3.1) with $k=$ 5, ..., 10, i.e. the employment effects of the average TFP growth rate in the last five to ten years. The results remain all insignificant and mostly negative. Hence, there is no employment impact of TFP growth rates that is a more long-term effect. All non-reported results can be obtained upon request.

Thus, no significant employment effects are expected to be induced within this decade. Consequently, the coefficient β_1 is insignificant in each column, i.e. it has no explanatory power. In addition, Table 3.5 shows that the number of observations decreases rapidly if only one decade is observed. Therefore, it becomes even more difficult to determine significant employment effects. Because of the low number of observations, it is not possible to check whether the calculations become significant when the number of lags is increased. Nevertheless, these findings support the theoretical predictions of Ngai & Pissarides (2007), too. The authors argue that TFP growth rates induce employment shifts if they diverge between manufacturing industries and services. The estimations for the first sub-period show that there is no significant relationship between TFP growth and employment growth if TFP growth rates do not diverge.

Table 3.6 displays the results for the decade from 1990 to 1999. Here, the first column provides a significant negative coefficient, which is comparable to the findings of Table 3.4. If the average TFP growth in the last two years increases by 1 percentage point, employment growth decreases by 0.05 percentage points. This finding indicates that employment shares shift to industries with lower TFP growth and thus supports the theoretical predictions. In contrast, columns 2 and 3 again show insignificant coefficients.

Table 3.7 presents the estimations for the last decade between 2000 and 2009. Since the stylized facts illustrate that sectoral TFP growth rates between manufacturing industries and services diverged especially in this period, the theoretical predictions may most appropriately be tested here. The coefficient in column 2 shows that the relationship between growth rates of TFP and employment is now negative and significant if three lags are used. In addition, the estimated effect is considerably larger than in the previous periods. Employment growth declines

Table 3.6: Lagged Employment Effects of average TFP Growth Rates (1990-1999)

Variables	Fixed-Effects Regression (1)	(2)	(3)
$\Delta\widehat{\text{TFP}}_{t-2}$	-0.0469*		
	(0.0267)		
$\Delta\widehat{\text{TFP}}_{t-3}$		-0.0795	
		(0.1069)	
$\Delta\widehat{\text{TFP}}_{t-4}$			0.0429
			(0.2294)
Other Controls	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes
R^2	0.5258	0.1919	0.2485
Prob > F	0.0000	0.0000	0.0000
No. of Obs.	438	385	332

Dep. Variable: Employment growth in year t: ΔE_{it}.

Notes: Clustered standard errors (by industry) in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

by 0.08 percentage points if the average TFP growth in the previous three years increases by 1 percentage point.

In summary, my findings support the theoretical predictions of Ngai & Pissarides (2007) that diverging TFP growth rates between manufacturing and services lead to employment shifts toward services. First, if the analysis focuses on the whole 1980 to 2009 period and uses two lags, the employment effect is negative and significant. For the 1980s, there is no employment effect since TFP growth rates do not diverge until the mid-1990s. The results for the 1990s and especially for the last decade between 2000 and 2009 also provide evidence of a negative relationship between TFP growth and employment growth.

Table 3.7: Lagged Employment Effects of average TFP Growth Rates (2000-2009)

Variables	Fixed-Effects Regression		
	(1)	(2)	(3)
$\Delta\widehat{\text{TFP}}_{t-2}$	-0.0206		
	(0.0129)		
$\Delta\widehat{\text{TFP}}_{t-3}$		-0.0842***	
		(0.0259)	
$\Delta\widehat{\text{TFP}}_{t-4}$			-0.0637
			(0.0473)
Other Controls	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes
R^2	0.4276	0.4704	0.4630
Prob > F	0.0000	0.0000	0.0000
No. of Obs.	357	306	255

Dep. Variable: Employment growth in year t: ΔE_{it}.

Notes: Clustered standard errors (by industry) in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

3.4 Robustness Checks

3.4.1 Employment Effects of Annual TFP Growth Rates

In equation (3.1), I assume that employment shifts do not occur after differences in TFP growth rates in single years. To check whether this assumption is appropriate, I estimate the employment effects of annual TFP growth rates with various lags. The estimated fixed-effects equation looks as follows:

$$\Delta E_{it} = \alpha + \beta_1 \Delta TFP_{it-k} + \delta' C_{it} + \lambda_i + \gamma_t + \epsilon_{it}, \qquad \text{with } k = 0, 1, 2, ..., 5 \qquad (3.2)$$

Equation (3.2) is constructed in the same way as equation (3.1). It differs, however, in the measurement of total factor productivity growth. Here, I include annual TFP growth rates with various time lags to explain employment shifts. Accordingly, my first explanatory variable, ΔTFP_{it-k} is the annual growth rate of total factor productivity in industry i in year $t-k$. ΔTFP_{it-k} is included in equation (3.2) without a time lag, k=0, as well as with lags from one to five years (k=1, 2, ..., 5). The remaining variables of equation (3.2) equal those of equation (3.1).

The estimation results for equation (3.2) are reported in Appendix B.2 and B.3, Tables B.2 to B.5. Table B.2 presents the estimated coefficients of equation (3.2) for the whole time period from 1980 to 2009 and confirms my findings from before. The first column shows the estimated employment effect of annual TFP growth if no lag is used. The coefficient is negative, but insignificant. This is to be expected since differences in TFP growth rates do not immediately lead to employment changes. Columns 2 to 6 present the results if TFP growth rates with one to five lags are included in the model, i.e. if the employment changes due to TFP growth rates one to five years ago. As before, the coefficient is negative and significant if two lags are used. Next, I estimate each decade separately. The results are reported in Tables B.3 to B.5, Appendix B.3. Altogether, the results vary a lot with the number of chosen lags and thus have to be interpreted with caution. In the 1980s, the estimated coefficient shows a positive relationship between TFP growth and employment growth if one lag is used. This finding contradicts the theory. However, the estimations for the last two decades from 1990 to 1999 and 2000 to 2009 again provide some evidence in line with the theoretical predictions. Table B.4 presents the results for the 1990s. Now, the estimations confirm the theory by Ngai & Pissarides (2007) if two or five lags are used. In contrast, however, the coefficient is positive and significant if four lags are used. Table B.5 shows the results for the latest decade between 2000 and 2009. The findings are similar to the estimation for the previous decade. The data confirm the theory if three or five lags are used.

In summary, the estimations of equation (3.2) show that the employment effects of annual TFP growth rates vary more than the results of equation (3.1). Hence, they have to be interpreted with caution. However, the results are broadly in line with the findings before. The estimations for the whole sample period, the 1990s and 2000s provide evidence of a negative relationship, which is theoretically predicted. TFP growth affects employment growth with a lag of at least two years. Thus, it seems to be more relevant to assume lagged employment shifts than to consider rather average than annual TFP past growth rates.

3.4.2 Average Employment Effects of Past TFP Growth Rates

Since establishments may not adapt the employment within a single year if TFP growth rates diverge, I additionally estimate the impact of the average TFP growth rate in past periods on the average employment growth in subsequent periods:

$$\widehat{\Delta E_{it+k}} = \alpha + \beta_1 \Delta\widehat{\mathrm{TFP}_{it-l}} + \delta' C_{it} + \lambda_i + \gamma_t + \epsilon_{it}, \qquad \text{with } k, l = 2, 3 \tag{3.3}$$

Equation (3.3) is again constructed in the same way as equation (3.1). The only difference is the definition of employment growth. Here, I use the average employment growth rate in subsequent years.[23]

Table 3.8 displays the results for equation (3.3). Here, I calculate the effects

[23]For example, in the year 2000, I estimate the effect of the average TFP growth in the years 1998 and 1999 on the average employment growth in 2001 and 2002 (if k=l=2).

Table 3.8: Average Employment Effects of past TFP Growth Rates

	Fixed-Effects Regression							
Variables	Overall		1980-1989		1990-1999		2000-2009	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
k=l=**2**								
$\Delta\widehat{\text{TFP}}_{t-l}$	-0.0249*		-0.1085		0.0285		-0.0037	
	(0.0137)		(0.0736)		(0.0728)		(0.0088)	
k=l=**3**								
$\Delta\widehat{\text{TFP}}_{t-l}$		-0.0217		0.0399		0.0407		-0.0278***
		(0.0349)		(0.0515)		(0.1294)		(0.0039)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.4871	0.5419	0.4836	0.4911	0.4672	0.5086	0.6613	0.7309
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
No. of Obs.	1190	1079	270	177	332	232	255	153

Dep. Variable: Average employment growth in subsequent years: $\widehat{\Delta E_{it+k}}$.

Notes: Clustered standard errors (by industry) in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

of average TFP growth rates in the previous two or three years on the average employment growth in the following two or three years, i.e. k=l=2, 3. As before, I estimate equation (3.3) for the whole time period from 1980 to 2009 as well as within three sub-periods. Columns 1 and 2 present the regression results for the entire time period. The coefficient is negative and significant if two lags are used, which is in line with the previous results and supports the theoretical predictions. Columns 3 to 6 show the estimated coefficients for the first two sub-periods from 1980 to 1989 as well as from 1990 to 1999. Like in previous specifications, the β_1 coefficients remain insignificant. The last two columns, 7 and 8, provide the results for the last sub-period from 2000 to 2009. The findings confirm the results from former specifications. Despite the low number of observations, the estimated coefficient is negative and significant at the 1%-level if three lags are used.

3.4.3 Dynamic Panel Models

In addition, I estimate equation (3.1) with the lagged dependent variable on the right-hand side of the equation. Thus, I apply a dynamic fixed-effects (OLS) estimation that controls for potential serial correlation (Wooldridge (2002)). By adding the lagged dependent variable, I test if the current employment growth is unrelated to the employment growth in the previous period. If this is the case, the results for the static panel data model from before retain their validity. Still, there might be an additional bias due to the potential endogeneity of some of the independent variables used. In particular, wages, the average establishment size and the industry-specific GDP are likely to be endogenous with respect to the employment growth. To address this concern, I additionally apply the system GMM estimator.

The estimated equation for the dynamic fixed-effects model is given by:

$$\Delta E_{it} = \alpha + \rho \Delta E_{it-1} + \beta_2 \Delta \widehat{TFP}_{it-k} + \delta' C_{it} + \lambda_i + \gamma_t + \epsilon_{it}, \qquad \text{with } k = 2, 3, 4. \quad (3.4)$$

Equation (3.4) is constructed in the same way as equation (3.1). But here, I add the lagged dependent variable of the employment growth, ΔE_{it-1}, to apply a dynamic fixed-effects regression model. Table B.6, Appendix B.4 provides the results of the estimation.[24] As before, I estimate the employment effects of the average past TFP growth rate with two to four lags. Columns 1 to 3 present the regression results for

[24]Table B.6 shows the regression results for the entire time period as well as for the most recent sub-period from 2000 to 2009. The estimations of all other sub-periods are in line with the results from before.

the entire time period. The coefficient of TFP growth is negative and significant if two lags are used, which confirms my previous results. Moreover, the coefficient of the lagged dependent variable, ρ, is insignificant, i.e. the current employment growth is unrelated to the lagged employment growth. Hence, I can conclude that serial correlation is not a problem in my earlier regression analysis. Columns 4 to 6 of Table B.6 present the results for the most recent sub-period from 2000 to 2009. The results also confirm the findings from before. The employment effect of TFP is negative and significant with three or four lags. The lagged dependent variable is insignificant if I use one or four lags. In the case of three lags, ρ becomes significant at the 10%-level which provides some evidence of serial correlation. Since this is the only specification where the effect of the lagged dependent variable becomes significant, I conclude that serial correlation is not a problem in my empirical analysis.

Finally, I re-estimate the dynamic panel model by applying the system GMM regression model developed by Arellano & Bover (1995) and by Blundell & Bond (1998). I use the system GMM estimator instead of the difference GMM estimator by Arellano & Bond (1991) because the latter suffers from a large finite sample bias in dynamic panel data models with rather persistent time series. The difference GMM estimator uses first differences to eliminate fixed-effects and implements lagged levels of the endogenous variables as instruments. Hence, this approach generates rather weak instruments because the correlation between time persistent endogenous variables, i.e. the growth rates, and the instruments, i.e. lagged levels (which do change), is rather weak. The system GMM estimator tries to solve this problem by considering lagged levels as well as lagged differences as instruments. It is a system of two equations: The first equation equals the differenced equation the difference GMM approach uses. The second equation uses the first differences of the variables as instruments for the levels. This reduces the weak instrument problem of the difference GMM estimator.[25] If the instruments are tested to be valid, they account for endogeneity caused by omitted variables as well as reverse causality.[26] The system GMM estimator assumes all independent variables to be endogenous if they are not explicitly defined to be exogenous. Here, I treat the past average TFP growth, the median wage, the average establishment size, the industry-specific GDP and the initial size of each industry as endogenous with respect to employment growth. In contrast, to reduce the number of endogenous variables and therefore the number of instruments, I define the overall workforce growth and the effects of German reunification as exogenous. A major concern with the system GMM estimator is the proliferation of instruments.[27] The number of instruments grows rapidly with T, i.e. the time period that is analyzed, and thus can outgrow the number of cross-section observations (here: the number of industries). This may overfit the variables that are treated as endogenous and therefore would weaken the Hansen J-test of the joint validity of instruments. Therefore, to further minimize instrument inflation, I use the "collapse" option in STATA in all regressions.[28]

Table 3.9 presents the results of the system GMM estimation. Here, I present the estimated coefficients for the whole time period as well as for the most recent decade from 2000 to 2009.[29] If the whole time period is estimated, the β_1 coefficient of TFP growth is negative, but now, it is insignificant. Columns 4 to 6 present

[25] For a more detailed discussion see Blundell & Bond (1998).
[26] For a more detailed description of the system GMM estimator see Roodman (2009a).
[27] For further information see Roodman (2009b).
[28] The "collapse" option specifies that the system GMM estimator creates one instrument for each variable and lag rather than one for each year, variable and lag. Thus, in relatively small samples covering a long time period, the "collapse" option helps to avoid the bias that may occur if the number of instruments exceeds the number of cross-section observations. For a more detailed description see Roodman (2009b).
[29] The results for the remaining sub-periods are also in line with the fixed-effects regression model.

Table 3.9: System GMM Estimation

Variables	Two-Step System GMM Regression					
		Overall			2000-2009	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\widehat{\text{TFP}_{t-2}}$	-0.0953			0.0096		
	(0.1185)			(0.0598)		
$\Delta\widehat{\text{TFP}_{t-3}}$		-0.1969			-0.1843***	
		(0.2087)			(0.0740)	
$\Delta\widehat{\text{TFP}_{t-4}}$			-0.1305			-0.0315
			(0.2163)			(0.0827)
No. of Obs.	1304	1247	1190	357	306	255
No. of Industries	51	51	51	51	51	51
No. of Instruments	36	35	34	20	19	18
AR(1) p-value	0.01	0.01	0.02	0.01	0.01	0.03
AR(2) p-value	0.59	0.53	0.81	0.11	0.17	0.39
Hansen J-test, p-value	0.49	0.32	0.62	0.39	0.41	0.21

Dep. Variable: Employment growth in year t: ΔE_{it}.

Reported p-values for A(1) and A(2) refer to the Arellano-Bond test for first and second order autocorrelation in the first differences equations.

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

the results for the most recent period from 2000 to 2009. Here, the coefficient is negative and highly significant if the employment effect of the average TFP growth in the last three years is estimated. In addition, the effect is substantially larger than in the fixed-effects regression model. An increase in the past average TFP growth rate by 1 percentage point decreases the employment growth by 0.18 percentage points, which supports the theoretical predictions by Ngai & Pissarides (2007). Thus, accounting for endogeneity broadly confirms the results from the fixed-effects regressions. However, the size of the estimated coefficients is considerably larger, i.e. the effects from before may be underestimated due to endogeneity.

