Empirical Evidence on the Impact of Technological Change on the Labor Market

Inaugural-Dissertation

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Introduction

The Impact of Technology on the Labor Market

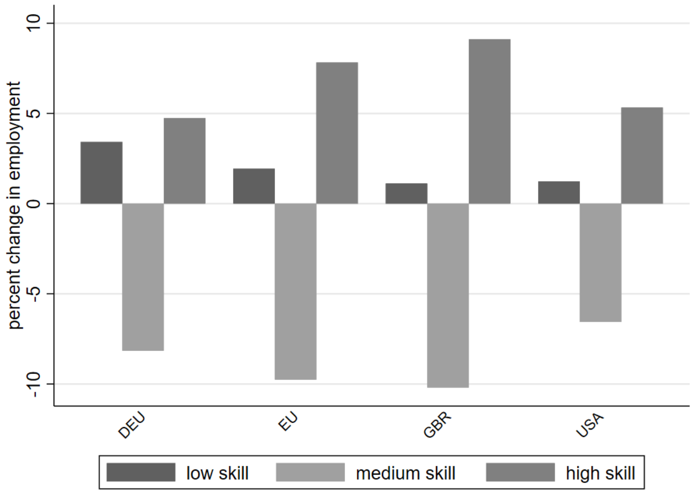
Rapid technological progress has led to a strong debate about its impact on the labor market. Concerns revolve around the displacement effect of technology leading to higher unemployment (Susskind, 2020), as supported by studies highlighting substantial automation risks in many occupations (Frey and Osborne, 2017). However, the displacement effect is countered by the potential of new technologies to increase productivity and create new tasks, as reflected in the productivity and reinstatement effect (Acemoglu and Restrepo, 2018).

The impact of technology on labor demand is conceptualized in the task framework presented in Autor et al. (2003), which views jobs as bundles of tasks performed by either labor or technological capital. On the one hand, technological capital displaces labor in tasks where it has a comparative advantage. In particular, routine tasks characterized by repetitive patterns and rules are affected. On the other hand, automation lowers the cost of automated tasks, thereby increasing the demand for complementary non-automated tasks and raises output per worker and wages, which is captured by the productivity effect (Acemoglu and Restrepo, 2018). In addition, the reinstatement effect describes the emergence of new tasks and occupations, such as software engineers and data scientists, expanding the range of labor tasks and mitigating the decline in labor share (Acemoglu and Restrepo, 2018; Autor et al., 2024).

Due to the task-biased nature of technology, the gains from technological change are unevenly distributed across the labor market. Therefore, a large body of literature has used the task framework to explain the polarization of employment and wages [1]. Figure 1 shows that employment polarization has occurred across industrialized countries. The share of employment in medium-skilled occupations has declined significantly in all countries, as this is where most of

[1] see Autor et al. (2006); Goos and Manning (2007); Goos et al. (2009, 2014); Michaels et al. (2014)

Figure 1.: Employment polarization of the labor market



Notes: High-skill occupations include jobs classified under the ISCO-88 major groups 1, 2, and 3. That is, legislators, senior officials, and managers (group 1), professionals (group 2), and technicians and associate professionals (group 3). Middle-skill occupations include jobs classified under the ISCO-88 major groups 4, 7, and 8. That is, clerks (group 4), craft and related trades workers (group 7), and plant and machine operators and assemblers (group 8). Low-skill occupations include jobs classified under the ISCO-88 major groups 5 and 9. That is, service workers and shop and market sales workers (group 5), and elementary occupations (group 9). Occupations in agricultural, fishery and mining are excluded. Source: OECD Employment Outlook 2017.

the routine jobs have been located. At the same time, employment has grown in both high- and low-skill occupations. However, this trend has been more pronounced for employment than for wages (Dustmann et al., 2009; Green and Sand, 2015).

The overall impact of technology on the labor market depends on the size of the displacement effect relative to the productivity and reinstatement effects. Gregory et al. (2022) estimate the effect of routine-biased technological change in Europe and find that the productivity and reinstatement effects can outweigh the strong displacement effect. However, the overall effect depends on the type of technology, the country setting and the level of analysis. For example, studies of the impact of robots on total employment find either positive effects (Adachi et al. (2024) for Japan), no effects (Dauth et al. (2021) for Germany), or negative effects (Acemoglu and Restrepo (2020) for the US).

As new technologies emerge, the range of tasks that can be automated expands (Brynjolfsson et al., 2018; Felten et al., 2021). Artificial intelligence (AI), an emerging but rapidly growing technology, is characterized by a higher degree of autonomy that allows for the automation of more complex tasks. Thus, AI has the potential to affect workers at higher levels of the income distribution (Webb, 2020). However, the labor market implications of AI are still difficult to predict (Autor, 2022). While early evidence shows no aggregate employment effects, there is evidence of positive employment effects at the establishment level and for higher skilled workers (Acemoglu et al., 2022; Peede and Stops, 2023). In addition, there is evidence that AI is changing the task structure of jobs (Peede and Stops, 2023).

The impact of technology on the content of tasks within occupations is as important as the impact of technology on the employment share between occupations (Atalay et al., 2020; Freeman et al., 2020). Within occupations, the share of routine tasks is declining, while non-routine cognitive and interactive tasks are becoming more important.[2] As a result, the adoption of new technologies is associated with increased skill requirements and the introduction of new skills.[3] Although workers can adjust their skills in response to labor demand, this happens only gradually (Acemoglu and Restrepo, 2018), resulting in skill mismatches (Deming and Noray, 2020; Modestino et al., 2023).

The task structure of jobs varies not only over time, but also between workers within the same occupation (Autor and Handel, 2013). While Deming and Kahn (2018) find that cognitive and interactive tasks are associated with higher posted wages within detailed job titles, Autor and Handel (2013) use survey data to show that task differences can explain individual-level wage differences. In addition, differences in the task content across demographic groups, such as gender and age, may predict differences in the wage returns to tasks (Black and Spitz-Oener, 2010; Cortes et al., 2020; Deming and Noray, 2020).

Female Labor Force Participation and Demographic Change

Technological change has been accompanied by two major trends: a significant increase in female labor force participation (Olivetti and Petrongolo, 2016) and demographic change characterized by population aging. The first trend, increasing female participation, has been observed across countries and is illustrated in Figure 2a by the evolution of the female employment-to-population ratio. Although the increase in female labor force participation started earlier in the United States and the United Kingdom, Germany and several other European countries have now almost caught up.

This evolution took place against a backdrop of changing social norms (Goldin, 2006) and was

[2] see Atalay et al. (2020); Deming and Kahn (2018); Deming (2017)
[3] see Acemoglu et al. (2022); Dillender and Forsythe (2022); Kalyani et al. (2023)

Figure 2.: Labor market trends

(a) Female employment-to-population ratio

(b) Old-age-dependency ratio

Notes: The female employment-to-population ratio corresponds to the proportion of a country's female population 15+ that is employed. Old-age dependency ratio, is the ratio of older dependents–people older than 64–to the working-age population–those ages 15-64. Data are shown as the proportion of dependents per 100 working-age population. Source: International Labour Organization (via World Bank) and World Bank.

accompanied by several developments, including a closing of the gender gap in education (Fortin et al., 2015), institutional changes that allowed for more flexible work arrangements (Bachmann and Felder, 2020; Fitzenberger et al., 2004), and medical innovations, that gave women control over their family planning (Goldin and Katz, 2002). In addition, the college premium created a pull factor for high-skilled women to enter the labor market, while creating demand for household production services at the lower end of the income distribution (Cerina et al., 2021). However, significant gender gaps remain, especially at the top of the income distribution, mainly due to occupational segregation by gender (Blau and Kahn, 2017) and fewer hours worked by women (Goldin, 2014).

Concurrently, shifts in the labor market due to technological change are potentially increasing women's labor market opportunities. Ngai and Petrongolo (2017) show that the rise of the service economy has contributed to an increase in women's wages and hours worked. In addition, studies have highlighted the increasing importance of social skills and women's comparative advantage in these skills (Cortes et al., 2023; Deming, 2017). While some studies show that task-biased technological change and a corresponding change in task prices contributed to a closing of the gender wage gap (Beaudry and Lewis, 2014; Black and Spitz-Oener, 2010; Yamaguchi, 2018), other studies only find a small effect of technological progress on the closing of the gender gap (Cortes et al., 2020; Storm, 2023).

The second trend, demographic change associated with population aging, is currently taking place in many OECD countries. Although a further increase in female participation will contribute to an increase in the labor supply, the overall labor supply is expected to decline as a result of demographic change, leading to a higher old-age dependency ratio (Gagnon, 2014). As shown in Figure 2b, the old-age dependency ratio has increased significantly since the 1990s, with Germany showing an even larger increase compared to the EU27 countries, the UK and the US.

As demographic changes reduce the overall labor supply and particularly affect the availability of young entrants to the labor market (Klinger and Fuchs, 2020). This demographic shift contributes to a further tightening of the labor market, as many developed countries are currently experiencing (Duval et al., 2022). As the labor market tightens, companies must either raise wages (Fuest and Jäger, 2023), intensify their recruitment efforts (Landais et al., 2018), or adjust their hiring standards (Lochner et al., 2021) in order to fill their positions. As a result, demographic change and labor shortages may impede the acceleration of technological progress. Technological progress tends to increase the need for new skills, especially digital skills (Braxton and Taska, 2023; Modestino et al., 2023), while a tighter labor market makes it harder for firms to find workers with these skills.

This dissertation

In my dissertation, I provide empirical evidence to contribute to a comprehensive understanding of how technology impacts the labor market, particularly examining how it intersects with increasing female labor force participation, demographic change and labor shortages.

In **Chapter 1** (co-authored by Ronald Bachmann, Piotr Lewandowski and Karol Madón), we analyze the impact of increasing robot exposure on job separation and job finding rates in Europe. In particular, we analyze the role of labor costs in explaining cross-country differences in the impact of robots. We also examine heterogeneities across different groups of workers. The research is motivated by mixed evidence on robots' impact on employment and the role of developmental differences (De Vries et al., 2020). However, country studies are not able to explore possible explanations for cross-country differences.

To this end, we combine worker-level data from the European Labor Force Survey with data on robot adoption from the International Federal of Robotic for the years 1998 to 2017. Moreover, the use of worker-level data allows us to control for worker characteristics and to examine heterogeneity at the individual level. While most studies focus on the impact of technology on aggregate employment, our research focuses on employment transitions, which provides information on the underlying mechanisms behind changes in unemployment and employment.

Overall, we find small negative effects of robot exposure on job separations, but no effect on job finding. There are significant cross-country differences, especially with respect to initial labor costs. Countries with average and lower labor costs experience more benign effects of robot exposure. In addition, routine workers as well as younger and prime-age workers in these countries benefit from the introduction of robots. In summary, our results provide evidence for the dominance of the productivity effect over the displacement effect and point to the complementarity between routine work and technology for Eastern European countries.

In **Chapter 2** (co-authored by Ronald Bachmann), we examine the impact of technological progress on the gender wage gap. We examine whether changes in the occupational structure as a result of technological change have had a different impact on women than on men and whether this has led to a reduction in the gender wage gap over the period 1984-2017 for Germany. We use a decomposition analysis to identify factors beyond technological change that contribute to the narrowing of the gender wage gap. The research is motivated by evidence indicating that women may benefit from technological change due to their differential exposure to automation (Black and Spitz-Oener, 2010) and their comparative advantage in social skills (Cortes et al., 2023), which are increasingly valued in the labor market (Deming, 2017).

For our analysis, we combine individual-level data from the German Socio-Economic Panel with data from the BIBB/BAuA Employment Survey, which provides detailed information on job tasks at the worker level. We find that women are increasingly employed in non-routine interactive and manual occupations. However, we find that the overall narrowing of the gender wage gap is primarily driven by a narrowing of the pay gap within occupations rather than between occupations. The decomposition analysis reveals a notable reduction in unexplained factors, which is consistent with a reduction in discrimination over time. While the analysis provides ambiguous results on the role of job tasks, it highlights the role of institutional factors such as part-time employment.

Our results suggest that changes in the occupational structure as a result of technological change have increased the representation of women in interactive and manual occupations. However, the sorting of women into these occupations and changes in tasks within occupations have not contributed significantly to the closing the gender gap.

In **Chapter 3** (co-authored by Eduard Storm), we focus on the labor market implications of AI. In this context, we examine the wage effects of the increasing demand for AI skills on workers and analyze its main drivers. To date, most studies on the impact of AI have focused on employment and labor demand (Alekseeva et al., 2021; Babina et al., 2024). There is evidence that AI has already changed job tasks and led to increased employment opportunities for high-skilled workers at the firm level, although without significant effects at the aggregate level (Acemoglu et al., 2022; Peede and Stops, 2023). Thus, our research is motivated by the scarcity of evidence on the wage effects of AI.

The analysis combines new German online job vacancy data with administrative data from the German Institute for Employment Research. First, we present descriptive evidence on the diffusion of demand for AI skills and document that demand for AI skills has increased substantially from 2017-21, diffused broadly across regions, but is only concentrated in few occupations. Second, we estimate the impact of AI on wages. While we use OLS as a baseline, we recognise endogeneity concerns arising from the non-random adoption of AI technologies. Therefore, we strengthen our OLS results with an instrumental variable approach. To address this, we develop a leave-one-out instrument that excludes demand for a worker's current occupation within their commuting zone.

To guide our analysis, we formulate hypotheses based on the Acemoglu et al. (2022) model. We distinguish between the displacement effect and the productivity effect of AI, and also offer tentative evidence on the reinstatement effect. Consistent with productivity-effects of AI, we document a positive relationship between AI skill demand at the occupation-region-year level and worker-level wages. We find that young, high-skilled workers with expertise in cognitive job tasks are main beneficiaries, while older workers experience wage losses. Moreover, we provide suggestive evidence that AI has introduced new tasks with positive implications for wages.

In **Chapter 4**, I examine whether firms adjust their job requirements in the face of increasing labor shortages by analysing the adjustment of skill requirements in online job advertisements. While I focus primarily on educational requirements, I also assess the impact of experience in a complementary analysis. In addition, I investigate whether firms respond by implementing alternative hiring strategies and examine variations across occupational categories and firm types. The paper is motivated by the increasing labor market tightness in Germany over the past decade, which is expected to be further exacerbated by demographic changes. As competition for skilled labor intensifies, firms can improve the likelihood of finding suitable candidates by increasing their recruitment efforts.

For the analysis, I use online job vacancy data for Germany from 2017 to 2023 to extract skill requirements using natural language processing, and use data from the German Federal Employment Agency to construct a measure of labor market tightness. The data are combined at the detailed regional and occupational levels, recognizing the importance of regional and occupational dimensions in identifying labor shortages. I analyze the relationship between skill requirements and labor market tightness using an OLS model and include a set of fixed effects and flexible time trends to account for level differences in labor market tightness and time trends across regions and occupations. The results of the empirical analysis show that the increase in labor market tightness is associated with a decrease in educational skill requirements. Moreover, I show that firms provide more training to medium-skilled workers, which suggest internal skill development. However, my complementary analysis shows mixed results for experience requirements. The heterogeneity analysis reveals significant variation across occupations and firm types.

The decline in skill requirements may exacerbate the mismatch of new hires, particularly with respect to technological advances. The adoption of new technologies is associated with increased skill requirements and the introduction of new skills (Modestino et al., 2023). While technological progress contributes to increasing labor shortages by changing demand across occupations and the task content within them, it can also be hampered by labor shortages that hinder further adoption and innovation due to a lack of skilled workers.

Bibliography

Acemoglu, D., Autor, D., Hazell, J., and Restrepo, P. (2022). Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics*, 40(S1).

Acemoglu, D. and Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review*, 108(6):1488–1542.

Acemoglu, D. and Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, 128:2188–2244.

Adachi, D., Kawaguchi, D., and Saito, Y. U. (2024). Robots and employment: Evidence from Japan, 1978-2017. *Journal of Labor Economics*, 42(2).

Alekseeva, L., Azar, J., Giné, M., Samila, S., and Taska, B. (2021). The demand for AI skills in the labor market. *Labour Economics*, 71:102002.

Atalay, E., Phongthiengtham, P., Sotelo, S., and Tannenbaum, D. (2020). The evolution of work in the United States. *American Economic Journal: Applied Economics*, 12(2):1–34.

Autor, D. (2022). The labor market impacts of technological change: From unbridled enthusiasm to qualified optimism to vast uncertainty. NBER Working Paper 30074, National Bureau of Economic Research.

Autor, D., Chin, C., Salomons, A., and Seegmiller, B. (2024). New frontiers: The origins and content of new work, 1940–2018. *The Quarterly Journal of Economics*, page qjae008.

Autor, D. H. and Handel, M. J. (2013). Putting tasks to the test: Human capital, job tasks, and wages. *Journal of Labor Economics*, 31(S1):S59–S96.

Autor, D. H., Katz, L. F., and Kearney, M. S. (2006). The polarization of the us labor market. *American economic review*, 96(2):189–194.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, 118(4):1279–1333.

Babina, T., Fedyk, A., He, A., and Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics*, 151:103745.

Bachmann, R. and Felder, R. (2020). Labour market transitions, shocks and institutions in turbulent times: A cross-country analysis. *Empirica*, 48(2):329–352.

Beaudry, P. and Lewis, E. (2014). Do male-female wage differentials reflect differences in the return to skill? Cross-city evidence from 1980–2000. *American Economic Journal: Applied Economics*, 6(2):178–194.

Black, S. E. and Spitz-Oener, A. (2010). Explaining women's success: Technological change and the skill content of women's work. *The Review of Economics and Statistics*, 92(1):187–194.

Blau, F. D. and Kahn, L. M. (2017). The gender wage gap: Extent, trends, and explanations. *Journal of Economic Literature*, 55(3):789–865.

Braxton, J. C. and Taska, B. (2023). Technological change and the consequences of job loss. *American Economic Review*, 113(2):279–316.

Brynjolfsson, E., Mitchell, T., and Rock, D. (2018). What can machines learn and what does it mean for occupations and the economy? *AEA Papers and Proceedings*, 108:43–47.

Cerina, F., Moro, A., and Rendall, M. (2021). The role of gender in employment polarization. *International Economic Review*, 62(4):1655–1691.

Cortes, G. M., Jaimovich, N., and Siu, H. E. (2023). The growing importance of social tasks in high-paying occupations: Implications for sorting. *Journal of Human Resources*, 58(5):1429–1451.

Cortes, G. M., Oliveira, A., and Salomons, A. (2020). Do technological advances reduce the gender wage gap? *Oxford Review of Economic Policy*, 36(4):903–924.

Dauth, W., Findeisen, S., Suedekum, J., and Woessner, N. (2021). The adjustment of labor markets to robots. *Journal of the European Economic Association*, 19(6):3104–3153.

De Vries, G. J., Gentile, E., Miroudot, S., and Wacker, K. M. (2020). The rise of robots and the fall of routine jobs. *Labour Economics*, 66:101885.

Deming, D. and Kahn, L. B. (2018). Skill requirements across firms and labor markets: Evidence from job postings for professionals. *Journal of Labor Economics*, 36(S1):S337–S369.

Deming, D. J. (2017). The growing importance of social skills in the labor market. *The Quarterly Journal of Economics*, 132(4):1593–1640.

Deming, D. J. and Noray, K. (2020). Earnings dynamics, changing job skills, and STEM careers*. *The Quarterly Journal of Economics*, 135(4):1965–2005.

Dillender, M. and Forsythe, E. (2022). Computerization of white collar jobs. NBER Working Paper 29866, National Bureau of Economic Research.

Dustmann, C., Ludsteck, J., and Schönberg, U. (2009). Revisiting the german wage structure. *The Quarterly journal of economics*, 124(2):843–881.

Duval, M. R. A., Duval, R., Ji, Y., Li, L., Oikonomou, M., Pizzinelli, C., Shibata, M. I., Sozzi, A., and Tavares, M. M. (2022). Labor market tightness in advanced economies. IMF Staff Discussion Notes No. 2022/001, International Monetary Fund.

Felten, E., Raj, M., and Seamans, R. (2021). Occupational, industry, and geographic exposure to Artificial Intelligence: A novel dataset and its potential uses. *Strategic Management Journal*, 42(12):2195–2217.

Fitzenberger, B., Schnabel, R., and Wunderlich, G. (2004). The gender gap in labor market participation and employment: A cohort analysis for West Germany. *Journal of Population Economics*, 17(1):83–116.

Fortin, N. M., Oreopoulos, P., and Phipps, S. (2015). Leaving boys behind: Gender disparities in high academic achievement. *Journal of Human Resources*, 50(3):549–579.

Freeman, R. B., Ganguli, I., and Handel, M. J. (2020). Within-occupation changes dominate changes in what workers do: A shift-share decomposition, 2005–2015. *AEA Papers and Proceedings*, 110:394–399.

Frey, C. B. and Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological forecasting and social change*, 114:254–280.

Fuest, C. and Jäger, S. (2023). Können höhere Löhne zur Überwindung des Fachkräftemangels beitragen? *Wirtschaftsdienst*, 103(4):253–258.

Gagnon, J. (2014). Demographic change and the future of the labour force in the EU27, other OECD countries and selected large emerging economies. In *Matching economic migration with labour market needs*. OECD.

Goldin, C. (2006). The quiet revolution that transformed women's employment, education, and family. *American economic review*, 96(2):1–21.

Goldin, C. (2014). A grand gender convergence: Its last chapter. *American economic review*, 104(4):1091–1119.

Goldin, C. and Katz, L. F. (2002). The power of the pill: Oral contraceptives and women's career and marriage decisions. *Journal of political Economy*, 110(4):730–770.

Goos, M. and Manning, A. (2007). Lousy and lovely jobs: The rising polarization of work in britain. *The review of economics and statistics*, 89(1):118–133.

Goos, M., Manning, A., and Salomons, A. (2009). Job polarization in Europe. *American Economic Review*, 99(2):58–63.

Goos, M., Manning, A., and Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review*, 104(8):2509–2526.

Green, D. A. and Sand, B. M. (2015). Has the canadian labour market polarized? *Canadian Journal of Economics/Revue canadienne d'économique*, 48(2):612–646.

Gregory, T., Salomons, A., and Zierahn, U. (2022). Racing with or against the machine? Evidence on the role of trade in Europe. *Journal of the European Economic Association*, 20(2):869–906.

Kalyani, A., Bloom, N., Carvalho, M., Hassan, T., Lerner, J., and Tahoun, A. (2023). The diffusion of new technologies. NBER Working Paper 28999, National Bureau of Economic Research.

Klinger, S. and Fuchs, J. (2020). Wie sich der demografische Wandel auf den deutschen Arbeitsmarkt auswirkt. In *IAB-Forum, IAB-Institute for Employment Research.*

Landais, C., Michaillat, P., and Saez, E. (2018). A macroeconomic approach to optimal unemployment insurance: Theory. *American Economic Journal: Economic Policy*, 10(2):152–181.

Lochner, B., Merkl, C., Stüber, H., and Gürtzgen, N. (2021). Recruiting intensity and hiring practices: Cross-sectional and time-series evidence. *Labour Economics*, 68:101939.

Michaels, G., Natraj, A., and Van Reenen, J. (2014). Has ict polarized skill demand? evidence from eleven countries over twenty-five years. *Review of Economics and Statistics*, 96(1):60–77.

Modestino, A. S., Burke, M. A., Sadighi, S., Sederberg, R., Stern, T., and Taska, B. (2023). No longer qualified? changes in the supply and demand for skills within occupations. Discussion Paper 16542, IZA.

Ngai, L. R. and Petrongolo, B. (2017). Gender gaps and the rise of the service economy. *American Economic Journal: Macroeconomics*, 9(4):1–44.

Olivetti, C. and Petrongolo, B. (2016). The evolution of gender gaps in industrialized countries. *Annual review of Economics*, 8:405–434.

Peede, L. and Stops, M. (2023). AI skills on the labour market. Mimeo.

Storm, E. (2023). Task returns and the gender pay gap. Ruhr Economic Papers 1021, RWI-Leibniz Institute for Economic Research.

Susskind, D. (2020). *A world without work: Technology, automation and how we should respond.* Penguin UK.

Webb, M. (2020). The impact of artificial intelligence on the labor market. *SSRN Electronic Journal.*

Yamaguchi, S. (2018). Changes in returns to task-specific skills and gender wage gap. *Journal of Human Resources*, 53(1):32–70.

1. The Impact of Robots on Labour Market Transitions in Europe*

Abstract: We study the effects of robot exposure on worker flows in 16 European countries between 2000-2017. Overall, we find small negative effects on job separations and no effects on job findings. We detect significant cross-country differences and find that labour costs are a major driver: the effects of robot exposure are generally larger in absolute terms in countries with relatively low or average levels of labour costs than in countries with high levels of labour costs. These effects are particularly pronounced for workers in occupations intensive in routine manual or routine cognitive tasks but are insignificant in occupations intensive in non-routine cognitive tasks. A counterfactual analysis suggests that robot adoption increased employment and reduced unemployment, especially in European countries with relatively low or average levels of labour costs, and that these effects were driven mainly by lower job separations.

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1.1. Introduction

The use of robots has multiplied during the last two decades. Between 2000 and 2017, robot exposure, as measured by the number of industrial robots per 1,000 workers, has quadrupled in Europe, and it has doubled in Germany, a European leader in robot adoption. In high-income countries, robot adoption has increased GDP, labour productivity, and wages (Graetz and Michaels, 2018). But it has also ignited fears, especially among policymakers and the general public, of considerable job losses.

However, the international evidence on the employment effects of robot exposure is mixed. Robot adoption has reduced total employment in the US (Acemoglu and Restrepo, 2020) but not in other highly industrialised countries such as Germany or Japan (Adachi et al., 2024; Dauth et al., 2021). It also appears that the employment effects of robots may depend on the development level. Robot adoption was associated with a decline in employment shares of jobs intensive in routine manual tasks in high-income countries but not in emerging or transition economies (De Vries et al., 2020). The reasons for such cross-country differences and the labour market mechanisms behind the aggregate employment effects of automation remain largely unexplored.

This paper fills this gap by investigating the impact of industrial robots on worker flows in Europe, paying particular attention to the role of labour costs for cross-country differences. We focus on worker flows as they constitute a key mechanism behind changes in employment and unemployment levels and are essential for worker welfare. For example, adjustment to robots through changes in the job separation probability affects workers' welfare very differently than adjustment through changes in the job finding rate: while job separations, in particular firings, often lead to immediate and potentially long-lasting earnings losses, the job finding rate is an important determinant of unemployment duration, which in turn implies a gradual loss of human capital and deteriorating labour-market prospects. Therefore, optimal policy responses differ strongly between these two cases. Worker flows are also a common short term labour market indicator that reacts almost immediately to shocks (Bachmann and Felder, 2020; Elsby et al., 2012), in contrast to long-term employment changes which have been the focus of most previous literature on automation (Acemoglu and Restrepo, 2020; Dauth et al., 2021).

We answer three main research questions: First, what was the effect of rising robot exposure on job separation and job finding rates in Europe, and what role did labour costs play in the observed cross-country differences? Second, how did the effects differ between worker groups? Third, how did automation-driven job findings and job separations contribute to changes in employment rates?

To answer these questions, we estimate labour market transition probabilities from employment to unemployment (a proxy for job separations and, hence, for job stability) and from unemployment to employment (a proxy for job findings) in 16 European countries. We use individual-level data from the European Union Labour Force Survey (EU-LFS), combined with annual data on robot exposure by country and sector from the International Federation of Robotics (IFR). To account for potential endogeneity in robot adoption, we use a control-function approach; and, as an instrument, the average robot exposure in comparable countries, which has been applied by, e.g., Acemoglu and Restrepo (2020)and Dauth et al. (2021). We control for potential confounders, such as general investment, participation in global value chains and trade, and labour demand shocks. As our analysis takes place at the industry-occupation level, we capture direct effects at firms adopting robots and indirect effects through spillovers which could occur, for instance, through the reallocation of output and workers to firms adopting robots (Acemoglu and Restrepo, 2020).

Conceptually, technological innovations can trigger a range of mechanisms beyond direct substitution of labour. They include reductions in prices and wages, new investments, introduction of new products and market expansion, increases in incomes and sectoral reallocations which jointly have an a priori ambiguous impact on the labour market (Calvino and Virgillito, 2018; Pianta, 2006; Vivarelli, 2014). While industrial robots seem to be a technology particularly conducive to labour substitution, their effects on employment and labour-market transitions are not clear-cut either. On the one hand, they can directly reduce employment as machines replace humans in performing specific tasks (the labour-saving effect). On the other hand, the product demand effect – i.e., an increase in activity through a productivity-enhancing technology – and the demand spillover effect – i.e., demand for other sectors' output resulting from higher value added and incomes in the technology-adopting sector – can increase employment (Gregory et al., 2022). Empirically, the positive impact of robots on productivity has been found in cross-country, sector-level studies (Graetz and Michaels, 2018) and firm-level studies (Acemoglu et al., 2020; Duan et al., 2023; Koch et al., 2021). Moreover, the product demand effect and the demand spillover effect tend to dominate over the labour-saving effect for routine-replacing technologies in Europe, increasing employment (Gregory et al., 2022).

Labour costs can play a vital role in shaping the labour market effects of labour-saving technologies, particularly industrial robots. As the price of robots is roughly uniform worldwide (Graetz and Michaels, 2018), the higher labour costs are, the more likely the substitution of labour with robots is, all other things being equal. Therefore, robot adoption is likely to have a weaker impact on job separation rates and job finding rates in countries with lower levels of labour costs than in countries with higher labour costs. Indeed, lower labour costs may explain why the effects of robot adoption on routine jobs have been more benign in emerging countries than in high-income countries (De Vries et al., 2020). To account for this mechanism, we interact robot exposure with labour costs at the beginning of the observation period. These initial labour costs are plausibly exogenous to the robot adoption during the observation period and are not affected by feedback effects from robot adoption to labour costs.

We find that, on average, robot exposure has a small and significant negative impact on the likelihood of job separation s, but has no effect on the likelihood of job finding. In addition, lower initial labour costs were generally associated with a more beneficial impact of robot adoption on labour market flows. In particular, in countries with initially low or average levels of labour costs, robot exposure reduced job separations more strongly.[1] Moreover, the effect of robot exposure on job findings was positive and significant in countries with low or average initial labour costs, but insignificant in countries with very low and very high initial labour costs. As explained in detail later, these small effects in countries with the lowest initial labour costs (such as Poland and Slovakia) likely reflect skilled workforce shortages that limited the scope of employment expansion driven by robot adoption associated with the rising role of these countries in European value chains (Altzinger and Landesmann, 2008).

To evaluate the heterogeneity in the effects of robot exposure on labour market flows, we focus on occupational tasks performed by workers, which are a crucial determinant of robots' substitutability of human labour. We apply widely-used categories of routine and non-routine cognitive, and routine and non-routine manual job tasks proposed by Acemoglu and Autor (2011) and distinguish occupational groups accordingly. We find more beneficial effects for workers in routine occupations than for workers in non-routine occupations. These are particularly

[1] In our sample, the lowest initial labour costs were recorded in the Central Eastern European countries that joined the EU in 2004, such as Poland, Slovakia, and Hungary; while the highest initial labour costs were recorded in the Nordic countries, the German-speaking countries, and Belgium.

pronounced for job separations where robots reduced separations amongst workers in routine manual and routine cognitive occupations. The increase of job findings in countries with medium labour costs occurred mainly among routine occupations. However, we also find a small positive effect in non-routine analytical and non-routine manual occupations. As we discuss in more detail in the conclusions, these results provide evidence to what extent job tasks matter for the substitutability of workers with robots, and the potentially important role of scale effects in shaping the labour market effects of automation in Europe.

We also find important differences between workers belonging to different age groups. In most countries, young and prime-aged workers benefited from robots, while the results for older workers are mixed. Robot exposure reduced job separations and increased job findings among young and prime-aged workers, except for countries with the highest levels of initial labour costs. For older workers, robots increased job separations and decreased job findings across all industries, but decreased job separations and had no impact on job findings in manufacturing.

Finally, using a counterfactual analysis, we assess the contributions of robot-driven job separations and hirings to changes in aggregate employment levels. We find that rising robot exposure increased aggregate employment levels in European countries by about 1-2% of the working-age population between 2004 and 2017. Our reduced-form estimation results reflect the sum of the abovementioned effects of robots: the labour-saving effect, the product-demand effect, and the demand-spillover effect. We show that lower job separations were the key driving factor behind the positive, aggregate employment effects of robot adoption in Europe.

Our paper makes the following contributions to the literature. First, we provide the first evidence on the flow mechanisms behind the aggregate employment effects of automation in a European cross-country setting. Up to now, the literature has mainly focused on employment stocks or structures, focusing either on regional (Acemoglu and Restrepo, 2020; Dauth et al., 2021) or worker-level (Bessen et al., 2023; Dauth et al., 2021; Domini et al., 2021; Koch et al., 2021) effects of robot exposure in specific countries, or have examined the effects of robotisation in a cross-country setting using industry-level data (Aksoy et al., 2021; De Vries et al., 2020; Klenert et al., 2023). Our results are consistent with country-specific findings on worker flows. For example, Domini et al. (2021) found that automation episodes in French manufacturing firms were associated with lower separation rates.

Second, we identify differences in (initial) labour costs as a driver of cross-country differences in the labour market effects of robot adoption. Previous cross-country studies of employment effects of automation (De Vries et al., 2020; Klenert et al., 2023) did not shed much light on the factors that may explain international differences. They used broad country categorisations and did not quantify the role of differences in countries' labour costs (or other factors), as we do here. At the same time, lower labour costs have been a key trigger of industrial development in peripheral countries (both in Europe and globally) and their integration in global value chains (Bellak et al., 2008; Milberg and Winkler, 2013), especially in highly-automated sectors such as the automotive industry (Grodzicki and Skrzypek, 2020). Our findings that the labour market impacts of industrial robots were more benign in European countries with lower labour costs align with arguments that robot investments in those countries were driven by modernisation and attempts to expand product lines rather than a need to reduce labour inputs (Cséfalvay, 2020; Jürgens and Krzywdzinski, 2009), suggesting dominant scale effects.

Third, we indicate age-related differences in the labour market impacts of robots. Our findings are consistent with arguments that young workers more familiar with emerging technologies benefit more from the adoption of new technologies (Cavounidis and Lang, 2020; Fillmore and Hall, 2021), which empirically were also highlighted by Albinowski and Lewandowski (2024).

Fourth, using our causal estimates of the impact of robots on labour market flows to indirectly calculate robots' contributions to changes in employment levels, we contribute to the literature focused on employment impacts of automation. We find a positive effect of robots on employment in several European countries, in line with the findings of Koch et al. (2021) for Spain, Dauth et al. (2021) for Germany, and Adachi et al., 2024 for Japan, and results of Gregory et al. (2022) for routine-replacing technologies more broadly. Our findings also complement Klenert et al. (2023) who found a positive aggregate employment effect of robots at the industry level in Europe and align with Fernández-Macías et al. (2021) suggestion that robots intensify the long-term trend of industrial automation rather than introduce a ground-breaking change in the scope of automation. They contrast, however, with results for the US that robots reduced employment and widened wage inequality (Acemoglu and Restrepo, 2020, 2022).

The remainder of the paper is organised as follows. In Section 2, we present our data, particularly the EU-LFS data containing the worker-level information and the data on robots from the International Federation of Robotics (IFR); and we provide descriptive evidence. In Section 3, we discuss measurements and our econometric methodology. In Section 4, we present and discuss our results. In Section 5, we summarise and conclude the discussion.

1.2. Data and Descriptive Evidence

1.2.1. Data Sources and Definitions

Our worker-level dataset is drawn from the European Labour Force Survey (EU-LFS) for the years 2000–2017 (Eurostat, 2019), a period of rapid robotisation in many industrialised countries. The EU-LFS includes information on all European Union member states. However, due to missings in key variables in EU-LFS and the lack of availability of other data discussed below for specific countries, our sample is limited to 16 countries: Austria, Belgium, the Czech Republic, Denmark, Finland, Germany, Greece, Hungary, Italy, Poland, Portugal, Slovenia, Spain, Sweden, Slovakia, and the United Kingdom.

The EU-LFS provides representative and harmonised information on individuals aged 15 years or older who live in private households. The EU-LFS data are available as repeated cross-sections. The respondents reported their labour market status during the month of the survey and one year earlier. Using this information, we follow Bachmann and Felder (2020) to measure transitions from one year to the next between particular labour market states (employment, unemployment, and non-participation) at an individual level. We classify a person as having made a transition from employment (unemployment) to unemployment (employment) if the person reported being employed (unemployed) one year before the survey and being unemployed (employed) in the month of the survey. However, we cannot account for employment transitions within that year. We compare these individuals to their employed (unemployed) counterparts in the year before the survey and the month of the survey. We exclude individuals who moved from and into non-participation.

The data on robots come from the International Federation of Robotics (IFR), which provides annual information covering the current stock and the deliveries of industrial robots across countries, by industry[2] and by application (e.g., assembling and disassembling, welding, laser cutting), and accounting for depreciation (IFR, 2017). The data are based on consolidated information collected by nearly all industrial robot suppliers worldwide. The IFR ensures that

[2]For a detailed description of the sectors covered, see Table 1.B.5 in Appendix 1.B

the data are internationally comparable and have high reliability. For the Western European countries, we use the data on robots from 2000 to 2016. For the Central and Eastern Europe (CEE) countries, data on robots are only available from 2004 onwards. As the stock of robots in CEE was negligible before 2004, this does not limit our analysis. According to the International Organization for Standardization (ISO 8373:201), an industrial robot is an "automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications". Moreover, an industrial robot usually operates in a series of movements in several directions to grasp or move something (ISO, 2012).

Apart from industry-level data on robots (International Federation of Robotics, 2017), we use data on GDP per capita, gross fixed capital formations in sectors, and gross value added from the EU KLEMS Growth and Productivity Accounts database. We construct yearly GDP per capita growth rates and merge them with a lag at the country level. We map data on investment (gross fixed capital formation) and gross value added to occupations and merge them with the EU-LFS data on the occupational level. We also control for participation in global value chains using data from the Research Institute on Global Value Chains (RIGVC UIBE, 2016). In addition, we account for trade flows by using total export data from the UN Comtrade database. These data are available at the commodity level, are assigned to industries using a crosswalk available on the webpage of the World Integrated Trade Solutions (World Integrated Trade Solutions, 2021), and are aggregated and merged with the EU-LFS data at the one-digit sector level.

To quantify workers' exposure to robots, we merge the EU-LFS data with the IFR data described above. To this end, we use harmonised information on the occupation (International Standard Classification of Occupations – ISCO) and the sector (Statistical Classification of Economic Activities in the European Community – NACE) of an individual, applying it to the current and the retrospective information. For the currently unemployed, we assign each individual to an occupation based on the last job performed before becoming jobless.

Merging the worker-level data from the EU-LFS with the industry-level data requires additional calculations to ensure the required granularity. The EU-LFS provides information on the economic sector at the one-digit NACE level. Such sectoral disaggregation is too broad for the precise measurement of robot adoption, as there are substantial differences in robot use between two-digit sectors within a given one-digit sector, particularly in manufacturing (International

Federation of Robotics, 2017). We, therefore, use the data on two-digit occupations contained in the EU-LFS together with external information on the distribution of occupations across sectors to assign robot adoption at the two-digit occupational level.

To obtain this more precise mapping of industry-level variables, we apply an occupation-industry matrix calculated using the distribution of two-digit occupations across two-digit sectors in a given country and time. We use data provided by Eurostat for the period 2000-2017 via the tailor-made extraction procedure.[3] We follow Ebenstein et al. (2014) and Baumgarten et al. (2013) to transform two-digit industry-level variables (Y_{sct}) into two-digit occupation-specific variables (Y_{oct}) according to:

$$Y_{o,s,c,t} = \begin{cases} \sum_{s=1}^{S} \frac{L_{o,s,c,t}}{L_{o,c,t}} Y_{s,c,t} \ if \ s \ \in S^E \\ 0 \ otherwise \end{cases} \tag{1.1}$$

where L_{osct} denotes the level of employment in occupation o, sector s, country c, and year t. We also use the broad industry classification in the EU-LFS dataset and define S^E as a set of sectors which are adopting robots according to IFR data. Thus, we differentiate between sectors adopting and not adopting robots. Using this approach, we can assign industry-specific information to each worker based on a two-digit level occupation and broad industry classification. In particular, it allows us to measure the exposure of a specific occupation (at the two-digit level) to robots. Importantly, we allow occupational exposure to robots to differ between sectors that adopt robots and those that do not. Thus, robot exposure of managers employed in manufacturing differs from exposure of managers employed in services.

To account for cross-country differences in the effects of robots, we focus on differences in initial labour costs in manufacturing (Eurostat, 2020). We transform labour costs (and GDP in a robustness check) into relative values by taking logs and deducting Slovenia's value, which is close to the average labour costs in our sample. We use data from 2004 because the Eurostat data on labour costs in CEE countries are available only from 2004 onwards. As the data on robots in these countries are also available from 2004 onwards, the variables to control for initial conditions capture differences in the first year for which all key data are available. We use GDP per capita as a robustness check, also using the Eurostat data. Table 1.A.1 in Appendix 1.A

[3] See *https://ec.europa.eu/eurostat/documents/1978984/6037342/EULFS-Database-UserGuide.pdf*; the service is available through the Eurostat user support at *https://ec.europa.eu/eurostat/help/support*. The same data and methodology were used by Aghelmaleki et al. (2022).

provides an overview of the relative labour costs and GDP per capita in 2004 across countries.

Finally, we classify workers into five groups according to the predominant task of their occupation: non-routine cognitive analytical, non-routine cognitive interpersonal, routine cognitive, routine manual, and non-routine manual physical (details in Table 1.B.6 in 1.B). In doing so, we follow Fonseca et al. (2018) and Lewandowski et al. (2020). First, we calculate the task content of occupations using the methodology of Acemoglu and Autor (2011), based on the Occupational Information Network (O*NET) data adapted to the European data by Hardy et al. (2018), who present methodological details.[4] Second, we allocate occupations to groups according to the task with the highest value. For instance, we classify an occupation as routine manual if the routine manual task intensity of that occupation is higher than the intensities of other task content measures; as routine cognitive if the routine cognitive task intensity is the highest; and so forth. The allocation of occupations to task groups is shown in Tables 1.A.3-1.A.4 in Appendix 1.A. We keep these allocations constant to ensure comparability and exogeneity to robot adoption across countries.

The descriptive statistics of the final estimation sample are presented in Table 1.A.2 in Appendix 1.A.

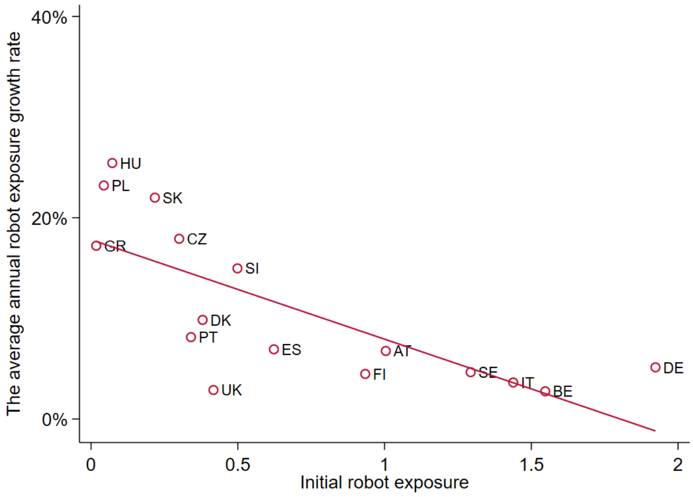
1.2.2. Descriptive Evidence

In the early 2000s (the beginning of our study period), there was significant cross-country variation in robot exposure (Figure 1.1). It ranged from virtually zero robots per 1,000 workers in Central and Eastern European countries (Hungary, Poland, Slovakia) and in Greece; to about two robots per 1,000 workers in Western European countries such as Belgium, Italy, and, in particular, Germany.

Between 2000 and 2017, robot exposure converged across European countries. The countries with the lowest initial level of robot exposure, such as Poland, Hungary, and Slovakia, experienced the highest average growth rate (about 25% per year); while the countries with initially high levels of robot exposure experienced lower growth rates. Overall, the correlation between initial robot exposure and its average growth rate over the observation period was strong and negative (-0.75), indicating considerable convergence in robot exposure across European coun-

[4] O*NET is a US dataset of occupational descriptors that has been commonly applied to European data (Fonseca et al., 2018; Goos et al., 2014; Hardy et al., 2018; Lewandowski et al., 2020), as the differences between occupational demands in the US and in European countries are small (Handel, 2012; Lewandowski et al., 2022).

Figure 1.1.: Initial robot exposure and the average robot exposure growth rate, by country



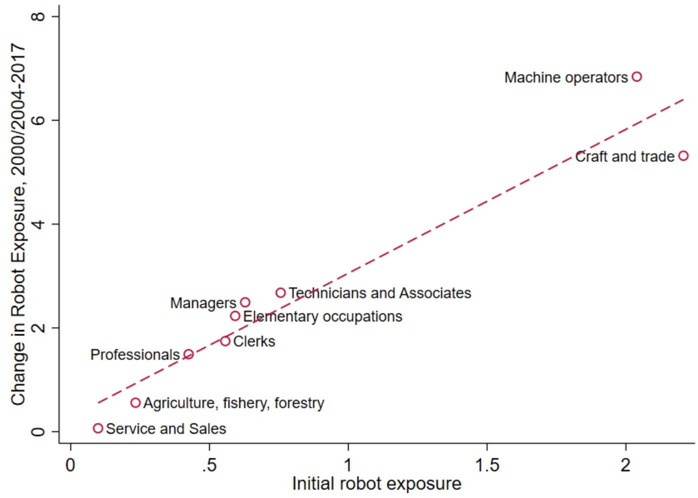
Note: Robot exposure – the number of robots per 1,000 workers. The detailed data on industrial robots start in 2000 for Denmark, Finland, Germany, Italy, Spain, Sweden, and the United Kingdom; in 2003 for Austria; in 2004 for Belgium, the Czech Republic, Hungary, Poland, and Slovakia; and in 2005 for Greece, Portugal, and Slovenia. The robot exposure growth rate refers to the average annual growth rate from the initial date to 2017. – Source: authors' calculations based on the IFR data.

tries. However, we observe differences in robot applications across countries. In countries with low initial labour costs, robots tend to be used for welding and soldering, while in countries with relatively high initial labour costs to handle operations and tend machines (see Figure 1.D.1). Nonetheless, there is no a priori evidence suggesting that some robot applications are affecting labour markets differently than other robot applications.

Robot exposure also differed strongly between occupation groups (Figure 1.2). Initial robot exposure was by far the highest for machine operators (2.04) and craft and trade workers (2.21). While technicians and associates had a medium initial level of robot exposure (0.76), the level was lowest for service and sales (0.10) and agriculture, fishery, and forestry workers (0.23). In contrast to robot exposure across countries, which converged over time, the exposure across occupations diverged: it increased in all occupations, but the correlation between initial robot exposure and the average robot exposure growth rate by occupation was strong and positive (0.96). The two occupational groups that initially faced the highest exposure levels also had the highest growth rates of exposure (e.g. machine operators: 6.84; craft and trade workers: 5.32). In the remaining occupations, the growth rate was much lower (e.g., 2.68 for technicians and associates and 0.07 for service and sales workers).

Turning to the labour market variables, at the country level, there was a moderately negative correlation between the changes in the job separation rate and the robot exposure growth rate

Figure 1.2.: Initial robot exposure and the average robot exposure growth rate, by occupation group



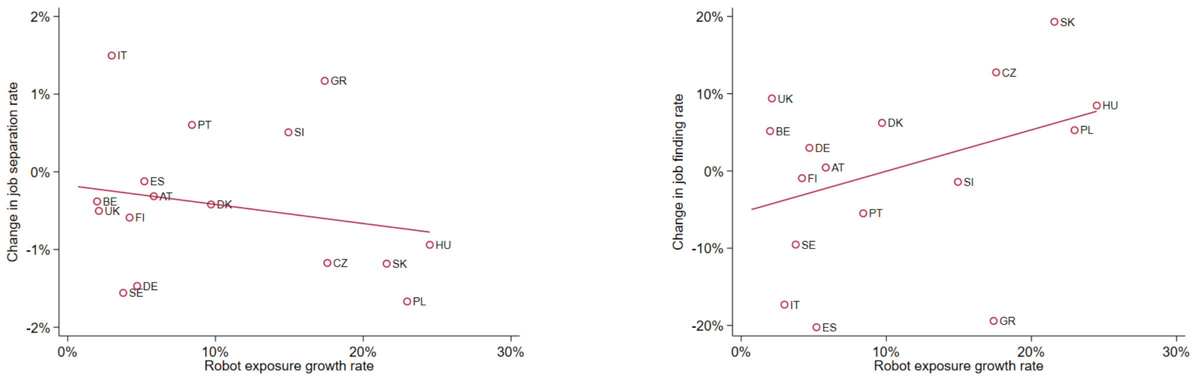
Note: Robot exposure – the number of robots per 1,000 workers. The detailed data on industrial robots start in 2000 for Denmark, Finland, Germany, Italy, Spain, Sweden, and the United Kingdom; in 2003 for Austria; in 2004 for Belgium, the Czech Republic, Hungary, Poland, and Slovakia; and in 2005 for Greece, Portugal, and Slovenia. The robot exposure growth rate refers to growth from the initial date to 2017. The figures displayed refer to averages by occupation groups across all countries. For the change in robot exposure by occupation group and country, see Figure 1.D.2 in Appendix 1.D. – Source: authors' calculations based on the EU-LFS and IFR data.

-0.24, see Figure 1.3).[5] Thus, in countries with a stronger increase in robot exposure, job stability has remained constant or even improved. There is also a positive correlation between the changes in the job finding rates and the robot exposure growth rates (0.37, see Figure 1.3), which means that in countries with a stronger increase in robot exposure, the chances of finding a job improved more. Different country clusters partly drive these patterns. First, a group of CEE countries recorded high robot exposure growth rates and a relatively strong reduction in job separation rates and increases in job finding rates. Second, a cluster of countries with robot exposure growth rates, such as France and several Southern European countries, recorded increases in job separation rates and declines in job finding rates.

