Skill Adaptation to Shifting Job Tasks in the German Labor Market

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Abstract

Technical change and offshoring alter the demand for the performance of production tasks at which different skill groups have comparative advantages. As some tasks are substituted whereas others are complemented by new technology and foreign labor, there are shifts in wages, employment, and skills. These shifts are commonly studied at rather aggregate levels. This thesis complements the existing literature by studying shifts in tasks and skill adaptation that take place within jobs in the context of the German labor market. It can be shown that for the particularly vulnerable group of low-skill manufacturing workers training that is aimed at adaptation to offshoring-induced job task shifts may enable workers to benefit from the gains of offshoring. On-the-job training is discussed as an instrument to antagonize rising labor market polarization that can take effect in the short term.

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List of Acronyms

ERM European Restructuring Monitor

IAB German Institute for Employment Research

ICT information and communication technology

ISCED International Standard Classification of Education

ISIC International Standard Industrial Classification

KldB German occupational classification

NACE Nomenclature of Economic Activities

RBTC routine-biased technical change

SOEP German Socio Economic Panel

SME small and medium-sized enterprise

MB marginal benefit

MC marginal cost

WeGebAU Förderung der Weiterbildung Geringqualifizierter und beschäftigter älterer Arbeitnehmer in Unternehmen

Chapter 1

Introduction

Concerns are raised in both public and scholar debates that jobs and wages of low- and medium-skilled workers in advanced countries are under increasing pressure given rapid automation and offshoring of production tasks.[1] Especially workers who perform tasks that are rather substituted than complemented by either new technologies or foreign labor are considered to be negatively affected. These concerns have been fueled mainly by estimations based on occupation-level data on job task content (see, e.g., Frey and Osborne (2017), Oldenski (2014), Blinder (2009), Firpo et al. (2011), and Jensen and Kletzer (2010)). Looking at the job level instead, Arntz et al. (2017) demonstrate that, at least for the risk of automation in the US, there is a serious upward bias in occupation-level estimates. They argue that this may be due to workers increasingly shifting to tasks that are complemented rather than substituted by new technologies. While some workers may become displaced, others may adjust the tasks they perform on-the-job. It is these shifts in tasks - shifts that happen within jobs - that are of primary interest in this work.

Aggregate task shifts are in the focus of much recent work on the wage and employment effects of technical change and offshoring, especially since the rise of the so-called task-based approach to labor markets where tasks and skills are conceptually distinguished. Task shifts within occupations and within jobs have in turn hardly been studied. One notable exception is the study of Fedorets (2018) that assesses the wage effects of occupational task shifts, though without

[1] Technological anxiety is not a new phenomenon. Mokyr et al. (2015) review the history of technological anxiety and draw a comparison of historical with contemporary manifestations. In their words, the “developed world it is now suffering from another bout of [...] angst” (p.31).

explicitly linking task shifts to their potential sources. A major difficulty that may explain the shortage of research in this direction is the limited availability of joint data on job tasks and wages on the one hand and a general sparsity of time-variant data on job tasks on the other hand.[2]

In the face of rising opportunities for automation and offshoring, workers' wages are affected in a number of ways. There is increasing wage pressure as workers increasingly have to compete with machines, foreign labor, and other workers that have already been displaced from their jobs. At the same time, both technical progress and increasing international integration give rise to considerable aggregate gains. Who participates in these gains is, on the one hand, a matter of economic mechanisms, and, on the other hand, a matter of policy. A potential economic mechanism that has, to the best of my knowledge, not yet been studied, but is particularly tangible for policy interventions is the upgrading of tasks and skills given that firms' internal valuation of tasks shifts in the face of new opportunities for automation and offshoring.

When workers' job tasks change, it may become necessary or worthwhile to adapt the respective skills. Skill adaptation can take the form of learning-by-doing or further professional training, of which the latter is of primary interest in the current study. For a firm, assigning new tasks to an employee may be feasible only in combination with training. At the same time, when a worker takes over new tasks that have become more valuable to the firm, investment in human capital that was not economically viable, may become feasible. Low-skilled manufacturing workers are often considered to be particularly vulnerable to automation and offshoring. Training participation is usually found to be generally lower for low-skilled workers than for high-skilled workers, but is nevertheless common. Of those low-skilled manufacturing workers who receive training, about three out of four receive training to help them adapt to shifting job tasks.[3]

The present work contributes to the literature on the labor market effects of technical change and offshoring in three ways. First, it provides insights into the economic mechanisms behind task shifts with skill upgrading at the individual level and embeds these mechanisms in a broad discussion of literature.[4]

[2] See section 7.1 for a discussion of available data sources for Germany.

[3] See section 2.6 for stylized facts on training participation.

[4] I use the term skill upgrading to denote individuals' accumulation of human capital. Other authors have used this term to refer to the performance of tasks by higher-skilled individuals, which does not necessarily imply human capital accumulation (see, e.g., Costinot and Vogel, 2010).

Second, it provides a first empirical assessment of the degree to which task shifts with skill upgrading affect workers' wages. In the context of offshoring, it can be shown that training that is aimed at adaptation to shifting job tasks may enable workers to benefit from the gains of offshoring. Third, it points out challenges for policies that aim at counteracting the negative and augmenting the positive effects of technical change and offshoring. While this work is focused on the German labor market, conceptual considerations are transferable to other advanced economies facing task demand shifts.

The thesis is outlined as follows. In the second chapter, I give an overview of the development of job tasks, wages, employment, shifting workplace requirements, and training participation in the German labor market. In the third chapter, I start out by sketching conceptual approaches that have been influential in the study of aggregate technology- and offshoring-related shifts in labor markets, and complement the conceptual background by elaborating a simple conceptual framework to depict individual-level task shifts with skill upgrading. The forth chapter contains a review of controversies over the role of skill demand shifts in rising inequality and polarization. The fifth and sixth chapter are devoted to the details on skill-biased technical change and offshoring as major drivers behind skill demand shifts. In each of the two chapters I first show some stylized facts for the respective phenomenon and then summarize the theoretical literature and empirical findings on how this phenomenon affects workers' labor market outcomes. In the seventh and eights chapter I empirically investigate the potential of skill adaptation to enable participation in the gains from technical change and offshoring. The ninth chapter concerns policy related considerations of skill upgrading in the context of rising inequality. It is followed by a general conclusion.

Chapter 2

Stylized Facts on the Structure of and Shifts in the German Labor Market

The prevalence of some occupational tasks has declined over the past years whereas other tasks have gained in importance. Along with occupational tasks, also the structure of wages as well as employment have shifted. These changes in the labor market can be read as a manifestation of aggregate task demand shifts, which can be, among other factors, induced by technical change or offshoring.[1] Occupational tasks differ in their susceptibility to be substituted by machines or by foreign labor and are thus not equally affected by technical change and offshoring.

Demand shifts may affect the aggregate composition of tasks in a number of ways. Task shifts have been studied as a phenomenon that may be driven by sectoral shifts, such as from the manufacturing sector towards the service sector (Autor and Dorn, 2013), via market entry and exit of firms using different task inputs (Fonseca et al., 2018), or by shifts between or within occupations (Spitz-Oener, 2006). At an even lower level, task shifts can take place within jobs. In the following, some stylized facts shall be presented to give an overview of occupational tasks, employment, and wages in the German labor market and how these have shifted.[2]

[1] See chapter4 for a broader discussion of alternative forces behind shifts in the labor market.

[2] An overview of data sources used for own calculations is provided in Appendix A.

Some conceptual clarifications shall be forestalled at this point. It will be shown in the following that some skill groups and specific occupational groups are more strongly affected by automation and offshoring. These relationships derive from the nature of tasks performed by these groups and the context rather than from a direct relationship between skills and substitutability, occupations and substitutability, or jobs and substitutability. It is tasks that are being automated or offshored, not necessarily jobs.

As will be discussed in more detail later in sections 5.2 and 5.3, routine tasks are usually considered to be more susceptible to automation because these can be codified and thus replaced by automated routines whereas other tasks can are complemented (Autor et al., 2003). At the same time, routineness may affect offshorability, which is discussed further in section 6.2. Apart from non-routineness, also the need for face-to-face interaction and on-site work as well as decision-making and problem-solving are considered to make tasks less easily automated or offshored (Firpo et al., 2011).

When tasks that can be performed by machines or be performed abroad are not uniformly distributed across skill or occupational groups, the substitution of tasks can translate into shifts in the wage structure, unequal changes in the incidence of unemployment, or shifts in the aggregate employment structure (Freeman and Katz, 1995; Goos et al., 2014; Krugman, 1994). Substitutable tasks are relatively prevalent among low- and medium-skilled workers, so that demand shifts are likely to raise overall inequality as well as inequality and/or unemployment within these skill segments. At the same time, low wages in the low-skill segment may render the substitution of technically substitutable tasks economically gainless. Thus, rising inequality and labor market polarization is driven by technological possibilities on the one hand and economic conditions on the other hand.

2.1 The Nature of Tasks

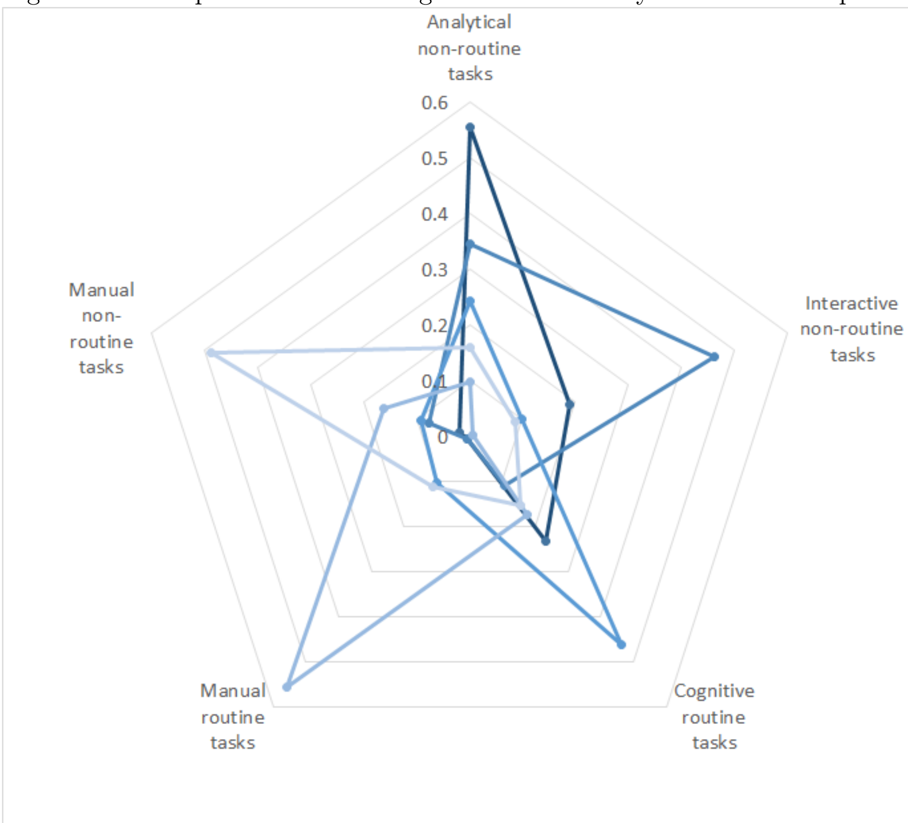
The currently most common classification of tasks was developed by Autor et al. (2003) using US data. Spitz-Oener (2006) use this classification to study the development of tasks in the German labor market based on survey data. They provide a mapping of specific activities to task categories as shown in Table 2.1. A major distinction is made between routine and non-routine tasks. They differ in the degree to which they can be accomplished by following explicit rules.

Table 2.1: Mapping of Activities to Task Categories

Task category	Activities
Non-routine analytic	Researching, analyzing, evaluating and planning, making plans/constructions, designing, sketching, working out rules/prescriptions, constructions,
Non-routine interactive	Negotiating, lobbying, coordinating, organizing, teaching or training, selling, buying, advising customers, advertising, entertaining or presenting, and employing or managing personnel
Routine cognitive	Calculating, bookkeeping, correcting texts/data, and measuring length/weight/temperature
Routine manual	Operating or controlling machines and equipping machines
Non-routine manual	Repairing or renovating houses/apartments/ machines/vehicles, restoring art/monuments, and serving or accommodating

Note: Based on Spitz-Oener (2006).

Figure 2.1: Occupational Task Configurations in 2013 by Main Task Component



Note: Own calculations based on Dengler et al. (2014) data for the year 2013. Occupation weights for aggregation retrieved from German Socio Economic Panel (SOEP) 2013.

In contrast to Spitz-Oener (2006), Dengler et al. (2014) construct task measures following the classification of Autor et al. (2003) based on expert-coded data from the German BERUFENET database rather than based on survey data. Figure 2.1 gives an overview of occupational task configurations in the German labor market for the year 2013 depending on the dominant task component. The five axes of the radar chart represent the intensity indices for the five task classifications. Five configurations are shown - one for each dominant task component. These shall be investigated subsequently in clockwise direction.

Starting with occupations in which analytic non-routine tasks are most important, these occupations hardly involve any manual task content, neither routine nor non-routine. This configuration includes occupations such as lawyer, computer scientist, and architect. The dominance of analytical non-routine tasks is very pronounced as also the intensities of interactive non-routine tasks and cognitive routine tasks are relatively low. For these occupations, the intensity of analytical non-routine tasks is more than twice as high as the intensity of any other tasks. Occupations in which interactive non-routine tasks are most important, such as child care worker, nurse, and marketing expert, in turn also involve a comparably high analytical non-routine task content. The intensities of other tasks are relatively low. Similarly, for occupations in which cognitive routine tasks are dominant, such as technician, accountant, and biologist, the analytical non-routine task content is relatively high whereas other task intensities are comparably low. For these first three occupational configurations, analytical non-routine tasks thus seem to be of relatively high importance. For occupations that are dominated by routine manual tasks, such as textile worker, pressman, and welder, the dominance is rather strong as other task intensities are very low in comparison. Also for occupations dominated by manual non-routine tasks, such as cleaner, security guard, and caterer, other task intensities are comparably low.

When it is tasks that are being substituted by machines or foreign labor rather than occupations or jobs, the configuration of tasks within occupations and within jobs are likely to change. As substitutable task content decreases, human resources are likely to be reallocated to other task categories.

2.2 Aggregate Development of Tasks over Time

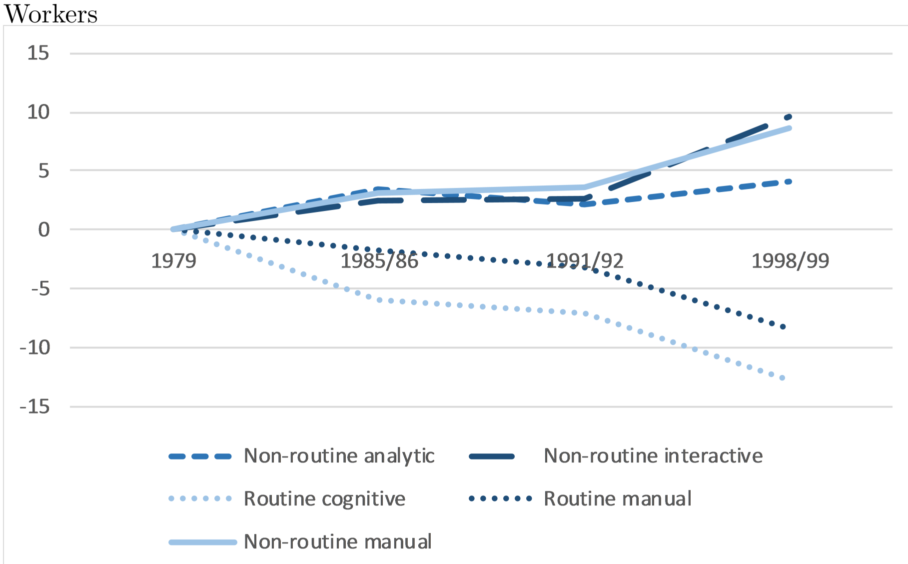
The aggregate development of tasks in the German labor market is depicted separately for workers with different educational levels in Figures 2.2, 2.3, and 2.4.[3] The task measures are based on Spitz-Oener (2006). While later data of the original data source (BIBB/IAB Qualification and Career Survey) and the follow-up survey (BIBB/BAuA Employment Survey) are available, forward projection to more recent years is limited by comparability of items over time and an unclear mapping between items reflecting specific activities and task categories.

Figure 2.2 depicts the development of low-skilled workers' tasks. Low-skilled workers are defined as workers without occupational training. The intensity of routine tasks, both cognitive and manual, has decreased by about 10 percentage

[3]Note that the classification of workers into qualification groups differs from the classification later used in the empirical analyses.

points between 1979 and 1998/99. At the same time, non-routine task content increased. Thereof, analytic task content increased by almost 5 percentage points and interactive and manual content increased by almost 10 percentage points.

Figure 2.2: Percentage Point Changes in Aggregate Task Inputs, Low-Skilled Workers

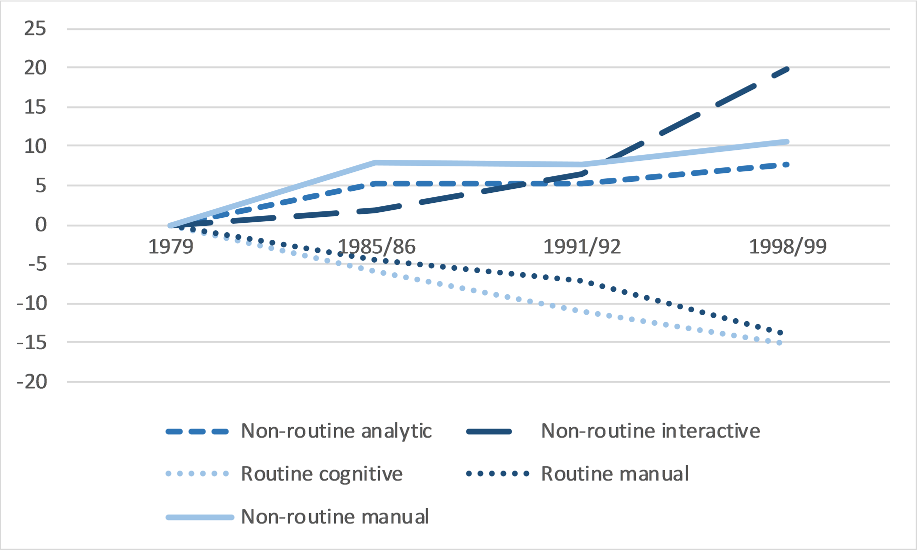


Note: Based on Spitz-Oener (2006).

The development for medium-skilled workers, defined as workers with a vocational qualification who may have completed an apprenticeship or graduated from a vocational college, is shown in Figure 2.3. The development of routine tasks and non-routine analytic and manual tasks strongly resembles the development for low-skilled workers, but the rise in non-routine interactive tasks is about twice as high as for low-skilled workers.

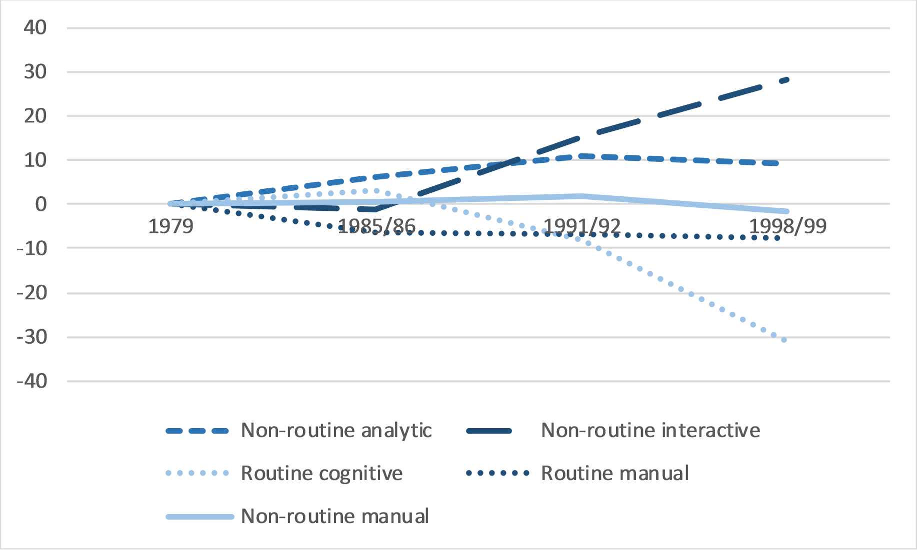
Finally, the development of tasks of high-skilled workers is depicted in Figure 2.4. High-skilled workers are defined as workers holding a degree from a university or technical college. For them, the intensity of non-routine manual tasks has hardly changed. Routine task content has decreased strongly with a decline by about 10 percentage points for manual tasks and 30 percentage points for cognitive tasks. Non-routine analytic task content has increased by 10 percentage points and non-routine interactive task content has increased by about thirty percentage point.

Figure 2.3: Percentage Point Changes in Aggregate Task Inputs, Medium-Skilled Workers



Note: Based on Spitz-Oener (2006).

Figure 2.4: Percentage Point Changes in Aggregate Task Inputs, High-Skilled Workers



Note: Based on Spitz-Oener (2006).

While it may appear that the trends have intensified between 1991/92 and 1998/99, concerns have been raised about inconsistencies between the surveys in terms of the surveys' reference population, the mode of interrogation, inconsistencies in the survey design, and the choice of items (Dengler et al., 2014). Rohrbach-Schmidt and Tiemann (2013) reassess the comparability of task measures used by (Spitz-Oener, 2006). They caution that the importance of the documented decreases in routine cognitive tasks should not be overemphasized because of measurement issues and concerns about the practical definition of routine-cognitive tasks.

2.3 Development of Wages

Many advanced countries have experienced rising wage inequality since the beginning of the 1980s. While in the US, the rise in inequality was particularly pronounced in the 1980s, similar developments have taken place in Germany about one decade later (Dustmann et al., 2009). Figure 2.5 shows the developments of the 10th, 50th, and 90th percentile of the wage distribution in Germany since 1993.[4] During the 1990s, the wage at the 10th percentile grew relatively stronger than the wages at the median and at the 90th percentile. This has changed during the 2000s. Especially between 1996 and 2006, growth in the wage at the 10th percentile has been rather low.

Baumgarten (2013) investigates the development of wages of German male manufacturing workers between 1996 and 2007 both between and within groups. He provides a detailed overview of changes in wage inequality based on data from linked employer-employee data provided by the Institute for Employment Research (IAB). Table 2.2 shows his measured changes in log wage inequality. He finds that the between-skill component of wage inequality has grown over time, but most of the increase in inequality between 1996 and 2007 was due to shifts within skill groups (64 percent). Most shifts happened within industries (80 percent) and between establishments (65 percent). With regard to rising inequality within skill groups, a bit more than half of the rise (55.4 percent) happened between establishments, leaving the rest (44.6 percent) of the increase to be explained by mechanisms taking place within establishments. Further considering shifts between wage segments, Baumgarten compares shifts in the 15th to 50th log wage percentile and changes in the 50th to 85th percentile.

[4] Data for the years before 1993 are available but are not included due to strong fluctuations around the German unification.

Figure 2.5: Cumulative Wage Growth by Percentiles, Germany

Note: Own calculations based on SOEP.

Table 2.2: Shifts in Wage Inequality in German Manufacturing

Growth in log wage inequality growth between 1996 and 2007 [%]	58.2
Share in log wage inequality growth [%]	
- Between skill groups	36.0
- Within skill groups	64.0
- Between industries	20.0
- Within industries	80.0
- Between establishments	65.0
- Within establishments	35.0
Share in log wage inequality growth within skill groups [%]	
- Between establishments	55.4
- Within establishments	44.6

Source: Baumgarten (2013). Skill groups are defined by 20 age X education cells, where five age groups and four educational groups are distinguished.

For German male manufacturing workers wage dispersion increased relatively stronger in the lower part of the wage distribution than in the upper part.

Bönke et al. (2015) note that most studies focus on inequality in yearly earnings. They complement the existing literature by measuring inequality in terms of lifetime earnings. Based on rich administrative data, they find that West German men that were born in the 1960s experience about 85 percent more inequality in lifetime earnings than their fathers. About 20 to 40 percent of the increase in lifetime earnings inequality can be accounted for by increasingly long unemployment spells that affect workers at the bottom of the distribution. The remaining increase in lifetime earnings inequality is due to cohort-specific wage dispersion. Patterns of intra-generational wage mobility remain stable across generations. Mobility in yearly earnings is high at the beginning of the working life, decreases gradually and becomes negligible after age 40.

Overall, major shifts in the German wage structure have taken place. Wage inequality has risen and for manufacturing workers the rise has been documented to have taken place between as well as within skill groups, industries, and establishments. Apart from rising wage inequality, longer unemployment spells have added to the deteriorating situation of low-skilled workers.

2.4 Job Polarization

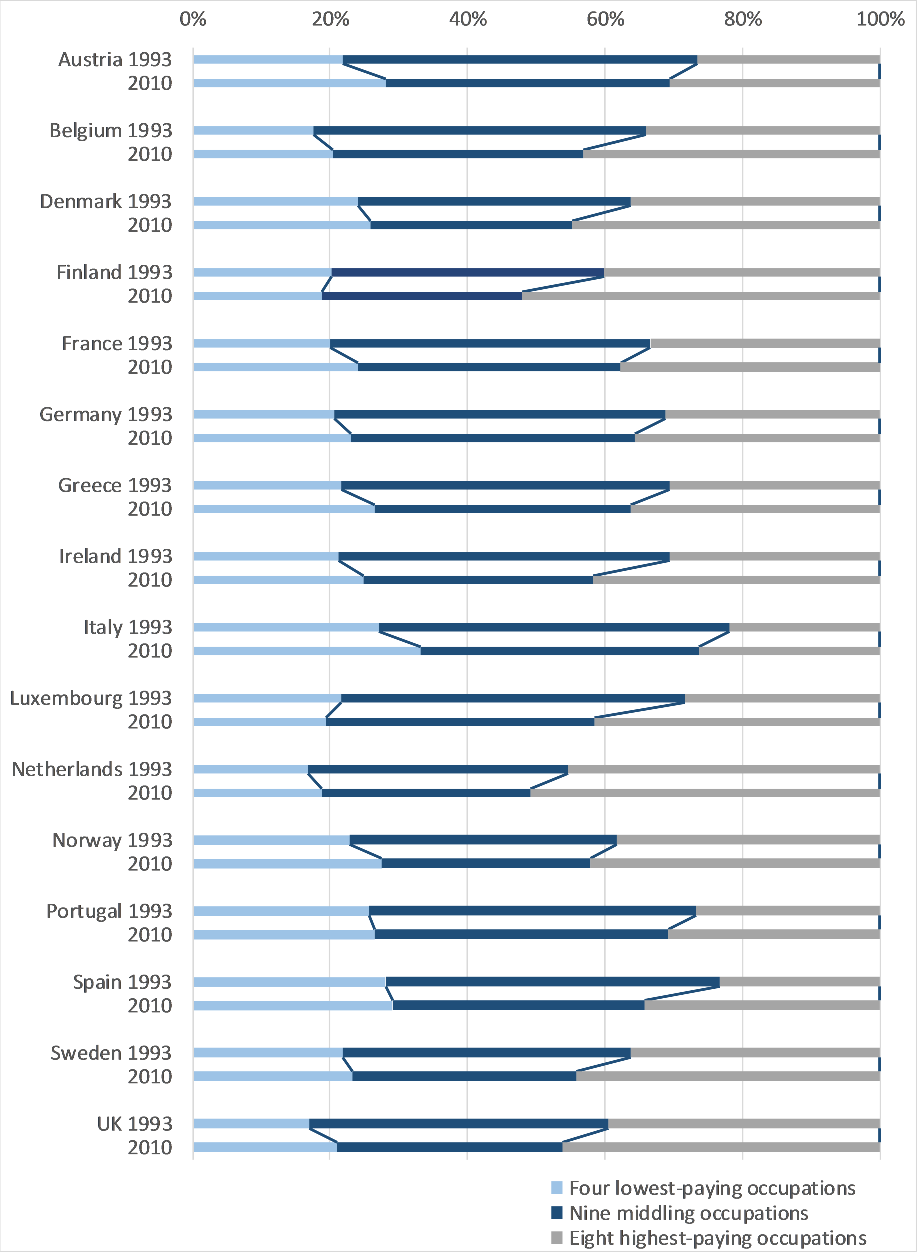
Goos et al. (2014) show that a considerable job polarization has taken place in

Europe since the 1990s. Job polarization can be understood as "growth in lousy jobs [...] together with [...] growth in lovely jobs and a decline in the number of middling jobs [...]" (Goos and Manning, 2007, p.119). Whether jobs are lousy, lovely, or middling is in this context considered a matter of wage.

Figure 2.6 shows the employment shares (measured in hours worked) for the 16 Western European countries studied by Goos et al. (2014) for the years 1993 and 2010. The employment shares are divided into three groups depending on their mean European occupational wage across the years considered. In all of the countries the middling occupational group shrunk whereas the group of high-paying occupations grew. The group of lowest-paying occupations grew in most countries, but not in all. In Finland and Luxembourg the group of low-paying occupations declined. Goos et al. discuss the relationship between job polarization and technical change as well as offshoring. Both of the latter are considered to decrease the share of middling relative to high-skilled and low-skilled occupations due to the nature of tasks. They show that several middling occupations are characterized by high routine intensity and high offshorability (based on a measure of Blinder and Krueger (2013) that will be discussed in section 6.2).

Similar to shifts in the wage structure, also shifts in the composition of employment can be further decomposed. Goos et al. (2014) distinguish between within- and between- industry shifts. About 45.5 percent of the overall rise in low-paying occupations was driven by shifts within industries. The respective share of the decrease (increase) in middling (high-paying) occupations is around 51.5 (55.3) percent. Dauth et al. (2014) argue that task demand shifts are not equally distributed across regions. They find that employment polarization in West Germany between 1980 and 2010, in terms of employment growth in occupations along a wage ranking, happened mainly in urban areas. They refer to the idea that agglomeration favors workers performing interactive tasks because agglomeration eases the exchange of ideas (Davis and Dingel, 2012; Michaels et al., 2013). Senftleben-König and Wielandt (2014) consider the initial prevalence of tasks on local labor markets and find that regions that were characterized by a high routine-intensity of tasks in 1979 were more computerized by 2006. In these regions, the share of routine task content dropped stronger over the observed period. They note that workers could react to task demand shifts by moving between regions or selection into unemployment and test for these mechanisms but find no robust support for them.

Figure 2.6: Employment Shares in Europe from 1993 to 2010



Note: Based on Goos et al. (2014). Employment shares are measured in terms of hours worked and pooled within countries. Occupations are grouped according to the mean European occupational wage across all years.

2.5 Task and Requirement Shifts at the Workplace

So far, some empirical facts have been presented that indicate that shifts in the wage and employment structure have taken place at different levels. An important part of these shifts took place within skill groups, within industries, and even within establishments. In the following, I will focus on task shifts within occupations and specifically on shifts affecting workers at their current workplace.

Fedorets (2015) picks out the occupation ‘office clerk’ to illustrate that major task shifts occur not only between but also within occupations. Table 2.3 displays the shares of office clerks who report to perform specific tasks.[5] The tasks that seem to have gained most in terms of their prevalence among office clerks belong to the categories “research, evaluate, and measure”, belonging to the class of analytic task, and “teach or train others”, belonging to the class of interactive tasks. Interestingly, the share of clerks reporting to perform the analytic tasks “program” and “execute laws or interpret rules” has decreased.

Of these within-occupation shifts a considerable share is likely to stem from shifts at the workplace. Table 2.4 gives an overview of the shares of workers facing major restructuring at their workplace for selected KldB 1992 occupations. About half of the workers in the occupational group “clerk” faced major restructuring in their direct working environment between 2004 and 2006 and between 2010 and 2012. In 2006, 56.1 percent of all workers reported to have been faced with major restructuring in their direct working environment within the last two years. This share has slightly decreased to 51.7 percent in 2012. With 76.8 percent, the share was particularly high for machine operators in 2006, but it has decreased considerably by 2012. Workers who are particularly unlikely to witness major restructuring at the workplace include those in catering and accommodation occupations and in cleaning occupations.

Workers not only face shifting tasks but also increasing requirements at the workplace. Shares of workers facing increased workplace requirements are reported in Table 2.5. The notion of workplace requirements is rather broad and subject to much individual interpretation. Nevertheless, it seems sufficient to

[5] While a conceptual follow-up of the data source used by Fedorets (2015) is available (BIBB/BAuA Employment Surveys) and is used for descriptive statistics in the following, transferring the mapping between task categories and items to later years is not straight forward.