The test statistics of the system GMM model (Hansen's J-test) show that the instruments I use are valid. Furthermore, the system GMM estimator requires high first-order but no second-order autocorrelation. The test statistics for first-order and second-order autocorrelation show that all requirements for autocorrelation of the system GMM model are fulfilled. All p-values confirm that there is high first-order autocorrelation, but the test statistics for AR (2) are insignificant, i.e. the second differences of residuals are not serially correlated.

3.5 Conclusion

The purpose of the current chapter is to examine theoretical models that explain structural change as a technology-driven process. A very prominent paper by Ngai & Pissarides (2007) explains the shift of employment shares from manufacturing industries to services by diverging in sectoral TFP growth rates. The authors argue that employment shares shift to industries with low TFP growth rates, i.e. services, if the elasticity of substitution across final goods is below one. Therefore, this chapter analyzes the employment effects of diverging sectoral TFP growth rates to test the theoretical predictions of Ngai & Pissarides (2007). In order to calculate the employment effects, I use the "Establishment History Panel" at the 2-digit industry-level together with industry-level data on total factor productivity obtained from the EU KLEMS database. Altogether, I am able to analyze 30 years between 1980 and 2009. The data highlight that TFP growth rates between manufacturing industries and services essentially started to diverge in the mid-1990s. Furthermore, the data depict that employment in manufacturing decreased continuously, whereas employment in services grew. The results of my estimations provide evidence in favor of the theoretical predictions. The employment effects of diverging TFP growth rates are negative and significant, especially if average TFP growth rates over two or three periods are included in the calculations. Hence, the estimated coefficients indicate that industries with increasing TFP growth face a decreasing employment growth. Solely the results for the 1980s provide insignificant coefficients. However, this also confirms the theoretical predictions, because Ngai & Pissarides (2007) argue that TFP growth rates only induce employment shifts if total factor productivity diverges between sectors. Hence, it is in accordance with the theory if non-diverging TFP growth rates in the 1980s do not affect employment growth. In addition, multiple robustness checks confirm my results and show that the estimated coefficients do not suffer from serial correlation and endogeneity.

Chapter 4

International Trade and the Occupational Mix in Manufacturing: Evidence from German Micro Data

Summary:[1]

We use the Establishment History Panel from 1975 to 2010 provided by the German Federal Employment Office to examine the impact of international trade on the occupational structure of the German manufacturing sector. To capture trade, we match the Establishment History Panel with UN Comtrade trade data. To do so, we develop an improved matching approach that takes the input and output structure of the German manufacturing sector into account. We identify three different trade channels: import intensity, import competition, and export intensity. Using a fixed-effects Poisson regression model, we find diverse occupational effects from trade at the industry-level, while establishment-level estimations show only few significant effects.

[1]This chapter is based on a paper that is joint work with Dominik Boddin.
We are grateful to Johannes Bröcker for support and helpful and valuable suggestions, especially on the matching approach and the empirical strategy.

4.1 Introduction

The impact of international trade on employment has been a widely discussed topic in the economic literature, political debates, and the popular press. Surprisingly enough, rather little empirical research has been conducted to shed light on how trade openness impacts the employment in different occupations, despite the fact that the employment structure in industrialized nations have undergone a substantial change during the past decades. In Germany, for instance, the share of employment in service occupations within manufacturing experienced a steep increase of about 29% since 1975. During the same time period the inflation-adjusted trade volume increased approximately by a factor of five. While much has been written on structural change as an inter-sectoral process[2], we, by contrast, focus on intra-sectoral employment changes within the German manufacturing sector.

The purpose of the current chapter therefore is to examine the role of international trade as one potential driving force behind the change of the occupational mix within establishments in the manufacturing sector. We identify three potential channels through which establishments are affected by trade and thus adapt their employment: first, the import of inputs and intermediate goods used in the production process ("import intensity"), second, the import of goods that compete with final goods of domestic establishments ("import competition"), third the export of goods that are produced by domestic establishments ("export intensity").

To our knowledge, this chapter is among few papers that examine the effect of international trade on the employment of very disaggregated occupational groups and the only one that simultaneously considers three trade channels. In contrast to

[2] See for example Kuznets (1966), Jorgenson & Timmer (2011) and Alvares-Cuadrado & Long (2011).

other studies that only distinguish between highly aggregated employment groups, e.g. high-skilled and low-skilled employees or production and non-production workers, we are able to investigate much more precisely, which employees benefit or suffer from the increasing exposure to international trade. This might be of great relevance for policy implications - e.g. in the field of labor market policies or educational policies - because our results allow for more targeted actions compared to studies that analyze more aggregated employment groups. In our empirical analysis, we focus on Germany, which is among the most active countries in international trade. We use the "Establishment History Panel" (in German: Betriebs-Historik-Panel (BHP)), a very detailed micro data set provided by the German Federal Employment Office covering the years from 1975 to 2010, a time span that exceeds all other studies in the field. The data set allows us to have a unique insight into the occupational mix of all German establishments in the manufacturing sector over a 36-year period and to observe changes in the employment composition in detail. Beyond the estimation at the industry-level, we are able to estimate the impact of international trade at the establishment-level and control for establishment fixed-effects, which improves the estimation quality in comparison to various other studies that only use industry-level data.[3]

Applying a new, improved matching method, we match the BHP at the industry-level with trade data provided by the UN Comtrade database at the commodity-level, as the core data set does not contain information on activities in international trade. We then apply a fixed-effects Poisson model for the estimations at both the industry- and the establishment-level. The former level of aggregation allows us to estimate our empirical model with data that are all on the same level, whereas the latter specification is able to control for the substantial establishment

[3]See for example Feenstra & Hanson (1996).

heterogeneity.

The results at the industry-level indicate that import intensity and import competition decrease employment and export intensity increases employment. It is the employment in unskilled service occupations that mainly faces job losses from an increase in imports of intermediates. Employees in lower skilled occupations, especially in services and administration, suffer most from an increase in competition with foreign firms, whereas the employment of these occupations rises the most from an increase in exports. Among the production occupations the employment of technicians reacts the most to changes in trade. Our results at the establishment-level only show few significant trade effects on the occupational mix.

This chapter is related to four strands of literature. First, there is a large body of literature that explores employment effects of changes in the import intensity. This channel is commonly named "offshoring" or "trade in tasks". According to Grossman & Rossi- Hansberg (2008), firms are able to unbundle the production process into a continuum of tasks. Decreasing costs of offshoring are associated with an increasing number of tasks that can be outsourced to low-wage countries. Offshorable tasks are generally considered to be routine tasks, whereas non-routine tasks remain in the domestic firm (Baldwin & Robert-Nicoud (2007)). As production tasks are more likely to be the ones that are of a routine nature and do not require physical proximity, outsourcing is supposed to decrease the employment of (low-skilled) production occupations. While these papers can give theoretical explanations for changes in the occupational mix, few empirical studies distinguish between different occupational groups (e.g. Hogrefe (2013)). Most papers only distinguish between aggregated employment groups, for example between routine vs. non-routine tasks (e.g. Becker, Ekholm & Muendler (2013)) or between different skill levels (e.g Hijzen et al. (2005)). Using disaggregated plant data for Germany, Becker, Ekholm & Muendler (2013) estimate that offshoring leads to a significant shift toward non-routine tasks and high-skilled workers, in particular if offshoring to low-income countries is considered. Hijzen et al. (2005) and Hogrefe (2013) confirm these findings. However, these studies focus exclusively on the employment effects of offshoring. In contrast, we analyze the employment effects of three trade channels on very disaggregated occupational groups.

Second, there is a growing literature on the employment effect of import competition. Increasing import competition is supposed to reduce employment, especially in production occupations, since imported final goods substitute the goods of domestic suppliers. In contrast to most papers in the field[4], we analyze the employment effects of rising import competition on a much more disaggregated level. An exception is the paper by Biscourp & Kramarz (2007), who regard the effect of all three trade channels on the employment at the firm-level. Their focus, however, is the skill structure rather than the occupational mix of firms. The authors confirm job losses due to increasing imports of final goods. Furthermore, they observe that especially large firms mostly reduce the employment in (low-skilled) production occupations.

Third, there is a comparatively small literature on the role of exporting as a determinant of the occupational mix. Preexisting literature in this field[5], however,

[4]Among the papers are Autor, Dorn & Hanson (2013), who analyze the regional employment effects of import competition from China in the United States. They conclude that regions competing with Chinese imports to a high degree have suffered from rising unemployment. This result is confirmed by Tomiura (2003) for Japan.

[5]Among the papers are Bernard & Jensen (1997), Mauron, Thesmar & Koenig (2002), and Biscourp & Kramarz (2007). Biscourp & Kramarz (2007) find that for French firms exports have a negative impact on the unskilled share in manufacturing employment, but a positive impact on the share of production jobs because increasing exports require a rise in the production of domestic firms. Davidson et al. (2013) distinguish between different occupational groups. They find that exporters, especially multinational exporters, have an occupational distribution toward the more skilled.

mainly focuses on total employment effects or, at most, distinguishes between a limited number of groups of employees such as production and non-production or high-skilled and low-skilled.

Fourth, this chapter contributes to the growing literature that discusses the link between international trade and firm organization. However, the emphasis of this literature is mainly on firm organization from a management perspective rather than on the organization formed by different occupational groups.[6]

In contrast to the standard approach in the literature, we do not match the trade data by using a correspondence table between the commodity classification of the trade data and the industry classification of the BHP. Instead, we use the "Statistic concerning Materials and Commodities received by the Industries" (in German: Material- und Wareneingangserhebung im Verarbeitenden Gewerbe, hereafter called "Input Statistic") and the "Survey of Production" (in German: Produktionserhebung im Bereich Verarbeitendes Gewerbe), both provided by the German Federal Statistical Office. The first allows us to allocate the imported intermediate goods according to the input structure of the German manufacturing sector to obtain a measure of "import intensity". The latter allows us, on the one hand, to construct a measure of "import competition" by allocating imports according to the output structure of the German manufacturing sector. On the other hand, we construct a measure for "export intensity" by allocating export flows according to the output structure. We believe that the approach described in the current chapter improves the accuracy of allocation compared to previous studies.

The rest of the chapter is organized as follows. In the next two sections, we

[6]For instance, Caliendo & Rossi-Hansberg (2012) develop a model that shows an increase in management layers as a result of exporting. Marin et al. (2014) implement trade in tasks into a theory of the firm organization à la Marin & Verdier (2012). They show both theoretically and empirically that offshoring leads to a more decentralized management.

present the data and some stylized facts about changes in the employment in Germany. Section 4 discusses the matching approach, the estimation strategy and the empirical results. The final section concludes and summarizes.

4.2 Data

We base our calculations on the "Establishment History Panel" (in German: Betriebs-Historik-Panel (BHP)) provided by the Research Data Center of the German Federal Employment Office.[7] The "Establishment History Panel" is a detailed micro-level data set that covers all establishments in Germany from 1975 to 2010 (for the 1975-1990 period, it includes only establishments in West Germany) with at least one employee subject to social insurance contributions before June 30th of the respective year.[8] For our calculations, we are able to use a 50% random sample of the entire data set. The BHP builds on the "Employee History" (in German: Beschäftigten-Historik (BeH)) of the IAB. It cumulates the individual data of the BeH to the establishment-level and assigns individual establishment numbers ("artificial establishment number"). Thus, it is possible to identify the establishments in subsequent years and create a panel data set for the entire 1975-2010 period. Because the "Establishment History Panel" is based on the "Employee-History", it provides very detailed information on the general employment structure of each establishment, e.g. the total number of full-time employees, the composition of employment regarding employees' educational and vocational qualifications and

[7]For our research, we have access to the data via on-site use at the Research Data Center of the German Federal Employment Agency at the Institute for Employment Research (in German: Institut für Arbeitsmarkt- und Berufsforschung (IAB)), at various external FDZ locations and via remote data access.

[8]Since 1999, there are also all establishments with at least one part-time employee included in the panel.

the occupational status according to the Blossfeld occupational groups (Blossfeld (1987) and Appendix C.1). In addition, the data set also contains information on general establishment characteristics, such as the 3-digit classification of economic activities and a proxy for activities in R&D.[9] For our analysis, we concentrate on the manufacturing sector. Since the BHP only provides information on establishments rather than on firms, changes in the occupational mix of firms are not observable because we do not know if single establishments are part of a parent firm or not.

We match the BHP with a data set that contains constructed time-consistent industry codes, because the classification of economic activities changes several times within the 1975-2010 period.[10] Hence, we are able to consistently control for industry-specific effects at the 3-digit level (according to the classification of economic activities 93) in our regressions.

We additionally match the BHP with trade data, which we obtain from the UN Comtrade database. For the matching process, we use the Input Statistic and the Survey of Production provided by the German Federal Statistical office that gives us detailed information on the input and output structure of the German manufacturing sector. A more detailed description of the matching process used will be provided in section 4.4.1. We only consider establishments with at least 20 employees.[11] Overall our sample consists of 379.805 observations, which includes 69.069 different establishments. For every establishment, the data set contains informa-

[9]For further information concerning the BHP, see Gruhl et al. (2012) (German version) or Hethey-Maier & Seth (2010) (English version).

[10]For a more detailed description concerning the construction of the data set, see Eberle, Jacobebbinghaus, Ludsteck & Witter (2011).

[11]We have to restrict the establishment size as the Survey of Production, our basis for the derivation of German export flows, only captures establishments with at least 20 employees. For further information, see section 4.4.

tion on the number of employees in each Blossfeld occupational group (Blossfeld (1987)). The classification includes three main categories: production, service, and administration - each of which contains three to four sub-categories ordered by their skill level.

4.3 Stylized Facts

Using the occupational information of the BHP, we can show that the increasing share of service employment, measured at the establishment-level, is much higher than indicated by standard measurements at the industry-level (Henze (2014)).

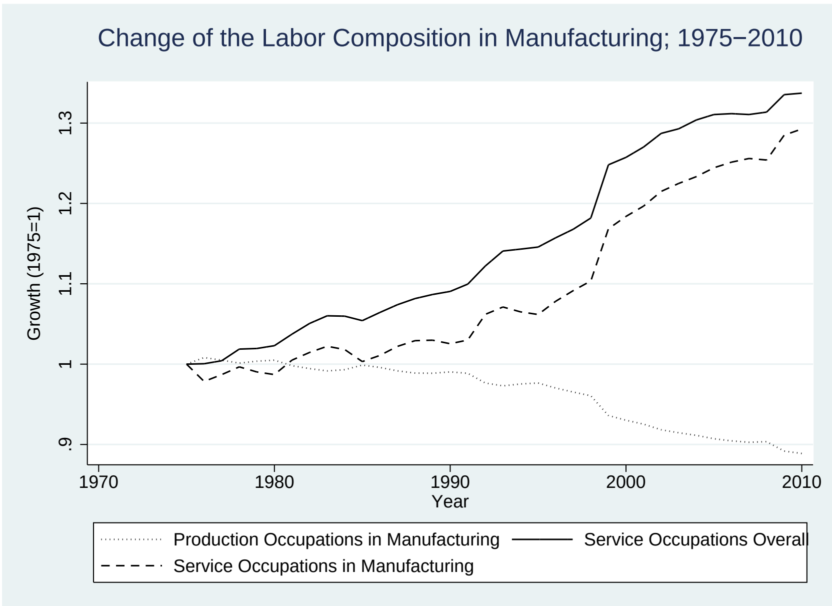

Figure 4.1:
Change in the occupational Mix in Manufacturing
Source: Establishment History Panel, authors' computation.