Thus, overall, the descriptive statistics show a positive association between the growth in robot exposure and favourable labour market developments: i.e., lower job separation rates and higher job finding rates. However, these descriptive results may reflect reverse causality or common trends, especially because robot adoption may be highest in the sectors with the

[5]To avoid year-specific fluctuations, we take the average of the transition rates during the first three years and the last three years for which the data are available. Then we take the difference. Job separation and finding rates display strong variation between countries over time, with cyclical fluctuations playing an important role (see also Bachmann and Felder, 2020). In our sample, the average job separation rate ranged from 1.3% in Sweden to 5.0% in Spain, while the average job finding rate ranged from 30% in Greece to 54% in the UK (see Figure 1.D.3 in the appendix).

Figure 1.3.: Changes in job flow rates and average robot exposure growth rates



(a) Job separations (b) Job findings

Note: The changes in the job flow rates are calculated based on the differences between the three-year averages of the last three years and the first three years for which both IFR and EU-LFS data are available. The first three years are 2000-2002 for Denmark, Finland, Germany, Italy, Spain, Sweden, and the United Kingdom; 2003, 2004, and 2006 for Austria; 2004-2006 for Belgium, the Czech Republic, Hungary, Poland, and Slovakia; and 2005-2007 for Greece, Portugal, and Slovenia. The last three years are 2015-2017. For the average job flow rates by country, see Figure 1.D.3 in Appendix 1.D. – Source: authors' calculations based on the EU-LFS and IFR data.

highest productivity and the best labour-market prospects. This would lead to a spurious correlation between robot adoption and beneficial labour-market developments. In the following, we investigate the causal effects of robots on labour market transitions using within-country, between-sector differences in robot exposure, as well as instrumental variables.

1.3. Methodology

1.3.1. Estimation Framework and Instruments

We focus on two key labour market flows: (1) job separations (being employed in year $t-1$ and unemployed in year t) and (2) job findings (being unemployed in year $t-1$ and employed in year t).[6] Our outcome variables are indicator variables equal to one if a given flow occurs and equal to zero if it does not.

Following Graetz and Michaels (2018) and Acemoglu and Restrepo (2020), we calculate robot exposure as the number of robots per thousand workers at the two-digit sector level ($R_{s,c,t}$):

$$R_{s,c,t} = \frac{ROB_{s,c,t}}{EMP_{s,c,1995}} \tag{1.2}$$

[6]We have to exclude workers transitioning from employment into inactivity and from inactivity into unemployment because the EU-LFS data do not include information about the last occupation or sector of employment of inactive individuals.

where $ROB_{c,s,t}$ is the total stock of industrial robots, and $EMP_{c,s,1995}$ is employment (in thousands of workers) in sector s, country c, and year t. We use employment levels from 1995 – i.e., before our study period – as denominators. This ensures that changes over time result only from changes in the number of robots and are independent of changes in employment (which could be endogenous to robot exposure).

To estimate the causal effects of robot adoption, we need to account for the potential endogeneity of robot exposure to labour market outcomes. This could, for instance, be the case if worker shortages lead to an increase in the relative price of labour relative to capital, and firms react by investing in industrial robots. We, therefore, use an instrumental variables strategy, generalising the "technology frontier" instrument previously applied by Acemoglu and Restrepo (2020) and Dauth et al. (2021).[7] We instrument the robot exposure in country c, sector s, and year t with the average robot exposure in most advanced European economies ($I_{c,s,t}$). For each of the 11 Western European countries in our sample, we use average robot exposure from other countries. This average robot exposure is computed from the 10 European countries for which we have robot data, omitting the country for which the instrument is computed.[8] For each of five Eastern European countries in our sample, we instrument robot exposure with the average robot exposure in the 11 Western European countries for which robot data are available. Instrumented robot exposure is thus given by the formula:

$$I_{s,c,t} = \frac{\sum_{c \neq k}^{C,\ k\ \in C} \sum_{s}^{S} \frac{ROB_{s,k,t}}{EMP_{s,k}^{1995}}}{C},\ where\ C = \begin{cases} 11\ if\ c\ \in E \\ 10\ if\ c\ \in W \end{cases} \tag{1.3}$$

where $ROB_{k,s,t}$ stands for the total stock of industrial robots in country k (*country* $k \neq$ *country* c), sector s and year t and $EMP_{k,s}^{1995}$ for the employment level in thousand workers in country k and sector s in (1995). C is the number of countries in a particular group.

We use the definition of the robot stock and of the instrument defined by equations 1.2 and 1.3 and use the sector-occupation mapping (see equation 1.1) to map robot exposure at the sectoral level to individual workers (for details, see *Technical details* in Appendix 1.C).

[7] Examples of studies instrumenting robot adoption in European economies with adoption in peer economies include Anelli et al. (2021), Damiani et al. (2023), Doorley et al. (2023), and Nikolova et al. (2024).

[8] Our sample includes five Eastern European countries (E): the Czech Republic, Hungary, Poland, Slovenia, and Slovakia; and 11 Western European countries (W): Austria, Belgium, Denmark, Finland, Germany, Greece, Italy, Portugal, Spain, Sweden, and the United Kingdom. For instance, the instrument for Austria is calculated as the average robot exposure in Belgium, Denmark, Finland, Germany, Greece, Italy, Portugal, Spain, Sweden, and the United Kingdom. The instrument for each Eastern European country is calculated as the average across all 11 Western European countries.

As a baseline model, we estimate probit regressions of the following form:

$$\Pr\left(\text{flow} = 1|X\right)_{i,o,s,c,r,t} = F\left(R_{o,s,c,t-1}, X_{it}, M_{o,c,t-1}, T_{s,c,t-1}, C_{c,t-1}, B_{r,t-1}, \rho_s, \delta_t, \mu_c, \mu_c \times \tau\right) \tag{1.4}$$

where $Pr(flow)_{i,o,s,c,r,t}$ is the likelihood of a given worker flow (eu or ue). Flow $eu(ue)$ indicates that a person i, in occupation o, sector s, country c, region r made a transition from employment (unemployment) in year $t-1$ to unemployment (employment) in year t.

Our main variable of interest is $R_{o,s,c,t-1}$ – robot exposure in occupation o, in sector s, country c in the previous year.[9] In all regressions, we account for individual characteristics (X_{it}) such as gender, age, education, and native or migrant worker status. We also add industry group (ρ_s) and year (δ_t) fixed effects to control for potential changes across years and industries that are common to all countries. For industries, we follow Dauth et al. (2021) and consider manufacturing and six industry groups outside of manufacturing: agriculture and mining, utilities, construction, general services, business services, public services and education. We also add country fixed effects (μ_c) and country-specific linear trends ($\mu_c \times \tau$) to account for country-specific differences and trends over time. Robot exposure data are merged with the EU-LFS data at the country-occupation-industry level (sectors with and without industrial robots, according to International Federation of Robotics, 2017). Hence, the variance used for identification is the difference in robot exposure between occupations within a country and industry group.[10]

To control for macroeconomic conditions, we include a vector of several macro indicators ($M_{o,c,t-1}$) : sectoral gross value added, the ratio of investments to the gross capital formation (see Stehrer et al., 2019), and we account for the effects of globalisation using sector-specific measures of participation in global value chains proposed by Wang et al. (2017). We transform two-digit industry indicators into two-digit occupation-specific variables according to equation 1.1. We also control for lagged GDP growth at the country level ($C_{c,t-1}$), for country-specific trade flows at the sector level ($T_{s,c,t-1}$), especially growth in exports, and labour demand shocks at the regional level (NUTS2) ($B_{r,t-1}$) calculated with the Bartik (1991) method.

[9] For those employed in year $t-1$ and in year t, we assign robot exposure based on the occupation performed in t, but using the value of robot exposure in year $t-1$. For those employed in year $t-1$ and unemployed in year t, we assign robot exposure based on the last occupation performed before becoming jobless, using the value of robot exposure in $t-1$. For those unemployed in year $t-1$ and in year t, we assign robot exposure based on the last occupation performed before becoming jobless, using the value of robot exposure in year $t-1$. For those unemployed in year $t-1$ and employed in year t, we assign robot exposure based on the occupation performed in t, but using the value of robot exposure in year $t-1$.

[10] We also estimated models without industry fixed effects, and obtained results in line with our baseline results presented in the paper. These additional results are available upon request.

As we are particularly interested in reasons for cross-country differences, we allow the effect of robots to vary between countries at different development levels. To this end, we use two measures of the initial conditions of a country (L_c): labour costs in 2004, in our main specification; and GDP per capita in 2004 as a robustness check.[11] We interact these measures with robot exposure. Therefore, the main specification of our model is an augmented version of equation 1.4:

$$\Pr\left(\text{flow} = 1|X\right)_{i,o,s,c,r,t} = F(R_{o,s,c,t-1}, R_{o,s,c,t-1} \times L_c, R_{o,s,c,t-1} \times (L_c)^2, \\ X_{i,t}, M_{o,c,t-1}, T_{s,c,t-1}, C_{c,t-1}, B_{r,t-1}, \rho_s, \delta_t, \mu_c, \mu_c \times \tau) \quad (1.5)$$

where all variables are the same as in equation 1.4, and in addition, we interact country-specific labour costs in 2004, L_c with robot exposure ($R_{o,c,t-1}$). We implement the IV specification with a control function approach (Aghelmaleki et al., 2022) with instrumental variables described in the previous subsection. This approach allows for the estimation of marginal effects when using interaction terms.[12]

To implement our instrumental variable approach, we use the control function method which is a limited information maximum likelihood approach and follows a two-step procedure. In the first step, we regress all exogenous variables – including the instruments – on the endogenous variable. In the case of N endogenous variables, we estimate N first-stage regressions. In the second step, we include residuals obtained from the first stage as control variables in the original equation to eliminate endogeneity (Wooldridge, 2015). Applying this method to our baseline specification, all exogenous variables, including the instrument, are regressed on our robot exposure variable in the first stage. For the second stage, we predict the residual of the first stage and include this as an additional regressor in equation 1.4 and 1.5 . This approach allows us to isolate the changes in exposure driven by technological progress and simultaneously remove occupation-specific shocks that affect robot adoption and the probability of transitioning out of or into a particular occupation. Our results can be interpreted as the average causal effect

[11] We use 2004 labour costs as this is the first year for which labour costs are available. Moreover, five out of the six Central and Eastern Europe in our sample joined the EU in 2004. The labour costs are a proxy for the relative price of robots and labour. Still, they are not a proxy for the share of potentially automatable jobs: the cross-country correlation between the level of initial labour costs and the employment share of routine occupations is only 0.15. At the same time, the cross-country differences in average labour costs in Europe are quite persistent, the correlation between their 2004 and 2016 values is 0.97. Hence, the 2004 labour costs are a solid proxy for relative prices of robots and labour over the period studied.

[12] See Petrin and Train (2010) for a discussion of the control function approach for non-linear (including discrete choice) models, and Bachmann et al. (2014) for an application to labour market transitions.

of robot exposure on the job separation likelihood for those employed and on the job finding likelihood for those unemployed during the study period.[13]

1.3.2. Counterfactual Analysis

To assess the economic significance of estimated effects, we perform a counterfactual historical analysis. We calculate counterfactual scenarios of labour market flows and the employment levels that these flows imply. In the counterfactual scenario, we keep robot exposure constant in each country and sector from 2004 onwards. This means that new robot installations would have only compensated for the depreciation of robot stock and the aggregate changes in the labour force.

The counterfactual analysis proceeds in four steps (see Section 2 in Appendix 1.C for the detailed methodology used to calculate the counterfactual). First, we use the estimated coefficients from 1.4 and actual values of all variables to predict job separation (EU) and job finding (UE) likelihoods. Second, we use the same coefficients and the counterfactual values of robot exposure to calculate the counterfactual flow likelihoods. Third, we use the predicted and the counterfactual flow likelihoods from the first two steps to recursively calculate each country's predicted and counterfactual employment levels until 2017. To do so, we use the actual employment levels in 2004 as the starting point. Fourth, we calculate the effect of robot exposure on employment as the relative difference between the counterfactual and the predicted scenarios for each country and year.

1.4. Econometric Results

In this section, we present our econometric results, first for all workers, then for workers belonging to different task and age groups. Next, we present the counterfactual analysis to assess the economic significance of the impact of robot exposure on worker flows and their contributions to the resulting changes in employment rates. Finally, we show robustness checks.

[13]While the short-term effects of robots may be affected by potential selection effects (workers may avoid entering occupations heavily exposed to robots), they are unlikely to affect our findings. First, firm-level evidence from European countries shows that robot-adopting firms tend to grow faster and pay better than similar firms not adopting robots (Bessen et al., 2023; Koch et al., 2021). Second, investments in automation tend to be bulky and sporadic (Domini et al., 2021), so it is difficult for workers to anticipate their future exposure to robots. Third, our results show that job findings, which would be the driver of selection effects, are much less affected by robots than job separations. Finally, our analysis of cumulative impacts combines the results for job separations and job findings and therefore considers potential selection effects.

1.4.1. The Impact of Robots on Labour Market Transitions in Europe and the Role of Labour Costs

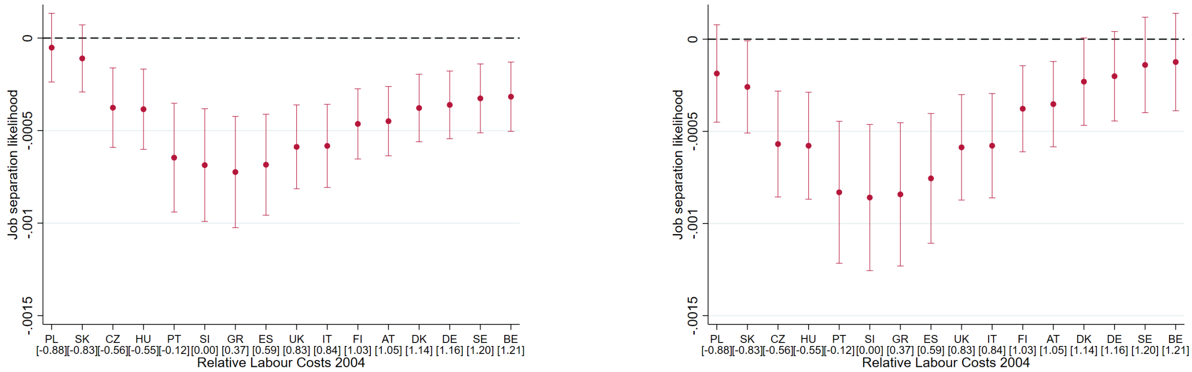
We start by investigating the causal effects of robot exposure on job separations using our baseline specification, equation 1.4. We report the coefficients of interest (Table 1.1), followed by the marginal effects of robot exposure (Figure 1.4), which allow for an interpretation of the effect sizes.

Table 1.1.: The effect of robot exposure on the likelihood of job separation

	(1) Probit	(2) CF	(3) Probit	(4) CF
A: All Sectors				
Robot Exposure	-0.003**	-0.005***	-0.011***	-0.012***
	(0.001)	(0.001)	(0.002)	(0.003)
Robot Exposure X Labour Costs			-0.006***	-0.005***
			(0.001)	(0.001)
Robot Exposure X (Labour Costs)^2			0.011***	0.008***
			(0.002)	(0.002)
Country FE	Yes	Yes	Yes	Yes
Linear time trend	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No. of Observations	11.8 M	11.8 M	11.8 M	11.8 M
Kleibergen-Paap F-statistic		408 872.3		18 537.4
B: Manufacturing				
Robot Exposure	-0.001	-0.006***	-0.013***	-0.014***
	(0.001)	(0.002)	(0.003)	(0.004)
Robot Exposure X Labour Costs			-0.005***	-0.003*
			(0.001)	(0.002)
Robot Exposure X (Labour Costs)^2			0.014***	0.011***
			(0.003)	(0.004)
Country FE	Yes	Yes	Yes	Yes
Linear time trend	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No. of Observations	2.6 M	2.6 M	2.6 M	2.6 M
Kleibergen-Paap F-statistic		197 835.2		10 947.6

Note: The table presents the estimated coefficients of the probit and control function (CF) regressions. Standard errors (in brackets) are clustered at the occupation-year level. *** p<0.01, ** p<0.05, * p<0.1. Individual-level controls: age group, education group, gender, and native/non-native status. Aggregate-level controls: global value chain participation, gross value-added, the ratio of investment added to gross value-added, GDP growth, regional labour demand shocks, and growth in exports. For CF, robot exposure is instrumented using robot exposure in the Western European countries in the sample. For the full specification, see Table 1.B.1 in Appendix 1.B. For the first stage regressions of model (4), see Table 1.B.3 in Appendix 1.B.– Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

Figure 1.4.: Marginal effects of robot exposure on the likelihood of job separation



(a) All Sectors

(b) Manufacturing

Note: The figures show the marginal effects of robot exposure on the probability of transitioning from employment to unemployment for all sectors (A) and for manufacturing (B) based on regressions presented in Table 1.1, columns (2) and (4). The vertical lines represent the 95% confidence intervals. Robot exposure is instrumented using the average robot exposure in the Western European countries in the sample. Countries on the x-axis are ranked according to the initial labour cost (in parentheses) (for details, see Table 1.A.1). Figure 1.B.1 in the appendix presents the marginal effects with the linear labour costs scale on the x-axis. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

In the probit estimation without instruments, we find a significant negative effect of robot exposure on the likelihood of job separation (Table 1.1, column 1).[14] The IV results using the control function approach double the size of this effect (column 2 of Table 1.1): i.e., robot exposure reduces the job separation rate, which implies an increase in job stability.[15] Accounting for interactions between robot exposure and countries' initial labour costs (equation 1.5), we find a noticeable heterogeneity in this size depending on labour costs (columns 3 and 4 of Table 1.1). The estimated interaction term between robot exposure and countries' initial levels of labour costs suggests a non-monotonic and nonlinear relationship between job separation likelihood and robot exposure (columns 3 and 4, respectively).

The importance of initial labour costs is visible in the marginal effects of robot exposure on job separations by country.[16] We do so for our preferred specification, including the interaction of robots with labour costs, and display the results in Figure 1.4, with countries ordered according to their initial labour costs. The negative effect of robot exposure on job separations was much more pronounced for countries with average levels of labour costs (Figure 1.4). In particular, in

[14]The detailed results of the full specification are included in Tables 1.B.1 (for job separations) and 1.B.2 (for job findings) in the appendix. Clustering standard errors at the sector-year or occupation-country-year level does not affect the interpretation of our result- see Figures 1.D.10 and 1.D.11 in the appendix.

[15]The results of the first stage of the estimation are presented in Table 1.B.1 in the appendix. The Kleibergen-Paap F-statistic shows that the instrument is strong, meaning that it is a good predictor of actual robot exposure.

[16]We use the estimated quadratic fit pertaining to the initial labour costs (Table 1.1). For the sake of presentation, we use the values of labour costs recorded in particular countries to calculate the marginal effects of robot exposure conditional on them; and for the figures, we rank countries according to the value of their initial labour costs. Figure 1.B.1 in the appendix presents the marginal effects with the linear labour costs scale on the x-axis.

the country with an average level of initial labour costs – Slovenia – the marginal effect of robot exposure amounted to a reduction in the likelihood of job separation of -0.07 pp (the average job separation rate in our sample was 4 pp). In countries with labour cost levels in 2004 that were at least double the level in Slovenia – i.e., the level of labour costs in Germany – the effect of robot exposure was half the size (-0.04 pp).

Figure 1.4 also reveals a U-shape relationship between the effects of robot exposure and labour costs. In the countries with the lowest initial labour costs, namely Central Eastern European countries, the effects were also half the size (about -0.04 pp in Hungary and the Czech Republic) or even weaker (Poland and Slovakia) than in countries with medium labour costs. We attribute these weak effects in countries with the lowest labour costs to country-specific factors that counterbalanced the positive employment impact of low labour costs. First, the adoption of automation technologies tends to increase skill requirements (Chun, 2003; Goldin and Katz, 2010), but CEE countries specialised (both across and within sectors and occupations) in routine-intensive jobs (Hardy et al., 2018; Lewandowski et al., 2022) with lower skill requirements than in Western European countries, especially in manufacturing (Krzywdzinski, 2017). In CEE countries, skill shortages and mismatches were identified as crucial constraints on firm growth despite low labour costs (Sondergaard et al., 2012).[17]

Consequently, firms in CEE countries might have struggled to benefit fully from these investments, especially in terms of hiring, despite low labour costs. Second, in CEE countries, robot adoption primarily followed greenfield investment and integration into global value chains (Cséfalvay (2020)). The introduction of robots and other modern technologies was largely driven by modernisation and expansion of product ranges in CEE plants rather than the need to reduce labour intensity and labour costs (Jürgens and Krzywdzinski, 2009). It led to considerable growth in robot exposure but was driven by sectors that grew almost from scratch. As the robot exposure shock was thus substantial but concerned a relatively small segment of the economy, the overall effect on job separations was low in CEE countries.[18]

To quantify the economic importance of these effects, we use the estimated marginal effects to

[17]Sectoral studies of the highly automated automotive industry show that firms in CEE countries were less likely to move to more advanced tasks than similar firms in Germany, and therefore displayed a lower demand for skills in the aftermath of automation (Krzywdzinski (2017)). Cross-country evidence confirms the relative upgrading of occupational structures of supplier countries, such as CEE countries, in highly automated sectors over time (Fana and Villani (2022)).

[18]Slovakia recorded the largest robot exposure growth, driven by the automotive sector. In 1995 (we use 1995 employment levels to normalise robot exposure), the automotive industry had accounted for only 0.8% of employment in Slovakia. By 2017, its employment share increased four-fold, but was still below 3.5%.

assess the contribution of increasing robot exposure to the likelihood of a job separation between the early 2000s (average for 2000-2002) and the mid-2010s (average for 2014-2017). The effects were quantitatively relevant. On average, robot exposure in our sample increased by 1.44 units (between 2004 and 2017) decreasing the job separation likelihood by 0.06 pp. In the meantime, the average job separation rate declined by 0.15 pp. Hence, the change in the likelihood associated with robot exposure totalled 43%. However, country-specific results are more nuanced. For instance, in Germany, growth in robot exposure by 2.8 units (between 2004 and 2017) reduced the likelihood by 0.1 pp, while the probability of job separation decreased by 1.4 pp over the same period. Thus, the change associated with the increase in robot exposure amounted to 7% of the observed change. In some CEE countries, such as Slovakia, which experienced one of the greatest increases in robot exposure in the EU (by 10.50 units in manufacturing and by 2.6 units in total economy), the effects attributed to this factor were even more pronounced, as they amounted to 14% to the recorded change in job separations. We perform a systematic assessment of the contributions of robot exposure to employment in all countries in our sample in subsection 1.4.3.

We re-estimate our models on the subsample of workers in manufacturing, i.e., the sector with the highest robot usage. While this yields very similar results to those for the total economy (Table 1.1, Panel B; Figure 1.4, Panel B), the effects for manufacturing are slightly stronger in most countries. This aligns with intuition, as robot exposure is the largest in manufacturing. Therefore, the direct impacts of robot exposure are more substantial in manufacturing than in the entire economy, leading to higher marginal effects when analysing manufacturing only.

Next, we study the effect of robot exposure on the likelihood of job finding in European countries. Again, we start with the baseline specification (equation 1.4). We find that, on average, robot exposure did not affect job findings (Table 1.2, column 2).[19] However, as for job separations, we find important heterogeneity between more and less-developed countries concerning job findings. Once we account for the initial labour costs, we find that the effect of robot exposure on the likelihood of finding a job was significant and positive at the average level of initial labour costs (column 4 of Table 1.2). The coefficients on the interactions between robot exposure and initial labour costs (level and squared) suggest a non-linear relationship.

The marginal effects plotted by country reveal an inverse U-shape relation between labour

[19] Again, the instrument is strong, as indicated by the Kleibergen-Paap F-statistic (see Table 1.B.2 in the appendix).

costs and the effect of robot exposure on job finding (Figure 1.5): the positive impact was the largest in the countries with a medium level of labour costs, such as Slovenia (about 0.42 pp); but was close to zero or insignificant in the countries with the lowest initial labour costs in our sample, i.e., Poland and Slovakia. The results for the countries with the lowest labour costs likely result from the same factors discussed for job separations, i.e. skill shortages. In the countries with the highest labour costs, i.e., Denmark, Germany, Sweden, and Belgium, the estimated effect on the likelihood of job finding was negative (about 0.1 pp).

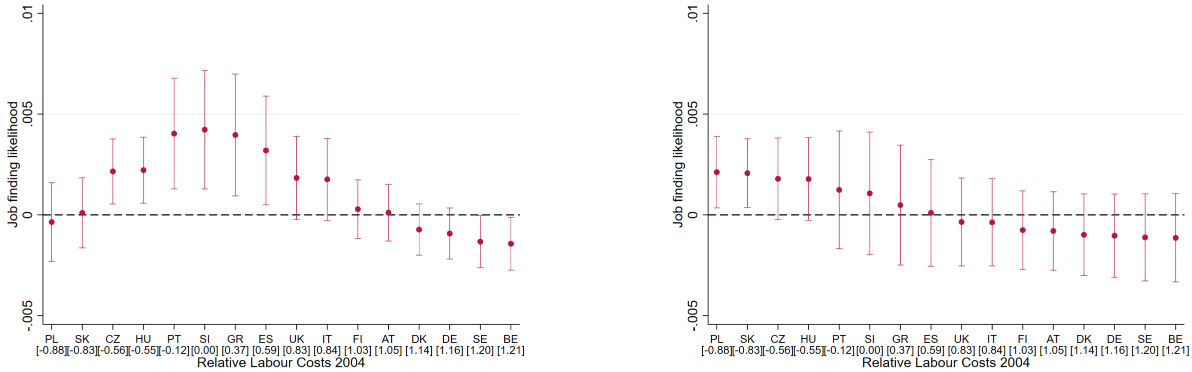
Table 1.2.: The effect of robot exposure on the likelihood of job finding

	(1) Probit	(2) CF	(3) Probit	(4) CF
A: All Sectors				
Robot Exposure	-0.002	0.002	0.018***	0.011***
	(0.001)	(0.001)	(0.003)	(0.004)
Robot Exposure X Labour Costs			0.008***	0.003
			(0.002)	(0.002)
Robot Exposure X (Labour Costs)^2			-0.022***	-0.012***
			(0.003)	(0.004)
Country FE	Yes	Yes	Yes	Yes
Linear time trend	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No. of Observations	1.3 M	1.3 M	1.3 M	1.3 M
Kleibergen-Paap F-statistic		27 783.8		3 714.4
B: Manufacturing				
Robot Exposure	0.000	0.002	0.005	0.003
	(0.001)	(0.002)	(0.003)	(0.004)
Robot Exposure X Labour Costs			0.001	-0.004*
			(0.002)	(0.002)
Robot Exposure X (Labour Costs)^2			-0.006	-0.001
			(0.003)	(0.004)
Country FE	Yes	Yes	Yes	Yes
Linear time trend	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
No. of Observations	0.26 M	0.26 M	0.26 M	0.26 M
Kleibergen-Paap F-statistic		14 791.2		2 457.2

Note: The table presents the estimated coefficients of the probit and control function (CF) regressions. Standard errors (in brackets) are clustered at the occupation-year level. *** p<0.01, ** p<0.05, * p<0.1. Individual-level controls: age group, education group, gender, and native/non-native status. Aggregate-level controls: global value chain participation, gross value-added, the ratio of investment added to gross value-added, GDP growth, labour demand shocks, and growth in exports. For CF, robot exposure is instrumented using robot exposure in the Western European countries in the sample. For the full specification, see Table 1.B.2 in Appendix 1.B. For the first stage regressions of model (4), see Table 1.B.4 in Appendix 1.B.– Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

We use the estimated effects to quantify the economic effects of increasing robot exposure. The average increase in robot exposure by 1.44 units corresponds to an increase in the job finding

Figure 1.5.: Marginal effects of robot exposure on the likelihood of job finding



(a) All Sectors (b) Manufacturing

Note: The figures show the marginal effects of robot exposure on the probability of transitioning from unemployment to employment for all sectors (a) and for manufacturing (b) based on the regressions presented in Table 1.2, columns (2) and (4). The vertical lines represent the 95% confidence intervals. The robot exposure is instrumented using robot exposure in the Western European countries in the sample. Countries on the x-axis are displayed in ascending order of initial labour cost (in parentheses). Figure 1.B.1 in the appendix presents the marginal effects with the linear labour costs scale on the x-axis. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

likelihood by 0.17 pp, despite the overall decrease in this likelihood by 2.54 pp. However, the effect differs across countries. The Czech Republic is an example of a CEE country that had low levels of labour costs in 2004 and recorded substantial increases in robot exposure between 2000 and 2017 (by 8.7 units in manufacturing and 2.4 units in total economy). This translates into an almost 0.5 pp increase in the likelihood of finding a job, equivalent to 30% of the increase recorded over this period. While, according to our estimates, in some most developed countries, the growth of robot exposure reduced the likelihood of finding a job, the effect is minor. For instance, an increase in robot exposure by 1.7 units in Sweden reduced this likelihood by 0.2 pp, equivalent to 4% of the recorded reduction in this likelihood.

Combined with the effects on job separations, the effects on job findings suggest different net effects on employment in various groups of countries. In the less developed Central Eastern European countries, the effect of robot exposure on employment was likely positive because of the reduced likelihood of job separation and the increased or insignificant likelihood of job finding. However, in most developed countries, the net effect was ambiguous because of the reduced likelihood of job separation and finding, negatively affecting labour market dynamics and turnover. We later formalise the analysis of robot exposure's aggregate consequences via labour market flows.

As a robustness check, we again re-estimate our model for a sub-sample of manufacturing workers. The results are noisy – they are slightly positive in countries with the lowest level of labour costs (Poland and Slovakia) and insignificant in other countries (Table 1.2, Panel B, and Figure 1.5, Panel B). However, later we will show that the job separation channel of the effects of robots is quantitatively more relevant than the job-finding channel. The comparison of the results for job findings for all sectors and manufacturing also indicates that the effects are less pronounced in the manufacturing sector. This is likely to be caused by a demand spillover effect, i.e. higher labour demand in the service sector, e.g. for the maintenance of robots, which has also been stressed by Dauth et al. (2021).

1.4.2. Heterogeneity according to Job Tasks and Age

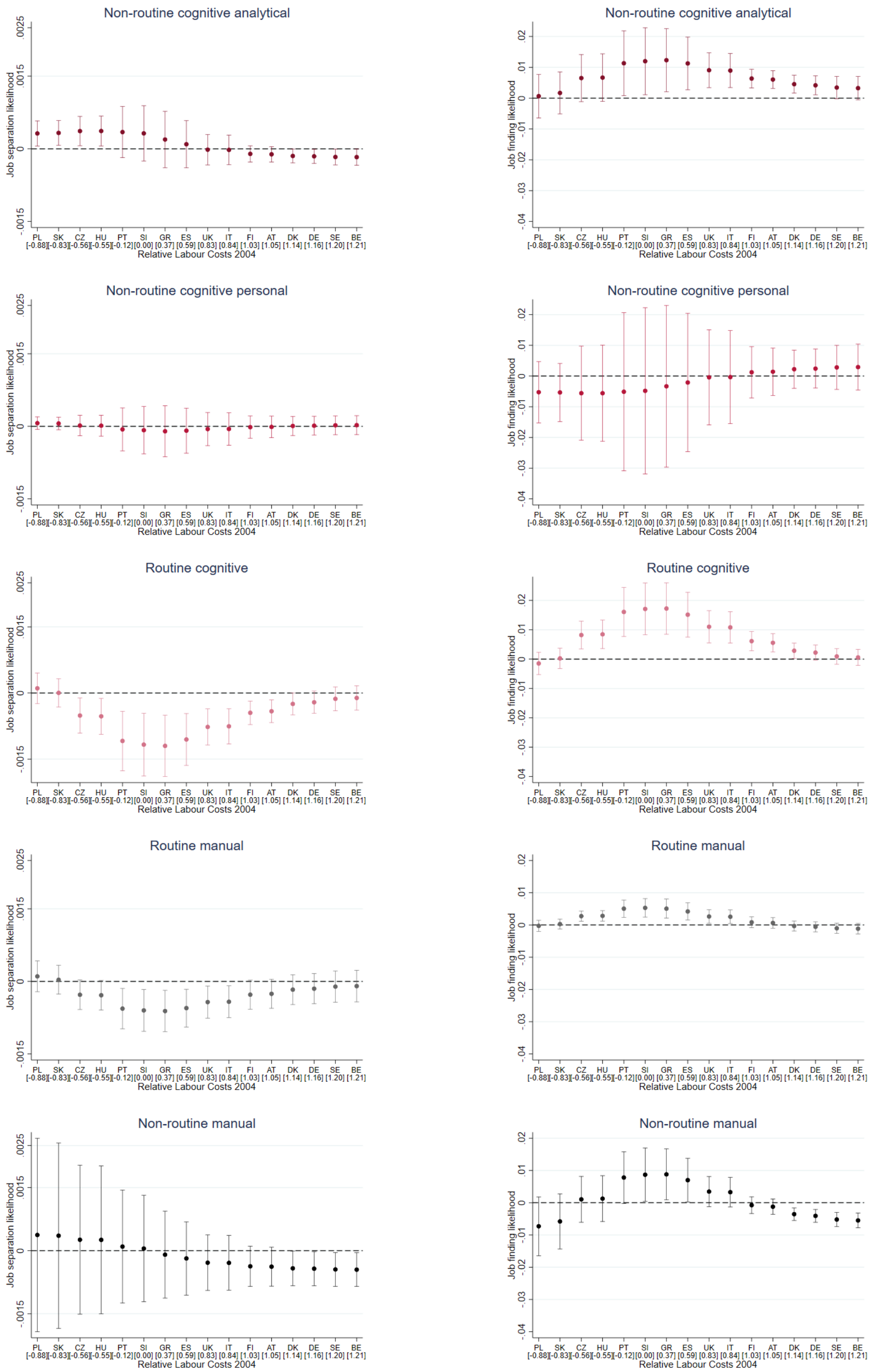
The effects of robot exposure are likely to differ between worker groups for at least three reasons. First, the substitutability of workers by robots depends strongly on the tasks they perform. Second, workers are likely to differ in their ability to adapt to technological change. Third, job-specific human capital or labour market regulations may lead to differences between workers of different age groups.

In order to examine whether the effects of robot exposure differ by job task, we estimate model (5), including an indicator variable (and interactions) for five occupational groups distinguished according to the dominant job task: routine cognitive (RC), non-routine cognitive analytical (NRCA), non-routine cognitive personal (NRCP), routine manual (RM), and non-routine manual (NRM). The allocation of occupations to task groups follows Lewandowski et al. (2020) (see data section and Tables 1.A.3-1.A.4 in Appendix 1.A for details). We focus on marginal effects from the model with interactions between robot exposure, initial labour costs (level and squared) and task dummy. We present the estimated coefficients and those from a model without interactions in Tables 1.D.1-1.D.2 in Appendix 1.D.

In countries with average levels of initial labour costs, the effect of robot exposure on job finding was slightly positive among RM workers (e.g. plant and machine operators, assemblers) and NRCA workers and positive among RC workers (e.g. associated professionals, clerks). These effects are sizable, at around 0.005, 0.012 and 0.018, respectively (Figure 1.6, right panel). The effect on job findings among NRM workers was positive in countries with average initial labour costs (0.009) and negative in countries with high initial labour costs (-0.005). For job separations, the effect of robot exposure was negative among RC and RM workers in countries with average

Figure 1.6.: Marginal effects of robot exposure on the likelihood of job separations and finding, by task groups

(a) Job separation (b) Job finding



Note: Marginal effects of robot exposure on the likelihood of job separation and on the likelihood of job finding at different development levels measured by labour costs in 2004 for different task groups. The vertical lines represent the 95% confidence intervals. The robot exposure is instrumented using robot exposure in the Western European countries in the sample. Countries on the x-axis are displayed in ascending order of initial labour costs (in parentheses). For regression estimates, see Tables 1.D.1-1.D.2 in Appendix 1.D. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, UIBE GVC, and O*NET data.

and low levels of labour costs and among NRM workers in countries with high levels of labour costs (Figure 1.6, left panel). Therefore, our results suggest that higher robot exposure improved job prospects in routine jobs in countries with average initial labour costs, particularly in Central and Eastern Europe, but also in some Southern European countries. While such an effect on routine workers may be surprising, it is worth noting that robot adoption in CEE countries primarily resulted from FDI and the integration of plants into global value chains (Cséfalvay, 2020). Hence, rising robot exposure was driven by expanding sectors rather than introducing new technologies in existing plants, a typical pattern in the most advanced economies. This improved the labour market prospects of CEE workers in RC and NRM occupations. Indeed, in countries with high initial labour costs, the effect of robot exposure on the likelihood of job flows among RM and RC workers was mainly insignificant.

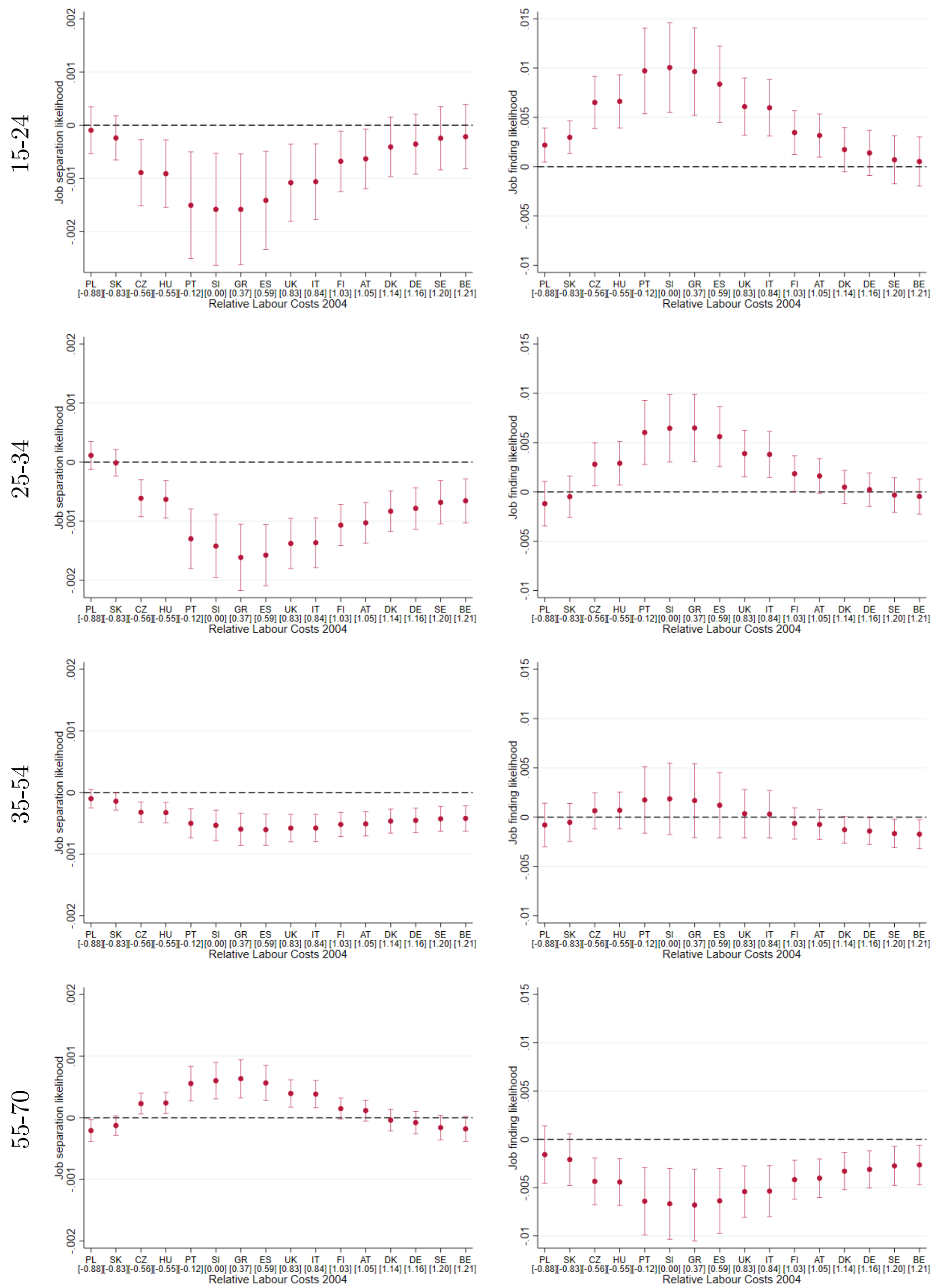
We also investigate the heterogeneity of the effects of robot exposure by worker age. There are two main arguments for why the impact of technology can differ between younger and older workers. First, technological change can reduce returns to old skills related to technology that become obsolete and increase returns to new skills related to emerging technology (Fillmore and Hall, 2021). Older workers are more likely to possess outdated skills, and their expected returns from investing in new skills are lower than younger workers. Accordingly, older workers can be more affected by technological change. Second, older workers are more likely to benefit from insider power and, as such, may be more protected from changes than younger workers, who are often outsiders or labour market entrants. Indeed, there is evidence that the de-routinisation of work in Europe has affected younger workers to a larger extent (Lewandowski et al., 2020) and that industrial robots in Germany have reduced the labour market prospects of younger workers (Dauth et al., 2021).

We find that robot exposure significantly reduced the likelihood of job separation for young workers (aged 25-34), prime-age workers (aged 35-54) and the youngest workers (aged 15-24) in most countries in our sample (Figure 1.7, left panel and Table 1.D.3 in Appendix 1.D).[20] However, exposure to robots increased the probability of job separation for older workers (aged 55-70) in countries with an average level of labour costs. For manufacturing (Figure 1.D.9 in Appendix 1.D), robot exposure significantly reduced job separations for all age groups, also for older workers, in countries with average labour costs, and to a lesser extent in countries with

[20]For marginal effects of robot exposure on the likelihood of job separation and job finding by age group in manufacturing, see Figure 1.D.9 in the appendix.

Figure 1.7.: Marginal effects of robot exposure on the likelihood of job separations and finding, by age group in manufacturing

(a) Job separation (b) Job finding



Note: Marginal effects of robot exposure on the probability of job separation and job finding at different development levels measured by labour costs in 2004. The vertical lines represent the 95% confidence intervals. The robot exposure is instrumented using robot exposure in the Western European countries in the sample. Countries on the x-axis are displayed in ascending order of initial labour cost (in parentheses). Robot exposure is instrumented using robot exposure in the Western European countries in the sample. For regression estimates, see Tables 1.D.3 and 1.D.4 in Appendix 1.D. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data low labour costs. However, we find insignificant effects for workers in high labour cost countries and for young workers. The marginal effect of robot exposure on the job finding likelihood was positive for young and prime-age workers in countries with an average level of labour costs (Figure 1.7, right panel, and Table 1.D.4 in Appendix 1.D). We find adverse effects on the job finding likelihood for older workers in most countries. Within manufacturing, the positive effects on job finding are even more pronounced for young (aged 25-34) and prime-age workers (aged 35-54) for countries with average labour costs, but coefficients for the youngest and oldest workers are insignificant.

Overall, robot exposure was beneficial for young workers as it reduced job separations and increasing job findings especially in countries with average labour costs. Prime-age workers also benefited from exposure to robots, especially in manufacturing. In contrast, the effects for older workers are mixed. While older workers in countries with average labour costs faced higher job separations and lower job findings, they experienced increased job stability in manufacturing. This indicates that older workers can benefit from the productivity-enhancing effects of robots by staying in manufacturing, but that they are less able to benefit from demand-spillover effects outside of manufacturing than younger workers. This may be related to the differences in skill sets: new technologies tend to reduce returns to skills that older workers have (Fillmore and Hall, 2021). Moreover, a shorter time to benefit from investment in new skills discourages older workers from learning these new skills (Cavounidis and Lang, 2020).

1.4.3. Implications for Employment and Mechanisms

In this subsection, we assess the economic impact of rising robot exposure on labour market flows and how they contributed to employment changes in European countries. To this end, we use the estimated coefficients from equation 1.5 (Tables 1.1-1.2) to calculate counterfactual trajectories of labour market flows and the resulting employment rates. We assume that in each country, robot exposure remained at the level recorded in 2004. We compare these trajectories with the actual evolution of the relevant labour market variables.

This analysis suggests that the rising robot exposure increased employment levels in most European countries. If the level of robot exposure had remained at the level recorded in 2004, in all CEE countries except for Poland, employment in 2017 would have been lower (and unemployment would have been higher) by about 1.0-2.5% of the working-age population (equivalent to 1.0-2.5 pp of the employment rate, Table 3). These effects were the largest in Slovakia (2.5% by 2017) and the smallest in Slovenia and Hungary (0.5-0.7% by 2017). In southern European countries, but Greece, the contribution of robots is smaller, but noticeable (0.3-1.0% of the working-age population). Overall, our counterfactual simulations show that an increase in robot adoption led to a rise in total employment by about 800 thousand additional jobs across all countries in our sample, which amounts to 0.47% of total employment. This suggests that the adoption of robots led to an expansion of the firms and sectors adopting automation technologies, which, in turn, translated into higher labour demand. Similar findings at the firm level were presented for France by Domini et al. (2021) and Acemoglu et al. (2020), and for Spain by Koch et al. (2021).

Table 1.3.: The estimated cumulative contribution of robots to employment between 2004 and 2017, with sub-contributions of job separations and job findings (in % of working-age population)

	Cumulative effect on employment (% of working-age population)	Of which: Job separatio	Job finding	Residual
Poland	-0.01	0.00	0.00	0.00
Sweden	0.02	0.02	0.00	0.00
United Kingdom	0.06	0.06	0.01	0.00
Belgium	0.08	0.09	-0.01	0.00
Denmark	0.09	0.10	-0.01	0.00
Greece	0.12	0.11	0.00	0.00
Germany	0.14	0.17	-0.02	0.00
Italy	0.25	0.21	0.03	0.00
Finland	0.28	0.23	0.05	0.00
Spain	0.45	0.36	0.08	0.00
Slovenia	0.47	0.38	0.08	0.01
Austria	0.66	0.63	0.03	0.00
Hungary	0.72	0.57	0.15	0.01
Portugal	1.03	0.93	0.10	0.00
Czech Republic	1.74	1.51	0.19	0.05
Slovakia	2.54	2.50	0.03	0.00

Note: Calculations based on model (4) from Table1.1 and Table 1.2. To asses the contributions of particular channels to the overall effect we utilize the decomposition method proposed by Fujita and Ramey (2009) (see Section 1.C in Appendix 1.Cfor technical details.) The residual indicates the difference between the counterfactual scenario (total effect) and the sum of semi-counterfactual scenarios (contributions of particular flows) which arises because the simulations are calculated recursively. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, UIBE GVC, and OECD data.

Finally, we decompose the overall contribution of rising robot exposure to employment into the sub-contributions of job separations and job findings. In all 16 countries studied, the contribution of job separations was larger than that of job findings, in many cases noticeably so (the contribution of job findings is negative in some countries, Table 1.3). Hence, improved job stability appears to be a key mechanism behind the labour market effects of robot adoption in Europe.

1.4.4. Robustness Checks

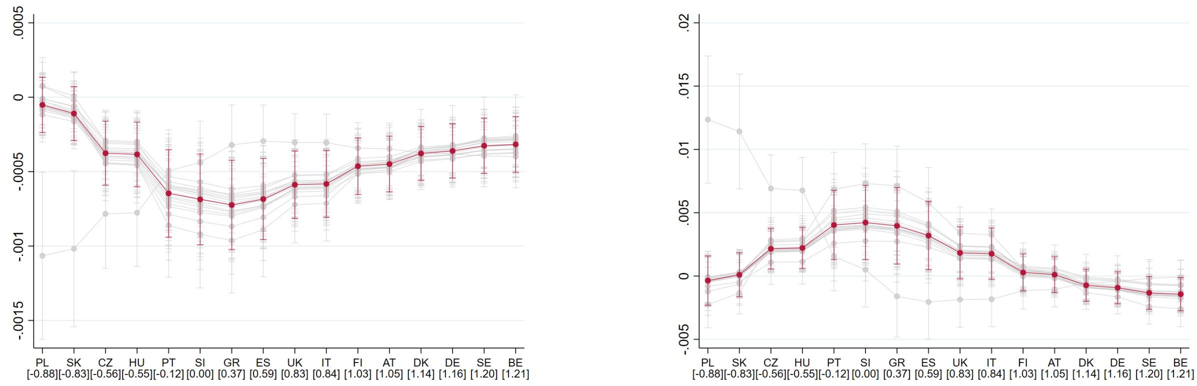
We conduct several robustness checks to test the validity of our regression results. First, to check whether any specific countries do not drive our results, we run 16 additional regressions, excluding one country at a time (Figure 1.8). Point estimates from all these regressions are within confidence intervals from our baseline specifications, apart from the regressions estimated on a subsample without Slovakia. Excluding Slovakia makes the results stronger for Central and Eastern European countries with the lowest initial level of labour costs, but it does not affect the results for other countries, including the most robot-exposed economies, such as Germany and Belgium. Slovakia recorded particularly large increases in robot exposure, but starting from very low levels and mostly due to the automotive sector.[21] Thus, the associated changes in overall labour market outcomes in Slovakia were moderate. As a result, the exclusion of Slovakia strengthens the estimated effects of automation, especially for job separations, in similar countries with low initial labour costs.

Second, we only include country fixed effects instead of country fixed effects and country-specific time trends. For job separations, only including country fixed effects does not affect our results. The coefficients of interest in the preferred specification increase slightly in absolute terms and remain sizeable and significant (Table 1.4, columns 1 and 3, and Figure 1.D.4 in Appendix 1.D). For job findings, the coefficients of interest remain similar in size in the specification with labour costs interaction and become significant and positive in the specification without interaction. However, as shown in the previous section, the overall impact of robots on employment is mostly through the job separation channel. Hence, the minor change in the job-finding likelihood leaves our overall results intact.