Table 2.3: Tasks Performed by Office Clerks

Tasks	Share of office clerks performing the tasks [%] 1991	1998/99
Analytic tasks		
- Research, evaluate and measure	4.1	12.3
- Design, plan and sketch	1.9	4.7
- Program	17.9	1.4
- Execute laws or interpret rules	16.2	7.9
- Equip or operate machines	2.6	6.8
Manual tasks		
- Repair, renovate or construct	1.0	0.8
- Manufacture, install or construct	0.6	0.7
- Serve and accommodate	0.1	8.9
- Pack, ship or transport	11.3	6.0
- Secure	4.6	3.1
Interactive tasks		
- Sell, buy or advertise	19.1	13.8
- Teach or train others	4.3	21.9
- Employ, manage personnel, organize	16.6	11.8

Source: Fedorets (2015). The definition of the occupation "office clerk" is based on the German German occupational classification (KldB) 1988 group 781.

reflect rising needs for adjustment to new or more complex job tasks. For the period 2004 to 2006, 51.6 percent of workers have reported that their workplace requirements have increased. The share has slightly decreased to 46.7 percent for the years 2010 to 2012. Especially workers in banking and insurance occupations seem to be affected by increasing requirements. Workers in catering and accommodation, and in cleaning occupations, report the least increases in workplace requirements.

2.6 Training Participation

When workplace requirements increase, workers may obtain the necessary skills through learning-by-doing or by taking training. Table 2.6 summarizes training participation rates in Germany over International Standard Classification of Education (ISCED) 1997 levels. The rates refer to participation in further professional training courses within the three years preceding the respective SOEP interview. Generally, the participation rates increase with the educational level. Table 2.7 refers to the subset of training participants and displays the

Table 2.4: Shares of Workers who Faced Restructuring at the Workplace

	Major restructuring at the workplace [%]	
	2004-2006	2010-2012
Overall	56.1	51.7
54 Machine operators	76.8	51.9
60 Engineers	64.0	57.5
66 Sales personnel	40.0	33.7
69 Banking and insurance occup.	65.4	55.7
71 Public transport occup.	62.3	54.2
74 Warehousing occup.	54.7	47.8
78 Clerks	50.6	51.6
85 Healthcare occup.	61.1	54.4
87 Teachers	54.4	46.2
91 Catering and accommodation occup.	34.7	36.3
93 Cleaning and waste disposal occup.	32.5	27.6

Note: Own calculations based on BIBB/BAuA data. Shares are reported for selected KldB 1992 occupations.

Table 2.5: Shares of Workers who Faced Increasing Workplace Requirements

	Workplace requirements increased [%]	
	2004-2006	2010-2012
Overall	51.6	46.7
54 Machine operators	45.7	48.5
60 Engineers	57.7	56.7
66 Sales personnel	37.8	30.6
69 Banking and insurance occup.	70.4	62.8
71 Public transport occup.	32.3	31.5
74 Warehousing occup.	36.6	29.7
78 Clerks	53.0	51.9
85 Healthcare occup.	53.9	51.0
87 Teachers	53.1	44.4
91 Catering and accommodation occup.	27.1	27.4
93 Cleaning and waste disposal occup.	23.1	21.2

Note: Own calculations based on BIBB/BAuA data. Shares are reported for selected KldB 1992 occupations.

Table 2.6: Training Participation Rate

ISCED 97 education level	2000	2004	2008	2014
1-3 Primary to upper secondary	28.80	26.50	29.80	25.98
4 Post secondary non-tertiary	41.13	37.44	41.12	39.76
5 First stage of tertiary	47.64	45.14	45.51	34.93
6 Second stage of tertiary	50.07	47.72	50.91	46.82
Overall	34.62	32.57	35.71	33.48

Own calculations based on SOEP.

Table 2.7: Share of Participants Adjusting to New Requirements

ISCED 97	2004	2008
1-3 Primary to upper secondary	76.49	72.33
4 Post secondary non-tertiary	65.54	61.92
5 First stage of tertiary	75.75	73.51
6 Second stage of tertiary	74.93	71.64
Overall	74.61	71.29

Own calculations based on SOEP.

shares of participants reporting to have taken training with the aim of adjusting to new requirements in their current job.

In 2004, SOEP participants have in addition been asked what could be a valid reason for them to take training. Table 2.8 summarizes the shares of workers who state that either 'Retraining for a different profession or job,' 'Adjusting to new demands in the current job,' or 'Get acquainted with new areas in order to be less inflexible' could be a valid reason for them personally. The share of low skilled workers (ISCED 1-3) for whom any of the flexibility-related answers apply is with 64.31 percent considerably smaller than for any other educational group. This is striking because it is commonly observed that it is especially workers in this educational group that perform tasks that are substitutable by machines or foreign labor. Apart from stating what would be valid reasons for training, workers could also opt for the response 'None of the above, not interested in training', where 'not interested' carries a special emphasis because printed in bold. Table 2.9 displays the shares of workers who opt for this response. About one out of four low-skilled workers is generally not interested in training. The share is considerably lower for any other educational group. A discussion of potential reasons behind the comparably high rate of general disinterest would

Table 2.8: Share of Workers Willing to Adjust

ISCED 97	2004
1-3 Primary to upper secondary	64.31
4 Post secondary non-tertiary	78.84
5 First stage of tertiary	74.77
6 Second stage of tertiary	83.80
Overall	68.91

Own calculations based on SOEP.

Table 2.9: Share of Workers Not Interested in Training

ISCED 97	2004
1-3 Primary to upper secondary	27.02
4 Post secondary non-tertiary	14.61
5 First stage of tertiary	16.24
6 Second stage of tertiary	9.91
Overall	22.90

Own calculations based on SOEP.

go beyond the scope of this work.

Restructuring at the workplace, increasing workplace requirements, and training aimed at adaptation to new requirements are very common in Germany. Task shifts therefore appear to be a phenomenon that not only takes place when workers switch their industry, occupation, or employer, but also when they remain in their job. An analysis of task reallocation and associated changes in remuneration within jobs in response to demand shifts therefore seems to be in order and is conducted in this work.

Chapter 3

Conceptual Background

The potential mechanisms through which technical change and offshoring affect employment outcomes are numerous. The main focus of this work lies on workers who face shifting job requirements. These workers do not remain unaffected by the market conditions surrounding them. Therefore, the elaboration of a conceptual framework for skill adaptation to task shifts at the individual level is preceded by very condensed reviews of two conceptual approaches that shed light on the effects of aggregate task demand shifts.

The task-based approach to labor markets reviewed in section 3.1 makes explicit the links between skills, tasks, and wages. The conceptual distinction of skills and tasks allows for the analysis of the reallocation of skill inputs among tasks at the aggregate level in the presence of shifts in production technology, such as shifts due to biased technical change or offshoring. As will be discussed in more detail in chapter 4, the task-based approach played an important role in controversies over the driving forces behind observed shifts in labor markets.

The skill-weights approach, reviewed in section 3.2, in turn lends itself to the study of skill adaptation to shifting task demand. Human capital investment decisions remain native to human capital theory, which used to be little informative about the demand side of the human capital market (Autor and Handel, 2013, pp.59-60).[1] The skill-weights approach yields insights into human capital investment and employment decisions depending on observable market parameters.

The conceptual framework for skill adaptation to task shifts elaborated in

[1] See Leuven (2005) for a survey of human capital literature on private sector training.

section 3.3 builds on a conceptual distinction between skills and tasks and features task reallocation in combination with skill upgrading. The framework provides some propositions that guide the empirical analyses of chapters 7 and 8.

3.1 The Task-Based Approach to Labor Markets

Before the uprising of the task-based approach to labor markets, shifts in the wage structure used to be studied in a simple supply and demand framework, sometimes referred to as 'the canonical model'. Heterogeneous types of labor were modeled to provide skills that directly translate into output (see, e.g., Card and Lemieux, 2001; Katz and Murphy, 1992). Shifts in the structure of wages, and in particular a rising skill premium, could be ascribed to skill-biased technical change, i.e. technical change in a factor-augmenting form. Some shortcomings of the framework, in particular its limited capability to account for labor market polarization and real wage declines for low-skilled workers, led to the development of the so-called task-based approach to labor markets (Acemoglu and Autor, 2011, pp.1117-1156). It includes a conceptual distinction between skills and wages, thus allowing for the reallocation of skills across tasks, and incorporates the idea of task-biased rather than skill-biased technical change. In this framework, tasks can not only be complemented by new technologies, but also be substituted (Autor et al., 2003). Some of its main features shall be outlined in the following.

A common formulation of the production function is

$$Y = \left[\int_0^1 y(i)^{\frac{\eta-1}{\eta}} di \right]^{\frac{\eta-1}{\eta}}, \tag{3.1}$$

according to which a final good Y is produced by aggregating the services y_i of a continuum of tasks i, which are represented on an interval [0,1]. Along this interval, some tasks are available whereas others are not (yet) feasible. Tasks are substitutable with elasticity η. If $\eta = 1$, i.e. the Cobb-Douglas case, the production function simplifies to

$$Y = \int_0^1 y(i)di. \tag{3.2}$$

The tasks provided for production can be performed by different types of labor or by capital. Different types of labor have distinct comparative advantages at different tasks. Higher indices denote more complex tasks, at which higher skilled workers have a comparative advantage. If capital becomes a competing source of task supply for some of the tasks that used to be performed by labor - often medium-skilled labor - the structure of wages can be affected in a non-linear way, potentially giving rise to labor market polarization.

Technical change can directly reduce the wages of the skill groups that previously used to perform the tasks that are becoming substituted by capital. In addition, as the labor market segment of these workers is surged with excess supply, reallocation of workers across tasks arises endogenously. Workers affected by substitution are reallocated to tasks for which they have lower comparative advantage. Two countervailing forces determine the wage impact on affected workers. On the one hand, wage pressure from initial task substitution push wages down. On the other hand, the new technology brings about cost savings and complements the remaining, non-automated tasks, towards which the affected workers are now reallocated. The workers whose initial tasks are substituted may experience negative wage impacts, but they do not necessarily do so.

As will be further discussed in chapter 4, the conceptual distinction between skills and tasks has helped to resolve empirical puzzles about shifts in the aggregate structure of wages. It has been widely used to study the wage impacts of technical change and offshoring. Moreover, it has inspired literature that studies shifts in the wage structure not only between but also within skill groups and occupations. While task reallocation is a central element in the task-based approach, skill endowments are usually taken to be fixed. The model abstracts from skill adaptation to shifting productivity potentials (i.e. shifts in the marginal productivity of workers in the current as well as in alternative tasks) and how wages of adapting workers are altered. As shall be outlined next, the skill-weights approach to human capital sheds light on human capital investment responses to aggregate shifts in productivity potentials.

3.2 The Skill-Weights Approach to Human Capital

The skill-weights approach developed by Lazear (2009) has two specific features that render it particularly interesting in the context of skill adaptation to shifting productivity potentials. First, single skills are general in the sense that all skills can be of productive use elsewhere. Second, combinations of skills can be specific depending on market parameters. Specificity of human capital arises from the match between the combination of skills possessed by workers and the weights that firms attach to these skills (these are the so-called 'skill-weights'). The more idiosyncratic the combination of skills possessed by a worker and the smaller the number of firms at which the worker can make extensive use of their skills, the more specific is the worker's human capital. The insights from the skill-weights approach are transferable to the context of aggregate task demand shifts.

If labor market segments are characterized by a high fraction of tasks that are easily substituted by capital or foreign labor, the affected labor market segment becomes thinner since workers with resembling skill sets are set free while the number of vacant jobs with matching skill requirements decreases. The model suggests that wage loss from involuntary turnover, i.e. displacement, can be expected to be stronger the higher the share of displaced workers is, if no new vacancies that match the skill-set of the displaced workers are created. With regard to workers that remain with their firms, human capital becomes more specific whereas investments into new skills can become relatively more general. In other words, firms' investments into workers' skills that would not have been made earlier because they would have increased the attractiveness of outside options become feasible as the number of outside options shrinks.

According to Lazear (2009, pp.932,933), a detailed definition of industries and occupations may serve as a proxy for skill-weights. In the same vein, Gathmann and Schönberg (2010) study the 'portability of skills' across occupations, using German data on occupational switch. They find that wages in the source and the target occupation of switching workers are more strongly related if the skill requirements of the two occupations are similar. The strength of the relationship, however, declines over the life cycle. Both the absolute strength of this relationship and the drop over time are stronger for high-skilled workers than for low-skilled workers. An interesting observation that motivates their focus on occupations rather than industries is that tasks performed in the same occupation seem to vary little across industries. This is a fist indication that occupation is a better proxy for skill-weights than industry.

The implications of the skill-weights approach were, among others, tested by Eggenberger et al. (2018) using Swiss data and Geel et al. (2011) using German data. Eggenberger et al. (2018) define specificity of an occupation as the overlap of skills (according to vocational training curricula) with other occupations. They find that there is a trade-off between earning a higher wage in a more specific occupation and higher occupational mobility with less specific training. Geel et al. (2011) construct a specificity measure that contrasts single skills needed to perform a job (based on BIBB/IAB Qualification Surveys) with the importance of the skill on the labor market as a whole. They find that firms bear higher costs for apprenticeship training that results in more specific skill portfolios and that higher specificity is associated with a lower probability of occupational change.

Further interesting findings on switches between occupations and tasks are provided by Fitzenberger et al. (2015), Ross (2017), and Lalé (2017). Using German data, Fitzenberger et al. (2015) find that occupation change of graduates from apprenticeship within the training firm results in persistent wage gains. Based on O*NET data, Ross (2017) finds that an increase in routine task content leads to a decrease in wage whereas an increase in abstract task content results in an increase in wage. Analyzing worker reallocation across occupations in the U.S., Lalé (2017, p.62) find that workers' costs of 'landing in the 'right' occupations has increased in recent years and argue that "declining islands - jobs involving routine tasks - and expanding islands - non-routine cognitive and non-routine manual jobs - are drifting away from each other".

3.3 A Conceptual Framework for Skill Adaptation to Task Shifts

In the following, I present a simple conceptual framework for skill adaptation to task shifts. While task demand shifts are commonly considered at a very aggregate level, I follow Fedorets (2018) in considering task shifts at a lower level. The conceptual framework provides implications for the individual productivity of workers stemming from changes in the production technology of a firm.

As in the task-based approach to labor markets, skills and tasks are explicitly distinguished in the conceptual framework outlined below. Shifts in the relative productive potential of tasks are considered to stem from forces at the aggregate level, such as technical change and rising offshoring opportunities, but their effects are studied at the job level. Generally, firms may or may not embrace new technologies and offshoring. I focus on a situation in which embracing change that alters the relative productive potential of tasks is favorable for the firm. This does not necessarily mean that it is favorable for all workers within the firm. Exogenous technical change and rising offshoring opportunities thus trickle down to the individual level, at which task and skill shifts are depicted.

In the skill-weights approach the weights that determine the value of the workers' skills are constant within employers but vary between employers. I disregard varying weights between employers but instead focus on a situation where the outside options of a worker are practically nonexistent. Instead, I consider shifts in the value of tasks at the current employer.

The Task Allocation Problem

A worker i's productive potential in terms of output at time $t = 0$ is given by an allocation problem between two types of tasks, τ_{it}^A and τ_{it}^M. The productive potential is given by

$$\ln Y_{it} = \beta_t l_{it} \tau_{it}^A + (1 - \beta_t)(1 - l_{it})\tau_{it}^M, \tag{3.3}$$

where β_t is a parameter capturing the relative weights attached to the tasks by the firm. Task inputs τ_{it}^A and τ_{it}^M can be interpreted in the sense of purely abstract and purely manual tasks. They can, however, also be interpreted in terms of more complex configurations.[2] I assume that generally workers hold a comparative advantage at one of the tasks, so that workers either contribute to τ_{it}^A or to τ_{it}^M, but never to both, i.e. $l = \{0, 1\}$. When worker i has a comparative advantage at task type A, all labor of i will flow into it, i.e. $l_{it} = 1$. The important distinction between skills and tasks is that skills are bound to workers but tasks are not. I assume that workers can costlessly (re-)allocate their labor inputs between tasks, which are substitutable with elasticity 1, i.e. the firm at which they are employed has a Cobb-Douglas production function. In turn, skills cannot be altered without cost.

[2] See for example the configurations depicted earlier in Figure 2.1. The separation into two types of tasks does not necessarily reflect a shift within a "Tayloristic" organization in the sense of Lindbeck and Snower (2000), but can also take the form of a shift from a single task towards a more complex configuration of tasks, i.e. towards a more "holistic" organization.

Initial Human Capital Endowment

Worker i is equipped with some initial ability for each task τ_i^j and human capital acquired over time H_{it}^j.[3] Equation 3.3 can then be rewritten as

$$\ln Y_{it} = \beta_t l_{it} \left(\tau_i^A + H_{it}^A\right) + (1-\beta_t)(1-l_{it}) \left(\tau_i^M + H_{it}^M\right). \tag{3.4}$$

I assume that allocation and human capital investment decisions before $t = 0$ have been made optimally. This means that, first, individuals having a higher initial ability in task type A, i.e. $\tau_i^A > \tau_i^M$, are allocated to task A in $t = 0$. Second, in $t = 0$ human capital has already been acquired up to the point where the marginal benefit (MB) of training no longer exceeds the marginal cost (MC).[4]

The cost function of training is assumed to be equal for H_{it}^A and H_{it}^M and given by a function satisfying $C(H_{it}^j) > 0$, $C(H_{it}^j)' > 0$, and $C(H_{it}^j)'' > 0$. The intuition for the functional constraints is that it is easier to move from being a complete beginner to being an intermediate than it is to move from being an intermediate to being an expert. Optimal allocation and investment up to $t = 0$ imply that MC = MB for the task to which i is allocated. There are no investments into human capital augmenting tasks that are not performed anyway. Acquired human capital sets at $t = 0$ are then determined by

$$\text{for } \tau_i^A > \tau_i^M \begin{cases} \beta_0 = \frac{\partial C(H_{it}^A)}{\partial H_{it}^A} \\ H_{i0}^M = 0 \end{cases} \tag{3.5}$$

$$\text{for } \tau_i^A < \tau_i^M \begin{cases} H_{i0}^A = 0 \\ (1-\beta_0) = \frac{\partial C(H_{it}^M)}{\partial H_{it}^M}. \end{cases} \tag{3.6}$$

Task Valuation Shifts at the Firm Level

Task demand shifts at the firm level take the form of a shift in β between $t = 0$ and $t = 1$. For ease of discussion, I assume $\beta_0 = 0.5$ and $\Delta\beta > 0$. As mentioned earlier, task demand shifts are commonly studied at the macro level. Technical change and rising offshoring opportunities can be considered to be exogenous at the firm level. When firms adapt their production technology, their internal

[3] I assume human capital investments to be task-specific, meaning that there are no positive spillover effects between H_{it}^A and H_{it}^M.

[4] Note that human capital up to $t = 0$ has been accumulated only for those tasks that the worker performs in $t = 0$.

valuation for different tasks changes. Whether and how firms adapt to these changes is a matter of decision maker's choices. The decision whether or not to adapt a new production technology may go hand in hand with a number of changes in complementary aspects of the firm's strategy as described by Milgrom and Roberts (1990, 1995). For example, firms may combine offshoring of production tasks with an expansion of domestic production workers' responsibilities, including the performance of quality controls. Manual tasks in turn become less valuable for the firm at the original location. The shift in β implicitly captures the technology- or offshoring-related substitutability of one task and complementarity of the other task.

Similar to Fedorets (2018), I consider shifts to take effect over time and alter the match between worker and tasks. While Fedorets considers bundles of tasks that the worker performs, I let workers specialize either in A or in M. This distinction is, however, minor for two reasons. First, the notion of bundles of tasks described by Fedorets and the notion of tasks divisible between workers are compatible when the latter are in itself understood as bundles. As mentioned before, τ_{it}^{A} and τ_{it}^{M} can themselves be understood as configurations of task components. Second and subsequently, the (re-)allocation of workers between tasks presented here resembles occupational choice considered by Fedorets. In fact, both can be broken down to a matter of seeking the highest productivity potential when the initial match is altered.

The shifting task valuation at the firm level can induce reallocation of workers across tasks and may as well give rise to further skill acquisition. Workers with $\tau_i^A > \tau_i^M$ already used to perform task type A, which has become increasingly valuable and stick with their task. For workers with $\tau_i^A < \tau_i^M$ reallocation from task type M to task type A may become attractive. In the following, I exclusively focus on workers that had a comparative advantage in M before the shift took effect.

Task Reallocation without Skill Adaptation

Before moving on to task reallocation with additional skill adaptation, I elaborate the condition under which task reallocation without skill adaptation takes place. To do so, I disseminate the (hypothetical) productive potential of the worker in each task type separately by varying the value of l.[5] The (hypotheti-

[5] Worker i's productive potential at task j is called 'hypothetical' when it is lower than the productive potential at the other task.

cal) productive potentials for a worker with $\tau_i^A < \tau_i^M$ are

$$\ln Y_{i1,l=0} = (1-\beta_1)\left(\tau_i^M + H_{i1}^M\right), \tag{3.7}$$

and

$$\ln Y_{i1,l=1} = \beta_1 \tau_i^A. \tag{3.8}$$

Reallocation is attractive when $\ln Y_{i1,l=1} > \ln Y_{i1,l=0}$ and thus takes place when

$$\beta_1 > \frac{H_{i1}^M + \tau^M}{H_{i1}^M + \tau^M + \tau^A}. \qquad \text{(No-Adaptation Reallocation Condition)}$$

Reallocation without skill adaptation thus takes place when the valuation of task type A starts to outweigh the initial share of M-specific human capital in total human capital.[6] The negative effect that a shift in β has on the productive potential of worker i can be averted by task reallocation if β_1 is high enough. However, the initial productive potential cannot be recovered fully.

Task Reallocation with Skill Adaptation

Let the (hypothetical) productive potential of worker i at task type A be augmentable by skill adaptation,[7] so that equation 3.8 becomes

$$\ln Y_{i1,l=1} = \beta_1(\tau_i^A + H_{i1}^A). \tag{3.9}$$

Shifting from task type M to task type A is attractive when

$$\beta_1 > \frac{H_{i1}^M + \tau^M}{H_{i1}^M + \tau^M + H_{i1}^A + \tau^A}. \qquad \text{(Reallocation Condition)}$$

The realized productive potential is the one that is the highest achievable. When the reallocation condition is fulfilled, reallocation and skill adaptation take place. While reallocation without skill adaptation cannot raise the productive potential of i back to the initial level, for reallocation with skill adaptation this is indeed possible. To summarize, the implications for the productive po-

[6] Note that the endowment of M-specific human capital does not change between $t = 0$ and $t = 1$ because investment has become less attractive and there is no decay of human capital.

[7] The cost of training is ignored for the time being but will be discussed in the next section.

tential of a worker who used to perform the task that is negatively affected are as follows

Proposition 1. *If the demand shift outweighs the worker's share of initial-task-specific human capital in total human capital, reallocation averts the direct negative effect on the worker's productive potential.*

Proposition 2. *For a skill adapter, the productive potential in the new task is higher the stronger the demand shift.*

Proposition 3. *If the value of the alternative task rises sufficiently, the productive potential of a skill adapter can rise above the initial level.*

Shifts in Wages

Productive potential can reasonably be presumed to translate into wage, though not perfectly. So far, the questions 'who bears the cost of skill adaptation?' and 'what is the time horizon over which the investment amortizes?' have not been addressed. These questions are relevant for the feasibility of training and the extent of the discrepancy between productive potential and wage.

Concerning the first question, the skill-weights approach lends itself to a very rough and only partial answer. As mentioned earlier, aggregate demand shifts that negatively affect a worker's outside options can allow a firm to make human capital investments that would not have been feasible before. Even when skill adapters, i.e. those for whom feasibility is given, do not directly bear the cost of training (in terms of paying a bill), they may do so indirectly when their wage is not rising in alignment with their productivity. With regard to the second question, it should be noted that a short time horizon, which may be given close to retirement or in the face of very rapid technical change, can impede skill adaptation.[8]

Whether a skill adapter's wage increases or decreases depends on several factors. For one, it depends on how strongly the increase in productive potential exceeds the (monetary) cost of skill adaptation. Furthermore, it depends on the worker's bargaining position, which in turn is related to the worker's outside options and coverage by collective agreements.[9] Also downward wage rigidity impedes the direct translation of changes in productive potential into wage.

[8]See Gries et al. (2017a) for a detailed discussion.

[9]Felbermayr et al. (2014) finds that the bargaining positions of unions are weaker in more internationally active plants.

While implications for the productive potential of a worker who used to perform tasks that were negatively affected by a task demand shift can be deduced from the above framework, in how far wages of skill adapters rise or not remains to be studied empirically in chapters 7 and 8.

Chapter 4

Controversies over Labor Market Shifts in Recent History

'The increase in wage inequality that is observed in most OECD countries since the 1980s is to a considerable degree driven by shifts in skill demand.' This assertion has become a common notion over the last decade. However, the degree to which skill demand shifts drove observed wage patterns was hotly debated in the past. Most studies focused on wage patterns in the US around the 1980s since these were most pronounced. The debate shall be summarized in the following to shed light on potential alternative drivers behind rising wage inequality and to carve out the actual role of skill demand shifts.

Observed skill-wage patterns could not be sufficiently explained by shifting supply factors. Potential sources of relative supply shifts include changes in the domestic structure of educational attainment and immigration. As Katz and Murphy (1992, p.52) note on the development in the US during the 1980s, "the groups with the largest increases in relative supplies tended to have the largest increases in relative wages". The common view was that demand shifts must have taken place that lowered the relative demand for lower skilled workers, while raising the relative demand and wages of the higher skilled.

The view that demand shifts were the dominant factor behind the rise in wage inequality was contested by so-called 'revisionists' who argued that the rise in wage inequality in the US (and other advanced economies) was an episodic event. A considerable fraction of the increase in wage inequality (at least in the US) was suspected to be due to other factors such as a fall in the real value of minimum wage, declining unionization, and a reallocation of labor induced by the 1982 recession (Card and DiNardo, 2002; Lemieux, 2006). The revisionist view challenged the description, interpretation, and economic significance of the observed trends in rising inequality. If the rise in inequality was indeed due to transitory events, there was no reason to worry about fundamental secular factors affecting the supply of and demand for skills that would create a further dispersion of earnings. After taking these alternative explanations of the revisionists into consideration, skill demand shifts are still found to be major drivers behind rising inequality both in the US (Autor et al., 2006, 2008) and Germany (Dustmann et al., 2009).

In the following, the literature that discusses the role of demand shifts in rising inequality is reviewed. First, the international controversies over the role of demand shifts are discussed. Then, I turn to the role of demand shifts in the German labor market. Finally, I summarize controversies about the relative importance of alternative potential drivers behind task demand shifts. While the two most prominent drivers - biased technical change and offshoring - are discussed in detail later in chapters 5 and 6, discussions about whether they are competing explanations or conceptually related phenomena are reviewed at the end of this chapter.

4.1 International Controversies over the Role of Demand Shifts

As surveyed by Levy and Murnane (1992) and Katz and Autor (1999), the US labor market has seen a dramatic increase in measured earnings and wage inequality in the 1980s. The gender gap in turn narrowed from the 1980s onwards (Bound and Johnson, 1992). Measured wage inequality rose considerably for both men and women. A considerable increase in wage differentials by education was observed, with a particularly strong increase in college graduates' relative wages. Juhn et al. (1993) report that between 1963 and the end of the 1980s, the wages for the least skilled workers declined by about 5 percent. At the same time, the wages for the most skilled workers rose by about 40 percent. The strong increase in wage inequality was seen as a net result of the divergence in earnings between the most and the least skilled labor, which Juhn et al. (1993, p.411) estimated to account for about 72 percent in the variance of log weekly wages. The rise in wage inequality did not only take place between educational groups but also within groups narrowly defined by education, age, labor market experience, and gender (Juhn et al., 1993; Katz and Murphy, 1992). Katz et al. (1995) show that the patterns of changes in the wage structure were similar for the UK and Japan, though they did not happen fully simultaneously. They argue that the development in France was likely to have been similar, too, but was offset by institutional factors. Some studies have argued that the relevant unit for the analysis of well-being is families rather than individuals, which is relevant because family structures have changed. Karoly (1992) have shown that irrespective of family characteristics, such as race, ethnicity, age, or headship type, the major conclusions on rising inequality also hold at the family level.

Early works used very simple supply and demand frameworks to investigate the potential causes behind the observed changes in the structure of wages. Arguably the strong focus on supply and demand conditions and thus on competitive forces has led many studies to strong conclusions on the causes for the observed wage structure shifts. The pure supply and demand framework is based on the idea that shifts that cannot be explained by the supply side must be explained by the demand side. As Bound and Johnson (1992, p.375) note, "[t]he obvious strategy for explaining the wage-structure developments of the 1980s is to look for the set of demand-shift factors that were sufficiently powerful to overcome the effects of demographic changes that would have caused the wage structure to move in the opposite direction".

Katz and Murphy (1992) set up a simple framework in which they examine between-group changes in relative wages using different demographic groups as distinct labor inputs. Specifically, they distinguish demographic groups by sex, education, and professional experience. Their model is a partial equilibrium model in which determinants of factor supplies are not specified and it is simply required that the observed prices and quantities must lie on the demand curve. For the empirical implementation of the model they focus on relative wage changes in wages, supply, and demand rather than absolute changes.[1] Katz and Murphy (1992, p.35) conclude that "[r]apid secular growth in the demand for more-educated workers, 'more-skilled' workers, and females appears to be the driving force behind observed changes in the wage structure."

Murphy and Welch (1992) investigate whether US data are consistent with

[1] The latter would further reflect factor-neutral demand shifts, such as technical change that affects the productivity of different factor inputs similarly.

a stable factor demand structure with wage changes driven by exogenous shifts in demographic characteristics of the labor force. The most notable shift in the population structure took place right before the 1980s when the crest of the baby boomers entered the labor market. Average levels of professional experience within all educational levels have fallen with the entry of the baby boomers. At the same time, unsurprisingly, the relative wages of younger workers have been falling compared to the wages of older workers. As the extraordinarily strong inflow of young workers faded out, the average level of professional experience started to increase again. The rise in the relative wages of newly entering workers that would have been considered consistent with the story of a stable factor demand, however, failed to appear. Interestingly, the prior trend of falling educational earnings differentials was reversed in the 1980s. Murphy and Welch discuss three scenarios in which the shifts in the 1980s would have been reasonable in their simple supply and demand framework. The first emphasizes the potential role of foreign competition in shifting relative factor demands. The second postulates that the demand shifts are simply the continuation of a trend. The third is a combination of the prior two scenarios.

Bound and Johnson (1992) apply a framework that not only accounts for supply and demand but also for institutions in order to "incorporate[] all of the major explanations" (Bound and Johnson, 1992, p.375). However, as later discussed by Katz and Autor (1999, pp.1504-1509), two major difficulties arise when trying to measure the influences of non-competitive factors in the framework used. The first issue concerns the issue of reliably estimating the direct influences of non-competitive factors on the wage structure. The second problem is that, even if one can adjust for non-competitive wage effects, employment is likely to change depending on actual wages rather than latent competitive wages.

Despite the limited focus on competitive forces and the difficulties in dealing with non-competitive forces, as far as these were taken into consideration, the literature has come to rather strong conclusions - not only about demand shifts being the main driving force behind the observed shifts in relative wages, but also about the factors driving these demand shifts. Explanatory approaches to the wage structure puzzle in the US and other advanced economies in the 1980s and 1990s mainly revolved around skill-biased technical change and increasing international trade. The debate clearly focused on shifts in the demand side of the labor market. The main controversies were regarding the question what drove these demand shifts.

As major concerns were raised about the role of institutions, there was a 'revisionist' shift in the literature - a shift from the question what the driving forces are behind skill demand shifts back to the question whether skill demand shifts were actually the driving force behind rising inequality.

Unequal de-unionization across skill groups was brought up as a potentially important institutional factor behind rising wage inequality. Freeman (1993) investigate the contribution of de-unionization to rising wage inequality. They find that in the US de-unionization contributed to the rise in inequality. Comparing the unionism-inequality facts in the US to other OECD countries, they argue that the relation between unionism and wage dispersion is not specific to the US. Countries that were highly unionized had smaller earnings differentials by industry than less unionized countries. Also the increase in the wage differential was smaller in more unionized countries. Card (1996) argue that two important forces produce important dynamics in the wage structure. Unions raise wages more for workers with lower levels of observed skills. At the same time, there is a selection process into unionization. Interestingly, not only employees, but also employers are involved in the selection process.

