ESSAYS IN LABOUR ECONOMICS

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Summary

This thesis includes three essays that study the labor market in Germany and the United Kingdom, focusing on firm responses to globalization, the career trajectories of young workers, and the trade-off between wages and job amenities. Chapter 1 studies how German manufacturing firms adjust their labor inputs in response to trade shocks from the rising trade integration with China and Eastern Europe over the 1988– 2010 period. Chapter 2 studies young workers' job transitions in their first decade after entering the labor market in Germany, using a dynamic multinomial choice model. Chapter 3 attempts to estimate the compensating wage differential for paid holiday entitlement in the United Kingdom.

Introductory

This thesis studies the adjustments within the British and German labour markets in response to the rapid economic shifts of recent decades. Developed economies have been reshaped by the forces of globalisation and technological change, leading to significant changes in the demand and supply of jobs. Understanding how firms, workers and employment relationship adapt to these changes is important for both academics and public policy. This thesis examines three distinct but closely linked dimensions of labour market dynamics: the response of firms to trade integrations, the early-career job transitions of young workers, and the relationship between wages and non-wage job amenities (paid holiday). By analysing unique administrative data from Germany and the United Kingdom, this thesis provides new insights into the mechanisms of labour market adjustment at the firm and worker level.

The first chapter shows the German firms' employment response to the trade shocks arising from the integration of China and Eastern Europe. Building on the seminal empirical work of Autor, Dorn and Hanson (2013) and Dauth, Findeisen and Suedekum (2021) on the "China shock", and the theoretical framework of firm heterogeneity (Melitz, 2003), this study uses German administrative data to quantify how different manufacturing establishments adjusted their workforce. The findings show that while rising import competition has a clear negative effect on firms' employment, increased export exposure leads to significant employment growth and enhanced firm survival rate. A key contribution of this paper is its focus on the heterogeneous impact on small and medium-sized enterprises (SMEs). We find that SMEs are not only the most responsive to these shocks but also use distinct adjustment margins, primarily through new hiring. This adaptability appears linked to their ability for internal reorganization, such as decentralizing decision-making, which allows them to seize the opportunities of globalisation.

The second chapter shifts the focus from the firm to the individual workers. It explores the early-career trajectories of young men in the German labour market during the first decade of the 21st century. The study speaks to the growing literature following Autor, Levy and Murnane (2003) on job polarisation and skill-biased technological change by directly modelling the job transitions of two cohorts over their first decade of employment. Using a dynamic multinomial choice model, we construct a transition matrix of non-routine, routine, manual non-routine jobs and the non-employment. The analysis finds a strong persistence in job types, particularly the challenges in transitioning from routine to non-routine roles. This finding suggests that while routine jobs may serve as an important entry point, especially for those re-entering from unemployment, they can also represent a barrier to upward mobility. We also find vocational training may leave workers with less transferable skills and thus discourage the upward mobility. This chapter contributes by highlighting the potential for early-career routine trap and the importance of targeted training to equip young workers with transferable skills, a challenge potentially faced by Germany's industry or even firm-dedicated vocational training system.

Finally, the third chapter studies the relationship between wages and paid holiday entitlement in the United Kingdom. Classical theory, as pioneered by (Rosen, 1974, 1986), predicts a trade-off, where workers "purchase" amenities like annual paid leave through lower wages. However, to my best knowledge, empirical studies rarely support that. Some literature (Lavetti, 2020) argues that empirical tests may be biased by unobserved firm heterogeneity. This study thus contributes to the literature by leveraging a matched employer-employee panel dataset and employing multi-level fixed-effects estimation strategy to control for sorting and isolate the relationship within a specific job. Yet, contrary to theoretical predictions, the analysis still shows a persistent positive correlation between paid annual leave and hourly wages. This result challenges the view that paid leave primarily serves as a substitute for monetary compensation. While it may still partly play such a role (missed due to our imperfect estimation), the evidence suggests that this is likely not its predominant function. Instead, the positive association with longer working hours suggests that paid leave may more operate as a compensating differential for other workplace disamenities, offering a new insight into the complicity of modern employment contract design.

Together, these three papers provide a multi-level analysis of labour market adjustments and employment relationship. By connecting the perspectives of the firm, the individual, and the employment relationship, this thesis offers a new picture of how the British and German labour markets have navigated the challenges and opportunities of a evolving global economy.

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Chapter 1

Labor Market Adjustments to Trade Shocks Among German Firms

Jointly with
Thomas Cornelissen
Marco Francesconi

Abstract

We study how German manufacturing firms adjust their labor inputs in response to trade shocks from the rising trade integration with China and Eastern Europe over the 1988–2010 period. Using administrative establishment-level data, we find that increased export exposure leads firms to expand their workforce and be more likely to survive, while increased import competition has the opposite impacts. Small and medium-sized enterprises (SMEs) are the most responsive. They use hiring as the main channel to effect their employment growth. This is likely due to the ability of SMEs to adapt their internal organizational structure by decentralizing decision making and promoting teamwork. Recruitment of, and higher pay for, medium-skilled full-time workers and apprentices may have mitigated the trends of increased job polarization. Finally, SMEs reduce separations, instead of expanding recruitment, if other firms in the same local labor market are subject to positive trade shocks.

Keywords: Firm decisions, Small and medium sized enterprises, Export opportunities, Import competition, Manufacturing industry, Local labor markets, China

1.1 Introduction

The substantial rise in trade volumes with China and other fast growing countries over the last three decades had profound labor market effects on many Western economies. This is likely to continue, despite China's recent economic slowdown and looming threats of trade wars. Most of the existing evidence points at severe adverse effects of greater import competition from China on manufacturing employment in the United States (e.g., Autor, Dorn and Hanson, 2013; Autor et al., 2014; Autor, Dorn and Hanson, 2016; Acemoglu et al., 2016), Denmark (Ashournia, Munch and Nguyen, 2014), France (e.g., Malgouyres, 2017; Aghion et al., 2024*b*), and the United Kingdom (De Lyon and Pessoa, 2021).

For Germany, instead, the studies by Dauth, Findeisen and Suedekum (2014, 2017, 2021) show a considerable beneficial effect of export demand induced by greater trade integration on employment and wages. Much, albeit not all, of this literature focuses on responses either at the worker's level or at the level of industry or local labor market. The evidence from the firm's perspective, instead, is scant and missing for Germany. Yet, employers are key decision makers who can shape how an economy adjusts to major trade shocks. The focus on firms is one of the distinctive contributions of this paper.

Another important feature of our work is the focus on German manufacturing firms. Germany is a compelling case in this context, because it allows us to analyze not only the impact of import penetration, as most of the literature does, but also the potentially positive shocks faced by companies exposed to export opportunities. Germany is the third top exporter in the world, behind the United States and China, with manufacturing exports accounting for the largest proportion of its total exports, around 84% in 2010 (World Bank, 2023). Unlike the US, Germany has a large trade surplus of about 5% of GDP and it is thus more likely to benefit from further trade opening. Cheaper imports of intermediate products from lower-wage economies, such as China and Eastern European countries, may also lower production costs, which in turn would improve Germany's competitive advantage on export.[1]

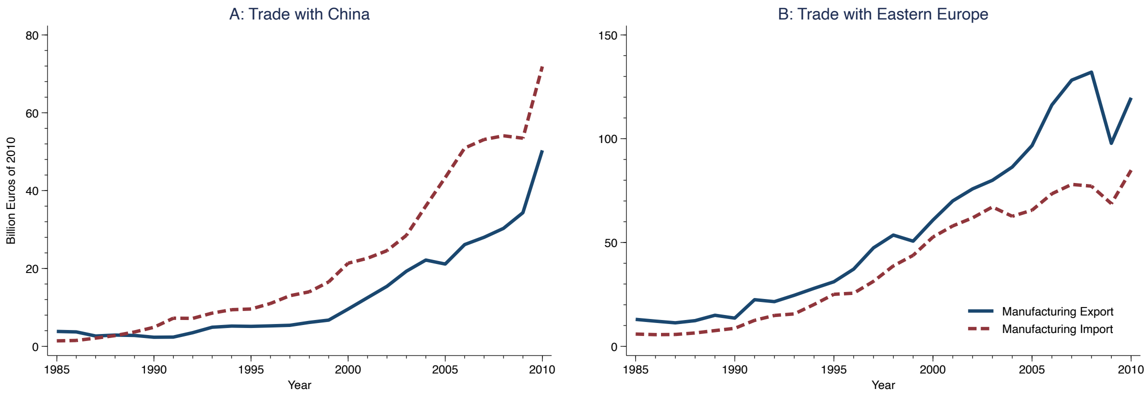
Figure 1.1 illustrates that the German manufacturing industry has been exposed to an impressive growth in both import and export volumes involving China and Eastern European countries (which, in short, we refer to as 'the East').[2] Productivity growth has substantially improved firms' trade competitiveness in the East. At the same time, economic growth in the East has contributed to greater global demand for high quality products, including German motor vehicles, precision tools, electrical machinery and equipment, and pharmaceutical

[1] See Dustmann et al. (2014) and Jäger, Noy and Schoefer (2022) for a broader analysis of the German labor market miracle in the mid-2000s.

[2] Many studies have linked the increased trade with China to China's access to the World Trade Organization in December 2001. Dauth, Findeisen and Suedekum (2014) argue that similar considerations have led to increased trade with Eastern European and former USSR countries. In the empirical analysis, our broad definition of Eastern Europe includes Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia, as well as the Russian Federation, Belarus, Estonia, Latvia, Lithuania, Moldova, Ukraine, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan.

products.

Figure 1.1. Germany's Manufacturing Trade with the East



Source: UN Comtrade, available at <https://comtradeplus.un.org/TradeFlow>.
Notes: In panel B, Eastern Europe is comprised of Bulgaria, Czech Republic, Hungary, Poland, Romania, Slovakia, Slovenia, as well as the Russian Federation, Belarus, Estonia, Latvia, Lithuania, Moldova, Ukraine, Azerbaijan, Georgia, Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, and Uzbekistan.

In this paper, we investigate how German companies adjust their labor inputs in response to trade shocks and how these responses differ across different companies.[3] We use unique administrative establishment-level panel data over the 1988–2010 period and match them with industry-level exposure to trade shocks arising from the greater trade integration of Germany with China and Eastern European countries. We measure trade shocks similarly to Dauth, Findeisen and Suedekum (2021) and follow Autor, Dorn and Hanson (2013) and Dauth, Findeisen and Suedekum (2014) to deal with their potential endogeneity by instrumenting German trade exposure with that of other comparable industrialized economies.

One of the main messages which comes from our analysis is that, on average, greater export demand shocks increase manufacturing employment growth and reduce establishment exits, while deeper import competition reduces employment growth and makes businesses more likely to leave the market. The former positive effect is consistent with the worker-level evidence found for Germany by Dauth, Findeisen and Suedekum (2014). The latter is in line with the negative firm-level results reported in De Lyon and Pessoa (2021) and Aghion et al. (2024*b*) for British and French companies, respectively. Our estimates suggest that the rise in trade integration over the 1988–2010 period created nearly 370,000 new jobs in firms whose industry was directly affected by trade shocks, and about a quarter of that job creation was by small- and medium-sized enterprises. Moreover, we find that close to 80% of the job creation was in continuing establishments (which would have survived with or without

[3]For simplicity, we use the terms firm, company, business, plant, organization, and establishment interchangeably. Our empirical analysis, however, is based on establishment data. One single firm can have multiple establishments.

trade exposure), close to 15% was in newly created companies, and about 5% was due to the survival of firms that would have exited in absence of trade exposure.

For both import and export exposure, the effects on firm employment and survival are entirely driven by small- and medium-sized establishments (SMEs). SMEs are the backbone of the German manufacturing sector, accounting for 98% of all manufacturing businesses and 70% of total manufacturing employment (e.g., Pahnke and Welter, 2019).[4] Interestingly, 95% of German exporting manufacturing companies are SMEs and 34% of German manufacturing SMEs are involved in exporting, compared to only 20% in the UK, 13% in the US, and 10% in France.[5]

Our study uncovers a new set of important results specifically for SMEs. This forms our third main contribution, opening up the discussion about the German economic resurgence in the first decade of the 21st century to the crucial role played by SMEs. Their employment response to positive export demand shocks seems to work largely through the hiring margin, primarily relying on full-time workers and apprentices. In particular, they adjust their workforce by recruiting male and medium-skilled workers (i.e., technicians, skilled manual employees, and semi-skilled administrators, typically in occupations requiring vocational training qualifications but not university degrees). Medium-sized businesses also react to greater export exposure from the East by increasing wages, both at the mean and in the top half of the wage distribution. SMEs' labor market adjustment in response to adverse import competition shocks is instead more evenly spread by gender and across the full skill distribution, as we find evidence of negative employment effects also among unskilled occupations. There is, however, no wage reaction to increased import competition.

SMEs' adjustments also depend on how strongly other firms in the same local labor market are affected by trade shocks. For example, in a local labor market exposed to more positive trade shocks, manufacturing businesses find it harder to grow through hiring and thus rely more on greater retention of continuing workers. Finally, although we find that export (import) shocks to SMEs in manufacturing lead to an increase (decline) in part-time employment among SMEs in services, most labor market spillover effects through this indirect propagation channel from manufacturing to services tend to be negligible.

This set of labor market responses illustrates SMEs' high degree of adaptability to increased global competition and opportunities in the labor market. This could be driven in part

[4]Most SMEs in Germany are family owned and family controlled, with high returns on equity (Schlömer-Laufen et al., 2014). According to many commentators, they represent a vibrant segment of the economy which is competitive, innovative, and growth oriented and in some ways comparable to, but also different from, the Silicon-Valley-type of entrepreneurship. For a summary of views on the German *Mittelstand*, see Pahnke and Welter (2019).

[5]These shares are derived from own calculations using 2016 data from the Eurostat Trade by Enterprise Characteristics (TEC) database available at <https://ec.europa.eu/eurostat/databrowser/view/ext_tec01/default/table?lang=en&category=ext_go.ext_tec>; The share for the U.S. is from a U.S. International Trade Commission report, using data from the National Federation of Independent Business (see <https://www.usitc.gov/publications/332/pub4125.pdf>).

by a simpler link between ownership and the internal labor market structure as well as by more intense organizational changes, with greater use of decentralized decision making and flexible teamwork.[6] SMEs' reliance on apprentices and especially medium-skilled workers, and their policy of paying those workers more, may have counteracted the labor market trends of increased job polarization (e.g., Autor and Dorn, 2013; Dustmann, Ludsteck and Schönberg, 2009; Goos, Manning and Salomons, 2014; Michaels, Natraj and Van Reenen, 2014) and between-firm wage inequality (Card, Heining and Kline, 2013).[7] This, in turn, may reflect the emphasis on apprenticeship schemes, which have been typically beneficial to SMEs and have long played a substantial role in the German industrial policy strategy (Deissinger, 1996).

Besides contributing to the large body of research that evaluates the labor market impacts of greater trade integration (e.g., Autor, Dorn and Hanson, 2013, 2016; Acemoglu et al., 2016), including the effects associated with increased export demand (e.g., Dauth, Findeisen and Suedekum, 2014, 2017, 2021; Feenstra, Ma and Xu, 2019), this paper adds to the small, but growing, literature on firm-level adjustments to import competition in countries other than Germany. In this context, it is worth emphasizing the work by Autor et al. (2020), which shows that import competition from China reduces sales, profitability, R&D investment, and patenting activity among US firms.[8] Conversely, Aghion et al. (2024*a*) find that French firms facing positive export demand shocks increase patenting activity, employment, and sales. In a follow-up study, Aghion et al. (2024*b*) find that French businesses exposed to growth in imports from China experience significant reductions in sales, employment, and innovation, and these are typically concentrated in low-productivity firms.[9] Finally, the evidence presented by De Lyon and Pessoa (2021) shows that UK plants in industries more exposed to Chinese products face a lower employment growth and a higher probability of going out of business than comparable companies in sectors more insulated from competition with China, with stronger effects for larger firms.[10]

[6]The idea that smaller firms can adapt more easily to a changing environment due to lower coordination costs has been put forward by Camacho (1991). For a wider overview on the limits to firm size and issues of ownership and control, see Holmstrom and Tirole (1989). The importance of SMEs has been recently emphasized by Galdon-Sanchez, Gil and Uriz-Uharte (2025), who show that SMEs are capable of using strategic information about their customers to their advantage, resulting in a significant increase in business revenues.

[7]While Keller and Utar (2023) document rising job polarization from import competition in Denmark, Autor, Dorn and Hanson (2015) find no job-polarisation effect from import competition in the US.

[8]Always in the US context, Hyun, Park and Smirnyagin (2021) show how the detrimental employment effects of import competition can hit establishments in other industries within the same firm, mainly through the firm's exit.

[9]Aghion et al. (2024*b*) also document that access to cheaper imports for *input* goods tends to have positive effects, although these are not always statistically significant.

[10]In further related work, Costinot, Sarvimäki and Vogel (2024) find that the earnings losses of workers whose employer is hit by a negative trade shock are persistently larger the more strongly other employers in the same local labor market are also exposed to the same shock. Arni et al. (2024) use an unanticipated appreciation of the Swiss Franc to identify heterogeneous impact of trade shocks on workers, depending on the degree to which their employer is affected by reduced competitiveness of its exports versus cheaper access to inputs, and according to the labor content of the inputs.

Our focus on labor market adjustments with an emphasis on heterogeneous effects speaks also to the trade literature, which addresses the question of how different types of firms respond differently to trade challenges and opportunities (e.g., Melitz, 2003; Bernard et al., 2003, 2012; Wagner, 2007, 2012). In line with this strand of research, we find that small firms' survival is more strongly affected by trade integration than that of medium and large enterprises. At the same time, however, we also find that SMEs grow more than large firms in response to favorable export demand shocks.

Finally, our analysis and results on SMEs broadly contribute to the large body of work that emphasizes the role played by organizations in shaping human resource management, personnel decisions, and how to understand the sources and implications of firm heterogeneity (for comprehensive surveys, see Bloom and Van Reenen, 2011; Oyer and Schaefer, 2011; Hoffman and Stanton, 2024).

The remaining part of the paper is organized as follows. Section 1.2 describes our empirical approach. Section 1.3 presents the data. Section 3.4 reports the main results on all firms, while Section 1.5 focuses on the labor market adjustment strategies used by SMEs. Section 3.5 concludes.

1.2 Research Design

Using the approach proposed by Dauth, Findeisen and Suedekum (2021), export exposure at the industry level is defined as

$$ExE^G_{jt} = \frac{EX^G_{jt}}{\Sigma_{i \in j} \overline{w}_{i,t-10} N_{i,t-10}}, \tag{1.1}$$

where EX^G_{jt} measures the real value of exports of industry j from Germany, G, to the East (i.e., China and Eastern Europe) in year t. We normalize the export volume by each industry's total domestic lagged real wage bill, where each firm i's full-time equivalent wage bill is calculated by the product of its full-time mean real wage, $\overline{w}_{i,t-10}$, and its full-time equivalent employment, $N_{i,t-10}$.[11] Thus, ExE^G_{jt} captures the value of industry exports relative to lagged labor costs. Import exposure is similarly defined:

$$ImE^G_{jt} = \frac{IM^G_{jt}}{\Sigma_{i \in j} \overline{w}_{i,t-10} N_{i,t-10}}, \tag{1.2}$$

where IM^G_{jt} measures the real value of imports into industry j from the East to Germany in year t.

To estimate trade exposure effects, we regress the 10-year growth rate of a firm-level

[11] For part-time and marginal part-time workers, we define full-time equivalent employment by assigning weights of 24/39 and 16/39, respectively. For a similar approach, see Dauth, Findeisen and Suedekum (2021).

outcome (such as employment or mean wages) on the 10-year change of export and import exposure as follows:[12]

$$\Delta Y_{ijt} = \alpha + \beta_1 \Delta ExE^G_{jt} + \beta_2 \Delta ImE^G_{jt} + \mathbf{X}'_{ij,t-10}\gamma + \tau_t + \varepsilon_{ijt}, \tag{1.3}$$

where ΔExE and ΔImE are the 10-year differences in the trade export measures defined in expressions (1.1) and (1.2), respectively, with $t \in \{1998, 2010\}$, i.e., regression (1.3) covers two long differences. ΔY_{ijt} captures the average annual arc growth rate of the outcome (in %) for firm i in industry j, which is also defined over a 10-year horizon, that is:

$$\Delta Y_{ijt} = \frac{Y_{ij,t} - Y_{ij,t-10}}{\frac{1}{2}(Y_{ij,t} + Y_{ij,t-10}) \times 10} \times 100. \tag{1.4}$$

The arc growth rate is common for measuring the growth rate of firm-level outcomes (see Davis, Haltiwanger and Schuh, 1998, among others). Instead of normalizing the change in the numerator by the base-year outcome, it normalizes it using the average of the base-year and end-year outcomes. This has the advantage that the rate can be defined even if the base-year outcome is zero. We divide the rate by 10 in order to be able to interpret it as an average annual growth. $\mathbf{X}_{ij,t-10}$ is a vector of controls, including indicator variables for establishment size, 108 commuting zones, and 4 broad manufacturing industries (capital, consumer, food, and industrial products), τ_t refers to a time period dummy variable, and ε is the error term. Finally, we divide ΔExE and ΔImE by their corresponding sample standard deviations, so that our effects can be interpreted as effects of a one-standard-deviation change of export and import exposure, respectively.[13]

Equation (1.3) has a straightforward difference-in-difference interpretation, as it removes both firm effects (through first-differencing) and time effects and leverages the different timing and different degrees of export demand and import penetration across firms. The coefficients of interest are β_1 and β_2, which capture the causal effects of export and import exposure, respectively, when there are no unobservable shocks that simultaneously affect trade and labor market outcomes. These shocks, however, can occur. For instance, suppose an industry faces a positive domestic product demand shock. This may increase employment and potentially reduce export volumes among firms in that industry, which would lead to a downward bias in the effect of export exposure.

To address this concern, we follow a common practice in the literature and instrument

[12] We are interested in the long-term effect of greater trade exposure, as we believe firms need time to adjust. This is also a standard practice in literature so that we can compare our results with that of the literature. We also did some experiments with other time horizons. The main results hold anyway.

[13] We refer to firms that are observed both in the base year and the end year of a 10-year change as "continuing" firms. However, we will also present employment effects for all establishments, including exiting and entering firms. Clearly, for exiting companies, employment is not observed in the end year, whereas, for entering firms, it is not observed in the base year. The advantage of the arc growth rate is that we can still compute an average annual growth rate by setting end-year (base-year) employment to 0 in these cases.

the exposure variables for Germany with trade flows to and from the East of other eight countries.[14] Specifically, we construct trade exposure in these other countries as follows:

$$\Delta ExE^O_{jt} = \frac{EX^O_{jt} - EX^O_{j,t-10}}{\Sigma_{i\in j}\overline{w}_{i,t-20}N_{i,t-20}} \times 100 \tag{1.5}$$

and

$$\Delta ImE^O_{jt} = \frac{IM^O_{jt} - IM^O_{j,t-10}}{\Sigma_{i\in j}\overline{w}_{i,t-20}N_{i,t-20}} \times 100, \tag{1.6}$$

where EX^O_{jt} and IM^O_{jt} measure industry j's export and import flows of the other eight high-income countries to and from the East in year t. As before, these are normalised by the base-year wage bill, which is now lagged by an *additional* 10 years compared to the base year. We do this to deal with any potential reverse causality in case the wage bill in the base year reacts in anticipation to future trade exposure. The rationale of this instrumentation is that other high-income countries are also exposed to the growing trade importance of the East, but their trade patterns are likely to be uncorrelated with the unobserved domestic shocks that affect German firms.