Third, we exclude variables from our baseline regressions that may be influenced by robot exposure and may be bad controls, particularly value-added and gross fixed capital formation. This does not affect our results (Table 1.4, columns 2 and 4, and Figure 1.D.5 in Appendix 1.D).

[21] In Slovakia, the robot exposure in the automotive industry was close to zero in 2004, but soared to over 280 robots per 1000 workers in 2016. No other country witnessed such a massive growth in robot exposure in any sector (the automotive industry in the Czech Republic recorded the second largest increase, by 95 robots per 1000 workers). At the same time, the automotive industry in Slovakia accounted for only 1.8% of total employment in 2004 and 3.2% of total employment in 2016.

Figure 1.8.: The effects of robot exposure on the likelihood of the flows for reduced sample regressions



(a) All Sectors

(b) Manufacturing

Note: Red lines represent the marginal effects of robot exposure on the probability of transitioning from employment to unemployment (left panel) and unemployment to employment (right panel) for the baseline regressions using the full country sample (Figures 1.4-1.5). Each grey line represents the results obtained from separate regressions, omitting one country at a time from the sample. If a particular country is excluded from the sample, we calculate the marginal effect for this country based on its labour cost value. For example, even if Germany is omitted from the regression, we calculate the marginal effect for Germany using its labour cost value (1.16) and present it in Table 1.A.1. Countries on the x-axis are displayed in ascending order of initial labour cost (in parentheses). The vertical lines represent the 95% confidence intervals. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, IFR, Eurostat, UN Comtrade, and UIBE GVC data.

Fourth, we re-estimate our models using the level of GDP per capita in 2004 instead of the 2004 labour cost index as a control for the cross-country differences in the initial development level. The results confirm the findings from our baseline specification for both job separations and job findings (Table 1.D.4 and 1.D.5, and Figure 1.D.6 and 1.D.7 in Appendix 1.D). Fifth, we use the percentiles of robot exposure instead of actual values of robot exposure as our variable of interest, in line with the literature (e.g. Graetz and Michaels, 2018).[22] The estimated marginal effects are qualitatively similar (Table 1.D.7 and 1.D.8, and Figure 1.D.8 in Appendix 1.D). Sixth, we test whether the results are robust to the use of alternative clustering specifications. Our results do not change when we apply alternative clustering by occupation, year and country (Figure 1.D.10) and by sector and year (Figure 1.D.11).

Fifth, we estimate linear probability models instead of probit models to facilitate a comparison between models and other studies in the literature. This does not change our results. The marginal effects of both models are almost the same as in the case of the probit estimation (Figures 1.D.12 and 1.D.13).

[22]The percentiles are defined based on sectors with non-zero values of robots.

Table 1.4.: The effect of robot exposure on the likelihood of job finding - robustness checks

Job separation	(1) CF	(2) CF	(3) CF	(4) CF
Robot Exposure	-0.008***	-0.008***	-0.013***	-0.013***
	(0.002)	(0.002)	(0.003)	(0.003)
Robot Exposure X Labour Costs			-0.003***	-0.002
			(0.001)	(0.001)
Robot Exposure X (Labour Costs)^2			0.007***	0.007***
Country FE	Yes	Yes	Yes	Yes
VA and GFCF	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Job finding	(1) CF	(2) CF	(3) CF	(4) CF
Robot Exposure	0.005***	0.006***	0.016***	0.018***
	(0.001)	(0.001)	(0.004)	(0.004)
Robot Exposure X Labour Costs			0.003	0.002
			(0.002)	(0.002)
Robot Exposure X (Labour Costs)^2			-0.015***	-0.016***
			(0.004)	(0.004)
Country FE	Yes	Yes	Yes	Yes
VA and GFCF	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Note: The table presents the estimated coefficients of the control function (CF) regressions. Standard errors (in brackets) are clustered at the occupation-year level. Individual-level controls: age group, education group, gender, and native/non-native status. Aggregate-level controls: global value chain participation, GDP growth, labour demand shocks, and growth in exports. VA and GFCF stand for value added and gross fixed capital formations. Robot exposure is instrumented using robot exposure in Western European countries. *** p<0.01, ** p<0.05, * p<0.1. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

1.5. Conclusion

In this paper, we have investigated the effects of robot exposure on worker flows in 16 European countries between 2000–2017. We aimed to answer three research questions. First, what were the effects of rising robot exposure on job separation and job finding rates in Europe, and what role did labour costs play in this context? Second, how did the effects differ between workers performing different tasks and differing in age? Third, what consequences did the effects of robot exposure on worker flows have for employment?

To answer these questions, we estimated worker flow probabilities using individual-level data from the EU-LFS and data from the IFR, which provides yearly information on robot exposure at the industry level. We explicitly included labour costs to analyse their role in the effects of robot exposure on worker flows. To account for the potential endogeneity of robot adoption, we used a control-function approach with instruments in the spirit of Acemoglu and Restrepo

(2020) and Dauth et al., 2021.

Our findings can be summarised as follows. First, overall, we found minor beneficial effects of robot exposure on job separations and no effect on job findings. We detected significant cross-country heterogeneities that depend on initial labour costs. On the one hand, in countries with relatively low or average levels of labour costs, higher robot exposure led to lower job separation rates, and, thus, improved job stability, to a much larger extent than in countries with high levels of labour costs. On the other hand, in countries with relatively low or average levels of labour costs, higher levels of robot exposure led to increased job findings.

Overall, our results support a negative link between labour costs and the employment effects of robots – the lower the labour costs, the more positive the employment outcomes. However, the relatively weak effects in countries with the lowest initial levels of labour costs (Central Eastern European countries such as Slovakia and Poland) induce a U-shaped relationship between labour costs and the effects of robot exposure on the transition probabilities. We think they result from another force, namely skill shortages in CEE countries (Krzywdzinski, 2017; Sondergaard et al., 2012), which constrained employment responses to robot adoption, i.e. productivity-improving investments that also raised skill requirements. Our results are, therefore, generally in line with the Marshallian laws of labour demand, which state that labour is more likely to be substituted by other factors of production if labour costs are relatively high.

Second, we found important differences between workers performing different job tasks. Perhaps surprisingly, we generally found more beneficial effects for routine workers than for non-routine workers. This result was most pronounced in countries with average initial labour costs. We found minor effects of robot exposure on labour market flows among workers in non-routine cognitive occupations. Our results contradict the notion that routine tasks are always strongly substituted by robots. Instead, our results point to the importance of labour costs for the substitutability of workers performing different job tasks by robots: i.e., in countries with average levels of labour costs, workers performing routine tasks seem to be complements of, rather than substitutes for, robots. This result is weaker in CEE countries, which can be explained by two factors. First, robot investment in these countries was mainly driven by FDI and greenfield investments, modernisations, and attempts to expand product ranges, especially in the automotive sector, which can explain the beneficial impacts on labour market flows that we have found. At the same time, these robot-adopting sectors were initially quite small, implying a modest impact on job separations. Second , the shortages of skilled workers and specialization of CEE countries mentioned above, particularly in less skill-demanding task, could have limited the response of hiring in the aftermath of robot adoption that probably required different skills than older technologies.

We also found heterogeneity across age groups. Except for countries higher labour costs, robots improved labour market prospects of young and prime-age workers in particular: they reduced job separation rates and increased job finding among these age groups. However, workers aged 55 years or older face challenges in certain environments. In particular, we detect some positive effects for older workers within manufacturing, which are likely due to the productivity-enhancing effects of robots. However, outside of manufacturing, the effects on older workers are less benign, indicating that they benefit less from demand-spillover effects than younger workers. Intergenerational differences in skills required to work with new technologies, e.g. working in service-sector firms which perform robot maintenance, are a probable mechanism behind this difference. Surveys of adult skills show that older workers have lower levels of skills needed in a technology-rich environment (OECD, 2013). The shorter period of time to benefit from investment in new skills also incentivises older workers to remain in sectors and occupations in which they have specific knowledge, even if technological progress reduces returns to their skills (Cavounidis and Lang, 2020).

Third, our counterfactual exercise showed that the effects of robots on worker flows had important implications for employment rates. Rising robot exposure increased employment, particularly in countries with low or average labour costs. These aggregate results were mainly due to reduced separations rather than increased hirings.

Our results have important policy implications. First, the overall effects of robots are positive in several countries. In Europe, this technology generally acted as an opportunity for workers rather than a threat. The key policy challenge is to identify the factors contributing to this technology being a complement to rather than a substitute for human labour. Our paper is a step in this direction. The next steps may include a more explicit analysis of the factors that enable workers to adjust to technological change, especially through the increased use of training. Second, our finding that the relative importance of hirings and separations as adjustment mechanisms to robot adoption differs strongly between countries implies that policy measures to support worker adjustment to technology have to take into account these country-specificities.

Third, it is important to improve our understanding of how labour market institutions mediate the impacts of robots (and other novel automation technologies) in various countries. As institutions generally differ between countries rather than within them, our framework and sample size do not allow identification of the role of institutional factors. However, Leibrecht et al. (2023) provided descriptive evidence that robots are positively correlated with unemployment in countries where collective bargaining is weak, while Kostøl and Svarstad (2023) showed that unions improve relative wages of routine workers, who are more substitutable with automation, thus potentially strengthening its substitution effects. Future research that provides causal findings on how collective bargaining and other institutions shape the labour market impacts of automation would have high scientific and policy relevance.

Bibliography

Acemoglu, D. and Autor, D. H. (2011). Skills, tasks and technologies: Implications for employment and earnings. In Card, D. and Ashenfelter, O., editors, *Handbook of Labor Economics*, pages 1043–1171. Elsevier.

Acemoglu, D., Lelarge, C., and Restrepo, P. (2020). Competing with robots: Firm-level evidence from France. *AEA Papers and Proceedings*, 110:383–388.

Acemoglu, D. and Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, 128:2188–2244.

Acemoglu, D. and Restrepo, P. (2022). Tasks, automation, and the rise in U.S. wage inequality. *Econometrica*, 90:1973–2016.

Adachi, D., Kawaguchi, D., and Saito, Y. U. (2024). Robots and employment: Evidence from Japan, 1978-2017. *Journal of Labor Economics*, 42(2).

Aghelmaleki, H., Bachmann, R., and Stiebale, J. (2022). The China shock, employment protection, and European jobs. *ILR Review*, 75(5):1269–1293.

Aksoy, C. G., Özcan, B., and Philipp, J. (2021). Robots and the gender pay gap in Europe. *European Economic Review*, 134:103693.

Albinowski, M. and Lewandowski, P. (2024). The impact of ICT and robots on labour market outcomes of demographic groups in Europe. *Labour Economics*, 87:102481.

Altzinger, W. and Landesmann, M. (2008). Relocation of production and jobs to Central and Eastern Europe—Who gains and who loses? *Structural Change and Economic Dynamics*, 19(1):1–3.

Anelli, M., Colantone, I., and Stanig, P. (2021). Individual vulnerability to industrial robot adoption increases support for the radical right. *Proceedings of the National Academy of Sciences*, 118(37):e2111611118.

Bachmann, R., Baumgarten, D., and Stiebale, J. (2014). Foreign direct investment, heterogeneous workers and employment security: Evidence from Germany. *Canadian Journal of Economics/Revue canadienne d'économique*, 47(3):720–757.

Bachmann, R. and Felder, R. (2020). Labour market transitions, shocks and institutions in turbulent times: A cross-country analysis. *Empirica*, 48(2):329–352.

Bartik, T. (1991). *Who Benefits from State and Local Economic Development Policies?* Upjohn Press.

Baumgarten, D., Geishecker, I., and Görg, H. (2013). Offshoring, tasks, and the skill-wage pattern. *European Economic Review*, 61:132–152.

Bellak, C., Leibrecht, M., and Riedl, A. (2008). Labour costs and FDI flows into Central and Eastern European Countries: A survey of the literature and empirical evidence. *Structural Change and Economic Dynamics*, 19(1):17–37.

Bessen, J., Goos, M., Salomons, A., and van den Berge, W. (2023). What happens to workers at firms that automate. *Review of Economics and Statistics*, pages 1–45.

Calvino, F. and Virgillito, M. E. (2018). The innovation-employment nexus: A critical survey of theory and empirics. *Journal of Economic Surveys*, 32(1):83–117.

Cavounidis, C. and Lang, K. (2020). Ben-Porath Meets Lazear: Microfoundations for dynamic skill formation. *Journal of Political Economy*, 128(4):1405–1435.

Chun, H. (2003). Information technology and the demand for educated workers: Disentangling the impacts of adoption versus use. *The Review of Economics and Statistics*, 85(1):1–8.

Caéfalvay, Z. (2020). Robotization in Central and Eastern Europe: Catching up or dependence? *European Planning Studies*, 28(8):1534–1553.

Damiani, M., Pompei, F., and Kleinknecht, A. (2023). Robots, skills and temporary jobs: Evidence from six European countries. *Industry and Innovation*, 30(8):1060–1109.

Dauth, W., Findeisen, S., Suedekum, J., and Woessner, N. (2021). The adjustment of labor markets to robots. *Journal of the European Economic Association*, 19(6):3104–3153.

De Vries, G. J., Gentile, E., Miroudot, S., and Wacker, K. M. (2020). The rise of robots and the fall of routine jobs. *Labour Economics*, 66:101885.

Domini, G., Grazzi, M., Moschella, D., and Treibich, T. (2021). Threats and opportunities in the digital era: Automation spikes and employment dynamics. *Research Policy*, 50(7):104137.

Doorley, K., Gromadzki, J., Lewandowski, P., Tuda, D., and van Kerm, P. (2023). Automation and income inequality in Europe. IZA Discussion Paper 16499, IZA - Institute of Labor Economics.

Duan, D., Chen, S., Feng, Z., and Li, J. (2023). Industrial robots and firm productivity. *Structural Change and Economic Dynamics*, 67:388–406.

Ebenstein, A., Harrison, A., McMillan, M., and Phillips, S. (2014). Estimating the impact of trade and offshoring on American workers using the current population surveys. *The Review of Economics and Statistics*, 96(4):581–595.

Elsby, M. W. L., Hobijn, B., and Şahin, A. (2012). Unemployment dynamics in the OECD. *The Review of Economics and Statistics*, 95(2):530–548.

Eurostat (2019). The Labour Force Survey. https://doi.org/10.2907/LFS1983-2018V.1.

Eurostat (2020). Labour cost, wages, direct remunderation by NCAE Rev. 1.1 activity - LCS survey 2004. https://ec.europa.eu/eurostat/data/database.

Fana, M. and Villani, D. (2022). Decomposing the automotive supply chain: Employment, value added and occupational structure. *Structural Change and Economic Dynamics*, 62:407–419.

Fernández-Macías, E., Klenert, D., and Antón, J.-I. (2021). Not so disruptive yet? Characteristics, distribution and determinants of robots in Europe. *Structural Change and Economic Dynamics*, 58:76–89.

Fillmore, I. and Hall, J. D. (2021). Technological change and obsolete skills: Evidence from men's professional tennis. *Labour Economics*, 73:102051.

Fonseca, T., Lima, F., and Pereira, S. C. (2018). Job polarization, technological change and routinization: Evidence for Portugal. *Labour Economics*, 51:317–339.

Fujita, S. and Ramey, G. (2009). The cyclicality of separation and job finding rates. *International Economic Review*, 50(2):415–430.

Goldin, C. and Katz, L. F. (2010). *The race between education and technology*. Belknap Press.

Goos, M., Manning, A., and Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review*, 104(8):2509–2526.

Graetz, G. and Michaels, G. (2018). Robots at work. *The Review of Economics and Statistics*, 100(5):753–768.

Gregory, T., Salomons, A., and Zierahn, U. (2022). Racing with or against the machine? Evidence on the role of trade in Europe. *Journal of the European Economic Association*, 20(2):869–906.

Grodzicki, M. J. and Skrzypek, J. (2020). Cost-competitiveness and structural change in value chains – vertically-integrated analysis of the European automotive sector. *Structural Change and Economic Dynamics*, 55:276–287.

Handel, M. J. (2012). Trends in job skill demands in OECD countries. OECD Social, Employment and Migration Working Papers 143, OECD.

Hardy, W., Keister, R., and Lewandowski, P. (2018). Educational upgrading, structural change and the task composition of jobs in Europe. *Economics of Transition and Institutional Change*, 26(2):201–231.

International Federation of Robotics (2017). World robotics industrial robots 2017.

Jürgens, U. and Krzywdzinski, M. (2009). Changing East–West division of labour in the European automotive industry. *European Urban and Regional Studies*, 16(1):27–42.

Klenert, D., Fernández-Macías, E., and Antón, J.-I. (2023). Do robots really destroy jobs? Evidence from Europe. *Economic and Industrial Democracy*, 44(1):280–316.

Koch, M., Manuylov, I., and Smolka, M. (2021). Robots and firms. *The Economic Journal*, 131(638):2553–2584.

Kostøl, A. R. B. and Svarstad, E. (2023). Trade unions and the process of technological change. *Labour Economics*, 84:102386.

Krzywdzinski, M. (2017). Automation, skill requirements and labour-use strategies: high-wage and low-wage approaches to high-tech manufacturing in the automotive industry. *New Technology, Work and Employment*, 32(3):247–267.

Leibrecht, M., Scharler, J., and Zhoufu, Y. (2023). Automation and unemployment: Does collective bargaining moderate their association? *Structural Change and Economic Dynamics*, 67:264–276.

Lewandowski, P., Keister, R., Hardy, W., and Górka, S. (2020). Ageing of routine jobs in Europe. *Economic Systems*, 44(4):100816.

Lewandowski, P., Park, A., Hardy, W., Du, Y., and Wu, S. (2022). Technology, skills, and globalization: Explaining international differences in routine and nonroutine work using survey data. *The World Bank Economic Review*, 36(3):687–708.

Milberg, W. and Winkler, D. (2013). *Outsourcing Economics: Global Value Chains in Capitalist Development.* Cambridge University Press.

Nikolova, M., Cnossen, F., and Nikolaev, B. (2024). Robots, meaning, and self-determination. *Research Policy*, 53(5):104987.

OECD (2013). *OECD Skills Outlook 2013: First Results from the Survey of Adult Skills*. OECD, Paris.

Petrin, A. and Train, K. (2010). A control function approach to endogeneity in consumer choice models. *Journal of marketing research*, 47(1):3–13.

Pianta, M. (2006). Innovation and employment. In *The Oxford Handbook of Innovation.* Oxford University Press.

RIGVC UIBE (2016). UIBE GVC index [dataset].

Sondergaard, L., Murthi, M., Abu-Ghaida, D., Bodewig, C., and Rutkowski, J. (2012). Skills, not just diplomas: Managing education for results in Eastern Europe and Central Asia. Report, The World Bank.

Stehrer, R., Bykova, A., Jäger, K., Reiter, O., and Schwarzhappel, M. (2019). Industry level growth and productivity data with special focus on intangible assets. Report on methodologies and data construction for the EU KLEMS Release 2019. Report, The Vienna Institute for International Economic Studies.

Vivarelli, M. (2014). Innovation, employment and skills in advanced and developing countries: A survey of economic literature. *Journal of Economic Issues*, 48(1):123–154.

Wang, Z., Wei, S.-J., Yu, X., and Zhu, K. (2017). Measures of participation in global value chains and global business cycles. NBER Working Papers 23222, National Bureau of Economic Research.

Wooldridge, J. M. (2015). Control function methods in applied econometrics. *J. Human Resources*, 50(2):420–445.

World Integrated Trade Solutions (2021). Product concordance [dataset]. `https://wits.worldbank.org/product_concordance.html`.

1.A. Appendix - Additional Descriptives

Tables

Table 1.A.1.: Relative labour costs (in manufacturing) and GDP in 2004 across countries

Country	Relative Labour Cost 2004	Relative GDP per capita 2004
Austria	1.05	0.73
Belgium	1.21	0.68
Czech Republic	-0.56	-0.22
Germany	1.16	0.61
Denmark	1.14	1.00
Spain	0.59	0.36
Finland	1.03	0.74
Greece	0.37	0.27
Hungary	-0.55	-0.52
Italy	0.84	0.56
Poland	-0.88	-0.79
Portugal	-0.12	0.03
Sweden	1.20	0.84
Slovenia	0.00	0.00
Slovakia	-0.83	-0.54
United Kingdom	0.83	0.61

Note: The table shows the initial conditions of the countries relative to Slovenia, the richest Central Eastern European country, which we use as a reference. – Source: authors' calculations based on the Eurostat data (lc_n04cost and sdg_08_10).

Table 1.A.2.: Sample descriptives

	EU		UE	
	mean	sd	mean	sd
Women	0.46	(0.5)	0.46	(0.5)
Men	0.54	(0.5)	0.54	(0.5)
Married	0.59	(0.49)	0.43	(0.5)
Native Share	0.89	(0.32)	0.86	(0.35)
Age				
Age 15-24	0.08	(0.27)	0.15	(0.36)
Age 25-34	0.26	(0.44)	0.29	(0.45)
Age 35-54	0.55	(0.5)	0.45	(0.5)
Age 55-70	0.12	(0.32)	0.12	(0.32)
Education				
Low: Lower secondary	0.21	(0.4)	0.35	(0.48)
Medium: Upper secondary	0.52	(0.5)	0.51	(0.5)
High: Tertiary education	0.27	(0.45)	0.14	(0.35)
Industry Groups				
Primary sector	0.03	(0.16)	0.04	(0.21)
Manufacturing	0.22	(0.41)	0.22	(0.41)
Utilities	0.02	(0.13)	0.01	(0.1)
Construction	0.07	(0.26)	0.11	(0.31)
Consumer service activities	0.17	(0.38)	0.23	(0.42)
Business service activities	0.19	(0.39)	0.17	(0.37)
Public Services and education	0.31	(0.46)	0.22	(0.42)
Task Groups				
Non-Routine Cognitive Analytical	0.16	(0.36)	0.07	(0.25)
Non-Routine Cognitive Personal	0.2	(0.4)	0.05	(0.22)
Routine Cognitive	0.22	(0.41)	0.24	(0.43)
Routine Manual	0.14	(0.34)	0.18	(0.38)
Non-Routine Manual	0.29	(0.45)	0.47	(0.5)
Labour Costs 2004	0.33	(0.89)	0.3	(0.9)
Robot Exposure	1.38	(4.72)	1.29	(4.79)
Global value chain participation backward	0.16	(0.09)	0.17	(0.09)
Gross value added	10.5	(1.61)	10.48	(1.61)
Investment to gross value added	0.83	(0.05)	0.83	(0.06)
Gdp growth	101.66	(2.94)	101.68	(2.97)
Export growth	0.38	(1.02)	0.42	(1.07)

Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, UIBE GVC, and O*NET data.

Table 1.A.3.: The allocation of occupations to task groups (ISCO-88)

Task group	ISCO-88 code	Occupation
NRCA	11	Legislators and senior officials
	21	Physical, mathematical, and engineering science professionals
	22	Life science professionals
	24	Other professionals
	31	Physical and engineering science associate professionals
NRCP	12	Corporate managers
	13	General managers
	23	Teaching professionals
	32	Life science and health associate professionals
	33	Teaching associate professionals
RC	34	Other associate professionals
	41	Office clerks
	42	Customer services clerks
	52	Models, salespersons, and demonstrators
RM	71	Extraction and building trades workers
	72	Metal, machinery, and related trades workers
	74	Other craft and related trades workers
	81	Stationary-plant and related operators
	82	Machine operators and assemblers
	93	Labourers in mining, construction, manufacturing, and transport
NRM	51	Personal and protective services workers
	61	Market-oriented skilled agricultural and fishery workers
	62	Subsistence agricultural and fishery workers
	71	Extraction and building trades workers
	72	Metal, machinery, and related trades workers
	73	Precision workers in metal and related trades workers
	83	Drivers and mobile-plant operators
	91	Sales and services elementary occupations
	92	Agricultural, fishery, and related labourers

Note: The allocation is based on Hardy et al. (2018), see data section for details.

Table 1.A.4.: The allocation of occupations to task groups (ISCO-08)

Task group	ISCO-08 code	Occupation
NRCA	21	Science and Engineering Professionals
	22	Health Professionals
	24	Business and Administration Professionals
	25	Information and Communications Technology Professionals
	26	Legal, Social, and Cultural Professionals
	31	Science and Engineering Associate Professionals
	35	Information and Communications Technicians
NRCP	11	Chief Executives, Senior Officials, and Legislators
	12	Administrative and Commercial Managers
	13	Production and Specialised Services Managers
	14	Hospitality, Retail and Other Service Managers
	23	Teaching Professionals
	32	Health Associate Professionals
RC	33	Business and Administration Associate Professionals
	34	Legal, Social, Cultural, and Related Associate Professionals
	41	General and Keyboard Clerks
	42	Customer Services Clerks
	43	Numerical and Material Recording Clerks
	44	Other Clerical Support Workers
	52	Sales Workers
RM	72	Metal, Machinery, and Related Trades Workers
	73	Handicraft and Printing Workers
	75	Food Processing, Woodworking, Garment, and Other Craft and Related Trades Workers
	81	Stationary Plant and Machine Operators
	82	Assemblers
	94	Food Preparation Assistants
NRM	51	Personal Services Workers
	53	Personal Care Workers
	54	Protective Services Workers
	61	Market-oriented Skilled Agricultural Workers
	62	Market-oriented Skilled Forestry, Fishery, and Hunting Workers
	63	Subsistence Farmers, Fishers, Hunters, and Gatherers
	71	Building and Related Trades Workers (excluding Electricians)
	74	Electrical and Electronic Trades Workers
	83	Drivers and Mobile Plant Operators
	91	Cleaners and Helpers
	92	Agricultural, Forestry, and Fishery Labourers
	93	Labourers in Mining, Construction, Manufacturing, and Transport
	95	Street and Related Sales and Services Workers
	96	Refuse Workers and Other Elementary Workers

Note: The allocation is based on Hardy et al. (2018), see data section for details.

1.B. Appendix - Additional Tables and Figures Empirical Section

Tables

Table 1.B.1.: The effect of robot exposure on the likelihood of job separation: full specification

Variables	Probit	CF	Probit	CF
	(1)	(2)	(3)	(4)
Robot Exposure	-0.003**	-0.005***	-0.011***	-0.012***
	(0.001)	(0.001)	(0.002)	(0.003)
Robot Exposure X Labour Costs			-0.006***	-0.005***
			(0.001)	(0.001)
Robot Exposure X (Labour Costs)^2			0.011***	0.008***
			(0.002)	(0.002)
Age Groups (Base Category: Age 15-24)				
Age 25-34	-0.170***	-0.170***	-0.170***	-0.170***
	(0.006)	(0.006)	(0.006)	(0.006)
Age 35-54	-0.354***	-0.354***	-0.353***	-0.354***
	(0.007)	(0.007)	(0.007)	(0.007)
Age 55-70	-0.340***	-0.340***	-0.340***	-0.340***
	(0.011)	(0.011)	(0.011)	(0.011)
Education Group (Base Category: Low education)				
Medium education	-0.189***	-0.188***	-0.189***	-0.189***
	(0.007)	(0.007)	(0.007)	(0.007)
High education	-0.388***	-0.386***	-0.388***	-0.387***
	(0.014)	(0.014)	(0.014)	(0.014)
Male	-0.081***	-0.082***	-0.080***	-0.081***
	(0.007)	(0.007)	(0.007)	(0.007)
Native	-0.175***	-0.175***	-0.175***	-0.175***
	(0.009)	(0.009)	(0.009)	(0.009)
Global Value Chain (Backwards)	0.004	0.068	-0.018	0.034
	(0.090)	(0.091)	(0.096)	(0.095)
Gross value added (Log)	-0.026**	-0.027***	-0.030***	-0.028***
	(0.010)	(0.010)	(0.011)	(0.011)
Investment to Gross value added	-0.102	-0.079	-0.095	-0.078
	(0.097)	(0.095)	(0.096)	(0.095)
GDP Growth	-0.018***	-0.018***	-0.017***	-0.018***
	(0.002)	(0.002)	(0.002)	(0.002)
Bartik instrument	-0.868***	-0.864***	-0.885***	-0.879***
	(0.137)	(0.137)	(0.138)	(0.137)
Export growth	0.017***	0.016***	0.016***	0.016***
	(0.003)	(0.003)	(0.003)	(0.003)
Residual 1		0.006***		
		(0.002)		
Residual 2				-0.002
				(0.004)
Residual 3				-0.002
				(0.002)
Residual 4				0.007**
				(0.004)
Industry Group (Base Category: Agriculture and Mining)				
Manufacturing	-0.071***	-0.062***	-0.056**	-0.053**
	(0.023)	(0.023)	(0.022)	(0.022)

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Table 1.B.1 – *Continued from previous page*

Variables	**Probit**	**CF**	**Probit**	**CF**
	(1)	**(2)**	**(3)**	**(4)**
Utilities	-0.276***	-0.271***	-0.265***	-0.264***
	(0.034)	(0.033)	(0.033)	(0.033)
Construction	0.172***	0.173***	0.178***	0.178***
	(0.027)	(0.027)	(0.026)	(0.026)
Consumer Services	-0.004	-0.005	-0.006	-0.006
	(0.023)	(0.024)	(0.023)	(0.023)
Business Services	-0.125***	-0.127***	-0.128***	-0.129***
	(0.022)	(0.022)	(0.022)	(0.022)
Public Services & Education	-0.259***	-0.259***	-0.261***	-0.260***
	(0.024)	(0.024)	(0.024)	(0.024)
Constant	0.807***	0.813***	0.791***	0.786***
	(0.222)	(0.222)	(0.221)	(0.221)
Country FE	Yes	Yes	Yes	Yes
Country linear trends	Yes	Yes	Yes	Yes
Industry Group FE	Yes	Yes	Yes	Yes
Observations	11.8 M	11.8 M	11.8 M	11.8 M

Note: The table presents the estimated coefficients of the probit and control function (CF) regressions. Standard errors (in brackets) are clustered at the occupation-year level. Year and industry group fixed effects are included. Individual-level controls: age group, education group, gender, and native/non-native. Aggregate-level controls: global value chain participation, gross value added, the ratio of investment added to gross value added, GDP growth, labour demand and growth in exports. For CF, robot exposure is instrumented using robot exposure in the Western countries in the sample. Residual 1 is the residual from the first stage regression for the specification without interactions. Residuals 1, 2, 3 and 4 are the residuals from the first stage regression for robot exposure, interaction of robot exposure with labour costs, and robot exposure with squared labour costs, respectively. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, UIBE GVC, and O*NET data.

Table 1.B.2.: The effect of robot exposure on the likelihood of job finding: full specification

Variables	**Probit**	**CF**	**Probit**	**CF**
	(1)	**(2)**	**(3)**	**(4)**
Robot Exposure	-0.002	0.002	0.018***	0.011***
	(0.001)	(0.001)	(0.003)	(0.004)
Robot Exposure × Labour Costs			0.008***	0.003
			(0.002)	(0.002)
Robot Exposure × (Labour Costs)^2			-0.022***	-0.012***
			(0.003)	(0.004)
Age Groups (Base Category: Age 15-24)				
Age 25-34	-0.411***	-0.411***	-0.411***	-0.411***
	(0.009)	(0.009)	(0.009)	(0.009)
Age 35-54	-0.675***	-0.674***	-0.674***	-0.674***
	(0.014)	(0.014)	(0.014)	(0.014)
Age 55-70	-1.116***	-1.115***	-1.115***	-1.115***
	(0.021)	(0.021)	(0.021)	(0.021)
Education Group (Base Category: Low education)				
Medium education	0.190***	0.189***	0.191***	0.190***
	(0.009)	(0.009)	(0.009)	(0.009)
High education	0.363***	0.361***	0.364***	0.363***

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Table 1.B.2 – *Continued from previous page*

Variables	**Probit**	**CF**	**Probit**	**CF**
	(1)	**(2)**	**(3)**	**(4)**
	(0.012)	(0.012)	(0.012)	(0.012)
Male	0.011	0.012	0.011	0.012
	(0.008)	(0.008)	(0.008)	(0.008)
Native	-0.082***	-0.082***	-0.081***	-0.082***
	(0.011)	(0.011)	(0.011)	(0.011)
Global Value Chain (Backwards)	-0.024	-0.097	-0.070	-0.121
	(0.077)	(0.078)	(0.082)	(0.080)
Gross value added (Log)	0.004	0.003	0.000	-0.001
	(0.012)	(0.012)	(0.012)	(0.012)
Investment to Gross value added	0.479***	0.459***	0.456***	0.460***
	(0.114)	(0.113)	(0.111)	(0.110)
GDP Growth	0.022***	0.022***	0.022***	0.022***
	(0.003)	(0.003)	(0.003)	(0.003)
Bartik instrument	1.010***	1.003***	1.015***	1.005***
	(0.145)	(0.145)	(0.146)	(0.145)
Export growth	-0.010**	-0.010**	-0.010**	-0.010**
	(0.005)	(0.005)	(0.005)	(0.005)
Residual 1		-0.006***		
		(0.002)		
Residual 2				0.019***
				(0.005)
Residual 3				0.013***
				(0.003)
Residual 4				-0.026***
				(0.006)
Industry Group (Base Category: Agriculture and Mining)				
Manufacturing	0.132***	0.123***	0.116***	0.124***
	(0.023)	(0.023)	(0.023)	(0.023)
Utilities	0.327***	0.323***	0.318***	0.324***
	(0.033)	(0.034)	(0.033)	(0.033)
Construction	0.110***	0.108***	0.104***	0.110***
	(0.027)	(0.027)	(0.027)	(0.027)
Consumer Services	0.152***	0.152***	0.152***	0.152***
	(0.023)	(0.023)	(0.023)	(0.023)
Business Services	0.295***	0.297***	0.295***	0.296***
	(0.022)	(0.023)	(0.022)	(0.022)
Public Services & Education	0.378***	0.377***	0.376***	0.376***
	(0.024)	(0.025)	(0.024)	(0.024)
Constant	-2.413***	-2.400***	-2.322***	-2.347***
	(0.352)	(0.351)	(0.351)	(0.348)
Year dummies	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Country linear trends	Yes	Yes	Yes	Yes
Industry Group FE	Yes	Yes	Yes	Yes
Observations	1.3 M	1.3 M	1.3 M	1.3 M

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Table 1.B.2 – *Continued from previous page*

Variables	**Probit**	**CF**	**Probit**	**CF**
	(1)	**(2)**	**(3)**	**(4)**

Note: The table presents the estimated coefficients of the probit and control function (CF) regressions. Standard errors (in brackets) are clustered at the occupation-year level. Year and industry group fixed effects are included. Individual-level controls: age group, education group, gender, and native/non-native. Aggregate-level controls: global value chain participation, gross value added, the ratio of investment added to gross value added, GDP growth, labour demand and growth in exports. For CF, robot exposure is instrumented using robot exposure in the Western countries in the sample. Residual 1 is the residual from the first stage regression for the specification without interactions. Residuals 1, 2, 3 and 4 are the residuals from the first stage regression for robot exposure, interaction of robot exposure with labour costs, and robot exposure with squared labour costs, respectively. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, UIBE GVC, and O*NET data.

Table 1.B.3.: The effect of robot exposure on the likelihood of job separation, First Stage regressions

Independent variable	(1) 1st First Stage Robot Exposure	(2) 2nd First Stage Robot Exposure $\times$ Labour Costs	(3) 3rd First Stage Robot Exposure $\times$ (Labour Costs)^2
Instrument	0.760***	0.016	-0.008
	(0.027)	(0.020)	(0.013)
Instrument X Labour Costs	-0.153	1.329***	-0.002
	(0.151)	(0.123)	(0.105)
Instrument X (Labour Costs)^2	0.740***	-0.103	1.410***
	(0.150)	(0.142)	(0.116)
Constant	6.856**	-10.927***	4.832**
	(3.136)	(2.797)	(2.205)
Observations	11.8 M	11.8 M	11.8 M
Kleibergen-Paap F-statistic	18 537.4		

Note: See notes to Table 1.B.1. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

Table 1.B.4.: The effect of robot exposure on the likelihood of job finding, First Stage regressions.

Independent variable	(1) 1st First Stage Robot Exposure	(2) 2nd First Stage Robot Exposure	(3) 3rd First Stage Robot Exposure
Instrument	0.700***	0.030	-0.016
	(0.031)	(0.027)	(0.019)
Instrument X Labour Costs	-0.254*	1.352***	-0.058
	(0.146)	(0.122)	(0.102)
Instrument X (Labour Costs)2	0.843***	-0.171	1.427***
	(0.140)	(0.143)	(0.119)
Constant	7.863**	-12.027***	5.759**
	(3.556)	(3.364)	(2.494)
Observations	1.3	1.3	1.3
Kleibergen-Paap F-statistic	3,714.4		

Note: See notes to Table 1.B.1. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

Table 1.B.5.: List of sectors covered with industrial robot data provided by International Federation of Robotics

IFR class	**Categories, divisions and classes of economic activities, ISIC, rev.4**	**Definitions**
A-B	Agriculture, hunting and forestry; fishing	Crop and animal production, hunting and related service activities, forestry and logging, fishing and aquaculture
C	Mining and quarrying	Mining of coal and lignite, extraction of crude petroleum and natural gas, mining of metal ores, mining support service
D	Manufacturing	
10-12	Food products and beverages; Tobacco products	
13-15	Textiles, leather, wearing apparel	Textiles; wearing apparel; dressing & dyeing of fur; luggage, handbags, saddlery, harnesses, and footwear
16	Wood and wood products (incl.) furniture	Manufacture of wood, products of wood (incl. wood furniture) and products of cork
17-18	Paper and paper products, publishing & printing	Manufacture of pulp, paper, and converted paper production; printing of products, such as newspapers, books, periodicals, business forms, greeting cards, and other materials; and associated support activities, such as bookbinding, plate-making services, and data imaging; reproduction of recorded media, such as compact discs, video recordings, software on discs or tapes, records, etc.

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Table 1.B.5.: (continued)

IFR class	Categories, divisions and classes of economic activities, ISIC, rev.4	Definitions
19	Chemical products, pharmaceuticals, cosmetics	Manufacture of basic pharmaceutical products and pharmaceutical preparations. This also includes the manufacture of medicinal chemical and botanical products.
20-21	Unspecified chemical, petroleum products	Transformation of crude petroleum and coal into usable products, transformation of organic and inorganic raw materials by a chemical process and the formation of products
22	Rubber and plastic products without automotive parts*	e.g., rubber tires, plastic plates, foils, pipes, bags, boxes, doors, etc.; rubber and plastic parts for motor vehicles should be reported in 29.3
23	Glass, ceramics, stone, mineral products n.e.c. (without automotive parts*)	Manufacture of intermediate and final products from mined or quarried non-metallic minerals, such as sand, gravel, stone or clay; manufacture of glass, flat glass ceramic and glass products, clinkers, plasters, etc.
24	Basic metals (iron, steel, aluminum, copper, chrome)	e.g., iron, steel, aluminum, copper, chrome, etc.
25	Metal products (without automotive parts*), except machinery and equipment	e.g., metal furniture, tanks, metal doors, forging, pressing, stamping and roll forming of metal, nails, pins, hand tools, etc.
28	Industrial machinery	e.g., machinery for food processing and packaging, machine tools, industrial equipment, rubber and plastic machinery, industrial cleaning machines, agricultural and forestry machinery, construction machinery, etc.
26-27	Electrical/electronics	
29	Automotive	
30	Other transport equipment	
E	Electricity and water supply	e.g., ships, locomotives, airplanes, spacecraft vehicles
F	Construction	General construction and specialised construction activities for buildings and civil engineering works. This includes new work, repairs, additions and alterations, the erection of prefabricated buildings or structures on the site, and construction of a temporary nature.
P	Education, research and development	

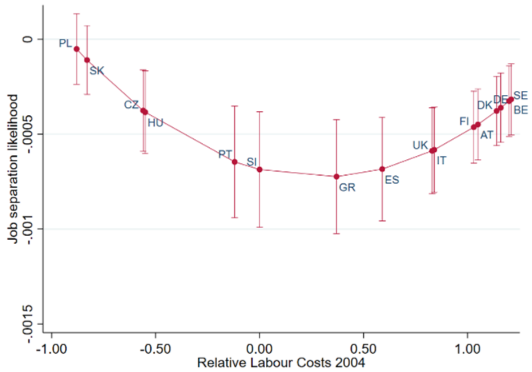
Table 1.B.6.: Construction of task contents measures based on O*NET data

Task content measure (T)	**Task items (J)**
Non-routine cognitive analytical	Analysing data/information
	Thinking creatively
	Interpreting information for others
Non-routine cognitive interpersonal	Establishing and maintaining personal relationships
	Guiding, directing, and motivating subordinates
	Coaching/developing others
Routine cognitive	The importance of repeating the same tasks
	The importance of being exact or accurate
	Structured vs. unstructured work
Routine manual	Pace determined by the speed of equipment
	Controlling machines and processes
	Spending time making repetitive motions
Non-routine manual physical	Operating vehicles, mechanised devices, or equipment
	Using hands to handle, control, or feel objects, tools
	Manual dexterity
	Spatial orientation

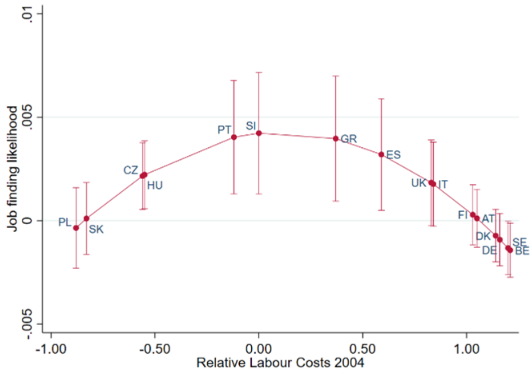
Source: Own elaboration based on Acemoglu and Autor (2011).

Figures

Figure 1.B.1.: Marginal effects of robot exposure on the likelihood of job separation / finding – across initial labour cost distribution.



(a) Job separation



(b) Job finding

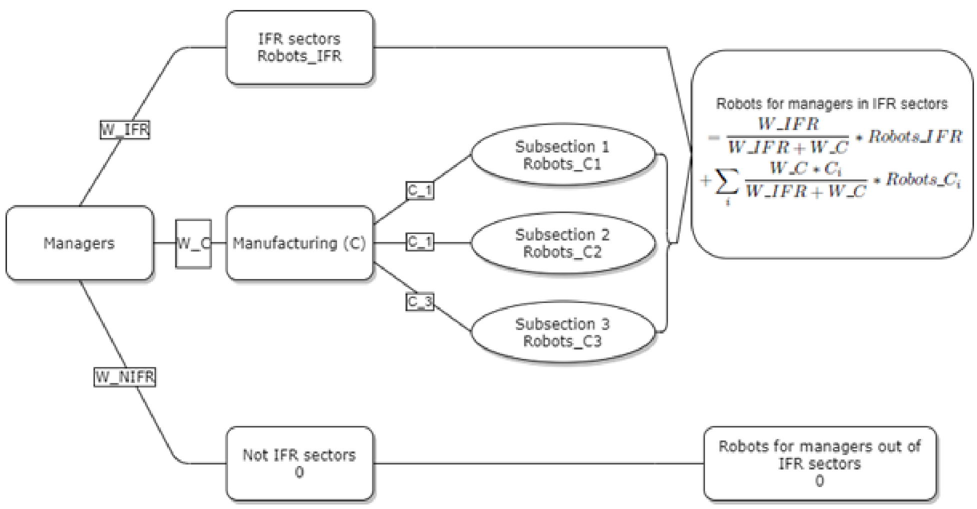
Note: See notes to Figure 5. Source: Authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

1.C. Appendix - Technical Details

1.C.1. Mapping

To map the IFR data on robots to individual workers, we use the information on economic sectors and occupations available in the EU-LFS. Sectors are coded at the one-digit level of NACE rev.1 between 2000-2007, and of NACE rev. 2 between 2008-2017. Occupations are coded at the two-digit level of ISCO-88 between 2000-2010, and of ISCO-08 between 2011-2017. The industries reported by the IFR are in accordance with the International Standard Industrial Classification of All Economic Activities (ISIC) revision 4 (see Table 1A, Appendix A). The IFR data distinguish between six main industries: (A-B) Agriculture, Hunting and Forestry; Fishing; (C) Mining and Quarrying; (D) Manufacturing; (D) Electricity, Gas, and Water Supply; (F) Construction; and (P) Education, Research and Development. We will call these industries the "IFR industries". The manufacturing industry, which is the industry with the highest robot stock, is divided further into 13 sub-industries. In each occupation, we classify workers into two subgroups depending on their sector of employment: those in the IFR sectors and those in the non-IFR (NIFR) sectors. We then use the sector-occupation mapping as in equation (1) to map robot exposure to workers in the IFR sectors. Workers in the NIFR sectors receive a zero weight as there are no robots in these sectors, and IFR sectors are reweighted such that weights sum up to one (see 1.C1).

Figure 1.C1.: Mapping of robot exposure to occupations across sectors with and without robots



Note: We classify each occupation into two groups depending on the sector of employment: IFR sector and not IFR sector. We use the structure of occupations across sectors provided by Eurostat as occupation weights to extrapolate exposure to robots (if managers account for 20% of all workers employed in construction, their weight equals 0.2, etc.). The not IFR sectors automatically receive zero weight, as there are no robots (e.g. Real estate activities; W_NIFR in the figure); the IFR sectors (agriculture, mining and quarrying, water supply, construction, education) receive one level of weight (if 10% of all managers work in agriculture, they receive 0.1 weight; W_IFR in the figure); and manufacturing, thanks to its more accurate data on robots, receives two levels of weights (if 10% of all managers work in manufacturing and 5% of them are employed in the automotive industry, they have 0.005 weight; W_C * C_1, etc. in the figure). Weights for the IFR sectors are reweighted to sum up to one. Finally, we end up with two types of managers: managers in the not IFR sectors with null exposure to robots and managers in the IFR industries with exposure to robots, given by the formula presented in the above figure.

1.C.2. Counterfactual Analysis Methodology

To assess the economic significance of the estimated effects, we perform a counterfactual analysis to quantify the effect of robot adoption on labour market flows. In the counterfactual scenario, in each country we keep the level of robot exposure between 2004-2017 at the 2004 level. This assumption means that new robot installations would have only compensated for the depreciation of robot stock and for the aggregate changes in the labour force.

In the first step, we use the coefficients estimated with equation (3) to calculate the predicted likelihood of job separation (EU) and job finding (UE) of individual i in country c and time $t \geq 2004$. In the second step, we use the estimated coefficients (the control function approach, with labour costs as a control for the initial conditions in a country) and substitute the actual level of robot exposure with its counterfactual value. Formally:

$$\Pr(\text{flow} = 1|\text{X})_{i,o,c,r,t} = \alpha * R_{i,c,t} + \beta * X_{i,c,t} + \epsilon_{i,c,t} \tag{1.C1}$$

$$\widehat{\Pr(\text{flow})}_{i,c,t} = \hat{\alpha} * R_{i,c,t} + \hat{\beta} * X_{i,c,t} \tag{1.C2}$$

$$\Pr(\widehat{\text{flow\_counter}})_{i,c,t} = \hat{\alpha} * R_{i,c,2004} + \hat{\beta} * X_{i,c,t} \tag{1.C3}$$

where $\widehat{\Pr(\text{flow})}_{i,c,t}$ is the likelihood of a given flow predicted with the model, $\Pr(\widehat{\text{flow\_counter}})$ is a counterfactual likelihood of the same flow, and $flow = \{EU, UE\}$. Then, for each country and year, we compute the share of individuals for whom the expected value of the flow is equal to one in a given simulation, namely:

$$\widehat{\text{flow}}_{c,t} = \frac{\sum_{i}^{I_{c,t}} 1\{flow = 1\}}{I_{c,t}}, \tag{1.C4}$$

where $I_{c,t}$ is the mass of individuals i observed for a particular flow in country c and time t.

In the third step, we use estimated probabilities of labour market flows to recursively calculate the levels of employment and unemployment flows and stocks, according to the formulas:

$$\widehat{\text{EU}}_{c,t} = \text{EMP}_{c,t} * \widehat{\text{eu}}_{c,t} \tag{1.C5}$$

$$\widehat{\text{UE}}_{c,t} = \text{UNEMP}_{c,t} * \widehat{\text{ue}}_{c,t} \tag{1.C6}$$

$$\widehat{\text{EMP}}_{c,t+1} = \begin{cases} \widehat{\text{EMP}}_{c,t} - \widehat{\text{EU}}_{c,t} + \widehat{\text{UE}}_{c,t} \text{ if } t \geq 2004 \\ \text{EMP}_{c,t+1} \text{ if } t < 2004 \end{cases} \tag{1.C7}$$

$$\widehat{\text{UNEMP}}_{c,t+1} = \begin{cases} \widehat{\text{UNEMP}}_{c,t} + \widehat{\text{EU}}_{c,t} - \widehat{\text{UE}}_{c,t} \text{ if } t \geq 2004 \\ \text{UNEMP}_{c,t+1} \text{ if } t < 2004 \end{cases} \tag{1.C8}$$

where $\widehat{\text{EU}}_{c,t}$ is an estimated flow from employment to unemployment (job separations), $\widehat{\text{UE}}_{c,t}$ is an estimated flow from unemployment to employment (job findings), $\widehat{\text{EMP}}_{c,t}$ and $\widehat{\text{UNEMP}}_{c,t}$ are estimated levels of employment and unemployment in country c and time t, respectively. The initial values of $\widehat{\text{EMP}}_{c,t}$ ($\widehat{\text{UNEMP}}_{c,t}$) are equal to actual employment (unemployment) levels in a particular country in 2004. We repeat all computations for predicted and counterfactual (marked with cf superscript) scenarios.

In the fourth step, we calculate the effect of the robot adoption on the labour market as a difference between the counterfactual and predicted scenarios for each year t, normalized with the working-age population $POP_{c,t}$, namely:

$$\Delta\text{EMP}_{c,t} = \frac{\widehat{\text{EMP}}_{c,t} - \text{EMP}^{cf}_{c,t}}{POP_{c,t}} * 100 \tag{1.C9}$$

where $\Delta EMP_{c,t}$ stands for the relative impact of robot adoption on employment in country c and time $t \geq 2004$, respectively.