Card et al. (2004) analyze the effects of unions on wage dispersion for the US, the UK, and Canada. The choice of these three countries is motivated by the fact that they are relatively similar in terms of collective bargaining institutions. Most importantly, there is a clear distinction between union and non-union sectors. In contrast to many other countries like Germany, there is no general mechanism that extends negotiated wage floors beyond the organized sector. This setting allows to identify the effects of unions and to assess whether the impact of unions on the wage structure are specific to the US or universal given the type of institutional setting. The study exhibits quite similar effects among the three countries. Considering within-group inequality they find that wage inequality is generally lower for union workers than nonunion workers, which is consistent with earlier findings. With regard to between-group inequality they find that for male workers unions compress the dispersion of wages across skill groups, thus complementing the equalizing effect on within-group wages. For female workers, unions in turn raise inequality between more an less skilled women, offsetting the equalizing within-group effect. Finally, Card et al. estimate in how far differences in (de)unionization-trends can account for differences in the development of wage structures between the three countries. They calculate that divergent trends in (de)unionization between the US and the UK can account for almost one-half of the differences in wage dispersion in the early

1990s. Overall, Card et al. show that unions - in the specific institutional setting of the US, UK, and Canada - systematically reduce the variance of wages for men, but not for women.

Another institutional factor that has gained attention is the reduction in the real minimum wage. According to Lee (1999, p.977), "[t]he magnitude of growth in 'underlying' wage inequality in the United States during the 1980s is obscured by a concurrent decline in the federal minimum wage, which itself could cause an increase in observed wage inequality". Using regional variation in the relative level of the minimum wage, he finds that most of the rising inequality in the lower tail of the income distribution is explained by the decreasing real value of the federal minimum wage, particularly for women. Ignoring the real value of the minimum wage mainly affects estimates of within-group inequality. Estimates of between-group inequality are found to be moderately overestimated. As found by Teulings (2003), the return to skill, which has been rising strongly, was hardly affected by changes in the minimum wage.

Further potential explanations for the reported rises in inequality are brought up by Lemieux (2006), who focuses on residual inequality. He argues that three factors played an important role in the rising within-group wage inequality during the 1980s. These factors are an increase in the extent of measurement error, a rising dispersion in unobserved skill, and a rising return to unobserved skill.

Card and DiNardo (2002) broadly review the major concerns about earlier findings on the role of skill demand shifts in general, and skill-biased technical change in particular, in driving rising wage inequality. They discuss, on the one hand, shifts in the wage structure that seem inconsistent with explanatory approaches that build on skill-biased technical change, and, on the other hand, shifts that are consistent with skill-biased technical change but may well be driven by other factors. Card and DiNardo (2002) claim that the shifts in the wage structure in the US during the 1980s are likely to be an episodic event rather than a secular tendency. They call for a reevaluation of the limited focus on skill-biased technical change as an explanation for the rise in wage inequality.

A reevaluation was provided by Autor et al. (2008) under the subtitle "Revising the Revisionists". In this and an earlier paper (Autor et al., 2006), they point to the significance of the different interpretation that comes with the revisionist view. If rising inequality was an episodic event mainly based on institutional dynamics, there was no reason to worry about secular dynamics causing the dispersion of wages to further drift apart. With the concession that "past is not prologue" and a view on later developments in the US, Autor et al. (2008, p.301) "concur that the falling minimum wage was a contributor to rising lower-tail (50/10 wage gap) wage inequality in the 1980s". Nevertheless, they find that "overall wage inequality continued growing from 1990 to 2005 but at a slower pace than in the 1980s, and the secular demand increases favoring more educated workers were [] less rapid in the 1990s and early 2000s than from the 1960s to the 1980s".

Autor et al. (2006, 2008) offer a simple but powerful extension to the skill-biased technical change framework that reconciles some of the revisionist critique while taking institutional shifts into consideration. A major difficulty in aligning the data with the skill-biased technical change hypothesis was that there was no symmetric bias in the bottom and the top of the skill distribution. Autor et al. (2008) show that a refined version of the hypothesis dissolves major contradictions between theory and empirical findings. A key point of this addition is the distinction between skills and tasks as elaborated in Autor et al. (2003) and discussed earlier in section 3.1. The hypothesis is based on the idea that new technologies substitute for routine tasks, but complement non-routine tasks. Thereby, the demand for workers located mostly at the top of the wage distribution increases. Routine tasks that used to be performed by low- and medium-skilled workers are substituted by technology. Workers performing manual tasks, i.e. mainly low-skilled workers, in turn should hardly be affected directly via new technologies. In contrast to the simple theory of skill-biased technical change, the more nuanced view of routine-biased technical change thus predicts a polarization of incomes and employment that fits the observed patterns in the US in the 1990s.

With the framework of routine-biased technical change at hand and a broader view of different potential drivers behind rising wage inequality, Autor et al. (2008) reassess wage and employment changes between 1980 and 2000. While earnings growth and the development of employment during the 1980s were rather monotone in skill, they polarized during the 1990s. Autor et al. (2008) caution that the development that has been seen so far may differ from the development that is to come. They mention the rising significance of international trade and outsourcing in the evolution of wages.

To summarize, from the controversy that was mainly focused on developments in the US, a number of general insights concerning the role of skill demand shifts in wage structure dynamics can be deduced. First, the institutional setting may affect the structure of wages and should therefore be taken into consideration. Second, shifts in the wage structure that are driven by demand shifts are a major concern for future policy. In turn, shifts that are induced by institutional changes lend themselves to the investigation of effects that future policy interventions may have, but they may not imply long-lasting dynamics that call for action. Third, the conceptual distinction between skills and tasks is important for the analysis of how demand shifts affect the wage structure.

4.2 The Role of Demand Shifts in the German Labor Market

Turning back to the German labor market, a number of lessons have been learned also for Germany from the above controversies. Before moving to the literature that gained from the insights of the debate on the role of demand shifts in the US, the development of the German labor market shall be reviewed.

As discussed in detail by Krugman (1994) and Freeman and Katz (1995), while the US faced strong shifts in the wage structure, European countries, including Germany in the 1980s, experienced rather strong increasing unemployment. The two phenomena - rising wage inequality and rising unemployment - are considered two sides of the same coin (Beißinger and Möller, 2000; Krugman, 1994). A falling domestic demand for substitutable tasks can show up in the form of falling wages for workers who used to perform these tasks or in the form of rising unemployment among these workers. The common conception is that labor market institutions determine whether biased technical change and globalization lead to rising inequality or unemployment. One simple mechanism is that if the wages for workers of relatively low productivity fall relative to the average, but the level of benefits keeps up with the average, there will be more workers who are not willing to work because their market wage falls below their reservation wage (Krugman, 1994, p.61).

Steiner and Wagner (1998) point to a close relationship between the German unemployment problem and a dramatic decline in the employment of unskilled labor in the manufacturing sector since the mid-1970s. Fitzenberger (1999, p.3) clarifies that even if employment shifts in Germany were caused by forces exogenous to wage setting, a sufficient flexibility of wages could have prevented the surge in unemployment. Without the rigidity of wages in Germany - or more broadly, what was named Eurosclerosis - it was believed that unemployment could have been traded for rising inequality. The other way around, Krugman

(1994, p.49) summarizes that "many people on both sides of the Atlantic believe that the United States has achieved low unemployment by a sort of devil's bargain, whose price is soaring inequality and growing poverty".

In contrast to other OECD countries, and especially the US, Germany was until recently not commonly perceived to be subject to increasing wage differentials (Steiner and Wagner, 1996). In particular, wage differentials across education groups have been considered to be relatively constant (Abraham and Houseman, 1999; Steiner and Wagner, 1998). Studying the development of wages and employment in West Germany throughout the 1970s and 1980s, Fitzenberger (1999) have challenged the view that Germany experienced hardly any shifts in the wage structure. This was later confirmed by Dustmann et al. (2009).

Dustmann et al. find that there has been a rise in wage inequality during the 1980s that was driven mainly by the top half of the income distribution. In the 1990s, the rise in wage inequality was accelerated and also took hold of the bottom half of the distribution. Specifically, they assess the standard deviation of log wages (as a measure of overall inequality) and log wage residuals after controlling for the education level, age category, and the interaction between education and age (as a measure of within-group inequality). They find that about 82 percent of the increase in overall wage inequality is due to within-group inequality. The remaining 18 percent are due to between-group inequality.

In the search for the drivers behind the shifts in the wage structure, Dustmann et al. take into consideration different potential sources, including the composition of the workforce and institutional factors as put forth in the US revisionist debate. They document a strong decline in unionization rates that began in the 1990s. Collective agreement coverage declined from 87.3 percent in 1995 to 72.8 percent in 2004. They find that over this period, de-unionization explains 28 percent of the increase in the wage gap between the 15th percentile and the median and 11 percent of the increase in the wage gap between the median and the 85th percentile. With regard to the composition of the workforce, they argue that the development of the bottom of the income distribution is likely to be partly driven by supply shocks. These are in particular the inflow of low-skilled labor as a consequence of the breakdown of the communist regimes in Eastern-Europe (and beyond) and the reunification of East and West Germany.

In comparing the development of wage structures in West Germany and the US, Dustmann et al. emphasize that there were similar developments at the top of the income distribution during the 1980s and 1990s. With regard to the lower tail of the distribution, the rise in inequality started in the 1990s in Germany, i.e. one decade later than in the US. Overall, the developments in the lower tail are read to be mainly a consequence of institutional factors and supply shocks. The resembling developments in the upper part of the income distribution between the US and Germany are in turn understood as an indication for demand shifts. Their findings on the structure of wages as well as employment are not easily reconciled with a simple theory of skill-biased technical change because the different parts of the income distribution are not symmetrically affected. They are, however, consistent with a version of biased technical change that distinguishes between skills and tasks.

Recent literature on rising wage inequality stresses the role of firm heterogeneity in rising within-group inequality. Recent contributions in this line include in Engbom and Moser (2017), Cardoso et al. (2018), Barth et al. (2016), and Song et al. (2018), and Mueller et al. (2017). In order to assess the relative role of the firm component, workers' wages are typically decomposed into a firm component, a worker component, and a matching component that captures the firm-specific productivity of a worker. For Germany, Card et al. (2013) finds that for male workers about 40 percent of the rise in variance of wages is attributable to the individual component and 25 percent is attributable to the firm component.

Baumgarten (2013) focuses on a specific aspect that may drive wage inequality that has not been discussed so far. Firm heterogeneity and the fact that exporting firms tend to pay higher wages have gained a lot of attention since Melitz (2003) has formally shown how new trade opportunities induce only the more productive firms to enter the export market and force low productivity firms to exit the market. The original framework does not entail wage differentials between exporters and non-exporters, which have been found in numerous studies. These can be incorporated into the framework when dropping the assumption of homogeneous labor in a frictionless market. Baumgarten finds that the rising wage differentials between exporters and non-exporters has a moderate net contribution to the rise in inequality of about 5 percent. Klein et al. (2013) further allow for heterogeneous effects of export activity across skill groups in the German manufacturing sector. They estimate that the association of export activity with between-skill-group wage inequality is highest when considering the difference between high- and medium-skilled workers in firms that engage strongly in offshoring. Of this difference, 29 percent are associated with export activity. Concerning the respective differences between low- and higher-skilled workers the contribution of export activity is rather low. Of the wage differential between low-skilled workers and medium-skilled, high-skilled, and university-skilled workers, the respective numbers are 1.0, 3.9, and 4.4 percent. A large amount of rising wage inequality, especially concerning the wage differential between low-skilled and higher-skilled workers thus remains to be explained by skill demand shifts.

Concerning the future development of labor markets in advanced economies that are subject to demand shifts, prediction is highly intricate. An assumption that enables prediction of future developments is that the nature of future demand shifts resembles the nature of past shifts. Maier et al. (2015) extrapolate developments in the German labor market in the years 1996 to 2007 in order to provide projections of future skill demands until 2025. Under this scenario, manufacturing jobs will lose in significance whereas employment in service occupations will increase. With regard to skill requirements, the demand for highly skilled labor is expected to continue rising whereas the demand for low-skilled labor continues to fall. Wolter et al. (2016) provide a scenario analysis that takes the rather new phenomenon of digitization an the structural changes due to the so-called Industry 4.0 (which has become a buzz word denoting the fourth industrial revolution in Germany and beyond) into consideration. They elaborate that these new phenomena will create a new working environment and further accelerate structural changes towards a service society. Moreover, the roles of new requirements at the workplace and continuing education after initial training are emphasized. Requirements are likely to change more rapidly not only between but also within industries and occupations.

4.3 Controversies over Alternative Drivers Behind Demand Shifts

Two potential drivers behind the observed shifts have been studied extensively in the literature on skills, wages and employment patterns. The first driver behind relative skill demand shifts is biased technical change. Technical change in the form of automation, standardization, and advancing information technology is viewed to decrease the relative demand for low- and medium-skilled labor and thus to be biased. Tasks performed by low- and medium-skill workers are often relatively more substitutable by technology (see section 2.1) whereas tasks performed by high-skilled workers are often rather complementary to technology.

The second driver is international trade. The traditional narrative of increasing global competition is that it puts domestic low-skill workers' wages under pressure while the high-skill segment gains due to international comparative advantage. This is based on the Factor Price Equalization Theorem (Ohlin, 1933; Samuelson, 1948) and the Stolper-Samuelson Theorem (Stolper and Samuelson, 1941). According to the first theorem, international trade equalizes the prices of identical factors of production across countries. According to the second theorem, if the relative wages of low-skill workers decrease, all industries should substitute towards this factor.

Technical change and international trade used to be discussed as competing explanations behind the observed labor market patterns. These shifts took place mainly within industries rather than between industries. It was argued that within-industry shifts in skill demands were attributable to technical change rather than trade (see, e.g., Berman et al., 1994). This view, however, is restricted to trade in final goods. When not only final goods are traded between countries but also intermediate inputs are internationally traded, within-industry shifts in skill-wage patterns can be explained by both technical change and trade in intermediate inputs. This is because intermediate inputs may belong to a different industry than the final goods produced. Trade in intermediate inputs often takes the form of offshoring, i.e. the relocation of business processes from one country to another. In the following, I focus on offshoring as a specific type of international trade.

More recent work stresses that both forces produce the same qualitative impact on domestic labor demand. The question whether increasing inequality and polarization are driven by one or the other is therefore fundamentally an empirical rather than a theoretical question (Feenstra and Hanson, 2003). By now, the conceptual divide between skill-biased technical change and offshoring has become blurred. Some recent literature conceptualizes offshoring as a form of technical change (see, e.g., Costinot and Vogel, 2010).

The literature on the drivers behind skill demand shifts has gained from the conceptual developments of the task-based approach to labor markets, which was outlined in section 3.1. As discussed in Acemoglu and Autor (2011, pp.1101-1118) and Autor and Handel (2013), the canonical model of the labor market does not distinguish between skills and tasks. This model was widely used for studying the effects of skill-biased technical chance. With regard to offshoring, it does not provide a suitable framework for studying the effects on inequality beyond the effect of trade through factor content. In the task-based approach, tasks can be performed by domestic labor, foreign labor, or capital. The productive capabilities and availability of these can change over time. Moving from the simple canonical model of the labor market to a task-based approach allows for an analysis of interactions among skill supplies, technological capabilities, and potential trade and offshoring opportunities. These in turn shape factor demands, the assignment of factors to tasks, relative productivity and thus relative wages. The more flexible task-based approach to labor markets thus allows for an analysis of the effects of both skill-biased technical change and offshoring within the same framework.

Despite their potentially analogue ways of affecting (domestic) skill demands and wages, it remains important to distinguish between technical change and offshoring. On the one hand, the development and adoption of technologies is more difficult to influence by policy than offshoring. While governments may incentivize investments in R&D and thereby spur innovation, the skill-bias of new technologies may not be foreseeable. Trade policy in turn provides straightforward instruments to control the flow (and to a certain degree the task content) of intermediate inputs. On the other hand, the implications of skill-biased technical change and offshoring differ with regard to cross-national (rather than domestic) outcomes. International wage dispersion is another dimension of inequality that may be of interest in its own right but is not in the focus of the present study.

Chapter 5

Biased Technical Change as a Driver Behind Demand Shifts

In the following, I begin with presenting some stylized facts on the prevalence of (different types of) innovations and a brief discussion of how they are related to job tasks and skill demand shifts. After a general discussion of technology-skill complementarity and the substitutability of tasks by technology, I turn to the literature that elaborates on the relationships between technical change, labor market outcomes, shifting skill requirements, and training.

5.1 Prevalence of Innovations Related to Task Shifts

Two types of innovations with very different implications for the development of employment outcomes are commonly distinguished. The first type, product innovation, is usually conceived to have a positive impact on employment. New products can either substitute old products or create new branches of production, which create additional employment opportunities (Hall et al., 2008; Harrison et al., 2014; Vivarelli, 2014). The second type, process innovation, allows for the production of a given good with fewer resources and thus potentially has a labor-saving impact. As put forth by the literature on biased technical change, innovative technologies can substitute for a subset of tasks that is commonly performed by medium- or low-skilled workers. As shown by Harrison et al. (2014), the overall employment effect of process innovation is, however, not necessarily negative. This is because increasing demand for products that can be produced more efficiently due to process innovation may in fact overcompensate the displacement effect of process innovation. Using data on manufacturing and services from France, Germany, Spain and the UK for the period 19982000, Harrison et al. (2014) find that - with the exception of German manufacturing - this is indeed the case. In German manufacturing, the reduction in employment that is driven by incremental productivity improvements in the production of existing products is relatively strong. It amounts to 7.5 percent over the two-year period. Since jobs are bundles of tasks of which only a part may become obsolete, process innovations may not only affect workers who become displaced, but also workers who stay with their employer and face shifting job tasks.

Apart from process and product innovations, also marketing and organizational innovations can affect workers. These innovations have gained relatively less attention in the literature. Caroli and van Reenen (2001) show that organizational change can affect the returns to skill - not just because it is related to technical change, but on their own behalf. Organizational change can take many forms. It can include new work practices such as job rotation, lean production, and team working. With regard to occupational tasks, such practices may involve decentralized coordination tasks, delayering of managerial tasks, and increased multitasking. As stressed by Caroli and van Reenen (2001, p.1483), "the debate over the deteriorating position of low paid workers has tended to stress the role of technology, trade, and labor supply" and "understanding the changing wage and employment position of the less skilled is intimately tied with the evolution of organizational forms."

Caroli and van Reenen also point to potential complementarities between technical and organizational change. These complementarities are discussed in more detail in Bresnahan et al. (2002). The latter find complementarities among information and communication technology (ICT), workplace reorganization, and new products and services in terms of factor demand and productivity. Firms that adopt ICT innovations moreover use relatively more skilled labor compared to non-adopters.

Figure 5.1 gives an overview of different types of innovation for large businesses and small and medium-sized enterprises (SMEs) separately. The indica-

Table 5.1: Shares of Workers Affected by Firm-Level Shifts

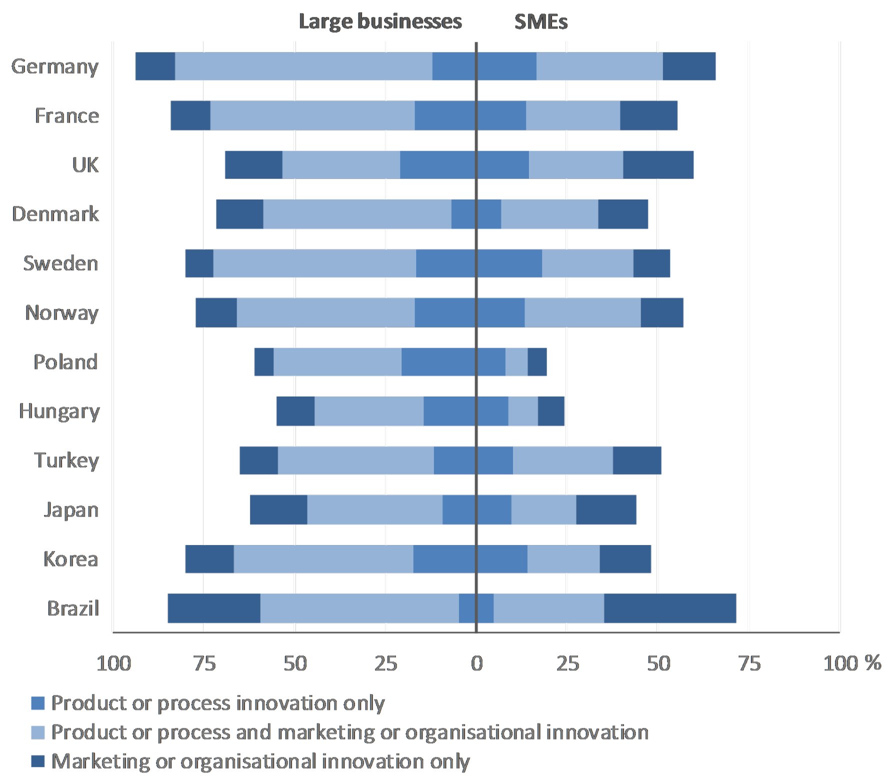
	Incidence at the firm-level in %	Share of workers affected in %
Process innovation	46.50	49.12
Product innovation	35.67	45.19
Reorganization	31.07	43.97
Layoff	30.93	39.90

Source: Own calculations based on BIBB/IAB 1999 data.

tors show the incidence rates of innovation as a percentage of businesses in their size category (with at least one innovation in the respective innovation category over the reference period). Larger firms tend to be more likely to be innovators. Innovators tend to adopt mixed modes of innovation, i.e. strategies combining new marketing or organizational methods alongside product or process innovations. Comparing large businesses to SMEs, mixed modes of innovation appear relatively more likely. Differences between large businesses and SMEs are likely to be partly driven by the unequal distribution of businesses across business sectors. Generally, innovation incidence rates are higher in manufacturing firms than in service firms (OECD, 2017a, p.154). Overall, the prevalence of mixed modes of innovation strategies stands out. It appears to be a manifestation of potential complementarities between technical and organizational change.

A more direct relationship between major shifts at the firm-level and shifting job tasks can be seen in Table 5.2. It is based on the BIBB/IAB 1999 survey, where workers were asked whether there were major changes at their employing firm in terms of process innovation, product innovation, reorganization, or layoff. If these instances happened, workers were asked whether their workplace has been directly affected. The incidence that translates most strongly into changes at the workplace is indeed process innovation. Of all the workers that witness the introduction of process innovation at their employing firm, 49.12 percent state that the innovation affects their workplace. The respective share is, with 39.90 percent, lowest for layoffs but still relatively high. One interpretation for the observation that remaining workers are affected by the layoff of peers is that tasks that have been performed by workers that have been laid off need to be performed by the remaining workers. In the context of task demand shifts, it is not necessarily complete jobs that become obsolete. The fraction of tasks that is still needed for production then has to be performed by workers remaining at the establishment.

Figure 5.1: Innovation Types by Business Size, 2012-2014



Source: Based on OECD (2017a, p.154, statlink dx.doi.org/10.1787/888933619353). Notes: Only Only a selection of countries is presented here. International comparability may be limited, partly due to differences in survey methodologies.

Table 5.2: Shares of Workers Facing New Technologies at the Workplace

	New technologies at the workplace [%]	
	2006	2012
Overall	70.1	66.3
54 Machine operators	88.6	83.7
60 Engineers	78.9	78.8
66 Sales personnel	45.5	45.7
69 Banking and insurance occup.	78.2	74.6
71 Public transport occup.	72.1	67.3
74 Warehousing occup.	67.0	66.1
78 Clerks	69.9	65.1
85 Healthcare occup.	76.1	70.1
87 Teachers	65.0	57.0
91 Catering and accommodation occup.	48.2	46.9
93 Cleaning and waste disposal occup.	43.8	36.7

Note: Own calculations based on BIBB/BAuA data. Shares are reported for selected KldB 1992 occupations.

In later versions of the survey (BIBB/BAuA 2006 and 2012), workers were only asked about changes at the firm-level that affected their direct working environment. Table 5.2 displays the shares of workers that were affected by the introduction of new manufacturing technologies, computer programs, machinery or equipment (summarized here as 'new technologies'). Overall, the share of workers affected by new technologies has decreased from 70.1 percent in 2006 to 66.3 percent in 2012. Disaggregated numbers are shown for selected (KldB1992 2 digit) occupation groups. The group of machine operators has the highest share of workers affected by new technologies (88.6 percent in 2006 and 66.3 percent in 2012), followed by engineers (78.9 percent in 2006 and 78.8 percent in 2012). Rather low shares can be seen for service occupations such as sales personnel and occupations related to catering and accommodation or cleaning. These are in turn more likely to be affected by the introduction of new products and services.

The questions in the BIBB/IAB and BIBB/BAuA surveys are subject to interpretation of the interrogated workers. There may be different understandings of what a worker's direct working environment ("unmittelbares Arbeitsumfeld") is and what is a change in the personal working environment ("Veränderungen im persönlichen Arbeitsumfeld"). Specifically, the latter may or may not refer to changes in the tasks performed by the responding workers.

5.2 Technology-Skill Complementarity

The technology-related mechanisms behind increasing wage inequality and employment polarization can conceptually be separated into skill-bias in technical change and capital-skill complementarity. The conceptual distinction is often neglected in the literature and both aspects are discussed under the heading of biased technical change, which broadly refers to technology-related shifts in the demand for skilled labor.[1]

Current technical change is often considered to be complementary to skill. However, in a historical context, many innovative technologies, such as the spinning jenny, weaving machines, and printing cylinders in the eighteenth and early nineteenth centuries, have overall been replacing rather than complementing skills (Acemoglu, 1998; Goldin and Katz, 1998). This gives rise to the question whether physical and human capital are generally complementary.

Goldin and Katz (1998) study the origins of technology-skill complementarity in a formal framework. They decompose the manufacturing process into "capital maintenance" and "production", of which the first depends on skilled workers whereas the second depends on unskilled workers. They argue that capital is always complementary to skill in the capital maintenance part of manufacturing, whereas physical capital together with unskilled labor can substitute for skilled labor in the overall manufacturing process. The shift from overall skill-replacing technologies to overall skill-complementary technologies in their framework arises mainly from shifts in factor intensities required between technologies. In other words, increasing skill-bias, shifting capital-output and capital-labor ratios are driven by the changing nature of innovations rather than an accelerating rate of innovation or changes in relative factor prices.

Acemoglu (1998) in turn argues that "new technologies are not complementary by nature, but by design". He argues that skill-complementary technologies have superseded earlier skill-replacing technologies because the direction of technical change is endogenous. The increasing supply of skilled labor is given as a reason for the increasing skill-complementary of today's new technologies and the increase of the demand for skilled labor. Van Reenen (2011) moreover

[1]For a clear conceptual distinction between capital-skill complementarity and skill-bias see, e.g., Caselli and Coleman (2006); León-Ledesma et al. (2010).

suggests that international trade plays a role in determining the direction of technical change. The direction of technical progress can be driven by market conditions, but also by other factors such as the cost efficiency of introducing new technologies well as the distribution of alternative production techniques (Jones, 2005). If the direction of technical change is determined by the prevalence of skills or abilities, and technology in turn raises the return to skills and thus skill supply, this can give rise to a positive feedback loop (Galor and Moav, 2000).

As discussed in detail in León-Ledesma et al. (2010), different combinations of substitution elasticity and bias in technical change can produce observationally equivalent situations. The implications with regard to growth accounting, inequality, or public policy may differ depending on the combination of the two parameters. While León-Ledesma et al. distinguish between capital and labor, their considerations carry over to different types of labor. Depending on how well different types of labor can perform different types of tasks, directed technical change may or may not lead to rising inequality or polarization. Policy approaches can be concerned with the direction of technical change or with building up workers' adaptive capabilities. Both approaches can be taken to seek for desired social outcomes, but the viability of the former seems very limited - even when technical change is endogenous.

5.3 Substitution of Routine Tasks

As the concept of skill-bias was superseded by the concept of routine-bias, capital-skill complementarity has become supplemented by the notion of substitution of routine tasks. Table 5.3, which is based on Autor et al. (2003), summarizes the impact that computerization, or more broadly automation, is commonly perceived to have on different types of tasks. While new technologies are complementary to non-routine analytic and interactive tasks, they have the potential to substitute for routine tasks. The effect that new technologies have on non-routine manual tasks is not straightforward. Since non-routine analytical tasks usually require a high skill level, technology-skill complementarity is an important component in the routine-biased technical change hypothesis. However, also tasks that require a high level of skill become potentially substitutable. Such tasks include, e.g., the interpretation of radiographs. In turn, some tasks that can potentially be complemented by new technologies do not necessarily require a high level of skill. Such tasks include, e.g., janitorial services and truck driving.

Table 5.3: Impact of Computerization on Job Tasks

	Routine tasks	Non-routine tasks
Analytic and interactive tasks	Substantial substitution	Strong complementarity
Manual tasks	Substantial substitution	Limited opportunities for substitution or complementarity

Source: Based on Autor et al. (2003)

Prominent findings on wage and employment polarization have spurred discussions that include the middle skill group as a group that faces a particularly strong impact of technical change because of the tasks performed by this group. Who is negatively affected by technical change and to which degree is a matter of initial job tasks, the impact that technology has on the set of tasks, and the potential for adjustment. The latter is often not considered. Arntz et al. (2016, 2017) caution that automation potential is overestimated when the potential adjustment of occupational or job tasks are ignored.

5.4 Labor Market Effects of Biased Technical Change

A broad survey of the theoretical and empirical literature on the employment impact of technical change is provided by Vivarelli (2014). Technical change can have a quantitative effect in terms of labor in employment and potential displacement of workers as well as a qualitative effect with regard to its relative employment impact on workers with different characteristics. Vivarelli discusses potential mechanisms that may compensate for the negative direct impact of process innovation on employment. According to ‘classical compensation theory’, market forces should fully compensate the initial labor-saving impact of process innovations. Such compensation mechanisms can be, e.g., the creation of jobs through the demand for new machinery, through an increase in incomes, or through increased investments by innovative entrepreneurs that can accumulate extra-profits. These compensation mechanisms may in turn be ineffective depending on institutional settings and the parameters that govern the respective compensation mechanisms. The direct negative impact of process innovation on employment can combine with compensation mechanisms (which can be more or less effective), and the labor-friendly nature of product innovation in many diverse outcomes. With regard to empirical evidence, Vivarelli (2014, p.138) concludes that "[o]n the whole, previous microeconometric evidence is not conclusive about the possible employment impact of innovation. Nevertheless, most recent panel investigations tend to support a positive link".

With regard to both employment and wage shifts, Autor et al. (2008) show that the trends in the US, especially polarization of skill demand shifts, can be reconciled by the routine-biased technical change (RBTC) hypothesis. Autor and Dorn (2013) later show that the developments in the lower tail of the wage distribution in the US were to a large degree accounted for by increases in wages and employment of service occupations. Hours worked in service occupations grew by 30 percent between 1980 and 2005 whereas employment in other occupations with similarly low skill requirements, such as production, operative, construction and assembler occupations, declined. Autor and Dorn hypothesize that these developments were driven by biased technical change on the one hand and consumer preferences, favoring variety over specialization, on the other hand. Goos and Manning (2007) make similar observations in the UK. They find that one-third of the rise in the log wage differential between the median and the 10th percentile and half of the differential between the median and the 90th percentile can be explained by RBTC. The job segments that grew most considerably are low-paying service occupations and professional and managerial occupations in finance and business activities. Clerical jobs and skilled manual jobs in turn declined. Goos et al. (2014) show that the RBTC hypothesis explains much of the common job polarization trends across 16 Western European countries over the period 1993 to 2010. Other papers that show the relationship between employment and wage polarization and RBTC include Acemoglu and Autor (2011), Costinot and Vogel (2010, under the heading "extreme-biased technological change"), and Michaels et al. (2014, under the heading "ICT-biased polarization").

For West Germany, Spitz-Oener (2006) investigate employment growth across skill levels from 1979 onward. She finds that the first, ninth, and tenth skill deciles of the 1979 skill-requirement distribution have grown particularly strong between 1979 and 1998/99. The first decile includes waiters, blacksmiths, domestic staff, hoteliers, and casters and has by far the highest routine and non-routine manual task content. It grew by about 1 percentage point. The ninth and tenth deciles include occupations such as engineers, consultants, tax accountants, merchandisers, dealers, and scientists. The deciles grew by about 2.5 and 3 percentage points. In the middle of the skill distribution, especially in the third decile, where occupations such as office clerks, machine operators, and galvanizers are located, there has been a 'hollowing out'. The trends in employment are consistent with a polarization of the labor market related to routine-bias rather than skill-bias. Overall, trends in skill demands have been relatively similar in the US, UK, and West Germany.

5.5 Biased Technical Change, Shifting Skill Requirements, and Training

Apart from shifts between occupational groups, Spitz-Oener (2006) finds that occupations in Germany have become more complex in the sense that there was a shift away from routine tasks towards analytical and interactive tasks. These shifts not only took place between occupations but also within occupations and even within occupation-education groups and were intensified by computerization. Skill upgrading thus is relevant not only in terms of general education but also in terms of adaptation to increasing requirements within occupation-education cells and probably within jobs. Adaptation to shifting requirements can take the form of learning-by-doing or formal further professional training. The latter is not limited to classical trainer-trainee interactions but can, for example, include online courses.