Some studies translate the industry-level trade shocks to the regional or local-labor market level using a shift-share design (Autor, Dorn and Hanson, 2013; Dauth, Findeisen and Suedekum, 2014). Others instead directly link the industry-level trade shocks to the units of observation (in our case, firms) via industry affiliation (Acemoglu et al., 2016; Autor et al., 2020; Dauth, Findeisen and Suedekum, 2021). We follow the second strategy, but the conditions for identification in both approaches are essentially the same and require the industry-level instrument, i.e., trade shocks to other industrialized countries, to be quasi random (Borusyak, Hull and Jaravel, 2022). In subsection 1.4.1, we will check this assumption by implementing balancing tests of the instruments with industry characteristics measured in a base year and a falsification test showing that the instrumented treatment has no effect on lagged outcomes that precede the onset of trade liberalization. The results provide evidence in support of our identifying assumption.

1.3 Data

We construct the export and import exposure variables from product-level bilateral trade data from the United Nations Commodity Trade Statistics Database (UN Comtrade), mapping 4-digit product-level bilateral trade flows into 91 3-digit industries.[15] Using exchange rates from the German Bundesbank, we convert all trade flows into 2010 Euros.

[14]These are Australia, New Zealand, Japan, Singapore, Canada, Sweden, Norway and the United Kingdom. This type of strategy has been widely used (see, for instance, Autor, Dorn and Hanson, 2013, 2016; Acemoglu et al., 2016; Dauth, Findeisen and Suedekum, 2014, 2017, 2021, among others).

[15]We use the crosswalk table between SITC and NACE from Dauth, Findeisen and Suedekum (2021).

Our establishment-level analysis is based on the German Establishment History Panel (BHP) provided by the Institute of Employment Research (IAB). The data cover the time period from 1975 to 2010 and represent a 50% random sample of all German establishments. It includes detailed information obtained from aggregating individual social security records at the establishment level, including employment shares by occupational groups, percentiles of the firm wage distribution, and pre-estimated firm fixed effects from an AKM model.

These data allow us to analyze detailed sub-groups of firms, as well as employment shares and the wage structure by educational and occupational groups. We convert wages into 2010 Euros using the consumer price index from the German Bundesbank. Censored wages were imputed by IAB following the method introduced by Card, Heining and Kline (2013).

We extract observations for the years 1988, 1998, 2000 and 2010 in order to construct two 10-year differences, 1988–1998 and 2000–2010. We exclude all firms in East Germany, to avoid using observations in the aftermath of the German reunification, and we exclude firms that changed industry or location.[16]

[16]We require this latter restriction in order to consistently match firms with their industry's or local labor market's trade exposure. This drops only a minor share (1%) of the sample.

Table 1.1. Summary Statistics

	1988–1998		2000–2010	
	Base year	Annual growth	Base year	Annual growth
Panel A: Number of employees per establishment				
Headcounts (total)	34.0	-0.304%	32.0	-1.405%
Part-time	1.3	1.366%	1.7	-0.726%
Apprentice	1.8	-2.318%	1.2	-0.510%
Full-time	30.8	-0.286%	26.3	-2.550%
Highly skilled	2.1	1.354%	3.0	0.261%
Medium skilled	21.8	-0.017%	19.7	-2.539%
Low skilled	6.6	-1.510%	5.8	-1.644%
Female	9.5	0.188%	9.2	-0.715%
Male	24.5	-0.787%	22.8	-1.804%
Panel B: Establishment wages (daily full-time wages in 2010 Euros)				
Mean	73.8	0.575%	79.9	-0.756%
25-th percentile	61.8	0.708%	67.2	-0.576%
Median	71.9	0.578%	77.6	-0.785%
75-th percentile	83.8	0.498%	90.4	-0.869%
Panel C: Establishment entry, exit, and size				
Entering firms	27.5%		21.7%	
Exiting firms	23.1%		28.8%	
Small ($\leq$ 10)	71.6%		70.6%	
Medium (10-249)	26.3%		27.5%	
Large ($\geq$ 250)	2.1%		1.9%	
Panel D: Trade exposure				
ΔExport exposure	17.4		30.9	
ΔImport exposure	21.1		33.6	
Number of firms	99,297		97,660	

Notes: The table shows descriptive statistics for manufacturing firms in the sample. Panels A and B report employment and wage outcomes in the base year of each respective decade and their annual growth rate across each decade, according to equation (1.4). Panel C reports sample shares of firm types, and Panel D shows the (non-standardized) trade exposure variables defined in equations (1.1) and (1.2).

For each of the decades, our full sample includes manufacturing establishments that existed at least once, either in the base year or the end year. We refer to establishments that exist in both of these years as "continuing" firms, indicating that they survived over a given 10-year period. Instead, we refer to companies that exist only in one of the two years as "exiting" or "entering" firms.

Table 1.1 shows summary statistics of base-year levels and annualized arc growth for each of the two decades. Although the mean establishment has slightly more than 30 employees, more than 70% of all firms are small (i.e., they employ fewer than 10 full-time equivalent workers). On average, employment in manufacturing declined in each of the two decades, with only few exceptions: the number of high-skilled employees grew in both decades, whereas the number of female and part-time workers grew in the first decade. Overall, about two thirds of employees in manufacturing are men.

Although real full-time wages went up in the first decade, they declined during the second. Around 50% of the establishments that ever existed in each of the two 10-year periods are either entering or exiting firms, leaving ample room for trade exposure to affect firm creation and firm destruction.[17]

Finally, in line with the substantial trade exposure increase in the 2000–2010 period shown in Figure 1.1, Table 1.1 confirms that the change of export and import exposure is around three times greater in the 2000–2010 decade than in its previous counterpart.

1.4 Results

1.4.1 Effects on Firms' Employment, Survival, and Wages

Table 1.2 present the results of our baseline model estimated by two-stage least squares (2SLS).[18] The first-stage estimates in the lower two panels show that changes in trade exposure of other high-income countries are strong statistically significant predictors of the changes in trade exposure among German firms, indicating that greater trade exposure in those countries is positively related to trade exposure in Germany.

The estimates in column (a) show that a one-standard-deviation increase in export exposure over a decade leads to a 2% faster annual growth in firm employment over that decade. In Appendix Table A.4 we decompose this effect into its parts driven by entering, exiting and continuing firms, and find that more than half of the overall effect is driven by entering firms and quarter is driven by exiting firms.[19] When focusing on continuing firms only, we find that these establishments grow faster by 0.7% per year (see column (b) of Table 1.2). This estimate implies that, over a 10-year period, the employment growth of a firm at the 75-th percentile of export exposure will be about 8 percentage points higher than that of a firm at the 25-th percentile of export exposure.[20] In column (c), we focus on the exit probability, and find that a one-standard-deviation increase in export exposure reduces establishment exits by nearly 2 percentage points.

[17] We report separate summary statistics for the sub-sample of continuing establishments that existed across each of the decades in Appendix Table A.2. Both wage and employment patterns are very similar to those shown in Table 1.1, except that continuing establishments are larger by about 10–20 employees on average.

[18] For comparison, the OLS results are in Appendix Table A.3.

[19] The decomposition in Appendix Table A.4 multiplies the dependent variable ΔHeadcounts with a binary indicator for being an entering, continuing, or exiting firm, respectively. This yields three dependent variables that exactly add up to the original ΔHeadcounts variable reported in Table 1.2, column (a). In this decomposition, the contribution of a group of firms is stronger if it represents a larger share of firms or it faces stronger employment growth.

[20] This is computed as $10 \times 0.71 \times \frac{40.34-9.51}{27.52} = 7.95$, where the fraction represents the difference between the 75-th and 25-th percentile of export exposure divided by the standard deviation of export exposure.

Table 1.2. The Effect of Trade Exposure on Firms' Employment, Exit, and Wages

	(a) ΔHeadcounts	(b) ΔHeadcounts (continuing firms)	(c) Exit	(d) ΔWages (continuing firms)
ΔExE^G (β_1)	2.0427***	0.7113***	-0.0192***	0.0656
	(0.362)	(0.122)	(0.007)	(0.070)
ΔImE^G (β_2)	-1.0601***	-0.4388***	0.0199***	0.0248
	(0.203)	(0.073)	(0.005)	(0.041)
	First stage: ΔExE^G			
ΔExE^O	0.1266***	0.1345***	0.1410***	0.1383***
	(0.012)	(0.012)	(0.013)	(0.012)
ΔImE^O	0.0653***	0.0530***	0.0713***	0.0515***
	(0.006)	(0.005)	(0.007)	(0.005)
F-test of excluded instruments	110.192	106.312	103.606	106.6
R^2	0.337	0.358	0.352	0.362
	First stage: ΔImE^G			
ΔExE^O	0.1507***	0.1573***	0.1574***	0.1562***
	(0.017)	(0.017)	(0.020)	(0.017)
ΔImE^O	0.3388***	0.2835***	0.3497***	0.2780***
	(0.018)	(0.018)	(0.021)	(0.017)
F-test of excluded instruments	241.697	201.836	186.915	196.536
R^2	0.593	0.577	0.609	0.574
Observations	196,957	97,345	152,780	94,701
F statistic	27.7	28.3	29.3	29.2

Notes: Each regression includes controls for establishment size (four indicator variables: 0–5, 5–20, 20–200, 200–2000), time period, 108 commuting zones, broad manufacturing industries (four dummy variables: food, industrial, capital, and consumer products), and an above-median firm share of skilled workers. Exposure variables are standardized. IVs are the other 8 high-income countries' export and import exposure to the East. The two time periods are: 1988–1998 and 2000–2010. Standard errors in parentheses are clustered at the period×commuting zone×3-digit-industry level. The clustering assumes that firms within the same industry often clustered in the region, a practice also adopted in the literature. We also conduct experiments with different levels of clustering, and the main results remain consistent The F-statistic is the Kleibergen-Paap statistic.

*** $p < 0.01$

For import exposure, the exact flip-side emerges, with a one-standard-deviation increase in import exposure leading to slower firm employment growth by about 1% per year in column (a) (0.4% for continuing firms, as shown in column (b)), and to a 2 percentage point increase in the probability of an establishment exiting. The employment effect of import exposure implies that after 10 years a firm at the 75-th percentile of import exposure will be about 1–2 percentage points smaller than a firm at the 25-th percentile.[21]

This evidence is in line with previous results showing that manufacturing employment in high-income countries has been hurt by exposure to import penetration from the East (e.g., Autor, Dorn and Hanson, 2013; De Lyon and Pessoa, 2021; Aghion et al., 2024*b*), but that manufacturing employment in Germany also benefited from export opportunities in the same regions (e.g., Dauth, Findeisen and Suedekum, 2014, 2017, 2021). Our analysis further adds that establishment entry and exit are key margins along which employment adjusts.

Finally, in column (d), we investigate the wage impact of ΔExE^G and ΔImE^G and find no statistically significant effects on continuing firms' wages. That is consistent with Dauth, Findeisen and Suedekum (2021)'s worker-level results, in which the positive earnings effects

[21] This is computed as $10 \times 0.44 \times \frac{23.51-3.60}{60.67} = 1.44$, where the fraction represents the difference between the 75-th and 25-th percentile of import exposure divided by the standard deviation of import exposure.

of export exposure are mainly driven through the employment margin. In a context of secular decline in employment and real wages in the manufacturing sector (as documented in Table 1.1) and in a time of weaker collective bargaining agreements focusing on employment security rather than wages (Kügler, Schönberg and Schreiner, 2018; Jäger, Noy and Schoefer, 2022), businesses might have had lower incentives to engage in profit-sharing with their workers. **The absence of broad wage effects may also be driven by high wage rigidity in Germany due to institutional reasons such as strong employer-representation on system, unions and employment protection laws.** While the absence of an overall wage effect seems to hold also across percentiles of the firm wage distribution (see Appendix Table A.6), we shall return to wage responses in greater detail in subsection 1.5.2, where we examine the effect across sub-groups of workers and establishments as well as along the wage distribution.

To support the credibility of our identification strategy, we perform two checks. First, Table 1.3 presents evidence from industry-level balancing tests for our instruments as suggested by Borusyak, Hull and Jaravel (2022). Specifically, we regress industry characteristics in a lagged base year on the instruments, ΔExE^{O} and ΔImE^{O}, i.e., the trade shocks to other industrialized countries defined in equations (1.5) and (1.6). Reassuringly, we find that both instruments are by and large unrelated to industry baseline characteristics in 1988.

Second, Table 1.4 reports results from a falsification test, where we run our baseline 2SLS regression for the 2000–2010 decade, leaving the right-hand side of the regression unchanged, but measuring the change in the dependent variables in the pre-period of 1978–1988, before the rise in trade exposure started.[22] It is reassuring that the coefficients in Table 1.4 are small and statistically insignificant. This rules out that long-run industry growth trends, which might have started before the onset of trade expansions with China and Eastern Europe, are correlated with the degree of trade exposure that materialized in the first decade of the 21-st century. Accordingly, in Appendix Table A.7, our baseline effects are confirmed when augmenting the baseline model by directly controlling for the 1978–1988 industry-level growth of the outcomes.

[22]This differs from the balancing tests in Table 1.3 in a number of ways. The dependent variable is a 10-year change rather than a base year level. Moreover, the regression is at the firm — rather than the industry — level, and finally the effects are for instrumented trade exposure, rather than the instrument itself. Note that for the 2000–2010 decade ($t = 2010$), the wage bill in the denominator of our instrumental variables is measured in 1990. Hence, looking at outcome changes over the 1978–1988 period ensures that there is no mechanical overlap between instruments and outcomes.

Table 1.3. Balance Tests

Balance variable	ΔExE^O	ΔImE^O
Log firm size	0.2011	-0.1097
	(0.144)	(0.255)
Log firm mean wage	0.2078	-0.1324
	(0.165)	(0.278)
Share of Exiting firms, 1978-1988	-0.0182	0.0052
	(0.014)	(0.034)
Share of skilled workers (education)	-0.0093	-0.0162
	(0.006)	(0.016)
Share of skilled workers (occupation)	-0.0169*	-0.0321
	(0.010)	(0.026)
Share of R&D workers	0.0009	0.0075
	(0.001)	(0.006)
No. of industry-periods	182	

Notes: Coefficients are obtained from regressions of industry-level covariates in 1988, controlling for 4 broad manufacturing industry indicator variables and a period fixed effect, and weighting by industry employment shares. Standard errors clustered at the 91 3-digit industry level are shown in parentheses.
* $p < 0.10$

Table 1.4. Falsification Tests

	(a) ΔHeadcounts	(b) ΔHeadcounts (continuing)	(c) Exit	(d) ΔWages (continuing)
ΔExE^G	0.3597	0.1894	0.0021	0.0816
	(0.284)	(0.154)	(0.009)	(0.057)
ΔImE^G	-0.0133	-0.0599	0.0080	-0.0472
	(0.213)	(0.117)	(0.007)	(0.045)
Observations	99,904	53,702	77,000	53,481
F statistic	24.3	27.4	19.5	28.3

Notes: The specifications are the same as those in Table 1.2. Standard errors in parentheses are clustered at the period×commuting zone×3-digit-industry level. The F-statistic is the Kleibergen-Paap statistic.

1.4.2 Impact Heterogeneity by Firm Size

Which establishments reacted most strongly to trade exposure? To address this question, we focus on firm size. Firm size is strongly related to productivity in equilibrium models of the firm size distribution and models with search frictions (Lucas Jr, 1978; Syverson, 2011; Moscarini and Postel-Vinay, 2013; Eslava, Haltiwanger and Urdaneta, 2024). This is also relevant to trade models, which predict that trade integration has heterogeneous effects across more or less productive firms (e.g., Melitz, 2003; Helpman, Melitz and Yeaple, 2004).

We define firm size classes based on full-time equivalent (FTE) employment, distinguishing small establishments (<10 FTE workers), medium establishments (10–249 FTEs) and large establishments ($\geq$ 250 FTEs), and we generate separate effects by firm size by interacting the trade exposure variables in equation (1.3) with firm size indicator variables (and expanding the instrument set with the corresponding interactions).[23]

[23]The threshold of 249 workers is also used by the OECD and German Statistical Office to identify small- and medium-sized enterprises (e.g., OECD, 2019).

The results in Figure 1.2 reveal strong heterogeneity in the impact of trade exposure by establishment size. The effects on both employment and firm exit are entirely driven by small- and medium-sized establishments. Large firms do not react in terms of employment or survival, but they do pay higher wages in response to export demand shocks.

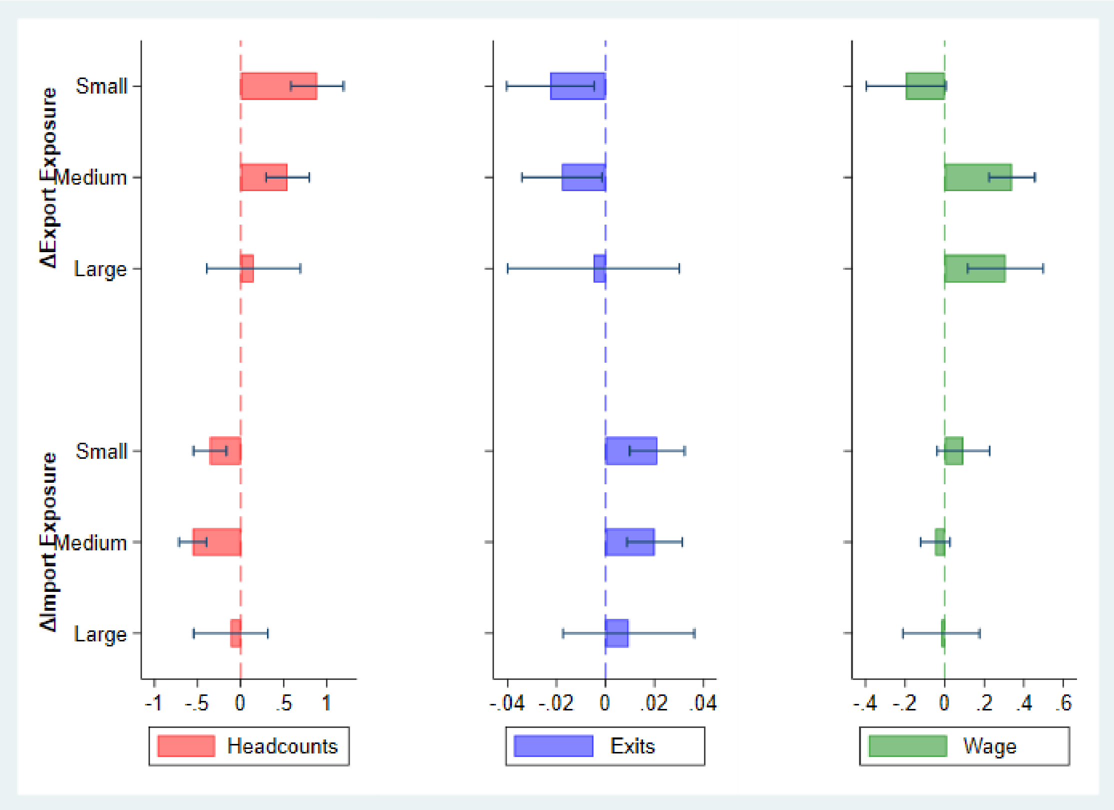
The fact that the firm exit effect (central panel of Figure 1.2) is concentrated among small- and medium-sized enterprises (SMEs) is plausible, as smaller establishments tend to have lower profit margins, and thus a given shock could more easily push them into bankruptcy. However, it may appear surprising that the employment effect for continuing firms (left panel) is also stronger among SMEs, given the prediction of Melitz-type models according to which the most productive companies will be able to benefit the most from export opportunities (Melitz, 2003; Helpman, Melitz and Rubinstein, 2008; Chaney, 2008).

Representing 98% of all establishments (see Table 1.1), SMEs however are the highly innovative backbone of the German economy and often world leaders in their market niche.[24] Large companies, on the other hand, might realize at least part of their trade benefits through foreign direct investments (Helpman, Melitz and Yeaple, 2004; Bernard et al., 2007), which would lead to employment growth abroad rather than in Germany. Large establishments may also be able to absorb trade shocks and adjust production without having to adjust total employment, for example by tapping into capacity reserves, restructuring internal work allocations, relying on capital deepening, or increasingly automating their production processes (e.g., Bloom, Draca and Van Reenen, 2016; Dauth et al., 2021; Acemoglu et al., 2022; Acemoglu, 2024).[25]

[24] Pahnke and Welter (2019) identify *Mittelstand* firms, as those highly successful SMEs in which the founding family retains a significant managerial or financial control of the organization. They document that *Mittelstand* companies account for 18% of the country's export turnover, 60% of employment, and 82% of all apprenticeship training. See also *The Economist* (2023).

[25] Mirroring our results to trade shocks, larger firms have also been shown to be less cyclically sensitive to business cycle fluctuations (e.g., Crouzet and Mehrotra, 2020).

Figure 1.2. Heterogeneous Effects on Employment, Exit, and Wages, by Firm Size



Notes: The specifications are the same as those in Table 1.2, except for the exclusion of exposure variables. Instead, we include 6 interaction terms that combine exposure variables with 3 establishment size dummies. The figure shows the coefficients of interaction variables. The interaction variables are standardized. IVs are the other 8 high-income countries' export and import exposure interacted with 3 size dummies. Periods: 1988–1998 and 2000–2010. Each bar is the estimate-specific 95% confidence interval.

Our estimates allow us to calculate the net job gains from Germany's trade exposure with the East. We do so by identifying firm size-specific effects of exposure on the total headcount measure (including exiting and entering firms) and then by combining these estimates with each company's industry-specific import and export exposure. Over the two decades of the observation period, trade exposure created 369,902 new jobs.[26] Breaking this figure down by establishment-size class, we find that small businesses created a net of 12,127 jobs, while medium-sized enterprises and large companies contributed to a net creating of 84,192 and

[26]Across all firms and over the two decades under analysis, we compute the net employment gain as $2 \times \frac{10}{100} \times \sum_{it}(\theta_i^{EXP}\Delta ExE_{it}^G + \theta_i^{IMP}\Delta ImE_{it}^G)\frac{1}{2}(Y_{i,t}+Y_{i,t-10})$, where ΔExE_{it}^G and ΔImE_{it}^G represent the export and import exposure to which establishment i's industry is exposed in decade t, θ_i^{EXP} and θ_i^{IMP} are the relative employment effects on total headcounts of export and import exposure for establishment i's size class (see Appendix Table A.5 for the results), and $\frac{1}{2}(Y_{i,t}+Y_{i,t-10})$ is establishment i's size for decade t from the denominator of the arc growth rate in expression (1.4). The factor $\frac{10}{100}$ scales the percent effect per hundred and transforms the annualized growth effect into a 10-year growth effect, while the factor 2 takes into account that the BHP is a 50% sample of all establishments. Our estimate of almost 370,000 additional jobs created by the trade integration with the East is comparable to the 440,000 estimate found by Dauth, Findeisen and Suedekum (2014) from their analysis at the local labor market level. Their higher figure is likely due to the fact that they also account for spillover effects, while we do not.

273,538 jobs, respectively. Despite the small absolute size of employment in SMEs, their contribution of 26% of job gains from trade exposure is striking. Decomposing net job creation into entering, exiting, and continuing establishments shows that continuing firms create 290,952 new jobs, while the remaining 54,526 and 24,424 jobs can be attributed to increased firm creation and reduced destruction, respectively.