Finally, we analyze to what extent the overall effects of robot adoption on employment are driven by the impacts on job separations (EU) versus on job findings (UE). To this end, we perform a semi-counterfactual analysis. To quantify the importance of the job separation channel (JS superscript), we multiply the predicted employment stock ($\widehat{\text{EMP}}^{s,JS}_{c,t}$) with the counterfactual likelihood of job separations ($\widehat{\text{eu}}^{cf}_{c,t}$) (likelihood of job finding ($\widehat{\text{ue}}_{c,t}$)), and calculate flows and levels recursively, using the formulas:

$$\widehat{\mathrm{EU}}_{c,t}^{s,JS} = \widehat{\mathrm{EMP}}_{c,t}^{s,JS} * \widehat{\mathrm{eu}}_{c,t}^{cf} \tag{1.C10}$$

$$\widehat{\mathrm{UE}}_{c,t}^{s,JS} = \widehat{\mathrm{UNEMP}}_{c,t}^{s,JS} * \widehat{\mathrm{ue}}_{c,t} \tag{1.C11}$$

$$\widehat{\mathrm{EMP}}_{c,t+1}^{s,JS} = \begin{cases} \widehat{\mathrm{EMP}}_{c,t}^{s,JS} - \widehat{\mathrm{EU}}_{c,t}^{s,JS} + \widehat{\mathrm{UE}}_{c,t}^{s,JS} \text{ if } t \geq 2004 \\ \mathrm{EMP}_{c,t+1} \text{ if } t < 2004 \end{cases} \tag{1.C12}$$

$$\widehat{\mathrm{UNEMP}}_{c,t+1}^{s,JS} = \begin{cases} \widehat{\mathrm{UNEMP}}_{c,t}^{s,JS} + \widehat{\mathrm{EU}}_{c,t}^{s,JS} - \widehat{\mathrm{UE}}_{c,t}^{s,JS} \text{ if } t \geq 2004 \\ \mathrm{UNEMP}_{c,t+1} \text{ if } t < 2004 \end{cases} \tag{1.C13}$$

where the initial values of $\widehat{\mathrm{EMP}}_{c,t}^{s,JS}$ and $\widehat{\mathrm{UNEMP}}_{c,t}^{s,JS}$ are the actual employment and unemployment levels, respectively, in a particular country in 2004.

To quantify the job finding channel (JF superscript), we use the counterfactual likelihood of job finding and the predicted likelihood of job separation, using the formulas:

$$\widehat{\mathrm{EU}}_{c,t}^{s,JF} = \widehat{\mathrm{EMP}}_{c,t}^{s,JF} * \widehat{\mathrm{eu}}_{c,t} \tag{1.C14}$$

$$\widehat{\mathrm{UE}}_{c,t}^{s,JF} = \widehat{\mathrm{UNEMP}}_{c,t}^{s,JF} * \widehat{\mathrm{ue}}_{c,t}^{cf} \tag{1.C15}$$

$$\widehat{\mathrm{EMP}}_{c,t+1}^{s,JF} = \begin{cases} \widehat{\mathrm{EMP}}_{c,t}^{s,JF} - \widehat{\mathrm{EU}}_{c,t}^{s,JF} + \widehat{\mathrm{UE}}_{c,t}^{s,JF} \text{ if } t \geq 2004 \\ \mathrm{EMP}_{c,t+1}^{s,JF} \text{ if } t < 2004 \end{cases} \tag{1.C16}$$

$$\widehat{\mathrm{UNEMP}}_{c,t+1}^{s,JF} = \begin{cases} \widehat{\mathrm{UNEMP}}_{c,t}^{s,JF} + \widehat{\mathrm{EU}}_{c,t}^{s,JF} - \widehat{\mathrm{UE}}_{c,t}^{s,JF} \text{ if } t \geq 2004 \\ \mathrm{UNEMP}_{c,t+1}^{s,JF} \text{ if } t < 2004 \end{cases} \tag{1.C17}$$

where the initial values of $\widehat{\mathrm{EMP}}_{c,t}^{s,JF}$ and $\widehat{\mathrm{UNEMP}}_{c,t}^{s,JF}$ are the actual employment and unemployment levels, respectively, in a particular country in 2004.

For each of semi-counterfactual simulations, we calculate its effect as a relative difference between the counterfactual and predicted scenarios, given by:

Job Separation (JS) Channel:

$$\Delta\widehat{\mathrm{EMP}}_{c,t}^{s,JS} = \frac{\widehat{\mathrm{EMP}}_{c,t} - \widehat{\mathrm{EMP}}_{c,t}^{s,JS}}{\mathrm{EMP}_{c,t}} * 100 \tag{1.C18}$$

Job Finding (JF) Channel:

$$\Delta\widehat{\mathrm{EMP}}_{c,t}^{s,JF} = \frac{\widehat{\mathrm{EMP}}_{c,t} - \widehat{\mathrm{EMP}}_{c,t}^{s,JF}}{\mathrm{EMP}_{c,t}} * 100 \tag{1.C19}$$

Note that because the simulations are calculated recursively, the difference between the counterfactual and the sum of semi-counterfactuals may differ from zero; we show this difference as a residual.

Finally, we use these values to assess the contributions of the separation and of the finding channels to the estimated effect of robot adoption on employment. We use a covariance-based decomposition, originally proposed by Fujita and Ramey (2009), to quantify the contributions of job separation and job finding rates to unemployment fluctuations, in line with the following equations:

$$\sigma_{\Delta\widehat{\text{EMP}}_{c,t}^{s,JS},\Delta\text{EMP}_{c,t}} = \frac{cov(\Delta\widehat{\text{EMP}}_{c,t}^{s,JS}, \Delta\text{EMP}_{c,t})}{var(\Delta\text{EMP}_{c,t})} \tag{1.C20}$$

$$\sigma_{\Delta\widehat{\text{EMP}}_{c,t}^{s,JF},\Delta\text{EMP}_{c,t}} = \frac{cov(\Delta\widehat{\text{EMP}}_{c,t}^{s,JF}, \Delta\text{EMP}_{c,t})}{var(\Delta\text{EMP}_{c,t})} \tag{1.C21}$$

1.D. Appendix - Online Appendix

Tables

Table 1.D.1.: The effect of robot exposure on the likelihood of job separation – by task group

Variables	**Probit**	**CF**	**Probit**	**CF**
	(1)	(2)	(3)	(4)
Robot Exposure	-0.000	-0.002	0.002	0.001
	(0.002)	(0.005)	(0.005)	(0.008)
Robot Exposure X Labour Costs			-0.009***	-0.005
			(0.003)	(0.007)
Robot Exposure X (Labour Costs)^2			0.003	-0.000
			(0.005)	(0.006)
NRCA X Robot Exposure	-0.000	0.000	-0.006	0.008
	(0.003)	(0.005)	(0.007)	(0.010)
NRCP X Robot Exposure	0.004	0.000	-0.005	-0.003
	(0.003)	(0.006)	(0.008)	(0.011)
RC X Robot Exposure	-0.003	-0.003	-0.021***	-0.019**
	(0.003)	(0.005)	(0.006)	(0.008)
RM X Robot Exposure	-0.001	-0.000	-0.012**	-0.007
	(0.003)	(0.005)	(0.005)	(0.008)
NRCA X Robot Exposure x Labour Cost			-0.001	-0.005
			(0.004)	(0.008)
NRCP X Robot Exposure x Labour Cost			0.004	0.001
			(0.005)	(0.008)
RC X Robot Exposure x Labour Cost			-0.003	-0.003
			(0.004)	(0.008)
RM X Robot Exposure x Labour Cost			0.003	0.001
			(0.004)	(0.007)
NRCA X Robot Exposure x (Labour Costs)^2			0.006	-0.001
			(0.006)	(0.010)
NRCP X Robot Exposure x (Labour Costs)^2			0.005	0.006
			(0.008)	(0.010)
RC X Robot Exposure x (Labour Costs)^2			0.017***	0.018**
			(0.006)	(0.008)
RM X Robot Exposure x (Labour Costs)^2			0.008	0.007
			(0.005)	(0.006)
NRCA	-0.285***	-0.285***	-0.220***	-0.234***
	(0.016)	(0.017)	(0.024)	(0.024)
NRCP	-0.386***	-0.382***	-0.333***	-0.333***
	(0.020)	(0.020)	(0.027)	(0.028)
RC	-0.171***	-0.169***	-0.124***	-0.124***
	(0.012)	(0.012)	(0.017)	(0.018)
RM	0.078***	0.077***	0.104***	0.093***
	(0.021)	(0.021)	(0.024)	(0.026)
NRCA x Labour Cost			0.155***	0.163***
			(0.016)	(0.016)
NRCP x Labour Cost			0.151***	0.152***
			(0.018)	(0.018)
RC x Labour Cost			0.031*	0.031*
			(0.016)	(0.016)
RM x Labour Cost			-0.014	-0.022

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Table 1.D.1 – *Continued from previous page*

Variables	Probit	CF	Probit	CF
	(1)	(2)	(3)	(4)
			(0.017)	(0.016)
NRCA x (Labour Costs)^2			-0.173***	-0.168***
			(0.023)	(0.023)
NRCP x (Labour Costs)^2			-0.160***	-0.160***
			(0.030)	(0.031)
RC x (Labour Costs)^2			-0.077***	-0.078***
			(0.023)	(0.023)
RM x (Labour Costs)^2			-0.020	-0.007
			(0.028)	(0.029)
Observations	11.8 M	11.8 M	11.8 M	11.8 M

Note: The table presents the estimated coefficients of the probit and control function (CF) regressions. Standard errors (in brackets) are clustered at the occupation-year level. Country, year, industry group fixed effects, and country linear trends are included. Individual-level controls: age group, education group, gender, and native/non-native. Aggregate-level controls: global value chain participation, gross value added, the ratio of investment added to gross value added, GDP growth, labour demand, and growth in exports. Robot exposure is instrumented using robot exposure in the Western European countries in the sample. NRCA – Non-routine cognitive analytical; NRCP – Non-routine cognitive interpersonal; RC – Routine cognitive; RM – Routine manual; NRM – Non-routine manual physical. NRM is a reference group. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, UIBE GVC, and O*NET data.

Table 1.D.2.: The effect of robot exposure on the likelihood of job finding – by task group

Variables	Probit	CF	Probit	CF
	(1)	(2)	(3)	(4)
Robot Exposure	-0.007***	-0.004	0.020**	0.022**
	(0.003)	(0.004)	(0.008)	(0.011)
Robot Exposure X Labour Costs			0.015**	0.014*
			(0.007)	(0.008)
Robot Exposure X (Labour Costs)^2			-0.034***	-0.036***
			(0.010)	(0.012)
NRCA X Robot Exposure	0.012***	0.018***	0.015	0.008
	(0.003)	(0.005)	(0.013)	(0.017)
NRCP X Robot Exposure	-0.006	0.001	-0.034	-0.034
	(0.005)	(0.010)	(0.023)	(0.036)
RC X Robot Exposure	0.011***	0.013***	0.031***	0.021
	(0.003)	(0.005)	(0.010)	(0.015)
RM X Robot Exposure	0.006**	0.007	0.000	-0.008
	(0.003)	(0.004)	(0.009)	(0.011)
NRCA X Robot Exposure x Labour Cost			0.007	-0.003
			(0.007)	(0.009)
NRCP X Robot Exposure x Labour Cost			-0.008	-0.007
			(0.010)	(0.015)
RC X Robot Exposure x Labour Cost			0.009	0.002
			(0.007)	(0.009)
RM X Robot Exposure x Labour Cost			-0.006	-0.011
			(0.007)	(0.008)
NRCA X Robot Exposure x (Labour Costs)^2			-0.007	0.012
			(0.014)	(0.017)

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Table 1.D.2 – *Continued from previous page*

Variables	Probit	CF	Probit	CF
	(1)	(2)	(3)	(4)
NRCP X Robot Exposure x (Labour Costs)^2			0.031	0.044
			(0.024)	(0.037)
RC X Robot Exposure x (Labour Costs)^2			-0.022*	-0.005
			(0.011)	(0.016)
RM X Robot Exposure x (Labour Costs)^2			0.010	0.022*
			(0.010)	(0.012)
NRCA	-0.060***	-0.070***	-0.001	0.004
	(0.017)	(0.018)	(0.028)	(0.029)
NRCP	-0.154***	-0.162***	-0.216***	-0.218***
	(0.033)	(0.034)	(0.051)	(0.051)
RC	-0.031***	-0.035***	-0.042**	-0.039*
	(0.011)	(0.012)	(0.021)	(0.022)
RM	-0.084***	-0.083***	-0.135***	-0.111***
	(0.015)	(0.016)	(0.025)	(0.026)
NRCA x Labour Cost			-0.037	-0.018
			(0.023)	(0.026)
NRCP x Labour Cost			0.048*	0.049*
			(0.026)	(0.027)
RC x Labour Cost			0.044**	0.049**
			(0.019)	(0.020)
RM x Labour Cost			-0.030	-0.009
			(0.028)	(0.026)
NRCA x (Labour Costs)^2			-0.044	-0.071*
			(0.037)	(0.040)
NRCP x (Labour Costs)^2			0.044	0.035
			(0.046)	(0.048)
RC x (Labour Costs)^2			-0.018	-0.028
			(0.032)	(0.033)
RM x (Labour Costs)^2			0.083**	0.047
			(0.037)	(0.037)
Observations	1.3 M	1.3 M	1.3 M	1.3 M

Note: The table presents the estimated coefficients of the probit and control function (CF) regressions. Standard errors (in brackets) are clustered at the occupation-year level. Country, year, industry group fixed effects, and country linear trends are included. Individual-level controls: age group, education group, gender, and native/non-native. Aggregate-level controls: global value chain participation, gross value added, the ratio of investment added to gross value added, GDP growth, labour demand, and growth in exports. Robot exposure is instrumented using robot exposure in the Western European countries in the sample. NRCA – Non-routine cognitive analytical; NRCP – Non-routine cognitive interpersonal; RC – Routine cognitive; RM – Routine manual; NRM – Non-routine manual physical. NRM is a reference group. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, UIBE GVC, and O*NET data.

Table 1.D.3.: The effect of robot exposure on the likelihood of job separation – by age group

Variables	Probit	CF	Probit	CF
	(1)	(2)	(3)	(4)
Robot Exposure	-0.003**	-0.007**	-0.004*	-0.015***
	(0.002)	(0.003)	(0.002)	(0.005)
Robot Exposure X Labour Costs		-0.004***		-0.005**

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Table 1.D.3 – *Continued from previous page*

Variables	**Probit**	**CF**	**Probit**	**CF**
	(1)	(2)	(3)	(4)
		(0.001)		(0.002)
Robot Exposure X (Labour Costs)^2		0.005		0.013**
		(0.003)		(0.005)
Age 25-34 X Robot Exposure	-0.000	-0.006*	-0.005***	-0.006
	(0.001)	(0.003)	(0.001)	(0.004)
Age 35-54 X Robot Exposure	0.000	-0.006**	-0.002*	0.002
	(0.001)	(0.003)	(0.001)	(0.004)
Age 55-70 X Robot Exposure	0.006***	0.007*	0.007***	0.030***
	(0.002)	(0.004)	(0.002)	(0.006)
Age 25-34 X Robot Exposure x Labour Cost		-0.005***		-0.006***
		(0.001)		(0.002)
Age 35-54 X Robot Exposure x Labour Cost		-0.002*		-0.000
		(0.001)		(0.002)
Age 55-70 X Robot Exposure x Labour Cost		0.004**		0.011***
		(0.002)		(0.003)
Age 25-34 X Robot Exposure x (Labour Costs)^2		0.006*		0.005
		(0.004)		(0.005)
Age 35-54 X Robot Exposure x (Labour Costs)^2		0.007**		-0.005
		(0.003)		(0.005)
Age 55-70 X Robot Exposure x (Labour Costs)^2		-0.003		-0.031***
		(0.004)		(0.007)
Age 25-34	-0.170***	-0.200***	-0.163***	-0.201***
	(0.006)	(0.011)	(0.006)	(0.012)
Age 35-54	-0.354***	-0.420***	-0.349***	-0.430***
	(0.007)	(0.013)	(0.008)	(0.014)
Age 55-70	-0.350***	-0.414***	-0.355***	-0.446***
	(0.011)	(0.020)	(0.011)	(0.019)
Age 25-34 x Labour Cost		0.093***		0.094***
		(0.009)		(0.009)
Age 35-54 x Labour Cost		0.045***		0.043***
		(0.009)		(0.009)
Age 55-70 x Labour Cost		0.028**		0.023*
		(0.012)		(0.013)
Age 25-34 x (Labour Costs)^2		0.001		0.005
		(0.016)		(0.016)
Age 35-54 x (Labour Costs)^2		0.079***		0.095***
		(0.016)		(0.017)
Age 55-70 x (Labour Costs)^2		0.076***		0.116***
		(0.023)		(0.022)
Observations	11.8 M	11.8 M	11.8 M	11.8 M

Note: The table presents the estimated coefficients of the probit and control function (CF) regressions. Standard errors (in brackets) are clustered at the occupation-year level. Country, year, industry group fixed effects, and country linear trends are included. Individual-level controls: age group, education group, gender, and native/non-native. Aggregate-level controls: global value chain participation, gross value added, the ratio of investment added to gross value added, GDP growth, labour demand, and growth in exports. Robot exposure is instrumented using robot exposure in the Western European countries in the sample. Aged 15-24 are a reference group.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, UIBE GVC, and O*NET data.

Table 1.D.4.: The effect of robot exposure on the likelihood of job finding – by age group

Variables	Probit	CF	Probit	CF
	(1)	(2)	(3)	(4)
Robot Exposure	0.004***	0.022***	0.013***	0.027***
	(0.001)	(0.005)	(0.002)	(0.006)
Robot Exposure X Labour Costs		0.006***		0.005**
		(0.002)		(0.002)
Robot Exposure X (Labour Costs)^2		-0.022***		-0.022***
		(0.005)		(0.007)
Age 25-34 X Robot Exposure	-0.005***	-0.004	-0.011***	-0.011**
	(0.001)	(0.004)	(0.002)	(0.006)
Age 35-54 X Robot Exposure	-0.006***	-0.004	-0.014***	-0.022***
	(0.001)	(0.004)	(0.002)	(0.007)
Age 55-70 X Robot Exposure	-0.011***	-0.020***	-0.023***	-0.051***
	(0.002)	(0.006)	(0.004)	(0.008)
Age 25-34 X Robot Exposure x Labour Cost		0.002		0.002
		(0.002)		(0.002)
Age 35-54 X Robot Exposure x Labour Cost		0.003*		-0.004
		(0.002)		(0.002)
Age 55-70 X Robot Exposure x Labour Cost		-0.003		-0.012***
		(0.003)		(0.004)
Age 25-34 X Robot Exposure x (Labour Costs)^2		-0.000		0.005
		(0.005)		(0.006)
Age 35-54 X Robot Exposure x (Labour Costs)^2		-0.003		0.014**
		(0.005)		(0.007)
Age 55-70 X Robot Exposure x (Labour Costs)^2		0.011*		0.038***
		(0.006)		(0.008)
Age 25-34	-0.404***	-0.428***	-0.396***	-0.423***
	(0.010)	(0.018)	(0.010)	(0.018)
Age 35-54	-0.666***	-0.728***	-0.654***	-0.715***
	(0.015)	(0.025)	(0.015)	(0.025)
Age 55-70	-1.098***	-1.161***	-1.081***	-1.139***
	(0.022)	(0.031)	(0.022)	(0.031)
Age 25-34 x Labour Cost		0.098***		0.095***
		(0.013)		(0.013)
Age 35-54 x Labour Cost		0.084***		0.087***
		(0.015)		(0.015)
Age 55-70 x Labour Cost		-0.020		-0.022
		(0.023)		(0.024)
Age 25-34 x (Labour Costs)^2		-0.019		-0.018
		(0.024)		(0.024)
Age 35-54 x (Labour Costs)^2		0.043		0.037
		(0.028)		(0.028)
Age 55-70 x (Labour Costs)^2		0.110***		0.103***
		(0.034)		(0.035)
Observations	1.3 M	1.3 M	1.3 M	1.3 M

Continued on next page

Table 1.D.4 – *Continued from previous page*

Variables	**Probit**	**CF**	**Probit**	**CF**
	(1)	(2)	(3)	(4)

Note: The table presents the estimated coefficients of the probit and control function (CF) regressions. Standard errors (in brackets) are clustered at the occupation-year level. Country, year, industry group fixed effects, and country linear trends are included. Individual-level controls: age group, education group, gender, and native/non-native. Aggregate-level controls: global value chain participation, gross value added, the ratio of investment added to gross value added, GDP growth, labour demand, and growth in exports. Robot exposure is instrumented using robot exposure in the Western European countries in the sample. Aged 15-24 are a reference group.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, UIBE GVC, and O*NET data.

Table 1.D.5.: The effect of robot exposure on the likelihood of job separation, initial development proxied with GDP

	(1) Probit	(2) CF	(3) Probit	(5) CF
A: All Sectors				
Robot Exposure	-0.003**	-0.005***	-0.010***	-0.009***
	(0.001)	(0.001)	(0.002)	(0.002)
Robot Exposure X GDP per capita			-0.008***	-0.005***
			(0.001)	(0.002)
Robot Exposure X (GDP per capita)^2			0.021***	0.012**
			(0.004)	(0.005)
No. of observations	11.8 M	11.8 M	11.8 M	11.8 M
Kleibergen-Paap F-statistic		372 874.1		22 886.2
B: Manufacturing				
Robot Exposure	-0.001	-0.006***	-0.008***	-0.008***
	(0.001)	(0.002)	(0.002)	(0.003)
Robot Exposure X GDP per capita			-0.006***	-0.000
			(0.002)	(0.002)
Robot Exposure X (GDP per capita)^2			0.019***	0.006
			(0.007)	(0.008)
No. of Observations	2.6 M	2.6 M	2.6 M	2.6 M
Kleibergen-Paap F-statistic		197 835.2		13 977.7

Note: See notes to Table 1.B.1. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

Table 1.D.6.: The effect of robot exposure on the likelihood of job finding, initial development proxied with GDP

	(1) Probit	(2) CF	(3) Probit	(5) CF
A: All Sectors				
Robot Exposure	-0.002	0.002	0.007***	0.003
	(0.001)	(0.001)	(0.002)	(0.002)
Robot Exposure X GDP per capita			0.007***	-0.001
			(0.002)	(0.003)
Robot Exposure X (GDP per capita)^2			-0.024***	-0.005
			(0.005)	(0.006)
No. of Observations	1.3 M	1.3 M	1.3 M	1.3 M
Kleibergen-Paap F-statistic		25 778.1		3 187.2
B: Manufacturing				
Robot Exposure	0.000	0.002	0.003	0.002
	(0.001)	(0.002)	(0.003)	(0.003)
Robot Exposure X GDP per capita			0.001	-0.006**
			(0.002)	(0.003)
Robot Exposure X (GDP per capita)^2			-0.007	0.002
			(0.007)	(0.009)
No. of Observations	260 180	260 180	260 180	260 180
Kleibergen-Paap F-statistic		14 791.2		2 236.7

Note: See notes to Table 1.B.1. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

Table 1.D.7.: The effect of percentiles of robot exposure on the job separation likelihood

	Probit		CF	
	(1)	(2)	(3)	(4)
Percentile Robot Exposure	-0.095***	-0.247***	-0.110***	-0.292***
	(0.022)	(0.032)	(0.026)	(0.042)
Percentile Robot Exposure X Labour Costs 2004			-0.025	0.025
			(0.019)	(0.024)
Percentile Robot Exposure X (Labour Costs 2004)^2			0.037	0.040
			(0.027)	(0.034)
No. of Observations	11.8 M	11.8 M	11.8 M	11.8 M
Kleibergen-Paap F-statistic		8.5 M		2.2 M

Note: See notes to Table 1.B.1. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

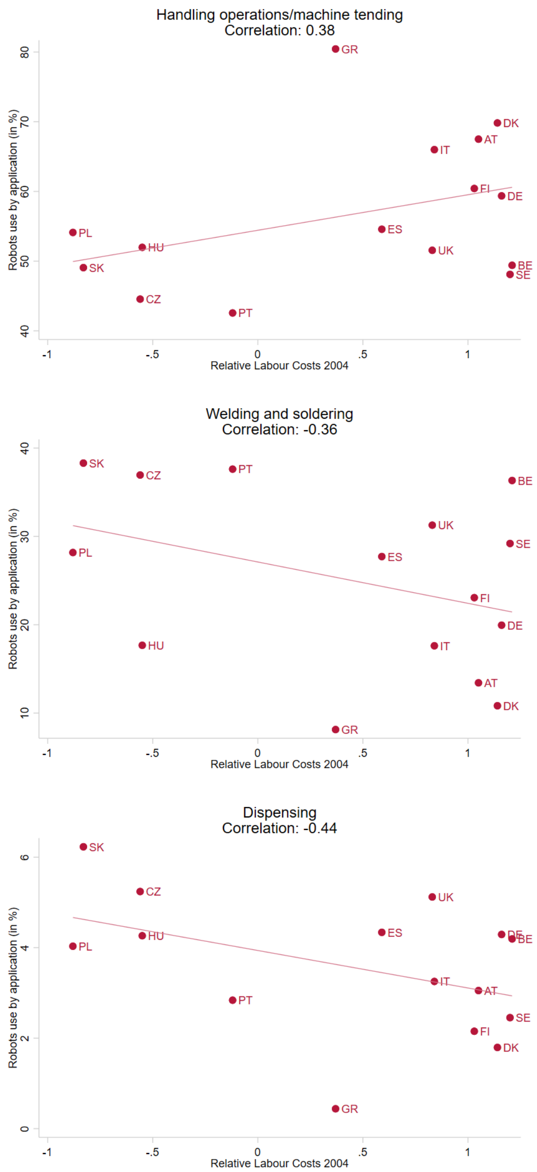
Table 1.D.8.: The effect of percentiles of robot exposure on the job finding likelihood

	Probit		CF	
	(1)	(2)	(3)	(4)
Percentile Robot Exposure	-0.022	0.015	0.133***	0.076
	(0.023)	(0.038)	(0.038)	(0.062)
Percentile Robot Exposure X Labour Costs 2004			0.150***	-0.031
			(0.043)	(0.044)
Percentile Robot Exposure X (Labour Costs 2004)^2			-0.281***	-0.061
			(0.055)	(0.067)
No. of Observations	1.3 M	1.3 M	1.3 M	1.3 M
Kleibergen-Paap F-statistic		771 655.9		187 741.6

Note: See notes to Table 1.B.1. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

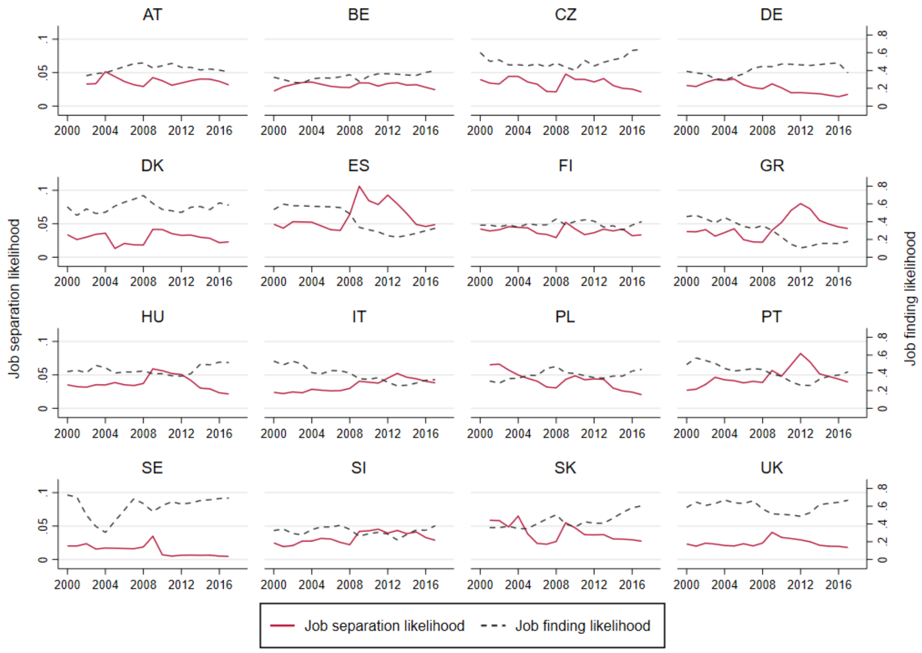
Figures

Figure 1.D.1.: Correlation between initial labour costs and robot application within countries



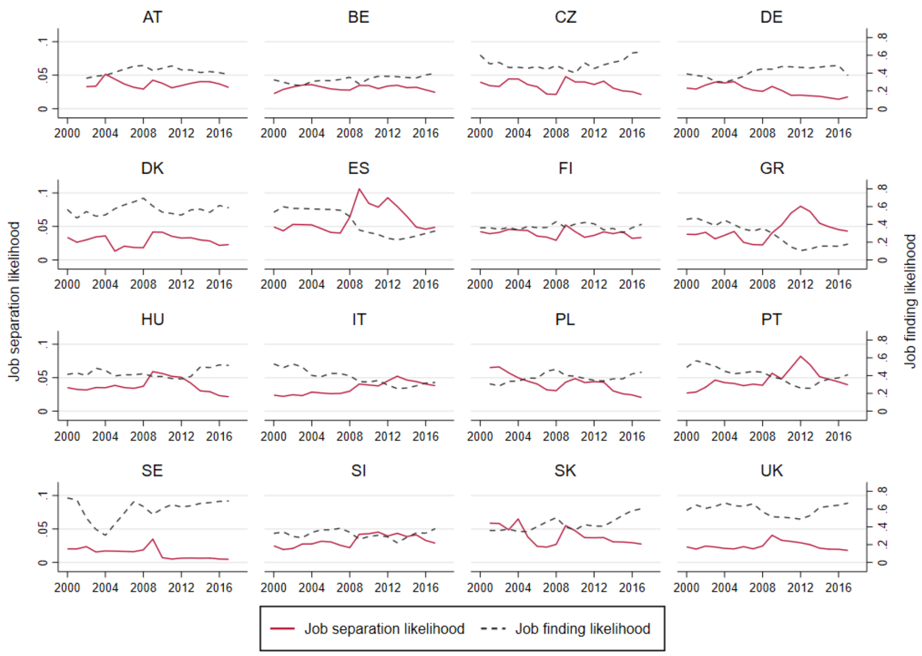
Note: Scales on y-axis differ. Robot application shares are calculated in 2016. – Source: authors' calculations based on IFR data.

Figure 1.D.2.: Change in robot exposure at one-digit occupation-level between 2000/2004-2016.



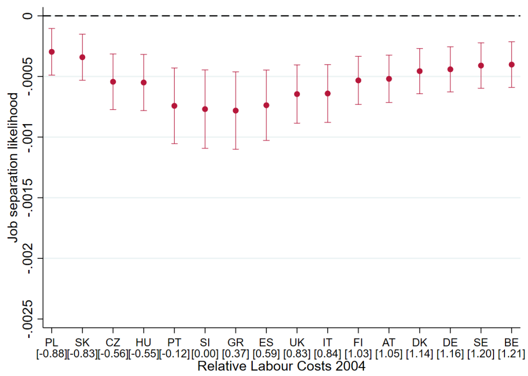
Note: The figure displays the changes in robot exposure between 2000/2004 and 2016 in occupation groups across all sectors by country. Robot exposure is measured as the number of robots per 1,000 workers. Occupations are classified according to the ISCO Standard: 1 Managers; 2 Professionals; 3 Technicians and Associates; 4 Clerks; 5 Services and Sales; 6 Agriculture, Fishery, Forestry; 7 Craft and Trade; 8 Machine Operators; 9 Elementary Occupations). – Source: authors' calculations based on the EU-LFS and IFR.

Figure 1.D.3.: Transition rates between employment and unemployment by country, 2000-2018.

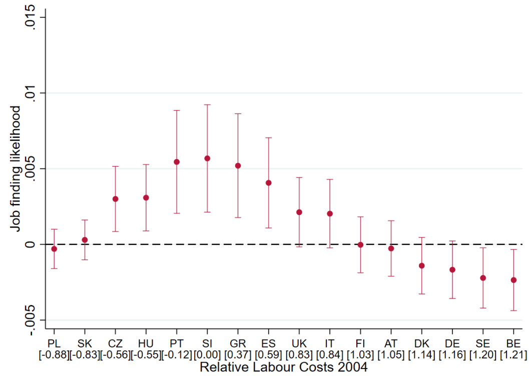


Note: The figure displays the average transition rates (a) from employment to unemployment and (b) from unemployment to employment by country. – Source: authors' calculations based on the EU-LFS.

Figure 1.D.4.: Effects of robot exposure on likelihood of the flows, regressions with country FE



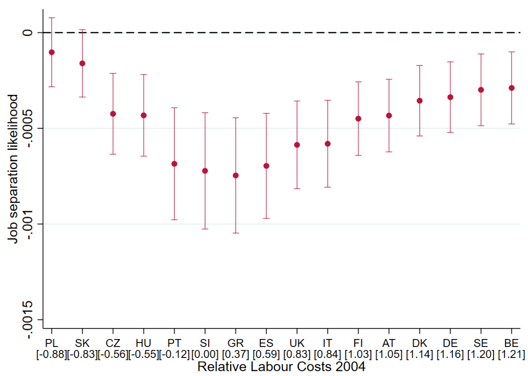
(a) Job separation



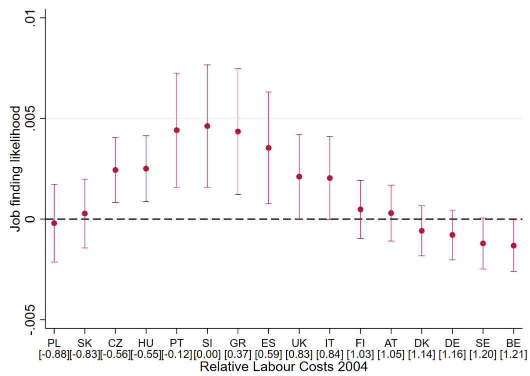
(b) Job finding

Note: The figures show the marginal effects of robot exposure on the probability of transitioning from employment to unemployment (left panel) and unemployment to employment (right panel), based on regressions presented in Table 4 column (3) . Robot exposure is instrumented using the average robot exposure in the Western European countries in the sample. Countries on the X-axis are ranked according to the initial labour cost (in parentheses). – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

Figure 1.D.5.: Effects of robot exposure on likelihood of the flows, regressions without controls for value added and gross fixed capital formations



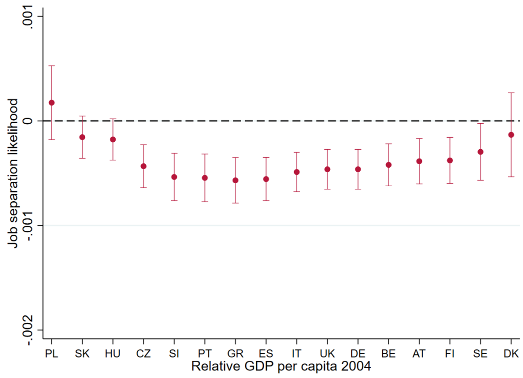
(a) Job separation



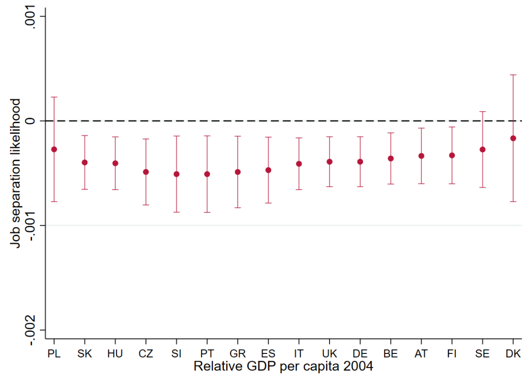
(b) Job finding

Note: The figures show the marginal effects of robot exposure on the probability of transitioning from employment to unemployment (left panel) and unemployment to employment (right panel), based on regressions presented in Table 4 column (4). Robot exposure is instrumented using the average robot exposure in the Western European countries in the sample. Countries on the X-axis are ranked according to the initial labour cost (in parentheses). – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

Figure 1.D.6.: Marginal effects of robot exposure on the likelihood of job separation, initial development proxied with GDP



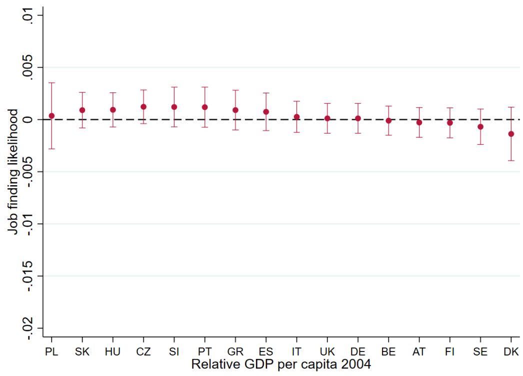
(a) All industries



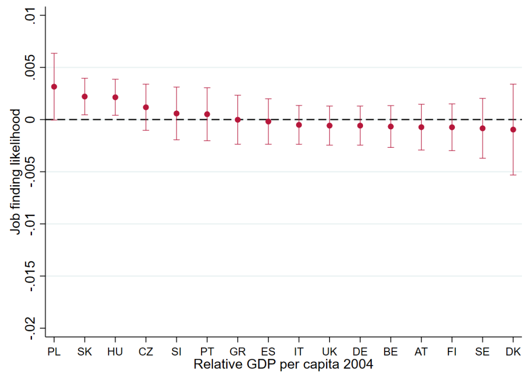
(b) Manufacturing

Note: The figures show the marginal effects of robot exposure on the probability of transitioning from employment to unemployment. The vertical lines represent the 95% confidence intervals. Robot exposure is interacted with GDP per capita in 2004. The results are obtained by instrumenting robot exposure with robot exposure in the Western European countries in the sample. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

Figure 1.D.7.: Marginal effects of robot exposure on the likelihood of job finding, initial development proxied with GDP



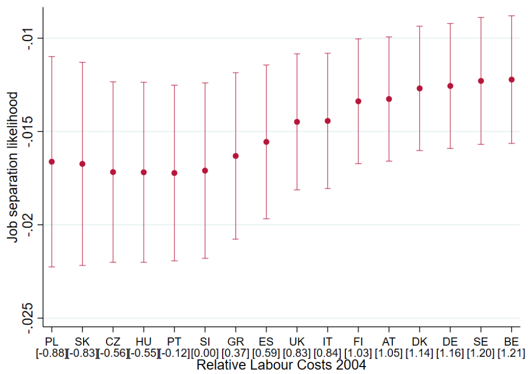
(a) All industries



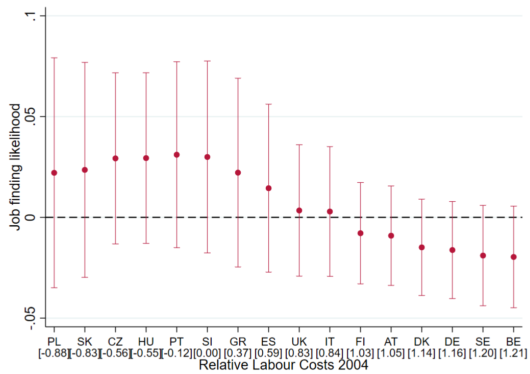
(b) Manufacturing

Note: The figures show the marginal effects of robot exposure on the probability of transitioning from unemployment to employment. The vertical lines represent the 95% confidence intervals. Robot exposure is interacted with GDP per capita in 2004. The results are obtained by instrumenting robot exposure with robot exposure in the Western European countries in the sample. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

Figure 1.D.8.: Marginal Effects of Percentiles of Robot Exposure for job separation/job finding likelihood



(a) Job separation



(b) Job finding

Note: The figures show the marginal effects of robot exposure on the probability of transitioning from employment to unemployment (left panel) and unemployment to employment (right panel), based on regressions presented in Table 1.D.7] and 1.D.8 column (4). The vertical lines represent the 95% confidence intervals. Robot exposure is instrumented using the percentiles of the average robot exposure in the Western European countries in the sample. Countries on the x-axis are ranked according to the initial labour cost (in parentheses).-Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data

Figure 1.D.9.: Marginal effects of robot exposure on the likelihood of job separations and finding, by age group in manufacturing

(a) Job separation (b) Job finding

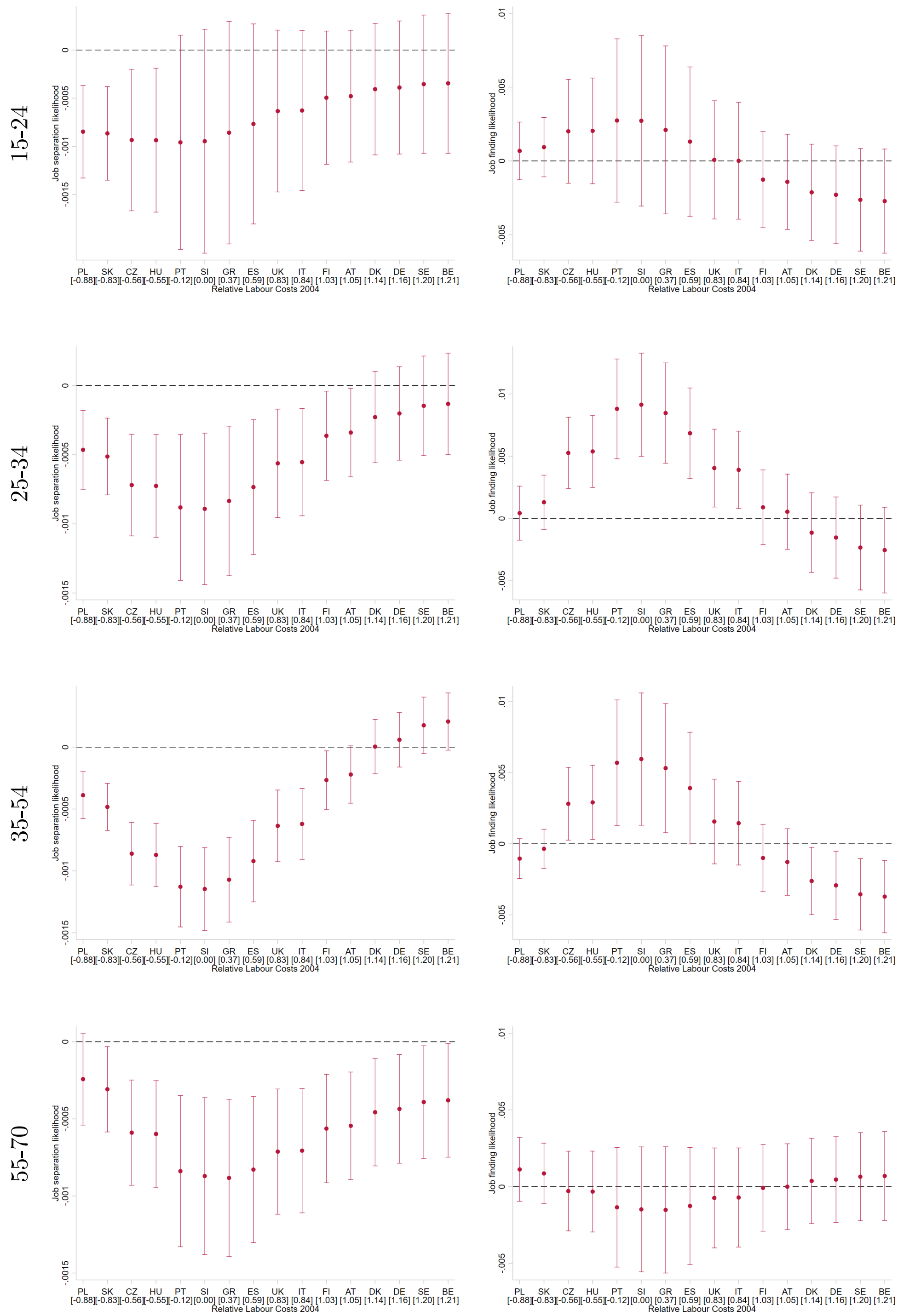
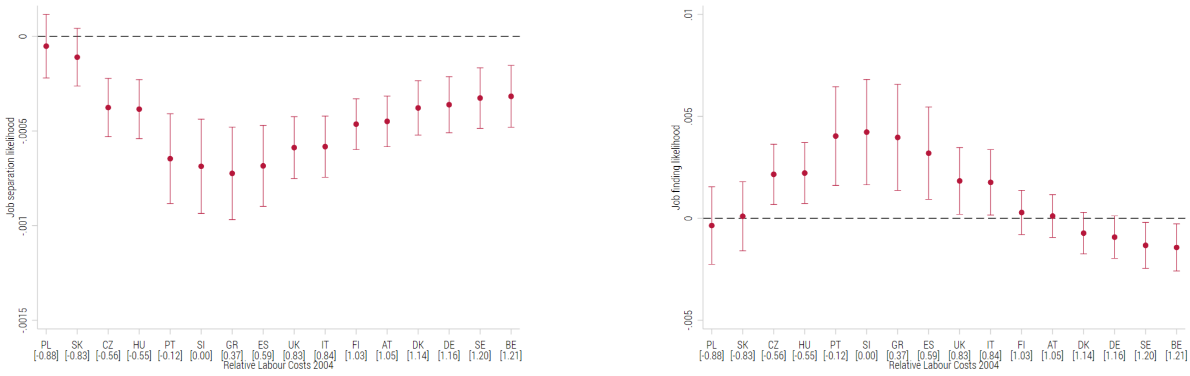


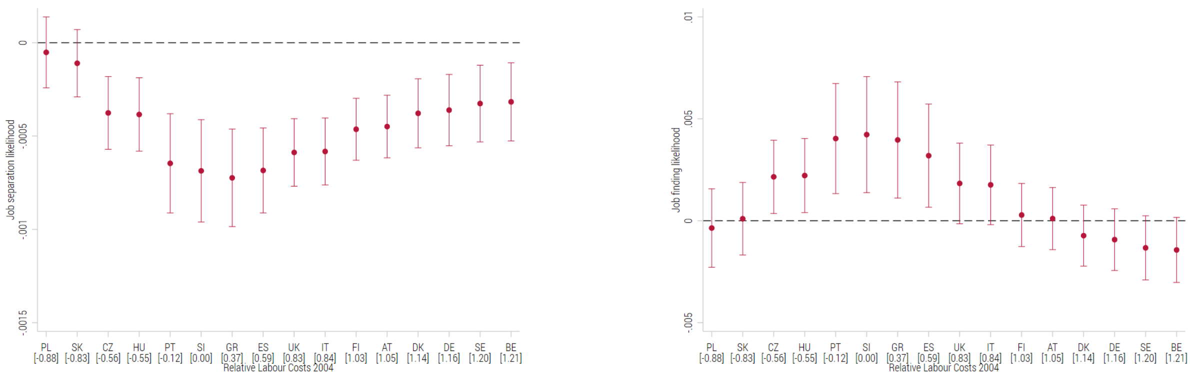
Figure 1.D.10.: Effects of robot exposure on likelihood of the flows, clusters by country, occupation, and year



(a) Job separation (b) Job finding

Note: The figures show the marginal effects of robot exposure on the probability of transitioning from employment to unemployment (see also Figure 1.5) and probability of transitioning from unemployment to employment (see also Figure 1.6) with standard errors clustered at country-occupation-year level. The vertical lines represent the 95% confidence intervals. Robot exposure is instrumented using the average robot exposure in the Western European countries in the sample. Countries on the x-axis are ranked according to the initial labour cost (in parentheses). Figure 1.B.1 in the appendix presents the marginal effects with the linear labour costs scale on the x-axis. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

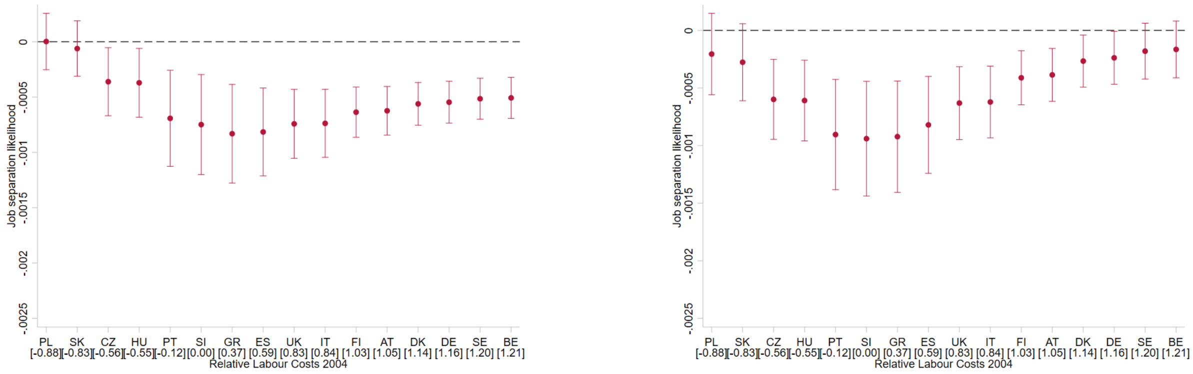
Figure 1.D.11.: Effects of robot exposure on likelihood of the flows, clusters by sector and year



(a) Job separation (b) Job finding

Note: The figures show the marginal effects of robot exposure on the probability of transitioning from employment to unemployment (see also Figure 1.5) and probability of transitioning from unemployment to employment (see also Figure 1.6) with standard errors clustered at sector-year level. The vertical lines represent the 95% confidence intervals. Robot exposure is instrumented using the average robot exposure in the Western European countries in the sample. Countries on the x-axis are ranked according to the initial labour cost (in parentheses). Figure 1.B.1 in the appendix presents the marginal effects with the linear labour costs scale on the x-axis. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

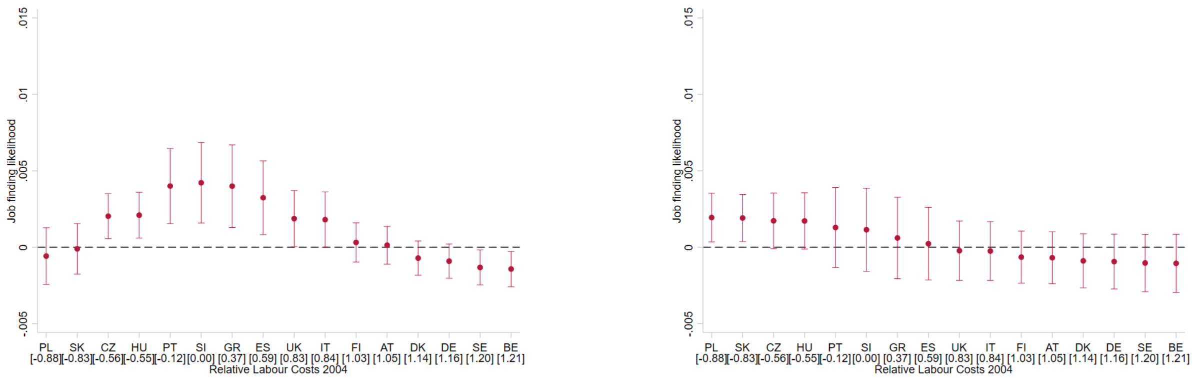
Figure 1.D.12.: Marginal effects of robot exposure on the likelihood of job separation, estimated with linear probability model



(a) All sectors (b) Manufacturing

Note: The figures show the marginal effects of robot exposure on the probability of transitioning from employment to unemployment (see also Figure 1.5) and probability of transitioning from unemployment to employment (see also Figure 1.6) with standard errors clustered at sector-year level. The vertical lines represent the 95% confidence intervals. Robot exposure is instrumented using the average robot exposure in the Western European countries in the sample. Countries on the x-axis are ranked according to the initial labour cost (in parentheses). Figure 1.B.1 in the appendix presents the marginal effects with the linear labour costs scale on the x-axis. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

Figure 1.D.13.: Marginal effects of robot exposure on the likelihood of job finding, estimated with linear probability model



(a) All sectors (b) Manufacturing

Note: The figures show the marginal effects of robot exposure on the probability of transitioning from employment to unemployment (see also Figure 1.5) and probability of transitioning from unemployment to employment (see also Figure 1.6) with standard errors clustered at sector-year level. The vertical lines represent the 95% confidence intervals. Robot exposure is instrumented using the average robot exposure in the Western European countries in the sample. Countries on the x-axis are ranked according to the initial labour cost (in parentheses). Figure 1.B.1 in the appendix presents the marginal effects with the linear labour costs scale on the x-axis. – Source: authors' calculations based on the EU-KLEMS, EU-LFS, Eurostat, IFR, UN Comtrade, and UIBE GVC data.