Hempell (2003) investigate the link between investments in ICT and training expenditures based on a panel of German firms in business-related and distribution services for the years 1994 to 1998. They find a strong positive relationship between ICT and firm-paid training. Productivity gains from training are highest in firms that employ a large fraction of highly educated workers and invest strongly in ICT. Their findings point not only to a higher need for training but to increasing incentives for firms to pay for the training of their employees.

With a focus on manufacturing firms, Bartel and Sicherman (1998) study participation in further professional training in the context of industry-level technical change. Also the manufacturing sector seems to face either a rising need for training or an increase in the incentives for training due to technical change. Using a sample of US male workers covering the years 1987 to 1992, they find that in industries subject to stronger technical change companies provide more formal training for their production workers compared to companies in manufacturing industries with lower rates of technical change. Workers with higher levels of education are generally more likely to receive further training. Interestingly, at higher rates of technical change, the training gap between the highly educated and the less educated workers shrinks.

Green (2012) studies how employees' skills have changed over time using British data between 1992 and 2006 in connection with computerization. He finds that computerization is associated with higher cognitive and interactive, as well as more generic skills and substitutes for repetitive physical tasks. Skill upgrading is only one out of a number of components that firms may adjust in the face of aggregate shifts in technology. Neirotti and Paolucci (2013) investigate the provision of training in the context of organizational practices. Using data on large Italian enterprises for the years 2003 to 2005, they find that firms in which training is a component of a high-performance work system tend stronger towards the adaptation of new technologies, reorganization, and the internal development of new competencies.[2]

While there are indications of a positive relationship between technical change and training participation, it remains unclear how technical change affects the wages of workers who face task shifts at the workplace and upgrade their skills. On the one hand, the tasks that they used to perform are subject to automation, which induces wage pressure. On the other hand, adapting workers may benefit from technology-related productivity increases. It is unclear, whether for skill adapters the threats or the gains from technical change prevail.

[2]See, e.g., Appelbaum (2000) for details on high-performance work systems.

Chapter 6

Offshoring as a Driver Behind Demand Shifts

Apart from technical change, also offshoring can induce shifts in skill demands and in the tasks that workers - including those who do not become displaced due to offshoring - perform on-the-job. After a brief introduction of the phenomenon and an overview of the prevalence of offshoring, theoretical literature on the induced mechanisms and empirical literature that assesses these mechanisms are reviewed. As will be discussed in more detail in the following sections, the conceptual divide between technical change and offshoring has started to fade out as offshoring is increasingly perceived as a special form of technical change.

6.1 Prevalence of Offshoring

Offshoring refers to the relocation of production tasks to foreign destinations. It is commonly viewed to involve the migration of jobs, but not the people performing them, to another country (Blinder, 2006). When jobs are conceptualized as bundles of tasks, the relocation of business activities does not necessarily translate into a loss of jobs in the domestic economy and a gain in jobs in the foreign economy. Whether the relocation involves the actual migration of jobs depends on the degree to which the bundle of tasks that constitute a job are fixed. As elaborated in section 3.3, job tasks may change in the face of technical change or rising offshoring opportunities. Offshoring may thus not only involve displacement, but also task shifts for the workers who remain with their offshoring employers in the context of larger organizational changes.

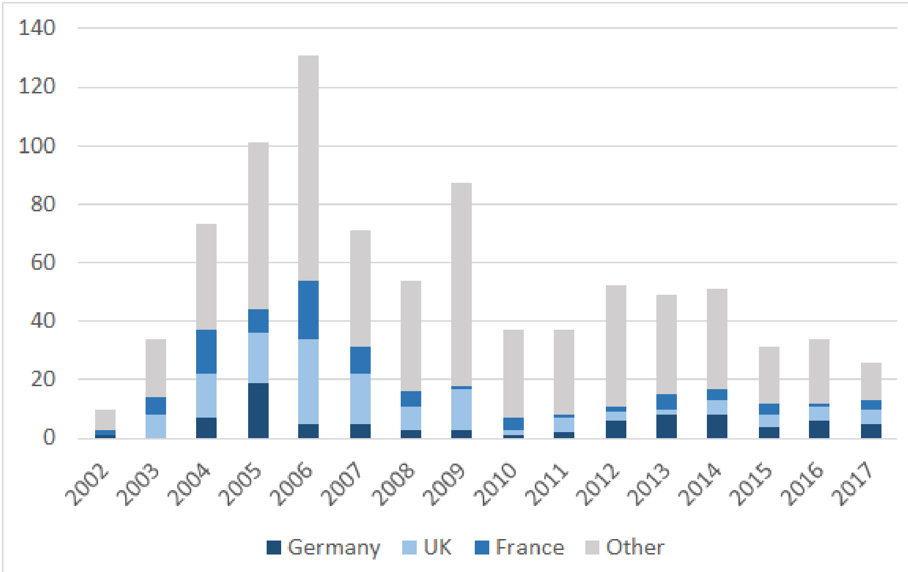
Offshoring can be understood as a relocation taking place at the firm level. As Gries et al. (2017b) elaborate, multinational enterprises can be represented as networks. These consist of network nodes that are linked by organizational ties. The notion of operational nodes is closely related to the notion of tasks but presents a coarser unit of analysis. When operational nodes are relocated, this is typically done to combine the comparative advantages of geographic locations with the resources and capabilities that exist in the network and ultimately maximize competitive advantage (Mudambi and Venzin, 2010). The shaping of the network is a matter of vertical and horizontal integration. Where nodes are geographically located and how strongly the nodes are organizationally tied to the rest of the network depends on several aspects. Among these are task content, factor prices, trading costs of intermediates, and the availability of technologies (Antràs and Helpman, 2004; Becker et al., 2013; Kohler and Smolka, 2014; Nunn and Trefler, 2013; Oldenski, 2012). Still, the relocation of nodes does not imply that the involved domestic jobs become fully redundant as firms can reorganize job tasks within the domestic part of the network. For example, assembly tasks may become relocated but quality assessment tasks may become even more important within the domestic part of the network.

The European Restructuring Monitor (ERM) provides information on major restructuring events since 2002, covering the European member states and Norway (Eurofond, 2017). Figure 6.1 depicts the number of announcements of major offshoring events captured by the ERM between 2002 and 2017. There appears to have been an extreme rise in offshoring announcements between 2002 and 2006. This rise may, however, partly reflect a gradual development in the operations of the ERM and an imperfect coverage of offshoring events. With regard to German companies, most major offshoring announcements took place in 2005, when 19 large companies announced extensive offshoring programs.

Table 6.2 shows the lower bounds of planned job reductions associated with the major offshoring announcements from Figure 6.1 by economic sectors. By far the most offshoring-related job reductions affect the manufacturing sector. Planned job reductions in the manufacturing sector were higher than in all other sectors jointly. As mentioned earlier, the job reductions, however, reflect only part of the impact that offshoring has on workers. While a considerable number of workers becomes displaced as part of offshoring, organizational changes also affect the remaining workforce.

As shown in Table 6.1, the main target locations of announced offshoring

Figure 6.1: Number of Major Offshoring Announcements in Europe



Note: Based on Eurofound (2017).

programs were the New Member States. About one quarter (25.68) of all offshoring programs was targeted towards them. About another quarter (23.19) was targeted at various locations, i.e. operations were planned to be relocated to a number of countries rather than one target country.

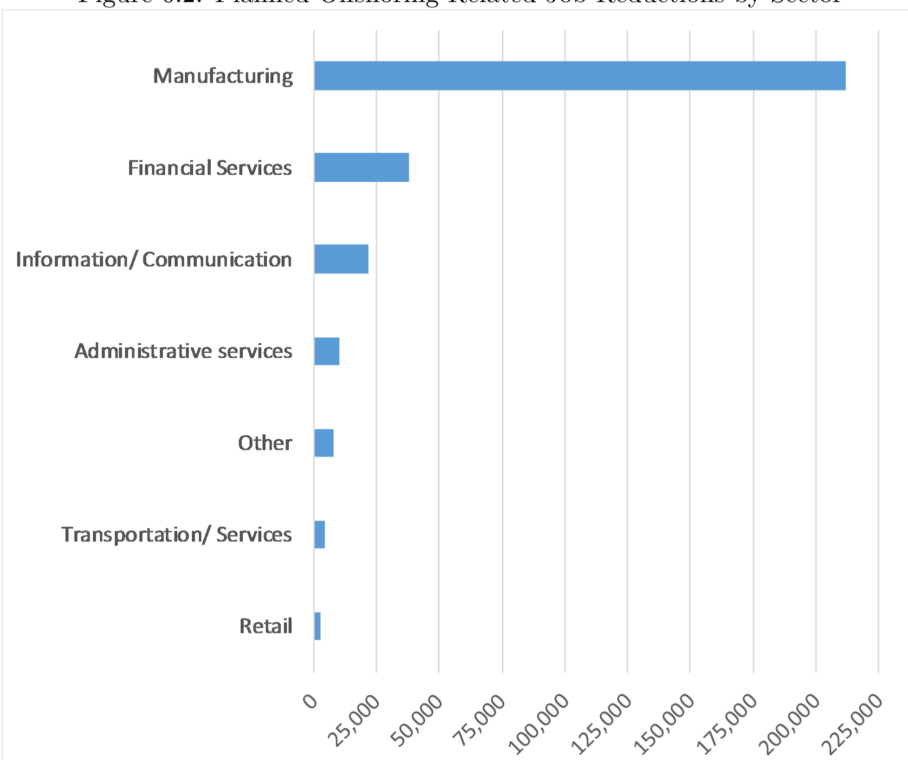
6.2 Offshorability of Tasks

'How many jobs are offshorable?' This question is not uncommon in the empirical offshoring literature. For example, Blinder and Krueger (2013) address this question using alternative approaches[1]. Comparing workers' self-reported measures of offshorability with measures of professional coders' assessment they find that the different measures largely agree. According to their preferred measure of offshorability (based on professional coders' assessment), about 25 percent of jobs in the US in the year 2008 were potentially offshorable.[2]

[1] The question is also addressed, e.g., in Blinder (2009) and a study of the McKinsey Global Institute (2005).

[2] Similar to occupation-level estimates of the risk of automation that Arntz et al. (2017) have shown to be upward biased, offshorability measures are often aggregated to the occupation-level rather than considered at the job-level.

Figure 6.2: Planned Offshoring-Related Job Reductions by Sector



Note: Based on Eurofound (2017). Numbers refer to lower bounds of planned job reductions throughout Europe.

Table 6.1: Target Locations of Announced Offshoring Programs

New location	Number of Offshoring Programs	Percent
New Member States	227	25.68
Various locations	205	23.19
EU15	125	14.14
Other European countries	81	9.16
China	73	8.26
India	57	6.45
Other Asian countries	55	6.22
USA	9	1.02
South and Central America	12	1.36
Other	40	4.52
Total	657	100

Based on Eurofond (2017).

Table 6.2 shows the offshorability measure of Blinder and Krueger in combination with job shares in the German labor market based on BIBB/BAuA 2012 data. The numbers are based on the "externally coded" offshorability measure of Blinder and Krueger (2013, their Table 2) and reweighted in order to account for differences in overall employment structure between Germany and the US whereas occupational contents are assumed to be similar.[3] The column 'Job share' indicates the relative share of the different occupations in total employment in Germany. The column 'Offshorable' shows how many jobs in that category are offshorable in the sense of Blinder and Krueger (2013). It is striking that 80.7 percent of all jobs in the category 'Production occupations' is classified as offshorable. The employment share of 7.2 percent may not appear to be extraordinarily high, but given the share of 'offshorable jobs', the impact of offshoring would be enormous if 'offshorable jobs' were indeed offshored.

The question posed above - 'How many jobs are offshorable?' - is accurate under the strict presumption that jobs are fixed bundles of tasks. If job tasks can shift over time, the question should rather be 'What is the current share of offshorable tasks?' It adds the conceptual distinction between jobs and tasks to the earlier question, accounts for the fact that tasks within jobs can shift, and

[3]Since different occupation codes are provided in the two data sources, I use the ISCO-08 to SOC 2010 crosswalk table provided by the US Bureau of Labor Statistics (version 2012, update June 2015, `www.bls.gov/soc/ISCO_SOC_Crosswalk.xls`). Since 3 digit ISCO-08 codes (provided in the BIBB/BAuA scientific use files) have multiple correspondences to 2 digit SOC codes (provided by Blinder and Krueger (2013)), I weight multiple correspondences using the US job share in Blinder and Krueger (2013).

Table 6.2: Estimated Offshorability of Jobs

Occupation	Job share [%]	Offshorable [%]
Management, business, and financial occupations	8.5	16.4
Professional and related occupations	32.8	20.5
Service occupations	14.3	0.7
Sales and related occupations	5.0	17.8
Office and administrative support occupations	13.9	41.2
Farming, fishing, and forestry occupations	1.4	0.0
Construction and extraction occupations	3.9	0.0
Installation, maintenance, and repair occupations	6.4	1.3
Production occupations	7.2	80.7
Transportation and material moving occupations	5.8	0.0
Other occupations	0.7	-

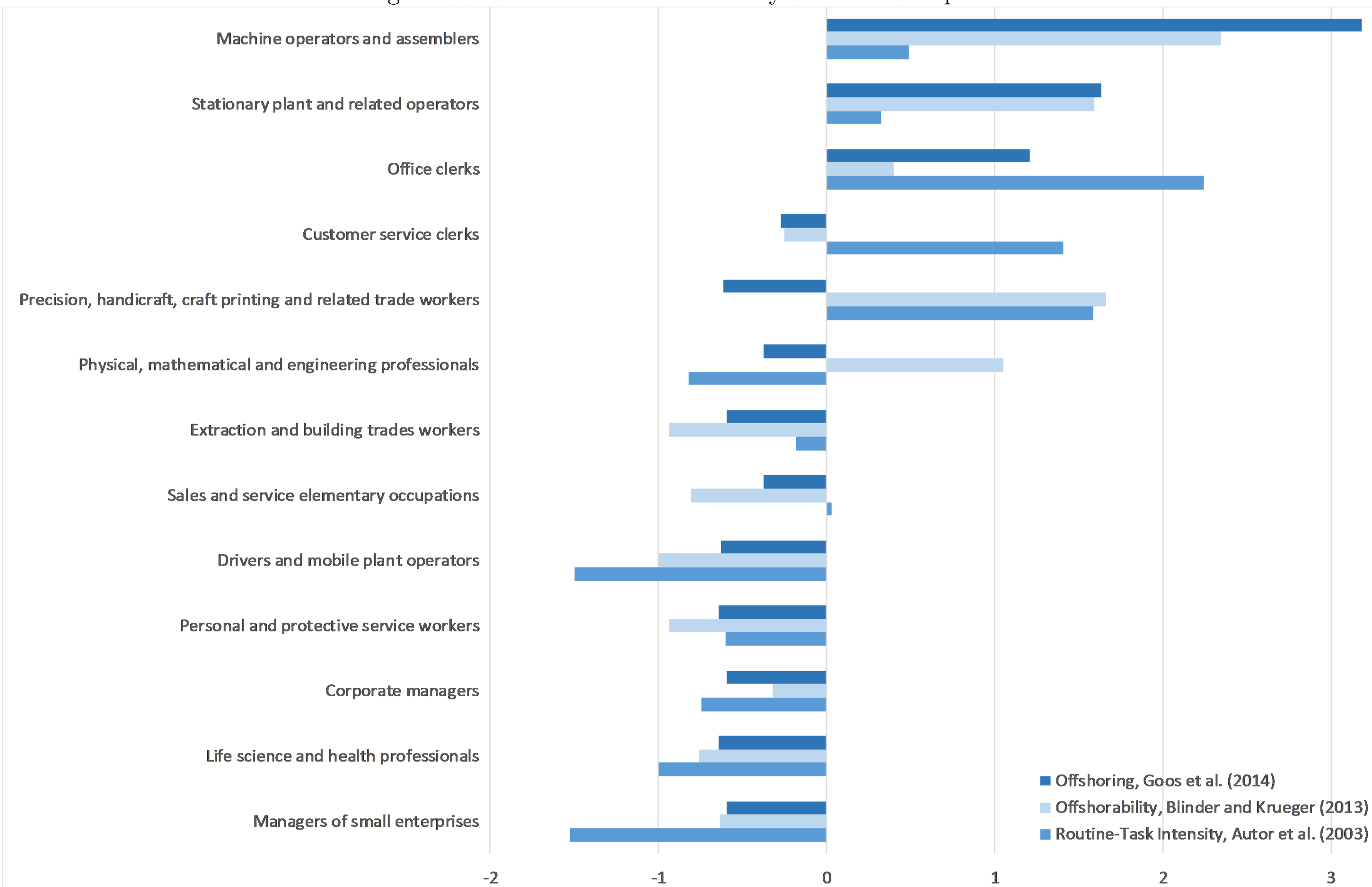
Note: Based on professional-coded offshorability (Blinder and Krueger, 2013). Calculated for German labor market shares based on BIBB/BAuA 2012 data.

refers to tasks as the relevant unit for offshorability.

As can be seen from Figure 6.3, which is based on replication data for Goos et al. (2014), actual offshoring, general offshorability, and routineness are not fully coincident but related. The different measures are standardized to have mean zero and a standard deviation of one, so that they are somewhat comparable. The first measure is based on offshoring information from the ERM and thus reflects actual offshoring. The second measure is the professional-coded measure of Blinder and Krueger (2013) mentioned above. Offshoring has relatively strongly affected machine operators and assemblers, stationary plant and related operators, and office clerks. These occupational groups are characterized by above-average offshorability of tasks and routineness. Interestingly, also trade workers' (5th category) occupational tasks can be considered easily offshorable, but the incidence of offshoring is below average.

Whether offshoring is actually viable depends on a wider range of factors than those directly task-related, though the latter are the most widely discussed. The literature has not yet settled on task characteristics that are commonly considered to determine offshorability. As summarized by Püschel (2015), task characteristics that are often taken into consideration are the need for face-

Figure 6.3: Standardized Measures by Selected Occupations



Note: Based on replication data for Goos et al. (2014).

to-face contact, routineness, and ICT dependence. Also the context of tasks determines whether they can be relocated. Even if the tasks involved in the production of an intermediate good are not bound geographically, the need for short-term availability of intermediate goods can require the geographic proximity of, e.g., suppliers and assemblers. Offshoring may also be precluded by data security concerns or be strategically unfit. The wide range of factors can hardly be captured exhaustively. Given that especially factors that render offshoring non-viable are difficult to address comprehensively, estimations of offshorability often reflect upper bounds.

6.3 Labor Market Effects of Offshoring

The nature of trade has changed dramatically in recent history, and with it the economic concepts used to pin down its effects. The traditional narrative of increasing global competition is that it puts domestic low-skill workers' wages under pressure while the high-skill segment gains. Pressure on the low-skill segment stems from the mechanics of international factor price equalization. Gains for the high-skill segment stem from international comparative advantage in high-skill intensive production. When increasing global competition affects final goods, shifts in relative factor prices take place between industries. Today, trade not only involves final goods, but increasingly intermediate goods as well as services. As elaborated by Feenstra and Hanson (1996a,b), increasing global competition in intermediate goods can cause shifts within single industries. The uprising of the task-based approach to labor markets has considerably altered the narrative of how increasing global competition affects labor markets.

Grossman and Rossi-Hansberg (2008) use the concept of tasks to theoretically study the labor market effects of offshoring. They take into consideration that workers with different skills have different comparative advantages in the performance of tasks. Distinguishing between two types of tasks and two types of labor, the focus lies on the effect of increased offshoring on the wages in the low-skill sector compared to wages in the skill-intensive sector. They show that offshoring operates in three distinct ways.

The first effect, called the productivity effect, has the potential to alter the standard understanding of trade theory that North-South trade bears a conflict of interest between low-skilled and high-skilled workers in the North. As falling costs of offshoring allow a firm to take advantage of factor price differentials between countries without sacrificing the gains from specialization, the firm's profitability increases. Grossman and Rossi-Hansberg show that the increase in productivity is greater in the labor-intensive sector than in the skill-intensive sector if low-skill tasks are more easily offshored and task trade has already been taking place. The labor-intensive sector expands relative to the skill-intensive sector, leading to an economy-wide increase in the demand for low-skilled labor. Thus, the productivity effect of decreasing trade costs resembles the effect of factor-augmenting technical progress. The second effect, called the relative-price effect is in turn known from standard trade theory, specifically the Stolper-Samuelson theorem (Stolper and Samuelson, 1941). As rising offshoring opportunities change factor supplies, the domestic composition of output (rather than factor intensities) is changed and favors high-skilled workers. The third effect, called the labor-supply effect, was elaborated earlier by Feenstra and Hanson (1996a). Offshoring increases the effective supply of labor. Workers who used to perform tasks that are offshored are reabsorbed by the labor market and their wages are driven down. If the relative-price effect and the labor-supply effect outweigh the productivity effect outweighs, workers whose tasks are offshored are disadvantaged by offshoring. If, however, the productivity effect dominates, both domestic low- and high-skilled workers benefit from offshoring.

The model is limited to the analysis of two types of tasks and two types of workers with fixed skill sets. The focus on two types of tasks and skills restricts the models' suitability to more broadly discuss the effects of offshoring on inequality and potential polarization. The geographic relocation of offshorable tasks may affect workers non-monotonously across skill levels, similar to the substitution of routine tasks through automation in the context of biased technical change. This may be the case when workers under pressure are not necessarily those with the lowest skill levels, but those performing easily offshorable tasks.

Given the empirical observation that large changes in factor allocation and factor prices have occurred at high levels of disaggregation, such as within industries, educational groups, and wage segments (as discussed in chapter 4), different theoretical approaches to embrace heterogeneity have evolved. Some theoretical frameworks build on the heterogeneity of firms and self-selection into export or (intermediate-)import markets (e.g. Amiti and Davis, 2012; Antràs et al., 2017; Davis and Harrigan, 2011; Halpern et al., 2015; Helpman et al., 2010), others stress the heterogeneity of workers and the allocative role of wages (e.g. Antràs et al., 2006; Costinot and Vogel, 2010).

Acemoglu et al. (2015) present a theoretical model in which offshoring not only directly affects the structure of wages but additionally determines the bias in technical change. They argue that initially the cost of offshoring is relatively high and an increase in offshoring opportunities causes domestic low-skilled workers' wages to fall, technical change to be skill-biased, and skill premia to rise. As the cost of offshoring sufficiently decreases, the direction of technical change goes into reverse and becomes an equalizing force. The impact of offshoring on inequality should thus be U-shaped. As in most theoretical frameworks of offshoring, the domestic skill endowment is taken to be fixed. While a fixed endowment is reasonable in the short run, in the longer run skill supply might adjust.

Concerning employment patterns rather than wage patterns, Baumgarten et al. (2018) present a general oligopolistic equilibrium model in which industries with different shares of offshorable tasks are linked through labor and capital markets. Their model features the incentive of capital owners to alter their investment decision and shift resources towards industries which benefit from offshoring above the average. They predict employment changes to be hump-shaped across industries and find strong empirical support using German data. While general-equilibrium feedback effects are included with regard to capital allocation across industries, the model abstracts from long-run skill supply effects. As in Acemoglu et al. (2015), long-run effects are taken into consideration, but the endowment of domestic workers' skills is considered to remain constant.

Empirical findings on employment effects suggest that increasing international integration has slowed down the shift from the manufacturing to the service sector because rising exports to new markets stabilized industry jobs (Dauth, 2017; Dauth et al., 2014). At the same time, it is mainly production jobs that are considered to be threatened by offshoring (see section 6.2). In a review of ERM company case studies of relocation across the EU, the European Foundation for the Improvement of Living and Working Conditions (2008) concludes that German-based companies were relatively successful in maintaining overall employment levels in case of relocation, though under strong organizational restructuring within Germany and some shifts of activities between countries. Still, offshoring has been shown to lower individual employment security of German manufacturing workers - irrespective of the skill level once accounting for job tenure (Geishecker, 2008).

Baumgarten (2009) studies the employment effect of offshoring by considering occupational stability rather than the risk of leaving employment or the current employer.[4] A major distinction of the approach taken by Baumgarten is that it also embraces adjustments within offshoring firms. He finds that in the German manufacturing sector occupational stability decreases with offshoring. The effect is less negative the higher the degree of non-routineness or interactivity of initial occupational tasks. As a drawback of the study, Baumgarten notes that there may be shifts within occupations, as shown by Spitz-Oener (2006), that cannot be captured. I will return to this issue in the next section.

Empirical studies on wage effects are sometimes complicated by interrelations between firm productivity, international markets, and wages. High productivity firms are likely to sort into international markets (Melitz, 2003), the presence in international markets may in turn drive productivity (Halpern et al., 2015), and the firm component plays an important role in determining wages (Card et al., 2013). In addition, the bargaining positions of unions are weaker in more internationally active plants (Felbermayr et al., 2014).

Hummels et al. (2014) address this issue in a study of the wage effects of offshoring based on Danish data. They simultaneously consider instrumented offshoring and instrumented exports. They are able to identify the effect of offshoring and exports within job spells, i.e. the effect on a worker during the tenure with a specific firm, depending on individual characteristics. They find that exporting increases wages for all skill types. Offshoring in turn increases the wages of high-skilled workers but decreases the wages of low-skilled workers. The combined net effect of trade is positive for about half of low-skilled workers and additionally depends on task characteristics. With regard to exporting and a focus on Germany, Schank et al. (2007, 2010) in contrast find that the exporter wage premium is rather low once observable and unobservable characteristics are controlled for and that the premium at the respective firms already exists before offshoring occurs. Klein et al. (2013) approach a similar question using different data, though also for German manufacturing workers, and a different methodology. They allow for heterogeneous effects for low- and high-skilled German manufacturing workers and find higher export wage premiums for high-skilled workers compared to low-skilled workers. In fact, the found export wage premium for low-skilled manufacturing workers in West Germany is rather an export wage discount. At the 75th percentile value of export shares, low-skilled workers are estimated to earn about 0.9 percent less compared to workers working at non-exporting firms.

[4] The approach is particularly interesting in the context of recent work by Jung and Kuhn (2018) discussed later in section 9.1.

Focusing on the empirical effect of offshoring on wages for male German manufacturing workers, Geishecker and Görg (2008) and Baumgarten et al. (2013) find that low-skilled workers are particularly vulnerable to the negative wage effects of offshoring. Baumgarten et al. (2013) follow the approach of Ebenstein et al. (2014) of distinguishing between industry exposure to offshoring and occupational exposure to offshoring. Interestingly, industry exposure to offshoring seems to have little impact on wages whereas occupational exposure has considerable effects. Taking occupational tasks into consideration, Baumgarten et al. (2013, p.149) add that "non-routine content can indeed shield workers against the negative wage impact of offshoring".

6.4 Offshoring, Shifting Skill Requirements, and Training

The task shifts within and between occupational groups described by Spitz-Oener (2006) for Germany may not only be related to technical change in the narrow sense but in the broader sense. By technical change in the narrow sense I mean technical change that is related to automation. As discussed in the previous section, technical change in the broader sense includes offshoring as a special case.

Becker and Muendler (2015) examine the relationship between offshoring and the composition of tasks in German workplaces. They find that the most pronounced task changes occurred within occupations and note that "[t]he previous practice of mapping tasks to occupations in a time and sector invariant manner used to obfuscate this source of variation despite its dominance" (p.593). They combine time-variant data on occupational contents with sector-level trade data in order to derive information about the degree of offshorability or tradability of jobs. As noted earlier, however, it is not necessarily jobs that are traded but may also be tasks within jobs. Both views are coherent with the notion of shifting occupational tasks. The analysis of task shifts within jobs rather than within occupations bears higher demands on the data necessary to study the phenomenon. With data at the occupation level at hand, Becker and Muendler find that the variability in tasks over time is related to offshorability. Job activities in terms of multitasking and performance requirements grow relatively more for work contents typically considered more offshorable. As mentioned in the discussion notes accompanying the article, there may be a trade-off between offshoring at the extensive margin (displacing workers) and the intensive margin (task shifts within jobs). As an example, Muendler notes local production workers. Some may become displaced whereas the remaining local production workers' jobs may require more coordination tasks to fit the newly imported intermediate input into the production chain, which in turn is likely to require the retraining of the incumbent workers.

Hummels et al. (2012) investigate the link between offshoring and training participation using Danish linked employer-employee data. They distinguish workers in two dimensions: workers employed at offshorers vs. workers employed at non-offshorers and, within the former, displaced vs. staying workers. They document an increase in training take-up rates related to offshoring. On the one hand, retraining rates of workers who have been displaced from offshoring firms are higher than retraining rates of other displaced workers. On the other hand, training rates are higher for workers staying at offshoring firms than for workers staying at other firms. They name the reorganization of production within the firm as a potential explanation for this second phenomenon.

Hogrefe and Wrona (2015) combine the BIBB/BAuA Employment Survey 2005/06 with data on intermediate imports and find a positive relationship between increased offshoring and individual skill upgrading. Their explanation for the phenomenon is, however, a very different one. They take the Grossman and Rossi-Hansberg (2008) model as a basis and argue that firm's cost savings are handed through to workers. By scaling up their wages, offshoring creates skill upgrading possibilities and thus leads to more training. In the model of Hogrefe and Wrona, the mechanism that links offshoring and individual skill upgrading neither depends on task-bias, nor on skill-bias.

Whereas Hogrefe and Wrona (2015) start from the supposition that workers' wages are scaled up by offshoring, I consider this not necessarily to be the case. The association between rising offshoring and increased training participation does not have to stem from rising wages but may as well stem from a depreciation of the tasks that workers used to perform in combination with rising opportunities in alternative tasks. It remains an open question whether skill adapters actually gain from increased offshoring.

Chapter 7

Empirical Analysis I - Skill Adaptation to Technical Change

As elaborated in chapter 3, for a worker who used to perform a task that was negatively affected in terms of marginal productivity at the employing firm, reallocation to another task may dampen the direct negative effect on the worker's productive potential. If reallocation is associated with skill adaptation, the productive potential in the new task is higher the stronger the demand shift and may even overcompensate the loss in productive potential in the original task. Whether a skill adapter's wage, which is presumed to reflect unobservable productive potential, actually increases is to be studied empirically. The hypotheses underlying the analysis are as follows.

Hypothesis H_0**.** *Skill adapters' wages decrease with or remain unaffected by the degree of technical change.*

Hypothesis H_1**.** *Skill adapters' wages increase with the degree of technical change.*

The main interest thus lies in the group of skill adapters. The group consists of workers who face task shifts at the job and take training. This implies that the group has access to training. In turn, the composition of the group of non-adapters is not straight forward. This group consists of workers who are distinct from each other in several dimensions. In this group there are workers who are affected by task shifts, workers who are not, and workers who are affected, but not to the degree that training becomes necessary or viable. Even if workers are not directly affected by task shifts in the workplace, technical change can nevertheless have an impact on wages. In addition, the group is likely to consist of workers who generally have access to training and workers who do not. Even if workers have access to training and are interested, their participation may be impeded. Comparisons between skill adapters and non-adapters are merely descriptive.

Two potential channels through which new technologies can affect wages are distinguished: one, the industry in which workers are employed and two, their occupation. In terms of the skill-weights approach of Lazear (2009) discussed in section 3.2, the degree to which workers are affected through the different channels is a matter of which is the better proxy for skill-weights.

7.1 Data

For the empirical analysis of the nexus between technical change, training, and wages, matched employer-employee data with wage and detailed training information that is connectable to offshoring data would be the first choice but is to this date not available. After describing the data that was used for the analysis, a few close alternatives are discussed.

The SOEP is used as the main data source. The SOEP has a feature that makes it particularly interesting with regard to analyzing skill adaptations in the face of task demand shifts, which is the availability of data on the objective of training participation. The period under study is restricted to the years 2000 to 2007 due to limited compatibility of the SOEP data with EU KLEMS data.[1] The focus lies on male low-skilled (ISCED 1-3) workers who were employed in the manufacturing sector (Nomenclature of Economic Activities (NACE)/International Standard Industrial Classification (ISIC) 15-36) at the beginning of the sample period, had worked for the same employer for at least three years before 2000,[2] and remained with the same employer through-

[1] Limitations in compatibility stem from changes in the provision of industry classification codes. Industries defined in different versions of the NACE classification cannot be mapped 1 by 1. The EU KLEMS March 2011 Update on the November 2009 release is the last version of the KLEMS in which the NACE revision 1 industry classification is used and industry data can be mapped to SOEP data without arbitrary manipulations.