Figure 4.1 shows the change in the occupational mix in the German manufacturing sector between 1975 and 2010. The dashed line shows the employment growth of full-time employees in service occupations in manufacturing establishments.[12] In the 36-year period, the employment in service occupations increased by 29%. For the German economy as a whole, it increased by 34% during the same period (solid line). In contrast, the employment in production occupations in the manufacturing sector decreased by 12%. These findings highlight the substantial change of the occupational mix in manufacturing, but give little evidence of driving forces behind the transition.

To shed light on this issue, Table 4.1 depicts the employment growth of each occupational group. Column 2 shows the absolute employment in 1975 and column 3 the overall change until 2010. It becomes obvious that the increase in the employment share in service occupations was largely driven by a decrease of the employment in production occupations. Within the 36 years of observation, more than half a million production jobs (about 20%) were lost - the biggest part coming from a decrease in the employment in unskilled manual occupations. Overall, the number of non-production workers in manufacturing slightly increased. This was mostly driven by an increase in the employment in administrative occupations, whereas employment in service occupations overall showed a slight decrease. Since the employment in production occupations decreased to such a large extent, the share of employment in service and administrative occupations increased. Moreover, it is the employment in the most skilled occupations that grew, whereas employment in unskilled occupations declined. This observation holds for both production and services. While the employment in the two least skilled occupations in production and services decreased by 15% to 34%, the two most skilled occupational groups experienced employment increases of 5% to 106%. In administration,

[12] Here, administrative occupations are considered to be related to services, too. Therefore, service occupations also include administrative occupations.

the employment in all categories showed an increase, while the employment in less skilled occupations experienced lowest employment growth. Thus, the occupational structure in manufacturing also changed toward the more skilled.

Table 4.1: Employment Growth of occupational Groups in Manufacturing, 1975-2010

Occupational Group	Abs. Employment (1975)	Growth overall
Production		
Unskilled manual occupations	1.506.494	-33.66%
Skilled manual occupations	934.780	-14.60%
Technicians	269.634	+4.74%
Engineers	82.243	+105.81%
Services		
Unskilled services	306.833	-18.91%
Skilled services	22.146	-19.32%
Semiprofessions	10.684	+66.26%
Professions	7765	+51.33%
Administration		
Unskilled commercial and administrative occupations	196.622	+6.31%
Skilled commercial and administrative occupations	412.995	+20.01%
Managers	70.592	+17.05%

Source: Establishment History Panel, authors' computation.

4.4 Empirical Evidence

4.4.1 Matching of Commodity Trade Data

As there is no long-term micro data set for Germany available that includes information on both employment structure and trade flows, we create our data set by merging trade data from the UN Comtrade database with the BHP. This requires converting commodity trade data into industry trade data. However, instead of following the standard approach in the literature of using correspondence tables[13] to assign each trade commodity to the most similar industries[14], we allocate the trade flows according to the actual input and output structure of the German manufacturing sector. For that, we use two data sets provided by the German Federal Statistical Office: the Input Statistic (in German: Material- und Wareneingangserhebung im Verarbeitenden Gewerbe) to allocate the imports and generate import intensity, and the Survey of Production (in German: Produktionserhebung im Bereich Verarbeitendes Gewerbe) to allocate German exports and imports to generate export intensity and import competition.

The Input Statistic is published every four years starting from 1978. It provides information on all incoming materials and commodities in Germany at the 2-digit or 3-digit level for all 3-digit manufacturing industries. With this information at hand, we derive the import intensity for the German manufacturing sector in the following way:

$$ImpInt_{it} = \sum_{c=1}^{N} \frac{x_{cit}}{x_{ct}} * \gamma_{ct} * Import_{ct}, \tag{4.1}$$

[13]For example correspondence tables that are provided by Eurostat or the UN Statistics Division: http://ec.europa.eu/eurostat/ramon/ or http://unstats.un.org/unsd/cr/registry.

[14]E.g. Altomonte et al. (2013) and Dauth, Findeisen & Südekum (2012) among many.

where import intensity $ImpInt_{it}$ is the calculated import flow into a specific industry i in year t. x_{cit} stands for the input of commodity c in this industry i in year t, x_{ct} is the total input of commodity c in year t over all industries, and $Import_{ct}$ is the import flow[15] for each commodity in a given year.[16] As the trade data do not distinguish between the usage of imports, e.g. manufacturing inputs or private and government consumption, we weigh the commodity-specific import with its share of manufacturing input, γ_{ct},[17] before we allocate the commodity imports to the industries. Accordingly, we avoid overestimating the importance of commodities mostly used by recipients other than manufacturing (e.g. consumer intensive goods such as textiles). By weighing the imports, we additionally make sure that to a great extent only intermediates rather than final goods are accounted for.[18]

A comparison between the "traditional" allocation process with standard correspondence tables and the approach described above reveals that our approach shows a much more detailed import structure (see Appendix C.3 and C.5 for a complete comparison). For example, the Input Statistic in 2000 shows that goods of "Leather and Leather Manufactures" are used in 17 industries as an input factor. Therefore, we allocate the imports of leather (proportionally to the value of leather

[15]All trade flows obtained from the UN Comtrade database are inflation-adjusted.

[16]For a detailed description of the data, the matching procedure and an overview over all classifications see Appendix C.2.

[17]The commodity-specific import shares of manufacturing are obtained from the input-output tables provided by the German Federal Statistical Office. Since the input-output tables for Germany are only available for the 1995-2010 period, we have to assume that the industry-specific input shares from 1975-1995 are constant. A comparison of later years shows that the input shares are rather stable. Therefore, our assumption seems to be appropriate.

[18]We believe that mostly recipients other than manufacturing use final good imports, whereas imports flowing into the manufacturing sector will mostly be intermediate goods. Accordingly, final goods are filtered out if we only use the share of imports flowing into the manufacturing sector. The only cases in which final goods are allocated to the manufacturing sector are if either the product is used as capital input (e.g. machinery) or if the establishment is partly reselling final products. Establishments that mostly or purely resell are part of the service sector.

inputs) to these 17 industries. Using a "standard" correspondence table instead, we would allocate leather imports to only four industries. Descriptive statistics show that the import intensity differs significantly depending on which approach is used (Spearmans rank correlation coefficient of $\rho = 0.8192$).

To obtain the export intensity, we allocate the commodity exports using the Survey of Production. The Survey of Production reports all commodities at the 9-digit level that are produced in each 4-digit industry for the 1995-2010 period.[19] The Survey of Production shows that most industries produce a wide range of products, including products that are typically related to other industries. The "traditional" matching procedure cannot account for this complex production structure, which would lead to an incorrect allocation of trade flows to industries and therefore bias any analysis that builds upon this matching approach. Analogously to our approach for import intensity, we derive export intensity by:

$$ExpInt_{it} = \sum_{c=1}^{N} \frac{z_{cit}}{z_{ct}} * Export_{ct}, \tag{4.2}$$

where export intensity $ExpInt_{it}$ is the calculated export of industry i in year t, z_{cit} is the output of commodity c in this industry i and year t, and z_{ct} stands for the total output of commodity c in year t. $Export_{ct}$ is the export flow for each commodity in a given year. Similar to the import flows, we are able to allocate the export commodities to industries on the basis of the actual production structure the Survey of Production provides. As before, a comparison highlights that our approach reveals a much more detailed export structure. The example of "Leather and Leather Manufactures" again shows that we allocate exports to 24 industries,

[19] We have to assume a constant output structure from 1975 to 1994 that is equal to the structure of 1995, because the Survey of Production only starts in 1995.

compared to only four industries in case of standard correspondence tables (for a complete comparison see Appendix C.4 and C.5).

To generate import competition, we again use the Survey of Production. This time, however, we allocate the imports according to the output structure such that the import competition is derived by:

$$ImpComp_{it} = \sum_{c=1}^{N} \frac{z_{cit}}{z_{ct}} * Import_{ct}. \tag{4.3}$$

Again, the result is a more detailed allocation compared to the standard approach. Here, we assume that establishments face import competition, when products are being imported that match the domestic establishments' production at the 6-digit commodity-level.[20]

In summary, we are able to analyze the input and output structure of the German economy in detail and accordingly create a much more precise allocation of commodity imports and exports to the industries to obtain import intensity, export intensity, and import competition. In the following section, we introduce these measures of trade exposure to estimate the effects of an increasing openness to trade on the occupational mix of German manufacturing establishments.

4.4.2 Empirical Strategy

In order to explain the effects of international trade on the occupational mix, we use a fixed-effects Poisson model. We investigate how international trade affects the absolute number of employees of different occupational groups, such that our dependent variable only consists of integer values (count data) that follow a Poisson

[20] We match the trade data with the Survey of Production at the 6-digit level as the trade data are not available at a more disaggregated level.

distribution. We estimate the employment effects of international trade both at the establishment-level and at the industry-level. To apply the fixed-effects Poisson model, we use the Generalized Method of Moments (GMM). One concern of our empirical analysis is to control for the substantial individual heterogeneity by including fixed-effects for establishments or industries (depending on the specification) in our estimations, i.e. introduce a dummy variable for each establishment or industry. For the estimations at the establishment-level, this would result in 69.069 dummy variables. Hence, applying a "standard Poisson regression model" with dummy variables to control for the individual heterogeneity is not feasible, since the maximum number of variables that STATA allows is exceeded in this case. We thus follow Blundell, Griffith & Windmeijer (2002) to apply a GMM estimation approach of the Poisson model in a panel data context that uses a moment condition rather than the full likelihood function. Thus, we are able to account for the substantial individual heterogeneity without using dummy variables for each establishment or industry.

A "standard Poisson regression model" that is commonly used for count data can be written as:

$$E\left(y_{jt}|x_{jt}\right) = exp\left(x_{jt}^{'}\beta\right), \tag{4.4}$$

where y_{jt} is the dependent discrete count variable for establishment j at time t, x_{jt} the vector of explanatory variables and β the vector of estimated coefficients.[21] This Poisson regression model can be rewritten as the following moment condition

[21] For regressions at the industry-level, the derivation of the moment condition is very similar to the one at the establishment-level. In case of industry-level estimations, we only substitute the index j for each establishment by the index i for each industry. Hence, we are able to account for the individual heterogeneity of each industry.

(under the assumption that all independent variables are strictly exogenous):

$$E\left[x_{jt}\left\{y_{jt}-exp\left(x_{jt}^{'}\beta\right)\right\}\right]=0. \tag{4.5}$$

An important issue in our estimations is the unobserved heterogeneity of industries and establishments. We use the moment condition according to equation (4.5) for panel data and additionally include a term for individual heterogeneity (a fixed-effect), η_j. For count data models, this term is generally added multiplicatively. Then, we obtain

$$E\left(y_{jt}|x_{jt},\eta_j\right)=exp\left(x_{jt}^{'}\beta+\eta_j\right)=\mu_{jt}\nu_j, \tag{4.6}$$

where $\mu_{jt}=exp(x_{jt}^{'}\beta)$ and $\nu_j=exp\left(\eta_j\right)$ is the permanent scaling factor for the individual mean. Hence, our regression model looks as follows:

$$y_{jt}=\mu_{jt}\nu_j+\epsilon_{jt}, \tag{4.7}$$

where ϵ_{jt} is the error term. If all x_{jt} are strictly exogenous[22], we finally can rewrite our sample moment condition as:

$$\sum_{j=1}^{N}\sum_{t=1}^{T}x_{jt}\left(y_{jt}-\mu_{jt}\frac{\bar{y_j}}{\bar{\mu_j}}\right)=0. \tag{4.8}$$

Here, $\bar{y_j}$ and $\bar{\mu_j}$ are the means of y_j and μ_j for panel j, i.e. the respective establishment. This moment condition, where the fixed-effects are substituted by the ratio of within group means is now equivalent to a "standard Poisson regression model"

[22]If the explanatory variables are strictly exogenous, the conditional mean of y_{jt} satisfies $E\left(y_{jt}|\nu_j,x_{jt}\right)=E\left(y_{jt}|\nu_j,x_{j1},...,x_{jT}\right)$.

with establishment fixed-effects. The "mean scaling" model can now be written as:

$$y_{jt} = \mu_{jt} \frac{\bar{y}_j}{\bar{\mu}_j} + \epsilon^*_{jt}.^{23} \tag{4.9}$$

Blundell, Griffith & Windmeijer (2002) describe this estimator as the "within group mean scaling estimator".

Finally, we are able to estimate our extensive micro data set by using a GMM Poisson model with the moment condition according to equation (4.8), which yields the same results as the "standard Poisson regression model" with dummy variables for each establishment or each industry, respectively. In addition, the GMM estimator has very strong robustness properties concerning the possible presence of overdispersion[24] and serial correlation (Wooldridge (2002)).

To estimate the effects of international trade on the occupational mix, we develop two specifications of our empirical model. As mentioned above, the BHP provides detailed information at the establishment-level, but our trade data are only available at the 3-digit industry-level. Hence, we first estimate our empirical model at the industry-level. To do so, we aggregate the information of the BHP to the 3-digit industry-level. This specification has the advantage that all variables are measured at the same level. Moreover, it allows us to compare our results with the related literature that mainly focuses on industry-level data. On the other hand, this specification does not allow us to control for a wide range of establishment characteristics as well as for establishment fixed-effects. Therefore, we apply a second specification that estimates our empirical model as disaggregated as possible.

[23] $\epsilon^*_{jt} = \epsilon_{jt} - (\epsilon_{jt}/\bar{\epsilon}_j)\,\bar{\epsilon}_j$.

[24] One of the crucial assumptions of the Poisson distribution is that the variance of the dependent variable Y equals its mean: $Var(Y) = E(Y)$. However, empirically, there is often the presence of overdispersion, i.e. the variance is larger than the mean.

Here, we estimate all variables except the trade flows and some control variables at the establishment-level which allows us to account for the unobserved establishment heterogeneity, i.e. establishment fixed-effects. However, we now measure the variables for employment and international trade at different levels. Thus, it might be difficult to determine employment effects within establishments due to changing trade flows of the corresponding industry. In addition, there is the chance that decisions about occupational structures are made at the firm-level rather than at the establishment-level. Accordingly, changes in the occupational mix of firms due to international trade might not be observable, since we only see single establishments without knowing whether they are part of a parent firm or not.

First, we estimate the employment effects of international trade at the industry-level. We set the respective industry identifier (3-digit industry classification) as the panel variable in our moment condition and thus control for all industry-specific characteristics that may also have an effect on the occupational mix of employment. Our estimated Poisson model looks as follows:

$$\begin{aligned} Y_{it} = exp\left(\beta_1 ln\left(ImpInt_{it}\right) + \beta_2 ln\left(ImpComp_{it}\right) + \beta_3 ln\left(ExpInt_{it}\right)\right) * \\ exp\left(\delta' ln\left(V_{it}\right) + \nu' ln\left(Z_t\right) + \eta_i\right) + \epsilon_{it}. \end{aligned} \quad (4.10)$$

The dependent variable, Y_{it}, measures the number of employees in industry i at time t attributed to a Blossfeld occupational group. We estimate equation (4.10) for each occupation (except agricultural occupations) included in the BHP.

The first independent variable is $ImpInt_{it}$, which measures the import intensity of industry i at time t, i.e. the (real) value of imported inputs. The second independent variable, $ImpComp_{it}$, includes import competition that is defined as the (real) value of imports of final goods. $ExpInt_{it}$ stands for the (real) value of exports. The estimated coefficients β_1, β_2 and β_3 show the effects on the employment of each occupational group if the exposure to international trade of the respective industry changes. V_{it} is a vector of control variables at the industry-level accounting for further determinants that may affect the employment, such as the average establishment size, average activities in R&D, and the average share of high-skilled workers. Z_t is another vector of control variables at the macro-level. As it is not feasible to estimate our empirical model with year fixed-effects, i.e. a dummy variable for each of the 36 years, we include macro variables to control for year-specific effects. We use German GDP and the annual "Ifo Business Climate Index"[25] to account for any business cycle effects. Additionally, we include the overall education level of the German population and the size of the labor force to control for any systematic changes of the working population.[26] As the respective industry is the panel variable, the moment condition accounts for industry fixed-effects, η_i. ϵ_{it} represents the error term.