2. Technological Progress, Occupational Structure and Gender Gaps in the German Labour Market*

Abstract: We analyze if technological progress and the change in the occupational structure have improved women's position in the labour market. We show that women increasingly work in non-routine manual and in interactive occupations. However, the observed narrowing of the gender wage gap is entirely driven by declining gender wag gaps within, rather than between, occupations. A decomposition exercise reveals that while explained factors have become more important contributors to the gender wage gap, the importance of unexplained factors factors has strongly declined. Therefore, unequal treatment based on unobservables, i.e. discrimination, is likely to have declined over time. Finally, technological change as measured by job tasks plays an ambiguous role. Institutional factors, and in particular part-time employment, are still a major driver of the gender wage gap.

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2.1. Introduction

Despite a significant reduction in the gender wage gap over the last decades in many industrialised countries, there remains a substantial gap, particularly at the top of the wage distribution (Blau and Kahn, 2017). At the same time, technological progress has changed the structure of occupations toward non-routine jobs that are less easily automated. It has also affected the task content within occupations, in particular increasing the value of social tasks (Black and Spitz-Oener, 2010; Cortes et al., 2023).

There is some evidence to suggest that technological progress has had a positive impact on women, and there are two main reasons for this: First, a smaller share of women were employed in routine occupations in the 1980s, making them less exposed to the substitution effects of technology.[1] Second, according to the neuroscience literature, women have a comparative advantage in social skills (Baron-Cohen et al., 2005; Chapman et al., 2006; Greenberg et al., 2018); they also have a comparative advantage in occupations that require these skills. Therefore, women sort into occupations with a higher level of social skills, assuming sorting based on comparative advantage (Cortes et al., 2023). However, women may not be able to benefit due to lower returns to tasks within occupations, as shown for Germany (Storm, 2023), and due to selection into occupations with lower wage growth, as shown for the US and Portugal (Cortes et al., 2020).

In this paper, we analyze how technological change has affected the occupational structure and thus the relative position of women in the German labour market over the period 1984-2017. We address three questions. First, how has the change in occupational structure affected women differently than men? Second, has the change in occupational structure led to a reduction in the gender wage gap? Third, which factors explain the narrowing gender gap within occupations?

Our analysis is based on data from the Socio-Economic Panel (SOEP) for West Germany over the time period 1984-2017. We focus on West Germany due to missing pre-1990 data for East Germany and persistent labor market differences between East and West Germany. We complement the SOEP with data from the BIBB Employment survey that provides individual-level data on tasks performed on the job. This allows us to categorize occupations into task groups, but also to create gender-specific and time-varying task intensities. First, we provide descriptive evidence on the evolution of female employment across task groups over time. Second,

[1] This is shown for Germany by Black and Spitz-Oener (2010), for Portugal Cortes et al. (2020) and for the US by Cortes et al. (2023).

we examine how the change in the occupational structure has affected the gender wage gap. Third, we conduct a Blinder-Oaxaca decomposition to determine factors that are related to the change in the gender wage gap over time, explicitly taking into account the role of composition effects. We include part-time workers as they make up a large share of the female work force in Germany. Moreover, our data allow us to also include workers in the upper part of the income distribution. To examine differences across occupations and study the importance of social skills[2], we distinguish between four categories (Koomen and Backes-Gellner, 2022): routine, non-routine manual (NRM), non-routine interactive (NRI), and non-routine cognitive (NRC).

Germany provides an interesting setting for the analysis, as it is a technological frontier country in Europe, e.g. in terms of robot adoption (Dauth et al., 2021), and features strong employment polarization, i.e. a strong decline of employment in routine occupations and a corresponding increase of employment in non-routine manual and cognitive occupations (Bachmann et al., 2019). Furthermore, the unconditional gender gap has declined from 30% to 24%, but a significant gap remains. While the share of women in academic occupations has increased significantly, women are still underrepresented in managerial positions. Furthermore, between 1985 and 2017, the share of non-working women decreased strongly from from 52% to 30%, while the corresponding share of non-employed men remained virtually unchanged.

Our results are as follows. First, we find that while the female share in non-routine manual and in interactive occupations increased strongly over time, the female share in non-routine cognitive and in routine occupations remained relatively constant. Second, we confirm the decline of the gender wage gap in Germany over the last decades previously found in the literature and show that this decline is entirely driven by a reduction of the gender wage gap within occupations, not between occupations. Third, our decomposition exercise reveals a strong increase of the explained part (composition effects) and a corresponding strong decrease of the unexplained part (payoffs to characteristics). Overall, these results are in line with a reduction in wage discrimination in the labour market.

Our results suggest that technological change, which leads to changes in the employment weights of occupational groups, has not been an important driver of the gender wage gap. Rather,

[2] Although there is no single definition, social skills, as commonly measured in the literature, typically include dimensions such as communication, teamwork and coordination, social perception, negotiation, and presentation (Atalay et al., 2020; Borghans et al., 2014; Cortes et al., 2023; Deming and Kahn, 2018; Deming, 2017). In addition, the concept of social skills can be extended to include customer service and service orientation (Langer and Wiederhold, 2023).

the narrowing of the gender wage gap is due to changes within task groups. Furthermore, while task intensities play a role in the gender wage gap within task groups, institutional aspects, especially part-time employment, are more important determinants.

The study contributes to the literature that studies the impact of technology on labour-market outcomes. To date, there is only a relatively limited number of studies that focuses on the impact on women. For Germany, Black and Spitz-Oener (2010) show that exposure to technology contributed to a narrowing of the gender wage gap in the time period 1979–1999. However, more recent evidence shows that while women sort into interactive occupations, they receive lower returns to interactive tasks within these occupations (Storm, 2023). Moreover, Genz and Schnabel (2023) show that digital investments lead to greater job losses for women. For the US, Cortes et al. (2023) show that the increasing importance of social skills within occupations is associated with women sorting into higher paying occupations. Comparing developments in the US and Portugal, Cortes et al. (2020) point out that women have indeed benefited from changes in occupational structures, but they have moved into occupations with lower wage growth. In particular, women are underrepresented in high-paying STEM occupations.

Our contributions are as follows. First, we provide evidence for Germany which complements the analysis of Cortes et al. (2023, 2020). Second, we take into account a large part of the labour market as our analysis also includes part-time and high-skilled workers, often not included in other studies due to data limitations. Third, the use of individual-level data allows us to study the importance of developments other than technological change not just between task groups, such as the overall increase in educational attainment, and increased availability of flexible work arrangements and childcare, taking into account both composition effects and changes in the pay-offs to such characteristics. Fourth, using individual-level data on tasks performed at the job, we can analyse the role of task changes within occupations over time.

2.2. Previous Literature

We relate to three strands of the literature that evaluate the impact of technological change on (i) occupational structures and skill requirements, (ii) gender gaps and female labour market participation, and (iii) the impact of technology on gender gaps.

There is a large body of evidence documenting the polarization of labour markets (Autor et al., 2003; Bachmann et al., 2019; Goos et al., 2009). Labour-market polarization can be explained by a model of work tasks (Autor et al., 2003) according to which technology acts as a substitute for routine work and as a complement to non-routine (cognitive) work. Task-biased technological change also affects skill requirements. Evidence from the early 2000s already showed that jobs had become more complex, and that analytical and interactive tasks had gained importance since the early 1980s (Spitz-Oener, 2006). More recently, the combination of cognitive and social skills has been found to be particularly important for labour-market success in terms of employment (Deming and Kahn, 2018; Weinberger, 2014) and wages (Böhm et al., 2024; Deming, 2017).

The literature on the gender wage gap shows that while this gap has declined in recent decades in many industrialised countries, there was less convergence in the upper part of the wage distribution (Blau and Kahn, 2017; Blau et al., 2024; Granados and Wrohlich, 2018). In Germany, the gender wage gap for full-time workers has fallen from 30% to 19% over the last decade (Granados and Wrohlich, 2018), but further narrows when gender differences in education, work experience and sector choice are taken into account (Anger and Schmidt, 2010; Bredtmann and Otten, 2014). Over the last decades, other factors have played an important role for the labour-market situation of women besides technological progress. First, increased female educational attainment coincides with changing social norms regarding working women. This has allowed women to enter higher-paying occupations (Fortin et al., 2015; Goldin, 2006). Second, changes in parental leave policies (Kluve and Schmitz, 2018; Kluve and Tamm, 2013; Schönberg and Ludsteck, 2014) and in labour market institutions, such as part-time work and alternative work arrangements (Bachmann and Felder, 2020; Fitzenberger et al., 2004), helped to reconcile family and career and therefore contributed to the strong increase in female labour-force participation.

The impact of technological progress on women has so far only been investigated by a relatively small, but growing number of papers. For Germany, Black and Spitz-Oener (2010) show that women have experienced a relative increase in the importance of interactive and analytical tasks and a greater decrease in the intensity of routine task than men. These gender-specific changes in tasks and in task prices explain part of the narrowing of the gender wage gap. Other studies emphasize the role of declining returns to manual skills (Yamaguchi, 2018) and the impact of computerization for the convergence of the gender wage gap (Beaudry and Lewis, 2014) and the decline in the part-time penalty (Elsayed et al., 2017). Cortes et al. (2023) show that the increasing importance of social skills in high-wage occupations since the 1980s has been an important factor in the sorting of women into these occupations.

Comparing developments in the US and Portugal, Cortes et al. (2020) point out that the overall impact of technology on the gender gap is ambiguous. While the change in the occupational structure would have led to a reduction in the gender wage gap, this effect is counteracted by the selection of women into occupations with lower wage growth on average. While women sort into NRC occupations, they select less into STEM NRC occupations that experienced the highest wage growth. Evidence from Germany also shows that women who move into male-dominated occupations experience stronger wage growth (Busch, 2020). However, Storm (2023) points out that women do not fully benefit due to lower returns to interactive tasks.

Furthermore, there is evidence that the rise of the service economy has led to a narrowing of the gender wage gap (Ngai and Petrongolo, 2017) and that the rise of low-skilled services is driven by the entry of high-skilled women into the labour market who outsource home production (Cerina et al., 2021).

2.3. Data

2.3.1. German Socio-Economic Panel

We use data from the German Socio-Economic Panel (SOEP) for the years 1984-2017. The SOEP is a representative annual panel survey of private households/persons in Germany.[3] For the analyses, we consider individuals between the ages of 20 and 64. We exclude observations with missing employment status, missing occupation code and missing wage information. We also exclude apprentices, self-employed persons, persons who worked in the armed forces, in sheltered workshops, or in agriculture, forestry, and fishing. To avoid structural breaks, we focus on persons working in West Germany. Moreover, the labor market situation of women differs significantly between East and West Germany (Jochmann-Döll and Scheele, 2020), which justifies a separate analysis. In order to fully capture the development of female employment, we consider all employees who are in full-time, part-time or marginal employment.

We use information on actual hours worked last month and actual monthly earnings to con-

[3]See Goebel et al. (2019) for a general data description and SOEP (2018) for details on the SOEP version used.

struct a measure of hourly earnings. We adjust wages for inflation using the Consumer Price Index with 2017 reference prices. Observations with zero wages are excluded, and wages below the first percentile of the annual wage distribution are set to the first percentile.[4] To classify occupations, we use the definition of occupational fields by the the German Federal Institute for Vocational Education and Training (BIBB) (Tiemann et al., 2008) which defines 54 different occupational groups based on similar tasks performed within an occupation.

Table 2.1.: Summary statistics for working men and women

	Men		Women	
	1985-89	2013-17	1985-89	2013-17
Hourly Wage	17.1	19.7	12.9	15.4
Education				
low education	0.12	0.09	0.26	0.09
medium education	0.64	0.54	0.57	0.6
high education	0.24	0.36	0.17	0.3
Part-time share	0.01	0.05	0.27	0.34
Work-experience FT (in years)	19.6	19.4	11.3	11.6
Tenure (in years)	12.8	12.3	9.0	10.3
Sector				
Manufacturing	0.43	0.35	0.26	0.13
Utilities & Construction	0.13	0.1	0.02	0.02
Retail, Transport, Logistics	0.12	0.16	0.17	0.18
Services	0.06	0.13	0.12	0.15
Public administration	0.17	0.19	0.29	0.43
Others	0.09	0.08	0.13	0.09
Firm size				
< 200 empl	0.41	0.42	0.54	0.5
$200 - 2000$ empl	0.25	0.24	0.23	0.22
> 2000 empl	0.34	0.34	0.22	0.28
Demographics				
Married/registered partnership	0.71	0.57	0.55	0.51
No. children household	0.7	0.54	0.43	0.45
Age	40.72	43.76	37.95	43.73
Migration background	0.13	0.26	0.11	0.24
Observations	14,104	24,839	8,334	25,663

Source: authors' calculations based on SOEP v.37.

The SOEP provides rich information on educational attainment, work experience, demographics, and job characteristics that we can use to examine the role of compositional changes in the workforce over time. To account for a sufficient number of observations in smaller occupational

[4] In the SOEP, information on hours worked by employees and their wages is self-reported. Therefore, the calculation of hourly wages may lead to unreasonably low wages. We bottom code wages and exclude observations to reduce the impact of these measurement biases.

fields, we pool the years 1985 to 1989 and 2013 to 2017 for the early and late periods. Therefore, data are aggregated by treating each year as a cross-section.

Table 2.1 shows characteristics for men and women in the periods 1985-89 and 2013-2017. Hourly wages have increased for both men and women over the period, but average wages for women in 2013-2017 are still below the level of men's wages in 1985-89, indicating a significant unconditional gender gap. Overall educational attainment has increased, but with similar trends for both sexes. However, the share of part-time work is significantly higher for women and increased further between 1985 and 2017. While only 5% of men work part-time in the period 2013-17, the share for women is 34%. In addition, men have more full-time work experience and work in companies with more employees than women. Furthermore, men have moved out of manufacturing, while women have mainly moved into public administration. In terms of demographics, men and women in the workforce have become more similar over time, and men are now less likely to be married and have children. Finally, the average age of both men and women has increased, but more so for women.

2.3.2. Data on Task Intensities

For the task categorization, we use four waves of the BiBB Employment Survey: the BiBB/IAB Employment Survey for 1986 and 1992 and the BiBB/BAuA Employment Survey for 2012 and 2018.[5] The Employment Survey data is a cross-sectional, representative employment survey for Germany that provides extensive information on working conditions, job content, and qualifications of the employed. In order to achieve comparability with the SOEP sample, the same groups as described above are excluded.

The BiBB Employment Survey is the only data source for Germany that allows for the analysis of changes and variations in task content within occupations and over a long period of time. However, there are data limitations due to some changes in task items and changes in question wording over time. We follow Rohrbach-Schmidt and Tiemann (2013) to mitigate these concerns in order to make task groups more comparable over time. Thus, we restrict the analysis to items available in both periods and aggregate individual items into more aggregated groups to

[5]For more information on the datasets see BIBB (1986, 1992, 2012, 2018) and Rohrbach-Schmidt and Hall (2013, 2020).

maintain a constant number of task items over time.[6] In addition, we closely follow Koomen and Backes-Gellner (2022) and distinguish between four task groups: routine and non-routine manual (NRM), non-routine interactive (NRI), and non-routine cognitive (NRC).[7] Table 2.A1 shows the assignment of task items to task groups. For the analysis we use the task measure of Antonczyk et al. (2009). Accordingly, each task intensity in period t is defined by

$$TI_{ijt} = \frac{\text{No. of tasks in groups performed by worker } i \text{ in period } t}{\text{Total no. of tasks performed by worker } i \text{ in period } t} \tag{2.1}$$

where j represents one of the four task groups. By dividing by the total number of tasks performed by a worker in each period, this also allows us to control for changes in reporting behavior over time. Since each TI_{ijt} is standardized by the total number of tasks, all TI_{ijt} add up to one.[8] To assign task groups, we aggregate the individual-level data to the occupational field level. We pool data from the 1986 and 1992 waves and determine tasks group based on the dominant task intensity within in occupational field. Table 2.A2 shows the assignment of occupational fields to task groups.

For the decomposition, we also examine the role of gender-specific task intensities. Therefore, we aggregate the data at the occupation-gender-period level. This allows us to examine variation across occupations, across gender, and over time. However, the variation in the data over time is limited. One reason is that the data only indicate whether a task is performed, not at what intensity; we cannot capture whether a task item has become more important over time. Second, we lose variation in task intensity by aggregating individual-level data to the occupational field level. However, the data do not allow us to examine variation at a more disaggregated level.

Table 2.2 shows the employment shares of the different task groups and the average task intensities for men and women and over time after merging the BiBB data with the SOEP data. The development will be discussed in more detail in Section 2.4.

[6]In addition, to achieve a harmonized classification while maximizing the number of task items, we exploit the richness of the Employment Survey and substitute skills for specific task items when they are valid proxies. For example, we use the skill advanced knowledge of law as a proxy for applying law.

[7]To precisely identify routine tasks, we follow Koomen and Backes-Gellner (2022) in using two questions from the Employment Survey: 1. ”How often does it happen in your work that one and the same work step is repeated down to the last detail?”; 2.”How often do you find that your work is prescribed down to the last detail?”.

[8]Since information on the importance of a task item is not available in all waves of the Employment Survey, we must make the assumption that all tasks are equally important.

Table 2.2.: Summary statistics task groups and task intensity

	Men		Women	
	1985-89	2013-17	1985-89	2013-17
Task groups				
Routine	0.36	0.29	0.24	0.15
NRM	0.19	0.16	0.15	0.18
NRI	0.14	0.18	0.22	0.33
NRC	0.31	0.37	0.39	0.33
Task intensity				
Routine	0.32	0.29	0.25	0.24
NRM	0.17	0.10	0.09	0.10
NRI	0.25	0.29	0.28	0.33
NRC	0.28	0.32	0.40	0.33

Notes: Task intensity and task groups are determined using BiBB/BAuA Employment Survey data and merged to the SOEP at the occupational field level. The shares are obtained by aggregating SOEP data using SOEP weights. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986, 1992, 2012 and 2018.

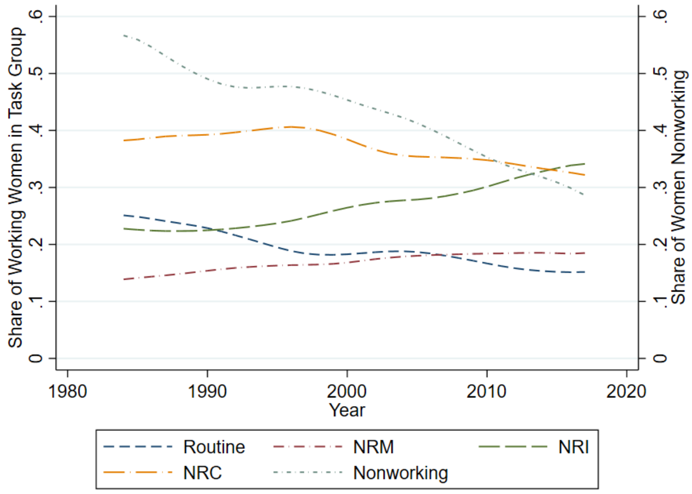
2.4. The Evolution of the Employment Structure and of Wage Gaps over Time

2.4.1. Employment Trends Across Task Groups

According to task-biased technological change, automation will lead to a decline in routine employment and an employment shift towards non-routine occupations. Moreover, women are more likely than men to select into interactive occupations due to their comparative advantage in interactive tasks. To answer our first research question regarding the evolution of the employment structure, we use two approaches: first, we describe the evolution of the distribution of total female employment across task groups. Then, we show the evolution of the share of women's employment relative to men's employment within a task group, i.e., the female share. Finally, we look at the change in the employment share of the different task groups, and the contribution of the evolution of female and male employment to this change.

The theoretical expectations regarding task-biased technological change are borne out by the evidence. Figure 2.1 shows the evolution of the distribution of female employment across task groups, as well as the evolution of the share of nonworking women in all women of working age. It becomes apparent that the share of routine occupations in total female employment declined over the years 1984 to 2017. Concurrently, the share of non-routine occupations in total female employment increased, and more so for interactive occupations than for manual occupations. By contrast, the share of non-routine cognitive occupations in total female employment declined. This was accompanied by a sharp decline in the share of women not working, from about 55% in 1985 to 30% in 2017. For comparison, the evolution of employment in task group in total male employment is displayed in Figure 2.A1.

Figure 2.1.: Trend in the share of nonworking women and task group shares in female employment

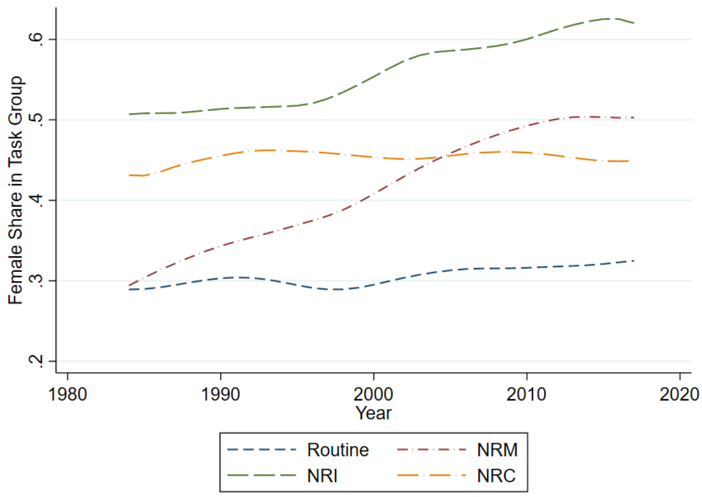


Notes: Share of nonworking women: share of nonworking women in all women of working age; Task group shares: employment share of the respective task group in total female employment. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986, 1992, 2012, and 2018.

A question emerging from the trend in the occupational structure of female employment displayed in Figure 2.1 is how this trend compares to the evolution of the occupational structure of male employment, and what the trends for women and men imply for gender employment gaps. Therefore, Figure 2.2 displays the evolution of the employment share of women relative to men, the female share, for the different task groups, over the time period 1984 to 2017. It becomes apparent that the female share in routine occupations was only 30% in 1985, suggesting that women were exposed less strongly than men to automation in the early period. This is in line with the results in Black and Spitz-Oener (2010) and Cortes et al. (2020) that women were differently exposed to automation due to their lower employment share in routine occupations. As a consequence of the relatively low initial level, the female share in routine occupations remained almost constant over time.

Figure 2.2 also shows that women increased their share in interactive occupations from 50% in 1985 to more than 60% in 2017. This speaks to the comparative advantage of women in

Figure 2.2.: Trend in the female share across task groups



Notes: Female share: employment share of women in total employment of respective task group. The female and male employment share within a task group add up to 1. The evolution of the male share is displayed in Figure 2.A2. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986, 1992, 2012, and 2018.

interactive tasks. In comparison, the female share in cognitive occupations remained almost constant over time, at about 45%. By contrast, the female share in non-routine manual occupations increased sharply from 30% in 1985 to 50% in 2017. This increase is much stronger in Figure 2.2 than in Figure 2.1.

To make the evolution of employment shares by task group and gender more transparent, Table 2.3 shows the change in the employment share of task group j in total employment, as well as the contributions of women and men to the change in employment shares. Therefore we define the change in the (gender-specific) employment share of task group j as follows:

$$\Delta e_j = \frac{E_{jt2}}{E_{t2}} - \frac{E_{jt1}}{E_{t1}} \tag{2.2}$$

$$\Delta e_{gj} = \frac{E_{gjt2}}{E_{t2}} - \frac{E_{gjt1}}{E_{t1}} \tag{2.3}$$

where E_t is total employment in period t, E_{jt} is employment in task group j in period t and E_{gjt} is gender-specific (i.e. female or male) employment in task group j in time period t.

The results show that the routine employment share in total employment declined by 9 pp. This was driven to some extent by a reduction of the share of women working in routine occupations (-2 pp), but more strongly by a reduction of the share of men working in routine occupations (-7 pp). Furthermore, while the share of men working in manual occupations also declined (-3 pp), the share of women in manual occupations increased (+3 pp). This resulted in an overall stable manual employment share in total employment.

In comparison, the employment share of interactive occupations in total employment experienced strong employment growth (+8.4 pp), mostly due to an increase in the share of women employed in interactive occupations in total employment (+7.3 pp), but to a smaller part also due to an increase in the share of men working in interactive occupations (+1.1 pp). Finally, the employment share of cognitive occupations in total employment remained relatively stable, as did the employment shares of women and men employed in routine occupations in total employment.

Table 2.3.: Change in employment shares in total employment by task group between 1985 and 2017

Task Group	Change Total	Change Women	Change Men
Routine	-9.11	-2.06	-7.06
NRM	-0.03	3.12	-3.15
NRI	8.41	7.31	1.1
NRC	0.74	0.64	0.1

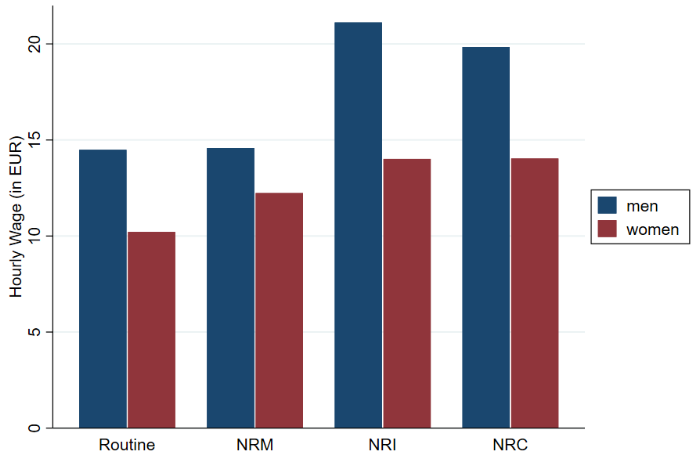
Notes: Change Total: change in employment share of each task group in total employment. The employment shares of all task groups in each period add up to one. The sum of total employment changes is zero. Change Women (Men): change in fe(male) employment in each task group in total employment. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986, 1992, 2012, and 2018.

2.4.2. Trends in Gender Wage Gaps Across Task Groups

The second question we want to answer in this paper is whether the change in the occupational structure and especially the selection of women into interactive occupations contributed to an improvement of the labour market condition of women in terms of wages. To answer this question, we first provide descriptive evidence on the gender wage gap by task group. Second, we perform a shift-share decomposition following Cortes et al. (2020) which allows us to decompose the reduction of the gender wage gap over time into a between-component, i.e. task groups with a low gender wage gap growing more strongly, and a within-component, i.e. a reduction of the gender wage gap within task groups.

Figure 2.3 shows average hourly wages for women and men in the period 1985-89. On average, workers earn relatively high wages in interactive and cognitive occupations, and relatively low

Figure 2.3.: Mean wages for men and women in the early period (1985-89)



Notes: Mean hourly wages for each task group by gender. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986 and 1992.

wages in routine and manual occupations. Accordingly, the selection of women into interactive occupations would imply a higher share of women working in higher-paying occupations, all else equal. Since the average wage in period t is the weighted sum of the average wage of women in task group j, it can be expressed as

$$w_{ft} = \sum_j w_{fjt} \frac{E_{fjt}}{E_{ft}} \tag{2.4}$$

where j indicates the task group and E_{ft} denotes total female employment in period t and E_{fjt} denotes female employment in task group j. Therefore, an increase in the share of women working in interactive occupations should also lead to an increase in average female wages. However, Figure 2.3 shows that there are significant unconditional gender wage gaps within task groups and that this gap is particularly large in interactive occupations. A persistence of these gender gaps within task groups limits the potential of the convergence in wages that could be achieved by occupational sorting across task groups. Therefore, wages of women need to catch up to those of men to fully benefit from the reallocation across task groups.

To explore this issue in more detail, we perform the shift-share analysis outlined in more detail in the Appendix 2.B.1. We can thus decompose the change in the unconditional gender wage gap between 1985 and 2017 into between- and within-effects.[9] Cortes et al. (2020) argue that the between-effect captures the impact of task-biased shocks on gender-specific reallocation

[9]The between-effect is the product of the change in employment shares weighted with mean wages across both periods, while the within-effect is the product of the change in average wages within task groups weighted using mean employment shares in the task group across both periods.

between task groups. The within-effect can be further decomposed into a common and gender-specific wage trends within task groups. While the common wage trends can be linked to technological change, gender-specific wage trends may capture other developments within task groups, including changes in workforce composition, changes in task content within occupations, or a reduction in discrimination.

Table 2.4 displays the results of this decomposition, i.e. the contribution of the between- and the within-effect to wage changes by gender and task groups, and the implications for the change of the gender wage gap. Overall, it becomes apparent that the narrowing of the gender wage gap by 5.7 percentage points (pp) was mainly driven by the within-effect which contributed 7.5 pp to the narrowing of the gender wage gap. By contrast, the between-effect hampered the narrowing of the gender wage gap, i.e. the gender wage gap would have been 1.6 pp smaller without the between-effect.

The positive contribution of the within-effect to women's wages is mainly due to strong of female wages within cognitive (+7.5%) and interactive occupations (+4.4%). While average wages for men in cognitive occupations also increased strongly (+4.9%), average wages for men in interactive occupations remained fairly constant, resulting in a strong positive contribution of the within-effect to women's wages in these two task groups. In contrast, there was little change in wages in routine and manual occupations, neither for women nor for men.[10]

The decomposition can be further refined by separating the within-effect into an effect which is common to both women and men, and a gender-specific wage effect. The results of this more detailed decomposition in Table 2.A3 show that the gender-specific wage trend can explain the full within-effect (-7.5 pp), while the contribution of the general wage trend to the gender wage gap is virtually zero. This stands in contrast to Cortes et al. (2020) who find for the US and Portugal that the general wage trend, which can be related to technological change, contributes negatively to the gender wage gap. The authors argue that this occurs because women on average sort into lower-paid occupations. Our results show that this is not the case in Germany.

Turning to the between-effect, its positive contribution to the gender wage gap can be analysed in more detailed using the results in Table 2.4. It becomes apparent that the reallocation of women, especially their selection into interactive occupations, contributed to an increase in average female wages (+1.6%). However, the reallocation of men out of routine and manual and

[10]The change in average wages for women and men is illustrated in Figure 2.A3.

into interactive and cognitive occupations contributed to a much stronger increase of male wages (+3.5%). While women were more successful than men in entering interactive occupations, they sorted into lower-paying manual occupations and sorted out of cognitive occupations.

The overall result regarding the between-effect is opposite to the evidence presented in Cortes et al. (2020) who find that the between-effect, which they describe as employment channel, contributed to a closing of the gender wage gap. There are a number of potential explanations for this result, including changing worker composition due to the strong increase of female labour force participation in Germany, and the prevalence of part-time employment for women on the German labour market. In the following section, we therefore analyse these factors in more detail.

Table 2.4.: Decomposition of the change in the gender wage gap

	Between-effect		Within-effect	
	men	women	men	women
Routine	-19.	-20.2	0.8	0.7
NRM	-7.2	9.3	-0.4	0.8
NRI	13.1	29.	0.6	4.4
NRC	16.5	-16.4	4.9	7.5
Change mean wage (in %)	3.5	1.6	5.8	13.3
Change GWG (in pp)	1.8		-7.5	
Change GWG overall (in pp)	-5.7			

Notes: Decomposition of the change gender wage gap (GWG) into a between- and within-effect over the period 1985-89 to 2013-17 (for details see Section 2.B.1). Source: authors' calculations based on SOEP v.37 and Employment Survey waves 198,1992, 2012 and 2018.

2.5. Decomposing the Gender Wage Gap

Given the differences between our results for Germany and the existing evidence for Portugal and the US (Cortes et al., 2020), we now explore in more detail the determinants of the gender wage gap and of its change over time. We therefore conduct a Blinder-Oaxaca (BO) decomposition separately for two time periods (see Appendix 2.B.2 for more details). In our analysis, we construct the counterfactual wage distribution by using the male wage distribution. This approach assumes that there is no wage discrimination against men.

The decomposition allows us to quantify the importance of composition effects. This decomposition also allows us to explore the "payoffs" to specific characteristics, which could have

Table 2.5.: Overall BO decomposition gender wage gap by period

	1985-89	(in %)	2013-17	(in %)
Overall		100		100
Difference	0.296***		0.240***	
	(0.039)		(0.049)	
Explained	0.037	12.6	0.189***	78.8
	(0.038)		(0.056)	
Unexplained	0.259***	87.4	0.051**	21.2
	(0.030)		(0.024)	
Explained				
Education	0.023*	7.7	0.016	6.7
	(0.012)		(0.017)	
Experience	-0.009	-3.1	0.126***	25.6
	(0.023)		(0.019)	
Job characteristics	0.036***	12.0	0.058***	24.3
	(0.011)		(0.016)	
Demographics	0.021***	7.1	0.007***	3.0
	(0.005)		(0.003)	
Task intensities	-0.033	-11.1	-0.019	-7.83
	(0.023)		(0.030)	
Unexplained				
Education	0.002	0.5	-0.004	-1.5
	(0.011)		(0.011)	
Experience	-0.010	-3.5	-0.083***	-34.7
	(0.021)		(0.023)	
Job characteristics	-0.064 **	-21.51	-0.040	-16.7
	(0.026)		(0.034)	
Demographics	0.040***	13.4	0.065***	26.9
	(0.010)		(0.013)	
Task intensities	0.023	7.8	-0.046	-19.0
	(0.055)		(0.090)	
Constant	0.268***		0.159*	
	(0.057)	90.62	(0.091)	66.15
Observations Men	14004		24367	
Observations Women	8240		25327	

Notes: BO decomposition of the GWG at the mean. The counterfactual is calculated putting a weight of 1 on group 1 (men). Percentages are relative to the unconditional gender wage gap in each period and are based on the mean estimate. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Education: primary, secondary, and tertiary education. Experience: full-time work experience, tenure, and part-time dummy. Job characteristics: 6 industry groups and firm size. Demographics: married, no. children in HH, dummy migration background, age groups. Task intensities: gender-specific task intensities for routine, NRM, NRI and NRC tasks. Reference groups are men and women with secondary education, no full-time work experience, who work full-time in manufacturing, are not married or in a registered partnership, have no children in HH, and no migration background. Task intensities are relative to the routine task intensity. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986,1992, 2012 and 2018.

changed over time given the changing position of women in the labour market. In doing so, we account for factors that are related to the strong increase in female labour force participation over the time period analysed. We pay particular attention to educational attainment, which strongly grew over time for women, and work experience, i.e. tenure, and part-time employment, which have played an important role for female employment in Germany over the last decades (Bachmann and Felder, 2020). To explore the potential role of technology, we use indicators for task intensities as explanatory variables. In addition, we also conduct separate analyses by task groups.

The results of the Blinder-Oaxaca decomposition in Table 2.5 show that the raw gender wage gap declined from 30% to 24% over the period 1985 to 2017. This was accompanied by a decline of the unexplained part of the decomposition (from 87.3% to 21.2%) and a corresponding increase of the explained part (from 12.7% to 78.8%). This is in line with evidence from Austria (Böheim et al., 2021) and indicates that the payoff to characteristics became more similar between men and women over time which may be due to a decline in wage discrimination towards women.

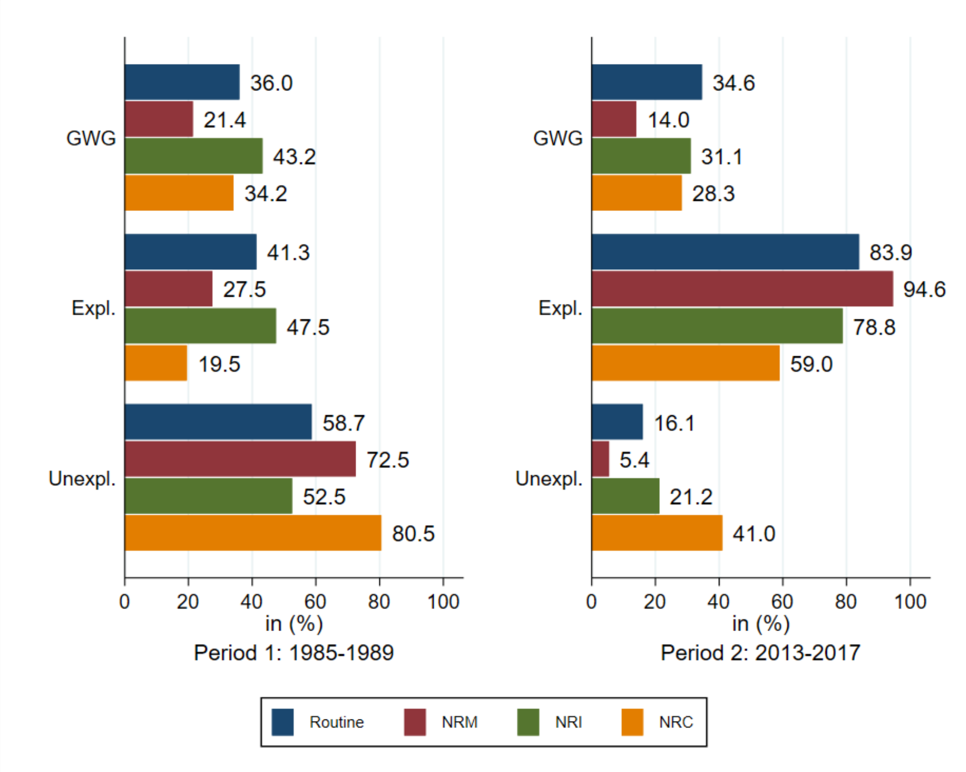
Looking at variable groups of explained factors,[11] the variable groups contributing to the gender wage gap in the early period are education (7.7%, significant at the 10% level only), job characteristics (12%) and demographics (7%). In the later period, labour market experience (25.6%) and job characteristics (24%) are the dominant factors for the observed part of the decomposition, while demographics play a less important role (3%). By contrast, we do not find that task intensities play a significant role for the explanation of the overall gender gap.

A detailed decomposition reveals that more women working part-time (captured by a part-time dummy) is the driving factor (-14.7% in 1985-89 compared to 30% in 2013-17) behind the increasing importance of explained factors between the two periods (see Table 2.A4). At the same time, the part-time wage penalty for women falls between the two periods as shown by the coefficient on part-time employment for the unobserved part of the decomposition (positive in the early period, negative and much larger in the later period). This could indicate that part-time work is becoming more of a norm in the labour market. Finally, unobserved factors captured by the constant also play a less important role for the gender wage gap. This result can be interpreted as further evidence for declining wage discrimination towards women.

Returning to composition effects, work experience in full-time employment also contributes to the gender wage gap (5.4% in 1985-89 and 17.0% in 2013-17). This can be explained by women having lower full-time work experience, probably because of more frequent career interruptions

[11] The variable groups are education (primary, secondary or tertiary education), experience (full-time work status, full-time work experience, job tenure), job characteristics (1-digit industries, firm size), demographics (age groups, marital status, number of children in household, migration background)

Figure 2.4.: BO decomposition by task group: gender wage gap and explained and unexplained share

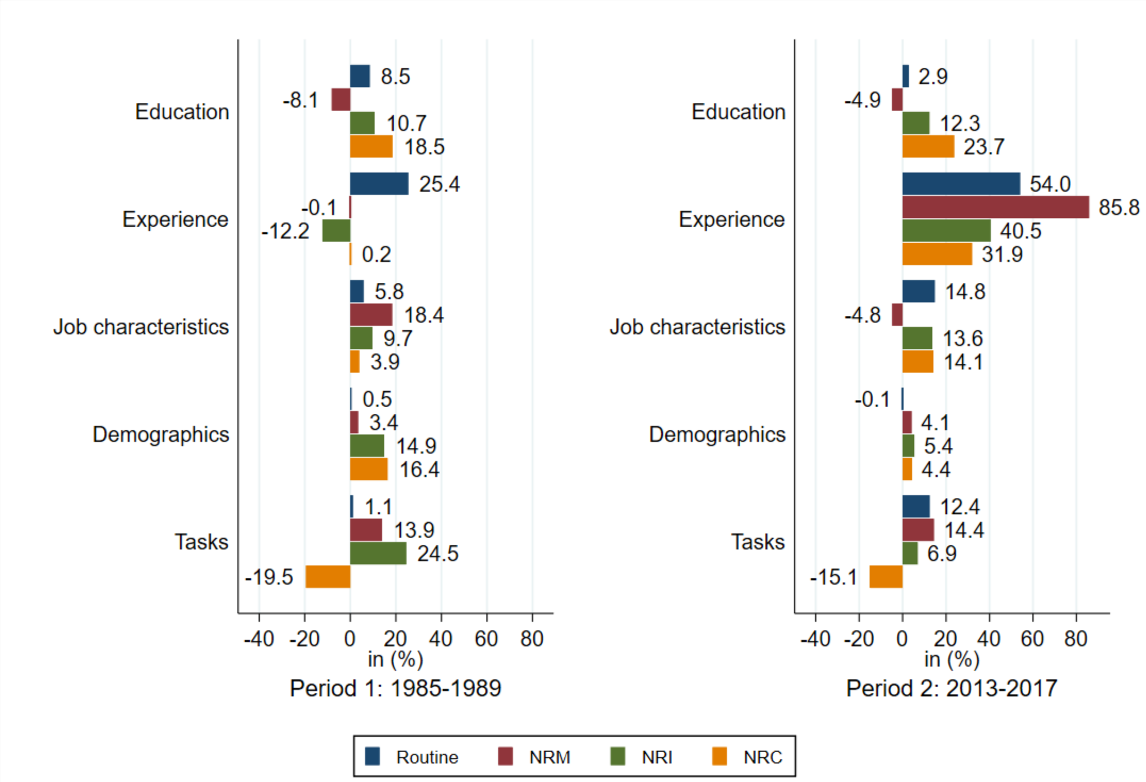


Notes: BO decomposition of the gender wage gap at the mean by task group. Each color presents a separate decomposition. The contribution shares of the explained and unexplained part are calculated based on the coefficients of the decomposition (see Table 2.A7). Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986,1992, 2012 and 2018.

for child rearing reasons. Sorting into different sectors also plays an important role (Table 2.1): while both men and women sorted out of the manufacturing sector, men sorted into the high-paying service sector and women sorted into the public sector. More women working in the public sector is a particularly important contributor to the gender wage gap (5.5% in 1985-89 and 16.7% in 2013-17).

Performing the same Blinder-Oaxaca decomposition separately by task group reveals two additional results. First, the gender wage gap declines particularly strongly in non-routine manual (from 21.4% to 14%) and non-routine interactive occupations (from 34.2% to 28.3%) (Figure 2.4). In the non-routine manual occupations, this decline is mainly driven by personal care occupations; in the non-routine interactive occupations, this decline is mainly driven by social and sales professions (Table 2.A2). Second, the increased contribution of the explained part, and the corresponding decreased contribution of the unexplained part, to the gender wage gap occurs in all task groups. This trend is particularly pronounced in non-routine manual occupations and (to a smaller extent) in routine occupations (Figure 2.4).

Figure 2.5.: Detailed BO decomposition by task group: explained part by variable group



Notes: BO decomposition of the gender wage gap at the mean by task group. Each color presents a separate decomposition. The contribution of the variable groups are calculated based on the coefficients of the decomposition (see Table 2.A7) and relative to the gender wage gap. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986,1992, 2012 and 2018.

A detailed decomposition of the explained part by task groups yields further insights (see Figure 2.5 where each color represents a different decomposition by task group).[12] Compared to the overall decomposition, task intensities plays a role for the evolution of the gender wage gap within task groups, and their importance for the gender wage gap changes over time. Differences in interactive task intensity contributed positively to (i.e. increased) the GWG in non-routine manual and cognitive occupations (Table 2.A7), but for different reasons: While women have a higher non-routine interactive task intensity in manual occupations, they have a lower non-routine interactive task-intensity in cognitive occupations (see Tables 2.A5 and 2.A6). Accordingly, a higher interactive task intensity is associated with higher wages (relative to men) in non-routine manual occupations and with lower wages relative to men in cognitive occupations.

In addition, non-routine cognitive tasks contributed negatively to the gender wage gap in non-routine cognitive occupations (strongly in the first period, less strongly in the second pe-

[12]The decomposition of the unexplained part does not show important differences between task groups, see Figure 2.A4.

riod), whereas they contributed positively to the gender wage gap in non-routine interactive occupations in the first period and in the second period. However, the non-routine cognitive task intensities is lower for women than for men in interactive occupations and higher for women than men in cognitive occupations (see Tables 2.A5 and 2.A6). This implies that a higher share of cognitive tasks within task groups, has positive wage impacts and reduced the GWG.

Overall, the detailed decomposition yields two main conclusions. First, the contribution of the different task intensities varies by task group. This implies that the gender-specific payoffs to same tasks differ by task groups. This is probably due to jobs consisting of task bundles which implies that the composition of tasks, in addition to the intensity of individual tasks, matters for their payoff (Autor and Handel, 2013) – and that this seems to matter for gender differences as well. Second, the importance of task intensities is falling relatively strongly over time in two out of the four task groups. This indicates that women are becoming more similar to men with respect to the tasks they perform and the corresponding payoffs they receive.

Apart from task intensities, there are also insights for other factors. First, labour-market experience is the only component that became more important across all groups. Therefore, women with strong labour-market attachment are a major driver of the decrease of the gender wage gap.

Second, job characteristics became more important for three of the four task groups, with non-routine manual occupations being the exception. This indicates that sorting into different industries is an important determinant of the gender pay gap. Third, demographic factors played a significant role for the gender wage gap in the early observation period, but are negligible in the second observation period. Therefore, differences in demographic characteristics, such as household context, have become less important for the gender pay gap over time.

2.6. Conclusion

In this paper, we analyse how the structural change of the labour market has affected employment and wage gaps between women and men in Germany in the period 1984 to 2017. Our analysis is based on panel data from the German Socio-Economic Panel and proceeds in three steps. First, we provide evidence on the evolution of the occupational employment structure of women and men. Second, we analyse how the gender wage gap has evolved over time and whether this was due to changes between or within occupations. Third, we perform a decomposition analysis to examine which factors explain the evolution of the gender wage gap. An important focus of our analysis is the role of technological progress which we capture by including the intensity of specific job tasks and by performing some of the analyses separately by task groups.

Our results are as follows. First, with respect to the occupational structure, we find that while the female share in non-routine manual and in interactive occupations increased strongly over time, the female share in non-routine cognitive and in routine occupations remained relatively constant. Second, we confirm the decline of the gender wage gap in Germany over the last decades previously found in the literature. A shift-share analysis shows that this decline is entirely driven by a reduction of the gender wage gap within occupations, not between occupations. This means that the overall change in the occupational structure of the labour market did not contribute to the narrowing of the gender wage gap. The dominating within-effect is caused by narrowing gender wage gaps in cognitive and interactive occupations. Our results stand in contrast to evidence in Cortes et al. (2020) which shows an important role of the between-effect for the evolution of the gender wage gap in the US and Portugal.

In the final step of the analysis, we therefore conduct a Blinder-Oaxaca decomposition to take into account composition effects with respect to various factors such as part-time employment (particularly relevant for German women), education and job tasks. The decomposition of the overall gender wage gap reveals a strong increase of the explained part (composition effects) and a corresponding strong decrease of the unexplained part (payoffs to characteristics). The increase in the explained part is driven by variables related to experience and job characteristics. The decline in the unexplained part is driven by a decline of the contribution of the constant. Overall, these results are in line with a reduction in wage discrimination in the labour market.