[2] I follow Helwig (2001, p.13) in using a threshold of three years because I am interested in

out the period under study. These workers may though have switched the occupation or business sector within their firm. I exclude individuals who were apprentices, interns, or self-employed at the start of the period under study. The included workers were born between 1947 and 1975 (i.e., workers turning at least 25 in 2000 and turning at most 60 in 2007). Due to missing data some workers cannot be tracked for the whole period but drop out before the end of the sample period. To correct for attrition bias I use staying probabilities, which are available along with inverse probability weights. I use wage data from the Cross-National Equivalent Files from the SOEP package.

Additional questions on further professional training are regularly included in the SOEP. In 2004, individuals were asked whether they underwent further work-related education within the last three years and for what purpose. Workers could choose multiple answers from the set 'Retraining for a different profession or job,' 'Introduction to a new job,' 'Qualification for professional advancement,' 'Adjusting to new demands in my current job,' and 'Other.' The training measure used in the following indicates whether courses taken specifically to adjust to new requirements in one's current job were taken. Workers who took this type of training are referred to as skill-adapters. Task shifts are thus not captured explicitly but implicitly for the group of skill adapters. Since detailed information on training participation covers the three years preceding the survey, I measure the effect of skill adaptation with some delay.

Two proxies for technical change are used. Both stem from EU KLEMS data (O'Mahony and Timmer, 2009). The first proxy, total factor productivity based on value added (TFP_{jt}), is provided as an index with base year 1995 in the original data source. Appendix B provides plots of industry-level variability in the original data. The natural logarithm is used, so that results can be interpreted in terms of elasticities. The measure is further adjusted to refer to the year 2000 as the base year. The second proxy is ICT capital services per hour worked ($CAPIT_{jt}$). Plots of industry-level variability of the original data are provided in Appendix C. Analogous the first proxy, the original data is logarithmized and base-year adjusted.

For each of the two proxies, the original proxy that varies at the industry level is reweighted with industry employment within a given occupation L_{kj} as a share in total employment in the occupation L_k. This reweighting procedure is based on Ebenstein et al. (2014) and serves to take account of the fact that the

displacement and employer switch that is related to labor market conditions rather than 'bad match'.

relevant unit for an analysis of exposure to technical change may be a worker's occupation rather than the industry. The reweighted version of TFP_{jt} is

$$TFP_{kt} = \sum_{j=1}^{J} \frac{L_{kj}}{L_k} \times TFP_{jt}. \tag{7.1}$$

The reweighted version of $CAPIT_{jt}$ is

$$CAPIT_{kt} = \sum_{j=1}^{J} \frac{L_{kj}}{L_k} \times CAPIT_{jt}. \tag{7.2}$$

In the following, some alternatives to the data used here shall be outlined. As an alternative to using proxies for technical change as a driver behind task demand shifts, direct (time-variant) measures of occupational tasks could potentially be used. Data on occupational tasks can be found in the BIBB/IAB Qualification and Career Surveys that are available for the years 1979, 1985/86, 1991/92, and 1998/99 and in the BIBB/BAuA Employment Surveys available for the years 2005/06 and 2012 (conceptual follow-up of the BIBB/IAB Qualification and Career Surveys). With regard to the individual level, these data are repeated cross-sections. A lack of panel structure does not allow for a sufficient control of unobserved individual heterogeneity. For the 2012 survey, a follow-up survey including a subset of the formerly interviewed individuals and information on tasks is available. However, individuals who have taken training in the meantime are systematically excluded. While there exists another follow-up for individuals who have taken training, the focus lies on training related to promotion rather than adaptation. Another data set including information on occupational tasks is provided by Dengler et al. (2014). They use an expert operationalization of tasks instead of survey data, taking the same classification of occupational tasks as Spitz-Oener (2006) (presented earlier in section 2.2) as a basis. As there is variability in the task measures, task reallocation within occupations could be studied, but it does not lend itself to the analysis of reallocation within jobs. Data is available only for three subsequent years (2011 to 2013). I use a measure of non-routineness of tasks as a control. This measure, which is based on Becker et al. (2013) and Baumgarten et al. (2013), refers to the non-routineness of tasks as observed right before the beginning of the period under study. The measure is constructed based on occupational data from the German BIBB/IAB study from 1998/99. It ranges from 0 (least occupational content of non-routine tasks) to 1 (most occupational content of non-routine tasks).

While matched employer-employee data would be desirable to rule out unobserved heterogeneity on the firm level, a downside lies in a lack of information on the aim of training. Matched employer-employee data sets are available from the German Institute for Employment Research (IAB). The LIAB data set combines a large representative annual establishment survey with administrative data on the individual level. Information on the individual level is rather limited in comparison to the SOEP data. Another IAB data set with interesting features is the Employee Survey for the Project "Further Training as a Part of Lifelong Learning" (WeLL). This data set has a special focus on skill adaptation in the course of working life, but it is rather small and limited in representativity. Also SOEP-based matched employer-employee data is available. The SOEP-LEE adds a one-shot employer survey to the regular SOEP for the year 2011. It includes information on how employers cope with demand shocks, which is relevant for the relationship between demand shocks, task shifts, and wages. As the observation of multiple workers per establishment is rather an exception (see Weinhardt et al. (2017) for details), the SOEP-LEE does not lend itself to ruling out unobserved heterogeneity at the firm level.

With regard to alternative proxies for technology-related task demand shifts, later versions of the EU KLEMS data include further measures of factor productivity. Compatibility of EU KLEMS data and SOEP data over time is limited due to the use of different industry classifications. Another potentially interesting proxy for task demand shifts due to technical change in the manufacturing sector is the economic depreciation rate, which reflects obsolescence (Sakellaris and Wilson, 2004). Data on average economic lives of capital goods at the industry level is available form the Research Data Center of the German Federal Employment Agency at the IAB (Müller, 2017). A similar difficulty as with the other alternative proxies arises. The use of different industry classifications impedes the accurate mapping of the data.

7.2 Empirical Framework

I estimate wage regressions where I include training participation, technical change (industry or occupational exposure), and an interaction term. The interaction term is the main object of interest. It captures skill adjustment that is induced by technical change under the assumption that the exposure to new technologies is exogenous. Note that skill adjustment via training can have other causes such as offshoring or organizational change. In turn, technical change does not necessarily have to be skill- or task-biased.

The wage equation for industry exposure to technical change is given by:

$$\begin{aligned}\ln(WAGE_{ijt}) = \alpha + \beta TFP_{jt} + \gamma TR_{it} + \delta TR_{it} \times TFP_{jt} \\ +\theta IC_{it} + \lambda WC_{it} + \iota_i + \tau_j + \psi_k + \mu_t + \epsilon_{ijt},\end{aligned} \tag{7.3}$$

where $WAGE_{ijkt}$ is the hourly wage of individual i employed in occupation k in industry j at time t. The first line contains a measure of technical change within the industry where a worker is currently employed in TFP_{jt} and a dummy indicating participation in training that was undergone with the aim of adjusting to new requirements on-the-job or at the workplace TR_{it}. It is followed by an interaction term between training participation and exposure to technical change at industry-level $TR_{it} \times TFP_{jt}$.

The second line contains control variables for demographic characteristics of the worker IC_{it} and workplace controls WC_{it} along with a number of fixed effects. At the worker level, I include marital status, a dummy for children, tenure, and a dummy for current part-time employment. At the workplace level I control for firm size, since firms can grow or contract over time and workers can move between subsidiaries, and for non-routineness of the current occupation (measured before the period under study).

I include individual fixed effects ι_i to capture persistent differences between individuals, industry fixed effects τ_j to capture persistent differences between industries, and time fixed effects μ_t to capture aggregate shocks. The remaining variance is captured by the error term ϵ_{ijkt}. Standard errors are clustered at industry level. If there is no heterogeneity in the wage effects of skill adjustment to technology-induced shocks, standard errors can be expected to be smaller (see Abadie et al., 2017).

I estimate a similar wage regression for occupational exposure to technical change. Instead of TFP_{jt} I include TFP_{kt} defined in section 7.1. The estimation follows a similar scheme.

$$\begin{aligned}\ln(WAGE_{ijkt}) = \alpha + \rho TFP_{kt} + \gamma TR_{it} + \eta TR_{it} \times TFP_{kt} \\ +\theta IC_{it} + \lambda WC_{it} + \iota_i + \tau_j + \psi_k + \mu_t + \epsilon_{ijkt}.\end{aligned} \tag{7.4}$$

Standard errors are accordingly clustered at occupation level. I apply the same procedures using $CAPIT_{jt}$ and $CAPIT_{kt}$ instead of TFP_{jt} and TFP_{kt} as alternative proxies for technical change.

7.3 Results

Estimation results for wage equations (7.3) and (7.4) using total factor productivity as a proxy for technical change are presented in Table 7.1. Specifications (1) and (2) refer to industry exposure to technical change whereas specifications (3) and (4) refer to occupational exposure. Specifications (1) and (2) differ only in the additional inclusion of occupation dummies. Specifications (3) and (4) in turn differ only in the additional inclusion of industry dummies. I find no significant interaction between technical change and skill adaptation. In three out of the four specifications the wage differential between skill adapters and non-adapters when there is no change in total factor productivity is positive and statistically significant. Adaptation to shifting tasks on-the-job via training, as far as it is not induced by technical change measured by TFP, is thus associated with a higher wage. The direct effect of technical change is not statistically significant.

The respective results using ICT capital services as a proxy for technical change are contained in Table 7.2. Again, specifications (1) and (2) refer to industry exposure to technical change whereas specifications (3) and (4) refer to occupational exposure. Also using the alternative proxy for technical change I find no significant interaction between technical change and skill adaptation. The direct effect of being a skill adapter is not significant when using the alternative proxy for technical change. While I find a negative and statistically significant negative effect of ICT capital in the industry on the wage of non-adapters, the effect becomes insignificant once I control for unobserved heterogeneity between occupations by including occupation dummies. Overall, I cannot reject the null hypothesis.

As noted earlier in section 7.1, a more fine grained measure of technical change that more closely relates to technology-induced shifts in job tasks would be desirable but is to date not available. Re-weighting the industry-level measures of technical change to reflect occupational exposure to technical change may still be insufficient to capture technology-induced shifts in the productive potential of workers taking place within jobs.

Table 7.1: Wage Regression Results, Technical Change Proxied by TFP

	(1)	(2)	(3)	(4)
Training	0.035*	0.037	0.049*	0.053**
	(0.020)	(0.022)	(0.025)	(0.026)
Technical change (TFP_{jt})	-0.070	-0.048		
	(0.063)	(0.084)		
Technical change (TFP_{kt})			0.146	0.138
			(0.137)	(0.133)
Training X TFP_{jt}	0.077	0.052		
	(0.087)	(0.109)		
Training X TFP_{kt}			-0.113	-0.174
			(0.222)	(0.229)
Individual fixed effects	yes	yes	yes	yes
Time dummies	yes	yes	yes	yes
Industry dummies	yes	yes	no	yes
Occupation dummies	no	yes	yes	yes
N	3719	3719	3719	3719
Adjusted R^2	0.771	0.774	0.771	0.774

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: All specifications include control variables described in section 7.2. Standard errors are clustered at the level of variation in the offshoring measure.

Table 7.2: Wage Regression Results, Technical Change Proxied by $CAPIT$

	(1)	(2)	(3)	(4)
Training	0.022	0.048	0.025	0.040
	(0.031)	(0.029)	(0.057)	(0.057)
ICT capital ($CAPIT_{jt}$)	-0.153***	-0.137		
	(0.042)	(0.128)		
ICT capital ($CAPIT_{kt}$)			0.21	0.175
			(0.251)	(0.233)
Training X $CAPIT_{jt}$	0.043	-0.030		
	(0.087)	(0.087)		
Training X $CAPIT_{kt}$			0.049	0.004
			(0.168)	(0.162)
Individual fixed effects	yes	yes	yes	yes
Time dummies	yes	yes	yes	yes
Industry dummies	yes	yes	no	yes
Occupation dummies	no	yes	yes	yes
N	3719	3719	3719	3719
Adjusted R^2	0.771	0.774	0.771	0.774

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: All specifications include control variables described in section 7.2. Standard errors are clustered at the level of variation in the offshoring measure.

Chapter 8

Empirical Analysis II - Skill Adaptation to Offshoring

Analogous to the analysis in chapter 7, it shall be assessed whether skill adaptation to shifting tasks in the face of offshoring affects wage. The analysis in this chapter is closely related to earlier work by Baumgarten et al. (2013). They have shown that low-skilled manufacturing workers are particularly vulnerable to the negative wage effects of offshoring and find that "non-routine [task] content effectively shields workers against the negative wage impact of offshoring". In contrast to Baumgarten et al., I exclusively focus on workers who stay with their employer and do not consider task content to be exogenous or fixed. Instead, I start from the premise that job tasks are adjustable. The hypotheses underlying the analysis are the following.

Hypothesis H_0**.** *Skill adapters' wages decrease with or remain unaffected by the exposure to offshoring.*

Hypothesis H_1**.** *Skill adapters' wages increase with the exposure to offshoring.*

Again, the main interest lies in the group of skill adapters and comparisons to non-adapters are merely descriptive. Skill adapters are workers who face task shifts at the job and take training. The group of non-adapters consists of workers who are directly affected by offshoring, workers who are not, and workers who are affected, but not to the degree that training becomes necessary or viable. Workers who are not affected in terms of shifting job tasks, may nevertheless be subject to changes in their wages. I distinguish between industry exposure to offshoring and occupational exposure to offshoring, of which the latter seems to be more relevant for skill adaptation.

8.1 Data

As for the analysis in the preceding chapter, SOEP waves 2000 to 2007 are the main data source. Again, data for male low-skilled (ISCED 1-3) workers who were employed in the manufacturing sector (NACE/ISIC 15-36) in 2000 and stayed in a stable employment relationship is used. Offshoring data stems from the input-output tables provided by the German Federal Statistical Office. As in Baumgarten et al. (2013), the diagonal of the intermediate import matrix of the German Federal Statistical Office is used to construct two distinct measures of offshoring. Due to data revisions, the series is consistent only up to 2007, which is the upper limit of the period under study. Details on the construction of the offshoring measures can be found in Baumgarten et al. (2013) and Ebenstein et al. (2014). The first measure reflects industry exposure to offshoring and is defined by

$$OS_{jt} = \frac{IMP_{jjt}}{Y_{jt}}, \tag{8.1}$$

where IMP_{jjt} denotes intermediate goods imported from foreign industry j for use in domestic industry j at time t. Plots of industry-level variability of the measure can be found in Appendix D. The second measure is a weighted version of the first. The weighting accounts for industry employment within a given occupation L_{kj} as a share in total employment in the occupation L_k. The reweighting procedure causes the offshoring measure to vary not between industries but between occupations and yields a measure of occupational exposure to offshoring. The formula for the second measure reads as

$$OS_{kt} = \sum_{j=1}^{J} \frac{L_{kj}}{L_k} \times OS_{jt}. \tag{8.2}$$

For ease of interpretation, mean-centered versions of the offshoring measures are used. The distribution of both measures is right-skewed. Centered industry exposure ranges from -0.03 to 0.27, meaning that in the industry with the highest occurrence of offshore production (manufacturing of radio, television and communication equipment and apparatus in 2001), the volume of within-industry intermediate imports corresponds to almost one third of total production in the industry. Occupational exposure ranges from -0.03 to 0.15. Interpreting this measure is less straightforward.

Similar to the analysis in chapter 7, a measure of non-routineness based on Becker et al. (2013) and Baumgarten et al. (2013) is used as a control. This measure is based on BIBB/IAB data from 1998/99 and does not vary over time.

8.2 Empirical Framework

In a two-step approach, I first estimate wage regressions and then investigate marginal effects. The setup of the first step of the empirical analysis is analogous to the setup in chapter 7. Training participation, offshoring (industry or occupational exposure), and an interaction term are included. Skill adjustment via training can have other causes than offshoring, such as technical or organizational change. At the same time, offshoring can potentially take place without shifting the tasks of domestically employed workers. The interaction term is of primary interest because it captures skill adjustment that is induced by offshoring under the assumption that the exposure to offshoring is exogenous to the worker.

The wage equation for industry exposure to offshoring is given by:

$$\begin{aligned} \ln(WAGE_{ijt}) = \alpha + \beta OS_{jt} + \gamma TR_{it} + \delta TR_{it} \times OS_{jt} \\ + \theta IC_{it} + \lambda WC_{it} + \iota_i + \tau_j + \psi_k + \mu_t + \epsilon_{ijt}. \end{aligned} \tag{8.3}$$

Again, the dependent variable is hourly wage $WAGE_{ijkt}$ of individual i employed in occupation k in industry j at time t. Among a set of further controls, it is regressed on a measure of industry exposure to offshoring OS_{jt}, a dummy for participation in training with the aim of adjusting to new requirements TR_{it}, and an interaction term $TR_{it} \times OS_{jt}$.

The second line contains control variables for demographic characteristics of the worker IC_{it}, workplace controls WC_{it}, and a number of fixed effects. Controls at the worker level include marital status, a dummy for children, tenure, and a dummy for current part-time employment. Controls at the workplace level include firm size and non-routineness of the current occupation (measured before the period under study).

Fixed effects are included at different levels. At the individual level, ι_i captures persistent differences between individuals. At the industry level, τ_j captures persistent differences between industries. Aggregate shocks are captured via the time fixed effects μ_t. The remaining unexplained variance is captured by the error term ϵ_{ijkt}. Standard errors are clustered at the occupational level. In the absence of heterogeneity in wage effects, standard errors are likely to be smaller (see Abadie et al., 2017).

The estimation for occupational exposure to offshoring follows the scheme

$$\begin{aligned}\ln(WAGE_{ijkt}) = \alpha + \rho OS_{kt} + \gamma TR_{it} + \eta TR_{it} \times OS_{kt} \\ +\theta IC_{it} + \lambda WC_{it} + \iota_i + \tau_j + \psi_k + \mu_t + \epsilon_{ijkt}.\end{aligned} \tag{8.4}$$

Standard errors are again clustered at the level of variation in the offshoring measure, i.e. here at the occupation level.

In the second step, the effects of skill adjustment on the linear prediction of wage are further scrutinized. The marginal effects of training are given by

$$\frac{\partial \ln(WAGE_{ijkt})}{\partial TR_{it}} = \gamma + \delta OS_{jt} \tag{8.5}$$

for industry exposure to offshoring and

$$\frac{\partial \ln(WAGE_{ijkt})}{\partial TR_{it}} = \gamma + \eta OS_{kt} \tag{8.6}$$

for occupational exposure to offshoring. The marginal effect includes two components. It includes the effect of being a training participant given that a worker faces average offshoring exposure (γ) and the effect of training that is altered by the degree to which offshoring exposure of the worker deviates from the average (δ or η). Thus, the wages of training participants can be compared to the wages of non-participants across the range of offshoring exposure. Note that this comparison is merely descriptive.

8.3 Results

Estimation results for wage equations (8.3) and (8.4) are shown in Table 8.1. Specifications (1) and (2) contain industry exposure to offshoring whereas specifications (3) and (4) contain occupational exposure to offshoring. When controlling for unobserved heterogeneity between occupations, the coefficients for the measures of offshoring exposure are positive and significant. The positive coefficients for offshoring exposure in specifications (2), (3), and (4) indicate that offshoring has a direct positive wage effect on non-adapters. Recall that the sample is restricted to workers staying with their employers throughout the whole period under study. A positive effect of offshoring that I find here is therefore not in contradiction to the positive effect found by Baumgarten et al. (2013) that refers to workers in stable employment relationships as well as workers in non-stable relationships. The group of non-adapters to which this direct effect is to be ascribed comprises workers who are affected by offshoring, but not to the degree that skill adaptation through training is necessary or viable as well as workers who are not affected by task shifts in their job but may benefit from the employer's efficiency gains. The positive effect of offshoring is therefore not surprising.

Table 8.1: Wage Regression Results, Offshoring

	(1)	(2)	(3)	(4)
Training	0.045**	0.041*	0.008	0.008
	(0.021)	(0.022)	(0.023)	(0.020)
Offshoring (OS_{jt})	0.201	1.298***		
	(0.132)	(0.462)		
Offshoring (OS_{kt})			1.694**	1.892***
			(0.681)	(0.574)
Training X OS_{jt}	-0.105	-0.097		
	(0.452)	(0.374)		
Training X OS_{kt}			1.361*	1.418*
			(0.803)	(0.786)
Individual fixed effects	yes	yes	yes	yes
Time dummies	yes	yes	yes	yes
Industry dummies	yes	yes	no	yes
Occupation dummies	no	yes	yes	yes
N	3669	3669	3737	3737
Adjusted R^2	0.773	0.777	0.773	0.776

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: All specifications include control variables described in section 8.2. Standard errors are adjusted for clusters in industries.

The effect of training aimed at adaptation is measured at the average exposure to offshoring. Comparing specifications (1) and (2) to specifications (3) and (4), the positive direct effect of training aimed at adaptation vanishes when I consider occupational exposure to offshoring rather than industry exposure. In turn, only for occupational exposure to offshoring a positive interaction exists between offshoring and training that is significant at the 10 percent level based on conservative standard errors. This indicates that occupation is not only a better proxy for skill requirements than industry, as suggested by recent literature, but also more suitable for studying the effect of offshoring-induced task shifts. The interaction effect shows that skill adapters wages increase with offshoring exposure. The null hypothesis can thus be rejected when offshoring exposure is measured at the occupational level. The following considerations are based on specification (4).

In order to assess the economic significance of the interaction, I calculate contrasts of predictions between low, medium, and high occupational offshoring exposure. The results shown in Table 8.2 refer to training participants only. Comparing the 50th to the 10th percentile, the difference in predictive margins amounts to 9.79 percent. Taking the average hourly wage of training participants in the year as a basis, this makes a difference of 1.99 EUR per hour. The difference in wages between the 10th and the 90th percentile amounts to 3.56 EUR per hour. Comparing the 90th to the 50th percentile, the difference is 1.57 EUR per hour.

Table 8.2: Contrasts of Predictive Margins

Average hourly wage of training participants 2004		20.34
	Contrasts of predictive margins	
	in percent	in EUR
Occupational offshoring exposure		
50th vs. 10th percentile	9.79***	1.99
90th vs. 10th percentile	17.51***	3.56
90th vs. 50th percentile	7.72***	1.57

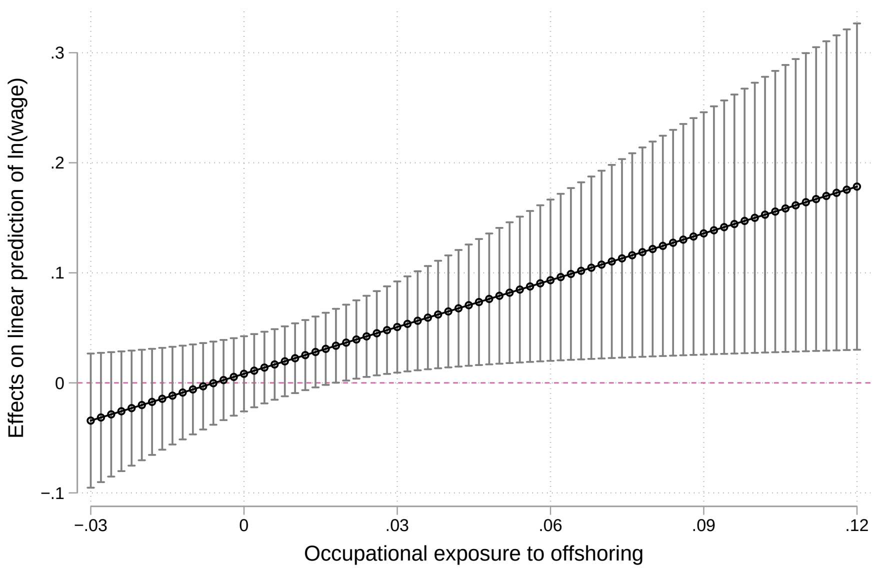
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Calculations are based on training participants and refer to the year 2004.

Above it was shown that the subgroup of skill adapters benefits from offshoring. I now compare skill adapters' wages to non-adapters wages. Even when there are higher returns to skill adaptation the higher the degree of offshoring exposure, it may still be that skill adapters in high offshoring segments earn lower wages than non-adapters if skill adapters are under stronger pressure than non-adapters. While this may be at odds with the view that a worker's productivity increases monotonously over time, training further raises productivity, it is plausible in situations of biased technical change and offshoring. Training may then be a measure to counteract a negative shock to the worker's productive potential but may not be sufficient to compensate for the shock. Even if the worker recovers the initial productive potential, the wage level may not pick up when the worker has to bear the cost of training.

Figure 8.1 shows the estimated effects of being a training participant on logged wage over the range of occupational offshoring exposures.[1] The discrete effects at different exposure values are shown, along with 90 percent confidence intervals. The positive interaction between training and exposure to offshoring that was found earlier is reflected in the positive slope. For average offshoring exposure the effect is very close to zero. In the high offshoring segments training participants have significantly higher wages than non-participants. I thus do not observe the case described above that would not be conceptually feasible.

Figure 8.1: Wage Effect of Training over Occupational Exposure to Offshoring



Note: Point estimates are presented along with 90 percent confidence intervals. Standard errors are adjusted for clustering at occupation level and calculated using the Delta-method.

8.4 Robustness Checks

In the following, I present robustness checks on the results for occupational offshoring exposure. In specification (1), I vary the set of included fixed effects. Instead of occupation and industry dummies I include industry-specific

[1]The notion 'effects of being a training participant' refers to the effect of the training variable on the prediction of wage rather than a causal effect.

time dummies. These capture time-varying shocks that may be related to offshoring. I find that the direct effect of offshoring becomes insignificant while the interaction term remains positive and significant.

Some of the variability in the offshoring measure that is used for identification stems from occupational change within the same employer. I assess whether controlling for switches between occupations affects the estimates. In specification (2) I include a dummy for occupation switch that is permanently set to one as soon as a worker switched the occupation. The results stay close to the main specification. Next, in (3) I include dummies that indicate whether a worker switched to an occupation with more or less routine task content. The results stay almost unchanged. In order to rule out that the positive interaction is driven by individuals who have higher trends in their wages irrespective of task shifts, are over-represented in training and systematically move into high offshoring segments, in (4) and (5) I rule out variation that stems from occupational mobility. An alternative strategy would be to include individual wage trends based on the years before training, which is not viable because the exact timing of training is not known. In (4) I restrict the sample to workers who did not change their occupation (variable pgjobch in the SOEP). The interaction term becomes insignificant, with the coefficient still very close to the main specification, while the direct effect of OS_{kt} remains positive and significant. Finally, in (5) I use offshoring exposure in the initial occupation rather than in the current occupation. In both (4) and (5) the reduction in variation comes with a loss of significance. The size of the interaction of interest, however, stays close to the coefficient in the main specification.

As can be seen from Table 8.4, the contrasts of predictive margins remain positive and significant for specifications (1) through (4). The size of the wage differences across the distribution of occupational offshoring exposure varies rather strongly across the specifications. It becomes apparent that the more restrictive sample of workers staying in their initial occupation used in specification (4) has a higher average hourly wage than the original sample. For specification (5) the estimates of the contrasts of predictive margins are close to the contrasts of the main specification, but they are not statistically significant, which is not surprising given that there is overall less variation in the data. Robustness check plots corresponding to Figure 8.1 can be found in Appendix E.

Table 8.3: Robustness Checks on Wage Regression Results

	(1)	(2)	(3)	(4)	(5)
Offshoring (OS_{kt})	-0.366	1.451**	1.451**	1.235**	0.924
	(0.311)	(0.572)	(0.558)	(0.602)	(0.602)
Training	-0.007	0.008	0.001	0.006	0.000
	(0.018)	(0.024)	(0.024)	(0.035)	(0.027)
Training X OS_{kt}	1.613**	1.425*	1.734*	1.648	1.353
	(0.785)	(0.827)	(0.874)	(1.038)	(0.927)
Switched occupation		0.005			
		(0.017)			
Less routine occupation			0.037		
			(0.027)		
More routine occupation			-0.029		
			(0.025)		
Individual fixed effects	yes	yes	yes	yes	no
Time dummies	yes	yes	yes	yes	yes
Industry dummies	no	yes	yes	yes	no
Industry-time dummies	yes	no	no	no	no
Occupation dummies	no	yes	yes	no	no
Occupation switchers excluded	no	no	no	yes	no
N	3737	3503	3357	2788	3766
Adjusted R^2	0.785	0.781	0.789	0.789	0.768

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: All specifications include control variables described in section 8.2.

Standard errors are adjusted for clusters in occupations.

Table 8.4: Contrasts of Predictive Margins, Robustness Checks

Robustness check (1)		
Average hourly wage of training participants 2004		20.34
	Contrasts of predictive margins	
	in percent	in EUR
Occupational offshoring exposure		
50th vs. 10th percentile	4.01*	0.81
90th vs. 10th percentile	7.17*	1.46
90th vs. 50th percentile	3.16*	0.64
Robustness check (2)		
Average hourly wage of training participants 2004		20.34
	Contrasts of predictive margins	
	in percent	in EUR
Occupational offshoring exposure		
50th vs. 10th percentile	8.54***	1.74
90th vs. 10th percentile	15.28***	3.11
90th vs. 50th percentile	6.74***	1.37
Robustness check (3)		
Average hourly wage of training participants 2004		20.34
	Contrasts of predictive margins	
	in percent	in EUR
Occupational offshoring exposure		
50th vs. 10th percentile	9.59***	1.95
90th vs. 10th percentile	16.92***	3.44
90th vs. 50th percentile	7.33***	1.49
Robustness check (4)		
Average hourly wage of training participants 2004		21.86
	Contrasts of predictive margins	
	in percent	in EUR
Occupational offshoring exposure		
50th vs. 10th percentile	8.64**	1.89
90th vs. 10th percentile	24.61**	5.38
90th vs. 50th percentile	15.97**	3.49
Robustness check (5)		
Average hourly wage of training participants 2004		20.34
	Contrasts of predictive margins	
	in percent	in EUR
Occupational offshoring exposure		
50th vs. 10th percentile	6.67	1.46
90th vs. 10th percentile	17.73	3.88
90th vs. 50th percentile	11.05	2.42

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 9

Discussion and Policy Implications

While I find that skill adapters benefit from offshoring, I do not find such an effect for automation-related task shifts. Given the lower variation in the measures used to capture the latter, this does not come as a surprise. The finding is consistent with the proposition that the productive potential of skill adapters may increase with task demand shifts even if the shift depreciates their initial tasks. However, it remains unclear whether the productive potential is raised to a degree that overcompensates for the depreciation of skills. A major difficulty lies in the empirical distinction between workers composing the group of non-adapters. They may or may not be actually affected by task shifts, and, if they are affected, they may lack the adaptive capabilities, interest, or the possibility to upgrade their skills. A lack of the possibility to upgrade skills may create a wage premium for skill adapters that is not necessarily based on increased productive potential through skill adaptation, but may be driven by limitations to skill adaptation.

Low-skilled manufacturing workers have previously been shown to be particularly vulnerable to the negative wage impacts of offshoring. While non-routineness was found to be a task characteristic that shields workers from negative wage impacts, occupational tasks can hardly be steered by policy; rather, they are determined by the market and technology. When it comes to skill adaptation, policy can leverage productivity gains from offshoring. Skill upgrading among employees maintains alignment between the tasks demanded by employers and the skills possessed by workers. It can be incentivized by policy and has a direct effect on the participating workers as well as indirect effects on aggregate outcomes.

In the following, some aspects that deserve further discussion shall be elaborated upon. These aspects are complementary and embed the present work in the broader discussion of policies to avert negative impacts from automation and offshoring. Among institutional conditions that may foster workers' adaptive capabilities, I discuss some policy interventions that have been designed to incentivize lifelong learning.

9.1 Segregation of Workers

So far, it has not been discussed who the adapting workers are. I have exploited the panel structure of the SOEP to account for individual fixed effects. These capture time invariant unobservable characteristics that affect wage equally over the whole time span considered. However, workers' adaptive capabilities can only imperfectly be reflected in the fixed effects and are likely to affect selection into training, both in terms of workers' self-selection and employers' assignment of workers to training programs. Selection is an econometric concern if it induces endogeneity. Selection on adaptive capabilities is less of a concern because it affects wage only if a process of adaptation is effectively taking place, which is reflected in our adaptive training measure. Note that I use the term adaptive capabilities to refer to the ability to learn to perform different tasks rather than the ability to grasp more abstract concepts. The difference is that the latter would render workers heterogeneous even in the absence of shifting tasks. If selection based on adaptive capabilities is at work, it is likely to increase allocative efficiency and workers who can gain productive potential from training will be the ones who undergo training.