In terms of wage effect heterogeneity (right panel of Figure 1.2), medium and large firms pay higher wages in response to increased export exposure. Medium-sized firms may need to raise wages in order to take advantage of positive export demand shocks, while accompanying changes in the composition of their workforce. Another rationale to increase wages (even in the absence of employment growth, as is the case for large firms) is to share part of the increased profits from their exporting activity with their workforce, as suggested by Egger and Kreickemeier (2012) and Amiti and Davis (2012). The lack of a wage effect among small firms is consistent with the notion that they act as price takers in the labor market.[27]

Because the employment adjustment to trade shocks is particularly important among SMEs, and because SMEs play a key role in the German economy, we next turn our attention to the behavior of this specific group of firms. In particular, we will focus on changes in employment composition and wage effects by worker type in greater detail. The emphasis on small companies, which tend to face more competitive environments than their larger counterparts, has gathered growing attention in recent years (see, for instance McElheran et al., 2024; Gertler et al., 2024; Galdon-Sanchez, Gil and Uriz-Uharte, 2025).[28]

1.5 Adjustment Strategies Among SMEs

1.5.1 Employment Responses

To better understand the employment adjustment of SMEs to trade exposure, we decompose the total employment change into worker inflows (hirings) and worker outflows (separations).[29] The 10-year change in employment of establishment i, $L_{it} - L_{i,t-10}$, can be represented by the sum over its annual worker inflows minus the sum over its worker outflows,

[27] When distinguishing firms by their average establishment wage fixed effect, as an alternative proxy for firm productivity, Appendix Figure A.2 reveals a qualitatively similar picture, with employment and exit effects being primarily driven by low and medium wage fixed-effect firms, and with wage increases being concentrated among high wage fixed-effects firms.

[28] Analyzing large establishments as a separate group is challenging, because they represent only 2% of the whole sample, and because they are clustered in only one third of the industries, which leads to small sample issues and to a more limited variation in trade exposure.

[29] In the BHP data, annual inflows are defined as the number of employees who were working in the establishment at the reference date as of June, 30-th of a given year but were not working there at the reference date of the previous year. Conversely, annual outflows are defined as the number of employees who were not working in the establishment at the reference date (June, 30-th) of a given year but were working there at the reference date of the previous year.

i.e.,

$$L_{it} - L_{i,t-10} = \sum_{t=1}^{10} \text{Inflow}_{it} - \sum_{t=1}^{10} \text{Outflow}_{it}. \tag{1.7}$$

In the arc growth rate for employment given in expression (1.4), we thus simply replace the change of employment in the numerator by either the sum of inflows or the sum of outflows. This yields inflow and outflow measures that add up exactly to the employment arc growth rate and allows us to decompose the extent to which the estimated employment changes are driven by worker inflows and outflows.

In column (a) of Table 1.5, we report the total employment effects for small and medium-sized establishments for reference. As can be seen from columns (b)–(d), the employment response is primarily driven by adjustments in hiring (inflow of workers) rather than separations. For the positive shocks from export exposure, the employment effect can be entirely explained by an increase in worker inflows (column (b)), which appear to be driven in large part by job-to-job transitions (column (c)). When experiencing positive trade shocks, therefore, SMEs tend to rely on hiring new workers, with the bulk of that hiring consisting of recruitment from other firms. This sort of job reallocation to firms with positive export exposure may have been facilitated by the secular decline in manufacturing employment (see Figure A.1). In subsection 1.5.4, we will ask whether the balance between relying on increased hiring versus reduced separations changes further with the tightness of the local labor market.

For the negative shocks induced by import exposure, lower worker inflows can explain about two-thirds of the overall employment adjustment, with the residual part being made up of greater (but not statistically significant) outflows.

Table 1.5. Effect of Trade Exposure on Employment Flows and Employment Contracts (SMEs only)

	(a) ΔHeadcounts	(b) Hiring	(c) Hiring (JTJ)	(d) Separation	(e) ΔFull-time	(f) ΔPart-time	(g) ΔApprentice
ΔExE^G (β_1)	0.758***	0.800***	0.606***	0.042	0.631***	0.087	1.201***
	(0.129)	(0.243)	(0.140)	(0.226)	(0.152)	(0.201)	(0.208)
ΔImE^G (β_2)	-0.468***	-0.294**	-0.184**	0.174	-0.371***	-0.112	-0.456***
	(0.077)	(0.243)	(0.080)	(0.125)	(0.090)	(0.118)	(0.127)
F statistic	28.7	28.7	28.7	28.7	28.7	28.7	28.7
Observations	94,353	94,353	94,353	94,353	94,353	94,353	94,353

Notes: The specifications are the same as model (b) in Table 1.2. Standard errors in parentheses are clustered at the period×commuting zone×3-digit-industry level. The F-statistic is the Kleibergen-Paap statistic.
** $p < 0.05$, *** $p < 0.01$

In columns (e)–(g), we analyze which types of employment grow the most. For both shocks, full-time employment and employment of apprentices react strongly, while SMEs' responses in terms of part-time employment are much smaller and statistically insignificant.

Export exposure has a particularly strong impact on apprenticeship, with a one-standard-deviation increase in export exposure leading to a 1.2 percentage point higher annual growth in apprentices' recruitment. SMEs may resort to training more apprentices in response to an export shock, either because their demand for skilled labor rises by more than what they can fulfil through the margin of hiring skilled workers, or because part of their demand is for very specific skills that are not readily available on the market (Mohrenweiser and Zwick, 2009).

We next explore if workers' gender plays a role in the SMEs' employment adjustment strategy. Juhn, Ujhelyi and Villegas-Sanchez (2013, 2014) argue that export demand encourages exporting firms to upgrade to more modern technology, which could lead to a lower demand for physically demanding skills, triggering a relative increase in female employment in blue-collar occupations. Indeed, they find evidence for this among Mexican firms in response to reductions in tariffs following Mexico's accession to the North American Free Trade Agreement. We, however, cannot detect matching evidence in the context of German SMEs. When investigating gender differences in employment growth in Table 1.6, we find that female employment rises *less* than male employment in response to export exposure, while the decline of employment in response to import exposure, if anything, is marginally stronger along the female employment margin. Not only do companies seem not to use part-time labor in response to trade shocks in general (as shown in column (f) of Table 1.5), they also do not make use of it differently by gender (see column (c), Table 1.6). Firms' employment adjustment instead goes primarily through full-time contracts, with no significant gender differentials in response to positive export shocks, but curtailing female employment more in response to negative import shocks. It is possible that firms expand female employment less in response to greater export exposure, and contract it more in response to higher import exposure, because of their pre-existing internal skill distribution and occupational composition.

Table 1.6. Employment Effects by Gender (SMEs only)

	(a) ΔHeadcounts	(b) Δ Full-time	(c) Δ Part-time
		Female	
ΔExE^G	0.5023***	0.5948***	0.0857
	(0.144)	(0.164)	(0.194)
ΔImE^G	-0.4138***	-0.4316***	-0.1222
	(0.086)	(0.096)	(0.114)
		Male	
ΔExE^G	0.8262***	0.5741***	0.0185
	(0.177)	(0.166)	(0.140)
ΔImE^G	-0.3680***	-0.2423***	-0.0288
	(0.099)	(0.097)	(0.075)
F statistic	28.7	28.7	28.7
Observations	94,353	94,353	94,353

Notes: The specifications are the same as model (b) in Table 1.2. Standard errors in parentheses are clustered at the period×commuting zone×3-digit-industry level. The F-statistic is the Kleibergen-Paap statistic.

*** $p < 0.01$

Turning our attention to the effects of trade exposure on the employment of workers by skill level (proxied by education), we focus on full-timers. We distinguish low-skill workers (i.e., school leavers without vocational qualifications), medium-skill workers (i.e., those who completed an apprenticeship or equivalent vocational qualification), and high-skill workers (i.e., those with a college degree or more).

Estimates from this exercise are reported in Table 1.7. The results in panel A show that export exposure has the strongest positive effects on medium and high-skilled employment, while the impact on low-skilled employment is about half the size and statistically significant only at the 10% level. In contrast, import exposure has relatively homogeneous negative effects across all education groups. In Appendix Table A.8, we decompose the overall effect on full-time employment into its components due to changes in low-, medium-, and high-skilled workers. We find that 70% of the employment change driven by export exposure and 50% of the change driven by import exposure are attributable to adjusting the employment of medium-education workers.[30]

Table 1.7. Effects of Trade Exposure by Workers' Education (SMEs only)

	(a) All	(b) Low	(c) Medium	(d) High
A. Annual employment growth				
ΔExE^G	0.6314***	0.2656*	0.5859***	0.5400***
	(0.152)	(0.145)	(0.160)	(0.157)
ΔImE^G	-0.3711***	-0.2348***	-0.3028***	-0.2606***
	(0.090)	(0.090)	(0.097)	(0.080)
F statistic	28.7	28.7	28.7	28.7
Observations	94,353	94,353	94,353	94,353
B. Skill group shares (percentage points)				
ΔExE^G		-0.1425	-0.5917	0.7342***
		(0.286)	(0.370)	(0.282)
ΔImE^G		-0.2709	0.5586**	-0.2877*
		(0.242)	(0.250)	(0.155)
Skill share at baseline (year 2000)		10%	86%	4%
F statistic		29.8	29.8	29.8
Observations		91,653	91,653	91,653

Notes: All specifications are the same as model (b) in Table 1.2 and based on the sample of full-time workers. In panel A, the dependent variable is the arc growth rate of employment of each specific skill group. In panel B, the dependent variable is the change in the skill share. Standard errors in parentheses are clustered at the period×commuting zone×3-digit-industry level. The F-statistic is the Kleibergen-Paap statistic.

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

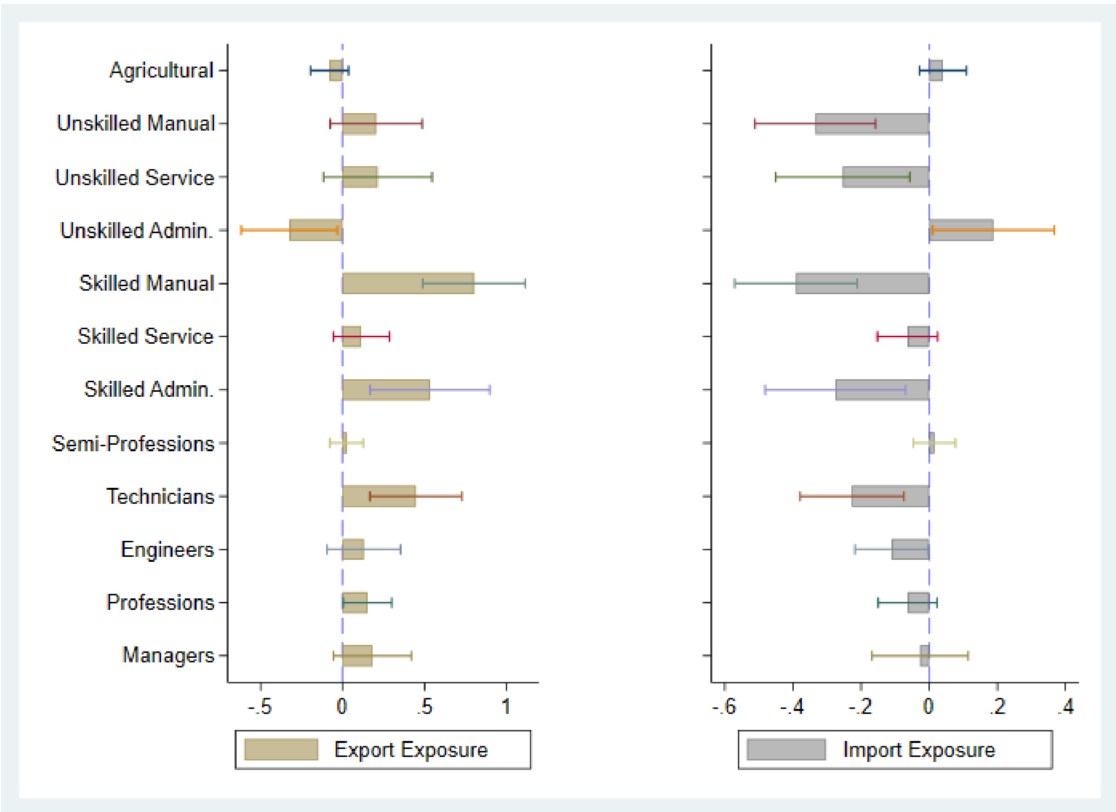
The results in panel B further document that the differential employment growth by skill

[30] The decomposition is based on the outcome measures as in expression (1.4), where the numerator includes skill-specific employment changes, while the denominator is defined on firm overall employment. This yields three outcome variables for low-, medium-, and high-skilled employment, which sum up to the outcome for overall firm employment. Dividing, for instance, the 0.44 coefficient on export exposure found for medium-skilled labor in Table A.8 by the coefficient on overall employment of 0.63, yields a share of 70% of employment growth that is explained by changes in medium-skilled employment.

group leads to changes in the skill composition. In response to a one-standard-deviation increase in export exposure, the share of highly skilled workers increases by 0.7 percentage points, compared to a baseline level of 4% for this share of skills in 2000. Export exposure, therefore, leads firms to moderately upskill their workforce. A one standard deviation increase in import exposure, on the other hand, raises the share of medium-skilled workers, at the expense of both the shares of low and high-skilled workers, leading to a lower skill spread.

In Figure 1.3, we define skills through broad occupational groups.[31] The positive export exposure effects (in the left-hand side panel of the figure) are concentrated on skilled manual and skilled administrative occupations, as well as technicians, with no other significant positive effects on unskilled occupations or the most skilled groups (e.g., engineers, professionals, and managers). Regardless of how we define skills — whether using education or occupation, we therefore tend to identify the strongest effects of export exposure on medium-skilled employment. For import exposure, instead, and in line with the results based on educational skill groups, the effects are more widespread across occupational categories (see the right-hand side panel of Figure 1.3).

Figure 1.3. Employment Effect of Trade Exposure by Occupational Groups (SMEs only)



Notes: The specifications are the same as those in Table 1.2. The figure shows the coefficients of export exposure (left panel) and import exposure (right panel) in the regressions of employment of 12 occupations defined by Blossfeld (1987). Periods: 1988–1998 and 2000–2010. Each bar is the estimate-specific 95% confidence interval.

[31]These groups are defined following IAB's guidelines and the protocol introduced by Blossfeld (1987).

The evidence that SMEs react to export shocks relying more on skilled than unskilled employment is line with insights from trade theory, according to which international trade requires more skilled labor. For example, exporting firms tend to be more technology-intensive and have additional incentives to invest in R&D expenditures, thereby increasing their demand for skills (e.g., Sampson, 2014). Moreover, the marketing, distribution, and transport logistics involved in international trade make it a more skill-intensive activity than domestic trade (Matsuyama, 2007; Brambilla, Lederman and Porto, 2012).

1.5.2 Wage Adjustments

Table 1.8 shows the effects of trade exposure on SME's wages. In panel A, we present results at the mean and at different points of the wage distribution. We also consider potential impact heterogeneity at the mean by worker education and gender in panel B. The first two columns of the table refer to all SMEs in the sample, while in the remaining columns we separate out small- from medium-sized companies.

Mirroring the benchmark results of Table 1.2 across all continuing firms, Table 1.8 finds little evidence of wage effects for the whole group of SMEs, both at the mean and at other points of the distribution (columns (a) and (b)). Distinguishing small- from medium-sized businesses, however, reveals a more nuanced picture in columns (c)–(f). Export exposure has a negative but statistically insignificant impact on mean wage growth among small enterprises (column (c)). It leads instead to positive and significant wage effects in medium-sized companies (column (e)). A one-standard-deviation increase in ExE^G raises average annual wage growth by 0.34 percentage points. There is also evidence of a gradient across the wage distribution in this case, with the effect being about 20% stronger at the 75-th percentile than at the median or the 25-th percentile.

When we allow for impact heterogeneity by education, we find that the average wage growth among medium-sized companies is concentrated on medium-skilled workers with apprenticeship qualifications, which is exactly the group for which we identify the strongest employment effects in Table 1.7. Positive export shocks to medium-sized firms, therefore, tend to benefit their semi-skilled workers in the top half of the wage distribution. For the same group of firms, we also find evidence of greater wage effects among female workers.[32]

Import exposure, on the other hand, has a small negative effect on average wages in medium-sized firms, albeit significant only at the 10% level (column (f)). While the effects at different percentiles of the wage distribution and across skill groups are statistically indistinguishable from zero, the average establishment wages paid to female workers in medium-sized firms tend to decline following an increase in import exposure.

[32]This differential could be driven by compositional changes, which affect the skill and occupational distributions differently by gender. This is something that cannot be disentangled with the BHP data, because they do not provide additional breakdowns of male and female wages into skill or occupational groups.

Table 1.8. Effect of Trade Exposure on SMEs' Wages

	All SMEs		Small		Medium	
	(a) ΔExE^G	(b) ΔImE^G	(c) ΔExE^G	(d) ΔImE^G	(e) ΔExE^G	(f) ΔImE^G
A. Baseline results						
ΔMean	0.0596	0.0279	-0.1455	0.0972	0.3396***	-0.0772*
	(0.074)	(0.043)	(0.117)	(0.073)	(0.067)	(0.040)
	[91,709; 29.8]		[57771, 31.8]		[339338, 20.6]	
Δ25% percentile	0.0579	0.0231	-0.1208	0.0835	0.3056***	-0.0650
	(0.083)	(0.049)	(0.133)	(0.080)	(0.073)	(0.044)
	[91709, 29.8]		[57771, 31.8]		[339338, 20.6]	
ΔMedian	0.0300	0.0411	-0.1812	0.1057	0.3168***	-0.0580
	(0.076)	(0.045)	(0.122)	(0.075)	(0.068)	(0.043)
	[91709, 29.8]		[57771, 31.8]		[339338, 20.6]	
Δ75% percentile	0.0615	0.0464	-0.1602	0.1211	0.3615***	-0.0709
	(0.078)	(0.046)	(0.127)	(0.080)	(0.072)	(0.044)
	[91709, 29.8]		[57771, 31.8]		[339338, 20.6]	
B. By skill and gender						
ΔLow-skill	0.1430	-0.0521	-0.0249	-0.0530	0.2508	-0.0618
	(0.181)	(0.104)	(0.431)	(0.254)	(0.174)	(0.092)
	[47555, 19.9]		[19155, 12.1]		[28400, 18.1]	
ΔMedium-skill	0.0125	0.0408	-0.1518	0.0912	0.2337***	-0.0395
	(0.116)	(0.053)	(0.211)	(0.094)	(0.051)	(0.034)
	[90819, 29.7]		[56887, 31.7]		[33932, 20.6]	
ΔHigh-skill	-0.1643	0.1403*	-0.0249	0.1371	-0.0945	0.1227
	(0.156)	(0.080)	(0.431)	(0.129)	(0.143)	(0.089)
	[30438, 22.7]		[8082, 24.5]		[22356, 19.1]	
ΔFemale	0.1235	-0.0106	-0.0975	0.0776	0.3633***	-0.1097**
	(0.101)	(0.057)	(0.193)	(0.108)	(0.084)	(0.051)
	[74667, 26.9]		[57771, 31.8]		[32627, 20.0]	
ΔMale	0.1240*	0.0153	0.0603	0.0365	0.1996***	-0.0142
	(0.074)	(0.052)	(0.121)	(0.094)	(0.064)	(0.046)
	[86375, 29.1]		[52564, 29.8]		[33811, 20.5]	

Notes: The specifications are the same as model d in Table 1.2.
Standard errors in parentheses are clustered at the period×commuting zone×3-digit-industry level. Number of observations and F-statistics are in the bracket [,]. The F-statistic is the Kleibergen-Paap F-statistic.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As mentioned, we find no evidence of a statistically significant wage effect for small businesses (columns (c) and (d)), although the point estimates suggest a negative impact in response to greater export exposure. When we additionally distinguish 'micro' firms (i.e., those employing fewer than 5 FTE workers) from the other small establishments, Appendix Figure A.3 shows that these companies react to more elevated export shocks with a statistically significant wage reduction.[33] In contrast, the positive wage effect found for medium-sized firms also emerges among large firms.

In sum, an increase in export exposure leads the smallest businesses to reduce their wage growth on the one hand and, on the other hand, medium and large firms to pursue a positive

[33] Appendix Figure A.3 also shows that, conditional on surviving, micro firms experience a growth in employment following a positive export exposure, despite their average wage decline. One explanation of this result is that micro firms cannot afford to increase wages and, in order to grow or just to survive, they have to lower the skill composition of their workforce. This strategy is likely to be compounded if they compete in the same local labor market with larger firms that can make more attractive wage offers as they grow. We investigate spillovers through the local labor market in subsection 1.5.4 below.

wage growth strategy. Export exposure may thus play a role in exacerbating between-firm wage inequality, albeit only slightly, in line with the evidence found by Helpman et al. (2016) for Brazilian firms. Moreover, within-firm wage growth in medium-sized enterprises is only marginally stronger in the top half of the distribution and, crucially, for medium-skilled workers with apprenticeship qualifications. This suggests that export exposure is unlikely to raise within-firm wage inequality substantially among SMEs.

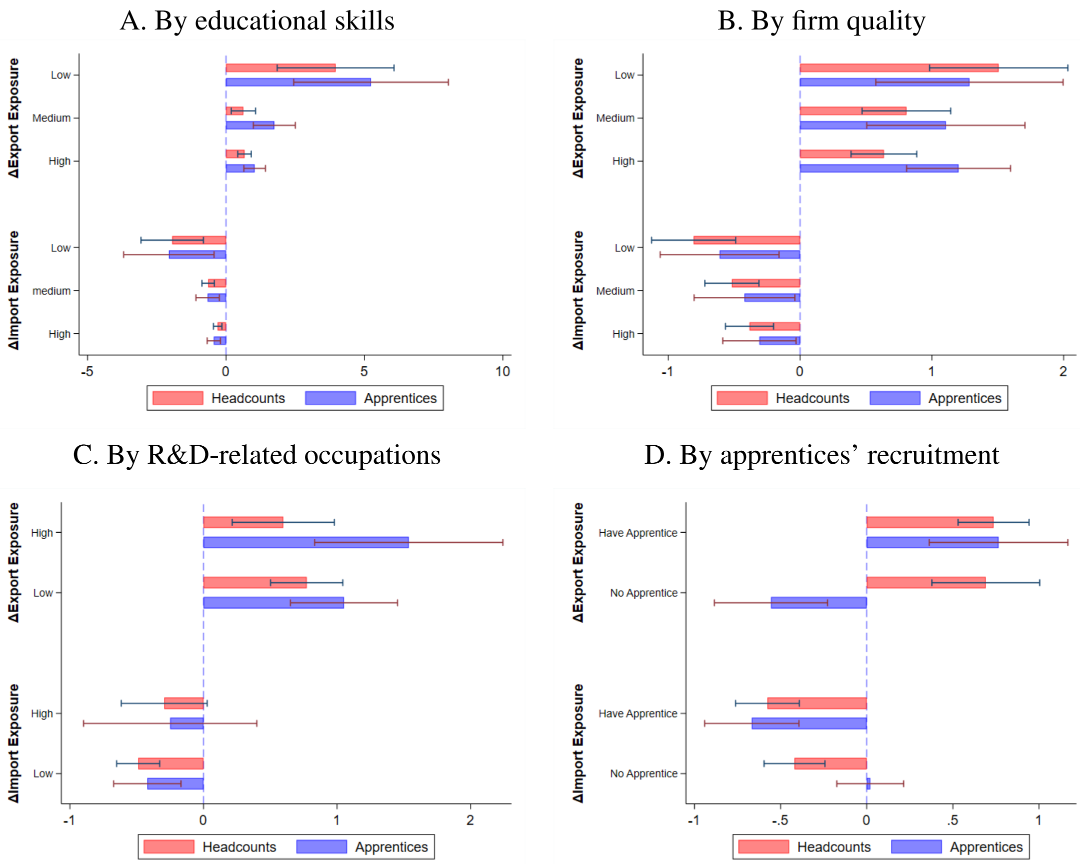
1.5.3 Ex-Ante Heterogeneity in the Adjustment Process

More productive firms could, in general, respond better to improved trade opportunities and companies that take advantage of positive export shocks may also endogenously strengthen their technological competitiveness through additional R&D activities (on these issues, see Melitz, 2003; Sampson, 2014, among others). We have documented that, following an increase in export exposure, small- and medium-sized businesses expand their employment by training more apprentices. We therefore now aim to test whether SMEs that are ex-ante more productive, or more R&D active, or train more apprentices, tend to grow more as a result of export exposure shocks. For completeness, we also examine the corresponding reactions to import exposure shocks.