To account for the role of technology, we control for gender-specific task intensities in the decomposition. While we find no effect of task intensities on the overall gender wage gap, we show that task intensities play a multifaceted role in the evolution of the gender wage gap within task groups. However, their contribution differs by task groups, i.e. by occupations, and declines over time. This is in line with the general picture that women become more similar to men during our observation period, reducing gender gaps in the labour market. Other factors, however, play a more important role. In particular, part-time employment contributes to a larger gender wage gap, but this contribution is double-edged: on the one hand, more women working part-time contributes to the gender wage gap; on the other hand, the wage penalty to working part-time has gone down over time.

Overall, our results show that structural change in the labour market affects women and men very differently as both initial levels and changes over time of occupational sorting differ strongly between women and men. However, the changing occupational structure, i.e. shifting employment weights between occupations, is not a major driver of the evolution of the gender wage gap in Germany. The same conclusion emerges from a decomposition analysis including task intensities. Therefore, technological change has apparently not been an important driver of the gender wage gap. Rather, changes of the gender wage gap within occupations play a role in this context. Furthermore, institutional aspects, and especially part-time employment, are important determinants of the gender wage gap. It is therefore likely that the differences between our results for Germany and those from Cortes et al. (2020) for Portugal and the US are largely caused by institutional factors.

Technological change therefore does not seem like neither boon nor bane for the position of women in the German labour market. This is likely the result of two competing forces. On the one hand, women have been argued to be better able to benefit from the increased demand for social skills than men (Cortes et al., 2023). On the other hand, there is evidence for a gender gap in digital skills (Bachmann and Hertweck, 2023) which means that women may benefit less from technological change than men. Therefore, appropriate measures to improve the digital literacy of women is crucial for further advancing women's position in the labour market.

Given the continued importance of institutional factors for gender disparities on the labour market, these factors should remain high on the policy agenda. Part-time employment, in particular, is still a major contributor to the gender wage gap, it seems important to enable women to increase their working time if they wish to do so. Measures dedicated to this objective, e.g. increased provision of flexible working time provisions (Maraziotis, 2024), should be considered in this context.

Bibliography

Anger, C. and Schmidt, J. (2010). Gender Pay Gap: Gesamtwirtschaftliche Evidenz und Regionale Unterschiede. *IW-Trends-Vierteljahresschrift zur empirischen Wirtschaftsforschung*, 37(4):3–16.

Antonczyk, D., Fitzenberger, B., and Leuschner, U. (2009). Can a task-based approach explain the recent changes in the German wage structure? *Jahrbücher für Nationalökonomie und Statistik*, 229(2-3):214–238.

Atalay, E., Phongthiengtham, P., Sotelo, S., and Tannenbaum, D. (2020). The evolution of work in the United States. *American Economic Journal: Applied Economics*, 12(2):1–34.

Autor, D. H. and Handel, M. J. (2013). Putting tasks to the test: Human capital, job tasks, and wages. *Journal of Labor Economics*, 31(S1):S59–S96.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, 118(4):1279–1333.

Bachmann, R., Cim, M., and Green, C. (2019). Long-Run Patterns of Labour Market Polarization: Evidence from German Micro Data. *British Journal of Industrial Relations*, 57(2):350–376.

Bachmann, R. and Felder, R. (2020). Labour market transitions, shocks and institutions in turbulent times: A cross-country analysis. *Empirica*, 48(2):329–352.

Bachmann, R. and Hertweck, F. (2023). The gender gap in digital literacy: A cohort analysis for germany. *Applied Economics Letters*, pages 1–6.

Baron-Cohen, S., Knickmeyer, R. C., and Belmonte, M. K. (2005). Sex differences in the brain: Implications for explaining autism. *Science*, 310(5749):819–823.

Beaudry, P. and Lewis, E. (2014). Do male-female wage differentials reflect differences in the return to skill? Cross-city evidence from 1980–2000. *American Economic Journal: Applied Economics*, 6(2):178–194.

BIBB (1986). Qualifikation und Berufsverlauf 1985/86 [dataset]. doi:10.4232/1.12563.

BIBB (1992). Erwerb und Verwertung beruflicher Qualifikationen 1991/92 [dataset]. doi:10.4232/1.2565.

BIBB (2012). BIBB/BAuA Employment Survey of the Working Population on Qualification and Working Conditions in Germany 2012 [dataset]. doi:10.7803/501.12.1.1.60.

BIBB (2018). BIBB/BAuA Employment Survey of the Working Population on Qualification and Working Conditions in Germany 2018 [dataset]. doi:10.7803/501.18.1.1.10.

Black, S. E. and Spitz-Oener, A. (2010). Explaining women's success: Technological change and the skill content of women's work. *The Review of Economics and Statistics*, 92(1):187–194.

Blau, F. D. and Kahn, L. M. (2017). The gender wage gap: Extent, trends, and explanations. *Journal of Economic Literature*, 55(3):789–865.

Blau, F. D., Kahn, L. M., Boboshko, N., and Comey, M. (2024). The impact of selection into the labor force on the gender wage gap. *Journal of Labor Economics*, (Forthcoming).

Böheim, R., Fink, M., and Zulehner, C. (2021). About time: The narrowing gender wage gap in Austria. *Empirica*, 48(4):803–843.

Böhm, M. J., von Gaudecker, H.-M., and Schran, F. (2024). Occupation growth, skill prices, and wage inequality. *Journal of Labor Economics*, 42(1):201–243.

Borghans, L., Ter Weel, B., and Weinberg, B. A. (2014). People skills and the labor-market outcomes of underrepresented groups. *IlR Review*, 67(2):287–334.

Bredtmann, J. and Otten, S. (2014). Getting what (employers think) you're worth: Evidence on the gender gap in entry wages among university graduates. *International Journal of Manpower*, 35(3):291–305.

Busch, F. (2020). Gender segregation, occupational sorting, and growth of wage disparities between women. *Demography*, 57(3):1063–1088.

Cerina, F., Moro, A., and Rendall, M. (2021). The role of gender in employment polarization. *International Economic Review*, 62(4):1655–1691.

Chapman, E., Baron-Cohen, S., Auyeung, B., Knickmeyer, R., Taylor, K., and Hackett, G. (2006). Fetal testosterone and empathy: Evidence from the empathy quotient (eq) and the "reading the mind in the eyes" test. *Social Neuroscience,*, 1(2):135–148.

Cortes, G. M., Jaimovich, N., and Siu, H. E. (2023). The growing importance of social tasks in high-paying occupations: Implications for sorting. *Journal of Human Resources*, 58(5):1429–1451.

Cortes, G. M., Oliveira, A., and Salomons, A. (2020). Do technological advances reduce the gender wage gap? *Oxford Review of Economic Policy*, 36(4):903–924.

Dauth, W., Findeisen, S., Suedekum, J., and Woessner, N. (2021). The adjustment of labor markets to robots. *Journal of the European Economic Association*, 19(6):3104–3153.

Deming, D. and Kahn, L. B. (2018). Skill requirements across firms and labor markets: Evidence from job postings for professionals. *Journal of Labor Economics*, 36(S1):S337–S369.

Deming, D. J. (2017). The growing importance of social skills in the labor market. *The Quarterly Journal of Economics*, 132(4):1593–1640.

Elsayed, A., de Grip, A., and Fouarge, D. (2017). Computer use, job tasks and the part-time pay penalty. *British Journal of Industrial Relations*, 55(1):58–82.

Fitzenberger, B., Schnabel, R., and Wunderlich, G. (2004). The gender gap in labor market participation and employment: A cohort analysis for West Germany. *Journal of Population Economics*, 17(1):83–116.

Fortin, N., Lemieux, T., and Firpo, S. (2011). Decomposition methods in economics. In *Handbook of labor economics*, volume 4, pages 1–102. Elsevier.

Fortin, N. M., Oreopoulos, P., and Phipps, S. (2015). Leaving boys behind: Gender disparities in high academic achievement. *Journal of Human Resources*, 50(3):549–579.

Genz, S. and Schnabel, C. (2023). Digitalization is not gender-neutral. *Economics Letters*, 230:111256.

Goebel, J., Grabka, M. M., Liebig, S., Kroh, M., Richter, D., Schröder, C., and Schupp, J. (2019). The German Socio-Economic Panel (SOEP). *Jahrbücher für Nationalökonomie und Statistik*, 239(2):345–360.

Goldin, C. (2006). The quiet revolution that transformed women's employment, education, and family. *American economic review*, 96(2):1–21.

Goos, M., Manning, A., and Salomons, A. (2009). Job polarization in Europe. *American Economic Review*, 99(2):58–63.

Granados, P. G. and Wrohlich, K. (2018). Gender Pay Gap besonders groß bei niedrigen und hohen Löhnen. *DIW Wochenbericht*, 85(10):173–179.

Greenberg, D. M., Warrier, V., Allison, C., and Baron-Cohen, S. (2018). Testing the empathizing–systemizing theory of sex differences and the extreme male brain theory of autism in half a million people. *Proceedings of the National Academy of Sciences*, 115(48):12152–12157.

Jochmann-Döll, A. and Scheele, A. (2020). The road to equal pay for women and men: Facts, causes, measures.

Kluve, J. and Schmitz, S. (2018). Back to work: Parental benefits and mothers' labor market outcomes in the medium run. *ILR Review*, 71(1):143–173.

Kluve, J. and Tamm, M. (2013). Parental leave regulations, mothers' labor force attachment and fathers' childcare involvement: Evidence from a natural experiment. *Journal of Population Economics*, 26:983–1005.

Koomen, M. and Backes-Gellner, U. (2022). Occupational tasks and wage inequality in West Germany: A decomposition analysis. *Labour Economics*, 79:102284.

Langer, C. and Wiederhold, S. (2023). The value of early-career skills. CESifo Working Paper 10288, CESifo.

Maraziotis, F. (2024). Flexibility for equality: Examining the impact of flexible working time arrangements on women's convergence in working hours. *British Journal of Industrial Relations*, 62(2):410–445.

Ngai, L. R. and Petrongolo, B. (2017). Gender gaps and the rise of the service economy. *American Economic Journal: Macroeconomics*, 9(4):1–44.

Rohrbach-Schmidt, D. and Hall, A. (2013). BIBB/BAuA Employment Survey 2012. Data and Methodological Reports 1, Federal Institute of Vocational Education and Training (BIBB).

Rohrbach-Schmidt, D. and Hall, A. (2020). BIBB/BAuA Employment Survey 2018. Data and Methodological Reports 1, Federal Institute of Vocational Education and Training (BIBB).

Rohrbach-Schmidt, D. and Tiemann, M. (2013). Changes in workplace tasks in germany—evaluating skill and task measures. *Journal for Labour Market Research*, 46(3):215–237.

Schönberg, U. and Ludsteck, J. (2014). Expansions in maternity leave coverage and mothers' labor market outcomes after childbirth. *Journal of Labor Economics*, 32(3):469–505.

SOEP (2018). German Socio-Economic Panel Study (SOEP-Core) v37.1, years 1984-2017 [dataset]. doi:10.5684/soep.core.v37.1.

Spitz-Oener, A. (2006). Technical change, job tasks, and rising educational demands: Looking outside the wage structure. *Journal of Labor Economics*, 24(2):235–270.

Storm, E. (2023). Task returns and the gender pay gap. Ruhr Economic Papers 1021, RWI-Leibniz Institute for Economic Research.

Tiemann, M., Schade, H.-J., Helmrich, R., Hall, A., Braun, U., and Bott, P. (2008). Berufsfeld-Definitionen des BIBB auf Basis der Klassifikation der Berufe 1992. Wissenschaftliche Diskussionspapiere 105, Federal Institute for Vocational Studies.

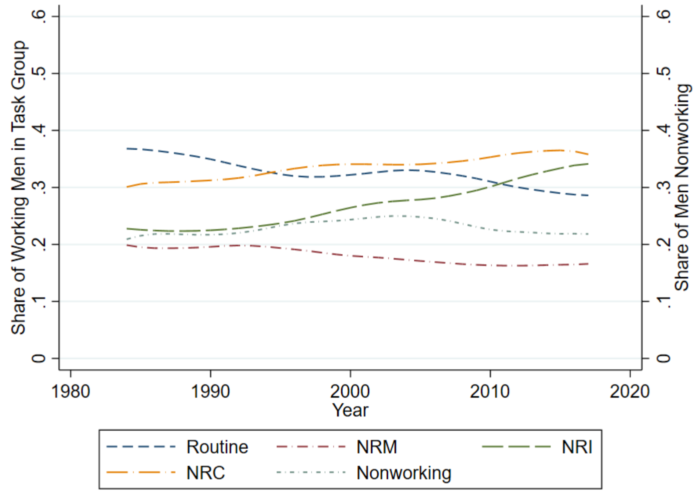
Weinberger, C. J. (2014). The increasing complementarity between cognitive and social skills. *Review of Economics and Statistics*, 96(5):849–861.

Yamaguchi, S. (2018). Changes in returns to task-specific skills and gender wage gap. *Journal of Human Resources*, 53(1):32–70.

2.A. Appendix - Additional Figures and Tables

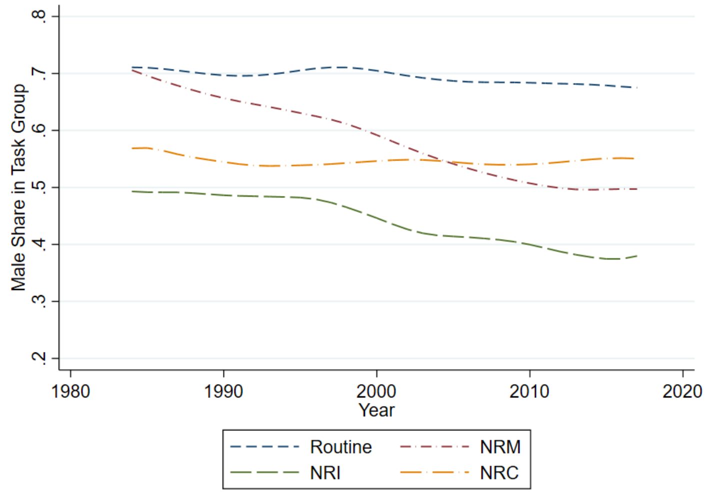
2.A.1. Figures

Figure 2.A1.: Trend in the share of nonworking men and working men across task groups



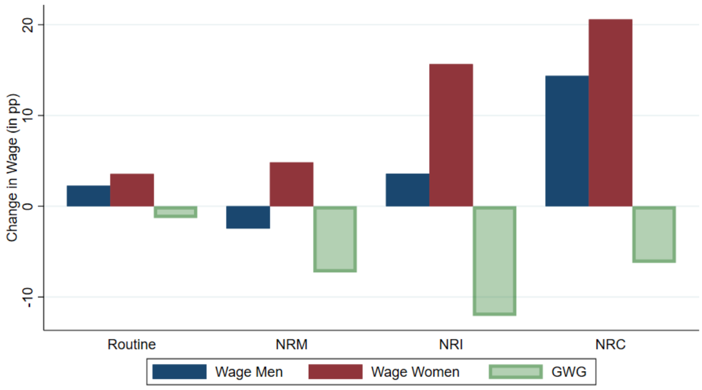
Notes: Share of nonworking men: share of nonworking men in all men of working age; Task group shares: employment share of the respective task group in total male employment. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986, 1992, 2012, and 2018.

Figure 2.A2.: Trend in the male share across task groups



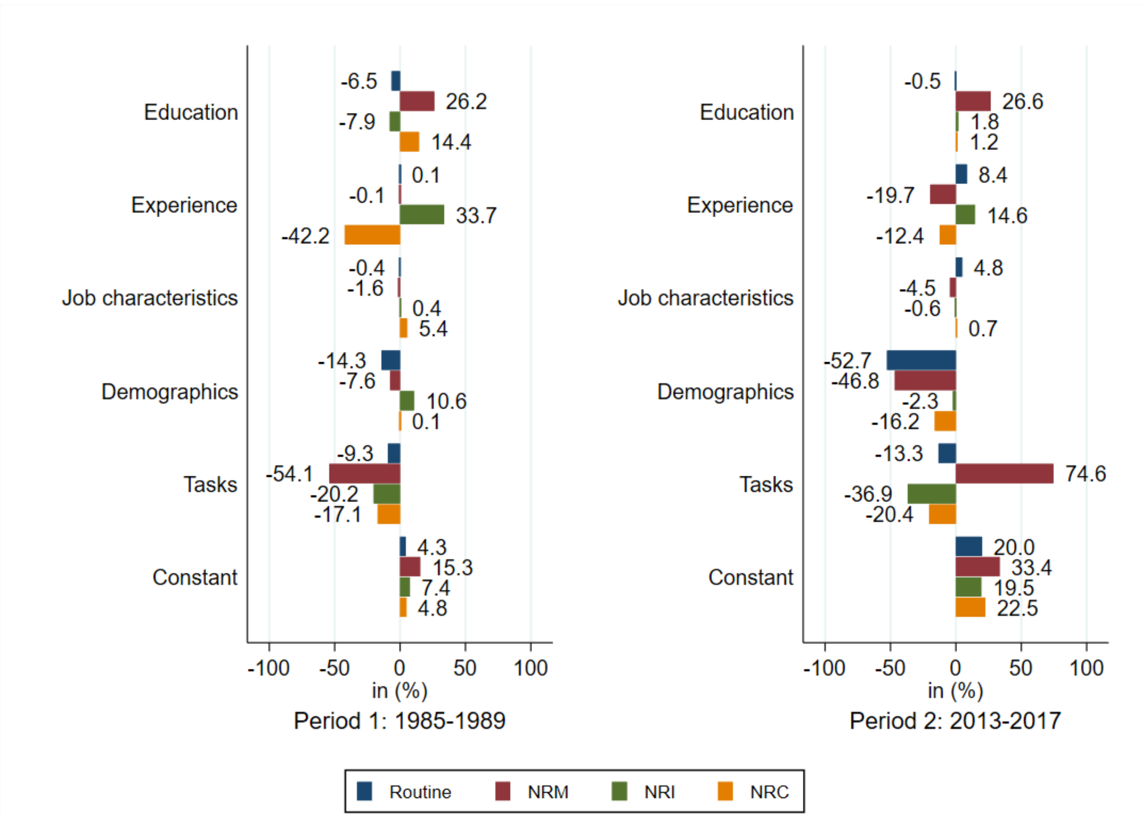
Notes: Male share: employment share of men in total employment of respective task group. The female and male employment share within a task group add up to 1. The evolution of the male share is displayed in Figure 2.A2. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986,1992, 2012 and 2018.

Figure 2.A3.: Change in wages and unconditional gender wage gap 1985-2017



Notes: Change in log wages and the gender wage gap between the period 1985-89 to 2013-2017. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986,1992, 2012 and 2018.

Figure 2.A4.: Detailed BO decomposition by task group: unexplained part by variable group



Notes: BO decomposition of the gender wage gap at the mean by task group. Each color presents a separate decomposition. The contribution of the variable groups are calculated based on the coefficients of the decomposition (see Table 2.A7) and relative to the gender wage gap. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986,1992, 2012 and 2018.

2.A.2. Tables

Table 2.A1.: Assignment of task items

Task Groups	Task Items
Routine	operating, manufacturing, storing, cleaning, measuring
NRM	repairing, accommodating, caring, protecting
NRI	teaching, consulting, buying and promoting, managing personnel, organizing for others
NRC	investigating, researching and constructing, programming, applying law, writing and calculations

Source: Employment Survey waves 1986,1992, 2012 and 2018 following Koomen and Backes-Gellner (2022).

Table 2.A2.: Assignment of task groups and gender wage gaps by occupational field

TG	Occupational Field	1985-89	2013-17	Δ
Routine				
1	Metal, plant construction, sheet metal construction, installation, assemblers	0.35	0.01	-0.33
1	Goods inspectors, dispatch finishers	0.36	0.19	-0.17
1	Butchers	0.32	0.17	-0.16
1	Metal production, processing	0.38	0.25	-0.13
1	Unskilled workers n.e.c.	0.26	0.14	-0.12
1	Agriculture, animal husbandry, forestry, horticulture	0.28	0.18	-0.10
1	Cleaning, waste disposal	0.27	0.19	-0.09
1	Precision engineering, related occupations	0.33	0.26	-0.07
1	Baking and confectionery	0.29	0.24	-0.05
1	Transport occupations	0.30	0.28	-0.02
1	Beverages, luxury food production, other food professions	0.44	0.46	0.01
1	Packers, warehouse, transportation workers	0.13	0.15	0.02
1	Chemical and plastic professions	0.37	0.38	0.02
1	Spinning professions and textile production	0.27	0.37	0.09
1	Paper production, processing, printing	0.27	0.38	0.11
1	Industrial and tool mechanics	0.12	0.30	0.19
1	Miners, mineral extractors and stone processing, building material production, ceramic, glass professions	0.49	0.68	0.19
1	Chefs	0.11	0.34	0.23
NRM				
2	Driving, aircraft construction, maintenance occupations	0.14	-0.21	-0.35
2	Personal care professions	0.36	0.07	-0.29

Continued on next page

Table 2.A2 – continued from previous page

Task Group	Occupational Field	1985-89	2013-17	Δ
2	Personal protection and security occupations	0.28	0.08	-0.20
2	Electrical professions	0.28	0.20	-0.07
2	Hotel, restaurant and catering occupations, housekeeping	0.11	0.05	-0.07
2	Building trades, woodworking and plastic processing	0.24	0.23	0.00
2	Healthcare professions without a license to practice	0.08	0.17	0.09
2	Janitors	0.19	0.31	0.12
NRI				
3	Social professions	0.34	0.12	-0.22
3	Sales professions (retail trade)	0.39	0.22	-0.17
3	Wholesale and retail traders	0.34	0.20	-0.14
3	Health professions with license to practice medicine	0.23	0.18	-0.06
3	Teachers	0.09	0.11	0.03
3	Other commercial professions (excluding wholesale, retail, banking)	0.11	0.17	0.06
3	Management, auditing, management consulting	0.16	0.24	0.09
NRC				
4	Technicians	0.30	0.06	-0.24
4	Office support occupations, telephone operator(s)	0.19	-0.02	-0.21
4	Specialist technical staff	0.15	-0.05	-0.20
4	Engineer(s)	0.20	0.03	-0.16
4	Advertising specialists	0.35	0.19	-0.16
4	IT core professions	0.28	0.13	-0.16
4	Legal professions	0.37	0.25	-0.13
4	Commercial office occupations	0.28	0.16	-0.13
4	Security professions	0.23	0.11	-0.12
4	Administrative professions in the public service	0.26	0.15	-0.11
4	Technical draughtsperson, related professions	0.23	0.18	-0.05
4	Designers, photographers, advertising producers	0.28	0.24	-0.04
4	Finance, accounting, bookkeeping	0.34	0.31	-0.03
4	Banking and insurance specialists	0.26	0.29	0.02
4	Chemists, physicists, natural scientists	0.24	0.28	0.04
4	Publishing, library, translation and related scientific professions	0.12	0.19	0.07
4	Surveying	0.15	0.28	0.13

Notes: This table shows the assignment of occupational fields to task groups and the gender wage gaps by occupational field over the period 1985-2017. The Δ column represents the difference in gender wage gaps between the two periods. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986, 1992, 2012, and 2018.

Table 2.A3.: Detailed decomposition of the gender wage gap

	Between-effect		Within-effect			
			Overall		Gender-specific	
	men	women	men	women	men	women
Routine	-19.	-20.2	0.6	0.3	0.2	0.4
NRM	-7.2	9.3	-0.5	-0.4	0.1	1.2
NRI	13.1	29.	1.0	1.6	-0.4	2.8
NRC	16.5	-16.4	6.0	5.7	-1.1	1.7
Change mean wage (in %)	3.5	1.6	7.1	7.2	-1.4	6.1
Change GWG (in pp)	1.8		-0.1		-7.5	
Change GWG overall (in pp)			-5.7			

Notes: Decomposition of the change gender wage gap (GWG) into a between- and within-effect over the period 1985-89 to 2013-17 (for details see Section 2.B.1). Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986,1992, 2012 and 2018.

Table 2.A4.: BO decomposition gender wage gap by period: full model

	1985-89	2013-17
Difference	0.296***	0.240***
	(0.039)	(0.049)
Explained	0.037	0.189***
	(0.038)	(0.056)
Unexplained	0.259***	0.051**
	(0.030)	(0.024)
Explained		
Education (Reference Group: Medium education)		
Low education	0.010***	0.000
	(0.004)	(0.003)
Higher education	0.013	0.016
	(0.010)	(0.015)
No educational info	0.000	0.000
	(0.000)	(0.000)
Tenure	0.018***	0.014***
	(0.004)	(0.004)
Part-time	-0.044*	0.071***
	(0.024)	(0.016)
Work experience full-time	0.016**	0.041***
	(0.008)	(0.010)
Industry sector (Reference Group: Manufacturing)		
Utilities + construction	-0.004	-0.002
	(0.002)	(0.003)
Retail, transport, logistics	0.008	0.003
	(0.009)	(0.011)
Services	-0.003	0.001
	(0.002)	(0.002)
Public administration + health	0.016	0.039**
	(0.011)	(0.017)
Others	0.003**	0.002
	(0.002)	(0.004)
Firm size (Reference Group: < 200 employees)		
No info	0.000	0.000
	(0.000)	(0.000)
200-2000 employees	0.001	0.002
	(0.001)	(0.002)
>2000 employees	0.013***	0.012*
	(0.004)	(0.006)
Married and registered partnership	0.010***	0.004**
	(0.002)	(0.002)
No. of children in household	0.003*	0.002**
	(0.002)	(0.001)
Migration background	-0.000	-0.000
	(0.000)	(0.000)
Age group (Reference Group: age 30-54)		
Age 20-29	0.010***	0.001
	(0.003)	(0.002)
Age 55-64	-0.002***	0.000
	(0.001)	(0.001)
Task intensities (Reference Group: Routine)		
NRM	0.009	-0.000

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Table 2.A4 – continued from previous page

	1985-89	2013-17
	(0.008)	(0.002)
NRI	-0.007	-0.008
	(0.016)	(0.012)
NRC	-0.035	-0.010
	(0.023)	(0.027)
Unexplained		
Education (Reference Group: Medium education)		
Low education	0.006	-0.002
	(0.005)	(0.004)
Higher education	-0.004	-0.001
	(0.008)	(0.009)
No educational info	-0.001	-0.001
	(0.000)	(0.001)
Tenure	0.006	-0.014
	(0.015)	(0.011)
Part-time	0.037*	-0.067***
	(0.022)	(0.017)
Work experience full-time	-0.053***	-0.002
	(0.019)	(0.016)
Industry sector (Reference Group: Manufacturing)		
Utilities + construction	-0.001	0.002
	(0.001)	(0.001)
Retail, transport, logistics	0.000	-0.010
	(0.006)	(0.007)
Services	0.004	-0.000
	(0.005)	(0.006)
Public administration + health	-0.047***	-0.035*
	(0.018)	(0.020)
Others	-0.005	0.000
	(0.005)	(0.004)
Firm size (Reference Group: < 200 employees)		
No info	-0.000	-0.001
	(0.001)	(0.001)
200-2000 employees	-0.007*	0.001
	(0.004)	(0.006)
>2000 employees	-0.009**	0.003
	(0.004)	(0.007)
Married and registered partnership	0.040***	0.052***
	(0.008)	(0.010)
No. of children in household	0.007	0.002
	(0.007)	(0.004)
Migration background	-0.003	0.007
	(0.003)	(0.005)
Age group (Reference Group: Age 30-54)		
Age 20-29	-0.007	0.004
	(0.006)	(0.006)
Age 55-64	0.003	-0.000
	(0.003)	(0.004)
Task intensities (Reference Group: Routine)		
NRM	0.019	-0.028
	(0.015)	(0.031)
NRI	0.026	-0.019

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Table 2.A4 – continued from previous page

	1985-89	2013-17
	(0.032)	(0.087)
NRC	-0.022	0.001
	(0.030)	(0.057)
Constant	0.268***	0.159*
	(0.057)	(0.091)

Notes: BO decomposition of the GWG at the mean. The counterfactual is calculated putting a weight of 1 on group 1 (men). Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Reference groups are men and women with secondary education, no full-time work experience, who work full-time in manufacturing, are not married or in a registered partnership, have no children in HH, and no migration background. Task intensities are relative to the routine task intensity. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986,1992, 2012 and 2018.

Table 2.A5.: Summary statistic women by task group

	Routine		NRM		NRI		NRC	
	1985-89	2013-17	1985-89	2013-17	1985-89	2013-17	1985-89	2013-17
Education								
Low education	0.58	0.27	0.21	0.10	0.15	0.05	0.13	0.04
Medium education	0.39	0.62	0.47	0.73	0.52	0.50	0.75	0.62
High education	0.02	0.09	0.31	0.15	0.34	0.43	0.12	0.33
No information	0.00	0.02	0.00	0.02	0.00	0.02	0.00	0.01
Work experience (full-time)	0.32	0.48	0.25	0.37	0.32	0.34	0.21	0.27
Share part-time	11.89	12.04	10.35	11.45	10.44	10.00	11.89	13.08
Tenure	9.16	8.73	7.44	9.33	8.96	9.12	9.50	12.61
Sector								
Manufacturing	0.49	0.28	0.09	0.03	0.15	0.09	0.24	0.18
Utilities + construction	0.01	0.01	0.01	0.00	0.00	0.00	0.05	0.05
Retail, transport, logistics	0.12	0.19	0.02	0.04	0.41	0.33	0.12	0.09
Services	0.05	0.18	0.08	0.04	0.02	0.06	0.24	0.30
Public administration	0.16	0.2	0.67	0.74	0.31	0.48	0.22	0.31
Others	0.17	0.14	0.13	0.14	0.1	0.05	0.13	0.08
Firm size								
No info	0.01	0.02	0.01	0.01	0.02	0.01	0.00	0.00
<200 employees	0.53	0.56	0.58	0.63	0.61	0.5	0.48	0.38
$200-2000$ employees	0.25	0.21	0.26	0.2	0.13	0.18	0.26	0.27
>2000 employees	0.20	0.20	0.15	0.16	0.24	0.31	0.26	0.34
Demographics								
Married/registered partnership	0.63	0.60	0.50	0.49	0.56	0.5	0.51	0.5
No. children in HH	0.54	0.42	0.57	0.51	0.44	0.45	0.3	0.44
Age	40.74	46.95	36.35	43.43	37.92	42.57	36.75	43.5
Migration background	0.24	0.42	0.14	0.28	0.06	0.22	0.05	0.15
Task intensity								
Routine	0.75	0.63	0.18	0.26	0.10	0.17	0.06	0.11
NRM	0.09	0.10	0.39	0.23	0.04	0.10	0.01	0.03
NRI	0.06	0.17	0.22	0.29	0.63	0.42	0.23	0.33
NRC	0.11	0.09	0.24	0.22	0.25	0.31	0.72	0.52
Wage	10.24	10.91	12.25	12.83	14.06	16.52	14.1	17.83
Observations	2770	3882	1207	4965	1630	8439	2633	8041

Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986,1992, 2012 and 2018.

Table 2.A6.: Summary statistic men by task group

	Routine		NRM		NRI		NRC	
	1985-89	2013-17	1985-89	2013-17	1985-89	2013-17	1985-89	2013-17
Education								
Low education	0.23	0.17	0.15	0.13	0.03	0.03	0.03	0.03
Medium education	0.71	0.71	0.74	0.74	0.45	0.40	0.57	0.39
High education	0.06	0.11	0.11	0.11	0.51	0.56	0.40	0.57
No information	0.00	0.02	0.01	0.01	0.00	0.01	0.00	0.01
Work experience (full-time)	0.01	0.05	0.01	0.06	0.03	0.07	0.00	0.03
Share part-time	11.89	12.04	10.35	11.45	10.44	10.00	11.89	13.08
Tenure	11.65	11.99	11.58	10.28	12.59	11.26	15.14	13.95
Sector								
Manufacturing	0.63	0.54	0.32	0.26	0.31	0.19	0.32	0.32
Utilities + construction	0.08	0.07	0.42	0.32	0.02	0.02	0.07	0.06
Retail, transport, logistics	0.14	0.24	0.08	0.07	0.21	0.27	0.09	0.08
Services	0.01	0.03	0.02	0.07	0.04	0.09	0.15	0.26
Public administration	0.04	0.03	0.09	0.18	0.34	0.37	0.3	0.23
Others	0.11	0.09	0.08	0.10	0.09	0.06	0.07	0.06
Firm size								
No info	0.00	0.01	0.00	0.01	0.01	0.00	0.00	0.00
$<$ 200 employees	0.43	0.47	0.58	0.64	0.46	0.41	0.25	0.28
$200 - 2000$ employees	0.28	0.26	0.18	0.16	0.2	0.22	0.29	0.27
$>$ 2000 employees	0.29	0.27	0.23	0.19	0.34	0.37	0.46	0.45
Demographics								
Married/registered partnership	0.68	0.6	0.66	0.53	0.75	0.58	0.75	0.56
No. children in household	0.73	0.54	0.62	0.55	0.77	0.55	0.66	0.53
Age	39.56	44.12	39.35	42.53	42.32	43.8	42.22	43.98
Migration background	0.21	0.39	0.17	0.30	0.04	0.18	0.05	0.16
Task intensity								
Routine	0.6	0.54	0.35	0.37	0.07	0.12	0.09	0.15
NRM	0.19	0.12	0.42	0.21	0.04	0.06	0.06	0.05
NRI	0.11	0.19	0.14	0.24	0.58	0.43	0.35	0.33
NRC	0.11	0.15	0.11	0.18	0.36	0.39	0.55	0.47
Wage	14.51	15.64	14.6	14.75	21.16	22.74	19.89	23.61
Observations	6067	7481	2930	4046	1575	4303	3432	8537

Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986,1992, 2012 and 2018.

Table 2.A7.: BO decomposition gender wage gap by task group and period

	Routine		Manual		Interactive		Cognitive	
	1985-89	2013-17	1985-89	2013-17	1985-89	2013-17	1985-89	2013-17
Difference	0.360***	0.346***	0.214***	0.140**	0.432***	0.311***	0.342***	0.283***
	(0.030)	(0.061)	(0.078)	(0.071)	(0.129)	(0.078)	(0.037)	(0.045)
Explained	0.149***	0.291***	0.059	0.133**	0.205**	0.245**	0.067	0.167***
	(0.055)	(0.098)	(0.084)	(0.063)	(0.090)	(0.120)	(0.043)	(0.044)
Unexplained	0.211***	0.056	0.155	0.008	0.227***	0.066	0.275***	0.116***
	(0.052)	(0.084)	(0.106)	(0.038)	(0.065)	(0.114)	(0.046)	(0.025)
Explained								
Education	0.031***	0.010	-0.017	-0.007	0.046	0.038*	0.063***	0.067***
	(0.008)	(0.009)	(0.014)	(0.006)	(0.029)	(0.023)	(0.022)	(0.022)
Experience	0.091**	0.187***	-0.000	0.120***	-0.053	0.126***	0.001	0.090***
	(0.040)	(0.049)	(0.067)	(0.032)	(0.035)	(0.040)	(0.021)	(0.019)
Job characteristics	0.021*	0.051*	0.039*	-0.007	0.042**	0.042*	0.013	0.040***
	(0.013)	(0.028)	(0.022)	(0.038)	(0.018)	(0.022)	(0.015)	(0.011)
Demographics	0.002	-0.001	0.007	0.006	0.064***	0.017	0.056***	0.012***
	(0.003)	(0.005)	(0.005)	(0.004)	(0.013)	(0.011)	(0.008)	(0.004)
NRM TI	0.027*	0.016	-0.026	0.010	-0.006	-0.029	0.028	-0.011
	(0.014)	(0.018)	(0.017)	(0.018)	(0.019)	(0.082)	(0.022)	(0.012)
NRI TI	-0.023	-0.002	0.056**	0.037*	-0.034	0.006	0.049*	0.003
	(0.017)	(0.008)	(0.022)	(0.020)	(0.033)	(0.014)	(0.026)	(0.010)
NRC TI	0.000	0.029	-0.000	-0.028	0.146**	0.045	-0.144***	-0.035*
	(0.004)	(0.053)	(0.031)	(0.027)	(0.069)	(0.058)	(0.051)	(0.020)
Unexplained								
Education	-0.001	0.017	-0.003	-0.006	0.002	-0.002	0.019*	0.002
	(0.014)	(0.019)	(0.013)	(0.008)	(0.030)	(0.027)	(0.011)	(0.012)
Experience	-0.051	-0.182***	-0.016	-0.066***	0.046	-0.007	0.000	-0.046
	(0.045)	(0.042)	(0.072)	(0.021)	(0.041)	(0.055)	(0.034)	(0.043)
Job characteristics	-0.034**	-0.046	-0.116*	0.105*	-0.087	-0.115	-0.058**	-0.058**
	(0.016)	(0.047)	(0.060)	(0.056)	(0.094)	(0.116)	(0.028)	(0.027)
Demographics	0.016	0.069**	0.033	0.047*	0.032	0.060*	0.016	0.064***
	(0.017)	(0.031)	(0.027)	(0.026)	(0.030)	(0.032)	(0.015)	(0.018)
NRM TI	0.007	0.096*	-0.277**	-0.250	0.036	0.129	-0.015	0.012
	(0.013)	(0.056)	(0.112)	(0.189)	(0.035)	(0.218)	(0.015)	(0.044)
NRI TI	-0.027	-0.042	0.029	-0.074	0.044	0.650	-0.034	0.073
	(0.019)	(0.107)	(0.132)	(0.146)	(0.822)	(0.715)	(0.096)	(0.137)
NRC TI	-0.020	0.004	-0.252***	-0.047	-0.063	-0.169	0.441	0.123
	(0.025)	(0.081)	(0.090)	(0.096)	(0.199)	(0.115)	(0.317)	(0.191)
Constant	0.322***	0.141	0.758***	0.299	0.218	-0.480	-0.094	-0.054
	(0.079)	(0.233)	(0.105)	(0.195)	(0.999)	(0.720)	(0.402)	(0.307)
Observations Men	6067	7481	2930	4046	1575	4303	3432	8537
Observations Women	2770	3882	1207	4965	1630	8439	2633	8041

Notes: BO decomposition of the gender wage gap at the mean by task group. The counterfactual is calculated putting a weight of 1 on group 1 (men). Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ Education: primary, secondary, and tertiary education. Experience: full-time work experience, tenure, and part-time dummy. Job characteristics: 6 industry groups and firm size. Demographics: married, no. children in HH, dummy migration background, age groups. Reference groups are men and women with secondary education, no full-time work experience, who work full-time in manufacturing, are not married or in a registered partnership, have no children in HH, and no migration background. Task intensities are relative to the routine task intensity. Source: authors' calculations based on SOEP v.37 and Employment Survey waves 1986,1992, 2012 and 2018.

2.B. Appendix: Decomposition of the Gender Wage Gap – Technical Details

2.B.1. Shift-Share Decomposition

Female wages in period t are a weighted average over female wages within task groups and can be described as follows:

$$w_{ft} = \sum_j w_{fjt} \frac{E_{fjt}}{E_{ft}} \tag{2.B1}$$

where j indicates the task group and $E_f t$ denotes total female employment in period t and $E_f jt$ denotes female employment in task group j.

Thus, the change in female log wages over time can be decomposed into two parts:

$$\Delta w_{ft} = \underbrace{\sum_j \overline{w}_{fjt} \Delta \left(\frac{E_{fjt}}{E_{ft}} \right)}_{BetweenTaskGroups} + \underbrace{\sum_j \Delta w_{fjt} \left(\frac{\overline{E}_{fjt}}{E_{ft}} \right)}_{WithinTaskGroups} \tag{2.B2}$$

The first part of the right-hand side describes the change in female wages due to the change in employment shares in task group j. If wages were the same across all task groups, the between effect would not matter. However, if there different wages are paid across task groups, female wages will increase if they shift employment towards higher paying occupations. The second part of equation 2.B2 describes the change in wages due to changes in wages within task group j. The upper bar indicates the mean in wages and employment share within task group j over the two time periods. The decomposition of male wages work accordingly.

This decomposition can be applied to changes in the gender wage gap (GWG). Therefore, changes in the gender wage gap are the difference between changes in male and female wages. The gender wage gap will be reduced if female wages grow more than male wages.

$$\Delta GWG = \Delta w_{mt} - \Delta w_{ft} \tag{2.B3}$$

By plugging in equation 2.B2 for female and male wages into 2.B3, the change in the GWG can be decomposed into a within and between effect.

$$\Delta GWG_{between} = \sum_j \overline{w}_{mjt} \Delta \left(\frac{E_{mjt}}{E_{mt}} \right) - \sum_j \overline{w}_{fjt} \Delta \left(\frac{E_{fjt}}{E_{ft}} \right) \tag{2.B4}$$

$$\Delta GWG_{within} = \sum_j \Delta w_{mjt} \left(\frac{\overline{E}_{mjt}}{E_{mt}} \right) - \sum_j \Delta w_{fjt} \left(\frac{\overline{E}_{fjt}}{E_{ft}} \right) \tag{2.B5}$$

2.B.2. Blinder-Oaxaca Decomposition

To explore the reduction of the gender wage gap in more detail, and thus to answer our third research question, we perform an Oaxaca-Blinder (OB) decomposition. This allows us to decompose the difference in mean wages between the two groups into an explained and an unexplained part. The explained part captures the contribution of differences in the characteristics of the two groups, such as differences in full-time work experience. The unexplained part captures how differences in returns to characteristics, such as different returns to experience, can explain differences in wages between the groups (Fortin et al., 2011). Therefore, we assume a linear model:

$$W_g = X_g \beta_g + v_g, \quad E(v_g) = 0, \quad g \in \{m, f\} \tag{2.B6}$$

where X_g are gender-specific characteristics and β_g presents gender-specific coefficients. Since error v_g is assumed to be zero in expectation, the difference in gender-specific mean wages can be expressed as follows:

$$\begin{aligned} \Delta W &= \mathbb{E}[W_m] - \mathbb{E}[W_f] \\ &= \mathbb{E}[X_m]\beta_m - \mathbb{E}[X_f]\beta_f \\ &= \underbrace{(\mathbb{E}[X_m] - \mathbb{E}[X_f])\beta_m}_{\text{explained}} - \underbrace{\mathbb{E}[X_f](\beta_m - \beta_f)}_{\text{unexplained}} \end{aligned} \tag{2.B7}$$

The decomposition is weighted using a discriminatory coefficients. For this application, we assume that wage discrimination only affects women and that there is no discrimination against men. Accordingly, the male coefficient represents the non-discriminatory coefficient.

Furthermore, the OB decomposition allows to further decompose the explained and unexplained part into contributions by groups of predictors. Therefore, we group our control variables into several categories: education, experience, demographics, job characteristics, and task intensities. For education, we differentiate between workers with primary, secondary and tertiary education. For experience, we account for full-time work experience, tenure and an indicator for part-time employment. We consider the latter to be important as a high share of women in the German labour force work part-time. We also control for age, migrant background, being married or in a registered partnership, and the number of children in the household, which is captured by demographics. In addition, job characteristics include broad industry dummies and controls for firm size. Finally, we also include controls for gender task intensities within occupations. Since the AFL task intensities add up to one, we exclude routine task intensities, so that the task intensities have to be interpreted with respect to this category. We estimate the decomposition for the whole sample and separately for each task group.

3. From Code to Cash: The Impact of AI on Wages*

Abstract: Artificial Intelligence (AI) can perform cognitively demanding tasks with more autonomy than previous technologies and is expected to have disruptive effects on labor markets. But how exactly does AI diffuse through labor markets? And how does AI already affect workers' wages? To answer these questions we use novel job vacancy data from Germany with access to original job descriptions. We find that demand for AI skills has increased substantially from 2017-21, diffused broadly across regions, but is only concentrated in few occupations. Combining our vacancy data with high-quality administrative data, we conduct OLS and IV estimations and present three main findings. First, we document a positive and robust relationship between AI skill demand at the occupation-region-year level and worker-level wages, consistent with productivity-enhancing effects of AI. Second, the main beneficiaries are young, high-skilled workers with specialized expertise in cognitive job tasks, while older workers experience wage losses. Third, we offer suggestive evidence that AI has introduced new tasks with positive implications for wages. Our findings provide valuable insights for policymakers by identifying early winners and losers of growing AI diffusion and offers promising avenues for future research.

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3.1. Introduction

AI is still a nascent technology, yet, a rapidly growing number of firms and workers are becoming exposed to this technology.[1] In contrast to previous technologies, AI technologies have greater levels of autonomy and the ability to perform more cognitively demanding tasks, which may impact high-skilled workers with many such job tasks disproportionately (Webb, 2020). In fact, AI has already affected the task structure of jobs, resulting in establishment-level employment growth for high-skilled jobs, though no aggregate employment effects yet (Acemoglu et al., 2022b; Peede and Stops, 2023). While a growing number of studies provide important insights on firms' employment and labor demand responses to rising AI diffusion[2], micro-level evidence on wage implications is still mostly absent.[3] However, because only certain workers are currently exposed to AI, policy-relevant wage effects are likely to be missed in most existing aggregate analyses.[4]

In this paper, we fill this gap by studying the wage impact of rising demand for AI skills on workers and identifying its key drivers. A comprehensive analysis requires detailed and up-to-date data on AI skill demand and access to high-quality labor market data. To this end, we employ natural language processing (NLP) methods to identify AI skills from the near-universe of German online job vacancies (OJV) between 2017 - 2021, and combine the resulting indicators on AI exposure with administrative records from the German Institute for Employment Research (IAB).

In the first step, our descriptive analysis, we use identified AI skills to define the relevant dimensions of workers' AI exposure. In our paper, AI exposure encompasses the occupation-region-year level of AI skill demand — our definition of a local labor market (LLM). We exploit variation along these three dimensions in our main analysis and provide three key stylized facts to illustrate the diffusion of AI in Germany, showing that AI skill demand: (i) has grown by 12.6% year-on-year between 2017-21, (ii) has diffused broadly across regions, but (iii) is concentrated only among few occupations.

[1] For example, the share of AI-adopting firms in Germany has increased from 6% in 2019 to 13% in 2023 based on firm-level survey data (Rammer, 2022; Schaller et al., 2023). Also, a greater number of workers are exposed to AI. Based on individual-level German survey data from 2019, up to 45% of workers already engage with AI technologies, though unbeknownst to more than half of them (Giering et al., 2021). Similarly, firm-level surveys from the US show only 3-6% of US firms had adopted AI by 2019, though almost 13% of US workers had been exposed to this technology at work (Acemoglu et al., 2022a; McElheran et al., 2023).

[2] See also, e.g., Alekseeva et al. (2021); Babina et al. (2024).

[3] A notable exception is Fossen and Sorgner (2022) who estimate the impact of occupation-level exposure to AI on American workers' wages, using the Felten et al. (2021) indicators and CPS data.

[4] See OECD (2024) for a comprehensive overview.

In the second step, our main analysis, we study worker-level wage effects associated with changes in AI skill demand in their LLM. To facilitate this analysis, we merge our AI exposure measure to administrative data at the LLM-level. Using OLS as a baseline method, we recognize endogeneity concerns due to non-random adoption of AI technologies across firms and thus support our OLS results with an IV approach. Therefore, we construct a leave-one-out-mean (LOOM) instrument that excludes demand for a worker's current occupation in her commuting zone. Intuitively, this instrument exploits national trends in AI skill demand that are plausibly orthogonal to local conditions. The identifying assumption of our LOOM instrument requires that national trends in AI skill demand must not affect local wages through any other channel than (AI) technology diffusion. We provide supporting evidence for the validity of our instrument by performing a placebo test in which we find null effects when we regress *past* wages on contemporanous AI skill demand.

To guide our empirical analysis, we derive three hypotheses from a conceptual background, which is grounded in the model of Acemoglu et al. (2022b) — henceforth AAHR. While AAHR focus on AI-induced implications for firms' labor demand, we apply the model's logic to a wage analysis (similar to Acemoglu and Restrepo (2019, 2022)) and highlight its key dichotomy: on the one hand, AI technologies spur further automation of tasks with negative consequences for the affected workers ("displacement effect"), but on the other hand, they also permit a more flexible task allocation and thus enable workers to become more productive ("productivity effect"). Depending on the relative size of these effects and the task structure of their jobs, workers may be differentially affected by an increase in the demand for AI skills. We empirically test our hypotheses and present three main findings.

In our first hypothesis, we posit that workers with higher AI exposure in their LLM exhibit stronger wage changes. To test this claim, we exploit differential variation in demand for AI skills over time within a worker's LLM. Approximating AI exposure with AI skill demand in job postings, we indeed find a modest positive relationship between rising AI exposure and worker-level wages between 2017-2021. Using OLS, a 10% increase in AI exposure corresponds to a wage increase by 0.7% in our most restrictive model. To alleviate concerns regarding confounding factors, we control for individual unobserved heterogeneity, year-specific shocks, regional and occupational differences in productivity, as well as various worker-and job-related controls. Using our IV approach instead, even suggests an increase in wages of 1.5%. Differences between OLS and IV emerge because our LOOM instrument reduces the impact of outliers and aligns the data with national averages, which results in higher average estimates. Through the lens of the AAHR model, these results are thus consistent with relatively stronger productivity effects for the average worker (rather than displacement effects).

Second, we hypothesize high-skilled workers face stronger AI exposure due to their current job's task structure and thus exhibit stronger wage changes. Our empirical analysis provides supporting evidence for this claim. Interacting several skill and job complexity measures with AI skill demand, we show that wage gains are most pronounced for high-skilled workers, such as experts and specialists (2% wage increase), workers in cognitive-intensive occupations (4.5%), and college graduates (2.8%). Considering these high-skilled workers constitute up to 33% of the overall workforce, only a fraction of workers benefit from rising demand for AI skills so far. For all other skill groups we find only negligible or statistically insignificant estimates. Our results are also consistent with skill obsolescence, favoring young and prime-aged workers (Deming and Noray, 2020). While workers aged 18-49 years exhibit wage gains of 2.2 - 2.8%, older workers experience a 1.2% decrease, suggesting a devaluation of their skills.