Selection into training may cause a group that is rather homogeneous in the absence of task shifts to diverge in terms of labor market outcomes. However, overall inequality could be higher if this separation through adaptive training did not take place. This is because lifelong learning programs designed to support firms in adjusting workers' skills impact not only the workers who are trained, but also those whose skills have been depreciated without adjustment. In the absence of training, the pool of (newly) unskilled labor grows relatively larger while the number of low-skill tasks shrinks due to offshoring. Offshoring would increase wage polarization and would further depress wages in the low-wage sector. While wage inequality continues to rise in Germany, wage mobility, which would defuse the situation, has decreased since the 1990s, according to Riphahn and Schnitzlein (2016). Skill upgrading of workers who are capable of adjusting to new tasks mitigates further downward wage competition in the pool of workers whose skills are depreciated in the face of task demand shifts through offshoring.

Training and displacement may be competing mechanisms to counter a mismatch between the tasks demanded by employers and the skills possessed by employees. Job protection is rather strong in the German labor market. Replacing employees with entrants that possess more suitable skill sets is therefore problematic. Displacing of a share of workers in combination with training the remaining employees is a more viable strategy for offshoring firms. In cases where such a dual strategy is pursued, a separation between workers with low adaptive capabilities into displacement and workers with high adaptive capabilities into skill upgrading is likely. With the focus on workers who stay with their employer, workers who become displaced within the period under study are not included in the empirical analyses. The selection process into displacement vs. non-displacement should therefore not distort the results limited to the selected group of non-displaced workers. Pre-employment selection effort for low-skilled workers is relatively lower than for high-skilled workers because the gap between good and bad matches is relatively smaller (Sengul, 2017). Nevertheless, employers also gradually gain information on low-skilled workers' characteristics that are costly to assess prior to employment and that are critical for adjustment processes.

At the same time, rising wages of skill upgraders may partly explain persistent earnings differences between displaced and non-displaced workers, which challenge existing labor market models. In a recent paper, Jung and Kuhn (2018) elaborate that the size of earnings losses of displaced workers are not only determined by the ability of displaced workers to recover after displacement, but also by the stability of non-displaced workers' employment paths. They argue that in most labor market models, there are two forces that produce mean-reversion of displaced workers' wages, which are responsible for displaced workers' predicted earnings losses to be rather small and temporary. The first is search. Displaced workers can engage intensively in search and climb back up the wage ladder. Search frictions are commonly included to dampen mean-reversion stemming from search. The second is job separation. It causes mean-reversion by hitting previously non-displaced workers and throwing them off the job ladder. With high separation rates, the differences between displaced workers and non-displaced workers become smaller. This second force is shown to be impeded by a tight link between wages and separation rates. Separation rates are lower in high surplus jobs, thus "the job ladder [becomes] a mountain hike that requires free climbing at the bottom but offers a fixed-rope route at the top. Reaching the top takes long, but once workers arrive at the top, the hike becomes a convenient and secure walk" (p.2). On these grounds, job stability of non-displaced workers is shown to be a main driver behind persistent earnings differences between displaced and non-displaced workers. In the light of potential task reallocation and skill upgrading of non-displaced workers, the strain and security in the lower and the upper parts of the "mountain hike" are likely to diverge even more.

To summarize, technical change, and specifically offshoring, may lead to a segregation of workers in a number of ways. It can induce a divide between affected and non-affected workers (in terms of shifting job tasks), training participants and non-participants, as well as displaced and non-displaced workers. The empirical analyses in this thesis are restricted to the selected group of non-displaced workers, but even within this group, task demand shifts from offshoring open a gap between workers.

9.2 Dimensionality of Skills

The degree of technological substitutability or complementarity of skills is by now commonly conceived to depend on the tasks at which these skills provide a comparative advantage. In earlier literature skills were often understood as a unidimensional measure, based on which labor's technological substitutability or complementarity is appointed. Consider for example manual vs. abstract tasks. When skills are unidimensional and there is a shift from manual to abstract tasks, one would probably argue that abstract tasks require "higher" skills than manual tasks and policy design would revolve around the question how to "increase" skills. In times of rapid technical change and globalization, a successful strategy for skill adaptation presumably lies in the provision of skills that allow for quick adjustment to shifting task demands. As noted by Nelson and Phelps (1966), workers' adaptive capabilities grow with general education. In the words of Welch (1970), a "'leverage' associated with added schooling is drawn from the dynamical implications of changing technology". Education augments the ability to process and interpret information, which is necessary to adapt to new technology and new tasks. Education fosters adaptive capabilities, which gives highly educated individuals a comparative advantage regarding the adjustment to and implementation of new technologies in times of rapid technical change (Bartel and Lichtenberg, 1987).

When, however, skills are multidimensional, i.e. skills needed to perform manual tasks, such as fine motor skills, are distinct from skills needed to perform abstract tasks, such as spatial imagination, the challenge for policy is not only to steer the overall amount of skills provided but also the quality of skills. Russ (2017), in an interdisciplinary conceptual accounting of developments in human capital formation and labor markets, goes so far as to claim that the multidimensionality of skills and the increasingly linked global economy give rise to a "trifurcation" of the labor market.[1] Specifically, it is claimed that the three labor markets are characterized by distinct production functions and that the boundaries between routine labor, skilled labor, and talent are becoming sharper. When the truth lies somewhere in the middle and skills are distinct, with particular skills easing the further acquisition of new skills, fostering the skills that ease adaptation is crucial in times of rapid labor demand shifts.

Bartel and Sicherman (1998) discuss the interactions between general education and further professional training in the context of technical change. They argue that the effect of technical change on training take-up is theoretically ambiguous. This is because technical change influences the rate at which human capital becomes obsolete. Increasing uncertainty related to human capital investments may potentially decrease human capital investment. With regard to the general mechanisms at play, they argue that "investments in training are the outcome of a supply and demand interaction of employers and workers, and technological change will influence the incentives of both parties". Concerning the relationship between general education and further professional training, the sign of the interaction is discussed as a matter of complementarity or substitutability. Education and further training are substitutes in the sense that generally skills can be accumulated in either way. They are complements in the sense of Nelson and Phelps (1966) and Welch (1970). Bartel and Sicherman find that complementarity dominates substitutability but substitutability increases

[1]The conceptual framework draws on a number of disciplines including labor economics, technology management, business innovation, human capital and knowledge management, psychology, and organizational behavior.

with the rate of technical change. They note that if general education fosters adaptive capabilities, substitutability between schooling and training decreases at higher rates of technical change. This means that in the face of rapid technical change, training rates of workers with low levels of general education should be expected to increase and converge to the training rates of highly educated workers.

9.3 Skill Upgrading as a Means to Counterbalance Task Demand Shifts

In how far labor market structures are affected by RBTC and offshoring depends not only on the severity of task demand shifts, but also on the degree to which demand shifts are counterbalanced by supply-side reactions.[2] The impact of a demand shift further depends on other factors that may mitigate or augment its effects. Autor (2015) name capital-skill complementarity, the elasticity of labor supply and the elasticity of product demand as such factors. Apart from these factors, which are to a large degree innate in the economy, also factors that can be considered alterable parameters of the economy may alter the effects of RBTC and offshoring. The alterable parameters mainly concern the supply of skills in the economy (see Gregg and Manning (1997) for a thorough discussion). In the words of Autor (2015), “human capital investment must be at the heart of any long-term strategy for producing skills that are complemented by rather than substituted for by technological change.”

Offshoring is increasingly seen as a special form of technical change. In the terms of Baldwin (2014), it is a geographical “unbundling” of the production and consumption of goods that characterized globalization after the late 1980s in contrast to earlier globalization. Similarly, in the terms of Gries et al. (2017b, p.326), the changing nature of trade can be understood as a “global disaggregation” of the value or supply network, where the concept of operational nodes in the production network are analogous to the concept of tasks. Baldwin argues that policies that were designed to meet the challenges of early globalization should be adjusted in the context of the “new-paradigm globalization”, which is technology-related rather than trade-related. He argues that globalization

[2] If demand and supply developed at the same pace, there should not be any effect on relative skill prices. Given that they interact but usually do not balance perfectly, Tinbergen (1974) has coined the term of a ‘race’ between technology and education, which has later been revived by Goldin and Katz (2009).

has become "more individual, more sudden and more unpredictable" (p.215) and contends that "education, technology and industrial policy need to be more nuanced, and more nimble. [...] Worker retraining will become more important; learning to learn may become as important to a worker's competitiveness as learning itself" (p.216). This view is shared here with an addition. Lifelong learning may not only "reduce the pains of globalization" (p.216), but it may increase the gains that can be realized from globalization.

Skill upgrading is, however, not the only policy instrument available to counter adverse effects from automation and offshoring. It can be complemented by policies ranging from promoting re-employment among displaced workers to redistribution. In the US, a dislocated worker program under the Workforce Investment Act and a program specifically for trade-displaced workers are in place. Concrete measures to reintegrate displaced workers include job search assistance, individual career counseling, training, as well as supportive services including subsidies for books, uniforms, tools, child care, and transportation (McConnell et al., 2016). In Canada, earnings supplements have been offered to promote rapid re-employment. Workers who re-entered employment within six months after displacement could receive a supplement to their earnings in the new job if this new job was lower-paying that compensated 75 percent of the negative wage differential between the old and the new job (Bloom et al., 2001). Evidence on the effectiveness of programs that address displaced workers is, however, sparse (OECD, 2018, pp.138-140).

Regarding redistributive measures, different scenarios with distinct implications are plausible. Many tasks that require relatively low skill levels are locally bound and can hardly be automated. Gains from technological progress and offshoring may trickle down to the local service sector if the demand for tasks in this sector rises sufficiently. If in turn the demand for these tasks does not rise sufficiently to counterbalance the inflow of low-skilled workers, increasing competition may drive wages of low-skilled workers further down. However, in addition to the products and services that exist today, new business models may evolve in response to lower wages in the service sector. If this is the case, rising demand for tasks at which low-skilled workers have a comparative advantage may at least dampen negative wage effects. As one may know the products and services that can be substituted by machines or foreign labor but cannot know which innovative business models will evolve, especially in the face of recent technological advances, assessing the role of redistributive policies in the future is not straight forward.

9.4 Institutional Context of Skill Upgrading

Skill upgrading as a (purely mechanical or policy-induced) supply side reaction to demand shifts can take place in the general and early vocational education system, in the form of "learning-by-doing", or in terms of further professional training on-the-job. While adjustments via the general education system take effect only in the long run, further professional training can counterbalance adverse effects on the structure of wages and employment earlier. The focus of this work lies on further professional training on-the-job, but interactions with earlier skill formation are likely.

Very recently, discussions about a lower adaptability of workers who went through vocational secondary education compared to workers who went through more general secondary education have evolved. Using the terms of Krueger and Kumar (2004a), the former can be considered 'skill-based' whereas the latter is rather 'concept-based'. Concept-based education and supposedly eases the adoption of new technologies both at the micro- and the macro-level (Krueger and Kumar, 2004b). Germany's dual system has long been a prime example of smooth school-to-work transitions. Which (secondary) educational system is preferable, however, depends on the advantages and disadvantages over the whole working life.

Hanushek et al. (2017) argue that the initial advantage of vocational graduates decreases with age and even turns into a disadvantage (in terms of employment) later in life when technological and structural change in the economy require adaptive capabilities. They further argue that the impact of vocational education varies with the country's institutional structure. The latter has been contested by Forster et al. (2016), who disentangle individual-level and institutional-level effects. They confirm that there is a relative disadvantage of vocational graduates over the long term in terms of employment, but they do not find a moderating effect of the institutional setting. In other words, it makes a difference whether secondary education is rather vocational or general, but it does not make a difference whether the graduate is situated in a setting characterized by a high prevalence of vocational training.

DiPrete et al. (2017) propose a conceptual framework for studying the interrelation between the educational system and the labor market that is based on the strength of linkages between educational credentials and later occupational positions.[3] Concerning the educational credentials, they do not only consider

[3]The concept of linkages is formally identical to the concept of entropy-based multigroup

the level of education but also the field of study. They argue that the strength of linkages can affect career mobility caused by technological changes that induce shifts in the structure of the labor market. Linkages are strong when graduates of a specific level and field of education are employed in a very restricted set of occupations and weak when they are employed in a variety of occupations. DiPrete et al. contend that, first, graduates from strongly linked educational programs are likely to be less mobile given their specific skill set, second, the strength of linkages is likely to vary over time, and third, the pattern of variation, which may differ by country, is likely to depend on technological change. The strength of linkages can be understood as a measure of specificity of educational programs. In contrast to earlier approaches on the specificity of educational programs that considered overall national institutional settings, the linkage approach aims at a more fine-grained consideration of specificity.

Overall, institutional factors that can potentially alter the upgradability of skills reach further than the factors determining the viability of on-the-job training. Ensuring the long-term upgradability of skills possessed at labor market entry can follow several alternative avenues with distinct emphases. In terms of Welch (1970), policy can focus on exploiting the "'leverage' associated with added schooling". In terms of Russ (2017), policy can follow the main objective of antagonizing a "trifurcation" of the labor market. In terms of Autor (2015), it can focus on "producing skills that are complemented by rather than substituted for by technological change". In terms of DiPrete et al. (2017), policy may strive to loosen the "linkages" in those segments of the labor market that are characterized by rapid technical change that renders skills obsolete. As far as potential upgradability of skills is given, actual skill upgrading in the form of further professional training on-the-job can, in the rather short term, keep workers who are negatively affected by shocks in stable productive employment.

9.5 Policies to Promote Skill Upgrading

As far as workers possess the ability to learn and adapt to new requirements on-the-job, further professional training may enable them to retrieve or augment their productive potential. The present work finds indications that at least in the context of offshoring, those engaging in skill adaptation to shifting tasks gain from offshoring in terms of wage. A further step is needed to deduce insights

segregation, which is a common concept in sociology.

for concrete policy design. This step concerns the identification of barriers to skill adaptation. In the absence of barriers to training, policy intervention is not necessary but may rather distort incentives and lead to unintended redistribution. The problem of barriers to training is a very common one that has been studied intensively. However, barriers to training are usually discussed in a context where training participation is understood as a measure to further accumulate productive skills rather than a measure counter adverse forces.

The context of skill depreciation through automation and offshoring may entail further barriers to training that have not been studied so far, such as inertia, negative association with change, and a lack of knowledge about the adaptive capabilities of workers. More commonly studied obstacles to skill upgrading in the form of further professional training include the lack of knowledge about and access to training programs, credit and time constraints, and a lack of incentives. As noted in the OECD (2017b) Skills Outlook, measures to remove the latter obstacles include the improvement of the tax system to provide stronger learning incentives, easing access to training, and promoting flexible working arrangements that allow workers to attend training programs. While the reduction of barriers enables the extension of further professional training, it seems worthwhile to also ask how further professional training programs can become more effective. The design of such training programs is to a large degree outside the scope of policy, but fostering adaptive capabilities and skills that are hardly substitutable can, to a large degree, be understood as a matter of general education.

In Germany, the program Förderung der Weiterbildung Geringqualifizierter und beschäftigter älterer Arbeitnehmer in Unternehmen (WeGebAU) of the Federal Employment Agency is the first country-wide program to specifically promote training of employed workers (Dauth, 2013). It was launched in 2006/2007 to promote skill adjustment of elderly employees (ages 45 and above) in SMEs with the aim to improve their employability (Dauth and Toomet, 2016).[4] In 2012 the program has been extended to also embrace low-skilled workers in SMEs below the age of 45 (Dauth et al., 2017). For eligible workers, the cost of training can be subsidized up to 100 percent. If the training takes place outside the firm, wage subsidies to compensate for reduced productivity during training

[4]As discussed in Bellmann and Leber (2011), firms that have difficulties to meet their skill demands on the external labor market are more likely to train their older employees. Subsidized training may thus not only be in the interest of workers, but also in the interest of firms.

amount to up to 100 percent of the wage. If the training takes place within the firm, the subsidy is limited to 50 percent. Training participation is commonly induced by employers.

A major restriction of the program lies in the precondition that only courses that focus on general rather than firm-specific learning are subsidized (Dauth et al., 2017). This restriction is consistent with the major aim of fostering the general employability of low-skilled and elderly workers but may prevent the program from encompassing training measures for skill adaptation in the face of shifting production technology and organizational change. In a review of the administrative implementation of the program, the German Federal Audit Office criticizes deficient adherence to eligibility criteria by local employment agencies (Bundesrechnungshof, 2009). Specifically, local employment agencies have been approving the sponsorship of training that provides firm-specific skills. With an enforcement of eligibility criteria, the inflow into the program has flattened out abruptly (Dauth et al., 2017). On the one hand, there may be non-compliance to the enforcement of unambiguous criteria. On the other hand, a clear distinction between general and specific human capital may be challenging. In the spirit of the skill-weights approach to human capital, any skills may be general in the sense that they are valuable for other employers (Lazear, 2009). Specificity of human capital may then be determined by (shifting) market parameters rather than the nature of skills. At the same time, workers who engaged in training to obtain skills that are valuable across a wide range of employers may still be more valuable for the firms who trained the workers than for recruiting firms due to information asymmetries (Katz and Ziderman, 1990). As noted by the Federal Audit Office, training subsidies should not be used to pass on the costs of training that would have been provided anyway to the insured community, i.e. the 'deadweight' of the program should be kept as small as possible. When general and specific training are difficult to tell apart, and become even more difficult to tell apart in the face of shifting market parameters, it becomes evermore difficult to identify which training would have been provided anyway.

The fact that it makes a difference whether policy aims at stabilizing existing work relationships or improving general employability is encompassed in the 'mountain hike' metaphor of Jung and Kuhn (2018). Workers who fall off the job ladder experience persistent wage losses that may not be recoverable by general training, even if it is indeed of value for recruiting firms. Policies to promote the acquisition of general training serve the dual purpose of stabilizing existing work relationships and improving general employability. At the same time, a strict focus on general training may undermine the potential of firm-specific training to stabilize employment relationships and raise or restore the productive potential of low-skilled workers at their current job.

Another, more broad, policy instrument to promote lifelong learning in Germany is the 'Bildungsprämie', which was introduced in 2008. It can take the form of a premium voucher worth up to 500 Euro, covering up to 50 percent of individual off-the-job training costs, or support in saving for further training. The instrument is based on self-initiative and not specifically targeted to low-skilled workers, who are generally less likely to partake in training. Assessing the effects of the program, Görlitz and Tamm (2016) find no significant effects on employment or wages but find that after training participation individuals are more often engaged in non-routine analytic tasks. They conjecture that employees are able to influence the task content of their job through training.

Evidence on the effectiveness and efficiency of training subsidies for on-the-job training of employed workers is to date rather limited. Dauth et al. (2017) exploit regional variations in the policy styles of German local employment agencies that affect the propensity of low-skilled employed workers to take training for identifying the effects of WeGebAU subsidies on employment and wages.[5] She finds that the subsidies increase the employment duration and earnings of workers whose receipt of subsidies can be ascribed to the policy style of the respective local employment agency (rather than unobservable characteristics that are related to employment duration or wage). Evaluations of related programs in other countries can hardly provide evidence of significant impacts. Assessing a pilot project in the UK, Abramovsky et al. (2011) find high levels of deadweight, i.e. the training that was undertaken under the pilot project was mainly training that would have been undertaken in the absence of subsidies. This may either reflect the limited potential of the project to increase training take-up, or systematic selection into the pilot project. Abramovsky et al. note that the recruitment of employers into the pilot program was often undertaken by training providers, which may tend to approach their usual clients. Another study by Hidalgo et al. (2014) evaluates an experiment in which the Dutch government issued training vouchers worth 1000 Euro each to low-skilled workers. They estimate that the vouchers increased training participation by 20 percent with a deadweight loss of 60 percent but find no significant effects on monthly

[5] See Doerr and Kruppe (2015) for details on regional policy styles of local employment agencies and how they relate to training participation.

wages or job mobility. Stenberg (2011) use longitudinal data on siblings to evaluate publicly provided education of adult low-skilled employees in Sweden. By using data on siblings, they improve the overlap in observable and unobservable characteristics between individuals enrolled in adult education programs and non-enrolled individuals. With an estimated average return on training of 4.4 percent with regard to annual earnings, Stenberg concludes that the individual return hardly exceeds the total societal cost.

A major difficulty in calculating the benefits of training lies in the fact that training that counteracts the depreciation of skills conceals what the worker would have earned in the absence of training. Task demand shifts may simultaneously cause the depreciation of skills, reallocation to alternative tasks, and skill upgrading. Further disentangling these effects is extremely challenging but would be necessary for a thorough accounting of the benefits of training. When training not only restores or augments the productive potential of non-displaced workers in the face of task demand shifts, but moreover prevents displacement, calculations of the benefits of training become even more challenging.

Chapter 10

Conclusion

Automation and offshoring shift the relative demand for tasks and affect not only the composition of tasks between jobs but also within jobs. When the match between skills possessed by workers and skills demanded by employers deteriorate, adaptation may take different forms. Workers may switch to another employer or industry, become displaced, or adapt to new job requirements through training. While wage and employment effects at the aggregate level have received a lot of attention over the past years, adaptation at the workplace and its effectiveness in averting negative impacts from task demand shifts is hardly understood. The present thesis addresses this gap and finds empirical support for the relevance of skill adaptation on-the-job as a means to antagonize task demand shifts.

In order to keep pace with innovations, workers may need to learn to perform tasks for which they do not yet have the efficient level of skills. An important prerequisite for skill upgrading is that workers are able to adapt. Ensuring that the workforce of the future is equipped with adaptive capabilities and prepared for lifelong learning can be understood as a matter of general education. Very recent debates, focused on education before full entry into the labor market, revolve around which institutional circumstances are favorable or detrimental for the adaptability of workers. Until insights from these debates can take effect, task demand shifts continue to impact the labor market. As automation and offshoring already today pose a challenge to society in terms of rising inequality and polarization in most advanced economies, measures to counter negative effects in the short and medium term are desirable.

Some attempts have been made in Germany and other countries to reduce barriers to further professional training. Which policies are effective and efficient is not clear at this point because evaluations are scarce and have provided very few reliable results. Policy interventions in the German labor market have been limited to training that specifically aims at general human capital. When the usability of skills depends on market parameters that are shifting, the definition of general human capital is not straight forward.

Skill adaptation to shifting tasks may enable workers to participate in the efficiency gains of their employers and may stabilize employment relationships for those workers whose tasks are commonly considered the most substitutable by machines and foreign labor. It therefore seems worth to promote further professional training not only as a means to preserve employability in the sense that workers can find another job as they become displaced, but also as a means to enable participation and avert further polarization.

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Appendix A

Notes on Data Availability and Replication Files

Table A.1 contains an overview of the main data sources used for own calculations and illustrations. Replication code written in STATA 15 is available upon request. Original data files are subject to access restrictions imposed by the distributors.

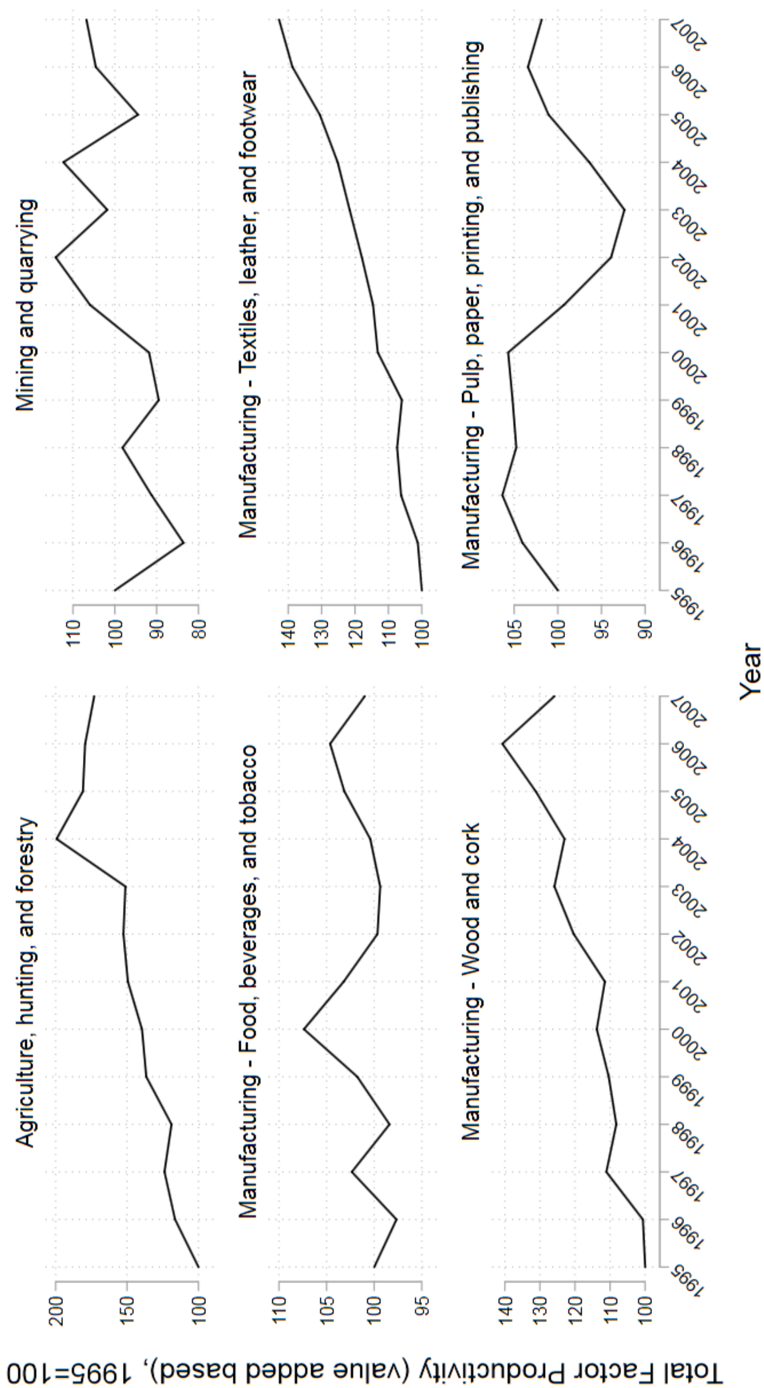
Table A.1: Data Sources

Data file/package	Available via	Data access type
SOEP v32 Data 1984-2015 (long)	DIW Berlin www.diw.de/en/soep	License agreement
BIBB/IAB Qualification and Career Survey 1998/99 (Jansen and Dostal, 2015)	BIBB Research Data Center (BIBB-FDZ) GESIS, www.gesis.org/en/home/	License agreement
BIBB/BAuA Employment Survey 2005/06 (Hall and Beermann, 2011)	BIBB Research Data Center (BIBB-FDZ) GESIS, www.gesis.org/en/home/	License agreement
BIBB/BAuA Employment Survey 2012 (Hall et al., 2015)	BIBB Research Data Center (BIBB-FDZ) GESIS, www.gesis.org/en/home/	License agreement
EU KLEMS Growth and Productivity Accounts November 2009, updated March 2011 (O'Mahony and Timmer, 2009)	www.euklems.net	Publicly available
Input-Output Tables	German Federal Statistical Office www.destatis.de/DE/Publikationen/Thematisch/VolkswirtschaftlicheGesamtrechnungen/AlteAusgaben/InputOutputRechnungAlt.html	Publicly available
Goos et al. (2014), Replication data	www.aeaweb.org/aer/data/10408/20111536_data.zip	Publicly available
Dengler et al. (2014), Occupational Tasks in the German Labour Market Industry Scoreboard	doku.iab.de/fdz/reporte/2014/MR_12-14_data.zip	Publicly available
Eurofond (2017), Eurofound, European Restructuring Monitor (ERM)	www.eurofound.europa.eu/observatories/emcc/erm/factsheets	
OECD (2011), Divided We Stand	www.oecd.org/dataoecd/9/59/39606921.xls	Subscription
OECD (2017b), Science, Technology and	dx.doi.org/10.1787/888933619353	Subscription

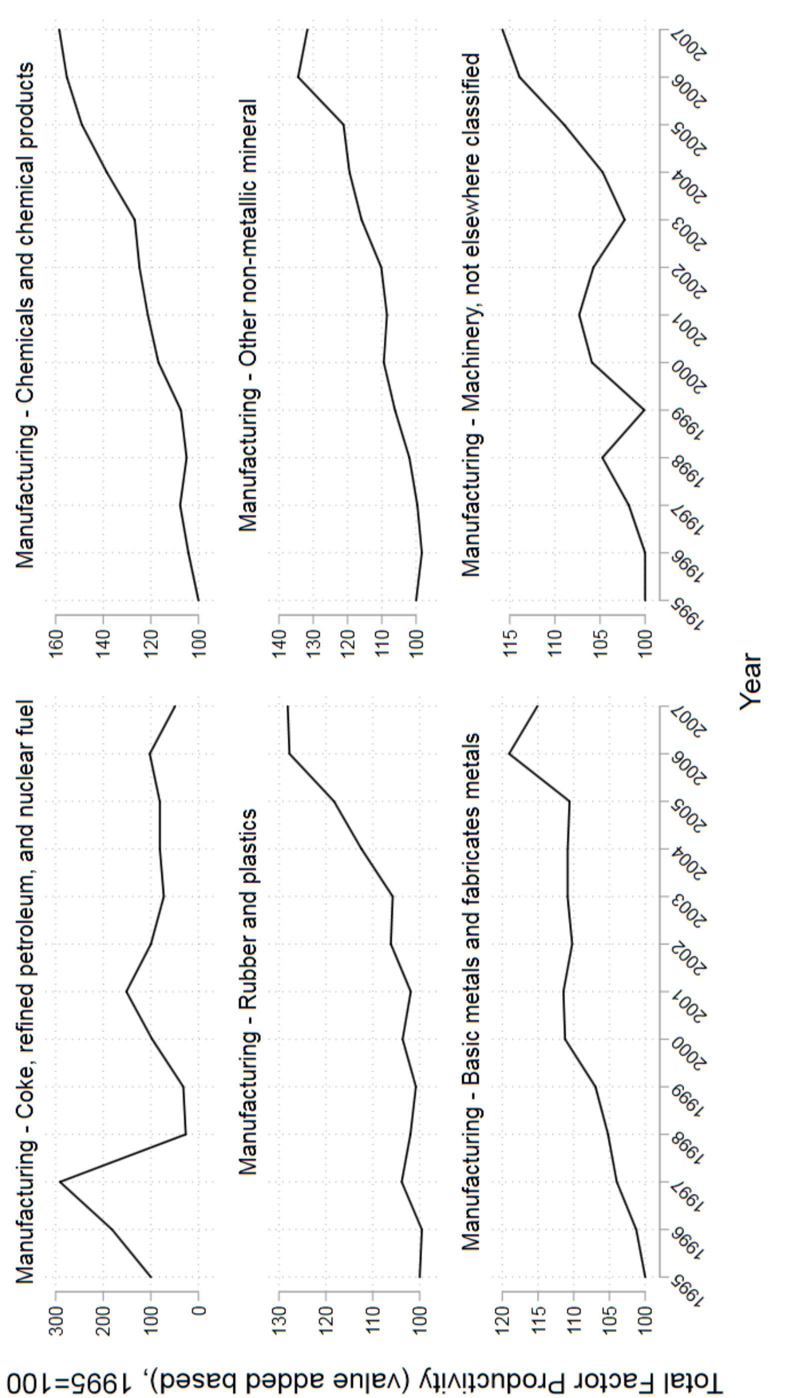
Appendix B

Variability in Measures for Total Factor Productivity

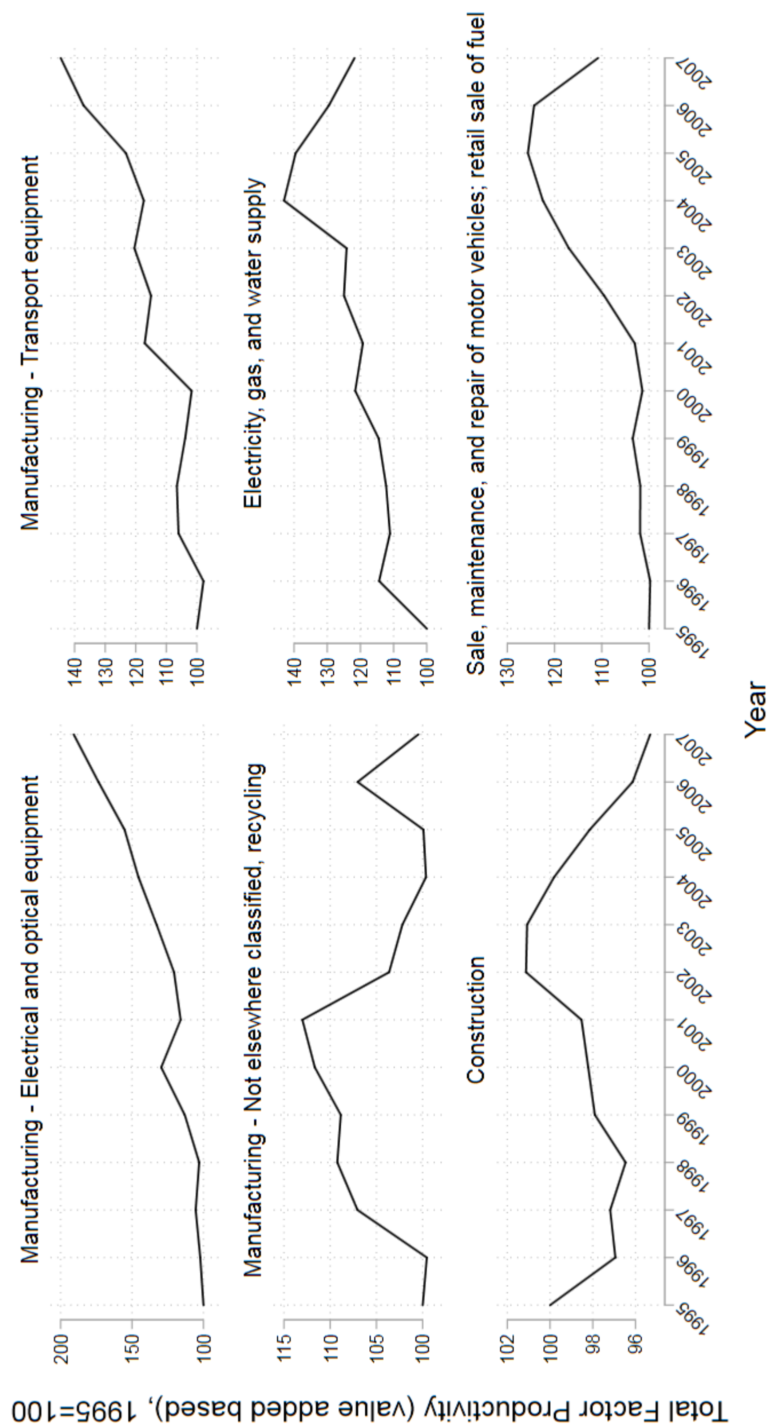
The following figures show the variability in total factor productivity (value added based, $TFPva\ I$, index, 1995 = 100, varying at industry level) used for the empirical analysis in chapter 7. EU KLEMS data are provided at different levels of NACE industry classifications, of which the lowest level available is used. Data for industries without variation or with very little variation are not plotted.