To simplify the interpretation, we convert all right-hand side variables of equation (4.10) into the logarithmic form before we include them into the estimation. Therefore, the estimated coefficients can be interpreted as elasticities. Since we control for the industry size in terms of total employment, we are able to interpret the estimated employment effects in relative terms, i.e. the coefficients indicate whether the occupational mix of an industry shifts toward a certain occupational group or not.

[25] In order to use the annual "Business Climate Index", we aggregate the monthly "Business Climate Index" that is published by the "Ifo Center for Business Cycle Analysis and Surveys".

[26] The data for German GDP, the education level, i.e. the percentage share of German citizens with post secondary education, and the overall labor force are obtained from the German Federal Statistical Office.

Second, we calculate our empirical model at the establishment-level:

$$Y_{jit} = exp\left(\beta_1 ln\left(ImpInt_{it}\right) + \beta_2 ln\left(ImpComp_{it}\right) + \beta_3 ln\left(ExpInt_{it}\right)\right) * \\ exp\left(\delta' ln\left(V_{jit}\right) + \nu' ln\left(Z_t\right) + \eta_j\right) + \epsilon_{jit}. \quad (4.11)$$

Here, we set the establishment identifier j as the panel variable and thus control for all unobserved establishment-specific characteristics. The empirical model represented by equation (4.11) is constructed in the same way as equation (4.10), but exploits the information of the BHP at the establishment-level. Hence, the dependent variable, Y_{jit}, measures the number of employees in each occupation in establishment j in industry i at time t, and V_{jit} is a vector of control variables at the establishment-level. Furthermore, we do not need to include industry fixed-effects, as the number of establishments changing their respective industry classification is negligible. Thus, the establishment fixed-effects, η_j, also control for any industry-specific fixed-effects. The remaining variables of equation (4.11) equal those of equation (4.10).

4.4.3 Results

Table 4.2 presents the results from our estimations at the 3-digit industry-level represented by equation (4.10). The estimations include all control variables as well as industry fixed-effects. We estimate equation (4.10) for each Blossfeld occupational group except agricultural occupations. Hence, columns 1 to 11 of Table 4.2 show the effects of a change in import intensity, import competition, and export intensity on the employment in each occupation. The reported coefficients are elasticities.

Table 4.2: Employment Effects of international Trade (3-digit Level); 1975-2010

	Fixed-Effects Poisson Model (GMM)										
	Production occupations				**Service occupations**				**Administrative occupations**		
Dependent Variable:	Unskilled manual	Skilled manual	Technicians	Engineers	Unskilled services	Skilled services	Semi-professions	Professions	Unskilled admin.	Skilled admin.	Managers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Import Intensity	-0.0086	-0.0166	-0.0024	-0.0109	-0.0417**	-0.0505*	-0.0703**	-0.0162	-0.0811***	0.0020	0.0494**
	(0.0109)	(0.0186)	(0.0093)	(0.0101)	(0.0171)	(0.0263)	(0.0339)	(0.0270)	(0.0147)	(0.0051)	(0.0196)
Import Competition	0.0019	-0.0111	-0.0457***	-0.0073	-0.1223***	-0.0614	-0.0717	0.0087	-0.2480***	-0.0362***	0.0347
	(0.0197)	(0.0177)	(0.0124)	(0.0085)	(0.0323)	(0.0470)	(0.0637)	(0.0247)	(0.0578)	(0.0113)	(0.0226)
Export Intensity	0.0069	-0.0123	0.0384***	0.0210	0.0931***	0.0749*	0.0987	-0.0135	0.2332***	0.0346***	-0.0480**
	(0.0202)	(0.0209)	(0.0129)	(0.149)	(0.0291)	(0.0441)	(0.0627)	(0.0342)	(0.0582)	(0.0127)	(0.0242)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	3.094	3.094	3.094	3.094	3.094	3.094	3.094	3.094	3.094	3.094	3.094

Notes: Clustered standard errors (by industry) in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Hence, the coefficient of 0.0384 for the effect of an increase in export intensity on the number of technicians in a given industry reports that an increase in export intensity by 1% leads to an increase in the employment of technicians by 0.04%.

The estimations show various employment effects from the different trade channels. Import intensity, i.e. the import of inputs and intermediate products, has negative employment effects on all occupations except skilled administrative occupations and managers. The coefficients are significant for all service occupations except professions and all administrative occupations except skilled administration, indicating that especially the employees in lower skilled service and administrative occupations suffer most from an increase in import intensity. These results are partly in line with the literature on offshoring that finds negative employment effects from outsourcing, especially for employees with less complex tasks (e.g. Hogrefe (2013)). However, we cannot identify a negative employment effect from offshoring on (low-skilled) production occupations.

In case of import competition, i.e. the import of goods that compete with final goods of domestic suppliers, the results provide evidence that the employees in most occupations suffer from a more competitive environment. The employment effects are negative for all occupations except unskilled manual, service professions, and managers. Significance is displayed for technicians, unskilled services, and all administrative occupations except managers. Moreover, the negative effects of import competition on the employment in unskilled service occupations and in unskilled administrative occupations are substantially larger than the effects of import intensity. These findings are also in line with the literature that finds job losses due to increased competition with imported goods (e.g. Biscourp & Kramarz (2007) and Autor, Dorn & Hanson (2013)).

Table 4.3: Employment Effects of international Trade (Establishment-Level); 1975-2010

	Fixed-Effects Poisson Model (GMM)										
	Production occupations				**Service occupations**				**Administrative occupations**		
Dependent Variable:	Unskilled manual	Skilled manual	Technicians	Engineers	Unskilled services	Skilled services	Semi-professions	Professions	Unskilled admin.	Skilled admin.	Managers
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Import Intensity	-0.0031	-0.0055	-0.0140**	-0.0130	-0.0065	0.0121	0.0097	0.0230	-0.0280**	-0.0023	0.0522**
	(0.0064)	(0.0170)	(0.0067)	(0.0126)	(0.0112)	(0.0179)	(0.0207)	(0.0278)	(0.0115)	(0.0038)	(0.0215)
Import Competition	-0.0126	-0.0176	-0.0398*	-0.0050	0.0028	0.0050	-0.0140	0.0101	-0.0150	-0.0314**	0.0382
	(0.0201)	(0.0231)	(0.0208)	(0.0113)	(0.0222)	(0.0833)	(0.0770)	(0.0287)	(0.0257)	(0.0140)	(0.0279)
Export Intensity	0.0207	0.0013	0.0448*	0.0256	-0.0244	-0.0177	0.0344	-0.0444	0.0291	0.0300*	-0.0820*
	(0.0254)	(0.0305)	(0.0269)	(0.0214)	(0.0248)	(0.1022)	(0.0862)	(0.0422)	(0.0303)	(0.0179)	(0.0488)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Establishment Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. of Obs.	379.805	379.805	379.805	379.805	379.805	379.805	379.805	379.805	379.805	379.805	379.805

Notes: Clustered standard errors (by industry) in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

For export intensity, i.e. the export of goods by domestic establishments, we find positive signs for the employment effects for all but three occupations. The coefficients for technicians, unskilled services, skilled services as well as unskilled and skilled administrative occupations are positive and significant; only for managers, the impact is negative and significant. Thus, it mainly seems to be that employees in lower skilled occupations gain from an increase in exports. The employment effect of export intensity on the employment in unskilled administrative occupations is considerably larger than the effect of import competition.

Table 4.3 presents the results from the regression model estimated at the establishment-level according to equation (4.11). The estimation strategy and column interpretation is identical to Table 4.2 with the difference that the employment of each occupational group is now observed at the establishment-level. Hence, the coefficient of 0.0448 for the export intensity effect on the number of technicians, for example, reports that an establishment will increase the number of technicians by 0.04% if the industry it belongs to experiences an export intensity growth of 1%.

Compared to the industry-level estimation, the establishment-level estimations only show few significant employment effects from the different channels of international trade. To a great extent, the signs of the coefficients are unchanged, implying an employment change in the same direction as before. The estimated coefficients, however, lose significance. This most likely has to do with the fact that trade information is measured at the industry-level, whereas the employment is measured at the establishment-level. Additionally, we now control for the substantial unobserved establishment heterogeneity.

Import intensity now shows a negative and significant impact on the employment of technicians and unskilled administrative occupations. Although the former group represents a high-skilled occupation, this result is in line with the literature that shows an increasing offshorability of high-skilled jobs (Baldwin & Robert-Nicoud (2007)). In contrast, the employment effect on managers is positive and significant.

In case of the import competition, the results now show negative and significant employment effects on technicians and skilled administrative occupations. The coefficients on all other occupations are insignificant. The estimation for the export intensity at the establishment-level shows that technicians benefit from increasing exports, whereas the employment of managers decreases, which is in line with Mauron, Thesmar & Koenig (2002), but contradicts Caliendo & Rossi-Hansberg (2012).

In summary, we find evidence at the industry-level that an increase in import intensity and in import competition decreases the employment in almost all occupations, whereas the employment increases in almost all occupations if export intensity increases. However, the estimations provide no evidence that international trade is a driving force behind the substantial employment decline in unskilled and skilled production occupations that is depicted in Table 4.1. At the establishment-level, we find that the three channels of international trade only affect the employment of a few occupations although the signs of the coefficients are in line with the estimations at the industry-level. Mostly administrative occupations and technicians show significant employment effects. As discussed before, these results may have three causes: First, employment effects might become insignificant if we account for establishment heterogeneity by using establishment fixed-effects as well as control variables at the establishment-level. Second, our estimated coefficients may be mostly insignificant because of level differences. While the employment of the respective occupation and most of the control variables are reported at the establishment-level, the trade variables are measured at the 3-digit industry-level. Third, there might be changes in the occupational structure of firms due to international trade we cannot identify, since we only observe single establishments, not firms, which may have more than one establishment.

4.5 Conclusion

In this chapter, we build on the fact that rather little empirical research has been conducted to investigate how trade openness impacts the occupational mix of manufacturing firms.

We identify three different trade channels: import intensity, import competition and export intensity. To investigate the employment effects of these three channels, we match the BHP with UN Comtrade data by using an improved matching approach novel in the literature. We take the input and output structure of the German manufacturing sector into account and allocate the trade flows accordingly. Using the example of leather goods, we show that our new approach is a more refined technique compared to the "traditional" allocation process with standard correspondence tables provided by Eurostat or the UN Statistics Division.

Our stylized facts highlight the change of the employment structure of manufacturing establishments. To identify the relationship between the three channels of international trade and the employment in different occupations, we apply a fixed-effects Poisson model that especially accounts for the substantial individual heterogeneity of industries and establishments. We estimate our empirical model both at the industry-level and at the establishment-level using industry fixed-effects or establishment fixed-effects, respectively.

Our results at the industry-level indicate that an increasing import intensity and import competition lead to decreasing employment, whereas rising export activities increase employment. The employees in unskilled and skilled service occupations suffer from an increase in imports of intermediate products. Hence, increasing imports contribute to the decline in employment of these two occupations displayed in Table 4.1. In contrast, employees of the same occupational groups benefit most from an increase in exports. However, our estimations cannot determine international trade as a driving force behind the substantial employment decline in unskilled and skilled production occupations described in Table 4.1. If we estimate our empirical model at the establishment-level, our results, however, suggest that only the employment of few occupations is affected by changes in international trade. Therefore, our results at the establishment-level cannot identify international trade as a major determinant for the substantial change in the occupational mix within German manufacturing establishments. The estimated coefficients lose significance, which is most likely due to level differences between the dependent variable and the independent variables and the inclusion of establishment fixed-effects. Furthermore, we are not able to identify changes in the occupational structure of (multinational) firms, since we only observe single establishments.

Thus, a natural step for future research would be to check to what extent our results can be confirmed with a data set at the firm-level, which additionally includes information on activities in international trade.

Chapter 5

Conclusion

This dissertation provides a collection of analyses that shed new light on the causes and consequences of structural change, both in terms of inter-sectoral reallocations of employment between manufacturing and services and intra-sectoral employment changes within the manufacturing sector. This conclusion summarizes my main findings.

In chapter 2, I show that structural change increases the demand for high-skilled workers and thus has a significant positive impact on the increasing wage gap in Germany. My estimations suggest that a 10% increase in the share of employees with occupations in services or administration leads to a 4.8% increase in the difference between the upper and the lower wage quartile. Furthermore, I show that the wage effect of structural change is much larger within the manufacturing sector. If the estimated coefficients are standardized, i.e. corrected for different levels of aggregations of the data, the wage effect of structural change is comparable with the wage effect of international trade. Finally, I aggregate the

BHP and re-estimate my baseline model. Various related papers, such as Blum (2008) and OECD (2011), use industry-level or macro-level data that exclude any intra-sectoral changes of employment and do not account for a wide range of control variables at the establishment-level also affecting the wage gap. My results highlight that the wage effect of structural change would be biased and/or ignored if aggregated data are used. Hence, it is of particular importance to use very disaggregated data that account for intra-sectoral employment shifts and are able to control for further variables at the establishment-level that also have an effect on the the wage gap.

Chapter 3 focuses on the driving forces behind structural change. Here, I test the theory of Ngai & Pissarides (2007) who explain structural change by diverging growth rates of total factor productivity between manufacturing and services. Ngai & Pissarides (2007) argue that employment shares shift to industries with low TFP growth rates if the elasticity of substitution between final goods is below one. To test the theory, I aggregate the BHP to the 2-digit level, which ensures that the industries differ sufficiently. The data show that TFP growth rates between manufacturing and services diverge from the mid-1990s onwards, i.e. TFP growth of the manufacturing sector exceeds the growth of TFP in services. Moreover, employment shares shift from manufacturing to services. My estimations confirm the theoretical predictions of Ngai & Pissarides (2007), i.e. industries with increasing TFP growth experience a decreasing employment growth. The results show that employment growth decreases by 0.03 to 0.08 percentage points if the average TFP growth rate in the two previous years increases by 1 percentage point.

Chapter 4 is joint work with Dominik Boddin. While chapter 3 analyzes the driving forces behind inter-sectoral reallocations of employment, we consider intra-sectoral employment changes within the German manufacturing sector. We match trade data obtained from the UN Comtrade database with the BHP by accounting for the actual input and output structure of the manufacturing sector and consider three channels of international trade: the imports of inputs and intermediate goods, the imports of final goods and the exports of goods. Our empirical model simultaneously estimates the effects of all channels of international trade on the employment of each occupational group included in the BHP at the industry-level as well as at the establishment-level. Our results at the industry-level indicate that imports decrease the employment and exports increase the employment. Lower skilled employees, most of all in services and administration, suffer from an increase in imports, whereas the same employees benefit from an increase in exports. For example, an increase in intermediate imports by 1% decreases the employment of unskilled service occupations by 0.04%. But if the exports rise by 1%, the employment of the same occupational group grows by 0.09%. In contrast, our findings at the establishment-level suggest that international trade only affects a few occupational groups. Altogether, our results provide no evidence that international trade is a driving force behind the substantial employment decline in unskilled and skilled production occupations the data reveal. Hence, the findings of this dissertation indicate that international trade rather has an effect on the wages of the employees than on the employment itself.