Overall, our results on the second hypothesis are consistent with relatively strong productivity effects for young, high-skilled workers and modest displacement effects for older workers. This micro-level evidence uncovers important heterogeneities, which were masked by prior research, and provides important policy implications by shedding light on early winners and losers of rising AI diffusion.

Our third hypothesis posits that AI technologies create new tasks and thus enables complementarities with labor, implying wage gains for workers with high AI exposure. To better gauge the impact of this *reinstatement effect* (Acemoglu and Restrepo, 2019), we create a metric, summarizing the demand for skills associated with other "4.0" technologies, such as cloud computing and embedded systems. These 4.0 technologies are conceptually related to AI technologies in terms of enhanced connectivity and data-intensive applications, yet, are nonetheless distinct from AI, e.g. in terms of task complexity and level of autonomy.[5]

In order to infer new tasks, we leverage the fact that other 4.0 technologies emerged prior to AI technologies and are thus at a later maturation stage (Kalyani et al., 2023). This is

[5]See Chiarello et al. (2021); Kalyani et al. (2023); Prytkova et al. (2024) for comparisons between various 4.0 technologies and Abrardi et al. (2022) for a recent literature review.

evident in our data in form of a relatively higher level of demand for skills associated with 4.0 technologies. Because of conceptual similarities of these technologies, we expect that adding the 4.0 measure in our analysis absorbs some of the AI-induced wage gains associated with the productivity effect. Yet, differences in maturation stages should leave all AI-induced wage gains resulting from the reinstatement effect unaffected. Indeed, we find supporting evidence for this claim: Despite controlling for alternative 4.0 measures, the robust relationship between AI skill demand and wages persists, consistent with unique reinstatement effects of AI technologies.

We run a battery of robustness tests to alleviate concerns regarding identification threats in our main analysis. First, we address concerns on the validity of our AI measure by constructing alternative AI measures. These exercises show that different AI measures display similar trends over time and yield similar estimates, lending credence to our baseline AI measure. Second, we test for misspecification of our baseline model. To this end, we run more flexible models to account for occupation-year-specific and region-year-specific demand shock and also estimate our model in changes (rather than levels) to account for potential downward rigidities in the level of wages. These robustness tests do not substantially alter our main findings either. Third, we address compositional effects that may drive our estimates, resulting from workers moving into different LLMs. Comparing our baseline (unrestricted) model with various (restricted) models shows that all specifications yield statistically indistinguishable estimates. This result rules out major compositional effects.

Our paper makes several contributes to the literature. First, we contribute to the growing literature providing important descriptive insights on the small, but growing diffusion of AI, typically in terms of actual technology adoption[6], innovation activities[7] or recruitment changes, especially changing skill requirements.[8] Descriptively, we add new insights on AI skill demand in Germany between 2017-2021, thereby contributing insights to the international diffusion of AI. More substantially, these papers study potential labor market outcomes, e.g. posted wages, whereas we study *realized* outcomes, using actual wages. This distinction is important because only few job vacancies contain precise wage information (6% in the US, Batra et al. (2023)) and posted wages do not necessarily translate to realized wages.

Second, we contribute to the literature on the (realized) labor market impact of AI. Most of

[6]See Rammer (2022) for evidence in Germany and Acemoglu et al. (2022a); McElheran et al. (2023) in the US.

[7]See Babina et al. (2024); Bessen et al. (2021); Rammer et al. (2022).

[8]See, e.g., Alekseeva et al. (2021); Borgonovi et al. (2023a); Goldfarb et al. (2023); Kalyani et al. (2023).

the papers in this nascent literature focus on employment outcomes, often employing occupation-/region- or industry-level analyses.[9] A few papers also present micro-level evidence with mixed results so far. While existing studies find no meaningful aggregated employment effects yet, there is evidence for displacement among establishments with high AI exposure (Acemoglu et al. (2022b) for the US; Copestake et al. (2023) for India) and for productivity effects among high-skilled workers (Peede and Stops (2023) for Germany). Our main contribution is that we analyze how these mechanisms translate to wages.

Third, we add the literature on wage implications of AI technology. Most of the existing literature either uses posted wages (e.g. Alekseeva et al. (2021)) or aggregate wage outcomes (Gathmann and Grimm, 2022; Webb, 2020). Because AI exposure is still mostly concentrated among certain high-skilled workers, policy-relevant heterogeneities are likely missed in these types of analyses. We thus contribute one of the first studies with micro-level evidence on the wage impact of AI, thereby identifying and supporting potentially vulnerable groups. A few other studies also analyze worker-level wage implications, using either survey (Fossen and Sorgner, 2022) or administrative data.[10] However, these studies lack precise and time-varying information on AI exposure. Combining a Big Data approach with high-quality administrative data, in turn, allows a more refined analysis on the relationship between wages and AI exposure.

Fourth, we contribute to the nascent literature on the implications of AI exposure on worker productivity. Some papers evaluate the capabilities of AI and derive comparative advantages of workers and AI technologies for a variety of job tasks.[11] Others conduct experiments to infer productivity gains associated with the use of AI technologies (Noy and Zhang, 2023). These studies typically focus on large language models such as ChatGPT, whereas we use more extensive measures of AI exposure. In terms of overarching contributions, we show that productivity gains translate to wage gains.

Finally, we make methodological contributions to the literature by proposing new indicators, which allows to measure AI exposure at the occupation- and region-level in Germany. Existing indicators are already widely used, though mainly for the US, which limits analyses for other

[9] See, e.g., Albanesi et al. (2023); Gathmann and Grimm (2022); Prytkova et al. (2024); Webb (2020).
[10] See, e.g., Arntz et al. (2024); Genz et al. (2021, 2019).
[11] See, e.g., Brynjolfsson et al. (2023); Eloundou et al. (2023); Gilardi et al. (2023).

countries.[12] Our AI indicators are derived from online job vacancies and contain up-to-date AI skills. We encourage follow-up research with our indicators to bolster international evidence on the (US-heavy) literature on the labor market impact of AI.

The paper proceeds as follows. In section 3.2 we present our conceptual framework to guide the empirical analysis. Section 3.3 provides an overview of our data, including our approach for the identification of AI skills and construction of AI exposure. In section 3.4 we present key stylized facts on the diffusion of AI skills, before discussing our methodology and results in section 3.5. We explore key mechanisms for our results in section 3.6 and discuss robustness tests in section 3.7. Finally, we conclude with section 3.8.

3.2. Conceptual Background

In this section we outline the theoretical framework that guides our empirical analysis. First, we briefly review the model proposed in Acemoglu et al. (2022b) (henceforth AAHR), who explore the impact of rising AI exposure on establishment's labor demand. In a second step, we apply their model's logic to wage implications and discuss three extensions, from which we derive testable hypotheses.

3.2.1. The AAHR Model: Productivity vs Displacement Effect

The AAHR model assumes a competitive market in which profit-maximizing establishments produce output by combining labor and AI technologies (capital). AAHR conceptualize recent advancements in AI in terms of productivity-enhancing advancements rather than the creation of new tasks. As AI technologies become more productive, firms will automate more production steps and thus allocate a rising number of tasks to AI technologies. Assuming perfect substitutability between labor and AI technologies, AAHR then show that the implications for labor demand are primarily characterized by two competing forces: the displacement effect and the productivity effect.

On the one hand, as AI technologies become more productive, firms find it profitable to ex-

[12] See Brynjolfsson et al. (2018); Felten et al. (2021, 2023); Webb (2020). Notable exceptions for AI indicators in the European context are Tolan et al. (2021), combining data from various European surveys and O*NET, and Engberg et al. (2024), combining data from the Electronic Frontier Foundation (EFF) and Papers With Code (PWC). Both of these measure are similar to Felten et al. (2021, 2023).

pand the set of tasks performed by these technologies. This reallocation comes at the expense of workers who previously performed these tasks, because the *displacement effect* reduces labor demand. For example, the increasing prevalence of chatbots, such as ChatGPT, may reduce demand for customer service agents (Korinek, 2023). On the other hand, automation of certain production steps allows firms to generate cost savings and subsequently employ a more flexible allocation of tasks. These efficiency gains generate a positive *productivity effect*, which raises labor demand. Revisiting our chatbot example, these bots can increasingly handle routine queries, thereby allowing customer service agents to perform more complex tasks, such as consulting tasks.

The net effect of AI adoption on labor demand depends on the relative magnitude of the displacement and productivity effect. The magnitude of this labor demand shift, in turn, depends on an establishment's exposure to AI: The higher the share of tasks that can be profitably performed by AI technologies, the stronger will be an establishment's AI exposure. While AAHR focus on establishments and labor demand, we are instead primarily interested in workers and wages. To guide our analysis, we discuss three extensions to the AAHR model, from which we derive testable hypotheses.

3.2.2. Extensions & Testable Hypotheses

First, we explore the implications of rising AI exposure on wages. The same forces that operate on labor demand should also translate into wage changes (Acemoglu and Restrepo, 2019, 2022). Because changes in labor demand are rising with exposure to AI technologies in the AAHR model, we likewise expect workers' wages to be more responsive to higher AI exposure. Building upon this mechanism, we present our first hypothesis:

Hypothesis 1: Displacement vs Productivity Effect

Workers with higher exposure to AI technologies experience stronger wage changes. A positive change in wages is consistent with a relatively strong productivity effect, while a negative change is consistent with a relatively strong displacement effect.

We test Hypothesis 1 by running worker-level wage regressions on a measure capturing AI exposure, based on job descriptions from vacancies. Doing so, we loosely follow AAHR and approximate AI exposure with the share of vacancies within a workers' local labor market which demand AI skills.

Second, AAHR assume perfect substitutability between labor and AI technologies and thus worker homogeneity. Yet, what distinguishes AI from previous technologies is a higher level of autonomy and their ability to perform more cognitively demanding tasks (e.g. predictions and recommendations, assistance in decision-making, see Abrardi et al. (2022)). For these reasons, scholars have hypothesized that AI technologies may affect the task allocation differently than previous technologies and tasks associated with high-skilled workers in particular (Felten et al., 2021, 2023; Webb, 2020). Integrating this worker heterogeneity into the AAHR model, we argue that the relative magnitude of productivity and displacement effects differs among workers, subject to their job's task structure. Since workers may be differentially exposed to AI, we expect heterogeneous shifts to labor demand and thus heterogeneous wage implications, summarized in our second hypothesis:

Hypothesis 2: Worker Heterogeneity

High-skilled workers exhibit stronger AI exposure because AI technologies can perform cognitively more demanding tasks. Consequently, they experience stronger wage changes than lesser-skilled workers.

We test Hypothesis 2 by extending our wage regressions to accommodate different skill groups. Skill-specific implications on wages are consistent with heterogeneity in the relative size of displacement and productivity effects among different skill groups. We posit high-skilled workers are likely to benefit disproportionately from the productivity effect, but may also be more prone to the displacement effect.

Third, AAHR focus is on the displacement-versus-productivity effects of recent AI advances. The AAHR model does not explicitly account for the *reinstatement effect*, however. Accordingly, new technologies also have a positive impact on employment by creating new tasks, which are complementary to labor (Acemoglu and Restrepo, 2019). By extending the range of production-related tasks in favor of labor, the reinstatement effect reflects the opposite of the displacement effect. Because skills associated with new tasks are initially scarce, we expect them to attract higher wage gains (Langer and Wiederhold, 2023), summarized in our third hypothesis.

Hypothesis 3: Reinstatement Effect

AI technologies not only benefit workers by enhancing their productivity in already existing tasks, but also by extending the range of tasks. Consequently, the creation of new tasks leads to higher wage gains for workers with the highest AI exposure.

We test our final hypothesis by creating a measure that summarizes demand for skills associated with other “4.0 technologies”, such as cloud computing and embedded systems. Compared to AI, these 4.0 technologies have started to diffuse in the 2000s and thus had more time to mature (Kalyani et al., 2023). Because AI technologies have only started to diffuse around 2015-16 (AAHR) and our analysis begins in 2017, new tasks are more likely to be associated with AI technologies, rather than other 4.0 technologies. Therefore, if there were a positive relationship between AI skill demand and wages at the worker level, which remains robust to including alternative 4.0 measures, we would interpret such evidence as consistent with reinstatement effects of AI technologies.

3.3. Data

In this section, we present our data and outline the steps necessary to identify AI skills in order to construct our measure for AI exposure. At the core of our study is the near-universe of German online job vacancies (OJV). We use data between January 2017 and June 2023 to identify AI skills, but restrict ourselves to 2017 - 2021 for our analysis (due to linkage of the OJV data with administrative data). We first present a description of our OJV data, including (i) a general overview, (ii) sample selection, and (iii) aggregation procedures. In a second step, we outline details on our identification strategy of AI skills from job postings and the construction of our AI exposure measure. Lastly, we present our administrative data, comprising information on workers’ wages, and summary statistics.

3.3.1. Online Job Vacancies

General Overview

Job postings are collected by our partner —Finbot AG, an IT-company from Meerbusch, Germany. Finbot is a subsidiary of Palturai GmbH, from Hofheim, Germany, and offers custom-made firm-, person- and job posting- data and market analysis. To this end, they scrape vacancies from job boards, company websites, temporary employment agencies, and head-hunters. Finbot consistently updates their online sources and scrapes all sources on a daily basis. Subsequently, Finbot performs basic cleaning procedures and removes duplicates from the same source (i.e. sources from the same url address).

Our OJV data offers some key advantages compared to other vacancy data commonly used in economic research. Often, researchers purchase preprocessed data, leaving ambiguities about underlying data quality. While we also receive our data from a commercial provider, our data has two key features. First, we have access to the original job vacancies, including all texts included in the posting. This unique access allows us to have more control over the data-generating process and to develop our own, transparent taxonomies. Second, Finbot merges job-posting firms with the German company registry ("Handelsregister"), which is possible for about 60% of the job postings. This linkage allows us to supplement firms' vacancy contents with a plethora of firm characteristics, e.g. their location.

We show in various validation exercises that our data is tilted towards high-skilled jobs. Therefore, we perform reweighting approaches with representative data, which deliver similar insights on the key trends in AI skill demand that we exploit for our empirical analysis; namely trends in AI skill demand (i) over time, (ii) across regions, and (iii) across occupations. We thus conclude that the skewness in our OJV data towards high-skilled worker is unlikely to distort our empirical analysis. In Appendix 3.B.2 we offer a more detailed discussion on the external validity of our data. Moreover, we provide more details on our OJV data and the data-generating process in Appendix 3.B and necessary NLP and data preparation steps in Appendix 3.B.1.

Sample Selection

We limit ourselves to the years 2017 - 2021 for our main analysis to match availability of our administrative data (see section 3.3.4 for details). Within this time horizon we only use vacancies advertising regular work, i.e. full- or part-time, thereby removing vacancies seeking apprenticeships, trainees, and other types of irregular work. We also apply various other filters and sample selection steps to ensure high data quality and maintain comparability with administrative data. These steps comprise, among others, removal of vacancies (i) posted by temporary employment agencies, with (ii) unusual contents, and (iii) missing information on key variables, and are discussed in Appendix 3.B.3.

Table 3.B1 provides a comprehensive overview of our sample selection, displaying the share of vacancies we lose at each step. Overall, we keep around 13% of all vacancies for our analysis. Most vacancies are omitted due to exclusion of postings from temporary work agencies and those that cannot be linked to the company registry. After cleaning and selecting the relevant data, we are left with 8.3 million vacancies from 242,000 companies. To put our final database in perspective, keep in mind there was a total of reported vacancies in Germany between 2017-2021 of 11 million vacancies, according to the IAB Job Vacancy Survey (Bossler et al., 2021; IAB, 2022).

Aggregation

For our main analysis, we aggregate our OJV data to accommodate a merge with administrative data (details in section 3.3.4). To facilitate this merge, we need to define a proper local labor market, through which we will measure AI exposure. But what is a worker's relevant local labor market? In principle, this definition should comprise the set of jobs that may be feasible for a worker to move into. Most studies on the labor market impacts of new technologies usually employ either a region-level analysis[13] or occupation-level analysis[14]. Part of this emphasis is due to data limitations, as diffusion of new technologies across regions *and* occupations is challenging to measure with conventional data. As we, and others before us have argued (Azar et al., 2020), however, these labor market definitions may be too broad.[15]

[13]See, e.g., Acemoglu and Restrepo (2019); Gathmann et al. (2023).

[14]See, e.g., Albanesi et al. (2023); Brynjolfsson et al. (2018); Webb (2020).

[15]Disregarding the regional dimension omits the fact that most workers do not engage in wide-ranging job searches and instead prefer to stay close to their home region (Heise and Porzio, 2022). Disregarding the occupational dimension, in turn, omits job-specific skill requirements that are highly relevant in the context of AI. For these reasons, a growing numbers of studies define a worker's relevant local labor market at the region-occupation-year level. Recent papers which use a similar LMR-definition, include, among others, Azar et al. (2020); Hervé (2023); Popp (2023); Rinz (2024); Schubert et al. (2022). Intuitively, to motivate this LMR-definition, Azar et al. (2020) apply the "hypothetical monopolist test" from the IO-literature to labor markets — the "hypothetical monopsonist test" — in order to define the smallest labor market for which a hypothetical monopsonist would find it profitable to implement a small reduction in wages. In the US context, they find that 6-digit SOC occupations by commuting zones by quarter are a conservative, yet reasonable, definition for LMRs. Our definition of a LMR is even more conservation (3-digit occupations), yet, broadly similar to theirs.

Unlike traditional data sources, we have sufficient statistical power to accommodate such a detailed definition of a local labor market. To this end, we aggregate 402 counties into 141 commuting zones, or interchangeably, labor market regions (LMR), following the classification of Kosfeld and Werner (2012). To be consistent with previous studies, we drop postings for jobs in the armed forces, agriculture, fishing and forestry. To ensure that our results are not driven by outliers, we also retain only those LMR-occupation combinations with at least 3 postings in a year. These restriction leave us with 122 (out of 144) occupations. Eventually, we combine the 141 LRMs with 122 3-digit occupations (KldB2010) for each year, resulting in 17,202 local labor markets for which we calculate AI exposure between 2017-21. We set the cutoff date June 30th each year to match the cutoff date in our administrative data (details in section 3.3.4).

3.3.2. Identification of AI Skills

Having established our vacancy data and aggregation procedure, we now proceed with details on our identification strategy for AI skills from job descriptions. To this end, we combine a keyword-based approach with manual annotation and assistance by ChatGPT 4.0. First, we create an initial keyword list of 97 AI skills, using keywords that have previously been used in the literature.[16] However, this list lacks information on (i) more recent innovations in the AI Space, e.g., transformer-based models (Devlin et al., 2019), (ii) specific tools commonly deployed to perform AI tasks, e.g. Python packages, and (iii) jargon commonly used in vacancies, e.g. abbreviations, German descriptions, etc. In a second step, we thus manually annotate a random sample to validate and extend existing AI skill keywords. After these adjustments, we end up with 140 relevant AI skills that we use for our analysis.

The most important AI skills are applied to broad concepts in machine learning, data mining, or deep learning (Figure 3.A1). These methods summarize algorithms, methods, and software libraries commonly deployed in AI. In addition, we also find more niche applications, which comprise specific domains in which AI skills are applied to (e.g., autonomous driving). See Table 3.A1 for a full overview of our keywords.

We acknowledge our definition of AI skills is broader than most existing taxonomies and may thus be more susceptible to "false positives", i.e. erroneously classifying certain skills as AI skills. In our robustness section 3.7 we present comparisons with alternative definitions from

[16]See Acemoglu et al. (2022b); Bessen et al. (2021); Büchel et al. (2021); Taska et al. (2022).

the literature. Importantly, neither the main message of our stylized facts nor our empirical results change once we adopt alternative keywords, lending credence to our identification of AI skills.

3.3.3. Construction of AI Exposure

Next, we describe the empirical counterpart to worker's AI exposure from our conceptual background in section 3.2. Within the AAHR model, AI exposure reflects the share of tasks that can be performed by AI technologies. AAHR approximate this exposure, using distinct patent- and crowdsource-based indicators provided by existing literature (Brynjolfsson et al., 2018; Felten et al., 2021; Webb, 2020). We instead approximate AI exposure, our key explanatory variable in our main analysis, with AI_{olt}, i.e. the share of vacancies in a worker's relevant local labor market that demand AI skills:

$$AI_{olt} = \frac{N_{olt}^{AI}}{N_{olt}} \tag{3.1}$$

where N_{olt}^{AI} reflects the numbers of vacancies within a local labor market that demand AI skills in year t ("AI vacancies") and N_{olt} represents all vacancies within a local labor market. We follow conventions in the literature by defining a vacancy an "AI vacancy" if we find at least one AI skill in the job description (Acemoglu et al., 2022b). Putting the number of AI vacancies in relation to all vacancies within a workers' local labor market thus provides a measure of differential AI exposure. We will exploit this variation in AI_{olt} in our main analysis to assess implications of AI exposure on wages.

While the theoretical counterpart to our exposure measure is task-based, our skill-based measure is closely related to this concept (for a detailed discussion see Acemoglu and Autor (2011)). We argue our vacancy-based exposure measures provides a more immediate measure to assess wage implications, compared to, say, patent-based data. It usually takes a lot of time for newly patented technologies to be used widely and unclear to what extent a technology is actually being adopted by firms. In comparison, OJV data offers near real-time insights on the diffusion of technologies in a worker's relevant local labor market, and thus a more immediate measure for AI exposure.

3.3.4. Administrative Data and Summary Statistics

Administrative Data

To facilitate our analysis of rising AI exposure on worker-level wages, we use the Sample of Integrated Labor Market Biographies (SIAB), a 2 percent representative sample of administrative data on all workers who are subject to social security contributions (SSC) and all workers receiving unemployment benefits for the period 1975-2021.[17] The SSC requirement excludes certain individuals, notably the self-employed and civil servants. The SIAB is drawn from the Integrated Employment Biographies (IEB) of the IAB and provides information on daily labor market spells, wages, and basic socio-economic characteristics (e.g., sex, nationality, education).

As is common in administrative data, wage information is top-censored. Censoring affects about five percent of all spells, though, some skilled groups are more heavily affected (Dauth and Eppelsheimer, 2020). To not disregard this data, we follow standard procedures and use the imputations for education and wages provided by the IAB-FDZ, which builds upon (Fitzenberger et al., 2006). In terms of sample selection, we focus on full-time workers aged 18-65 who are liable to social security and exclude workers with (i) zero wage and wages below the first percentile, and (ii) missing information on place of work, establishment and occupation. Currently, the data is available up until 2021. We thus restrict our OJV data to 2017-2021 to match data availability of the SIAB.

We further supplement the SIAB with two additional data sources. First, we use data from the Establishment History Panel (BHP), comprising all establishments covered by the IAB employment history. We use information on employment, industry, and the location of work of establishments between 2017-2021. Second, we complement indicators from the German Occupational Panel (Dengler et al., 2023). This data describes job characteristics and comprises, among others, the same (conceptual) task measures outlined in AAHR. The IAB Occupational Panel derives job descriptions from the BERUFENET database, comprising detailed job characteristics and maintained by the German Federal Employment Agency.[18]

[17] See Schmucker et al. (2023) and Graf et al. (2023) for a detailed description of the data.

[18] The data can be downloaded free of charge from the IAB webpage: `https://iab.de/en/daten/iab-occupational-panel/`.

Summary Statistics

We present summary statistics for the workers in our sample, including their exposure to AI and their daily wages, in Table 3.1. Here, we describe several indicators that characterize workers in terms of skill: In terms of formal education, 71% of workers earned a vocational degree, while 23% are college graduates. Using detailed occupational codes[19], instead, suggests 57% of workers are skilled professionals and 32% of workers are highly-skilled specialists or experts in their respective field. Similarly, using the task structure of occupations, only 18% and 8% of workers are employed in cognitively demanding occupations intensive in analytic and, respectively, interactive tasks. Regardless of skill measure, our descriptive insights show that high-skilled workers have higher AI exposure, consistent with existing literature[20], and that these skill groups tend to have higher daily wages.

We also observe that two thirds of workers are men, reflecting our restriction to full-time workers. Moreover, 85% of workers are employed in medium-sized or large firms with at least 250 employees and in large metropolitan areas (54%).

3.4. Stylized Facts: Diffusion of AI Skills

In this section, we present visual illustration of the variation we seek to exploit in our main analysis. To this end, we provide three key stylized facts on demand for AI skills in Germany from 2017 - 2021. These facts display variation in demand for AI skills (i) over time, (ii) across regions, and (iii) across occupations.

3.4.1. Demand for AI skills has grown substantially between 2017-21

To illustrate the diffusion of AI skill demand over time, Figure 3.1 displays the monthly share of AI vacancies from 2017 - 2021. In our sample, the average share of AI vacancies increased from 1.2% in 2017 to 2.1% in 2021, implying an annualized year-on-year (YoY) growth rate of 12.6%.

This upward trend aligns broadly with related literature, though we find somewhat higher

[19]To facilitate this comparison, we use the fifth digit of the KldB 2010 classification, which assigns (broad) occupations into four skill groups: unskilled, skilled, specialist, expert.

[20]See Webb (2020) for evidence in the US and Engberg et al. (2024) for evidence in several European countries.

Table 3.1.: AI exposure and average wages by socioeconomic characteristics

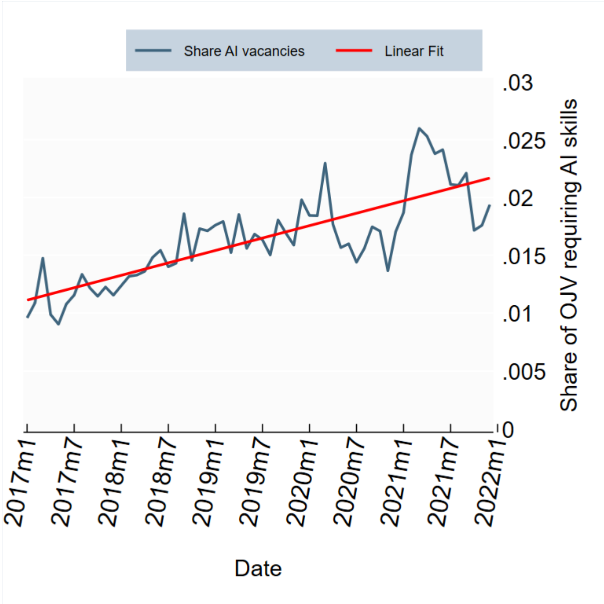
	(1) Share in Sample	(2) AI OJV Share	(3) Daily Wage (in EUR)
Men	0.68	0.010	138.0
Average Age	43.43		
Foreign nationality	0.09	0.008	104.7
College	0.23	0.019	204.0
Vocational	0.71	0.007	111.1
No degree	0.06	0.006	87.5
Unskilled	0.11	0.003	79.14
Skilled	0.57	0.006	106.9
Specialist	0.16	0.015	162.5
Expert	0.16	0.020	212.9
Routine	0.59	0.005	120.0
NR manual	0.15	0.002	88.8
NR interactive	0.08	0.008	147.4
NR analytic	0.18	0.030	187.7
Small firm (0-19)	0.15	0.007	96.3
Medium firm (20-249)	0.46	0.008	117.4
Large firm (250-999)	0.22	0.010	145.5
Very large firm (>999)	0.17	0.014	182.9
Region: Agglomeration	0.54	0.005	108.2
Region: Urbanized	0.30	0.008	123.2
Region: Rural	0.16	0.011	137.8
Observations	1,671,322	1,671,322	1,671,322

Note: The first column displays the share of workers in our sample with specific socioeconomic characteristics. The second column shows the group-specific AI exposure, defined as the share of vacancies with AI skills posted in their local labor market. The third column displays the average log daily wage for each group. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; SIAB version Version 7521 v1; own calculations.

shares of AI vacancies. Taska et al. (2022), henceforth TON, report the share of AI vacancies in Germany increased from 0.6% in 2017 to about 1% by 2021. Because we adopt a more extensive keyword list (outlined in section 3.3.2), our taxonomy implies that the share of AI vacancies has been about twice as large as in the existing literature. Once we adopt the original keyword list by TON (excluding German translations), our share of AI vacancies merely increases from 0.5% to 1%, thus consistent with their findings (see Figure 3.A2).[21] For the US, often considered the frontier country for advancements in AI, TON report an increase in the share of AI vacancies from 0.8% in 2017 to 1.4% in 2021. Considering our share of AI vacancies is about twice as large as theirs, due to methodological differences, our taxonomy would put the share of AI vacancies

[21] For example, replicating Acemoglu et al. (2022b), by using their exact keywords, the share of AI vacancies increases from 0.35% in 2017 to about 0.55% by 2021, implying a YoY growth rate of 8.8%. More recently, Borgonovi et al. (2023b) document an increase in AI vacancies in Germany from 0.3% to 0.4% between 2019 - 2022. All these studies use similar taxonomies to identify AI skills, which are provided by Lightcast.

Figure 3.1.: Trends in AI demand, 2017/01 - 2021/12



Note: Vacancies are defined as an "AI vacancy" if a job posting contains at least one AI-related skill in a given month. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021, own calculations.

in the US at a comparably higher level of approximately 2.8% in 2021.

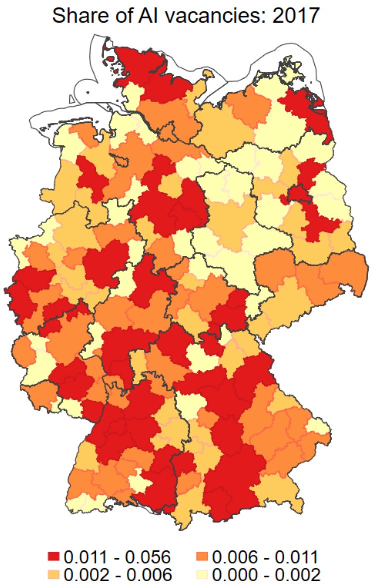
Overall, we find that alternative definitions of AI skills primarily lead to level differences. Importantly, however, they all display similar dynamics over time. This distinction is important because variation over time will be essential for our identification strategy (rather than the "exact" measurement of the level of AI vacancies). We show that our main results are robust to a variety of alternative definitions of AI skills in Appendix 3.A.

3.4.2. Demand for AI skills has diffused broadly across regions

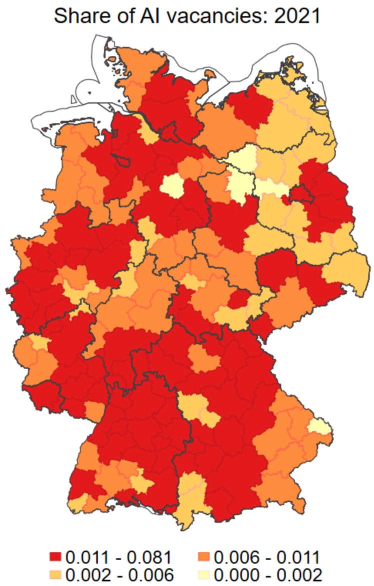
Having established credible trends over time in AI skill demand, we now illustrate regional diffusion of AI skills. Figure 3.2 displays the average share of AI vacancies for each of our 141 LMRs in 2017 and 2021. To this end we partition each LMR into one out of four equally sized groups. The first quartile comprises the 35 LMR with highest share of AI vacancies ("High-AI regions"). The three remaining quartils comprises regions with lower share of AI vacancies.

In 2017, demand for AI skills was concentrated in urban regions, especially in the South-west, with large clusters around Berlin, Munich, and Stuttgart (see also Gathmann and Grimm (2022)). At least 1% of all vacancies in these regions in the first quartile required AI skills. In the remaining regions, AI skill demand was still mostly negligible. To illustrate the regional

Figure 3.2.: Demand for AI skills in Germany across local labor markets, 2017-01 - 2021-12



(a) AI demand: 2017



(b) AI demand: 2021

Note: Local labor markets are assigned into four classes of task intensity. Each class corresponds to quartiles as of 2017 where lowest quartile implies lowest AI demand (yellow) and highest quartile implies hightest AI demand (red). Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021, own calculations.

diffusion of AI, we perform a descriptive counterfactual exercise. To this end, we reproduce the same map for the year 2021, but keep using the same boundaries (from 2017) to divide the four types of regions. Doing so, we find a broad diffusion across German regions. In fact, around 50% of LMRs would have been classified a "High-AI" region in 2017 in this counterfactual exercise. Overall, there are only a handful of regions, which would (in 2021) still be placed in the lowest quartile in 2017, in which AI has barely diffused, mostly in rural parts of East Germany.

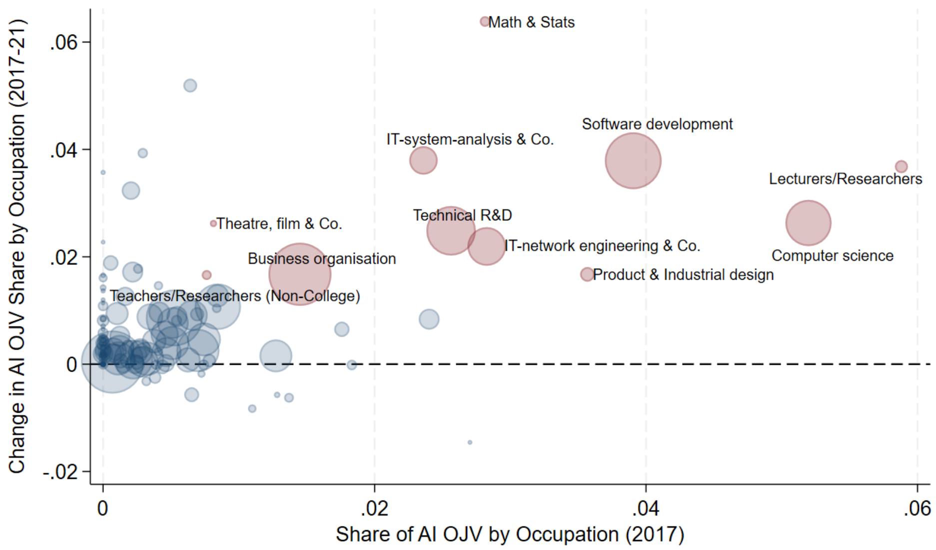
3.4.3. Demand for AI skills is concentrated among few occupations

Similar to the regional diffusion of AI skills, we finally assess the occupational diffusion. For this purpose, we first compute the share of AI vacancies for each of our 122 3-digit occupations for each year. The horizontal axis in Figure 3.3 displays these shares for our first period in 2017. We contrast this baseline level of occupational AI exposure the change in the share of AI vacancies between 2017 - 2021, depicted along the vertical axis.

This comparison shows a strong positive correlation ($\rho = 0.43$), suggesting that occupations with initially higher AI exposure are also those that experienced stronger exposure to AI skill demand in subsequent years. In particular, we identify 11 pioneering occupations, which are characterized by high baseline demand for AI skills in 2017 (80th percentile) and high subsequent change between 2017-21 (80th percentile). The Top 3 occupations with the highest AI skill demand are *1) Lecturers and researchers at universities and colleges* (Overall share of AI vacancies: 7.2%), *2) Computer science (7.1%)*, and *3) Mathematics and statistics (6.9%)*.[22]

Compared to regions, though, diffusion of AI skill demand across occupations has been much more concentrated. To be precise, for around 70% of occupations, we find little to no demand for AI skills throughout our time horizon. We provide a full overview of all occupations and their average share of AI vacancies from 2017-2021 in Table 3.A2.

Figure 3.3.: Dynamics in occupational demand for AI skills



Note: The X-axis displays the share of OJV with AI demand ("AI Vacancies") for 140 3-digit occupations as of 2017. The Y-axis displays the change in AI Vacancies between 2017 - 2021 for each occupation. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021, own calculations.

3.5. Empirical Analysis

In this section, we empirically test the implications of our conceptual background, presented in section 3.2. In particular, we aim to test the first hypothesis in our baseline model, arguing that workers with higher AI exposure also experience stronger wage changes. First, we run OLS wage regressions in which we account for worker FE and a rich set of control variables and fixed-effects. Second, we perform an IV estimation to address potential endogeneity concerns in

[22] The remaining pioneering occupations comprise: Software development and programming (6.8%), IT-application-consulting (5.0%), Technical research and development (4.5%), Product and industrial design (4.4%), IT-network engineering, IT-coordination, administration (4.3%), IT-system-analysis, Business organisation and strategy (2.7%), Theatre, film, television productions (2.1%), and Teachers at educational institutions other than schools (1.6%).

OLS. To permit a causal interpretation of our results, we use a leave-one-out instrument that exploits national trends in AI skill demand, which are plausibly exogenous to local trends.

3.5.1. OLS Wage Regressions

Methodology

We begin our analysis by running OLS regressions, using the log daily wage w_{ilot} for worker i, working in LMR l, and employed in occupation o in year t, as outcome variable:

$$lnw_{ilot} = \alpha_i + \beta_1 AI_{lot} + \beta_2 X_{it} + \beta_3 \psi_l + \beta_4 \omega_o + \beta_5 \theta_t + \epsilon_{ilt} \tag{3.2}$$

Our key covariate is A_{lot}, capturing the share of vacancies requiring AI skills —our measure of AI skill demand —in each year t in LMR l and occupation o. We control for a rich set of covariates in X_{it} at the worker level, comprising socioeconomic characteristics (age, education, gender, nationality), work experience controls (firm tenure), and employer-related controls (firm size, industry 2-digit according to WZ08) , and employer quality, approximated by AKM effects.[23] We include include worker FE (α_i) to control for individual unobserved heterogeneity and year FE (θ_t) to capture year-specific shocks such as COVID-19. In order to account for regional and occupational differences in productivity and technology adoption, we further include LMR FE (ψ_l) and occupation FE (ω_o) at the 3-digit KldB level. Because we include worker FE, these LMR- and occupation-specific effects are identified by workers moving between regions and occupations, thus effectively capturing wage differentials. Therefore, we exploit differential variation in demand for AI skills over time within a worker's local labor market.

We are primarily interested in the sign and magnitude of β_1. Through the lens of our conceptual background (section 3.2), this coefficient is informative on the relative size of the displacement and productivity effect. We interpret $\beta_1 > 0$ consistent with a relatively strong productivity effect. Similarly, we consider $\beta_1 < 0$ consistent with a comparably strong displacement effect.

In various robustness tests, we perform a battery of alternative specifications to check for model misspecification. In particular, we address three potential concerns. First, we use alter-

[23]We use AKM effects for the time period 2007 to 2013 to avoid reverse causality of AI exposure on firms' productivity

native definitions of our AI measure to alleviate concerns regarding mismeasurement of our key regressor. Second, we test the robustness of our baseline specification by (i) including LMR × Year FE and Occupation × Year FE to explicitly account for region- and occupation-specific shocks and (ii) estimating a model in changes to address concerns of limited downward rigidities in the level of wages. Third, we shed light on the role of regional and occupational mobility to inspect compositional effects as workers move into different LLMs. Overall, these robustness tests leave our key takeaways unchanged. We provide more details on these tests in section 3.7.

Results

We report our baseline results on demand of AI skills on worker-level wages in Table 3.2. All specifications include our worker-level controls, summarized in X_{it}, and worker FE. In the first column we add year FE to account year-specific shocks. Our point estimate of 0.09 shows positive wage implications in response to rising AI Diffusion. Adding LMR FE barely changes this estimate (column 2).

Table 3.2.: Wage regressions AI exposure: Occupation-LMR-level

	Dependent Variable: Log Wages		
	(1)	(2)	(3)
AI Share	0.089***	0.087***	0.073***
	(0.018)	(0.018)	(0.016)
Worker FE	✓	✓	✓
Year FE	✓	✓	✓
LMR FE		✓	✓
Occupation FE			✓
AI Share Mean		0.009	
Observations	1,500,688	1,500,688	1,500,688
R^2	0.89	0.89	0.89

Note: All specifications include the following controls: Socioeconomic controls include age, citizenship, education, and gender. Work controls include establishment tenure. Firm controls include establishment size and industry group. AKM effects for the time period 2007-2013. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; own calculations.

However, once we additionally control for occupational FE, our point estimate drops to 0.073 (column 3). This observation suggests that occupational variation has a stronger impact on wages than regional variation, presumably because AI skill demand is more concentrated along the occupational dimension (see Figure 3.3). Evaluated at the mean value of AI skill demand

(0.009), this estimate implies that a 10% increase in AI skill demand is associated with a wage increase of 0.7%.[24]

Overall, our OLS results consistently show modest but positive effects of increasing AI diffusion on worker-level wages. These results support our first hypothesis from section 3.2, which argues that workers with higher AI exposure experience higher wage changes. Through the lens of our conceptual background, these estimates are consistent with the productivity effect outweighing possible displacement effects during the early stages of rising AI skill demand.

We emphasize, however, that our baseline results should be interpreted with caution. OLS is helpful to learn about the relationship between wages and AI skill demand, but does not capture the causal impact of rising AI skill demand. Demand for AI skills is likely endogenous because skill demand is a function of underlying technology adoption and AI adoption is mainly concentrated among large, productive firms (Rammer et al., 2022). While we provide remedy against these identification threats by controlling for various firm-/ LMR-/ and occupation-level differences in our OLS specification, none of these actions resolves the inherent endogeneity problem. For this reason, we supplement our OLS analysis with an instrumental variable approach that permits causal interpretation.

3.5.2. IV Regressions

Identification

We address endogeneity concerns in our OLS specifications by constructing an instrument that exploits national trends in AI skill demand, which are plausibly exogenous to local conditions. To this end, we instrument for AI exposure in occupation o in LMR l by calculating the leave-one-out-mean (LOOM) of AI skill demand for each occupation, AI_{ot}, excluding its demand in

[24]For easier interpretation, we examine the impact of a 10% increase in AI skill demand, evaluated at its mean level. To normalize our coefficients accordingly, we first determine the percentage increase in AI skill demand that corresponds to a unit increase (i.e., in percentage points). Subsequently, we divide our point estimates by a normalizing factor that corresponds to a 10% increase in AI skill demand. For example, the mean level of AI skill demand in our baseline sample is 0.009. A one-unit increase corresponds to a move from 0.009 to 0.019, implying that our point estimate of 0.073 reflects an increase in AI skill demand by 111% (= 0.01/0.009). Dividing 0.073 by 11.1 then permits interpretation in response to a 10% increase in AI skill demand, yielding 0.007.

workers' home LMR $l \neq l'$, i.e. $AI^{IV}_{lot} = \sum_{l \neq l'} AI_{lot}$.[25] Using our LOOM variable, we then instrument for endogenous AI skill demand with a two-stage-least-squares (2SLS) approach:

$$lnw_{ilot} = \beta_1 AI^{IV}_{lot} + \beta_2 X_{it} + \beta_3 \psi_l + \beta_4 \omega_o + \beta_5 \theta_t + \epsilon_{ilt} \tag{3.3}$$

The identifying variation of AI^{IV}_{lot} comes from changes in national AI skill demand over time. Essentially, our LOOM instrument exploits the variation illustrated in Figure 3.1, showing that the (national) share of AI vacancies doubled between 2017 and 2021. We loosely interpret this rapid diffusion of AI skill demand as ”technology shocks” that may result from exogenous technological innovations outside of Germany, such as China and US — the technology leaders in AI (EFI, 2024). In the US, for example, demand for AI skills in job postings has accelerated starting in 2015-16 (Acemoglu et al., 2022b), with rising diffusion ever since. These types of external advances affect all domestic labor markets (though perhaps differently) and, as we argue, are exogenous shocks from the perspective of individual workers.

The LOOM instruments imply, by construction, a strong first stage and thus satisfy the relevance assumption. In our context, we expect a high correlation between endogenous local AI skill demand and instrumented national AI skill demand due to broad technology diffusion across regions (see Figure 3.2). We validate this presumption formally by reporting F-statistics of our first stage estimates.

Despite their high relevance, LOOM instruments also have limitations. On the one hand, they may suffer from reverse causality because both the instrument and the endogenous variable exploit contemporaneous variation. We do not expect reverse causality to be a major issue in our context, as we observe 141 LMRs with differential demand for AI skills. Thus, any local changes in the demand for AI skills are unlikely to have first-order aggregate effects. On the other hand, LOOM instruments are still vulnerable to spillovers due to broader regional trends or other confounding factors that may violate the exclusion restriction.

We address these identification threats twofold. First, we include a rich set of control variables, including $LMR \times Year$ and $Occupation \times Year$ FE to account for occupation- and region-

[25] LOOM instruments provide a simple and intuitive approach to address endogeneity concerns associated with local shocks and, for these reasons, have become increasingly popular in economic research, see, e.g., Azar et al. (2020); Popp (2023); Rinz (2024); Schubert et al. (2022). To give a specific example, consider a worker employed as a computer scientist (KldB: 431) in the LMR ”Berlin”. In order to instrument for the endogenous AI skill demand she is exposed to, we compute the average AI skill demand that computer scientists in all other LMRs — except Berlin — are exposed to.

specific shocks. This way, we aim to control for other confounding factors we do not observe and may possibly introduce omitted variable bias. Second, national trends in AI skill demand, our technology shocks, must not affect local wages through any other channel than technology diffusion. To check the validity of shock orthogonality, we perform a placebo test in which we run a regression with baseline characteristics that were realized *prior* to those shocks and should thus result in null effects, conceptually similar to a "pre-trend" test in a Difference-in-Difference setting:

$$lnw_{ilo,2012-16} = \alpha_i + \beta_1 AI_{lo,2017-2021} + \beta_2 X_{it} + \beta_3 \psi_l + \beta_4 \omega_o + \beta_5 \theta_t + \epsilon_{ilt} \tag{3.4}$$

Here, we regress wages from the period 2012 - 2016 on our AI skill demand between 2017 - 2021, such that wages in 2012 are regressed on AI skill demand in 2017 and so on. To support our claim that our research design satisfies the exclusion restriction, we require the null hypothesis $\beta_1 = 0$ to be true, i.e. no "pre-trends". Indeed, our results in Table 3.A3 shows we cannot reject the null hypothesis in our preferred specification. Pre-trends would be a problem in specifications, which omit occupation FE (columns 1 and 2). However, once we control for occupation FE (column 3) or even more flexible specifications (columns 4-6), we cannot reject the null hypothesis of no pre-trends. Because our baseline IV specification accounts for LMR FE and Occupation FE, we find no evidence rejecting the validity of our LOOM instrument.[26]

Results

We begin the discussion on our results with the presentation of the first stage of our 2SLS approach. Table 3.A4 shows high F-statistics for all our specifications, with an F-statistic of 1010.5 in our most restrictive specification, comprising worker-, year-, LMR- and Occupation FE (column 3). The strong correlation between the LOOM instrument and our baseline AI measure reaffirms the relevance of our instrument.

Next, we report the second stage of our IV results on the impact of rising AI skill demand on worker-level wages in Table 3.3. For comparability, we also include the corresponding OLS results. Overall, OLS and IV specifications provide qualitatively similar results, reinforcing a

[26]We have also constructed alternative LOOM instruments, in which we weight our baseline instrument with local occupational employment shares. Overall, these modified instruments provide similar insights, though, we prefer to use our baseline LOOM instrument for its simplicity. These supplemental results are not reported, but available from the authors upon request.

Table 3.3.: IV regressions AI exposure: Occupation-LMR-level

	Dependent Variable: Log Wages		
	(1)	(2)	(3)
IV:AI Share (Occ-LMR)	0.270***	0.273***	0.172***
	(0.024)	(0.024)	(0.027)
OLS:AI Share	0.089***	0.087***	0.073***
	(0.018)	(0.018)	(0.016)
Worker FE	✓	✓	✓
Year FE	✓	✓	✓
LMR FE		✓	✓
Occupation FE			✓
AI Share Mean		0.009	
Observations	1,500,688	1,500,688	1,500,688

Note: All specifications include the following controls: Socioeconomic controls include age, citizenship, education, and gender. Work controls include establishment tenure. Firm controls include establishment size and industry group. AKM effects for the time period 2007-2013. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; own calculations.

positive link between rising AI skill demand and worker-level wages. The validity of our IV results is supported by a strong F-statistic of 1010.5 in the first-stage. In quantitative terms, though, IV results display coefficient sizes more than twice as large as those using OLS. For example, consider our preferred specification, using LMR FE and occupational FE (column 3). The IV point estimate of 0.17 implies that a 10% increase in AI skill demand is associated with a wage increase of 1.5%. In contrast, OLS results imply only a wage increase by 0.7%. This comparison suggests that confounding factors tend to depress wages, causing attenuation bias.

We attribute the quantitative differences between OLS and IV to the distinct diffusion patterns of AI (see section 3.4). While AI skill demand has diffused broadly across regions, demand is rather concentrated in a few occupations. Because our LLM-definition comprises both of these dimensions, most of our LLMs have very low AI skill demand. Our LOOM instrument averages out AI skill demand across labor market regions, thereby harmonizing the data with national trends and reducing the impact of outliers.

This mechanism is illustrated in Figure 3.A3, which compares the distribution of our baseline AI exposure with the instrumented AI exposure based on our LOOM approach. While the adjustment to national trends reduces the impact of outliers, it raises the median AI exposure. For most LLMs, therefore, the instrument leads to higher values. Thus, according to our first hypothesis, we expect our LOOM instrument to yield higher estimates than our OLS model.

We cannot rule out other confounding shocks, however, for example productivity shocks concentrated in a broader region and encompassing many but not all regions. While these concerns warrant caution regarding interpretation, our identification tests in the section 3.5.2 make us confident that our IV results are informative on the causal implications of rising AI skill demand on worker-level wages.

3.6. Mechanisms

In this section, we build upon our baseline results on the positive relationship between AI skill demand and worker-level wages and shed light on underlying mechanisms. Grounded in our conceptual framework (section 3.2), we hypothesize that higher-skilled workers experience larger wage increases due complementarities with AI technologies (Hypothesis 2). Moreover, we expect workers to not only benefit from AI through productivity gains associated with already existing tasks, but also through the creation of new tasks (Hypothesis 3). To assess these mechanisms, we run the following OLS specifications[27]:

$$lnw_{ilot} = \alpha_i + \beta_1 AI_{lot} + \beta_2 GR_o + \beta_3 AI_{lot} \times GR_i + \beta_4 X_{it} + \beta_5 \psi_l + \beta_6 \omega_o + \beta_7 \theta_t + \epsilon_{ilt} \qquad (3.5)$$

in which we interact our AI measure with different group indicators GR_i to compare wage differences across worker types. Otherwise, this model is identical to our baseline specification eq. (3.5.1) and controls for the same set of variables. We calculate and report marginal effects for each group to permit a more intuitive interpretation of the relative size of productivity and displacement effects.