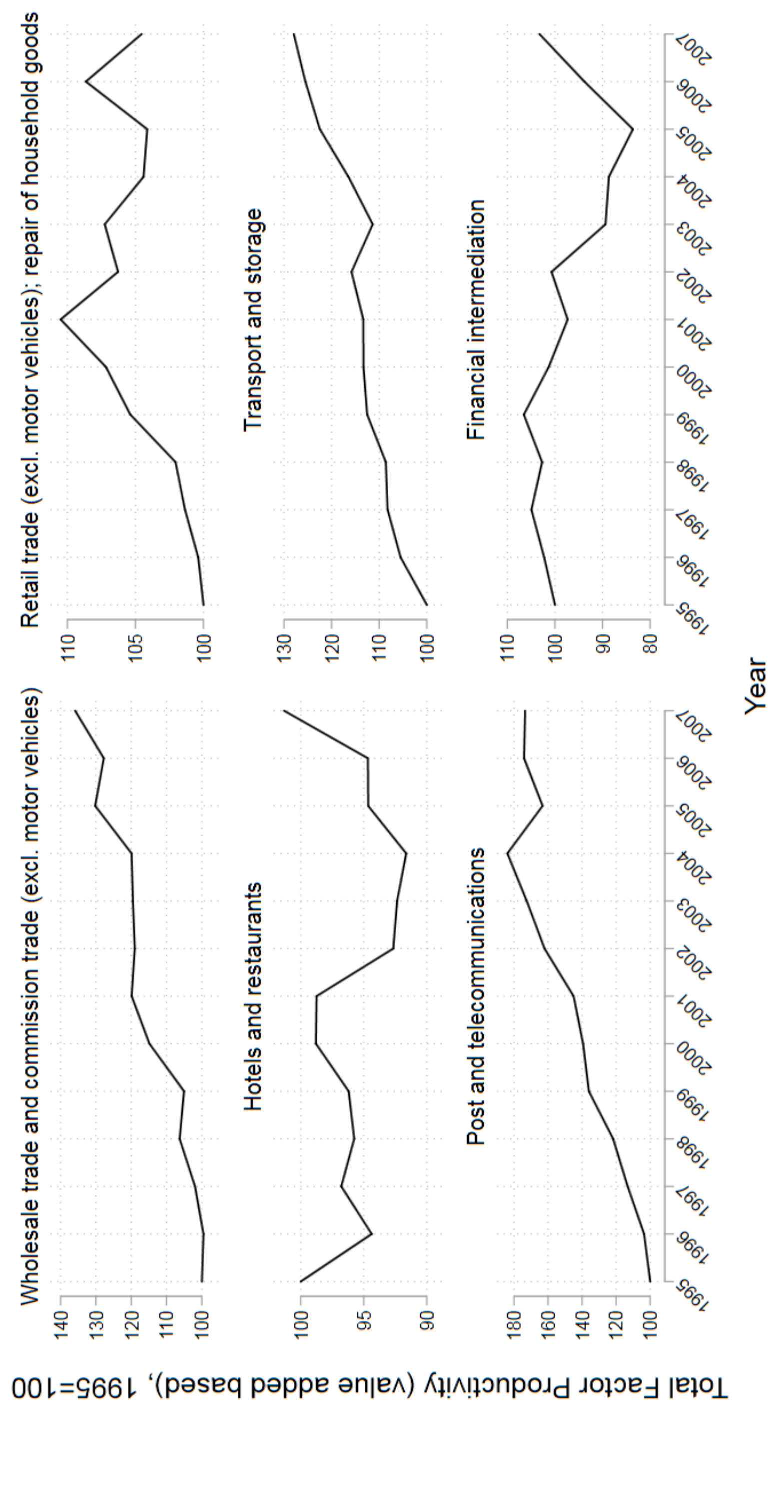
Source: EUKLEMS database, November 2009 release, March 2011 update.



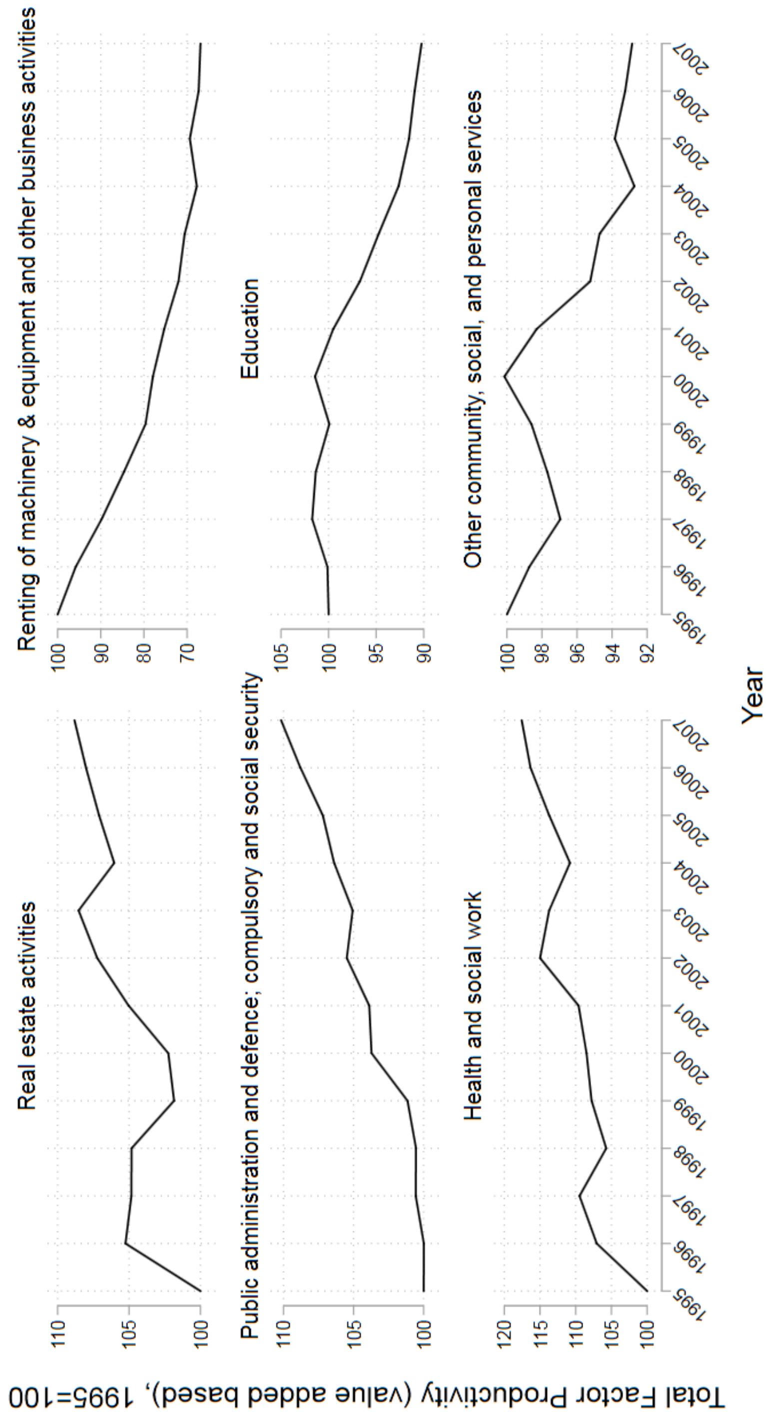
Source: EUKLEMS database, November 2009 release, March 2011 update.



Source: EUKLEMS database, November 2009 release, March 2011 update.



Source: EUKLEMS database, November 2009 release, March 2011 update.

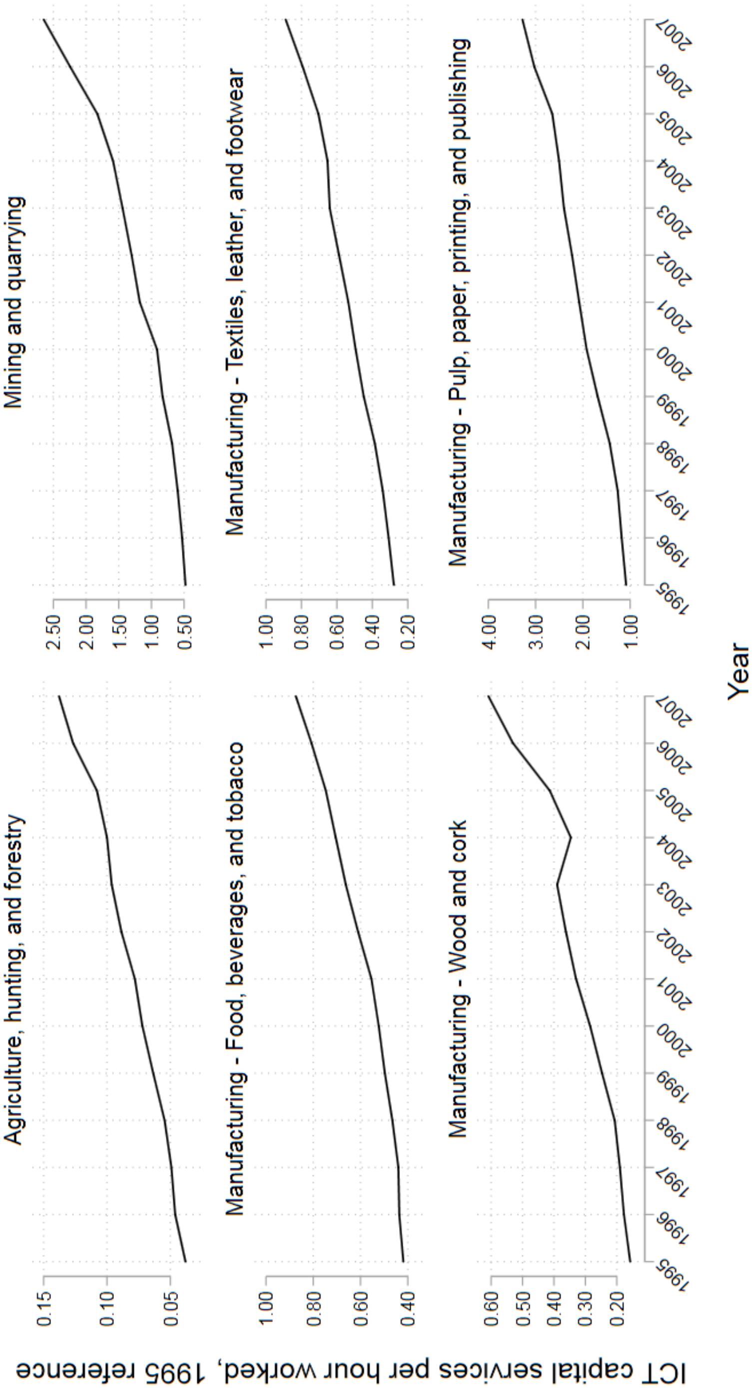


Source: EUKLEMS database, November 2009 release, March 2011 update.

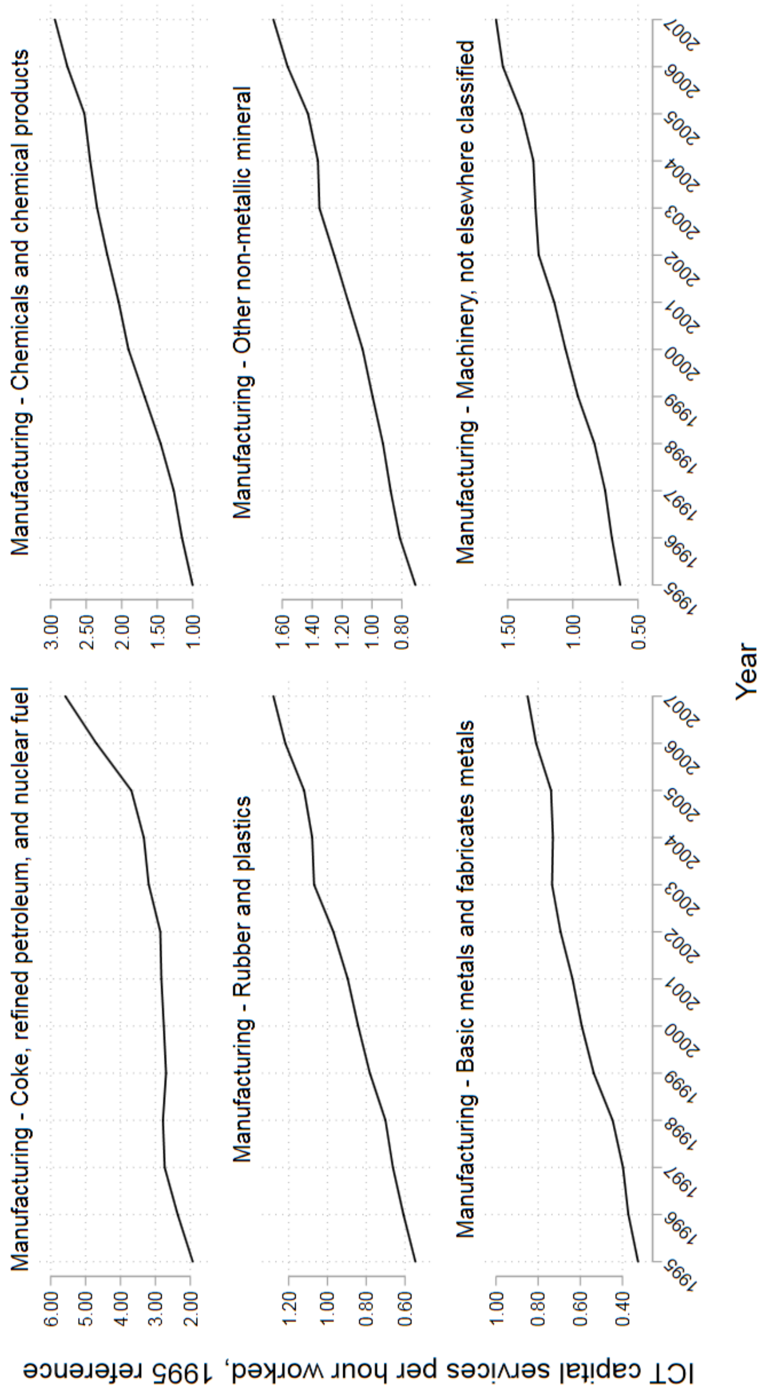
Appendix C

Variability in ICT Capital Services per Hour Worked

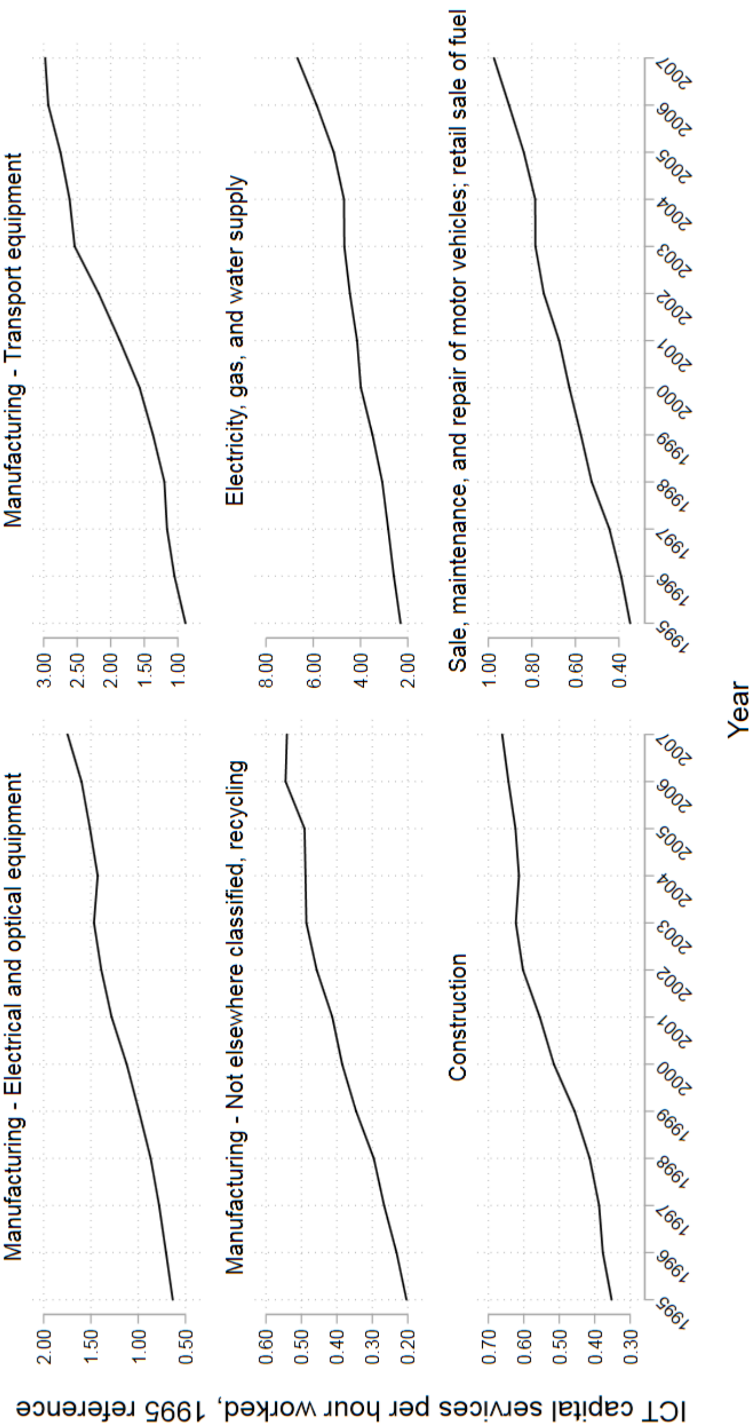
The following figures show the variability in ICT capital services per hour worked ($CAPIT\ QPH$, 1995 reference, varying at industry level) used for the empirical analysis in chapter 7. EU KLEMS data are provided at different levels of NACE industry classifications, of which the lowest level available is used. Data for industries without variation or with very little variation are not plotted.



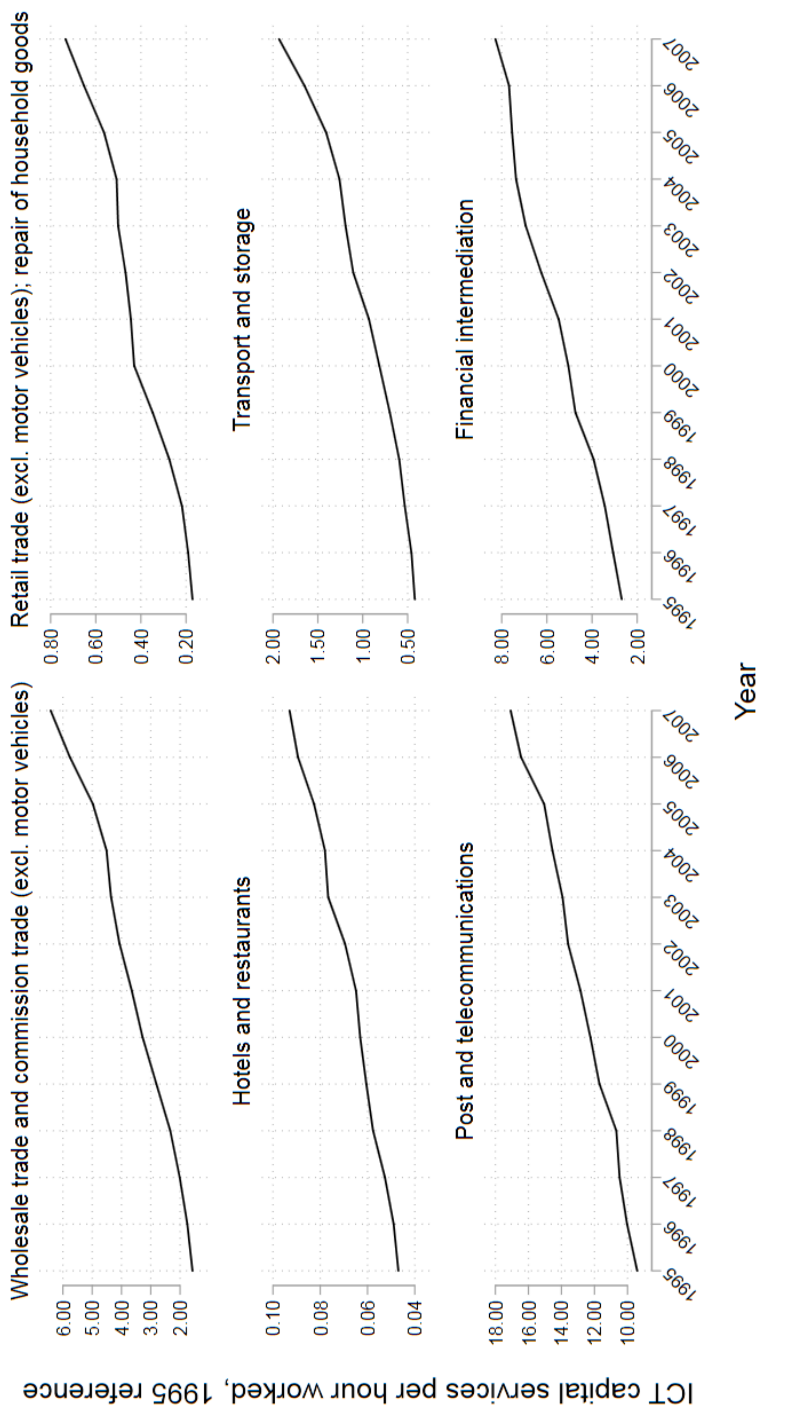
Source: EUKLEMS database, November 2009 release, March 2011 update.



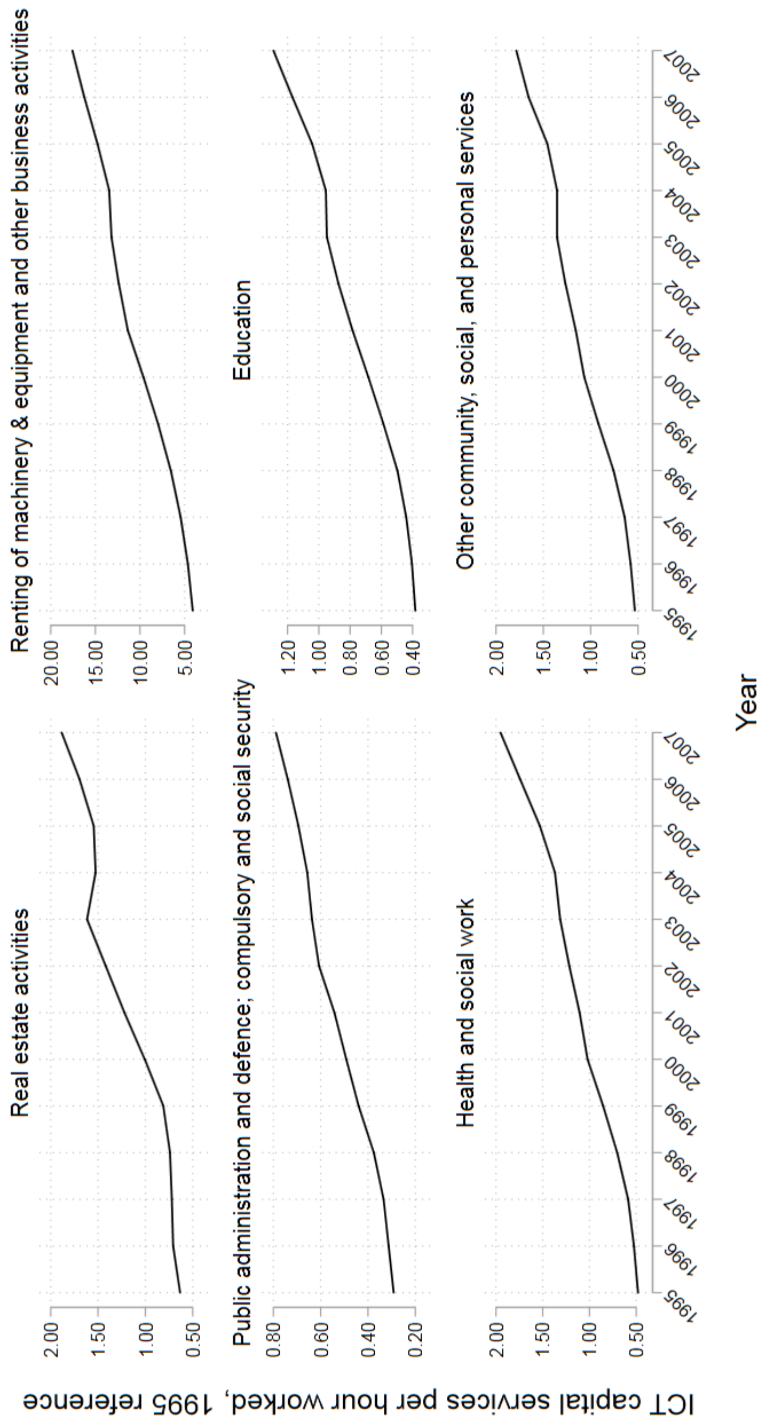
Source: EUKLEMS database, November 2009 release, March 2011 update.



Source: EUKLEMS database, November 2009 release, March 2011 update.



Source: EUKLEMS database, November 2009 release, March 2011 update.

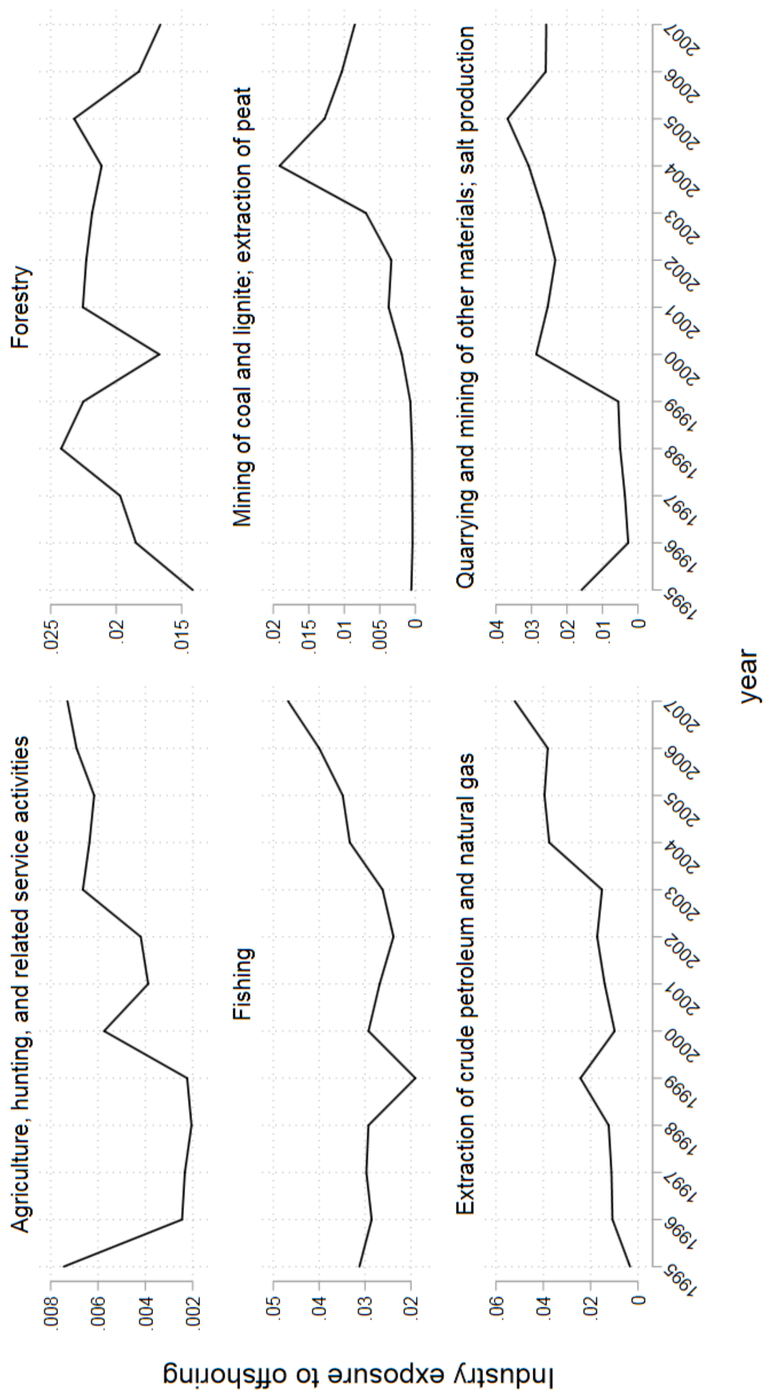


Source: EUKLEMS database, November 2009 release, March 2011 update.