Appendix A

Appendix to Chapter 2

A.1 Structure of Blossfeld Occupational Groups

Table A.1: Structure of Blossfeld occupational Groups (**Source:** Blossfeld (1987))

Occupational Group	Description	Examples
Production		
Agricultural occupations (AGR)	Occupations with a dominant agricultural orientation	Agricultural workers, gardeners, workers in the forest economy
Unskilled manual occupations (EMB)	All manual occupations that showed at least 60 percent unskilled workers in 1970	Miners, paper makers, wood industry occupations, printing industry occupations, unskilled workers
Skilled manual occupations (QMB)	All manual occupations that showed at most 40 percent unskilled workers in 1970	Glassblowers, bookbinders, precision instrument makers, electrical mechanics, brewers
Technicians (TEC)	All technically trained specialists	Machinery-, electrical-, construction- & mining technicians
Engineers (ING)	Highly trained specialists who solve technical and natural science problems	Construction engineering, electrical engineers, production, designers, physicists, mathematicians

Table A.1 (cont'd): Structure of Blossfeld occupational Groups

Occupational Group	Description	Examples
Service		
Unskilled services (EDB)	All unskilled personal services	Cleaners, waiters, servers
Skilled services (QDB)	Essentially order and security occupations as well as skilled service occupations	Policemen, firemen, locomotive engineers, photographers, hair-dressers
Semiprofessions (SEMI)	Service positions which are characterized by professional specialization	Nurses, educators, elementary school teachers, Kindergarten teachers
Professions (PROF)	All liberal professions and service positions which require a university degree	Dentists, doctors, pharmacists, judges, secondary education teachers, university professors
Administration		
Unskilled commercial and administrative occupations (EVB)	Relatively unskilled office and commerce occupations	Postal occupations, shop assistants, typists
Skilled commercial and administrative occupations (QVB)	Occupations with medium and higher administrative and distributive functions	Credit and financial assistants, foreign trade assistants, data processing operators, book-keepers, goods traffic assistants
Managers (MAN)	Occupations which control factors of production as well as functionaries of organizations	Managers, business administrators, deputies, ministers, social organization leaders

A.2 Industry-specific Regressions

Table A.2: The Effect of Structural Change on the Wage Gap: Industry-specific Estimations

Industry Code	**Classification of Economic Activities 1993 (3-digit)**	*Struc* **- Coefficient**
11	Growing of crops; market gardening; horticulture	0.504*** (0.119)
12	Farming of animals	0.789*** (0.149)
13	Growing of crops combined with farming of animals	0.732*** (0.092)
14	Agricultural and animal husbandry service activities	0.525*** (0.138)
20	Forestry, logging and related service activities	0.740** (0.286)
101	Mining and agglomeration of hard coal	0.111 (0.243)
103	Extraction and agglomeration of peat	-0.680 (0.507)
141	Quarrying of stone	0.291 (0.149)
142	Quarrying of sand and clay	0.221 (0.170)
145	Other mining and quarrying n.e.c.	0.975 (0.499)
151	Production, processing and preserving of meat	0.863*** (0.092)
152	Processing and preserving of fish	1.743*** (0.226)
153	Processing and preserving of fruit and vegetables	1.247*** (0.158)
155	Manufacture of dairy products	0.649*** (0.118)
156	Manufacture of grain mill products and starch products	0.638** (0.230)
157	Manufacture of prepared animal feeds	1.171*** (0.305)
158	Manufacture of other food products	0.674*** (0.085)
159	Manufacture of beverages	0.630*** (0.091)
171	Preparation and spinning of textile fibers	1.130** (0.393)
172	Textile weaving	1.227*** (0.142)
173	Finishing of textiles	1.508*** (0.194)
174	Manufacture of made-up textile articles, except apparel	1.592*** (0.195)
175	Manufacture of other textiles	2.018*** (0.203)
176	Manufacture of knitted and crocheted fabrics	1.397*** (0.187)
182	Manufacture of other wearing apparel and accessories	1.084*** (0.171)
183	Dressing and dyeing of fur; manufacture of articles of fur	2.387 (1.502)
192	Manufacture of luggage, handbags and the like	1.144*** (0.288)

Table A.2 (cont'd): Industry-specific Regressions

Industry Code	Classification of Economic Activities 1993 (3-digit)	*Struc* - Coefficient
193	Manufacture of footwear	1.510*** (0.229)
201	Saw milling and planing of wood; impregnation of wood	1.001*** (0.166)
202	Manufacture of veneer sheets (...) and other panels and boards	1.202*** (0.270)
203	Manufacture of builders' carpentry and joinery	1.084*** (0.157)
204	Manufacture of wooden containers	0.495 (0.295)
205	Manufacture of other products of wood and of articles of cork	0.947*** (0.161)
211	Manufacture of pulp, paper and paperboard	0.929*** (0.166)
212	Manufacture of articles of paper and paperboard	1.089*** (0.105)
221	Publishing	0.979*** (0.099)
222	Printing and service activities related to printing	0.421*** (0.055)
232	Reproduction of recorded media	-0.208 (0.237)
241	Manufacture of basic chemicals	0.478*** (0.103)
243	Manufacture of pesticides and other agro-chemical products	0.802*** (0.132)
244	Manufacture of pharmaceuticals and medicinal chemicals	0.385* (0.170)
245	Manufacture of soap and detergents (...) and toilet preparations	0.857*** (0.140)
246	Manufacture of other chemical products	0.403* (0.181)
247	Manufacture of man-made fibers	0.524 (0.481)
251	Manufacture of rubber products	0.969*** (0.279)
252	Manufacture of plastic products	1.069*** (0.051)
261	Manufacture of glass and glass products	0.967*** (0.147)
262	Manufacture of (non-)refractory ceramic goods (...)	0.953*** (0.199)
264	Manufacture of bricks, tiles and construction products	2.377*** (0.201)
265	Manufacture of cement, lime and plaster	0.499 (0.283)
266	Manufacture of articles of concrete, plaster and cement	0.825*** (0.107)
267	Cutting, shaping and finishing of stone	0.362 (0.241)
268	Manufacture of other non-metallic mineral products	1.159*** (0.274)
271	Manufacture of basic iron and steel and of ferro-alloys	0.278 (0.187)
272	Manufacture of tubes	0.710** (0.248)
273	Other first processing of iron and steel	1.255*** (0.195)

Table A.2 (cont'd): Industry-specific Regressions

Industry Code	**Classification of Economic Activities 1993 (3-digit)**	*Struc* **- Coefficient**
274	Manufacture of basic precious and non-ferrous metals	0.894*** (0.186)
275	Casting of metals	1.090*** (0.169)
281	Manufacture of structural metal products	0.667*** (0.076)
282	Manufacture of tanks, reservoirs and containers of metal	1.048*** (0.202)
283	Manufacture of steam generators, except central heating	1.261*** (0.241)
284	Forging, pressing, stamping and roll forming of metal	1.512*** (0.188)
285	Treatment and coating of metals; general mechanical engineering	0.637*** (0.120)
286	Manufacture of cutlery, tools and general hardware	1.072*** (0.092)
287	Manufacture of other fabricated metal products	1.024*** (0.079)
291	Manufacture of machinery for the production of mechanical power	1.042*** (0.082)
292	Manufacture of other general purpose machinery	0.365*** (0.079)
293	Manufacture of agricultural and forestry machinery	0.534 (0.376)
294	Manufacture of machine-tools	0.287** (0.088)
295	Manufacture of other special purpose machinery	0.487*** (0.064)
297	Manufacture of domestic appliances n.e.c.	1.284*** (0.203)
300	Manufacture of office machinery and computers	0.759** (0.236)
311	Manufacture of electric motors, generators and transformers	0.524** (0.177)
312	Manufacture of electricity distribution and control apparatus	0.914*** (0.115)
313	Manufacture of insulated wire and cable	1.474*** (0.189)
314	Manufacture of accumulators, primary cells and primary batteries	2.146*** (0.232)
315	Manufacture of lighting equipment and electric lamps	1.090*** (0.150)
316	Manufacture of electrical equipment n.e.c.	0.791*** (0.127)
321	Manufacture of electronic valves and tubes	0.435** (0.145)
322	Manufacture of television and radio transmitters	0.175 (0.129)
323	Manufacture of television and radio receivers (...)	0.424** (0.164)
331	Manufacture of medical and surgical equipment (...)	0.901*** (0.107)
332	Manufacture of instruments and appliances for measuring (...)	0.358*** (0.067)
333	Manufacture of industrial process control equipment	0.331 (0.206)

Table A.2 (cont'd): Industry-specific Regressions

Industry Code	**Classification of Economic Activities 1993 (3-digit)**	*Struc* **- Coefficient**
334	Manufacture of optical instruments and photographic equipment	0.659*** (0.146)
335	Manufacture of watches and clocks	1.945*** (0.433)
341	Manufacture of motor vehicles	0.169 (0.446)
342	Manufacture of bodies (coachwork) for motor vehicles	1.395*** (0.196)
343	Manufacture of parts and accessories for motor vehicles	1.144*** (0.165)
351	Building and repairing of ships and boats	1.362*** (0.239)
352	Manufacture of railway and tramway locomotives and rolling stock	1.517*** (0.418)
353	Manufacture of aircraft and spacecraft	-0.380 (0.472)
354	Manufacture of motorcycles and bicycles	1.548** (0.556)
355	Manufacture of other transport equipment n.e.c.	0.008 (0.538)
361	Manufacture of furniture	1.436*** (0.086)
362	Manufacture of jewelry and related articles	0.936*** (0.250)
363	Manufacture of musical instruments	0.544 (0.315)
364	Manufacture of sports goods	1.751*** (0.384)
365	Manufacture of games and toys	0.759 (0.436)
366	Miscellaneous manufacturing n.e.c.	0.584*** (0.155)
401	Production and distribution of electricity	0.212* (0.085)
402	Manufacture of gas; distribution of gaseous fuels through mains	-0.026 (0.237)
403	Steam and hot water supply	0.582 (0.411)
451	Site preparation	0.182 (0.151)
452	Building of complete constructions; civil engineering	0.609*** (0.039)
453	Building installation	0.648*** (0.053)
454	Building completion	0.656*** (0.113)
455	Renting of construction or demolition equipment	0.433 (0.319)
501	Sale of motor vehicles	0.349* (0.136)
502	Maintenance and repair of motor vehicles	0.582 (0.411)
503	Sale of motor vehicle parts and accessories	0.748*** (0.173)
504	Sale, maintenance and repair of motorcycles (...)	1.789 (1.119)
505	Retail sale of automotive fuel	-1.218 (0.884)
511	Wholesale an a fee or contract basis	0.206* (0.082)
512	Wholesale of agricultural raw materials and live animals	0.513** (0.189)

Table A.2 (cont'd): Industry-specific Regressions

Industry Code	**Classification of Economic Activities 1993 (3-digit)**	*Struc* **- Coefficient**
513	Wholesale of food, beverages and tobacco	0.212* (0.099)
514	Wholesale of household goods	0.293*** (0.078)
515	Wholesale of non-agricultural intermediate products	0.637*** (0.081)
516	Wholesale of machinery, equipment and supplies	0.420*** (0.112)
517	Other wholesale	0.220 (0.131)
521	Retail sale in non-specialized stores	-0.433** (0.164)
522	Retail sale of food, beverages and tobacco in specialized stores	-0.158 (0.270)
523	Retail sale of pharmaceutical and medical goods (...)	0.429** (0.139)
524	Other retail sale of new goods in specialized stores	0.276*** (0.074)
525	Retail sale of second-hand goods in stores	1.215 (0.681)
526	Retail sale not in stores	0.534* (0.255)
527	Repair of personal and household goods	0.593** (0.184)
551	Hotels	0.172 (0.179)
552	Camping sites and other provision of short-stay accommodation	0.929*** (0.238)
553	Restaurants	0.287 (0.152)
554	Bars	-0.324 (0.585)
555	Canteens and catering	0.490 (0.252)
601	Transport via railways	0.139 (0.104)
602	Other land transport	-0.724*** (0.163)
611	Sea and coastal water transport	0.074 (0.202)
612	Inland water transport	1.324*** (0.309)
621	Scheduled air transport	0.993** (0.324)
631	Cargo handling and storage	0.524** (0.169)
632	Other supporting transport activities	-0.006 (0.239)
633	Activities of travel agencies and tour operators (...)	-0.165 (0.423)
634	Activities of other transport agencies	-0.221* (0.109)
641	Post and courier activities	0.496 (0.262)
642	Telecommunications	0.349 (0.180)
651	Monetary intermediation	-1.806*** (0.428)
652	Other financial intermediation	0.729 (1.580)
660	Insurance and pension funding, except compulsory social security	-1.573* (0.632)

Table A.2 (cont'd): Industry-specific Regressions

Industry Code	**Classification of Economic Activities 1993 (3-digit)**	*Struc* **- Coefficient**
671	Activities auxiliary to financial intermediation (...)	1.075 (0.810)
672	Activities auxiliary to insurance and pension funding	0.200 (0.242)
701	Real estate activities with own property	0.234 (0.136)
702	Letting of own property	0.738*** (0.104)
703	Real estate activities an a fee or contract basis	0.458*** (0.099)
711	Renting of automobiles	0.429 (0.406)
712	Renting of other transport equipment	0.714 (0.600)
713	Renting of other machinery and equipment	0.421 (0.235)
714	Renting of personal and household goods n.e.c.	1.080***(0.326)
721	Hardware consultancy	0.122 (0.335)
722	Software consultancy and supply	0.103 (0.115)
723	Data processing	-0.203 (0.223)
725	Maintenance and repair of office machinery	0.622* (0.241)
731	Research and experimental development in natural sciences (...)	0.112 (0.097)
732	Research and experimental development in social sciences	0.173 (0.266)
741	Legal, accounting, book-keeping and auditing activities	0.537*** (0.087)
742	Architectural and engineering activities (...)	-0.028 (0.033)
743	Technical testing and analysis	0.024 (0.120)
744	Advertising	0.129 (0.112)
745	Labor recruitment and provision of personnel	0.257*** (0.052)
746	Investigation and security activities	-0.301 (0.247)
747	Industrial cleaning	-0.048 (0.147)
748	Miscellaneous business activities n.e.c.	0.207 (0.116)
751	Administration of the state and the economic and social policy (...)	0.143*** (0.033)
752	Provision of services to the community as a whole	0.210 (0.113)
753	Compulsory social security activities	0.504** (0.176)
801	Primary education	-0.840*** (0.213)
802	Secondary education	-0.036 (0.106)
803	Higher education	0.444** (0.169)
804	Adult and other education	0.296*** (0.086)
851	Human health activities	-0.158* (0.064)

Table A.2 (cont'd): Industry-specific Regressions

Industry Code	**Classification of Economic Activities 1993 (3-digit)**	*Struc* **- Coefficient**
852	Veterinary activities	0.123 (0.339)
853	Social work activities	-0.111 (0.069)
900	Sewage and refuse disposal, sanitation and similar activities	-0.152 (0.083)
911	Activities of business, employers' and professional organizations	0.675*** (0.119)
912	Activities of trade unions	2.212 (1.745)
913	Activities of other membership organizations	0.389*** (0.083)
921	Motion picture and video activities	0.654* (0.300)
922	Radio and television activities	0.016 (0.321)
923	Other entertainment activities	0.295 (0.183)
924	News agency activities	-0.708 (0.747)
925	Library, archives, museums and other cultural activities	0.432 (0.274)
926	Sporting activities	0.890** (0.326)
927	Other recreational activities	0.282 (0.329)
930	Other service activities	0.365 (0.188)
950	Private households with employed persons	-2.339 (1.351)
990	Extra-territorial organizations and bodies	0.645** (0.231)

Dep. Variable: Wage gap ($Q_{0.75}$-$Q_{0.25}$).

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.
All variables are logarithms, such that the coefficients can be interpreted as elasticities.

32 missing industries due to insufficient observations or confidentiality.