We proxy firm productivity with either terciles of the share distribution of skilled workers, or terciles of the AKM establishment wage fixed effects. We measure experience in R&D activities by having an above-median share of workers in R&D-related occupations, and experience in training apprentices by having employed apprentices. All measures refer to these characteristics in the base year.

The results from this analysis are displayed in Figure 1.4. They paint a mixed picture. There is no evidence that SMEs with a larger baseline share of highly skilled workers or a greater baseline value of AKM wage fixed effects grow more in response to an increase in export exposure (panels A and B). Instead, it is low-productivity companies at baseline that exhibit greater growth, although growth differentials across firms are not statistically significant at conventional levels. Low-productivity businesses, on the other hand, experience stronger negative employment adjustments to import exposure shocks, even though again the differences across firm types are not statistically significant. We also find no evidence that SMEs with prior above-median R&D involvement or with prior experience of apprenticeship training have a stronger overall growth following an increase in export exposure (panels C and D).

Figure 1.4. Heterogeneous Effects of Trade Exposure, by Characteristics at Baseline Year (SME only)



Notes: The specifications are the same as those in Table 1.2, except for the exclusion of exposure variables. Instead, we include interaction terms that combine exposure variables with ex-ante heterogeneity (educational skills, firm quality, R&D occupation and apprentice recruitment) dummies. The figure shows the coefficients of interaction variables. The interaction variables are standardized. IVs are the other 8 high-income countries' export and import exposure to the East interacted with heterogeneity dummies. Periods: 1988–1998 and 2000–2010. Each bar is the estimate-specific 95% confidence interval.

There is a marked persistence, however, in using apprenticeship schemes. Companies with prior experience in recruiting apprentices expand employment through this channel after a positive export exposure shock, while their counterparts tend to shy away from hiring apprentices even if they expand employment overall (panel D). Interestingly, the employment growth reported in column (g) of Table 1.5 and associated with the recruitment of apprentices following an export exposure shock is entirely explained by the hiring behavior of companies with prior experience of training apprentices. Finally, we detect no heterogeneity by R&D intensity and apprentices' recruitment in SMEs' employment responses to import exposure shocks.

In sum, we find little evidence that ex-ante productivity is a significant moderator of trade effects. This could be due, in part, to our focus on SMEs in the German manufacturing sector, which may be comparatively similar productivity-wise at baseline, limiting the role for additional heterogeneity. Differential SMEs' responses might thus be driven by factors other than their initial productivity differences, such as specific characteristics of the local labor market (LLM) in which they operate. We focus on this aspect next.

1.5.4 Spillover Effects within the Same LLM or on SMEs in Service Industries

Do SMEs' employment and wage adjustments depend on the trade shocks faced by *other* firms in the same local labor market? Our finding that a significant part of SMEs' employment adjustment works through medium-skilled workers — in particular, individuals with apprenticeship degrees — suggests that the labor market for this sort of workers is likely to be highly local, with businesses competing for these specific skill types with other firms in the same LLM. The strength of this competition at the LLM level will depend on the growth plans of other local firms in the same market, and hence on how trade shocks are absorbed by these other companies.[34]

To define a measure of competition intensity in a given local labor market, we first compute export and import exposure at the commuting zone level. As in Dauth, Findeisen and Suedekum (2014), we first aggregate up each industry's export and import exposures to the commuting zone level, based on the industry's share in the LLM manufacturing employment. We then create an indicator for a positive trade shock to the LLM that is equal to 1 if the LLM has an above-median export exposure *and* a below-median import exposure. That is, a large fraction of establishments in the same area will experience a positive export shock, while a small fraction will face a negative import shock. We expect this to lead more companies in the same LLM to expand and fewer businesses to scale down, and thus competition among firms in the hiring market to be strong.

Panel A of Table 1.9 reports the estimates from a regression where we interact SMEs' own trade exposure and the indicator for a positive trade shock to their local labor market. These interactions are the focus of our discussion.[35] The overall employment response to export or import exposure is not statistically different in LLMs with a positive trade shock (column (a)). There is significant variation, however, in SMEs' hiring and separation strategies. For new hires (column (b)), the interaction effect is strongly negative and large enough to offset the positive baseline effect of export exposure. This means that, in an area where many other firms have also received positive trade shocks, SMEs with greater export exposure are not able to expand through an increase in external recruitment. Their growth, instead, is achieved with a more intense internal retention strategy, including a significant reduction in separations (column (c)).[36]

[34]This argument fits well into the literature that emphasizes the importance of firms imitating each other as a response designed to mitigate competitive rivalry or risk (for an early review, see Lieberman and Asaba, 2006, among others). See also Helm (2020), Gathmann, Helm and Schönberg (2020), and Setzler and Tintelnot (2021).

[35]The impact of the LLM trade shock indicator itself cannot be separately identified in this specification as it is absorbed into the LLM fixed effects.

[36]Appendix Table A.9 shows that the decrease in labor turnover is driven by hires from, separations into, nonemployment. This might be unsurprising in an environment with elevated local labor market tightness, where

Table 1.9. Effects of Local Labor Market Trade Shocks (SMEs only)

	(a) ΔHeadcounts	(b) Hiring	(c) Separation	(d) ΔFull-time	(e) ΔApprentice	(f) ΔLow-skill	(g) ΔFemale	(h) ΔWage
A. Interaction of firms' own trade exposure with positive LLM trade shock								
ΔExE^G	0.7805***	0.9092***	0.1287	0.6512***	1.2916***	1.0073***	0.4842***	0.0387
	(0.138)	(0.262)	(0.243)	(0.162)	(0.223)	(0.197)	(0.160)	(0.087)
$\Delta ExE^G \times$ LLM	-0.2014	-0.9512**	-0.7499**	-0.1770	-0.7802**	-0.0408	-0.0813	0.0353
positive trade shock	(0.230)	(0.371)	(0.368)	(0.278)	(0.365)	(0.075)	(0.254)	(0.123)
ΔImE^G	-0.4868***	-0.3626**	0.1241	-0.3894***	-0.5042***	-0.5874***	-0.4300	0.0222
	(0.081)	(0.147)	(0.132)	(0.095)	(0.135)	(0.115)	(0.094)	(0.046)
$\Delta ImE^G \times$ LLM	0.2086	0.6545**	0.4459	0.2106	0.3952	0.2095	0.2443	0.1446*
positive trade shock	(0.137)	(0.323)	(0.317)	(0.207)	(0.282)	(0.231)	(0.163)	(0.087)
Kleibergen-Paap F statistic	13.2	13.2	13.2	13.2	13.2	13.2	13.2	12.5
Observations	94353	94353	94353	94353	94353	94353	94353	91709
B. Effect of LLM trade exposure on firms with low own trade exposure								
LLM ΔExE^G	0.0159	0.0543	0.0384	-0.0232	0.0425	-0.0179	-0.0217	0.1256**
	(0.079)	(0.134)	(0.131)	(0.087)	(0.123)	(0.124)	(0.088)	(0.050)
LLM ΔImE^G	0.0416	-0.1641	-0.2056	0.0051	0.1295	0.0679	0.0714	-0.0280
	(0.068)	(0.132)	(0.136)	(0.074)	(0.115)	(0.102)	(0.086)	(0.063)
Kleibergen-Paap F statistic	19.8	19.8	19.8	19.8	19.8	19.8	19.8	19.9
Observations	41,673	41,673	41,673	41673	41,673	41,673	41673	40615

Notes: Each regression includes controls for establishment size (four indicator variables: 0–5, 5–20, 20–200, 200–2000), time period, 108 commuting zones, broad manufacturing industries (four dummy variables: food, industrial, capital, and consumer products), and an above-median firm share of skilled workers. Panel B also includes firms' own export exposure as control variables. Exposure variables are standardized. IVs are the other 8 high-income countries' export and import exposure to the East. The F-statistic is the Kleibergen-Paap statistic. The two time periods are: 1988–1998 and 2000–2010. Standard errors in parentheses are clustered at the period×commuting zone×3-digit-industry level.

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

It also becomes harder for export-exposed SMEs to hire apprentices if their local labor market faces a positive trade shock (see column (e) of Table 1.9). Yet, LLM tightness does not affect companies' reliance on full-time employment, regardless of their trade exposure (column (d)). Likewise, it does not induce small- and medium-sized enterprises to de-skill their workforce or rely more on female workers (see columns (f) and (g), respectively), nor does it lead to statistically significant changes in wage growth (column (h)).

For SMEs facing increased import exposure, the estimates in panel A indicate that a positive export shock to other firms in the same LLM raises worker turnover. In particular, separations from these firms go up (column (c), although this effect is not statistically significant) as workers may leave to other local firms that experienced positive trade shocks, forcing import-exposed businesses to hire more and raise wages (columns (b) and (h), respectively).

Next, we investigate whether there are spillovers to other firms that are not heavily exposed to trade shocks. To this end, we focus on a sample of firms with a below-median export exposure *and* below-median import exposure. We then augment our baseline regression by including average export exposure and average import exposure at the LLM level.[37] The results are displayed in panel B of Table 1.9. The estimates in columns (a)–(g) indicate that an increase in export exposure to other firms in the local labor market changes neither the employment growth strategy nor the employment structure of the non-directly-affected SMEs. It does, however, raise their need to pay higher wages (column (h)). Increased import exposure of other firms in the local labor market, on the other hand, has no statistically significant effect, although the point estimates suggest that it may decrease churning (columns (b) and (c)) and may make it easier for non-directly-affected SMEs to recruit apprentices (column (e)).

Are there spillover effects of the East trade shocks in manufacturing that propagate to SMEs in service industries? To address this question, we regress the labor market outcomes of service SMEs on local labor market export and import exposures. The results in Appendix Table A.10 show that trade shocks to manufacturing SMEs do not generally lead to labor market adjustments in other small- and medium-sized enterprises that operate in service industries.[38] A couple of interesting exceptions emerge, however. First, favorable export shocks to SMEs in manufacturing lead to an increase in part-time employment among SMEs in services. The exact specular result emerges in the case of exposure to adverse import competition, i.e., this exposure curtails part-time employment in service SMEs. Increased exposure to import shocks also leads to a reduction in low-skill employment. Although manufacturing SMEs directly affected by trade integration rely neither on part-time employment nor on low-skill workers to adjust to trade shocks, their indirectly affected counterparts in services tend to

the role played by job-to-job worker reallocation becomes more salient than flows from and into nonemployment.

[37] As in the regressions reported in panel A, we cannot identify LLM fixed effects. We do retain own export and import exposure measures, even though they now have limited variation.

[38] Virtually identical estimates are found for all service firms, not just SMEs. These figures are not shown but are available from the authors. Our null results are broadly consistent with the worker-level estimates reported in Dauth, Findeisen and Suedekum (2017).

use both labor margins, and part-time employment in particular, presumably because this is cheaper and more flexible.

1.5.5 Organizational Change

Besides changing the structure of employment and wages, firms can make additional internal adjustments in terms of how they organize their workforce and production. To investigate whether SMEs implement organizational changes in response to the growing exposure to trade pressures, we use a different data source covering the period from 1995 to 2010 from the IAB Establishment Panel (IAB-BP), an annual representative establishment survey. Our measurement of organizational change aligns with the technological and organizational change indicator adopted by Battisti, Dustmann and Schönberg (2023). This indicator is the sum of responses to four yes-or-no questions about whether the surveyed firm: (a) shifted responsibilities; (b) delegated decisions; (c) introduced teamwork or working groups with their own responsibilities; and (d) introduced units or departments that perform their own cost and result calculations. These questions reflect the evolving nature of how firms operate, the technologies that accompany their change, and their evolving management practices.

Because SMEs are found to react more strongly to trade exposure than larger firms, we test whether SMEs engage in more organizational change than larger firms in the time period after the onset of trade exposure, compared to before. We do this based on the following difference-in-difference specification:

$$Y_{it} = \alpha + \beta(\text{post}_t \times \text{SME}_i) + \gamma_i + \lambda_t + \varepsilon_{it}, \tag{1.8}$$

where Y_{it} denotes our organizational change measure for firm i in year t, post_t indicates the years after 1998 (i.e., the onset of increased trade exposure), and SME is an indicator variable taking value 1 if firm i has fewer than 250 workers, and 0 otherwise.[39] γ_i and λ_t represent year and firm fixed effects to control for time- and firm-specific unobserved heterogeneity. The coefficient of interest is β, capturing whether SMEs engaged relatively more in organizational change after the onset of increased trade exposure.

Column (a) of Table 1.10 reveals a positive and statistically significant overall effect. After the onset of trade exposure with the East, the organizational change index rises comparatively more for SMEs as opposed to larger firms by 0.36, which corresponds to a substantial 50% percent increase over the baseline mean.

This overall effect is driven by a 14 percentage point higher probability of delegating decisions (column (c)) and a 17 percentage point higher probability of introducing teamwork

[39]The time period t refers to the following survey years: 1995, 1998, 2000, 2001, 2004, 2007, 2010, which correspond to the years in which the four organizational change variables have been asked in the IAB-BP survey.

Table 1.10. Association between Organizational Change and Export Exposure

	(a) Overall	(b) Function	(c) Decision	(d) Team work	(e) New units
Post × SME (β)	0.3558***	0.0142	0.1394***	0.1674***	0.0265
	(0.061)	(0.025)	(0.027)	(0.024)	(0.023)
Observations	20279	20140	20140	20140	20140
Mean dep. var.	0.724	0.294	0.201	0.136	0.099

Source: IAB Establishment Panel (IAB-BP), years 1995, 1998, 2000, 2001, 2004, 2007 and 2010 waves.

Notes: Column (a) displays the estimate β of the interaction term Post × SMEs in equation (1.8) on the overall organizational change indicator, which ranges from 0 to 4. Columns (b) to (e) show the β estimate for each of the four individual organizational change components, that is: (i) Function: shifting responsibilities within the firm; (ii) Decision: delegating decisions to lower levels; (iii) Team work: introducing teamwork or working groups with their own responsibilities; (iv) New units: introducing units or departments that perform their own cost and result calculations. All regressions include the year and firm fixed effects. Standard errors clustered at firm level are shown in parentheses.

*** $p < 0.01$

(column (d)). These estimates suggest that small- and medium-sized firms tend to decentralize decision-making and adopt collaborative work structures in response to increased trade exposure. The coefficients for "Function" and "New units" are positive but much smaller and never statistically significant, indicating that SMEs and larger organizations do not exhibit a significant difference in shifting responsibilities or introducing new units. SMEs, while having a shorter decision-making process, often face tighter resource constraints, which may contribute to this disparity.

These results suggest that SMEs have adapted their organizational structures to meet the demands of a more competitive and globalized market environment. Decentralization of decision making and promotion of teamwork may improve SMEs' flexibility and responsiveness, enabling them to better capitalize on export opportunities. Existing evidence suggests that trade openness is associated with job market polarization, bolstering the process according to which industries with faster technological growth shifted demand from middle-educated workers to highly educated workers (e.g., Michaels, Natraj and Van Reenen, 2014). Organizational change has been shown to reinforce this course of action, by reducing the demand for routine tasks relative to abstract task-based jobs (Battisti, Dustmann and Schönberg, 2023). However, German SMEs may help to attenuate polarization by easing routine workers' transition to jobs that require higher skills and investing in training. This aligns well with our findings that SMEs show a greater demand for both medium-skilled and highly skilled employees and apprentices.

1.6 Conclusion

This paper makes three main contributions. First, it provides evidence on the impact of trade shocks on labor market outcomes from the firm's perspective. Our knowledge from this perspective is still relatively limited. Specifically, we use administrative establishment-level panel data to analyze the effect on employment, wages, and workforce structure among German manufacturing companies over the 1988-–2010 period. Second, as Germany is the third largest exporter in the world with a substantial trade surplus, we can separately identify firms' responses to export demand and import competition induced by increased trade volumes with China and Eastern European countries (which, in short, we refer to as 'the East'). This broadens the standard approach in the literature that has often focused on import exposure only. Third, because of the results that we summarize below, ours is primarily a story about small- and medium-sized enterprises (SMEs), which account for 98% of all manufacturing businesses, 70% of total manufacturing employment, and 40% of manufacturing turnover in Germany.

One of our key results is that, while mean wages across all establishments are insensitive to trade shocks from the East, the rise in export demand heightens firms' employment and survival, whereas a deeper import penetration leads companies to curtail employment and to exit the market. Greater trade integration created nearly 370,000 new jobs in Germany between 1988 and 2010 among companies whose industry was directly affected by trade shocks, with one quarter of that job creation occurring in small- and medium-sized enterprises.

These responses are unevenly distributed across firms, with SMEs being the most affected. When exposed to export shocks, such businesses tend to adjust employment along the hiring margin, recruiting medium and highly skilled male full-time workers and apprentices, and thus leading to a moderate increase in the skill composition of the workforce. In local labor markets where many firms also receive positive trade shocks, however, SMEs that experience higher export demand find it difficult to hire apprentices, and rely less on hiring and more on retaining incumbent workers. There is also evidence that medium-sized companies raise wages for medium-skilled workers (including technicians and skilled manual and administrative personnel), while small firms respond with a reduction in wages. A more elevated import competition, on the other hand, induces SMEs to reduce medium-skill employment, in addition to scaling down on unskilled workers.

SMEs facing positive export shocks turned out to be the main beneficiaries of the rise in trade with the East, possibly taking advantage of a nimbler organizational structure. Indeed, SMEs responded to greater export exposure with more organizational adjustments, decentralizing decision making and promoting teamwork. Their employment growth strategies could have generated winners and losers with broad economic consequences. In particular, their reliance on hiring apprentices and medium-skilled workers and their policy of paying those workers more may offer a potential pathway to alleviate job polarization and reduce between-firm wage inequality (Card, Heining and Kline, 2013; Coşar, Guner and Tybout, 2016).

Our establishment-level results bolster the local-labor-market- and worker-level evidence previously found for Germany (e.g., Dauth, Findeisen and Suedekum, 2014, 2021). This is important because firms are key decision makers that shape the way in which a large open economy like Germany adjusts to globalization and carries out an effective trade integration. Our estimates provide a substantially different picture from what emerges from the recent available evidence from other countries, including the US (Autor et al., 2020), the UK (De Lyon and Pessoa, 2021), and France (Aghion et al., 2024*b*). These other economies, especially the US and the UK, faced severe negative effects induced by a growing Chinese import penetration, while the situation in Germany was different, with a large pre-existing export base and a substantial rise in market opportunities for German exporters.

Whether the results of this paper could apply in the current economic environment, in which Germany faces new challenges (e.g., the domestic labor market restructuring post COVID-19 with labor shortages and productivity slowdowns, the Russia-Ukraine war with its steep surge in energy prices, the slowing down of the Chinese economy, and the threat of global trade wars), is an open question that remains to be addressed. The resilience and adaptability of German SMEs, however, are likely to continue to be a key feature of the German economic landscape.

Chapter 2

Routine and Non-routine Jobs: Young Workers' Experience in Germany

Jointly with
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Abstract

This paper studies young workers' job transitions in their first decade after entering the labor market in Germany. Using a dynamic multinomial choice model, we estimate the transitions among manual non-routine, routine, non-routine jobs and unemployment for a cohort of young men who experienced recessions in their early job market years. We find entering either routine or non-routine jobs leads to certain levels of persistence. Transitions from routine to non-routine jobs are particularly challenging. This suggests that young workers in low-paying routine jobs might need targeted training to achieve upward mobility. On the other hand, despite a decline in some routine occupations, these jobs still serve as an easily accessible option for those re-entering the labor market. We also find that young workers with vocational training qualifications, in contrast to those with degree-level qualifications, seem to have a lower ability to achieve upward mobility.

Keywords: Young workers, Routine, Non-routine, Dynamic multinomial choice model, State dependence, Education, Germany.

2.1 Introduction

Routine jobs have declined faster than non-routine jobs over the past decades (see Figure B.2) due to routine-biased technological change (Cortes, 2016). While a number of researchers have made these observations (Autor and Dorn, 2013; Autor, 2015; Jaimovich and Siu, 2020), existing studies focus more on experienced workers and their static job-type segmentation rather than young workers and their occupational dynamics over their early career path. Young workers, however, are more vulnerable during business cycles and thus are relevant for policymakers. In addition, understanding young workers' transition patterns across labor market status, especially during recessions, helps to identify the broken linkages in the labor market and the target population for policy interventions.

A significant body of research has documented a trend of job polarization, where employment growth has been concentrated in high-skilled, non-routine cognitive occupations and low-skilled, non-routine manual jobs, while medium-skilled, routine work have declined (Autor, Levy and Murnane, 2003; Goos, Manning and Salomons, 2014). If routine jobs continue to be easily replaced and offer lower wages, it would be advantageous for young workers who begin with such jobs to eventually progress to more desirable non-routine positions. While specializing in a particular task allows workers to accumulate task-specific human capital, a routine job may lead to a prolonged period of being stuck in a less desirable occupation. Routine jobs, often associated with lower education levels, higher unemployment rates, relatively high turnover, and greater vulnerability to business cycles, can lead to a "routine-job trap." This trap can result in lower lifetime incomes and negatively impact workers' overall well-being. (Cortes et al., 2020). This structural labour market trend, driven by technological advancement and globalization, has created uncertainty for the millions of young workers whose education and future careers have been built on these medium-skilled routine jobs. To understand the micro-level consequences for the affected workers, research on young workers' ability to adapt and transition to non-routine jobs is in demand.

In this paper, we study workers' ability to transition between jobs requiring skills on different tasks and quantitatively examine the persistence of each job type. We then further evaluate how business cycles affect such transition and persistence. Motivated by Germany's unique institutional context, this paper also addresses these questions separately for workers who have taken different education paths: dual vocational training and academic degrees track. We couple a dynamic discrete choice framework à la Magnac (2000) with a mass-point structure to control for individual observed and unobserved characteristics.[1] This framework allows for time-varying covariates, which is crucial for estimating the impacts of recessions.

[1]There is a growing body of studies that use similar or simplified models (logistic or probit models) to investigate within state dependence of youth labor market experiences like low-wage jobs (Cai, Mavromaras and Sloane, 2018), drug consumption (Deza, 2015), health (Contoyannis, Jones and Rice, 2004), and youth education and crime (Mancino, Navarro and Rivers, 2016).

The transition nature of our model also frees us from restricting the analysis to a certain group of people that is affected by a single shock, so we can get a better understanding of the labor market dynamics.

We analyse the German labour market and restrict the analysis to male workers as jointly modeling fertility choice and occupation type is beyond the grasp of our state dependence model. We use the worker-level German administrative data, Sample of Integrated Labour Market Biographies (SIAB). The German labor market is featured by structured early-career apprenticeship, well-established employment agency, and unique industrial relations. In particular, we intend to understand whether apprenticeship and stronger labor protection in Germany ease workers' labor market transitions during economic downturns.

Using SIAB data, we show first, entering either routine and non-routine jobs leads to certain levels of persistence, even conditional on individual characteristics. We find strong evidence of a "routine job trap," where the probability of remaining in a routine job is a remarkably high at 88.8%. In contrast, non-routine job seems to offer greater "safeness": a non-routine worker has a 91.2% chance of remaining in a same type of job in the next period. The persistence holds when excluding unobserved worker heterogeneity. In fact, the estimates suggest state dependence is mainly explained by job types themselves than individual characteristics. We interpret this result as a direct empirical evidence of routine job trap and non-routine job safeness.