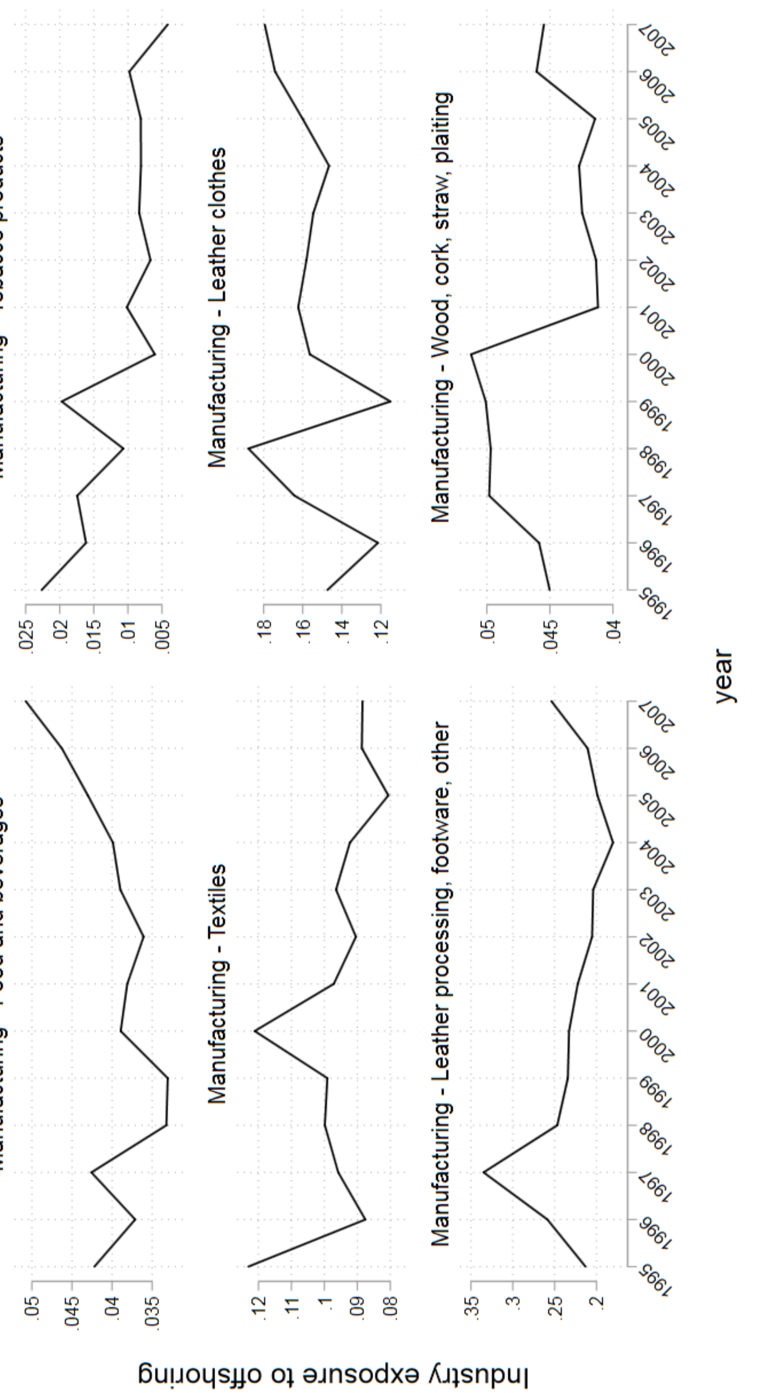
Appendix D

Variability in Offshoring Exposure

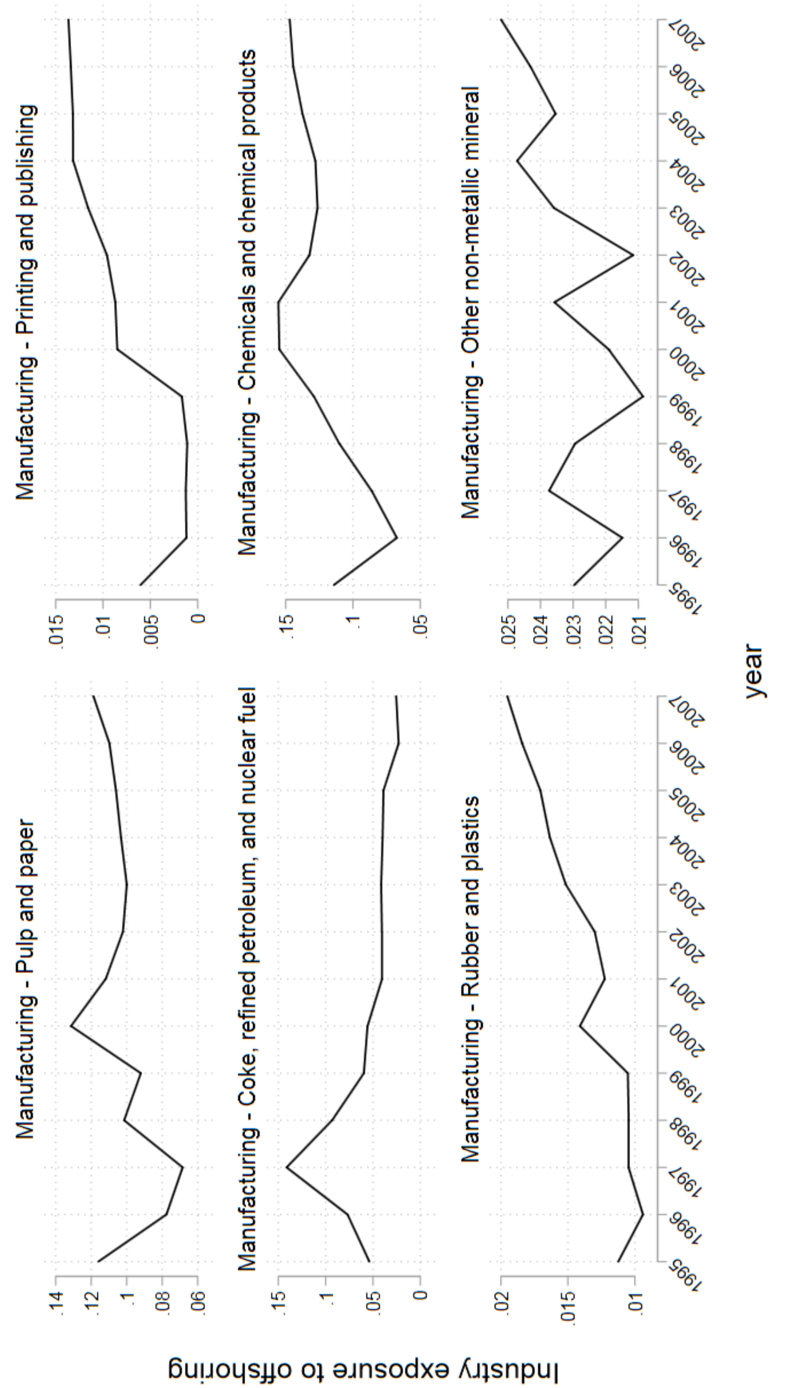
The following figures show the variability in the measure for industrial exposure to offshoring used in the empirical analysis of chapter 7. Data for industries without variation or with very little variation are not plotted.



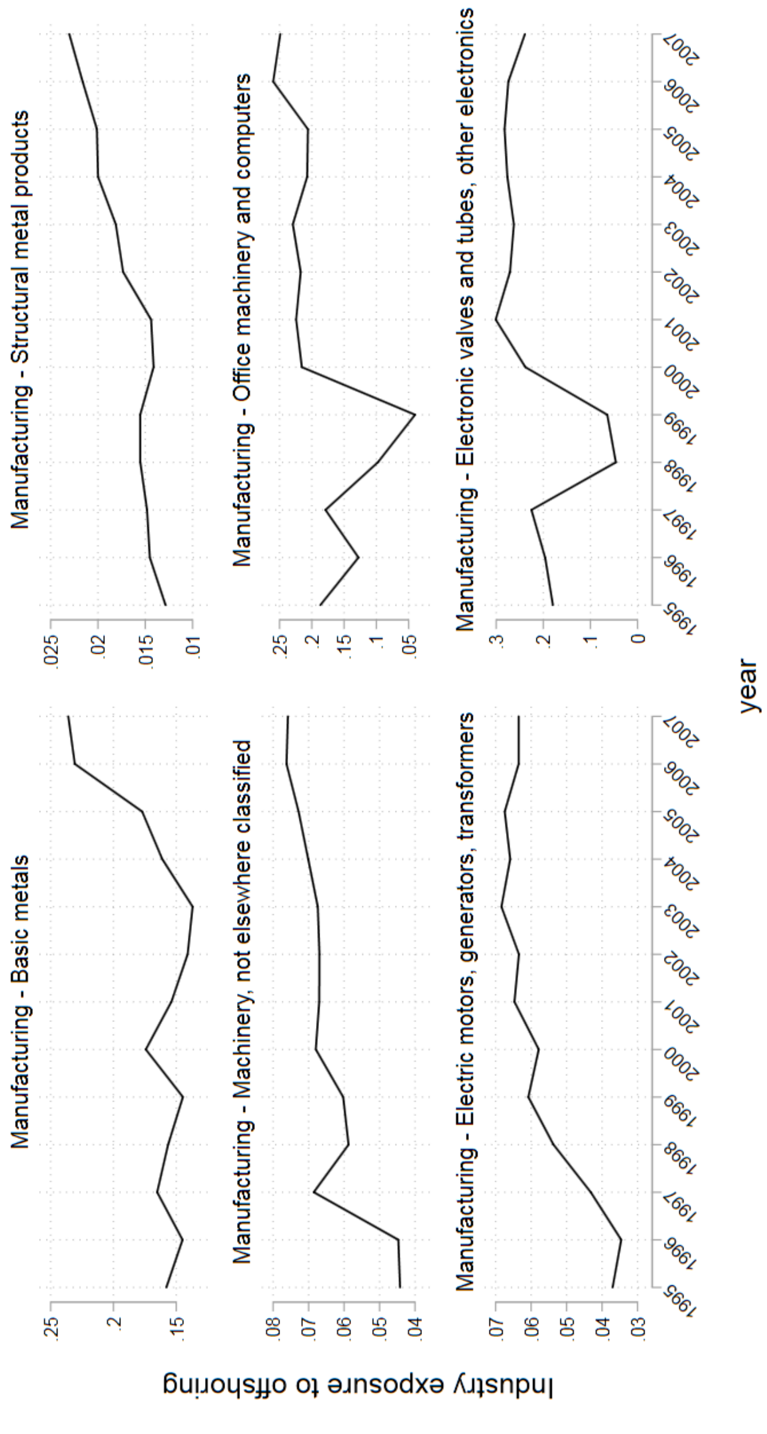
Source: Calculations based on inputoutput tables of the German Federal Statistical Office.



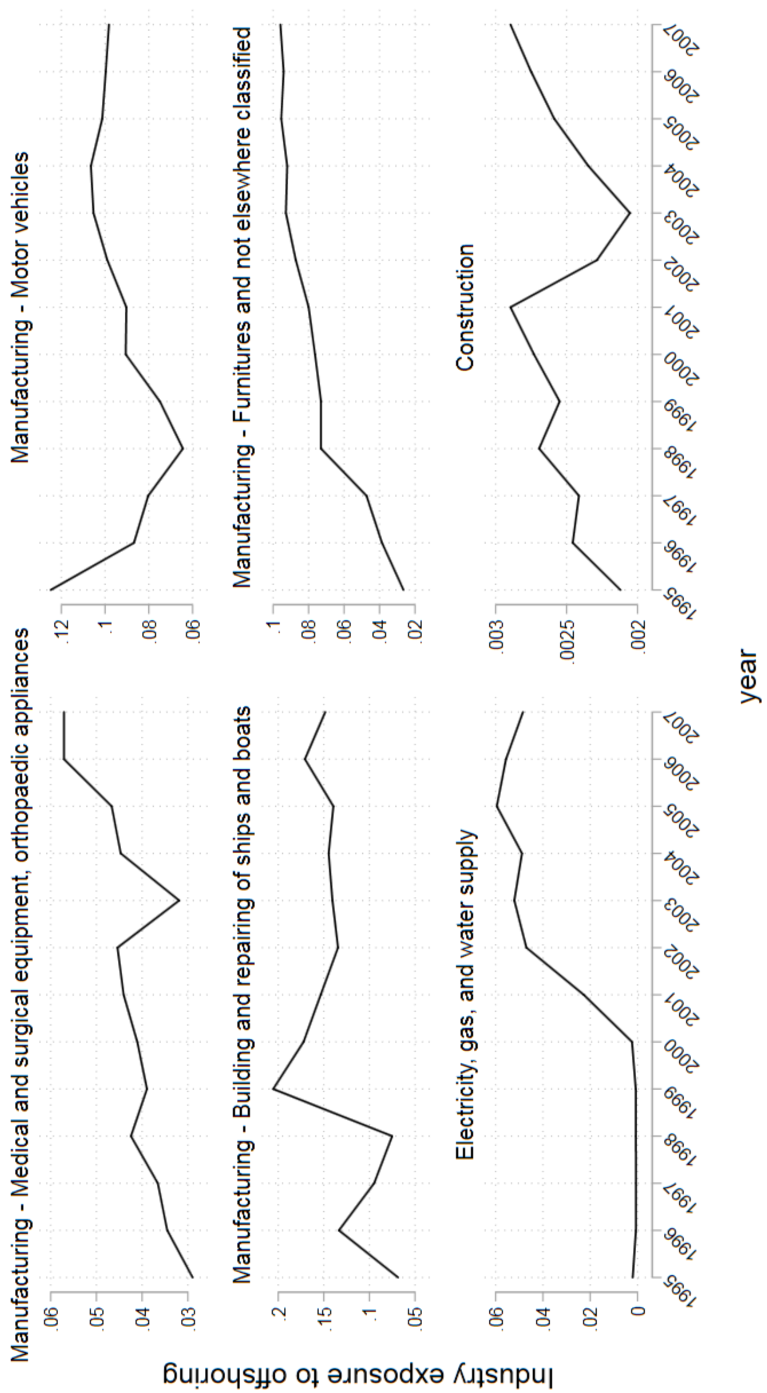
Source: Calculations based on inputoutput tables of the German Federal Statistical Office.



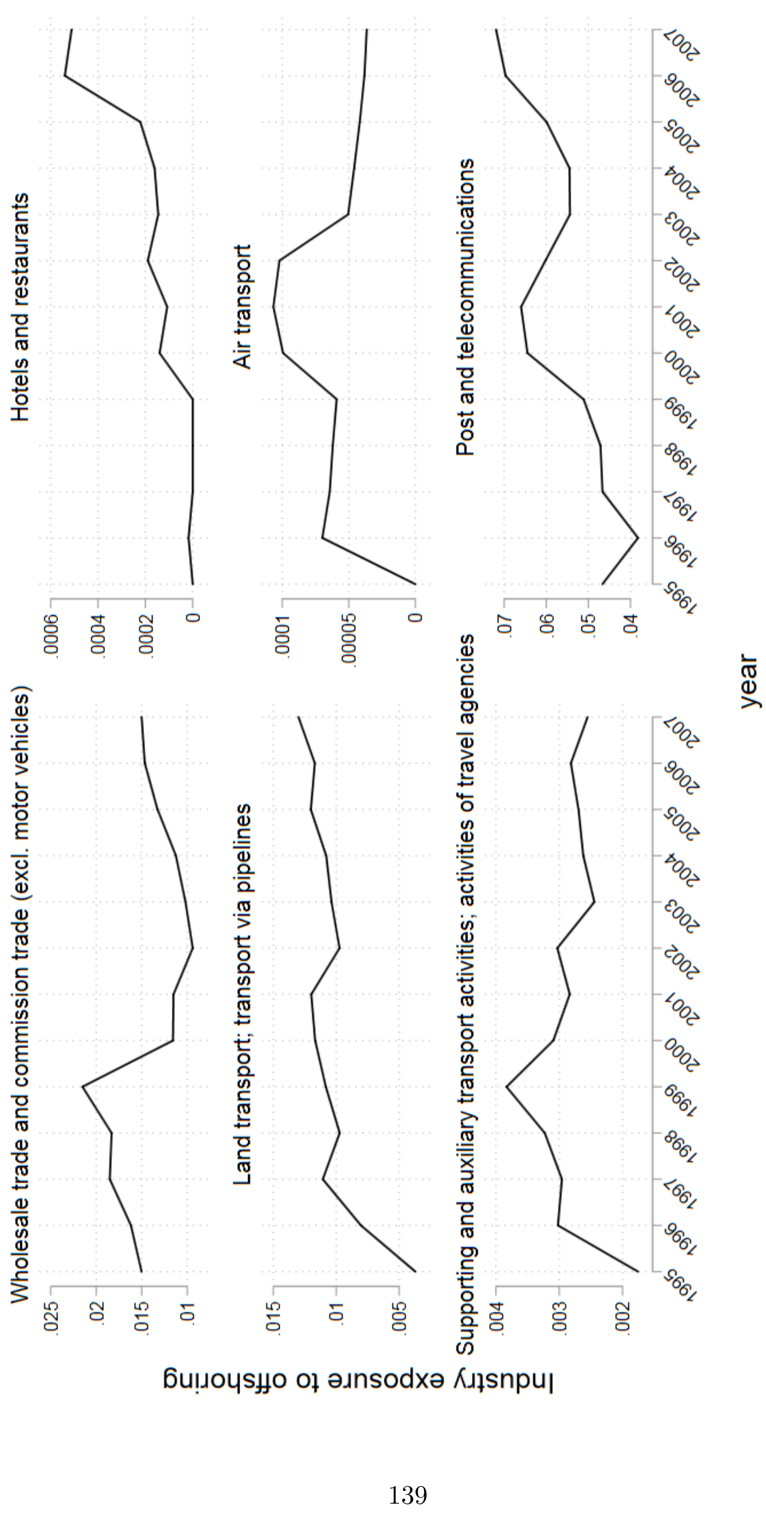
Source: Calculations based on inputoutput tables of the German Federal Statistical Office.



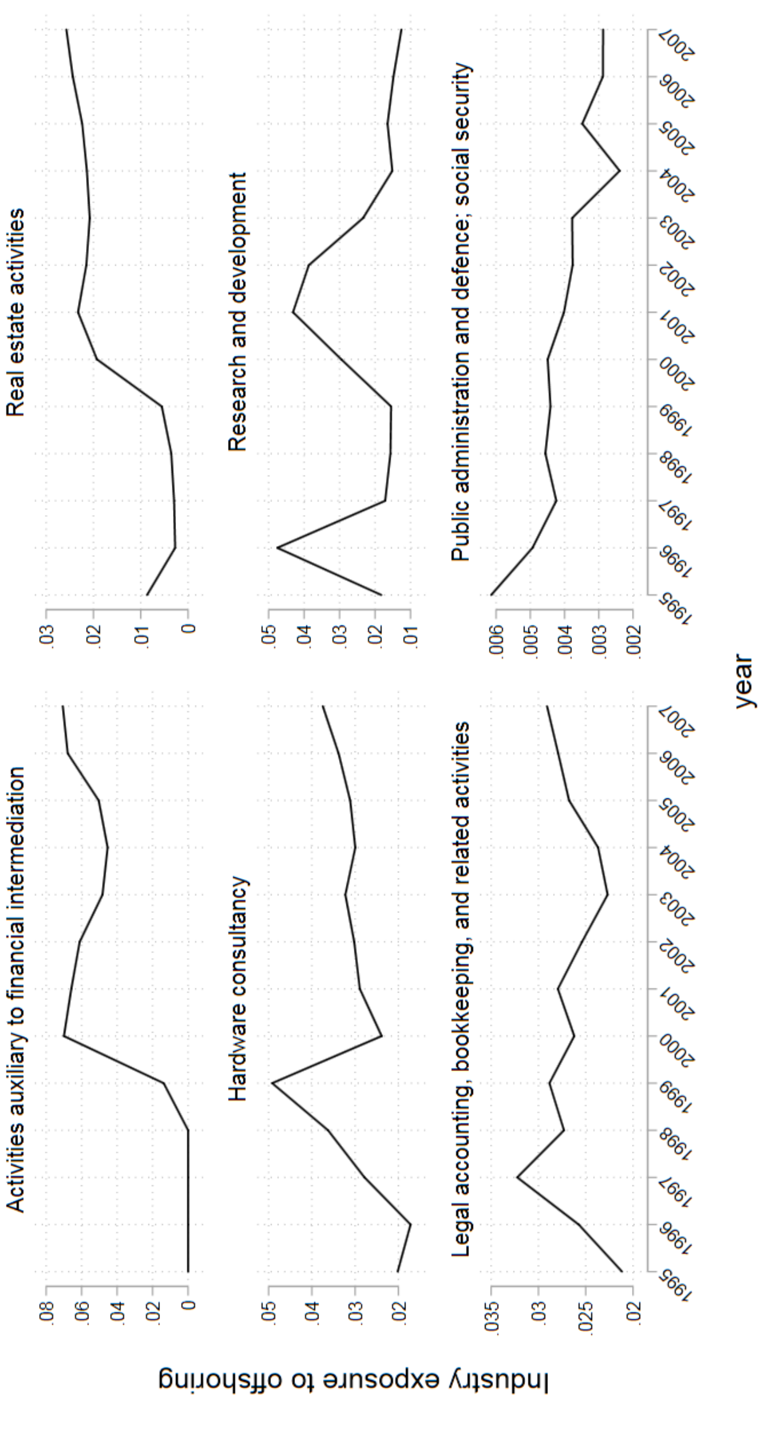
Source: Calculations based on inputoutput tables of the German Federal Statistical Office.



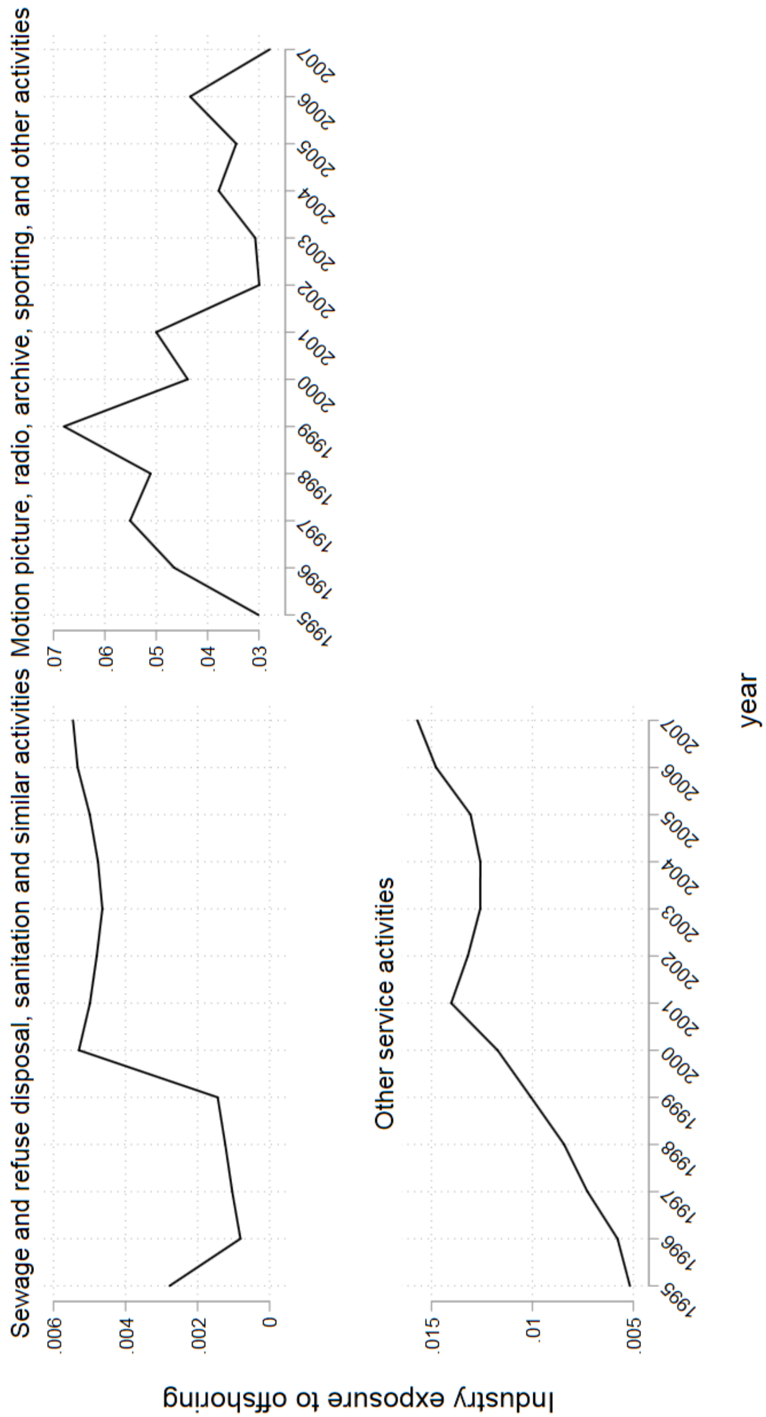
Source: Calculations based on inputoutput tables of the German Federal Statistical Office.



Source: Calculations based on inputoutput tables of the German Federal Statistical Office.



Source: Calculations based on inputoutput tables of the German Federal Statistical Office.

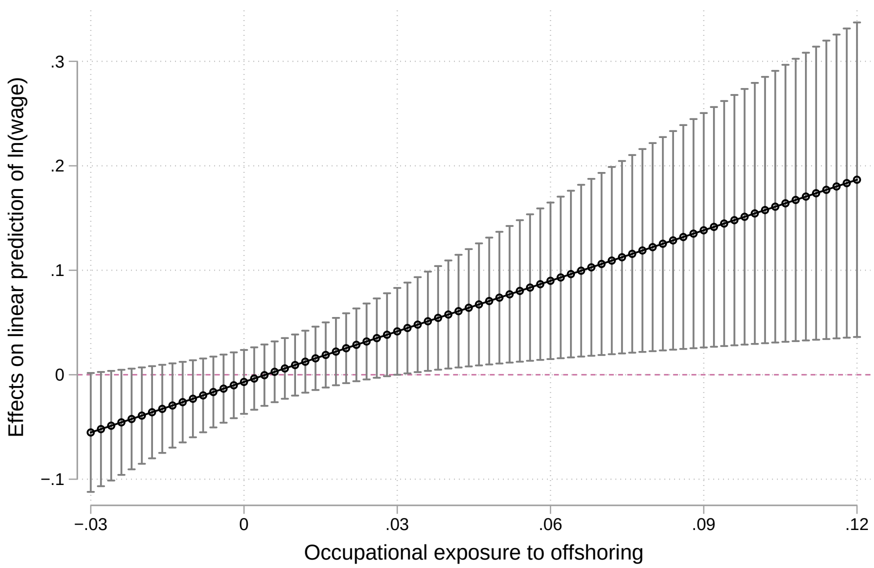


Source: Calculations based on inputoutput tables of thee German Federal Statistical Office.

Appendix E

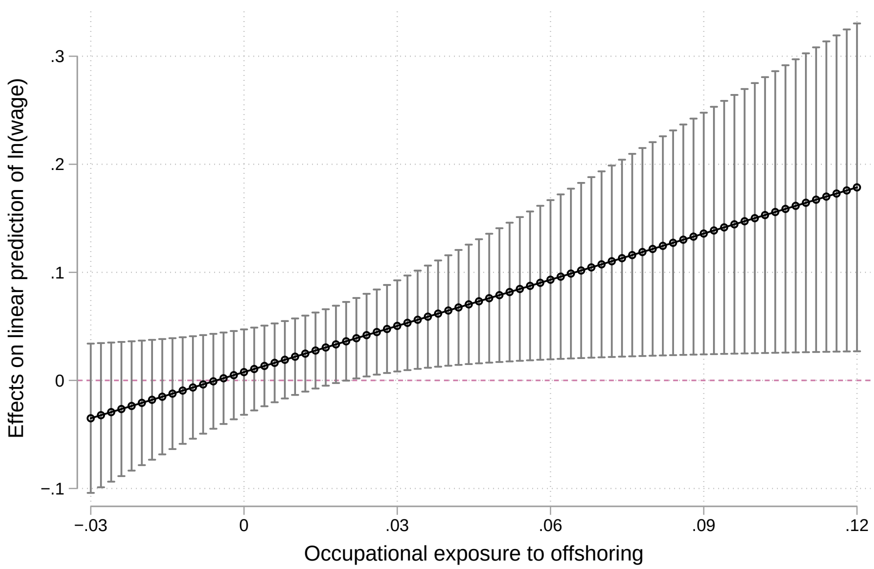
Marginal Effect Plots for Robustness Checks

Figure E.1: Wage Effect of Training over Occupational Exposure to Offshoring, Robustness Check (1)



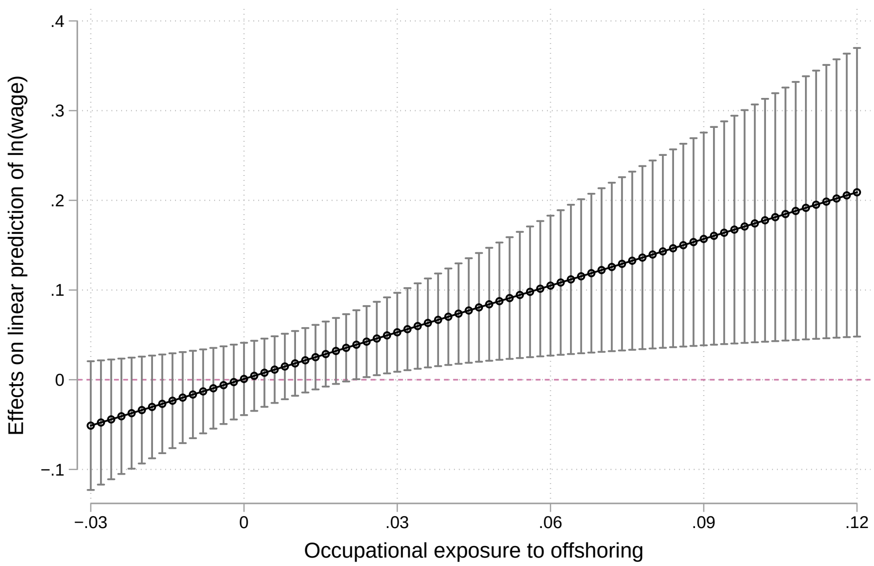
Note: Point estimates based on specification (1) in Table 8.3 are presented along with 90 percent confidence intervals. Standard errors are adjusted for clustering at occupation level and calculated using the Delta-method.

Figure E.2: Wage Effect of Training over Occupational Exposure to Offshoring, Robustness Check (2)



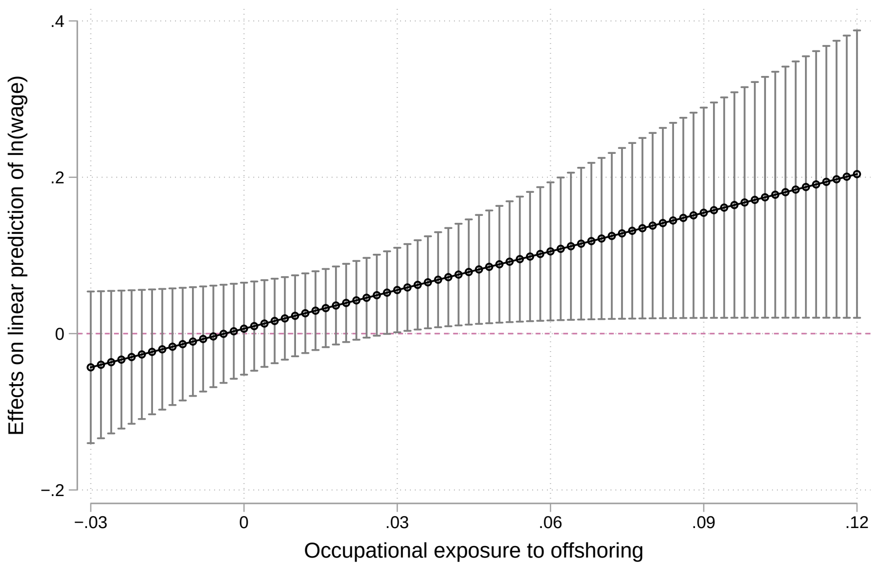
Note: Point estimates based on specification (2) in Table 8.3 are presented along with 90 percent confidence intervals. Standard errors are adjusted for clustering at occupation level and calculated using the Delta-method.

Figure E.3: Wage Effect of Training over Occupational Exposure to Offshoring, Robustness Check (3)



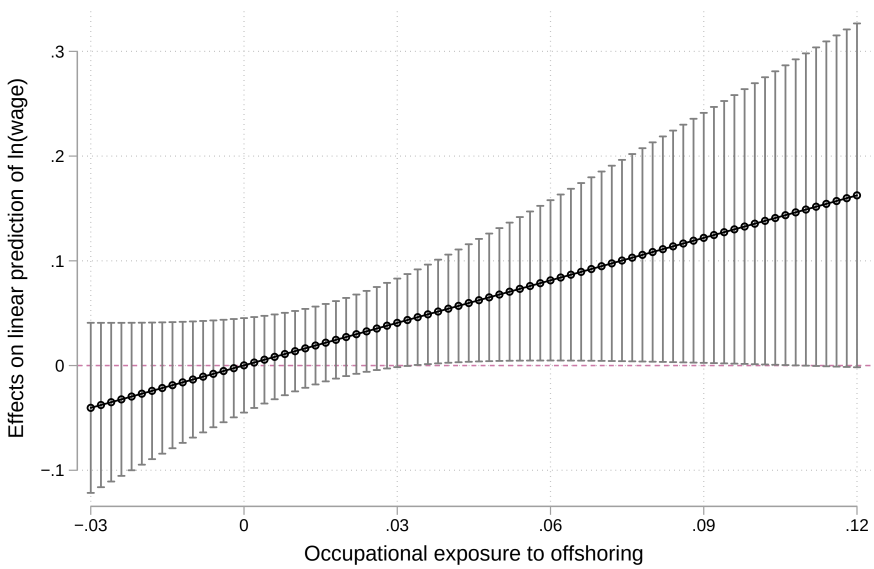
Note: Point estimates based on specification (3) in Table 8.3 are presented along with 90 percent confidence intervals. Standard errors are adjusted for clustering at occupation level and calculated using the Delta-method.

Figure E.4: Wage Effect of Training over Occupational Exposure to Offshoring, Robustness Check (4)



Note: Point estimates based on specification (4) in Table 8.3 are presented along with 90 percent confidence intervals. Standard errors are adjusted for clustering at occupation level and calculated using the Delta-method.

Figure E.5: Wage Effect of Training over Occupational Exposure to Offshoring, Robustness Check (5)



Note: Point estimates based on specification (5) in Table 8.3 are presented along with 90 percent confidence intervals. Standard errors are adjusted for clustering at occupation level and calculated using the Delta-method.