A.3 Robustness Checks

Table A.3: Pooled-OLS, Fixed-Effects and Random-Effects Estimation

Variables	Pooled-OLS				Fixed-Effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Structural Change								
Struc		0.7147***		0.7146***		0.4778***		0.4781***
		(0.0046)		(0.0046)		(0.0093)		(0.0094)
International trade								
Exports	0.0246***	0.0269***			0.0128***	0.0174***		
	(0.0049)	(0.0049)			(0.0036)	(0.0034)		
Imports			0.0646***	0.0652***			0.0295***	0.0332***
			(0.0038)	(0.0037)			(0.0029)	(0.0029)
Technological Progress								
R&D	0.0476***	0.0488***	0.0475***	0.0487***	0.0209***	0.0153***	0.0207***	0.0151***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Establishment Fixed-Effects	No	No	No	No	Yes	Yes	Yes	Yes
Industry Fixed-Effects	No	No	No	No	Yes	Yes	Yes	Yes
Year Fixed-Effects	No	No	No	No	Yes	Yes	Yes	Yes
Adj. R^2	0.1766	0.1923	0.1767	0.1924	0.7234	0.7257	0.7234	0.7257
No. of Obs.	1.87 Mill.	1.87 Mill.	1.87 Mill.	1.87 Mill.	1.87 Mill.	1.87 Mill.	1.87 Mill.	1.87 Mill.

Dep. Variable: Wage gap ($Q_{0.75}$-$Q_{0.25}$).

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.
All variables are logarithms, such that the coefficients can be interpreted as elasticities.

Table A.3 (cont'd): Pooled-OLS, Fixed-Effects and Random-Effects Estimation

Variables	Random-Effects			
	(9)	(10)	(11)	(12)
Structural Change				
Struc		0.5374***		0.5376***
		(0.0119)		(0.0119)
International trade				
Exports	0.0150**	0.0169**		
	(0.0059)	(0.0059)		
Imports			0.0330***	0.0319***
			(0.0052)	(0.0051)
Technological Progress				
R&D	0.0284***	0.0233***	0.0283***	0.0231***
	(0.0020)	(0.0020)	(0.0020)	(0.0020)
Other Controls	Yes	Yes	Yes	Yes
Establishment Fixed-Effects	No	No	No	No
Industry Fixed-Effects	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes
Adj. R^2	0.1635	0.1782	0.1636	0.1783
No. of Obs.	1.87 Mill.	1.87 Mill.	1.87 Mill.	1.87 Mill.

Dep. Variable: Wage gap ($Q_{0.75}$-$Q_{0.25}$).

Notes: Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All variables are logarithms, such that the coefficients can be interpreted as elasticities.

Table A.4: Fixed-Effects Estimation with clustered Standard Errors

Variables	Fixed-Effects Regression (1)	(2)	(3)	(4)
Structural Change				
Struc		0.4779***		0.4781***
		(0.0691)		(0.0691)
International trade				
Exports	0.0156	0.0175		
	(0.0152)	(0.0149)		
Imports			0.0320**	0.0332**
			(0.0172)	(0.0173)
Technological Progress				
R&D	0.0209***	0.0152***	0.0207***	0.0150***
	(0.0054)	(0.0057)	(0.0054)	(0.0057)
Other Controls	Yes	Yes	Yes	Yes
Establishment Fixed-Effects	Yes	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes
Adj. R^2	0.7248	0.7257	0.7248	0.7257
Root MSE	0.3504	0.3497	0.3504	0.3497
Prob > F	0.0000	0.0000	0.0000	0.0000
No. of Obs.	1.87 Mill.	1.87 Mill.	1.87 Mill.	1.87 Mill.

Dep. Variable: Wage gap ($Q_{0.75}$-$Q_{0.25}$).

Notes: Clustered standard errors (by industry) in parentheses,
*** p<0.01, ** p<0.05, * p<0.1.
All variables are logarithms, such that the coefficients
can be interpreted as elasticities.

Table A.5: Controlling for regional Heterogeneity

Variables	Fixed-Effects Regression			
	(1)	(2)	(3)	(4)
Struc	0.4779***	0.4781***	0.4781***	0.4783***
	(0.0691)	(0.0691)	(0.0692)	(0.0691)
Exports	0.0175		0.0173	
	(0.0149)		(0.0149)	
Imports		0.0332**		0.0331*
		(0.0173)		(0.0173)
R&D	0.0152***	0.0150***	0.0152***	0.0150***
	(0.0057)	(0.0057)	(0.0057)	(0.0057)
Control Variables:				
Establishment Size	0.0594***	0.0593***	0.0590***	0.0588***
	(0.0076)	(0.0075)	(0.0076)	(0.0076)
Share HQ empl.	0.0593***	0.0593***	0.0592***	0.0592***
	(0.0070)	(0.0070)	(0.0071)	(0.0070)
Share female empl.	0.4667***	0.4669***	0.4659***	0.4663***
	(0.0798)	(0.0797)	(0.07994)	(0.0798)
Other Controls	Yes	Yes	Yes	Yes
Establishment Fixed-Effects	Yes	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes
Regional Fixed-Effects	No	No	Yes	Yes
Adj. R^2	0.7257	0.7257	0.7259	0.7259
Root MSE	0.3497	0.3497	0.3495	0.3495
Prob > F	0.0000	0.0000	0.0000	0.0000
No. of Obs.	1.87 Mill.	1.87 Mill.	1.87 Mill.	1.87 Mill.

Dep. Variable: Wage gap ($Q_{0.75}$-$Q_{0.25}$).

Notes: Clustered standard errors (by industry) in parentheses,
*** p<0.01, ** p<0.05, * p<0.1.
All variables are logarithms, such that the coefficients
can be interpreted as elasticities.

Table A.6: Fixed-Effects Estimation for West Germany

	Overall Effect	Effects in Sub-Periods			Effects Within Sectors	
		1980-1990	1990-2000	2000-2010	Manufacturing	Services
	(1)	(2)	(3)	(4)	(5)	(6)
Structural Change						
Struc	0.4585***	0.3916***	0.4037***	0.4119***	0.7776***	0.1282***
	(0.0101)	(0.0238)	(0.0196)	(0.0206)	(0.0141)	(0.0143)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Establishment Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.6850	0.7502	0.7376	0.7532	0.7284	0.6584
Root MSE	0.3416	0.2765	0.3046	0.3219	0.2985	0.3631
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
No. of Obs.	1.55 Mill.	419.335	575.743	660.252	561.868	990.751

Dep. Variable: Wage gap ($Q_{0.75}$-$Q_{0.25}$).

Notes: Robust standard errors in parentheses,
*** p<0.01, ** p<0.05, * p<0.1.
All variables are logarithms, such that the coefficients can be interpreted as elasticities.

Appendix B

Appendix to Chapter 3

B.1 Industry-specific TFP Growth Within Sub-Periods

Table B.1: Industry-specific TFP Growth within Sub-Periods

Industry Code	**Industry**	**TFP Growth**			**Trend**
		1980-1989	**1990-1999**	**2000-2009**	
10-14	Mining and quarrying	-0.41%	1.64%	1.57%	↗
15-16	Food products, beverages and tobacco	-0.38%	-0.56%	-0.77%	↘
17-19	Textiles, wearing apparel, leather and related products	1.99%	2.50%	3.58%	↗
20-22	Wood and paper products; printing and reproduction of recorded media	0.01%	2.32%	1.77%	↗
23	Coke and refined petroleum products	1.33%	-7.35%	21.48%	↗
24	Chemicals and chemical products	2.16%	3.28%	5.10%	↗
25-26	Rubber and plastics products, and other non-metallic mineral products	1.20%	1.97%	3.11%	↗
27-28	Basic metals and fabricated metal products, except machinery & equipment	1.61%	2.62%	1.68%	→
29	Machinery and equipment n.e.c.	0.72%	0.89%	0.54%	→
30-33	Electrical and optical equipment	2.80%	2.71%	7.72%	↗
34-35	Transport equipment	0.18%	0.61%	2.76%	↗
36-37	Other manufacturing; repair and installation of machinery and equipment	0.71%	1.97%	3.37%	↗
40-41	Electricity, gas and water supply	-0.75%	0.22%	0.26%	↗
45	Construction	0.38%	-0.42%	-0.24%	↘
50	Wholesale and retail trade and repair of motor vehicles and motorcycles	2.93%	1.67%	2.21%	↘
51	Wholesale trade, except of motor vehicles and motorcycles	0.12%	1.02%	6.60%	↗
52	Retail trade, except of motor vehicles and motorcycles	0.91%	1.04%	-0.56%	↘
55	Accommodation and food service activities	-1.56%	-1.27%	0.25%	↗
60-63	Transport and storage	1.86%	2.96%	1.44%	↘
64	Postal and courier activities	0.46%	1.13%	-0.58%	↘
65-67	Financial and insurance activities	0.01%	1.65%	-0.86%	↘
70	Real estate activities	2.08%	1.33%	0.57%	↘
72	IT and other information services	-0.93%	-0.41%	1.28%	↗
73-74	Professional, scientific, technical, administrative and support services	-0.93%	-2.27%	-2.14%	↘
75	Public administration and defense; compulsory social security	0.59%	1.49%	0.86%	→
80	Education	1.32%	0.35%	-1.01%	↘
85	Health and social work	1.32%	1.21%	0.26%	↘
92	Arts, entertainment, recreation	-*	-1.46%	-0.83%	→
93	Other service activities	-*	0.56%	0.71%	→

Source: EU KLEMS database, author's computation.

* TFP data for these industries are only available from 1991 onwards.

B.2 Lagged Employment Effects of Annual TFP Growth Rates

Table B.2: Lagged Employment Effects of annual TFP Growth Rates (1980-2009)

Variables	Fixed-Effects Regression					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTFP_t	-0.0056 (0.0118)					
ΔTFP_{t-1}		0.0005 (0.0162)				
ΔTFP_{t-2}			-0.0230** (0.0111)			
ΔTFP_{t-3}				0.0094 (0.0125)		
ΔTFP_{t-4}					0.0206 (0.0175)	
ΔTFP_{t-5}						-0.0073 (0.0077)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.5174	0.5130	0.5176	0.5224	0.5324	0.5343
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
No. of Obs.	1365	1307	1250	1198	1147	1097

Dep. Variable: Employment growth in year t: ΔE_{it}.

Notes: Clustered standard errors (by industry) in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

B.3 Lagged Employment Effects of Annual TFP Growth Rates Within Sub-Periods

Table B.3: Lagged Employment Effects of annual TFP Growth Rates (1980-1989)

Variables	Fixed-Effects Regression					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTFP_t	-0.0077 (0.0601)					
ΔTFP_{t-1}		0.1025** (0.0437)				
ΔTFP_{t-2}			-0.0357 (0.0333)			
ΔTFP_{t-3}				-0.0450 (0.0320)		
ΔTFP_{t-4}					0.0657 (0.0508)	
ΔTFP_{t-5}						0.0304 (0.0375)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.3616	0.4357	0.4375	0.2952	0.3179	0.4077
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
No. of Obs.	463	413	364	318	272	228

Dep. Variable: Employment growth in year t: ΔE_{it}.

Notes: Clustered standard errors (by industry) in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table B.4: Lagged Employment Effects of annual TFP Growth Rates (1990-1999)

Variables	Fixed-Effects Regression					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \mathrm{TFP}_t$	-0.0007					
	(0.0129)					
$\Delta \mathrm{TFP}_{t-1}$		0.0149				
		(0.0124)				
$\Delta \mathrm{TFP}_{t-2}$			-0.0216**			
			(0.0094)			
$\Delta \mathrm{TFP}_{t-3}$				0.0454		
				(0.0655)		
$\Delta \mathrm{TFP}_{t-4}$					0.0578**	
					(0.0247)	
$\Delta \mathrm{TFP}_{t-5}$						-0.0600***
						(0.0174)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.5341	0.5240	0.5265	0.2099	0.2617	0.2393
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
No. of Obs.	540	487	434	383	334	286

Dep. Variable: Employment growth in year t: ΔE_{it}.

Notes: Clustered standard errors (by industry) in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Table B.5: Lagged Employment Effects of annual TFP Growth Rates (2000-2009)

Variables	Fixed-Effects Regression					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTFP_t	-0.0251 (0.0173)					
ΔTFP_{t-1}		-0.0302 (0.0311)				
ΔTFP_{t-2}			-0.0124 (0.0202)			
ΔTFP_{t-3}				-0.0586*** (0.0166)		
ΔTFP_{t-4}					-0.0156 (0.0269)	
ΔTFP_{t-5}						-0.0703*** (0.0268)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.2939	0.3751	0.4271	0.4959	0.4618	0.4881
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
No. of Obs.	458	407	356	305	254	203

Dep. Variable: Employment growth in year t: ΔE_{it}.

Notes: Clustered standard errors (by industry) in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

B.4 Dynamic Fixed-Effects Model

Table B.6: Dynamic Panel Estimation

Variables	Dynamic Panel Estimation (Fixed-Effects)					
	Overall			2000-2009		
	(1)	(2)	(3)	(4)	(5)	(6)
Two Lags						
Lagged Dep. Variable	-0.0098			-0.1161		
	(0.0536)			(0.0909)		
$\Delta\widehat{\text{TFP}}_{t-2}$	-0.0390*			-0.0124		
	(0.0228)			(0.0261)		
Three Lags						
Lagged Dep. Variable		-0.0424			-0.1818*	
		(0.0568)			(0.0999)	
$\Delta\widehat{\text{TFP}}_{t-3}$		-0.0631			-0.0908***	
		(0.0567)			(0.0346)	
Four Lags						
Lagged Dep. Variable			-0.0482			0.0335
			(0.0566)			(0.0931)
$\Delta\widehat{\text{TFP}}_{t-4}$			-0.0484			-0.1005*
			(0.1211)			(0.0600)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.5136	0.5187	0.5256	0.4349	0.4878	0.5287
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
No. of Obs.	1304	1247	1190	357	306	255

Dep. Variable: Employment growth in year t: ΔE_{it}.

Notes: Clustered standard errors (by industry) in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Appendix C

Appendix to Chapter 4

C.1 Structure of Blossfeld Occupational Groups in Manufacturing

Table C.1: Structure of Blossfeld occupational Groups in Manufacturing (**Source:** Blossfeld (1987))

Name of Occupational Group	**Description of the Occupational Group**	**Examples**
Production		
Unskilled manual occupations (EMB)	All manual occupations that showed at least 60 percent unskilled workers in 1970	Miners, rock breakers, paper makers, wood industry occupations, printing industry occupations, welders, unskilled workers, road and railroad construction workers
Skilled manual occupations (QMB)	All manual occupations that showed at most 40 percent unskilled workers in 1970	Glassblowers, bookbinders, typesetters, locksmiths, precision instrument makers, electrical mechanics, coopers, brewers
Technicians (TEC)	All technically trained specialists	Machinery technicians, electrical technicians, construction technicians, mining technicians
Engineers (ING)	Highly trained specialists who solve technical and natural science problems	Construction engineering, electrical engineers, production designers, chemical engineers, physicists, mathematicians

Table C.1 (cont'd): Structure Blossfeld occupational Groups in Manufacturing

Name of Occupational Group	**Description of the Occupational Group**	**Examples**
Service		
Unskilled services (EDB)	All unskilled personal services	Cleaners, security guards
Skilled services (QDB)	Essentially order and security occupations as well as skilled service occupations	Locomotive engineers, registrars
Semiprofessions (SEMI)	Service positions which are characterized by professional specialization	Interpreters, Educators
Professions (PROF)	All liberal professions and service positions which require a university degree	Statisticians, economists, social scientist
Administration		
Unskilled commercial and administrative occupations (EVB)	Relatively unskilled office and commerce occupations	Postal occupations, office hands, typists
Skilled commercial and administrative occupations (QVB)	Occupations with medium and higher administrative and distributive functions	Credit and financial assistants, foreign trade assistants, data processing operators, book-keepers, goods traffic assistants
Managers (MAN)	Occupations which control factors of production as well as functionaries of organizations	Managers, business administrators, deputies, CEOs

C.2 Detailed Description of the Matching Process

As the BHP does not include establishment-level information on trade activities, we merge the BHP with trade data obtained from the UN Comtrade database. To do so, we use the industry classification of the respective establishment in the BHP as identifier. Thus, we have to convert commodity imports and exports into industry imports and exports.