Direct transitions between routine and non-routine are relatively infrequent. At the surface-level, barriers to enter into non-routine job are uniformly high for manual non-routine and routine job. But after controlling for unobserved individual heterogeneity, the probability of a routine worker moving to a non-routine is higher than that of a manual routine worker. We also observe that although manual non-routine and routine workers face the highest risk of transitioning to non-employment, routine and manual non-routine job is still the primary re-entry gates for the previously non-employed. Furthermore, the labor market responds to macroeconomic shocks in a asymmetric way. During economic downturns, the burden of adjustment falls disproportionately on routine and non-routine workers. A one-percentage-point rise in the unemployment rate increases the probability of transitioning to non-employment by a substantial 22.1% for routine workers and 20.8% for manual non-routine workers. Non-routine professionals, however, are largely insulated from this risk, facing a more modest 9.4% increase. There is also a pattern of downward mobility, where the manual non-routine sector works as a "buffer" for displaced routine workers. Unable to find stay or find a better positions, routine workers are pressured to accept more accessible, but often less stable, manual non-routine jobs to avoid unemployment.

We find young male workers who choose apprenticeship system are harder to achieve upward job transitions. Thus, routine workers in Germany are more vulnerable to cyclical economic volatility. Data shows that nearly 60% of academic track graduates work in non-routine roles, a destination reached by only 14.5% of their vocational counterparts. This sorting also translates into differences in career mobility; an academic graduate is nine times more likely to move from a routine to a non-routine job than a vocational graduate (9.0% vs. 1.0%). This advantage is most pronounced for those re-entering the workforce, where an academic track worker is over four times more likely to secure a non-routine position (31.6% vs. 7.3%). As a result, during a recession, a routine worker undertook vocational track faces a roughly 20% higher risk of job loss, while an academic graduate in a non-routine role is nearly insulated.

This paper makes several contributions to the literature on labor market dynamics and the impact of business cycles on job transitions (Moscarini and Thomsson, 2007; Dvorkin, 2014). Utilizing SIAB for Germany, we highlight the unique responses of German labor market, particularly among young workers. By focusing on tasks rather than occupations, our analysis captures the complexities of skill deployment and adaptation. By taking a shorter-term view compared with macro literature (e.g., Carrillo-Tudela and Visschers 2023), our study sheds light on the immediate labor market adjustments that young workers make in response to economic pressures, providing evidence that these adjustments can differ significantly based on the institutional context of the labor market.

This paper adds to the literature that studies the impact of technology on labor market (e.g., Autor, Levy and Murnane 2003; Acemoglu and Restrepo 2020). Many researchers have studied the impact of the technology on routine and non-routine jobs in the U.S. and German context. In both cases, there is evidence showing that while routine jobs declined, aggregate employment has not. The question remains that, from workers' point of view, how easy is it to transition from routine jobs to non-routine jobs? This is what our research tries to inform. Our paper is not the only one that studies routine jobs' role in a worker's career, especially in the German context (Gathmann and Schönberg 2010; Dauth et al. 2021; Adda and Dustmann 2023). Dauth et al. (2021) use German data and robotics shocks to show that young workers adjust along the margin of moving to service sector and go to college instead of apprentice programs when robotics are more widely used. Compare to these studies, our paper provides a more complete view on young workers' choices in the labor market. To the best of our knowledge, the evidence is sparse side. Our paper contributes to the literature by presenting direct evidence on how young workers at different education pathes navigate through early labor market transition.

This paper also speaks to the literature on job mobility and resilience during recessions. For instance, Weinstein and Patrick (2020) then show high cognitive and people skill requirements are less sensitive to recessions, indicating that recessions disproportionately hurt routine workers. Given a relative decline in routine jobs, however, it could be that routine job workers lost their jobs or it is harder for new entrants or re-entrants to find new routine jobs, and the distinction is useful for policymakers to identify the group that is affected most. This is something our transition model results can inform.

The paper is structured as follows: We first present our model framework and then discuss the data. Finally, we show our empirical findings before concluding the paper.

2.2 Routine and Non-routine Jobs

There are two readily available and widely used strategies for mapping a task into a specific occupation: the mappings created by Spitz-Oener (2006) based on the BIBB-IAB or BIBB-BAuA employee surveys and by Dengler, Matthes and Paulus (2014) based on BERUFENET expert database of the German Federal Employment Agency. We adopt the later mapping strategy for its consistency with the U.S. literature.[2] BERUFENET expert database is similar to the Dictionary of Occupational Titles (DOT) or the Occupational Information Network (O*NET) used by Autor, Levy and Murnane (2003). We thus rely on expert knowledge about the tasks that are usually performed in a specific occupation. Following Dengler, Matthes and Paulus (2014), we further differentiate routine tasks from non-routine tasks according to whether an occupational task could be performed by machines (routine tasks can be performed by machines).

Table 2.1. Task requirements based on BERUFENET

Task	Requirements
Cognitive non-routine (Non-routine, thereafter)	Management, planning, planning and supervision, fields of competencies, economy, leadership, direction, controlling, sciences, software development, programming languages, network certifications, monitoring, music, singing, ballet, musical instruments, optics, applying laws, design, design (art), analysis, control, therapy, programming, commerce, counseling, service, support, training, marketing, advertising
Routine	Technology, metrics, administration, graphics, network technology, network protocols, operating systems, certificates, languages, knowledge of goods and products, competencies, sensor technology, electronics, mechanics, mechatronics, hydraulics, processing, revision, test, inspection, measurement, monitoring, procedures, diagnostic, cultivation, farming, construction, manufacture, production, harvesting, operating machines, setting up machines, typesetting
Manual non-routine	Dancing, refurbishing, service, therapy (manual focus), special/custom/bespoke productions, handicraft businesses (e.g., bakery, carpentry)

2.3 Econometric Models

In this section we first describe the dynamic multinomial choice model used to analyze the transitions among four labor market states for young men and then we explain our modeling of the individual effects and initial condition.

[2] The mapping data set is provided by our data provider, the German Institute for Employment Research (IAB).

2.3.1 Modeling Labor Market Transitions

Each individual will appear in one of the four mutually-exclusive labor market states, *manual non-routine* (denoted by 0), *routine jobs* (denoted by 1), *non-routine jobs* (denoted by 2), and *non-employment* (denoted by 3), in each period. The dependent variable, y_{it}, denotes the state for individual i at period t, where $t = 1, 2, \ldots, T$ with T denoting the total number of periods.

Starting from the second period (*i.e.*, $t = 2$), the latent propensity * of individual i to be in state k at time t is modeled as

$$y^*_{ikt} = \sum_{j=0}^{3} \gamma_{jk} I(y_{i(t-1)} = j) + x'_{it}\beta_k + \alpha_{ik} + \varepsilon_{ikt} \;\; for\ any\ k \in \{0,1,2,3\}\ and\ 2 \leq t \leq T. \quad (2.1)$$

The indicator function $I(\cdot)$ equals one if the statement in the parentheses is true and zero otherwise.[3] The vector x_{it} includes time-varying covariates, and α_{ik} is the time-invariant individual effect specific to state k. The error term ε_{ikt} represents the idiosyncratic shock to the propensity. j is status in last period. By definition, the sum $\sum_{j=0}^{3} I(y_{i(t-1)} = j)$ must equal one, we, therefore, set $\gamma_{3k} = 0$ for each $k \in \{0,1,2,3\}$ to avoid perfect collinearity in (2.1).

The propensity, or utility, y^*_{ikt}, is unobservable to researchers; instead, we observe $y_{it} = k$ if state k reflects the greatest propensity y^*_{ikt} among the four states. Since only the differences in propensities or utilities matter in determining the observed state y_{it}, we choose *school* as the base state and set all parameters in its latent propensity at zero, *i.e.*, $\gamma_{j3} = 0$ for any $j \in \{0,1,2,3\}$, $\beta_3 = 0$, and $\alpha_{i3} = 0$ for any individual i, for location normalization.[4]

Assume that the error terms ε_{ikt} are *i.i.d.* extreme value type-I (or equivalently, standard Gumbel) conditional on individual i's lagged state $y_{i(t-1)}$, covariates x_{it}, and individual effects α_i, then the probability that individual i being in state k at period t is calculated as (McFadden, 1974):[5]

$$P(y_{it} = k \mid y_{i(t-1)} = j, x_{it}, \alpha_i) = \frac{exp(\gamma_{jk} + x'_{it}\beta_k + \alpha_{ik})}{\sum_{l=0}^{3} exp(\gamma_{jl} + x'_{it}\beta_l + \alpha_{il})}. \quad (2.2)$$

This transition probability from state j to k is heterogenous across individuals by allowing for individual effects $\alpha_i \equiv (\alpha_{i0}, \alpha_{i1}, \alpha_{i2}, \alpha_{i3})$ and is time-varying by including covariates x_{it}. In the estimation, we included four time-varying covarites: age, dummy variables for vocational training and degree, and national unemployment rate. The impact of the national unemployment rate is allowed to vary by the starting state (status at the first observed period) so we can study the impact of business cycle on transition probabilities.

Like other non-linear models, interpreting the parameters (e.g., β_k and γ_{jk}) is often not straightforward because they cannot be directly viewed as the marginal effects of the explana-

[3] We return to the issue of initial conditions ($t = 1$) in the next subsection.

[4] Choosing an alternative base state will not affect our identification.

[5] This closed-form expression of conditional choice probability in (2.2) not only greatly reduces the computation cost but also ease the analysis of marginal effects, relative to those based on other error assumptions such as conditional/multinomial probit (Hausman and Wise, 1978).

tory variables. Taking the derivative of the right-hand side of (2.2) with respect to vector x_{it}, we can derive the marginal effects of the time-varying covariates x_{it} on the transition probability:

$$P(y_{it} = k \mid y_{i(t-1)} = j, x_{it}, \alpha_i) \times \left[\sum_{l=0}^{3} (\beta_k - \beta_l) P(y_{it} = l \mid y_{i(t-1)} = j, x_{it}, \alpha_i) \right]. \tag{2.3}$$

The impact of changing environment,such as the unemployment rate in x_{it}, on transitions is heterogeneous across individuals and variant over time. The sign of β_k does not necessarily imply a positive or negative effect of its corresponding covariate on the transition probability as shown in formula (2.3).

Each state dependence parameter γ_{jk}, however, provides a clear interpretation itself; it is the difference between two log odds ratios for each individual and pair of states (j,k) as explained below.[6] To view this point, we can verify the equation,

$$\gamma_{jk} \quad = \quad ln \left[\frac{P\left(y_{it} = k \mid y_{i(t-1)} = j,\ x_{it},\ \alpha_i\right)}{P\left(y_{it} = 3 \mid y_{i(t-1)} = j,\ x_{it},\ \alpha_i\right)} \right] - ln \left[\frac{P\left(y_{it} = k \mid y_{i(t-1)} = 3,\ x_{it},\ \alpha_i\right)}{P\left(y_{it} = 3 \mid y_{i(t-1)} = 3,\ x_{it},\ \alpha_i\right)} \right], \tag{2.4}$$

by plugging in (2.2) together with the normalization $\gamma_{3k} = \gamma_{j3} = 0$ for each k, j in $\{0,1,2,3\}$. A parameter of great interest is γ_{11} (i.e., $j = k = 1$, where 1 denotes $routine\, jobs$). A positive γ_{11} implies that routine-job workers ($y_{it} = 1$), relative to those who are in the non-employment ($y_{it} = 3$), are more likely to continue to work a routine job than going to non-employment in the next period $t+1$. While interpreting these numbers are possible, the meaning of these interpretation is not intuitive, so in the results section, we report model predicted transition matrix together with the estimates for these parameters.

The interpretation of γ_{jk} as odds ratio comparisons, as shown in (2.4), does not vary with individuals or time. In contrast, the marginal effects of the changing economic environment or other factors on the transition probabilities, as shown in (2.3), are heterogeneous across individuals and change over time. To understand how the past state or other covariates such as the unemployment rate affect the future labor market states, we need to model the unobserved individual effects.

2.3.2 Modeling the Individual Effects and Initial Condition

Two major econometric methods that can be used to model the individual effects α_i in the dynamic discrete choice framework are fixed-effects models and random-effects models. Fixed effects models do not specify the parametric distribution of α_i or model the initial choices

[6] The interpretation given below is based on our first-order Markov process in model (2.1). We could extend this process to high-orders and get similar interpretations for the state dependence parameters by conditioning on a longer history of past states. The cost of doing so involves losing more periods of data in the estimation of the transition stage and estimating 18 more state dependence parameters.

individuals make, offering a robust way of separating state dependence from unobserved individual heterogeneity (e.g., Chamberlain, 1980, Magnac, 2000, Honoré and Kyriazidou, 2000, Egger, Pfaffermayr and Weber, 2007, and Givord and Wilner, 2015). A common mechanism applied in the fixed effects models is to cancel out the individual effects and initial choices in the conditional likelihood function by focusing on a subset of all possible transition paths, so the parameters of interest in the latent propensity (2.1) can be identified without distributional information on the individual effects and initial conditions.

We choose a random effects method, however, or more specifically a mass-point model, for modeling individual effects to learn both the structural parameters and the marginal effects of policy-makers' interest. The complete characterization of individual heterogeneity can later be used in the simulations. In contrast, the fixed-effects models condition out individual heterogeneity, making it impossible to conduct a counterfactual analysis.

We apply the Wooldridge (2005) method to address the initial condition problem and model the individual effects α_i as a vector function of (y_{i1}, z_i), where y_{i1} is the initial state of individual i and z_i is a vector of observable time-invariant individual characteristics. Table 2.2 provides the summary statistics for the time-invariant individual characteristics variables we include in the estimation. The individual effects specific to state k are then given by

$$\alpha_{ik} = \sum_{j=0}^{3} \delta_{jk} I(y_{i1} = j) + z_i'\theta_k + \eta_{ik} \;\; for \, k \in \{0,1,2,3\}. \tag{2.5}$$

The vector z_i includes the observable characteristics of individual i that persistently affect his propensity to be in each state during each period, and η_{ik} represents his unobserved characteristics that persistently affect his propensity to be in state k, which is often called **unobserved** individual heterogeneity. We set $\delta_{3k} = 0$ for any $k \in \{0,1,2,3\}$ to avoid perfect collinearity in (2.5) and set $\delta_{j3} = 0$ for any $j \in \{0,1,2,3\}$, $\theta_3 = 0$, and $\eta_{i3} = 0$ for location normalization.

Instead of assuming a known distributional family (such as a normal distribution) for the unobserved heterogeneity $\eta_i \equiv (\eta_{i0}, \eta_{i1}, \eta_{i2})$, we adopt a mass-point approach by assuming that η_i is a discrete random vector that takes on M possible outcomes: $\eta^1, \ldots, \eta^M$, with corresponding probabilities $\rho_1, \ldots, \rho_M$, where $\rho_m \in [0,1]$ and $\sum_{m=1}^{M} \rho_m = 1$. The mass-point model does not impose shape restrictions such as symmetry or unimodality and flexibly estimates the supporting points and associated probabilities, reducing the risk of bias caused by the misspecification of the distribution of the unobserved heterogeneity.

In the special case of $M = 1$, the mass-point model is equivalent to a multinomial logit model without unobserved individual heterogeneity. If the true distribution of η is indeed continuous, then using a large M will allow for a sufficiently good approximation.[7] We estimate the mass-point model using varying numbers of mass points and find that using an M

[7] In most applications of the mass-point model a small M is adopted; e.g., Blank (1994) assumes three types of individuals when analyzing the dynamics of part-time work.

greater than 3 will result in an economically insignificant probability associated with the least likely mass point. As a result, we focus on the case $M = 3$ and interpret our target sample as a mixture of three types of individuals according to their unobserved heterogeneity. We will show that these three types have intuitive interpretations.

2.3.3 Estimation of the Mass-point Dynamic Multinomial Choice Model

We use the conditional maximum-likelihood method to estimate all the parameters in equations (2.1) and (2.5) as well as the support of the mass points and associated probabilities. For individual i, conditional on his initial state, covariates, and being type m, the probability of observing his labor market history, that is $P(y_{i2},\ldots,y_{iT} \mid y_{i1},x_{i2},\ldots,x_{iT},z_i,\eta_i = \eta^m)$, is given by

$$\prod_{t=2}^{T}\left[\frac{\sum_{k=0}^{3}\sum_{j=0}^{3} I(y_{i(t-1)} = j, y_{it} = k)exp(\gamma_{jk} + x_{it}'\beta_k + \sum_{l=0}^{3}\delta_{lk}I(y_{i1} = l) + z_i'\theta_k + \eta_k^m)}{\sum_{k=0}^{3}\sum_{j=0}^{3} I(y_{i,(t-1)} = j)exp(\gamma_{jk} + x_{it}'\beta_k + \sum_{l=0}^{3}\delta_{lk}I(y_{i1} = l) + z_i'\theta_k + \eta_k^m)}\right] \tag{2.6}$$

by the assumption that the error terms ε_{ikt} are extreme value type I distributed and independent across every subscript dimension. Averaging over the types of unobserved heterogeneity we obtain the conditional probability

$$P(y_{i2},\ldots,y_{iT} \mid y_{i1},x_{i2},\ldots,x_{iT},z_i) = \sum_{m=1}^{M}\rho_m \times P(y_{i2},\ldots,y_{iT} \mid y_{i1},x_{i2},\ldots,x_{iT},z_i,\eta_i = \eta^m). \tag{2.7}$$

Denote $B = (\beta_0,\beta_1,\beta_2)$, $\Theta = (\theta_0,\theta_1,\theta_2)$, and 3 by 3 matrices $\Gamma = [\gamma_{jk}]$ and $\Delta = [\delta_{jk}]$ for $j,k = 0,1,2$. We then estimate the parameters jointly by maximizing the log likelihood function

$$L\left(\Gamma,B,\Delta,\Theta,\eta^1,\ldots,\eta^M,\rho_1,\ldots,\rho_M\right) = \sum_{i=1}^{n} ln\left[P(y_{i2},\ldots,y_{iT} \mid y_{i1},x_{i2},\ldots,x_{iT},z_i)\right], \tag{2.8}$$

subject to $0 \leq \rho_1 \leq \ldots \leq \rho_M \leq 1$ and $\sum_{m=1}^{M}\rho_m = 1$. We estimate the model using constrained maximum likelihood method.

2.4 Data

We use the Sample of Integrated Labour Market Biographies (SIAB) from 1999 - 2010 to study the German labor market.[8] SIAB is a 2% sample of individual administrative social security records, made available by the German Institute for Employment Research (IAB).

[8]There are two major changes in the SIAB data: the introduction of new social security notification system in 1999 and the change of occupation coding in 2011. Because the analysis requires a balanced panel, we make this sample restriction to ensure that the variables can be consistently defined over time.

SIAB records all employment spells except for civil servants and the self-employed. The data also contain unemployment spells merged from the unemployment registry.

The data only record labor market activity (including employment, benefit claims, and job seeking); thus, we can not observe whether workers are in school. Since 1999, however, the new social security notification has allowed us to differentiate the apprenticeship contract from others, which is an important part of our analysis.[9] The apprenticeship often involves 3-4 days a week of paid practical training or work in the workplace and thus appears in our data. The apprenticeship contract usually lasts 2 to 3 years, and upon finishing, workers can obtain a vocational training qualification. German education system integrates vocational training into its formal curriculum. Most apprenticeship programs thus are firm-provided on-the-job training combined with publicly funded school education. An apprenticeship typically starts after secondary school if children choose this track instead of the academic track or work as an untrained worker.[10]

We restrict the analysis to young male workers who were born between 1971 and 1985 and entered the labor market in 1999 or 2000. A worker is considered to have entered the labor market if he is in contact with any employment agencies or if he is employed (excluding mini job contracts). Workers who entered the labor market before the age of 15 are excluded.[11] For those entering the labor market after 23 years old, we exclude anyone who does not have a degree. This reduces the possibility of including workers who were in any unreported employment or self-employment before entering the social security records. Thus, in our sample, workers who enter labor market late are mostly university graduates.

We follow these workers for 21 biannual period (including the initial period). For each period, we categorize these young male workers into four mutually exclusive states according to their employment status and occupation information if employed: apprenticeship, routine job, non-routine job, and non-employment. When multiple job spells exist during a half-year period, we first take the job with the highest income as the main job and assign the spell of the longest duration to that period.

Individuals can be missing from the data when they were not in any employment relationship subject to social security records or not in contact with any unemployment agencies. We treat those missing spells as inactive/non-employment spells and mitigate their influence by restricting the sample to those that can be observed at the first and last periods of interest. We also drop individuals that are missing from the data for more than five biannual periods. Our final sample contains 8013 individuals. Further restrictions can be imposed for the robustness tests.

[9] Marginal part-time workers are also added to the data in the same year.

[10] see Dustmann (2004) for more details about the German education system and the choice of different educational tracks.

[11] Children younger than 14 are usually not allowed to work; exceptional cases are rare.

Table 2.2. Summary statistics

	Mean	S.D.
Wages	61.9	(66.9)
Age	18.8	(3.5)
		Share
East		22%
Manual non-routine		24%
Routine		41%
Non-routine		19%
Non-employment		16%
No postsecondary education		6%
Apprenticeship training		82%
Upper secondary track		12%
Observations		8013

Notes: This table provides summary statistics for the sample we use in the main analysis. Standard deviations (S.D.) are reported in parentheses.

2.5 Empirical results

This section presents the findings on on the transition probabilities between different employment states.

2.5.1 Job Transition in Germany

Table 2.3 reports the within-state and cross-state dependence parameters estimated from our model, but for more intuitive interpretations, we construct a transition matrix based on our estimates in Table 2.4. In the top panel, we tabulate the lagged states and the current states using the data, and in the bottom panel, we report the model estimated transitional probabilities.

First, the estimates show a high degree of state persistence. The diagonal elements of the matrix in both panels represents the probability of a worker remaining in the same state in the next period. These elements are consistently the largest values in each row. For example, a worker in a routine occupation has a 88.8% chance of staying in a routine job. Similarly, persistence is very high for non-routine workers (91.2%) and manual non-routine workers (78.3%). The non-employment state is the least persistent, with a 68.4% probability of staying in non-employed, suggesting significant flows of them would back into the labor market.

Although the numbers in the diagonal are smaller in the bottom panel(estimated probability), they are not substantially smaller. This suggests that the observed individual characteristics and unobserved individual heterogeneity only explain a small proportion of the within-state dependence. In other words, conditional on individual preference, we still see a strong persistence in routine and non-routine jobs, and this persistence is larger than that of the manual non-routine's, where the latter is mostly driven by the feature of the manual non-routine occupations (as it usually involves less-skilled service job and more frequent job switches and higher turnover). We interpret this result as a direct empirical evidence of routine job trap and non-routine job safeness.

Table 2.3. State Dependence or Individual Heterogeneity?

Destination State→ Starting State ↓	Routine	Non-routine	Non-Par
Routine	7.671	3.885	3.910
	(0.287)	(0.398)	(0.250)
Non-routine	3.664	7.038	4.649
	(0.420)	(0.413)	(0.353)
Non-Par	3.039	3.467	5.614
	(0.251)	(0.333)	(0.160)

Notes: This table presents the transition matrix estimated using the 3-type mass-point model. These are the estimates for γs in Equation (2.8). Rows correspond to the starting states and columns correspond to the destination states. The base state is non-manual job. Standard errors are in parentheses. The estimation is based on 8108 individuals.