Index for Import Intensity

To generate import intensity at the industry-level, we use the Input Statistic to allocate the import value by commodity (from the UN Comtrade database) according to the input shares of this particular good in the industry production. The Input Statistic shows the use of commodity inputs at the 2- and 3-digit industry-level[1] and is published every four years from 1978 onwards. The BHP covers the years 1975-2010 such that we have to assume constant input structures for four years.

As both the product classifications of the import data and of the Input Statistic vary over the years, we use correspondence tables to reclassify the classification of the commodity trade into the classification of the commodity input. Table C.2 shows the process. Column 2 and column 7 show the product classification of the UN Comtrade import data[2] and the Input Statistic, respectively. Columns 3 to 6 depict the correspondence tables we use to reclassify the data. Partly, the correspondence tables are incomplete. In these cases, we directly allocate the import

[1] The level of commodity aggregation varies by industry. Hence, we need to aggregate commodities to the 2-digit level before allocating the import values to the various industries.

[2] Import commodities are classified at the 5-digit level for both SITC classifications and at the 6-digit level for HS classifications. In case of the SITC classification, import values are partly incomplete at the 5-digit level. Hence, we use 4-digit level import data (and 3-digit level import data for SITC1) for the remainder that is not included in the 5-digit data.

values into the correct Input Statistic classification "by hand" using the "Product Classifications for Production Statistics" (in German: Güterverzeichnis für Produktionsstatistiken) provided by the German Federal Statistical Office. Table C.7, Appendix C.6 gives an overview of the matching success before and after hand allocation. On average, we can match 99.18% of the imports.[3] As the analysis is restricted to the manufacturing sector, we additionally weigh the commodity import data with input shares in manufacturing. Input-output tables[4] provided by the German Federal Statistical Office show the share of imports used in manufacturing by commodity. Hence, we eliminate imports used for other purposes such as private, government or service consumption. After distributing the import values according to the input shares, we aggregate the import values by industry to obtain an index of import intensity for every industry. Finally, we convert the import intensity from the industry classification of the Input Statistic (Table C.2, column 8) into the industry classification of the BHP (Table C.2, column 9). Appendix C.3 contains an example of the commodities "Leather and Leather Manufactures" to illustrate the allocation process in 2000.

[3]Before hand allocation we can successfully match 64.35% of the import values.

[4]The Input-Output Statistic is only available from 1995 onwards. For earlier years we also use the Input-Output table of 1995 and thus assume a constant composition of import use for the years 1975-1995. A comparison of later years shows that import shares in manufacturing by commodity are rather stable. Thus it seems that our assumption is valid.

Index for Export Intensity

To generate export intensity, we follow a strategy that is very similar to the process described above. We use the Survey of Production to convert commodity exports into industry exports. The Survey of Production shows the output of industries at the 9-digit commodity-level. We allocate the export values by commodity according to the output shares of that particular good in the industry production. The matching process follows the method described above and is depicted in Table C.3. Column interpretation is identical except that columns 6 and 7 now show the Survey of Production rather than the Input Statistic. As the Survey of Production is only available from 1995 onwards, we also use the 1995 survey data to allocate exports for previous years. Thus we assume a constant output structure until 1995. On average, we can match 99.55% of the exports (see Table C.7, Appendix C.6).[5]

Index for Import Competition

To obtain coefficients for import competition, we again use the Survey of Production with the only difference that we allocate import values by commodity according to the output structure. Thus, again Table C.3 shows the reclassification of import classifications into output classification. On average, we can match 99.87% of all imports.

[5]Before hand allocation we can successfully match 63.14% of the export values.

Table C.2: Matching Process for Import Intensity Data

Import Data			Correspondence Tables								Input Statistic				BHP	
(1)	(2)		(3)		(4)		(5)		(6)		(7)		(8)		(9)	
Year	Product Classification		Correspondence 1		Correspondence 2		Correspondence 3		Correspondence 4		Product Classification	Year	Industry Classification		Industry Classification	Year
1975	SITC1	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	to	WI75	1978	Sypro	to	WZ93	1975
1976	SITC1	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	to	WI75	1978	Sypro	to	WZ93	1976
1977	SITC1	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	to	WI75	1978	Sypro	to	WZ93	1977
1978	SITC2	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	to	WI75	1978	Sypro	to	WZ93	1978
1979	SITC2	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	to	WI75	1978	Sypro	to	WZ93	1979
1980	SITC2	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	to	GP82	1982	Sypro	to	WZ93	1980
1981	SITC2	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	to	GP82	1982	Sypro	to	WZ93	1981
1982	SITC2	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	to	GP82	1982	Sypro	to	WZ93	1982
1983	SITC2	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	to	GP82	1982	Sypro	to	WZ93	1983
1984	SITC2	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	to	GP82	1986	Sypro	to	WZ93	1984
1985	SITC2	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	to	GP82	1986	Sypro	to	WZ93	1985
1986	SITC2	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	to	GP82	1986	Sypro	to	WZ93	1986
1987	SITC2	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	to	GP82	1986	Sypro	to	WZ93	1987
1988	SITC2	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	to	GP89	1990	Sypro	to	WZ93	1988
1989	SITC2	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	to	GP89	1990	Sypro	to	WZ93	1989
1990	SITC2	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	to	GP89	1990	Sypro	to	WZ93	1990
1991	HS 1992	to	Prodcom95	to	Prodcom94	to	GP95	to			GP89	1990	Sypro	to	WZ93	1991
1992	HS 1992	to	Prodcom95	to	Prodcom94	to	GP95	to			GP89	1994	Sypro	to	WZ93	1992
1993	HS 1992	to	Prodcom95	to	Prodcom94	to	GP95	to			GP89	1994	Sypro	to	WZ93	1993
1994	HS 1992	to	Prodcom95	to	Prodcom94	to	GP95	to			GP89	1994	Sypro	to	WZ93	1994
1995	HS 1992	to	Prodcom95	to	Prodcom94	to	GP95	to			GP89	1994	Sypro	to	WZ93	1995
1996	HS 1992	to	Prodcom95	to	Prodcom94	to					GP95	1998	WZ93	to	WZ93	1996
1997	HS 1992	to	Prodcom95	to	Prodcom94	to					GP95	1998	WZ93	to	WZ93	1997
1998	HS 1992	to	Prodcom95	to	Prodcom94	to					GP95	1998	WZ93	to	WZ93	1998
1999	HS 1992	to	Prodcom95	to	Prodcom94	to					GP95	1998	WZ93	to	WZ93	1999
2000	HS 1992	to	Prodcom95	to	Prodcom94	to	GP95	to			GP02	2002	WZ93	to	WZ93	2000
2001	HS 1992	to	Prodcom95	to	Prodcom94	to	GP95	to			GP02	2002	WZ93	to	WZ93	2001
2002	HS 2002	to	Prodcom2002	to							GP02	2002	WZ93	to	WZ93	2002
2003	HS 2002	to	Prodcom2002	to							GP02	2002	WZ93	to	WZ93	2003
2004	HS 2002	to	Prodcom2002	to							GP02	2006	WZ03	to	WZ03	2004
2005	HS 2002	to	Prodcom2002	to							GP02	2006	WZ03	to	WZ03	2005
2006	HS 2002	to	Prodcom2002	to							GP02	2006	WZ03	to	WZ03	2006
2007	HS 2002	to	Prodcom2002	to							GP02	2006	WZ03	to	WZ03	2007
2008	HS 2007	to	Prodcom2008	to							GP09	2010	WZ08	to	WZ08	2008
2009	HS 2007	to	Prodcom2008	to							GP09	2010	WZ08	to	WZ08	2009
2010	HS 2007	to	Prodcom2008	to							GP09	2010	WZ08	to	WZ08	2010

Notes:

For 1975-1977: 3-level Matching: SITC 1 trade data at 5-digit level; remainder at 4-digit and 3-digit level.
For 1978-1990: 2-level Matching: SITC 1 trade data at 5-digit level; remainder at 4-digit level.

Table C.3: Matching Process for Import Competition & Export Intensity Data

Export Data			Correspondence Tables						Survey of Production				BHP	
(1)	(2)		(3)		(4)		(5)		(6)		(7)		(8)	
Year	Product Classification		Correspondence 1		Correspondence 2		Correspondence 3		Product Classification	Year	Industry Classification		Industry Classification	Year
1975	SITC1	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	1995	WZ93	to	WZ93	1975
1976	SITC1	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	1995	WZ93	to	WZ93	1976
1977	SITC1	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	1995	WZ93	to	WZ93	1977
1978	SITC2	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	1995	WZ93	to	WZ93	1978
1979	SITC2	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	1995	WZ93	to	WZ93	1979
1980	SITC2	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	1995	WZ93	to	WZ93	1980
1981	SITC2	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	1995	WZ93	to	WZ93	1981
1982	SITC2	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	1995	WZ93	to	WZ93	1982
1983	SITC2	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	1995	WZ93	to	WZ93	1983
1984	SITC2	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	1995	WZ93	to	WZ93	1984
1985	SITC2	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	1995	WZ93	to	WZ93	1985
1986	SITC2	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	1995	WZ93	to	WZ93	1986
1987	SITC2	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	1995	WZ93	to	WZ93	1987
1988	SITC2	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	1995	WZ93	to	WZ93	1988
1989	SITC2	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	1995	WZ93	to	WZ93	1989
1990	SITC2	to	SITC3	to	Prodcom95	to	Prodcom94	to	GP95	1995	WZ93	to	WZ93	1990
1991	HS 1992	to	Prodcom94	to					GP95	1995	WZ93	to	WZ93	1991
1992	HS 1992	to	Prodcom94	to					GP95	1995	WZ93	to	WZ93	1992
1993	HS 1992	to	Prodcom94	to					GP95	1995	WZ93	to	WZ93	1993
1994	HS 1992	to	Prodcom94	to					GP95	1995	WZ93	to	WZ93	1994
1995	HS 1992	to	Prodcom94	to					GP95	1995	WZ93	to	WZ93	1995
1996	HS 1992	to	Prodcom94	to					GP95	1996	WZ93	to	WZ93	1996
1997	HS 1992	to	Prodcom94	to					GP95	1997	WZ93	to	WZ93	1997
1998	HS 1992	to	Prodcom94	to					GP95	1998	WZ93	to	WZ93	1998
1999	HS 1992	to	Prodcom94	to					GP95	1999	WZ93	to	WZ93	1999
2000	HS 1992	to	Prodcom94	to					GP95	2000	WZ93	to	WZ93	2000
2001	HS 1992	to	Prodcom94	to					GP95	2001	WZ93	to	WZ93	2001
2002	HS 2002	to	Prodcom2002	to					GP02	2002	WZ93	to	WZ93	2002
2003	HS 2002	to	Prodcom2002	to					GP02	2003	WZ03	to	WZ03	2003
2004	HS 2002	to	Prodcom2002	to					GP02	2004	WZ03	to	WZ03	2004
2005	HS 2002	to	Prodcom2002	to					GP02	2005	WZ03	to	WZ03	2005
2006	HS 2002	to	Prodcom2002	to					GP02	2006	WZ03	to	WZ03	2006
2007	HS 2002	to	Prodcom2002	to					GP02	2007	WZ03	to	WZ03	2007
2008	HS 2002	to	Prodcom2002	to					GP02	2008	WZ03	to	WZ03	2008
2009	HS 2007	to	Prodcom2008	to	Prodcom2009	to			GP09	2009	WZ08	to	WZ08	2009
2010	HS 2007	to	Prodcom2008	to	Prodcom2009	to			GP09	2010	WZ08	to	WZ08	2010

Notes:

For 1975-1977: 3-level Matching: SITC 1 trade data at 5-digit level; remainder at 4-digit and 3-digit level.
For 1978-1990: 2-level Matching: SITC 1 trade data at 5-digit level; remainder at 4-digit level.

C.3 Example Allocation of Imports of "Leather and Leather Manufactures" to the Industries of the BHP

This section provides an example of creating trade data at the industry-level by using input-output information. Here, we present the example of "Leather and Leather Manufactures" imports including footwear (in German: Leder und Lederwaren, "Leather" in the following).

"Our Approach"

Figure C.1 shows a pie chart that depicts how we allocate imported leather commodities to various industries. Using the Input Statistic, we allocate leather imports to 17 industries in which leather products are used as inputs. All industries that receive less than 0.5% of the import values are summarized as "Rest". Table C.4 shows the allocation structure in detail. The column "Share" shows the share of leather imports that is allocated to each industry given in the column "Industry". This share is identical to the share of leather inputs that is used in these industries.

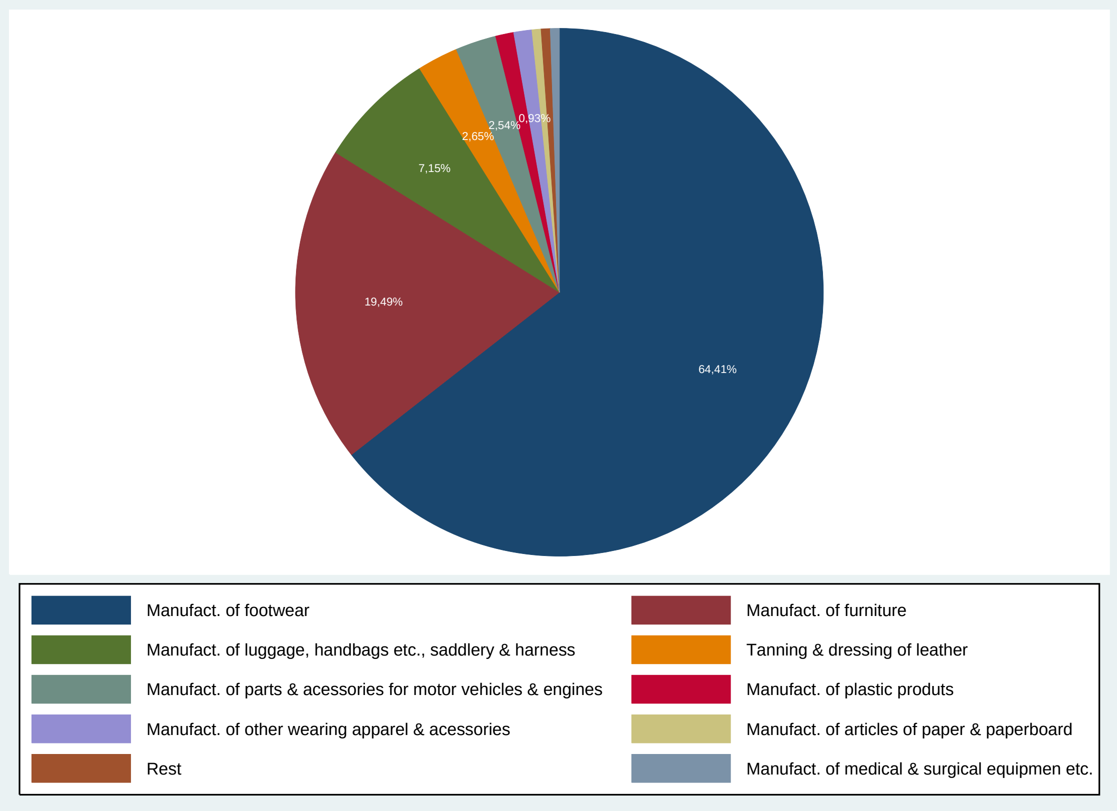

Figure C.1:
Allocation of Leather Imports to the Industries of the BHP (in 2000)
Source: UN Comtrade database and Input Statistic, authors' computation.