Second, other than the trap and safeness, we also observe other interesting patterns. The off-diagonal elements show the nature of labor market mobility. Transitions into non-employment are an important margin. Manual non-routine workers face the highest risk of transitioning to non-employment, with a probability of 13.1%. In contrast, non-routine jobs appear to be the most stable, with only a 4.9% transition probability into non-employment. For workers re-entering the workforce from non-employment, the states are not uniform. They are most likely to enter manual non-routine (16.0%) or routine (17.0%) jobs, and least likely to secure a non-routine cognitive position (8.0%). This suggests that routine and non-routine occupations may serve as the primary entry gates for the previously non-employed.

Finally, direct transitions between different states are relatively infrequent, suggesting a degree of segmentation. The probability of a routine worker moving to a non-routine job is only 1.5%. For a manual non-routine worker, the probability is higher, though still low, at 2.2%. This is different from what we observed in the raw transition matrix where the probabilities of transitioning to non-routine from manual non-routine and routine are close. The disparity suggests that when we excluding worker heterogeneity, upwards mobility for manual non-routine is stronger than that for routine jobs. At the surface-level, barriers to enter into non-routine job are uniformly high for manual non-routine and routine job. However, workers in manual non-routine jobs actually have a stronger potential for upward mobility compared to those in routine jobs.

Table 2.4. Transition probabilities

Panel A: Raw transition prob.				
Destination State→ Starting State ↓	Manual non-rou	Routine	Non-rou	Non-emp
Manual non-rou	0.873	0.024	0.012	0.091
Routine	0.001	0.928	0.013	0.047
Non-rou	0.013	0.023	0.925	0.040
Non-emp	0.139	0.118	0.060	0.684
Composition	23.9%	40.7%	19.5%	15.9%

Panel B: Model-estimated transition prob.				
Destination State→ Starting State ↓	Manual non-rou	Routine	Non-rou	Non-emp
Manual non-rou	0.783	0.064	0.022	0.131
Routine	0.027	0.888	0.015	0.070
Non-rou	0.017	0.022	0.912	0.049
Non-emp	0.160	0.170	0.080	0.590

Notes: This table shows the transition probability calculated from data (Panel A) and from the model (Panel B). Rows correspond to the starting states, and columns correspond to destination state. Each cell shows the transition probability from one state to the other conditional on the starting state, so the numbers in a row add up to one. Bootstrapped standard errors are reported in parentheses. Data source: SIAB.

2.5.2 The Impact of Business Cycles

To further understand how labour market respond to macroeconomic shocks, we use our model to further estimate the marginal effect of the aggregate unemployment rate on transition probabilities. We report the marginal effects of the unemployment rate in Table 2.5. We highlight two results here. First, negative economic shocks significantly increase the probability of workers transitioning into non-employment (Non-emp). As shown in the final column of the table, this effect is pervasive across all states but highly asymmetric. The cyclical sensitivity is most pronounced for routine and manual non-routine workers, whose probabilities of entering non-participation increase by a substantial 22.1% and 20.8%, respectively. In contrast, workers in non-routine jobs are more stable, though not entirely immune, with their probability of transitioning to non-employment increasing by a relatively modest 9.4%. This suggests that job security for workers in routine and manual occupations is more fragile over the business cycle.

This outflow to non-employment is associated with a decrease in outflows to other states. The negative values along the diagonal indicate that persistence within each occupational state is procyclical; that is, a rise in unemployment reduces the probability of a worker remaining in their current occupational category. For instance, the probability of a manual non-routine worker remaining in that state falls by 3.2%. This effect is again weakest for non-routine workers (-0.4%), underscoring the stability of non-routine positions.

Furthermore, inter-states mobility is reduced during economic downturns. The negative off-diagonal elements show that job-to-job transitions become less frequent. For example, the probability of a routine worker transitioning to a non-routine role decreases by 1.5%, and the probability of a manual non-routine worker moving to a routine job falls by 1.5%. This suggests that career progression or occupational change diminish when the labor market slackens.

However, there is an exception that show the pressure on displaced workers: the transition probability from routine to manual non-routine jobs increases by 3.3%. This maybe interpreted as a downward mobility. For many workers, moving from a routine job (like a factory or clerical position) to a manual non-routine job (often in the service sector) can be seen as a step down in terms of pay, stability, or skill-level. Yet, the manual non-routine sector may act as a "buffer" during recessions. While other sectors are reducing workers and freezing hiring, these jobs (e.g., in delivery, cleaning, basic services) may still be available for displaced routine job worker due to their flexible nature and lower barriers to entry.

Table 2.5. Percent change in the transition probability if unemployment rate increases by one percentage point

Destination State→ Starting State ↓	Manual non-routine	Routine	Non-routine	Non-emp
Manual non-routine	-0.032	-0.015	-0.058	0.208
Routine	0.033	-0.018	-0.015	0.221
Non-routine	-0.005	-0.027	-0.004	0.094
Non-Par	-0.018	-0.009	-0.074	0.018

Notes: This table shows the calculated marginal effect of the unemployment rate. The calculation is based on a one-percentage-point increase in the unemployment rate and is conditional on the actual state in the lagged period. All 28 periods are calculated separately and are then averaged. Data source: SIAB.

2.5.3 Heterogeneity in Job Transition and the Impact of Business Cycle: Vocational Training vs Academic Track

To study heterogeneity in labor market dynamics, we leverage a key institutional feature of the Germany: its special post-secondary educational system. We estimate the model on two distinct subsamples: young men from the renowned dual vocational training system (Duales Ausbildungssystem) and those from the university-preparatory academic (degree) track. The results, presented in the tables 2.6 and 2.7 show how workers in these two tracks experience distinct career trajectories with profound differences in career outcomes and exposure to macroeconomic shocks.

Occupational Sorting and the Dual Economy

The descriptive statistics confirm that the two tracks function as distinct channels into separate segments of the German labor market. The vocational system, a cornerstone of Germany's industrial strength, prepares individuals for skilled roles within the craft and manufacturing sectors. The labor force composition reflects this, with vocational graduates predominantly employed in Routine (43.9%) and Manual Non-routine (26.4%) occupations.

In contrast, the academic track is the main route to professions requiring analytical skills. The labor market for these individuals is overwhelmingly composed of non-routine jobs (59.7%). This clear occupational sorting shows that the educational system is highly effective at channeling talent, creating a well-defined skilled workforce for routine tasks and a separate class of professionals for managerial and knowledge-intensive non-routine tasks.

Table 2.6. Transition probabilities and the impact of business cycle on young men from vocational track

Raw Transition Prob.				
Destination State→ Starting State ↓	Manual Non-routine	Routine	Non-routine	Non-emp.
Manual Non-routine	0.876	0.024	0.010	0.090
Routine	0.013	0.930	0.010	0.047
Non-routine	0.017	0.026	0.900	0.048
Non-emp	0.158	0.133	0.054	0.656
Composition	26.4%	43.9%	14.5%	15.2%

Model estimated Transition Prob.				
Destination State→ Starting State ↓	Manual Non-routine	Routine	Non-routine	Non-emp.
Manual Non-routine	0.079	0.062	0.023	0.130
Routine	0.025	0.894	0.010	0.070
Non-routine	0.030	0.024	0.887	0.058
Non-emp	0.179	0.194	0.073	0.554

Marginal effect of national unemployment rate				
Destination State→ Starting State ↓	Manual non-routine	Routine	Non-routine	Non-emp.
Manual Non-routine	-0.317	-0.004	-0.028	0.198
Routine	0.039	-0.020	0.014	0.201
Non-routine	0.008	-0.020	-0.005	0.098
Non-emp	-0.013	-0.006	-0.084	0.017

Table 2.7. Transition probabilities and the impact of business cycle on young men from degree track

Raw Transition Prob.				
Destination State→ Starting State ↓	Manual Non-routine	Routine	Non-routine	Non-emp.
Manual Non-routine	0.819	0.045	0.065	0.071
Routine	0.007	0.900	0.055	0.038
Non-routine	0.004	0.018	0.955	0.024
Non-emp	0.057	0.121	0.219	0.604
Composition	6.5%	25.4%	59.7%	5.4%

Model estimated Transition Prob.				
Destination State→ Starting State ↓	Manual Non-routine	Routine	Non-routine	Non-emp.
Manual Non-routine	0.751	0.045	0.111	0.093
Routine	0.007	0.854	0.090	0.049
Non-routine	0.006	0.028	0.934	0.032
Non-emp	0.064	0.146	0.316	0.474

Marginal effect of national unemployment rate				
Destination State→ Starting State ↓	Manual non-routine	Routine	Non-routine	Non-emp.
Manual Non-routine	0.018	-0.093	-0.062	-0.025
Routine	-0.158	0.013	-0.045	-0.112
Non-routine	-0.005	-0.012	0.000	-0.007
Non-emp	0.000	-0.047	-0.003	0.017

Career Progression and the Role of Skill Specificity

The different paths of skill acquisition on each track directly effect career mobility. The academic track highlights abstract, transferable skills, creating fluid pathways for advancement. The probability of an academic graduate moving from a Routine to a Non-routine job is 9.0%, and re-entry from non-employment directly into a non-routine role is 31.6%.

The vocational track, however, often highlights industry-specific skills. While this creates highly productive workers, such skill specificity seems to limit upward mobility into different career types. The probability of a vocational worker transitioning from a Routine to a Non-routine role is just 1.0%. This suggests that while the dual system provides a clear pathway to stable, middle-skilled careers, the inherent nature of the specialised training creates high barriers to entry for analytical non-routine professions, leading to less flexible career trajectories.

Asymmetric Exposure to Business Cycle Shocks

The most striking difference between the two groups lies in their resilience to macroeconomic shocks. Workers from the vocational track are highly exposed to cyclical volatility. This is consistent with their concentration in Germany's export-oriented manufacturing and industrial sectors, which are sensitive to global demand and technological advancement. A one-percentage-point increase in the unemployment rate increases their job loss risks by 20.1% (for Routine workers) and 19.8% (for Manual Non-routine workers). This vulnerability suggests that these workers bear a disproportionate share of the adjustment costs during a recession.

On the other hand, workers from the academic track are more insulated from macroeconomic shocks. For them, a rise in unemployment does not increase the risk of job loss; the marginal effects on transitions to non-emp are zero or negative. The job security for a non-routine professional is almost acyclical (0.000), indicating their roles are deemed indispensable even in a downturn. This suggests that an academic degree in the German context offers not just access to higher-skilled jobs, but also a shield against negative economic shocks.

In sum, the German dual education system, while a source of labour market strength in providing middle-skilled workforce, also creates risks to workers with less transferrable skills. The vocational path, while providing a solid pathway for a skilled routine career, ties young workers to the fate of cyclically sensitive industries. The academic track, however, leads to careers that offer greater upward mobility and more insulation from the volatility of the business cycle.

2.6 Conclusion

Technology boosts productivity, improves life quality, but leaves some workers behind. This paper studies the dynamics of the German labor market by estimating the transition probabilities between manual non-routine, routine, and non-routine occupational states. By employing a model that disentangles true state dependence from unobserved individual heterogeneity, we have provided evidence revealing the structure of job mobility, the nature of occupational persistence, and the asymmetric impact of the business cycle.

Our first key finding is that state dependence exists, particularly for routine and non-routine jobs. The high persistence in these states is not simply a product of individual worker characteristics but is a feature of the occupations and their corresponding task requirements. This suggests the German labor market as containing both a "routine job trap" and "non-routine job safeness." The former describes a state where the routine job limits pathways to other occupations. This conclusion is strengthened by our finding that, after controlling for heterogeneity, upward mobility is potentially weaker from routine jobs than from manual non-routine jobs. The latter reflects the security offered by high-skilled, non-routine cognitive jobs.

Second, our analysis of business cycle effects shows that business cycle widens existing labor market inequalities. We find that workers in manual non-routine and routine occupations bear the most consequences of recessions, facing a higher risk of transitioning into non-employment. In contrast, non-routine jobs are largely insulated from these shocks. The labor market for middle- and lower-skilled workers not only becomes more vulnerable during downturns but also less fluid, as pathways for upward mobility are further disappeared. We also identify a key adjustment mechanism : a rise in downward mobility, where displaced routine workers are pushed into the more flexible, but often less stable, manual non-routine jobs.

Finally, the heterogeneity analysis of Germany's two educational tracks further elaborate these findings. The dual vocational training system serves as an channel into Germany's skilled workforce but simultaneously channels young workers onto career paths with limited upward mobility and high exposure to cyclical risk. The academic track, in contrast, offers more transferable skills and thus a higher chance of securing a non-routine careers as well as some insulation from cyclical economic volatility.

The policy implications of this research are significant. As some characteristics of routine jobs are particularly vulnerable to economic shocks, it highlights the need for robust lifelong learning and reskilling programs to create pathways to help workers in those roles. Policies aimed at strengthening the transferability of vocational skills and social safety nets for cyclically exposed workers are needed. Future research could extend this analysis to explore the dynamics for female workers and investigate the role of firm-level characteristics in mediating these transitions.

This paper is not without limitations. The low transition rate may be due to some mechanical reasons. To move out of routine jobs, one usually needs to change professions. This requires further education/qualification. To capture this, one would need to consider a longer outcome duration and to define 'further education' as a state to transition into. Additionally, there is a strong role of certificates in Germany – one can't easily change across professions. Change implies investing in education and gaining a new certificate. A further mechanical issue for the low numbers is that the probability of transition within such a short half-year period is naturally low.

Chapter 3

Wages and Paid Holiday in the UK: : Compensating Wage Differentials?

Abstract

I study the compensating wage differential for paid holiday entitlement (paid annual leave) in the United Kingdom. Hedonic theory predicts a negative trade-off between wages and paid holiday. However, empirical evidence are often confounded by worker and firm heterogeneity. Using a matched employer-employee panel from 2005 to 2020, I estimate a series of fixed-effects models to account for sorting, guided by a hedonic search framework. Contrary to the prediction, I find a persistent significant positive relationship between paid annual leave and hourly wages. My preferred estimate indicates that one additional day of paid annual leave is associated with a 0.10% wage increase. On the other hand, estimates show a positive relationship between working hours and paid annual leave. This finding implies that paid leave allowance likely is a complementary component of a 'good job' package, where firms that pay more also offer better non-pecuniary benefits.

Keywords: Wages, Paid holiday, Compensating wage differentials, Hedonic search model, AKM model, UK.

3.1 Introduction

Non-monetary benefits or fringes, such as paid holiday, are important parts of work compensation. Literature found that sorting can be attributed to compensating wage differential. Yet, the question remains is compensating wage of what specific amenity. There are studies on pension, fatality risk and commuting etc. many of which are firm or occupation specific. But little literature has studied within-occupation non-wage benefits. Among the non-monetary benefits, paid holiday is arguably one of the most valued family-friendly benefits in modern society.

Literature on estimating compensating wage differentials for non-wage benefits dates back to at least the study by Woodbury (1983), which they found that wages and fringes substitute each other by estimating the structure of utility function. Recent studies have found more evidence supporting the theory of compensating differentials for pension, fatality risk, and other job amenities(Gruber, 2000; Dey and Flinn, 2005; Goldman, Sood and Leibowitz, 2005).; but only a few studies, namely Bryan (2006), Altonji and Usui (2007) and Fakih (2018), have focussed on paid holiday. Yet, these authors found a stubborn positive correlation between wages and paid holiday, which is exactly the opposite of what the theory of compensating wage differentials would suggest. A possible explanation is that these studies were unable to control comprehensively for firm heterogeneity.

The primary goal of this paper is to empirically test the Compensating Wage Differential (CWD) theory within the UK labor market, specifically focusing on paid annual leave—a highly valued but understudied non-wage benefit. While theory predicts a trade-off, literature has struggled with a 'puzzle' of positive correlations. This paper positions itself as a further attempt to resolve this puzzle by examining whether this positive correlation is merely a result of unobserved firm heterogeneity or a fundamental characteristic of how 'good jobs' are structured.

In this paper, I study the relationship between wages and paid holiday by examining the prediction of compensating wage differential theory. I use the Annual Survey of Hours and Earnings (ASHE) data, which are the only available employer-employee matched data in the UK. My empirical strategy is guided by a hedonic search model, based on the framework in Lavetti and Schmutte (2018), which links the hedonic price of amenities to the wage equation. I then empirically estimate the compensating wage differential for paid annual leave using a reduced-form, AKM-type model that follows the seminal work of Abowd, Kramarz and Margolis (1999).

The theoretical model of compensating wage differentials predicts a negative trade-off between wages and non-wage amenities. According to this framework, workers being offered more generous paid leave should receive lower wages, all else being equal. Contrary to this prediction, this paper finds no evidence of such a trade-off in the UK labor market. Instead, I document a robust positive relationship between paid annual leave and hourly wages. This finding is not a simple correlations; it persists and remains statistically significant even after rigorously controlling for unobserved worker heterogeneity, firm-level premiums, and even worker-firm match effects.

My estimates further suggest a potential explanation for this puzzle: paid leave may not be a substitute for wages but rather a inseparable complementary component of a 'good job' package. The persistent positive relationship between wages and paid annual leave, and the positive relationship between working hours and paid annual leave, together imply that paid leave might more function as a non-wage compensation for other job disamenities, such as long working hours.

This finding sheds light on the complex and multifaceted nature of the price of amenity and disamenity compensation. It suggests the standard model of a trade-off between wages and amenity is incomplete. Specifically, a desirable amenity like paid leave may not trade off against wages, but rather serve to compensate for a workplace disamenity, such as long or inflexible working hours. This reveals a more complex interplay between job attributes and calls for future research to move beyond simple wage-amenity models to explore how the entire package of job characteristics is valued.

This paper contributes to the literature by providing renewed estimation of the compensating wage differential for paid holiday in the United Kingdom. Using 15 years of rich administrative data from the Annual Survey of Hours and Earnings (ASHE) from 2005 to 2020, I examine the relationship between paid leave and hourly wages. My primary contribution is threefold. First, I develop a simple hedonic search model, akin to Lavetti and Schmutte (2018), to provide a clear theoretical framework for interpreting our empirical results in a market with frictions. Second, I go beyond simple specifications and implement a series of increasingly rigorous fixed-effects models, progressing from worker fixed effects to a two-way worker-firm fixed-effects model, and finally to a demanding worker-firm match fixed-effects specification. This allows us to control for unobserved sorting and isolate the wage effect of changes in paid leave within a specific job. Third, I find a persistent and statistically significant positive relationship between paid annual leave and wages. Our preferred estimate from the match fixed-effects model indicates that an additional day of paid leave is associated with a 0.10% increase in hourly wages. This finding further confirms the pervious finding in literature that paid leave is not a simple trade-off against wages but rather a complementary component of a 'good job' package, a result consistent with significant sorting and labour market frictions. This is consistent with the 'job package' framework recently documented by Lachowska et al. (2023). Using revealed preference data, they show that hours are often constrained by employers and that firms offer high-wage/long-hour bundles to attract workers. My results extend this by demonstrating that paid leave is also a key component of these bundles.Alternatively, other than trading wages for holidays, workers with sufficient bargaining power may successfully negotiate for both, driving the stubborn positive correlation, as suggested by Lagos (2025).

The remainder of this paper is structured as follows. Section 3.2 outlines the conceptual framework, detailing the biases from worker and firm heterogeneity and presenting our hedonic search model. Section 3.3 describes the empirical strategy and the data. Section 3.4 presents the empirical results, and Section 3.5 concludes.

3.2 Conceptual Framework

The theory of compensating wage differentials suggests that workers accept higher wages for accepting jobs with undesirable characteristics, or equivalently, workers sacrifice wages for accepting jobs with desirable characteristics, such as the paid holiday entitlement in this paper. Rosen (1974, 1986) rationalised the theory by an equilibrium in which a sorting function based on workers and firms decision describes the effect of accepting a job with a particular set of job characteristics on wages.

The identification of Rosen (1974)'s hedonic wages model needs the assumption that labour market is perfect and frictionless. This is a concern for the unbiasedness of those corresponding empirical estimates. The reason is that in a perfectly competitive labour market with heterogeneous worker preference and firm technology, a weighted average of the curvature of firms' isoprofit functions and workers' indifference curves determines hedonic price function; The weight is however related to the distribution of both forms of unobserved heterogeneity parameters (Lavetti, 2020).

I explain the role of worker and firm heterogeneity on estimating compensating wage differentials for paid holiday in section 3.2.1 and 3.2.2 by Figure 3.1. Then, I present a simple hedonic search model that akins Lavetti and Schmutte (2018)'s framework, in which empirical log wage equation can link to the wage equilibrium.

3.2.1 Unobservable worker heterogeneity

I first start with explaining why unobserved worker heterogeneity, such as ability, in which economist has long interest, matters for the estimation of the effect of paid holiday on wages. In Figure 3.1, indifference curve v_1 depicts a worker's preference for wages and paid holiday. He/she maximises his/her utility by choosing a job offer characterised by wages and paid holiday (w_1, h_1) along the offer curve I_1. If workers are homogenous, the simple cross-sectional variation in wage-paid holiday pairs (w, h) identifies the compensating wage differentials for paid holiday.

The existence of unobserved worker heterogenity however can cause bias in the cross-sectional estimates. For example, in a labour market where workers have different ability, high ability workers can choose (w_2, h_2) on offer curve I_2, while low ability workers

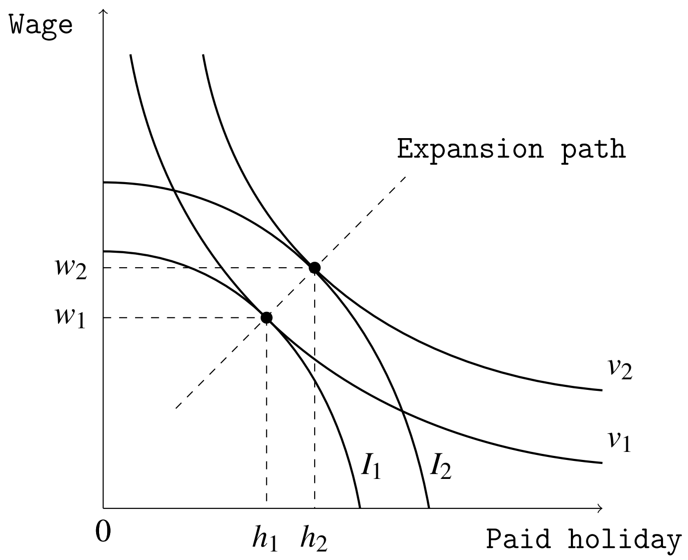

Figure 3.1. Equilibrium Wage-Paid Holiday Relationships

choose (w_1, h_1) on offer curve I_1. The variation in wage-paid holiday pair thus come from two sources: variation along each offer curve and the expansion path in Figure 3.1. In this case, high ability workers sacrifice more potential earnings for paid holiday and thus causes a upward slope of the expansion path regardless of the downward sloping offer and indifference curves.

3.2.2 Firm Heterogeneity

Although hedonic model incorporating worker heterogeneity has produced estimates closer to the theoretical prediction (Hwang, Reed and Hubbard, 1992), imperfectly competitive labour market introduced another type of bias into the estimates. In imperfectly competitive labour market, workers job mobility is associated to the total compensation offered by different firms. For example, in the presence of search friction, workers who learn about their ability and competitive advantage may move to offer curve I_2. Switching job not only increases their wages but is also likely to increase other job benefits, such as paid holiday. This can cause the equilibrium move from (w_1, h_1) to (w_2, h_2) along the expansion path. Moreover, Lavetti and Schmutte (2018) argues that merely including worker effect in hedonic model may increase the total bias since this isolates perhaps the most problematic variation. A large number of empirical evidence from matched employer-employee data suggests that sorting across firms with different compensation practices, as an important labour market feature, explains a large amount of wage variation (Abowd, Kramarz and Margolis, 1999; Abowd et al., 2012; Abowd, McKinney and Zhao, 2018; Card, Heining and Kline, 2013; Card, Cardoso and Kline, 2016; Card et al., 2018).

3.2.3 Hedonic Search Framework with Differentiated Firms and Endogenous Wage-paid-holiday Choice

A natural solution to incorporate worker and firm heterogeneity is a wage AKM model (Abowd, Kramarz and Margolis, 1999), while the interpretation of its estimates is ambiguous. I therefore aim to better interpret the estimates of empirical hedonic AKM model with paid holiday, following Lavetti and Schmutte (2018) who combine Hwang, Mortensen and Reed (1998)'s and Card et al. (2018)'s framework to a on-the-job search model incorporating search frictions and endogenous job-level safety choice across jobs in different firms and occupations. Their model link the empirical AKM wage model to the structural primitives in Rosen (1974)'s theory. The model suggests that if the probability of receiving retention offers from incumbent firms equals the probability of receiving outside offers, the structural profit maximising log wage equation is identical to the additively separable hedonic AKM model. The unbiased estimates for compensating wage differentials from the hedonic AKM model then have a preference-based interpretation.

On the other hand, the model suggests that if incumbency firms have advantages over the outside firms in retaining theirs workers, the structural model differs from hedonic AKM model by containing a match component. However, Lavetti (2020) acknowledge that even with a match effect, the structural interpretation of hedonic AKM model might still require additional condition, such as if the wage determination involves Nash bargaining, Nash bargaining parameters must not vary within match in a way that is correlated with the target amenity (paid holiday in this paper) . But Card et al. (2018) argue worker bargaining power is less plausible for explaining wage variation in an economy that lacks strong unions [1].

I construct a similar model embedding the endogenous wage-paid holiday choice. The model offers theoretical insights into the empirical estimates, such as the unobserved components left in the residual and their impact on estimates.

Model Setup

Time t is discrete and infinite. There are fixed number of workers $i \in \{1, \dots N\}$ with a fixed level of skills $s(i) \in \{1, \dots S\}$. Each worker supply a single unit of labour inelastically and choose whether and where to work in each period after receiving job offers with a fixed rate from firms $j \in \{1, \dots J\}$.

[1] ASHE data record whether there is collective agreement at the individual level

Worker Problem

Workers choose job offers that expire in the end of each period to maximise their indirect utility of working in firm j:

$$v_{sijt} = f\left(w_{sijt}, h_{sijt}\right) + a_{sj} + \varepsilon_{sijt}, \tag{3.1}$$

where $f\left(w_{sjt}, h_{sjt}\right)$ is the indirect utility provided by firms, which is increasing and concave in both arguments. a_{sj} is the utility from firm-specific amenity common to all workers with skill level s. ε_{sijt} captures Type One Extreme Value (EV1) distributed idiosyncratic taste for employment in firm j at time t. Additionally, given posted wages, the number of firms are large, and workers can accept any available offer, logit choice probabilities can be closely approximated by exponential probability (Card et al., 2018):

$$p_{sj} = K_s \exp\left(\bar{v}\right) \tag{3.2}$$

where K is a constant common for all firms and $\bar{v} = f\left(w_{sjt}, h_{sjt}\right) + a_{sj}$

Firm Problem

Profits of firm j in period t are:

$$L_{sjt}\left[Q_{sjt} - C\left(w_{sjt}, h_{sjt}\right)\right], \tag{3.3}$$

where L_{sjt} is the total employment of workers with skill level s in period t. Q_{sjt} is the revenue per worker. $C\left(w_{sjt}, h_{sjt}\right)$ is the unit cost of labour.

Firms choose optimal wage-paid holiday pair $\left(w_{sjt}, h_{sjt}\right)$ for each skill type of labour to maximise their steady state profit:

$$\max_{w,h}[Q - C(w,h)]L^*. \tag{3.4}$$

Steady State Employment

In steady state, all firms make same offer to purticular type of labour with skill s in each period. The law of motion of employment is:

$$L_{t+1} = p(\bar{v})L_t + \lambda p(\bar{v})\left[N - L_t\right], \tag{3.5}$$

where L_{t+1} is the total employment for workers with s level skill in period t+1. pL_t is the expected number of last period workers retained in t + 1. $\lambda p(\bar{u})\left[N - L_t\right]$ is the expected number of offers chosen by outside workers.

Then, substitute steady state condition $L_{t+1} = L_t = L$ into equation (3.5). If incumbent firms does not have any advantage over retaining workers ($\lambda = 1$), the steady state employment level is:

$$L^*(\bar{v}) = pN = K_s \exp(\bar{v}) N. \tag{3.6}$$

Otherwise ($\lambda < 1$), the steady state employment level is:

$$L^*(\bar{v}) = \frac{\lambda K_s \exp(\bar{v}) N}{\Omega(\bar{v})}, \tag{3.7}$$

where $\Omega = 1 - (1-\lambda) K \exp(\bar{v})$ captures the incumbency advantage.

Equilibrium

Following Hwang, Mortensen and Reed (1998) and Lavetti and Schmutte (2018), I assume indirect utility over wage and paid holiday is given by $f(w,h) = \ln w + H(h)$. Also, suppose the function of the unit cost of labour is $C(w,h) = w \exp(y(h))$. The cost function thus implicates that the marginal cost of providing paid holiday to high wage worker is higher. This implication is intuitive since high wage workers are often more productive and less replaceable. Additionally, I assume that a type s worker in firm j generates revenue $Q_{sj} = T_j \theta_s$, where T_j is the exogenous firm-specific productivity; θ_s is the exogenous worker-type-specific productivity.

Substituting the equation 3.6 and 3.7 of steady state employment level into the first order condition of firm profit maximisation problem with respect to w and taking logarithm yield following two log wage equations:

when $\lambda = 1$

$$\ln w = \ln T_j + \ln \theta_s - y(h) + A \tag{3.8}$$

when $\lambda < 1$

$$\ln w = \ln T_j + \ln \theta_s - y(h) + \ln \left(\frac{1}{1 + \Omega(\bar{v})} \right) \tag{3.9}$$

Equation 3.8 is identical to AKM wage model, where A is just a constant depending on the assumption of functional form. When $\lambda = 1$, the framework is indeed identical to Card et al. (2018), who have rationalised the AKM wage model. On the other hand, when $\lambda < 1$ the equation 3.9 yields an additional conponent, which includes the incumbency advantage over hiring. Typical empirical application of equation 3.9 is through adding different match effects, though such application requires within worker-firm match variation, which is not common in data (Woodcock, 2015; Lavetti and Schmutte, 2018; Lavetti, 2020).

The first order condition of firm profit maximisation problem with respect to h yields:

$$\frac{f_w(w,h)}{f_h(w,h)} = \frac{C_w(w,h)}{C_h(w,h)} \Rightarrow y'(h) = H'(h) \tag{3.10}$$

which suggests that worker's willingness to sacrifice wages in exchange for paid holiday equals the marginal cost to the firm of offering it in the equilibrium.

Takeaway

The main takeaway from the model is that if $\lambda = 1$, the marginal effect of paid holiday on log wages equals the worker preference for paid holiday. If $\lambda < 1$, the marginal effect of paid holiday on log wages equals:

$$\frac{d\ln w}{dh} = -H'(h)\left[1 - \left(\frac{1-\Omega(\bar{v})}{1+\Omega(\bar{v})}\right)\right], \tag{3.11}$$

where the worker preference is numerically lower than the marginal effect of paid holiday. This suggests that the match quality leads to upward bias but is unlikely to change the sign of estimates.

The $f(w,h)$ structure might omit benefits and amenities that correlates to both paid holiday and wages. One may thus wish to include as many of them as possible. However, it is worth to noting that theoretically, workers have downward sloping indifference curve for the correlated amenities/benefits and wages. Thus, omitting them is also unlikely to change the sign. Another improvement is by looking at the occupation-specific compensating wage differentials for paid holiday; The model would incorporate all fixed occupation-specific amenity and benefit similiar to Lavetti and Schmutte (2018)'s setup.

3.3 Empirical Approach

This section introduces the empirical models that derives from the hedonic search framework.

3.3.1 Baseline Specification

I estimate the below wage equation 3.12 derived from equation 3.8.

$$\log(w_{it}) = \gamma h_{it} + x_{it}\beta + \psi_{j(it)} + \phi_i + \varepsilon_{it}, \tag{3.12}$$

where $log(w_{it})$ is the log hourly wage of individual i in year t. x is a set of control variables. ϕ is the personal fixed effect, controlling for unobserved individual heterogeneity, such as ability. ψ is the fixed effect of firm, which allows for variation in wages across jobs in the same establishment and accommodates arbitrary sorting on the basis of paid leave and the worker effect. It absorbs the effect on wages of all time invariant unobserved amenities.

ε is the error term. Then, γ can be interpreted as the effect of paid leave on wages, holding other unobserved establishment-level amenities constant.

The identification of this two-way fixed effect model 3.12 follows that of standard AKM model, which exploits the worker mobility. In other words, it requires that there is a set of firms in the data that are indirectly connected through their workers. Yet, identifying γ further necessitates workers switching jobs to choose between wages and paid leave, excluding any other amenities correlated with paid leave except for controls. This is extremely challenging to achieve using observed data. However, this model can control for many time-invariant unobserved effects and thus the underlying amenities. If there are still some uncontrolled amenities correlated with paid leave, it means that when estimating this model γ identifies the variation in wages associated with the bundle of amenities correlated with paid leave. Although the interpretation then becomes ambiguous, it is still informative for the understanding of the wage and paid leave relationship.

Besides, I also introduce the match effect into the model 3.13 similar to Woodcock (2015).

$$\log(w_{it}) = \gamma h_{it} + x_{it}\beta + M_{ij(it)} + \varepsilon_{it}, \tag{3.13}$$

where $M_{ij(it)}$ captures the returns to characteristics of the worker-firm match. But variations of paid leave within jobs over time are limited, especially after controlling for seniority. I thus instead use 3.12 as the baseline model for interpretation.

3.3.2 Data

I use matched employer-employee data from the 2005-2020[2] Annual Survey of Hours and Earnings (ASHE), which sampled 1% of the UK employee jobs taken from Pay As You Earn records. Each year in April, the UK Office for National Statistics send employers questionnaires to fill in if their employees are selected. The sample includes approximately 300,000 employees and is kept as stable as possible. Since the Statistics of Trade Act 1947 requires employers to submit required information, ASHE is the most accurate hours and earnings data and is the only available matched employer-employee data in the UK. Unlike many other matched employer-employee data, such as those from Germany and the USA, ASHE has a detailed breakdown of earnings and working hours, which is important for studying paid holiday entitlement for its close relationship with working hours and other compensation practice. It also contains many non-wage benefits, including paid holiday (annual leave), pension arrangements and benefits in kind. Those are variables that are often not available in large-scale administrative matched employer-employee data but are crucial for this paper.

[2] The interest variable, annual leave, only becomes available from 2005

3.4 Results

3.4.1 Hourly wage and paid leave

In some cases, literature considers that paid holiday is no different from reducing the working hours, and the paid feature is simply part of the annual earnings. The relationship between working hour and paid leave is debatable (Altonji, Oldham et al., 2003).

This section explores the factors that determine the allocation of paid annual leave. Table 2 presents the results of five regression models where the number of paid annual leave days is the dependent variable. The models are designed to identify the key demographic, job, and firm-level characteristics associated with more generous leave policies. These variables are often correlated with wages. Thus, exploring the determinants also helps finding the appropriate control variables for the regressions of hedonic wage functions.

The analysis begins with the simplist model and progressively incorporates a richer set of control variables and fixed effects to account for confounding factors. All models include controls for year, region, and job tenure, in addition to the standard set of control variables noted at the bottom of the table.

A variable of interest is gender and working hours. Model (1) shows a negative and statistically significant gender coefficient of -0.9640. This initial result suggests a substantial gap, with female workers receiving nearly one less day of paid annual leave on average compared to their male counterparts.

Model (2) introduces controls for working hour and Occupation FE. The inclusion of these variables causes a notable sign reversal for the gender coefficient, which becomes positive and significant at 0.1640. This indicates that the raw gap observed in Model (1) was driven by the sorting of women into occupations or work patterns (e.g., fewer hours) that offer less annual leave. Once these job characteristics are held constant, women are associated with receiving slightly more annual leave than men. This positive relationship, though smaller in magnitude, persists through Model (3), which controls for industry, and Model (4), which controls for firm-level heterogeneity. Explanation may be the fact that females traditionally have more family responsibility and tend to demand more holidays (Maume, 2006).

Model (5) introduces worker FE, the most stringent specification, which controls for all time-invariant individual characteristics. As gender is a time-invariant trait, its effect is absorbed by the worker fixed effect and thus cannot be estimated separately. This is a standard outcome in such models and implies that variation in leave is being explained by factors that change over time for a given individual, rather than by fixed traits like gender.

The Working hour variable shows a consistently positive and highly significant relationship with annual leave across all specifications where it is included. It shows better paying jobs have in general higher holiday allowance. In the preferred worker fixed-effects model (Model 5), an increase of one working hour per week is associated with an increase of 0.085

days of annual leave for the same individual over time. This suggests that longer working hours are a strong predictor of more generous leave entitlements.

In conclusion, the analysis in Table 2 shows that while a simple comparison suggests women receive less paid leave, this is a result of occupational sorting and working patterns. After controlling for job-specific characteristics, this relationship reverses. More significantly, the amount of paid annual leave an individual receives is strongly and positively associated with their working hours and is overwhelmingly determined by time-invariant individual characteristic and the policies of their specific employer.

Table 3.1. The determinants of paid annual leave

	(1) Annual Leave	(2) Annual Leave	(3) Annual Leave	(4) Annual Leave	(5) Annual Leave
Gender	-0.9640***	0.1640***	0.1555***	0.1202***	
	(0.0557)	(0.0281)	(0.0208)	(0.0193)	
Working hour		0.0662***	0.0461***	0.1056***	0.0852***
		(0.0038)	(0.0047)	(0.0040)	(0.0033)
Year FE	Y	Y	Y	Y	Y
Regional FE	Y	Y	Y	Y	Y
Tenure FE	Y	Y	Y	Y	Y
Occupation FE		Y		Y	Y
Industry FE			Y		
Firm FE				Y	Y
Worker FE					Y
R^2	0.1061	0.2709	0.2128	0.5621	0.6869
Obeservations	996277	996277	996277	958931	916857

Control variables comprise dummies for full-time and permanent workers as well as the cubic polynomial for age and firm size.
Standard errors clustered at the year X region X 2-digit industries in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

3.4.2 Estimating compensating wage differential of annual leaves

Table 3.2 present the results of wage regressions using 4 different spcifications. Specification in column (1) controls for individual heterogeneity. Estimates from column (1) shows a positive association between annual leave and wages. This is in line with previous study such as Bryan (2006). This positive correlation cleanly contradicts the prediction of compensating wage differential theory. As I discussed earlier in the conceptual framework, merely controlling for individual fixed effect may lead to bias. I then estimate 3.12 and 3.13 where the specifications further include firm and match effects.

Model (2) replaces industry fixed effects with firm fixed effects, controlling for any time-invariant unobserved characteristics of the employer. This is a demanding specification that isolates the effect of changes within a given firm such as time-invariant amenity, which may correlate with annual leave. The coefficient on annual Leave remains highly significant but its magnitude decreases to 0.0012, suggesting that some of the effect in Model (1) was attributable to sorting of higher-wage workers into firms that offer more generous leave policies.

Model (3) employs the most rigorous specification by incorporating worker-firm match fixed effects (Match FE). This approach absorbs all time-invariant heterogeneity specific to the worker, the firm, and the combination of that worker at that firm. Consequently, the coefficient is identified from changes in annual leave within a specific job spell. The estimated effect on Annual Leave further moderates to 0.0010 but remains statistically significant at the 1% level. This result indicates that for a given worker at a given firm, an increase of one day of paid annual leave is associated with a 0.10% increase in their hourly wage.

Finally, Model (4) builds upon the match fixed-effects specification by introducing a control for non-pecuniary benefits (Any in Kind). This is done to test whether the provision of annual leave is correlated with other forms of compensation that could confound the result. The inclusion of this variable has no impact on the coefficient for Annual Leave, which remains 0.0010. The coefficient for Any in Kind is itself positive and significant, suggesting that in-kind benefits are associated with an approximately 1.18% wage premium.

Table 3.2. The effect of paid annual leave on log hourly wages

	(1)	(2)	(3)	(4)
Annual Leave	0.0018***	0.0012***	0.0010***	0.0010***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Working Hours	-0.0069***	-0.0079***	-0.0094***	-0.0094***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Any in Kind				0.0118***
				(0.0013)
Year FE	Y	Y	Y	Y
Regional FE	Y	Y	Y	Y
Tenure FE	Y	Y	Y	Y
Occupation FE	Y	Y	Y	Y
Industry FE	Y			
Firm FE		Y		
Worker FE	Y	Y		
Match FE			Y	Y
R^2	0.9123	0.948	0.9544	0.9544
Observations	945079	916857	854278	854278

Control variables comprise dummies for full-time and permanent workers as well as the cubic polynomial for age and firm size.

Standard errors clustered at the years X regions X 2-digit industries in parentheses.

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

3.5 Conclusion

As shown by the findings from the study using American and Canadian data, the positive correlation between holiday entitlement and hourly wages also exist in the UK. However, the correlation obtained from the descriptive survey regression can mix the effects of personal characteristics, and job and firm heterogeneity on hourly wages. The step-by-step regression ‘trial’ does suggest that the correlation is sensitive to the mentioned characteristics.

I use an empirical AKM style model founded by hedonic search model to test the prediction by compensating wage differentials. The core finding of this study is the persistent, positive, and statistically significant relationship between paid annual leave and hourly wages, even after controlling for a comprehensive set of individual, job, and firm characteristics. The most rigorous specification, which includes worker-firm match fixed effects to account for all time-invariant heterogeneity, confirms this result. The preferred estimate suggests that an additional day of paid annual leave is associated with a 0.10% increase in hourly wages, directly contradicting the notion of a wage-for-leave trade-off.

This seemingly counter-intuitive result can be understood through the lens of the more nuanced conceptual framework presented in Section 3.2. The simple hedonic model's assumptions of a perfect, frictionless market are likely violated. The positive coefficient is consistent with a labour market characterised by significant heterogeneity and sorting. High-ability workers may sort into high-productivity firms that offer superior compensation packages, including both higher wages and more generous benefits like paid leave. This creates a positive correlation along an "expansion path" that dominates any negative trade-off along a single offer curve. The hedonic search model further rationalises this finding, suggesting that match-specific quality can generate a positive covariance between wages and amenities, leading to an upward bias in the estimated coefficient. Yet, the empirical results either suggest this bias is so substantial that it overwhelms any underlying negative trade-off or there is little compensating wage differential for paid annual leave.

While the fixed-effects strategy is robust to time-invariant sorting, some limitations remain. The estimated coefficient may capture the effect of a 'bundle' of amenities, where generous leave is correlated with other unobserved desirable job characteristics (e.g., better work environment, greater job security) that are also rewarded with higher wages. The identification, which relies on within-job variation in leave entitlement, may also be driven by specific events like promotions that are not fully controlled for.

In conclusion, this study demonstrates that in the contemporary UK labour market, paid annual leave does not necessarily function as a simple compensating differential. Instead, it appears to be a complementary component of a 'good job' package, where firms that pay more also offer better non-pecuniary benefits. which together compensates for other dis-amenities. This underscores the importance of moving beyond simple hedonic models and incorporating labour market frictions, sorting, and firm-level heterogeneity to fully understand the complex structure of employee compensation. Future research could further disentangle these effects by incorporating more detailed data on other job amenities or by structurally estimating the parameters of a hedonic search model.

Speaking to the policy relevance of this paper, if paid leave is a complement to wages, then policies that mandate minimum holiday entitlements may not necessarily result in the "wage penalty" predicted by classical economics. This implies that increasing statutory leave may improve worker well-being without triggering a decline on hourly pay. Also, any interventions aimed at reducing inequality must look at the "total package." If low-wage workers are also receiving fewer benefits, the welfare gap is then wider than the wage gap suggests.

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Appendix A

A.1 Chapter 1: Labor Market Adjustments to Trade Shocks Among German Firms

Table A.1. Top 5 Manufacturing Industries in Terms of the Growth in Trade Value for Each of the Two Decades under Analysis

Rank	Industry	Δ Value	Industry	Δ Value
	1988-1998		2000-2010	
	Export			
1	341 Vehicles	4.0	341 Vehicles	13.5
2	295 Special purpose machinery	2.9	343 Parts and accessories for vehicles	8.7
3	343 Parts and accessories for vehicles	2.9	291 Machinery for the production and usage	6.3
4	292 General purpose machinery	1.9	295 Special purpose machinery	5.3
5	312 Electricity dist. and control apparatus	1.7	241 Basic chemical	4.4
	Import			
1	182 Other wearing apparel and accessories	4.8	300 Office machinery and computers	9.9
2	341 Vehicles	4.7	321 Electronic valves and tubes	7.4
3	300 Office machinery and computers	2.3	343 Parts and accessories for vehicles	5.8
4	361 Furniture	1.9	323 Television and radio receivers	4.9
5	343 Parts and accessories for vehicles	1.7	351 Ships and boats	4.9

Source: UN Comtrade.
Notes: Trade values are expressed in constant Euros (2010; billion).

Table A.2. Summary Statistics (Continuing Firms)

	1988-1998		2000-2010	
	Base year	Annual Growth	Base year	Annual Growth
Panel A: Number of employees per establishment				
Headcounts(total)	52.1	-0.362%	45.4	-0.154%
Part-time	1.9	1.404%	2.4	0.100%
Apprentice	2.7	-2.661%	1.8	-0.097%
Full-time	47.1	-0.207%	37.7	-1.283%
High Skilled	3.1	1.744%	4.3	1.150%
Medium Skilled	34.5	0.041%	32.3	-1.226%
Low skilled	13.7	-1.466%	5.2	-1.030%
Female	14.0	-0.080%	12.8	0.248%
Male	38.0	-0.602%	32.5	-0.356%
Panel B: Establishment wages (daily full-time wages in 2010 EUR)				
Mean	74.9	0.703%	81.1	-0.696%
25-th percentile	61.2	0.895%	67.2	-0.578%
Median	72.6	0.682%	78.6	-0.735%
75-th percentile	86.0	0.576%	92.5	-0.797%
Panel C: Establishment size				
Small ($\leq$ 10)	61.2%		61.9%	
Medium (10-249)	34.6%		35.2%	
Large ($\geq$ 250)	3.3%		2.9%	
Panel D: Trade exposure				
ΔExport Exposure	17.2		34.6	
ΔImport Exposure	20.2		28.4	
Number of Firms	49,016		48,329	

Notes: The table shows descriptive statistics for manufacturing firms in the sample. Panels A and B report employment and wage outcomes in the base year of each respective decade and their annual growth rate across each decade, according to equation (1.4). Panel C reports sample shares of firm types, and Panel D shows the (non-standardized) trade exposure variables defined in equations (1.1) and (1.2).

Table A.3. The Effect of Trade Exposure on Firms' Employment, Exit, and Wages (OLS Estimates)

	(1) ΔHeadcounts	(2) ΔHeadcounts (continuing)	(3) Exit	(4) ΔWages (continuing)
ΔExport Exposure	0.3617***	0.2321***	0.0009	0.0296
	(0.069)	(0.028)	(0.002)	(0.018)
ΔImport Exposure	-0.1636**	-0.0897***	0.0101***	0.0515***
	(0.065)	(0.029)	(0.032)	(0.020)
Observations	196,957	97,345	152,780	94,701

Notes: Each regression includes controls for establishment size (four indicator variables: 0–5, 5–20, 20–200, 200–2000), time period, 108 commuting zones, broad manufacturing industries (four dummy variables: food, industrial, capital, and consumer products), and an above-median firm share of skilled workers. Exposure variables are standardized. IVs are the other 8 high-income countries' export and import exposure to the East. The two time periods are: 1988–1998 and 2000–2010. Standard errors in parentheses are clustered at the period×commuting zone×3-digit-industry level.