Table C.4: Allocation of Leather Imports to the Industries of the BHP (in 2000)

GP 95	WZ 1993	Share	Industry
19	102	0.00026313	Mining and agglomeration of lignite
19	174	0.00136164	Manufacture of made-up textile articles, except apparel
19	175	0.00033050	Manufacture of other textiles
19	182	0.00927598	Manufacture of other wearing apparel and accessories
19	191	0.02651121	Tanning and dressing of leather
19	192	0.07146845	Manufacture of luggage, handbags and the like (...)
19	193	0.64408863	Manufacture of footwear
19	212	0.00616514	Manufacture of articles of paper and paperboard
19	221	0.00040870	Publishing
19	222	0.00072203	Printing and service activities related to printing
19	252	0.01072427	Manufacture of plastic products
19	286	0.00135952	Manufacture of cutlery, tools and general hardware
19	331	0.00556807	Manufacture if medical and surgical equipment (...)
19	343	0.02539422	Manufacture of parts and accessories for motor vehicles (...)
19	361	0.19478314	Manufacture of furniture
19	365	0.00027423	Manufacture of games and toys
19	366	0.00130114	Miscellaneous manufacturing n.e.c.

Notes:

This example presents how we allocate leather imports (product classification "GP 95" = 19) to all industries that use leather as inputs according to the Input Statistic.

Source: UN Comtrade database and Input Statistic, authors' computation.

C.4 Example Allocation of Exports of "Leather and Leather Manufactures" to the Industries of the BHP

"Our Approach"

Figure C.2 depicts how we allocate leather exports to industries and Table C.5 shows the allocation structure in detail. The interpretation is identical with Figure C.1 and Table C.4 for the imports. Using the Survey of Production, we identify 24 industries that produce leather goods and thus receive a share of the allocated leather exports.

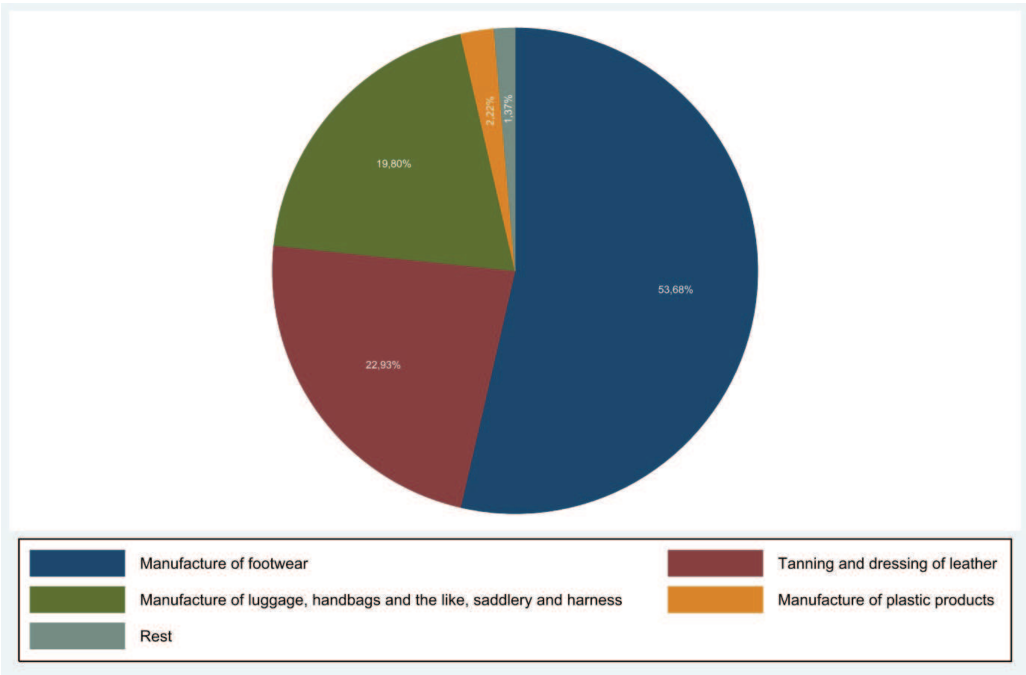

Figure C.2:
Allocation of Leather Exports to the Industries of the BHP (in 2000)
Source: UN Comtrade database and Survey of Production, authors' computation.

Table C.5: Allocation of Leather Exports to the Industries of the BHP (in 2000)

GP 95	WZ 1993	Share	Industry
19	174	0.0024244	Manufacture of made-up textile articles, except apparel
19	175	.*	Manufacture of other textiles
19	177	.*	Manufacture if knitted and crocheted articles
19	182	0.0003852	Manufacture of other wearing apparel and accessories
19	191	0.2293406	Tanning and dressing of leather
19	192	0.1979861	Manufacture of luggage, handbags and the like (...)
19	193	0.5367885	Manufacture of footwear
19	212	0.0009021	Manufacture of articles of paper and paperboard
19	221	.*	Publishing
19	222	.*	Printing and service activities related to printing
19	246	.*	Manufacture of other chemical products
19	247	.*	Manufacture of man-made fibers
19	251	0.0003326	Manufacture of rubber products
19	252	0.0222259	Manufacture of plastic products
19	261	.*	Manufacture of glass and glass products
19	291	.*	Manufacture of machinery for the production and use of mechanical power
19	292	.*	Manufacture of other general purpose machinery
19	295	.*	Manufacture of other special purpose machinery
19	331	0.0006351	Manufacture of medical and surgical equipment (...)
19	332	.*	Manufacture of instruments and appliances for measuring (...)
19	343	.*	Manufacture of parts and accessories for motor vehicles (...)
19	354	.*	Manufacture of motorcycles and bicycles
19	361	.*	Manufacture of furniture
19	366	.*	Miscellaneous manufacturing n.e.c.

Notes:

This example presents how we allocate leather exports (product classification "GP 95" = 19) to all industries that produce leather goods according to the Survey of Production.

* 15 missing industries due to confidentiality (insufficient number of firms that produce leather goods within these industries).

Source: UN Comtrade database and Survey of Production, authors' computation.

C.5 "Traditional" Allocation Approach

Figure C.3 and the corresponding Table C.6 show the allocation of leather imports or leather exports following the standard way to use correspondence tables (here taken from the UN Statistics Division, as e.g. by Altomonte et al. (2013) and Dauth, Findeisen & Südekum (2012) among many). The results differ a lot compared to our approach. Not only is commodity trade merely allocated to four industries, but also - except the industry of "Manufacturing of Footwear" - these industries do not seem to be the most relevant ones judging by the input and output structure. Accordingly, we argue that using input and output tables rather than correspondence tables, we are able to allocate imports much more accurately.

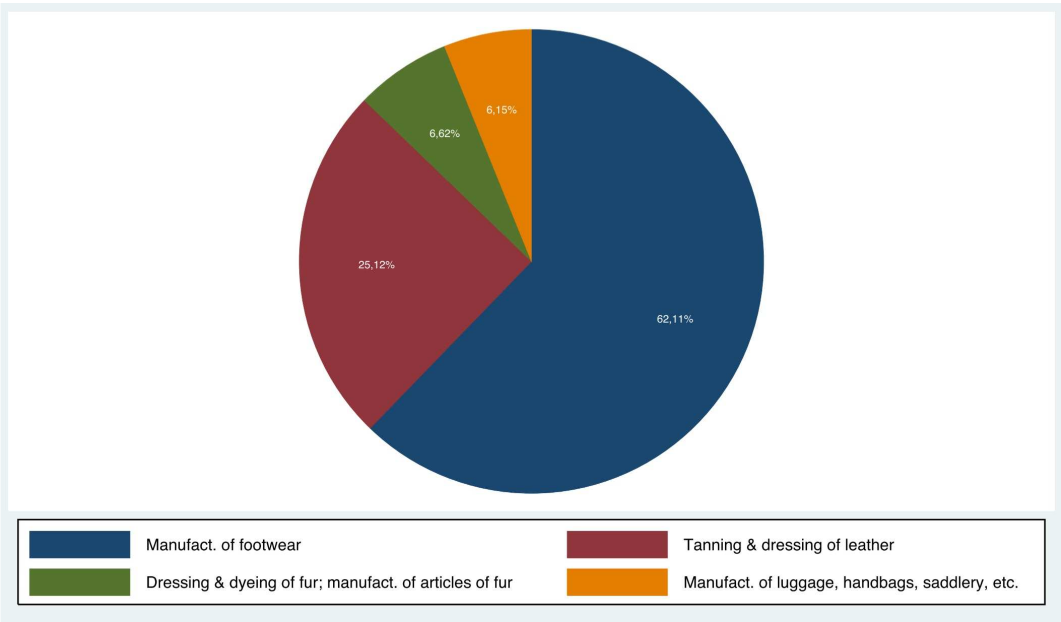

Figure C.3:
Allocation of Leather Imports and Exports to the Industries of the BHP in 2000 ("Traditional Approach")
Source: UN Comtrade database and UN Statistics Division, authors' computation.

Table C.6: Allocation of Leather Imports to the Industries of the BHP (in 2000)

SITC, Rev. 3	WZ 1993	Share	Industry
61 & 85	191	0.25124481	Tanning and dressing of leather
61 & 85	192	0.06148816	Manufacture of luggage, handbags and the like, saddlery and harness
61 & 85	183	0.06618976	Dressing and dyeing of fur; manufacture of articles of fur
61 & 85	193	0.62107728	Manufacture of footwear

***Notes*:**

This example presents the "traditional" matching procedure of leather imports. Here, we combine the SITC, Rev. 3 commodity groups 61 ("Leather, Leather Manufactures, n.e.s., and dressed Furskins") and 85 ("Footwear"). Thus, this commodity group contains the same goods as the "GP 95" group above.

Source: UN Comtrade database and UN Statistics Division, authors' computation.

C.6 Comparison of Matched Commodity Trade Data Before and After Hand Allocation

Table C.7: Matched Commodity Trade Flows before and after Hand Allocation

Year	**Imports**				**Exports**	
	Intensity		**Competition**			
	After Hand Allocation	**Before Hand Allocation**	**After Hand Allocation**	**Before Hand Allocation**	**After Hand Allocation**	**Before Hand Allocation**
1975	98.54%	43.05%	98.59%	43.24%	97.88%	68.64%
1976	98.44%	42.75%	98.55%	43.00%	98.24%	68.75%
1977	98.21%	48.09%	98.46%	48.48%	98.42%	69.70%
1978	99.30%	45.67%	99.96%	46.37%	99.95%	54.81%
1979	99.38%	44.88%	99.96%	45.50%	99.95%	54.83%
1980	99.73%	43.97%	99.97%	44.24%	99.95%	54.39%
1981	99.76%	42.41%	99.97%	42.65%	99.92%	53.21%
1982	99.76%	42.34%	99.97%	42.57%	99.93%	52.33%
1983	99.75%	43.56%	99.97%	43.81%	99.94%	52.45%
1984	99.76%	44.35%	99.97%	44.59%	99.96%	52.36%
1985	99.74%	44.35%	99.97%	44.61%	99.95%	52.58%
1986	99.72%	48.79%	99.97%	49.07%	99.96%	53.17%
1987	99.73%	49.64%	99.97%	49.91%	99.96%	52.61%
1988	95.15%	48.44%	99.97%	51.46%	99.97%	53.48%
1989	95.45%	48.51%	99.98%	51.41%	99.97%	52.85%
1990	95.13%	47.48%	99.97%	50.60%	99.97%	52.98%
1991	99.89%	60.25%	100.00%	60.45%	100.00%	61.35%
1992	99.87%	61.08%	100.00%	61.22%	100.00%	60.92%
1993	99.89%	61.52%	100.00%	61.47%	100.00%	60.10%
1994	99.86%	62.31%	100.00%	62.26%	100.00%	61.16%
1995	99.88%	63.50%	100.00%	63.43%	100.00%	61.31%
1996	100.00%	78.86%	100.00%	61.51%	100.00%	60.85%
1997	100.00%	78.45%	100.00%	60.91%	100.00%	61.19%
1998	98.63%	80.69%	100.00%	62.05%	100.00%	61.50%
1999	100.00%	80.83%	100.00%	62.43%	100.00%	60.68%
2000	99.52%	78.28%	100.00%	60.63%	100.00%	58.88%
2001	99.49%	77.78%	100.00%	61.00%	100.00%	60.91%
2002	99.46%	93.36%	100.00%	78.98%	100.00%	76.70%
2003	99.48%	93.51%	100.00%	79.18%	100.00%	73.61%
2004	99.50%	93.78%	100.00%	79.40%	100.00%	73.32%
2005	99.54%	93.72%	100.00%	78.57%	100.00%	75.52%
2006	99.59%	93.67%	100.00%	78.40%	100.00%	74.75%
2007	99.56%	93.20%	100.00%	76.32%	100.00%	71.87%
2008	99.60%	79.86%	100.00%	76.11%	100.00%	71.67%
2009	99.56%	82.19%	100.00%	80.70%	94.99%	93.87%
2010	99.65%	81.38%	100.00%	79.90%	94.96%	93.84%
Average	99.18%	64.35%	99.87%	59.07%	99.55%	63.14%

Notes:

In the years from 2002 to 2010 we eliminate imports classified as HSCode 999999 "Commodities not specified according to kind" since we are not able to match these imports with commodities in the Input Statistic at all.

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Eidesstattliche Erklärung

Ich erkläre hiermit an Eides Statt, dass ich meine Doktorarbeit mit dem Titel "Structural Change, Wage Inequality, and the Occupational Mix of Firms: Evidence from German Micro Data" selbstständig und ohne fremde Hilfe angefertigt habe und dass ich alle von anderen Autoren wörtlich übernommenen Stellen, wie auch die sich an die Gedanken anderer Autoren eng anlehnenden Ausführungen meiner Arbeit, besonders gekennzeichnet und die Quellen nach den mir angegebenen Richtlinien zitiert habe.

Ich versichere an Eides statt, dass ich mich an keiner anderen Fakultät einer Doktorprüfung unterzogen habe. Meine Prüfung zum Diplom-Volkswirt habe ich an der Christian-Albrechts-Universität zu Kiel abgeschlossen.

Kiel, 16.04.2015

Philipp Henze

Hilfsmittel

Die Aufbereitung der Daten für diese Dissertation am Forschungsdatenzentrum (FDZ) der Bundesagentur für Arbeit (BA) im Institut für Arbeitsmarkt- und Berufsforschung (IAB) in Nürnberg, am Statistischen Landesamt Bremen sowie per Datenfernverarbeitung aus Kiel erfolgte mit "STATA 11" und "STATA 12". Die Datenerhebung sowohl für deskriptive Statistiken als auch die Regressionsanalyse wurde ebenfalls mit diesen Programmen durchgeführt. Einige Ergebnisse wurden für die deskriptiven Statistiken mit "Microsoft Excel" weiterverarbeitet. Das vorliegende Dokument, einschließlich aller Tabellen und Verzeichnisse, wurde schließlich mit "MikTex 2.7" erstellt.

Kiel, 16.04.2015

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Curriculum Vitae

Education

06/2015	Doctoral Degree in Economics Kiel University
04/2010-06/2015	Ph.D. Studies in Economics Kiel University, Doctoral-Programme "Quantitative Economics"
10/2005-04/2010	Diploma in Economics Kiel University, Specialization: "International Economics"

Working Experience

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