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

Table A.4. Decomposition of the Effect of Trade Exposure on Firms' Employment for Entering, Continuing, and Exiting Firms

	(1) Entrants	(2) continuings	(3) Exiting
ΔExport Exposure	1.1724***	0.3710***	0.4993***
	(0.255)	(0.065)	(0.172)
ΔImport Exposure	-0.5086***	-0.2492***	-0.3023***
	(0.135)	(0.042)	(0.109)
Kleibergen-Paap F statistic	27.7	27.7	27.7
Observations	196,957	196,957	196,957

Notes: Dependent variables are the interaction of headcounts and a dummy for being an entering, exiting, or continuing firm, respectively. These three dependent variables add up exactly to the overall headcounts variable and thus allow decomposing the overall effect into three parts. For example, entering firms contribute 84% (1.72/2.042) to the overall export exposure effect of 2.042 in column 1 of Table 1.2. The specifications are the same as those in Table 1.2. Standard errors in parentheses are clustered at the period×commuting zone×3-digit-industry level. The F-statistic is the Kleibergen-Paap statistic.

*** $p < 0.01$

Table A.5. Heterogeneous Effect of Trade Exposure on Employment by Baseline Establishment Size

	ΔHeadcounts
ΔExport Exposure × Small	1.8812***
	(0.347)
ΔExport Exposure × Medium	1.3142***
	(0.282)
ΔExport Exposure × Large	1.0839***
	(0.618)
ΔImport Exposure × Small	-0.7184***
	(0.202)
ΔImport Exposure × Medium	-1.0150***
	(0.1735)
ΔImport Exposure × Large	-0.3501
	(0.537)
Kleibergen-Paap F statistic	9.766
Observations	196,957

Notes: The specifications are the same as those in Table 1.2. Standard errors in parentheses are clustered at the period×commuting zone×3-digit-industry level. The F-statistic is the Kleibergen-Paap statistic.

*** $p < 0.01$

Table A.6. The effect of Trade Exposure on Firms' Wages at Different Percentiles

	(1) ΔMean	(2) Δ25% percentiles	(3) ΔMedian	(4) Δ75% percentiles
ΔExport Exposure	0.0656	0.0663	0.0390	0.0679
	(0.070)	(0.079)	(0.072)	(0.075)
ΔImport Exposure	0.0248	0.0190	0.0364	0.0428
	(0.041)	(0.047)	(0.043)	(0.044)
Observations	94,701	94,701	94,701	94,701
Kleibergen-Paap F statistic	29.2	29.2	29.2	29.2

Notes: The specifications are the same as those in Table 1.2. Standard errors in parentheses are clustered at the period×commuting zone×3-digit-industry level. The F-statistic is the Kleibergen-Paap statistic.

Table A.7. Robustness Check: The Effect of Trade Exposure on firms' Employment, Exit, and Wages (controlling for the 1978-1988/1990-2000 industry-level growth of the outcome variables)

	(1) ΔHeadcounts	(2) ΔHeadcounts (continuing)	(3) Exit	(4) ΔWages (continuing)
ΔExport Exposure	1.5733***	0.6311***	-0.0146**	0.0994
	(0.292)	(0.110)	(0.007)	(0.077)
ΔImport Exposure	-0.8194***	-0.3998***	0.0197***	0.0171
	(0.173)	(0.069)	(0.005)	(0.043)
Industry Pre-trend(1978-1988)	✓	✓	✓	✓
Observations	196,957	97,345	152,780	94,701
Kleibergen-Paap F statistic	35.8	34.4	36.1	24.4

Notes: The specifications are the same as those in Table 1.2. Standard errors in parentheses are clustered at the period×commuting zone×3-digit-industry level. The F-statistic is the Kleibergen-Paap statistic.
** $p < 0.05$, *** $p < 0.01$

Table A.8. Decomposing the Trade Exposure Effect on Full-Time Employment by Educational Skill Group

	All	Low	Medium	High
	(1)	(2)	(3)	(4)
ΔExport Exposure	0.6314***	0.0594	0.4365***	0.1403***
	(0.152)	(0.041)	(0.130)	(0.034)
ΔImport Exposure	-0.3711***	-0.1238***	-0.1912**	-0.0624***
	(0.090)	(0.033)	(0.077)	(0.017)
Kleibergen-Paap F statistic	28.7	28.7	28.7	28.7
Observations	94,353	94,353	94,353	94,353

Notes: Dependent variables are the interaction of headcounts and a dummy for being an low, medium, or high skilled firm, respectively. These three dependent variables add up exactly to the overall full-time employment variable and thus allow decomposing the overall effect into three parts. For example, medium-skill firms contribute 69% (0.4365/0.6314) to the overall export exposure effect of 0.6314 in column 1 of Table 1.2. The specifications are the same as those in Table 1.2. Standard errors in parentheses are clustered at the period×commuting zone×3-digit-industry level. The F-statistic is the Kleibergen-Paap statistic.
** $p < 0.05$, *** $p < 0.01$

Table A.9. Effects of Local Labor Market Trade Shocks (SMEs)

	(1) ΔHeadcounts	(2) Hiring	(3) ΔHiring (from other firms)	(4) ΔHiring (from non-employment)	(5) Separation	(6) ΔSeparation (to other firms)	(7) ΔSeparation (to non-employment)
A: Interaction of firms' own trade exposure with positive LLM trade shock							
ΔExport Exposure	0.7805***	0.9092***	0.6307***	0.2785*	0.1287	-0.0671	0.1957
	(0.138)	(0.262)	(0.150)	(0.158)	(0.243)	(0.146)	(0.134)
ΔExport Exposure × LLM positive trade shock	-0.2014	-0.9512**	-0.2101	-0.7412***	-0.7499**	-0.2515	-0.4984**
	(0.230)	(0.371)	(0.226)	(0.266)	(0.368)	(0.232)	(0.210)
ΔImport Exposure	-0.4868***	-0.3626**	-0.1896**	-0.1730*	0.1241	0.0647	0.0594
	(0.081)	(0.147)	(0.085)	(0.091)	(0.132)	(0.077)	(0.077)
ΔImport Exposure × LLM positive trade shock	0.2086	0.6545**	-0.0042	0.6587*	0.4459	0.1678	0.2781
	(0.137)	(0.323)	(0.148)	(0.349)	(0.317)	(0.171)	(0.193)
Kleibergen-Paap F statistic	13.2	13.2	13.2	13.2	13.2	13.2	13.2
Observations	94,353	94,353	94,353	94,353	94,353	94,353	94,353
B: Effect of LLM trade exposure on firms with low own trade exposure							
LLM ΔExport Exposure	0.0159	0.0543	0.0013	0.0529	0.0384	-0.0255	0.0639
	(0.079)	(0.134)	(0.081)	(0.092)	(0.131)	(0.077)	(0.077)
LLM ΔImport Exposure	0.0416	-0.1641	-0.0475	-0.1166	-0.2056	-0.0598	-0.1458**
	(0.068)	(0.132)	(0.089)	(0.097)	(0.136)	(0.087)	(0.072)
Kleibergen-Paap F statistic	19.8	19.8	19.8	19.8	19.8	19.8	19.2
Observations	41,673	41,673	41,673	41,673	41,673	41,673	41,673

Notes: Each regression includes controls for establishment size (four indicator variables: 0–5, 5–20, 20–200, 200–2000), time period, 108 commuting zones, broad manufacturing industries (four dummy variables: food, industrial, capital, and consumer products), and an above-median firm share of skilled workers. Panel B also includes firms' own export exposure as control variables. Exposure variables are standardized. IVs are the other 8 high-income countries' export and import exposure to the East. The F-statistic is the Kleibergen-Paap statistic. The two time periods are: 1988–1998 and 2000–2010. Standard errors in parentheses are clustered at the period×commuting zone×3-digit-industry level.

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

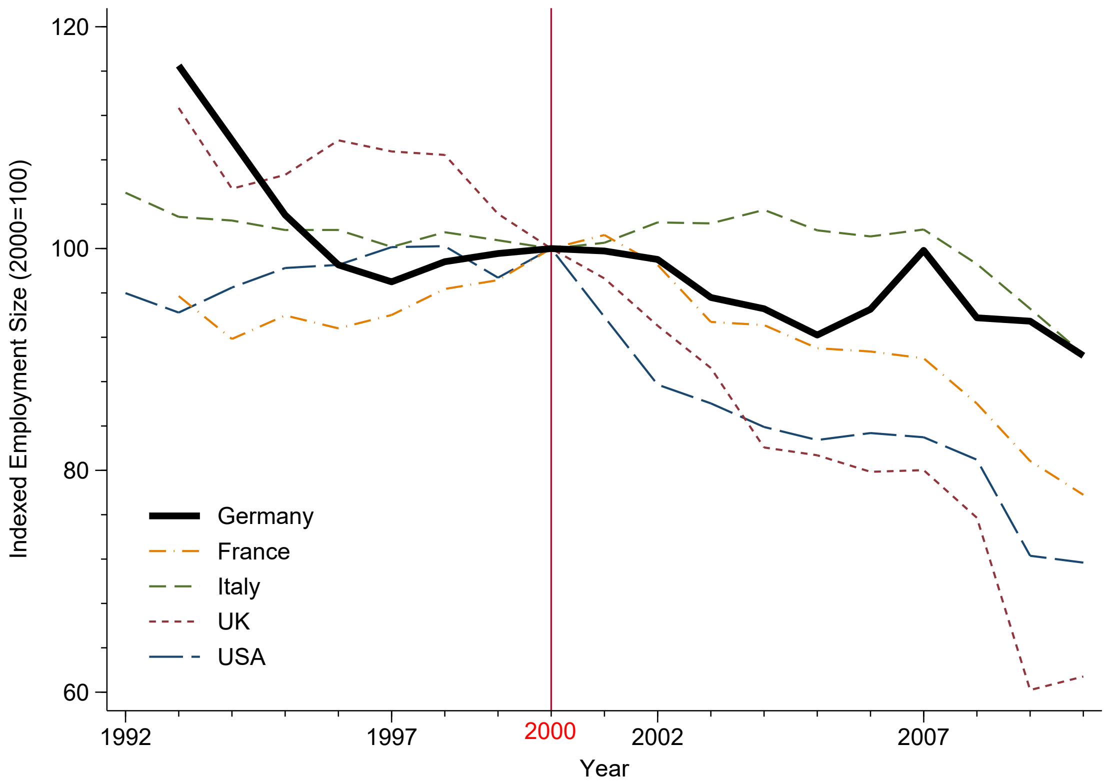
Table A.10. Effects of Local Labor Market Trade Shocks (SMEs in Service Sector)

	(1) ΔHeadcounts	(2) Hiring	(3) Separation	(4) ΔFull-time	(5) ΔPart-time	(6) ΔApprentice	(7) ΔLow-skill	(8) ΔFemale	(9) ΔWage
LLM ΔExport Exposure	0.0017	-0.0609	-0.0626	-0.0456	0.1519**	-0.0224	-0.0046	0.0104	-0.0149
	(0.029)	(0.101)	(0.088)	(0.032)	(0.074)	(0.036)	(0.038)	(0.034)	(0.019)
LLM ΔImport Exposure	-0.0478	-0.0902	-0.0424	-0.0025	-0.3128***	-0.0017	-0.1187***	-0.0485	-0.0176
	(0.035)	(0.114)	(0.096)	(0.036)	(0.101)	(0.036)	(0.041)	(0.040)	(0.024)
Kleibergen-Paap F statistic	131.1	131.1	131.1	131.1	131.1	131.1	131.1	131.1	146.9
Observations	575,131	575,131	575,131	575,131	575,131	575,131	575,131	575,131	503,985

Notes: The specifications are the same as those in panel A of Table A.9. Standard errors in parentheses are clustered at the period×commuting zone×3-digit-industry level. The F-statistic is the Kleibergen-Paap statistic.

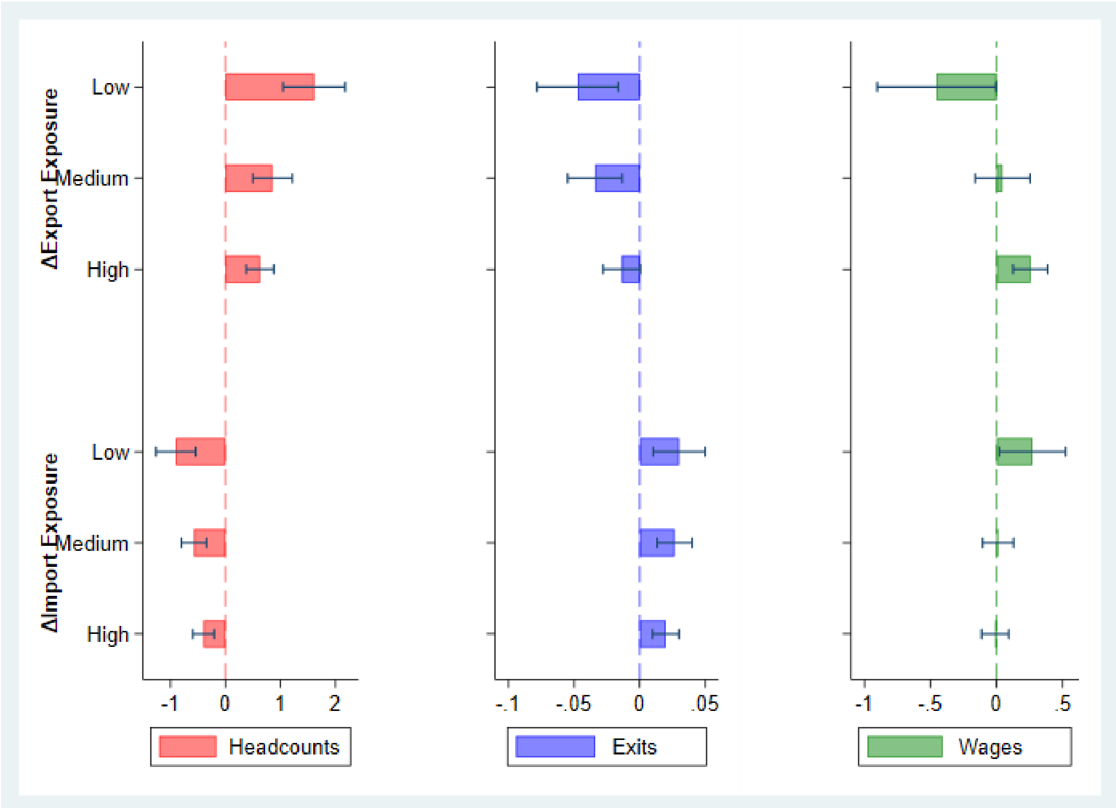
** $p < 0.05$, *** $p < 0.01$

Figure A.1. Manufacturing Employment, 1992–2010



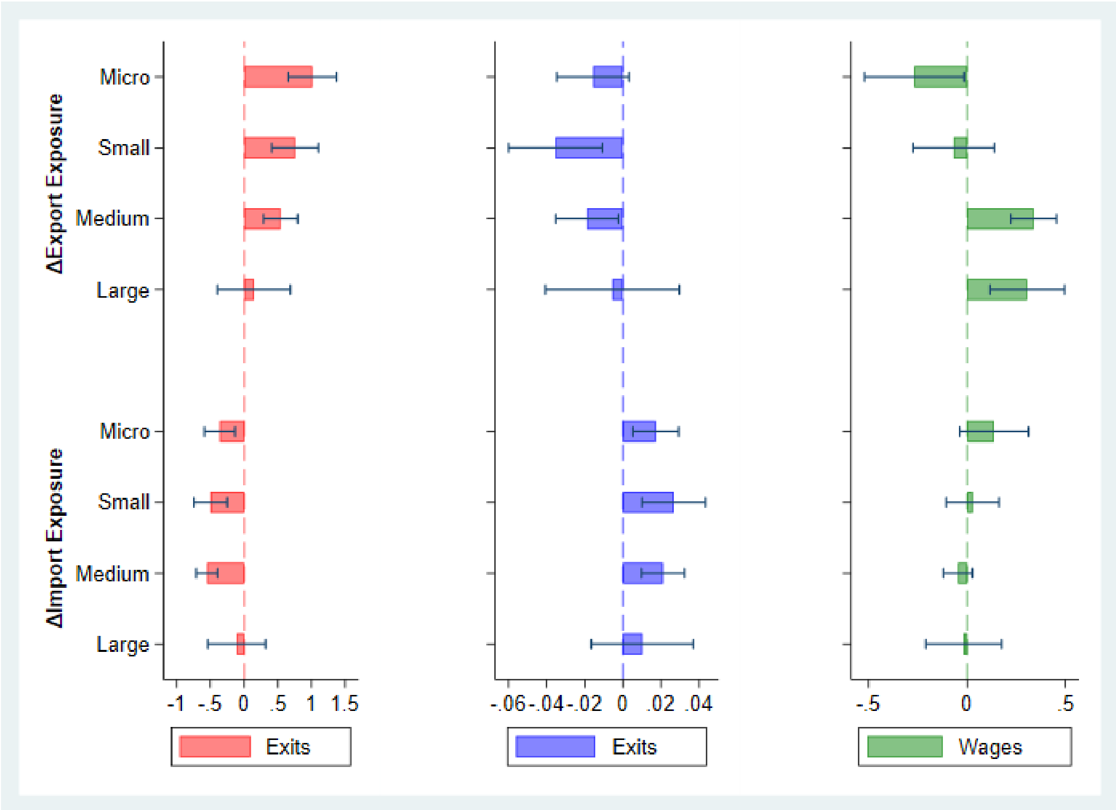
Source: ILOSTAT Labor Force Statistics via <https://ilostat.ilo.org/topics/employment>
Notes: Indexed employment, which represents the number of employees in each year divided by the number of employees in 2000 multiplied by 100, serves as a indicator of the trend in manufacturing employment. By using 2000 as the base year, it provides a comparison of manufacturing employment trend across countries over time .

Figure A.2. Heterogeneous Effects on Employment, Exits and Wages by Establishment Wage Fixed Effect



Notes: The specifications are the same as those in Table 1.2, except for the exclusion of exposure variables. Instead, we include 6 interaction terms that combine exposure variables with 3 establishment wage fixed effect (AKM) tercile dummies. The figure shows the coefficients of interaction variables. The interaction variables are standardized. IVs are the other 8 high-income countries' export and import exposure interacted with 3 fixed effect dummies. Periods: 1988-1998 and 2000-2010. Confidence intervals are at 95%.

Figure A.3. Heterogeneous Effects on Employment, Exits and Wages by Baseline Establishment Size



Notes: The specifications are the same as those in Table 1.2, except for the exclusion of exposure variables. Instead, we include 6 interaction terms that combine exposure variables with 4 establishment size dummies ($<$ 5, 5-9, 10-249, $\geq$ 250). The figure shows the coefficients of interaction variables. The interaction variables are standardized. IVs are the other 8 high-income countries' export and import exposure interacted with 4 size dummies. Periods: 1988-1998 and 2000-2010. Confidence intervals are at 95%.

Appendix B

B.1 Chapter 2: Routine and Non-routine Jobs: Young Workers' Experience in Germany

Figure B.1. Experience Effect on Wages: Manual non-routine vs Routine vs Non-routine

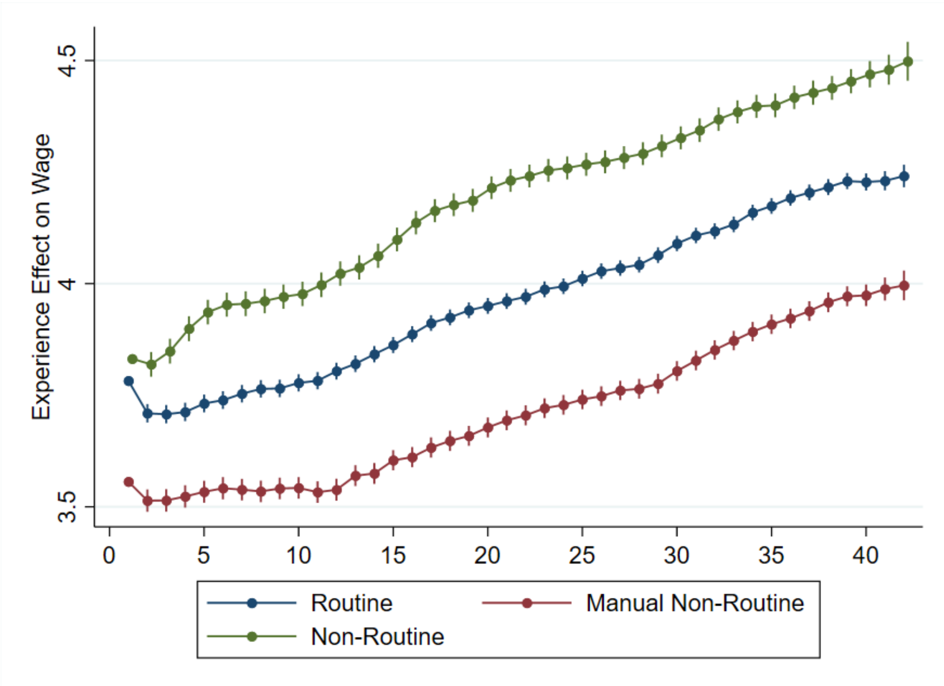


Figure B.2. Routine, Manual, and Analytical Jobs (Log Employment; West Germany; Males; Ages 25–54; relative to 2007)

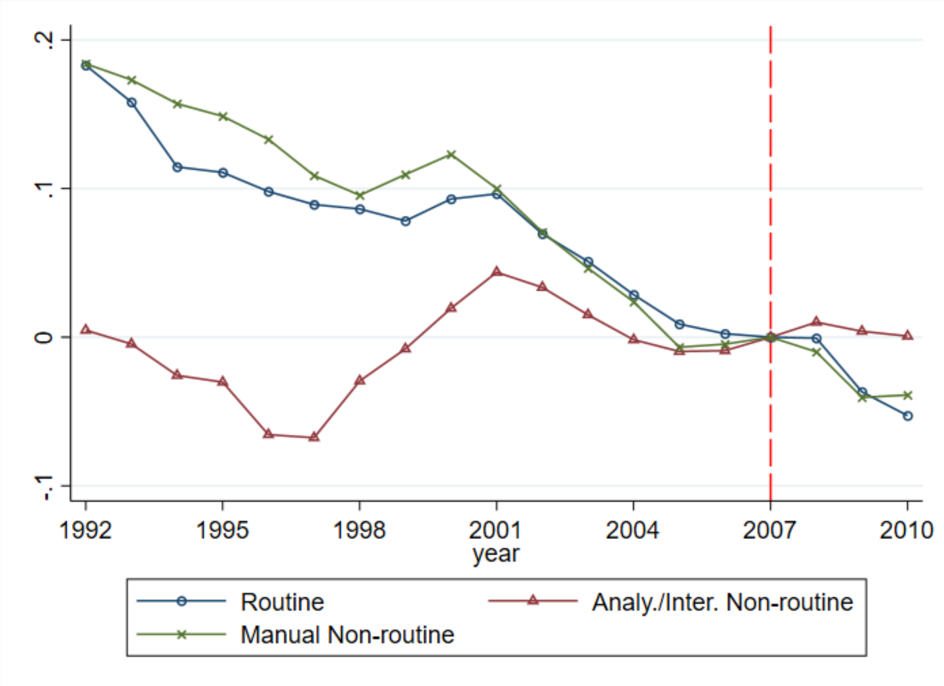


Figure B.3. Routine, Manual, and Analytical Relative Wages (West Germany; Males; Ages 25–54)