3.6.1. Skill Heterogeneity

High-skilled workers perform many cognitively demanding tasks that AI technologies only recently managed to performed at similar productivity. They are thus more exposed to rising AI skill demand than other worker types (Webb, 2020) Because our second key hypothesis states

[27] Note that we perform this analysis using OLS (rather than IV) because OLS can handle models like ours, with high-dimensional FE, better and permits the calculation of marginal effects for the interaction terms. In contrast, the IV implementation is more complicated. Because IV results are in line with our OLS estimates, though with higher estimates, we consider OLS a conservative baseline, which provides a lower bound for the results in this section.

that AI-induced wage changes will be stronger for more exposed workers and because our baseline results show a positive relationship between AI skill demand and wages, we thus expect high-skilled workers to benefit disproportionately from rising AI skill demand.

To explore this skill heterogeneity, we employ three conceptually distinct skill measures. First, we use measures on occupation-specific task complexity that encompasses the range of tasks, problem-solving abilities, and relevant knowledge domains in a job. Second, we examine education as a measure for formal skill requirements, including relevant training, knowledge acquisition and cognitive development. Third, we distinguish between age groups to disentangle differences in experience and accumulated human capital.

I. Occupational task complexity

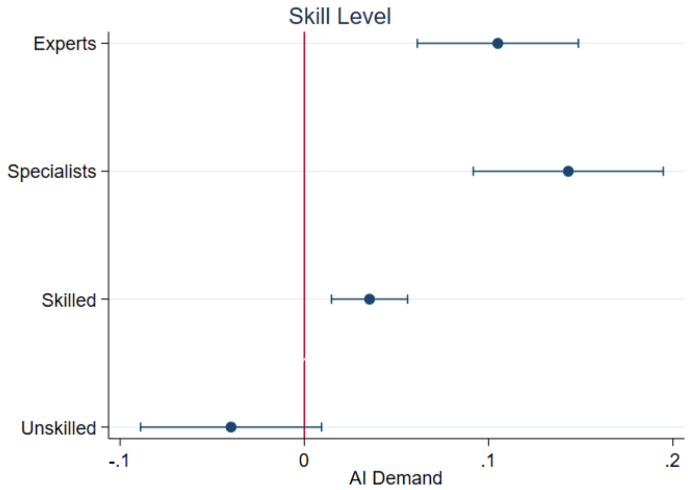
Starting with occupational task complexity, we distinguish between four skill groups: unskilled, professional, specialist and expert. To facilitates this categorization, we use the fifth digit of the occupational code, which distinguishes between these skill groups.

Figure 3.4 shows the marginal effects on wages for each of these skill levels. Indeed, we find that the association between demand for AI skills and wages is stronger for higher-skilled workers, suggesting that our baseline results mask substantial heterogeneity across skill levels. In particular, we observe significant marginal effects of 0.14 for specialists and 0.10 for experts and higher mean AI exposure among these groups, with a mean value of 0.015 and 0.02 for specialists and, respectively, experts. Evaluated at their respective mean values of AI exposure, these results imply that a 10% increase in AI exposure corresponds to a wage increase of around 2% for both, professionals and specialists. We also find a modest wage increase associated with skilled workers, on the order of 0.2%, yet no statistically significant estimates for unskilled workers.

Overall, these results provide evidence in favor of our second hypothesis, suggesting stronger wage responses of high-skilled workers in response to rising demand for AI skills, and are consistent with previous worker-level evidence (Fossen and Sorgner, 2022). In fact, our baseline results are entirely driven by specialist and expert workers —a group that comprises only 33% of all workers in our sample.

We underscore our evidence on skill heterogeneity with an additional analysis on complementarities between AI technologies and job-specific task complexity. To this end, we assign

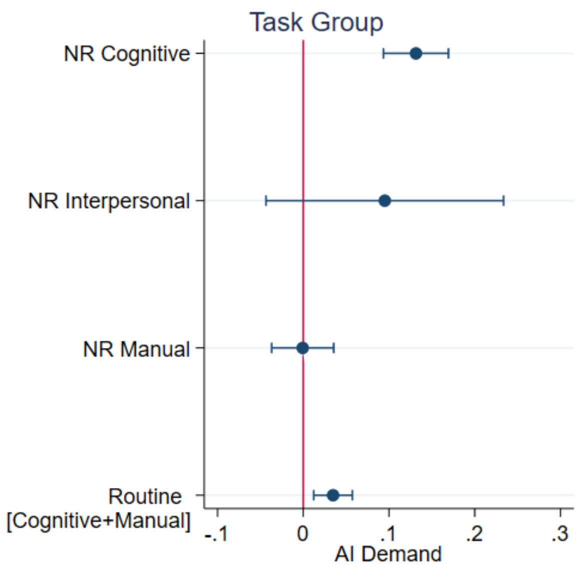
Figure 3.4.: Marginal effect of AI demand by occupational skill level



Note: The figure shows the marginal effect of AI demand on wages by skill level. The horizontal lines present 95% confidence intervals. The model includes worker, year , LMR and occupation FE. The model also includes these controls: Socioeconomic: age, citizenship, education, and gender; Work: establishment tenure; Firm: establishment size, industry groups, AKM (2007-2013) effect. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; SIAB version Version 7521 v1; own calculations.

occupations into four task groups, using data from the German Occupation Panel (Dengler et al., 2023). Depending on their underlying task structure, we classify occupations into one of these four groups: (i) Non-Routine (NR) cognitive, (ii) NR Interpersonal, (iii) NR Manual, or (iv) Routine.

Figure 3.5.: Marginal effect of AI demand by task group



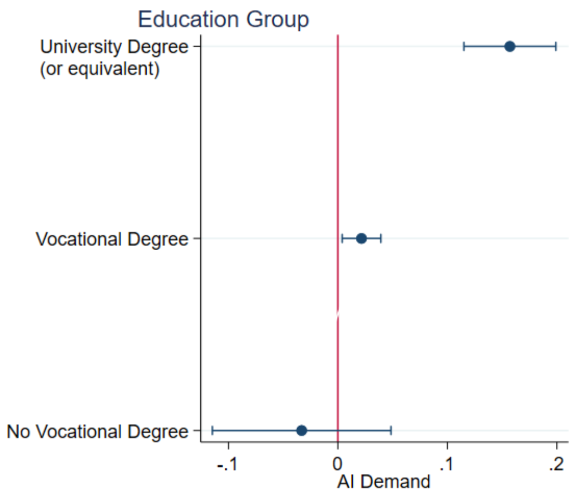
Note: The figures shows the marginal effect of AI demand on wages by task group. See notes Figure 3.4. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; SIAB version Version 7521 v1; own calculations.

Figure 3.5 summarizes the results of this exercise and shows that our baseline results are primarily driven by workers employed in cognitive-intensive occupations such as IT- and scienceoriented jobs. Evaluated at their respective mean AI exposure of 0.03, a 10% increase in demand for AI skills implies a wage increase of 4.5% for these workers. In contrast, we find only negligible positive estimates for workers in routine-intensive occupations and no significant results for workers in interpersonal- or manual-intensive occupations. Our results are thus consistent with the notion of relatively stronger productivity effects for high-skilled workers. We find no evidence for displacement effects, however.

II. Formal skill requirements (Education)

In a second step, we use formal job requirements to explore skill heterogeneity between educational groups (see Figure 3.6). Unsurprisingly, the positive link between wages and AI skill demand is concentrated among workers with a college degree with a marginal effect 0.16. Evaluated at the mean value of AI skill demand for this group (= 0.018), a 10% increase in AI skill demand implies wage gains on the order of 2.8% for college graduates. We find only negligible results for workers with a vocational degree and no significant effects at all for workers with no formal degree.

Figure 3.6.: Marginal effect of AI demand by education group



Note: The plot shows the marginal effect of AI demand on wages by education group. See notes to Figure 3.4.
Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; SIAB version Version 7521 v1; own calculations.

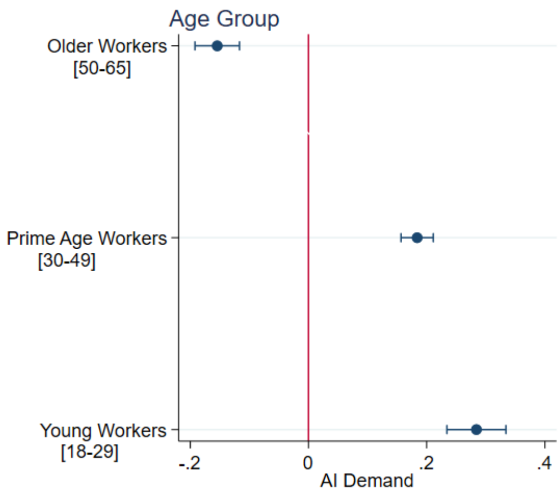
Overall, using education measures mirrors our results on occupational task complexity, reinforcing the evidence on skill heterogeneity in AI skill demand. As is the case for expert and specialist workers, college graduates are substantially more exposed to AI skill demand than non-college graduates (0.018 vs 0.006) and also represent only a small share of the workforce (23%).

III. Age profiles (Experience)

In our third and final step, we proxy differential skill levels with age profiles to shed light on the role of experience and accumulated human capital. We distinguish between three age groups: (i) young workers: 18-29, (ii) prime-age workers: 30-49, and (iii) older workers: 50-65.

Figure 3.7 summarizes marginal effects of our point estimates and displays strong age-specific heterogeneities. Despite similar levels of AI exposure for all age groups (0.008 - 0.010), we only find positive effects on young workers (0.28) and prime-age workers (0.18). Evaluated at the respective mean level of AI exposure, a 10% increase in AI skill demand is associated with a 2.8% wage increase for young workers and 2.2% for prime-age workers. In contrast, we find negative marginal effects for old workers. Accordingly, a 10% increase in AI skill demand corresponds to a 1.2% wage decrease for workers aged 50 or more.

Figure 3.7.: Marginal effect of AI demand by age group



Note: The plot shows the marginal effect of AI demand on wages by age groups. See notes to Figure 3.4. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; SIAB version Version 7521 v1; own calculations.

This age heterogeneity suggests that AI skills are not complementary to work experience, which we reinforce in supplementary analysis, using experience groups instead (Figure 3.A4).[28] We view these results consistent with Deming and Noray (2020), who show that skill obsolescence lowers returns to experience, especially in STEM jobs — exactly the type of jobs in which AI skill demand has diffused more intensely and for which we find most pronounced wage changes. Hence, young workers may be the primary beneficiaries of rising AI skill demand because their

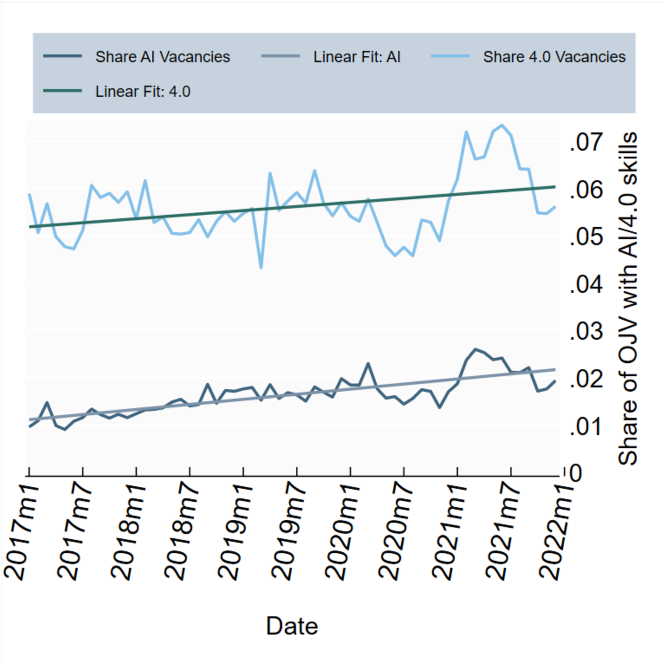
[28]We distinguish between three experience groups: (i) workers with less than 5 years of experience, with experience between 5 and 15 years, and workers with more than 15 years of experience

(newly acquired) skills are valued more than the (devalued) skills of older workers.

3.6.2. Reinstatement Effect

So far, we have interpreted our results through the lens of productivity gains associated with already existing tasks. According to our third hypothesis, however, new technologies also lead to the creation of new tasks, thereby extending the range of production-related tasks (Acemoglu and Restrepo, 2019). This reinstatement effect suggests complementarities between new technologies and labor, especially skilled labor, and should thus contribute to the positive relationship between AI skill demand and wages, which we have established in our main analysis. It is an empirical challenge, however, to define "new tasks", let alone the exact timing of their emergence.

Figure 3.8.: AI demand and 4.0 demand, 2017/01 - 2021/12



Note: Vacancies are defined as an "AI vacancy" if a job posting contains at least one AI-related skill in a given month. Similarly, vacancies are defined as a "4.0 vacancy" if a job posting contains at least one skill associated with other 4.0 technologies (excluding AI) in a given month. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; own calculations.

In order to assess the role of the AI-induced reinstatement effects more comprehensively, we create a measure that summarizes demand for competing skills, which are associated with other "4.0 technologies", e.g. cloud computing and embedded systems.[29] 4.0 technologies are characterized by data-intensive tasks and greater connectivity than previous technology waves (Arntz et al., 2024). Importantly for our purposes, these alternative 4.0 technologies are often related to AI technologies. However, unlike AI, they diffused earlier, starting in the 2000s (Kalyani et al., 2023). Due to these differences in the maturation stage, we expect our AI measure to contain unique information on the reinstatement of labor, which is not accounted for with alternative 4.0 technologies. For example, our AI measure contains novel skills that have not existed until recently, such as skills associated with large language models, which have only gained prominence starting in 2018 (Devlin et al., 2019).

Figure 3.8 confirms that demand for skills associated with other 4.0 technologies is more widespread compared to skill associated with AI technologies, consistent with earlier emergence of 4.0 technologies. By 2021, about 2% of job postings require AI skills. In contrast, about 6% of job postings require skills related to other 4.0 technologies. While both technology groups show a positive trend over time, the increase in demand for AI has been stronger than for 4.0 technologies. Because of the (i) level differences in demand for skills associated with AI and, respectively, 4.0 technologies and (ii) more rapid diffusion of AI since 2017, we expect our AI measure to have more potential to create new tasks in our short-term analysis.

In a second step, we provide more rigorous evidence for our claim that there are stronger reinstatement effects associated with AI compared to 4.0 technologies. To test this hypothesis, we include both measures in our baseline wage regressions, eq. (3.4). If the positive relationship between AI skill demand and worker-level wages remains robust to inclusion of alternative 4.0 measures, we interpret such evidence consistent with stronger reinstatement effects of AI technologies.

We report the results of this exercise in Table 3.4, which provides two key takeaways. First, inclusion of the 4.0 measure has little impact on the wage implications of our AI measure. In fact, our AI measure even remains quantitatively robust to our baseline specification (columns 1). Second, the point estimates of the 4.0 measure loses significance once we control for occupation- and region-specific shocks in more restrictive specifications (columns 3 and 4). In contrast, our

[29] To construct this 4.0 measure, we combine classifications on ICT-technologies from the European Skills, Competences, Qualifications, and Occupations (ESCO), provided by the European Commission, and insights from state-of-the-art literature (Chiarello et al., 2021; Kalyani et al., 2023). We provide more details on the construction of this measure in Appendix 3.C, including an overview of the most important 4.0 technologies (excluding AI). Furthermore, note that we exclude AI technologies, such that this "4.0 measure" and our AI measure are disjoint.

Table 3.4.: Wage regressions on reinstatement effect: AI technologies vs other 4.0 technologies

	Dependent Variable: Log Wages			
	(1)	(2)	(3)	(4)
AI Baseline	0.068***	0.053***	0.039***	0.030***
	(0.016)	(0.014)	(0.013)	(0.011)
4.0 Technologies	0.022**	0.017**	0.010	0.007
	(0.009)	(0.008)	(0.007)	(0.007)
LMR X Year FE		✓		✓
Occupation (1-digit) X Year FE			✓	✓
Observations	1,500,688	1,500,688	1,500,688	1,500,682
R^2	0.89	0.89	0.89	0.89

Note: All specifications include the following controls: Socioeconomic controls include age, citizenship, education, and gender. Work controls include establishment tenure. Firm controls include establishment size and industry groups. AKM effects for the time period 2007-2013. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; SIAB version Version 7521 v1; own calculations.

AI measure remains statistical significant at the 1% level, suggesting a more robust relationship between wages and AI exposure.

AI skill demand thus maintains its high predictive power over wage differences, even when we control for demand for skills that are associated with similar, yet, distinct 4.0 technologies. Combined, we view this evidence consistent with reinstatement effects that are unique to AI technologies. We acknowledge that our results provide only tentative evidence on the impact of AI-induced reinstatement effects on wages because we do not explicitly measure the introduction of new tasks. We leave this empirical challenge for future research.

3.7. Robustness

In this section we perform a series of robustness checks to ensure validity of our main results. First, we provide supporting evidence that our AI measure indeed identifies AI skills rather than broadly related skills. Second, we conduct several robustness checks to test for misspecification of our baseline model. Third, we address concerns regarding compositional changes due to job mobility and thus shed light on the role of regional and occupational mobility. Overall, these robustness checks support our main findings on the positive relationship between AI skill demand and worker-level wages.

I. Validity of AI measure

We bolster the validity of our AI measure by comparing it to four alternative measures. First, we use the same keywords as in AAHR, thereby imposing their underlying taxonomy on AI skills. Second, we exclude somewhat generic AI keywords that may not capture AI skills in a narrow sense —*"AI", "Artificial Intelligence", "ML", "Machine Learning"*. These keywords are also the most frequent ones, thus also providing insights on the impact of outliers in our taxonomy. For our third and fourth measures, we divide our baseline AI measure into two subcategories. The category "AI methods" reflects the "developer-perspective" of AI, comprising general algorithms, methods, and software. In contrast, the category "AI applications" reflects the "user-perspective" of AI, comprising (industry-)specific applications, such as autonomous driving, which are somewhat unique to the manufacturing sector. See Figure 3.A6 for a word cloud to illustrate the category-specific keywords.

Despite noticeable level differences, our alternative AI measures reaffirm insights from our baseline measure. Figure 3.A5 shows that all alternative AI measure display an increase in demand for AI skills between 2017-21. Even more reassuringly, we also find similar wage implications, when we replace our baseline AI measure with these alternative ones instead. Figure 3.A7 shows statistically significant point estimates for most of our AI measures, which are statistically indistinguishable from our baseline measure (except "AI applications").

Overall, we do not find evidence that suggests meaningful mismeasurement of our baseline AI measure. Alternative definitions display similar dynamics over time and have comparable implications for worker-level wages.[30] Notably, these robustness exercises suggest our baseline results primarily reflect demand for AI skills associated with the "developer-perspective" (AI methods), consistent with the early maturation stage of AI technologies.

II. Validity of baseline model

In a second step, we address concerns regarding misspecification of our baseline model, which may introduce omitted variable bias. We begin by running more flexible specifications that account for occupation- and region-specific time trends. To this end, we include (LMR $\times$ year) FE and (occupation $\times$ year) FE in our baseline wage regression, eq. (3.4) to account for

[30] In supplementary analysis, we also construct an AI measure that accounts for the number of AI skills posted in vacancies and thus captures the intensity of AI skill demand. We view this "intensity-based" measure harder to interpret than our baseline "share-based" measure, but it provides qualitatively similar results (Table 3.A5).

region- and occupation-specific demand shocks. We use 1-digit, 2-digit, and 3-digit definitions for occupations to capture differential occupational trends in AI skill demand at varying aggregation levels.

Table 3.A6 shows these robustness exercises reduce our point estimates, but our main findings on the positive impact of AI skill demand on wages remain robust. Recall our baseline point estimate is 0.073 (column 1). When we only control for either $LMR \times year$ FE and $occupation\ (1 - digit) \times year$ FE, this estimate drops to 0.057 (column 2) and 0.042 (column 3), respectively. By including both $LMR \times year$ FE and $occupation \times year$ FE, this estimate drops to 0.031 (column 4). The inclusion of 2-digit and 3-digit occupation time trends has only minor impact on these estimates (columns 5 - 6). According to our most restrictive robustness specification (column 6), a 10% increase in AI skill demand is associated with a 0.3% increase in wages, which we consider a lower bound for our OLS estimates (0.7% wage increase).

Subsequently, we estimate our model in wage changes (rather than levels of wages), similar to Fossen and Sorgner (2022) A potential concern with our baseline approach is that the level of wages may limit downward movements in wages, especially for continuously employed workers. Hence, our baseline approach may not be able to capture any displacement effects properly. To address this concern, we re-run our model in differences. In Table 3.A7 we report our results, comparing outcomes over (i) 1-year differences, (ii) 2-year differences, and (iii) the maximum of 4-your differences.

Overall, this exercise confirms the main takeaway from our baseline results. An increase in the *change* of AI exposure is associated with a positive change in wages in all specifications (columns 1-3). We thus reject concerns regarding overestimation of AI-induced wage implications due to downward wage rigidities. Notably, the size of the point estimates increases for longer time-differences, suggesting that the cumulative impact of rising AI exposure increases over time. Considering demand for AI skills is still relatively small in our time horizon, wage implications might thus become more pronounced in upcoming years.

Finally, we show that our estimates are robust to further sample restrictions on the SIAB and OJV data (Table 3.A8). These restrictions imply loss of statistical power, but ensure greater consistency. For example, we restrict our sample to (i) workers who are present in the SIAB data across all years and (ii) LMR-occupation cells with at least three postings across all years.

III. Compositional effects

Through the lens of the AAHR model, wage gains are interepreted as "on-the-job" gains, resulting from the productivity-enhancing features of AI *on the current job*. However, this interpretation masks possible compositional effects, if wage gains are actually realized because workers move into different local labor markets or occupations, i.e. "job-to-job" gains. To shed light on the role of mobility, we classify workers into three groups: (i) stayers (ii) regional movers and (iii) occupational movers. Regional movers have changed their work location (LMR) at least once between 2017-21, and vice versa for occupational movers who have changed their occupation (3-digit) at least once. Subsequently, we impose restrictions on mobility step-wise to identify the extent of implied job-to-job gains.

Figure 3.A8 illustrates the results of this exercise and permits a comparison between restricted models and our unrestricted baseline specification. Excluding regional movers reduces our baseline coefficient of 0.073 to 0.064. Further restrictions on occupational mobility further attenuate the coefficient to 0.061. Excluding workers who change either their location or their occupation reduces the estimate to 0.057, implying that both dimensions of mobility account for a combined 22% of our baseline (unrestricted) model.

These results suggest that occupational and regional mobility play a role, allowing workers to move into local labor markets with higher AI exposure. However, the size of the 95% confidence intervals of our estimates overlap. We thus cannot reject the hypothesis that all estimates are significantly different from each other. Taken together, the evidence in this section suggests that most of the AI-induced wage increases are driven by "on-the-job" wage gains.

3.8. Conclusions

In this paper we study the diffusion of AI skill demand and perform detailed analysis on its worker-level wage implications. Our analysis combines the near-universe of German online job vacancies from 2017 - 2021 with administrative data from the IAB. Our original data gives us access to the raw texts of job postings, allowing us to construct our own AI taxonomy in a transparent way. We use NLP methods to measure AI skill demand from the vacancy data and merge this measure to administrative data at a detailed occupation-region-year level. Subsequently, we use OLS and IV methods to assess the impact of rising AI skill demand on wages. To address endogeneity in AI skill demand, we propose a leave-one-out instrument that exploits national trends in AI skill demand that are plausibly orthogonal to local conditions in a worker's home region.

Our key finding is that AI skill demand has mostly modest, but positive implications on wages. In our baseline model, in which we account for worker-, regional, and occupational fixed effects, our OLS estimates suggest that a 10% increase in AI skill demand is associated with a 0.7% wage increase. In contrast, our IV approach implies even higher estimates of up to 1.5%. We interpret these positive results through the lens of the Acemoglu et al. (2022b) model, implying that the positive wage implications are attributed to productivity gains ("productivity effect") among workers most exposed to AI. We also provide suggestive evidence on positive wage implications of new tasks ("reinstatement effect") that were introduced solely due to rising adoption of AI technologies.

Exploring underlying mechanisms and heterogeneities, our analysis further reveals that the early "winners" of rising AI diffusion are young, high-skilled workers with specific expertise in cognitive job tasks. Depending on our skill measure, we find higher wage gains on the order of 2 - 4.5%, consistent with stronger productivity effects for these workers. In contrast, our findings suggest that older workers (aged 50 or older) are the primary early "losers", as reflected in a wage decline of 1.2%. This result is consistent with the "displacement effect" as AI increasingly automates tasks that were previously performed by workers. Overall, only a fraction of up to one third of the workforce, consisting of high-skilled workers, benefits from the rapid diffusion of AI skill demand since 2017. These disparities help explain why previous studies have found no discernible aggregate effects of AI on labor market outcomes.

Our results provide important insights for policymakers and a plethora of avenues for research. First, our new micro-level evidence helps identify early "winners" and "losers" of rising AI skill demand. These findings can help policymakers target vulnerable groups more effectively. Future research can support this process with deeper insights on skill transferability. Combining our focus on AI skills with a conceptual framework on skill portability (Gathmann and Schönberg, 2010) can help identifying suitable jobs for those workers affected detrimentally.

Second, we document how rapidly changing skill requirements affect workers' wages. Given that many firms are currently considering adoption of AI technologies (Schaller et al., 2023), AI skill demand will continue to rise.

Because the adoption of technology is accompanied by skill upgrading and the introduction of new skills, we expect an increase in matching inefficiencies in certain labor market segments (Modestino et al., 2023). We thus argue for a more targeted development of AI skills to alleviate such inefficiencies, including students who are currently acquiring skills for their future and workers who may be in need of further training. Future research can support these measures with more research on the supply of AI skills.

Lastly, we lack knowledge on worker-level adjustments once their employer adopts AI technologies. Our data does not permit such identification. We thus encourage follow-up research using linked employer-employee data to jointly analyze firms' and workers' responses to rising AI adoption.

Bibliography

Abrardi, L., Cambini, C., and Rondi, L. (2022). Artificial intelligence, firms and consumer behavior: A survey. *Journal of Economic Surveys*, 36(4):969–991.

Acemoglu, D., Anderson, G. W., Beede, D. N., Buffington, C., Childress, E. E., Dinlersoz, E., Foster, L. S., Goldschlag, N., Haltiwanger, J. C., Kroff, Z., et al. (2022a). Automation and the workforce: A firm-level view from the 2019 annual business survey. NBER Working Paper 30659, National Bureau of Economic Research.

Acemoglu, D., Autor, D., Hazell, J., and Restrepo, P. (2022b). Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics*, 40(S1).

Acemoglu, D. and Autor, D. H. (2011). Skills, tasks and technologies: Implications for employment and earnings. In Card, D. and Ashenfelter, O., editors, *Handbook of Labor Economics*, pages 1043–1171. Elsevier.

Acemoglu, D. and Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, 33(2):3–30.

Acemoglu, D. and Restrepo, P. (2022). Tasks, automation, and the rise in U.S. wage inequality. *Econometrica*, 90:1973–2016.

Albanesi, S., Dias da Silva, A., Jimeno, J. F., Lamo, A., and Wabitsch, A. (2023). New technologies and jobs in Europe. Working Paper 31357, National Bureau of Economic Research.

Alekseeva, L., Azar, J., Giné, M., Samila, S., and Taska, B. (2021). The demand for AI skills in the labor market. *Labour Economics*, 71:102002.

Arntz, M., Genz, S., Gregory, T., Lehmer, F., and Zierahn-Weilage, U. (2024). De-routinization in the fourth industrial revolution–firm-level evidence. ZEW Discussion Paper 24-005, ZEW - Centre for European Economic Research.

Arthur, R. (2021). Studying the UK job market during the COVID-19 crisis with online job ads. *PloS one*, 16(5):e0251431.

Ash, E. and Hansen, S. (2023). Text algorithms in economics. *Annual Review of Economics*, 15:659–688. First published as a Review in Advance on July 5, 2023.

Azar, J., Marinescu, I., Steinbaum, M., and Taska, B. (2020). Concentration in US labor markets: Evidence from online vacancy data. *Labour Economics*, 66:101886.

Babina, T., Fedyk, A., He, A., and Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics*, 151:103745.

Bamieh, O. and Ziegler, L. (2020). How does the COVID-19 crisis affect labor demand? An analysis using job board data from Austria. IZA Discussion Paper 13801, IZA - Institute of Labor Economics.

Batra, H., Michaud, A., and Mongey, S. (2023). Online job posts contain very little wage information. Working Paper 31984, National Bureau of Economic Research.

Bessen, J., Cockburn, I., and Hunt, J. (2021). Is distance from innovation a barrier to the adoption of Artificial Intelligence. Boston university working paper, Boston University.

Borgonovi, F., Calvino, F., Criscuolo, C., Samek, L., Seitz, H., Nania, J., Nitschke, J., and O'Kane, L. (2023a). Emerging trends in AI skill demand across 14 OECD countries. OECD Artificial Intelligence Papers 2.

Borgonovi, F., Calvino, F., Criscuolo, C., Samek, L., Seitz, H., Nania, J., Nitschke, J., and O'Kane, L. (2023b). Emerging trends in ai skill demand across 14 oecd countries. OECD Artificial Intelligence Papers 2, OECD.

Bossler, M., Gürtzgen, N., Kubis, A., Küfner, B., and Popp, M. (2021). Iab-stellenerhebung – version 0018 v1. Forschungsdatenzentrum der Bundesagentur für Arbeit (BA) im Institut für Arbeitsmarkt- und Berufsforschung (IAB).

Brynjolfsson, E., Li, D., and Raymond, L. R. (2023). Generative ai at work. NBER Working Paper 31161, National Bureau of Economic Research.

Brynjolfsson, E., Mitchell, T., and Rock, D. (2018). What can machines learn and what does it mean for occupations and the economy? *AEA Papers and Proceedings*, 108:43–47.

Büchel, J., Demary, V., Goecke, H., Kohlisch, E., Koppel, O., Mertens, A., Rusche, C., Scheufen, M., and Wendt, J. (2021). KI-Monitor 2021: Status quo der Künstlichen Intelligenz in Deutschland. Gutachten im Auftrag des Bundesverbandes Digitale Wirtschaft (BVDW) e.V.

Carrillo-Tudela, C., Kaas, L., and Lochner, B. (2023). Matching through search channels. Discussion Paper 16583, IZA - Institute of Labor Economics.

Chiarello, F., Fantoni, G., Hogarth, T., Giordano, V., Baltina, L., and Spada, I. (2021). Towards ESCO 4.0 – Is the European classification of skills in line with Industry 4.0? A text mining approach. *Technological Forecasting and Social Change*, 173:121177.

Company Lightcast (2023). Artificial intelligence in the UK: The relevance of AI in the digital transformation of the UK labour market. Technical report, Company Lightcast.

Copestake, A., Marczinek, M., Pople, A., and Stapleton, K. (2023). AI, firms and wages: Evidence from India. Mimeo.

Dauth, W. and Eppelsheimer, J. (2020). Preparing the sample of integrated labour market biographies (siab) for scientific analysis: a guide. *Journal for Labour Market Research*, 54(1).

Deming, D. J. and Noray, K. (2020). Earnings dynamics, changing job skills, and STEM careers*. *The Quarterly Journal of Economics*, 135(4):1965–2005.

Dengler, K., Janser, M., and Lehmer, F. (2023). The occupational panel for germany. *Journal of Economics and Statistics*, 243(6):711–724.

Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (NAACL-HLT)*, volume 1, pages 4171–4186.

EFI (2024). Research, innovation and technological performance in Germany - EFI report. Technical report, Commission of Experts for Research and Innovation (EFI), Berlin.

Eloundou, T., Manning, S., Mishkin, P., and Rock, D. (2023). GPTs are GPTs: An early look at the labor market impact potential of large language models. Working paper, Stanford University.

Engberg, E., Görg, H., Lodefalk, M., Javed, F., Längkvist, M., Monteiro, N. P., Nordås, H. K., Schroeder, S., and Tang, A. (2024). AI unboxed and jobs: A novel measure and firm-level evidence from three countries. IZA Discussion Paper 16717, IZA - Institute of Labor Economics.

ESCO (European Skills/Competences, qualifications, and Occupations) (2024). Classification of skills, competences, qualifications, and occupations. `https://esco.ec.europa.eu/de/classification/skill_main#overlayspin`. Accessed on January 31, 2024.

Federal Employment Agency (2023). Employed liable to social security (30 june) [dataset].

Felten, E., Raj, M., and Seamans, R. (2021). Occupational, industry, and geographic exposure to Artificial Intelligence: A novel dataset and its potential uses. *Strategic Management Journal*, 42(12):2195–2217.

Felten, E. W., Raj, M., and Seamans, R. (2023). Occupational heterogeneity in exposure to generative ai. *SSRN Electronic Journal*.

Fitzenberger, B., Osikominu, A., and Völter, R. (2006). Imputation rules to improve the education variable in the IAB employment subsample. *Journal of Contextual Economics*, 126(3):405–436.

Forsythe, E., Kahn, L. B., Lange, F., and Wiczer, D. (2020). Labor demand in the time of COVID-19: Evidence from vacancy postings and UI claims. *Journal of public economics*, 189:104238.

Fossen, F. M. and Sorgner, A. (2022). New digital technologies and heterogeneous wage and employment dynamics in the United States: Evidence from individual-level data. *Technological Forecasting and Social Change*, 175:121381.

Gathmann, C. and Grimm, F. (2022). The diffusion of digital technologies and its consequences in the labor market. beiträge zur jahrestagung des vereins für socialpolitik 2022: Big data in economics. Conference paper, ZBW - Leibniz Information Centre for Economicss.

Gathmann, C., Kagerl, C., Pohlan, L., and Roth, D. (2023). The pandemic push: Digital technologies and workforce adjustments. IZA Discussion Paper 16062, IZA - Institute of Labor Economics.

Gathmann, C. and Schönberg, U. (2010). How general is human capital? A task–based approach. *Journal of Labor Economics*, 28(1):1–49.

Gentzkow, M., Kelly, B., and Taddy, M. (2019). Text as data. *Journal of Economic Literature*, 57(3):535–574.

Genz, S., Gregory, T., Janser, M., Lehmer, F., and Matthes, B. (2021). How do workers adjust when firms adopt new technologies? IZA Discussion Paper 14626, IZA - Institute of Labor Economics.

Genz, S., Janser, M., and Lehmer, F. (2019). The impact of investments in new digital technologies on wages – worker-level evidence from Germany. *Jahrbücher für Nationalökonomie und Statistik*, 239(3):483–521.

Giering, O., Fedorets, A., Adriaans, J., and Kirchner, S. (2021). Künstliche intelligenz in deutschland: Erwerbstätige wissen oft nicht, dass sie mit ki-basierten systemen arbeiten. *DIW Wochenbericht*, 48:783–789.

Gilardi, F., Alizadeh, M., and Kubli, M. (2023). ChatGPT outperforms crowd workers for text-annotation tasks. *Proceedings of the National Academy of Sciences*, 120(30):e2305016120.

Goldfarb, A., Taska, B., and Teodoridis, F. (2023). Could machine learning be a general purpose technology? A comparison of emerging technologies using data from online job postings. *Research Policy*, 52(1):104653.

Graf, T., Grießemer, S., Köhler, M., Lehnert, C., Moczall, A., Oertel, M., Schmucker, A., Schneider, A., Seth, Stefan; Thomsen, U., and vom Berge, P. (2023). Schwach anonymisierte Version der Stichprobe der Integrierten Arbeitsmarktbiografien (SIAB) – Version 7521 v1 [dataset]. doi:10.5164/IAB.SIAB7521.de.en.v1.

Gürtzgen, N., Lochner, B., Pohlan, L., and van den Berg, G. J. (2021). Does online search improve the match quality of new hires? *Labour Economics*, 70:101981.

Heise, S. and Porzio, T. (2022). Labor misallocation across firms and regions. Working Paper 30298, National Bureau of Economic Research.

Hensvik, L., Le Barbanchon, T., and Rathelot, R. (2021). Job search during the COVID-19 crisis. *Journal of public economics*, 194:104349.

Hershbein, B. and Kahn, L. B. (2018). Do recessions accelerate routine-biased technological change? Evidence from vacancy postings. *American Economic Review*, 108(7):1737–1772.

Hervé, J. (2023). Specialists or generalists? Cross-industry mobility and wages. *Labour Economics*, 84:102391.

IAB (2022). IAB Job Vacancy Survey [dataset]. https://iab.de/en/the-iab/surveys/iab-job-vacancy-survey/.

Kalyani, A., Bloom, N., Carvalho, M., Hassan, T., Lerner, J., and Tahoun, A. (2023). The diffusion of new technologies. NBER Working Paper 28999, National Bureau of Economic Research.

Korinek, A. (2023). Generative AI for economic research: Use cases and implications for economists. *Journal of Economic Literature*, 61(4):1281–1317.

Kosfeld, R. and Werner, A. (2012). Deutsche arbeitsmarktregionen: Neuabgrenzung nach den kreisgebietsreformen 2007–2011. *Spatial Research and Planning*, 70(1).

Langer, C. and Wiederhold, S. (2023). The value of early-career skills. CESifo Working Paper 10288, CESifo.

McElheran, K., Li, J. F., Brynjolfsson, E., Kroff, Z., Dinlersoz, E., Foster, L. S., and Zolas, N. (2023). AI adoption in America: Who, what, and where. Working Paper 31788, National Bureau of Economic Research.

Modestino, A. S., Burke, M. A., Sadighi, S., Sederberg, R., Stern, T., and Taska, B. (2023). No longer qualified? changes in the supply and demand for skills within occupations. Discussion Paper 16542, IZA.

Noy, S. and Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. *Science*, 381(6654):187–192.

OECD (2024). Artificial intelligence and wage inequality. Technical Report 13, OECD Artificial Intelligence Papers.

Peede, L. and Stops, M. (2023). AI skills on the labour market. Mimeo.

Popp, M. (2023). Minimum wages in concentrated labor markets. *arXiv preprint*.

Prytkova, E., Petit, F., Li, D., Chaturvedi, S., and Ciarli, T. (2024). The employment impact of emerging digital technologies. Working Paper 10955, CESifo.

Rammer, C. (2022). Kompetenzen und Kooperationen zu Künstlicher Intelligenz: Ergebnisse einer Befragung von KI-aktiven Unternehmen in Deutschland. Technical report, BMWK - Bundesministerium für Wirtschaft und Klimaschutz.

Rammer, C., Fernández, G. P., and Czarnitzki, D. (2022). Artificial intelligence and industrial innovation: Evidence from German firm-level data. *Research Policy*, 51(7):104555.

Rengers, M. (2018). Internetgestützte erfassung offener stellen: Machbarkeitsstudie im rahmen eines essnet-projekts zu big data. *WISTA - Wirtschaft und Statistik*, 5:41.

Rinz, K. (2024). Labor market concentration, earnings, and inequality. *Journal of Human Resources*, 59(S). Published online before print October 12, 2020.

Schaller, D., Wohlrabe, K., and Wolf, A. (2023). KI, Cloud Computing und Blockchain – wo steht die deutsche Wirtschaft? *ifo Schnelldienst*, 76(8):3–9.

Schmucker, A., Seth, S., and vom Berge, P. (2023). Sample of integrated labour market biographies (siab) 1975 - 2021. fdz datenreport. Fdz data report, Research Data Center(BA) of the German Feedral Employment Agency (IAB).

Schubert, G., Stansbury, A., and Taska, B. (2022). Monopsony and outside options. *SSRN Electronic Journal*.

Shen, K. and Taska, B. (2020). Measuring the impacts of covid-19 on job postings in australia using a reweighting-estimation-transformation approach. *Australian Journal of Labour Economics*, 23(2):153–171.

Stops, M., Bächmann, A.-C., Glassner, R., Janser, M., Matthes, B., Metzger, L.-J., and Müller, Christoph, Seitz, Joachim (2021). Extracting skill requirements from job ads - the Machbarkeitsstudie Kompetenz-Kompass. *IAB-Forschungsbericht No. 7/2021.*

Taska, B., O'Kane, L., and Nania, J. (2022). Artificial Intelligence in the UK: The relevance of AI in the digital transformation of the UK labour market. Report, Lightcast.

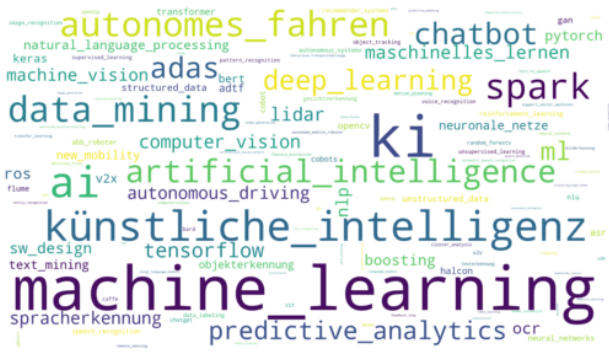
Tolan, S., Pesole, A., Martínez-Plumed, F., Fernández-Macías, E., Hernández-Orallo, J., and Gómez, E. (2021). Measuring the occupational impact of ai: Tasks, cognitive abilities and ai benchmarks. *Journal of Artificial Intelligence Research*, 71:191–236.

Webb, M. (2020). The impact of artificial intelligence on the labor market. *SSRN Electronic Journal*.

3.A. Additional Descriptives

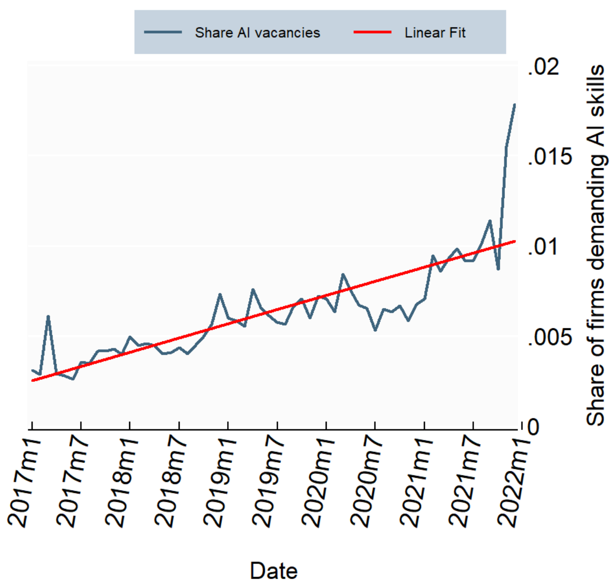
3.A.1. Figures

Figure 3.A1.: Word clouds of AI skills: Baseline definition



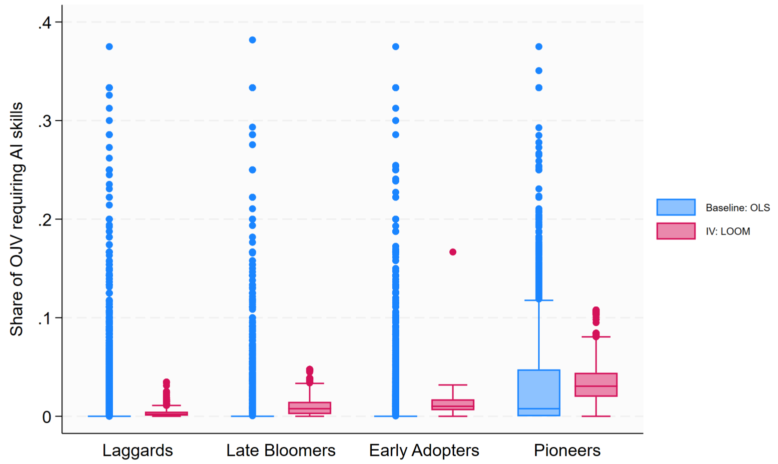
Note: This word cloud comprises keywords that are associated with AI skills. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; own calculations.

Figure 3.A2.: Share of German firms posting AI skills in online job vacancies, 2017 - 2021: Company Lightcast (2023) taxonomy



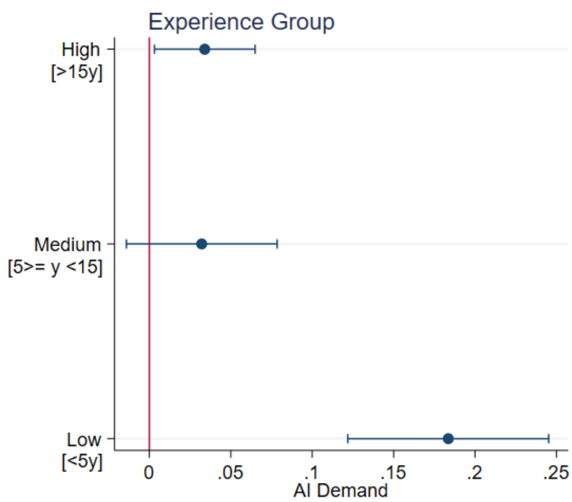
Note: Vacancies are defined as an "AI vacancy" if a job posting contains at least one AI-related skill in a given month. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; own calculations.

Figure 3.A3.: Distribution of AI skill demand across local labor markets by occupational groups, 2017 - 2021



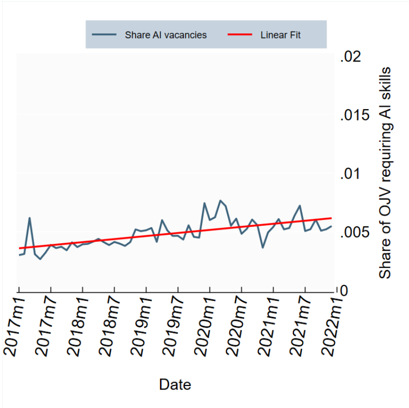
Note: The box-plot compares the distribution of our AI exposure measure ("OLS: Baseline"), with the distribution of our instrumented AI exposure ("IV: LOOM"). The occupational groups are defined based on their AI exposure in 2017 and their change in AI exposure between 2017 and 2021. AI Pioneers: (i) OJV AI share 2017 ranked $\geq$ p80, (ii) change OJV AI share ranked $\geq$ p80. AI Early Adopters: (i) OJV AI share 2017 ranked $\geq$ p80, (ii) change OJV AI share ranked $<$ p80. AI Late Bloomers: (i) OJV AI share 2017 ranked $<$ p80, (ii) change OJV AI share ranked $\geq$ p80. For AI Laggards: (i) OJV AI share 2017 ranked $<$ p80, (ii) change OJV AI share ranked $<$ p80.
Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; own calculations.

Figure 3.A4.: Marginal effect of AI demand by experience group

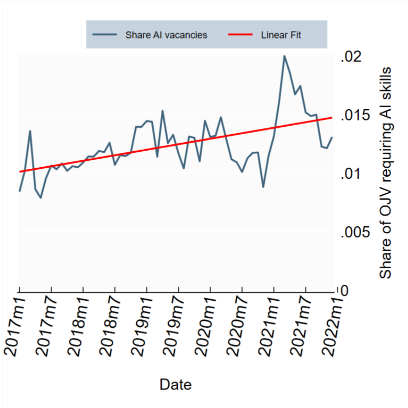


Note: The plot shows the marginal effect of AI demand on wages by experience groups. See notes to Figure 3.4.
Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; SIAB version Version 7521 v1; own calculations.

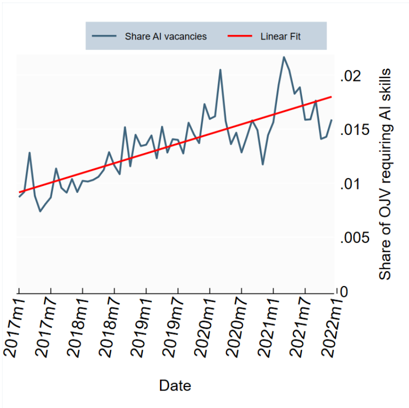
Figure 3.A5.: Trends in AI demand: Alternative AI measures



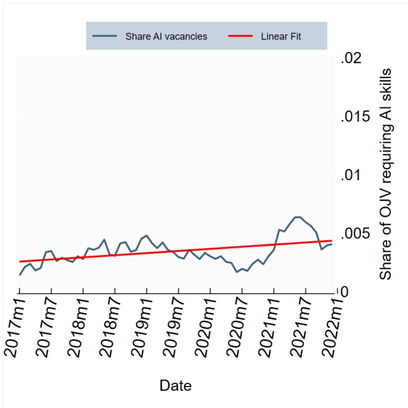
(a) Trends AI Demand: AAHR (2022) Taxonomy



(b) Trends AI Demand: Excluding Top 4 Keys Taxonomy



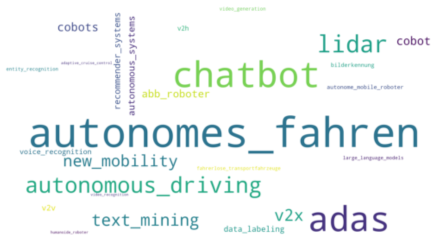
(c) Trends in AI Demand: Methods Taxonomy



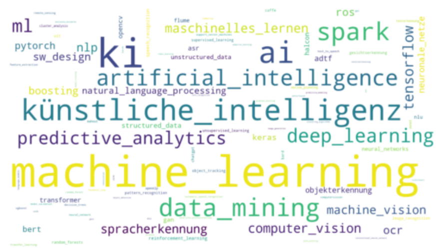
(d) Trends in AI Demand: Applications Taxonomy

Note: Vacancies are defined as an "AI vacancy" if a job posting contains at least one AI-related skill in a given month. Panel 3.A5a uses the AI taxonomy from **?**, while Panel 3.A5b excludes the four most important keywords —*AI, Artificial Intelligence, KI, Künstliche Intelligenz* —to explore the role of outliers. Finally, Panel 3.A5c is based on keywords associated with the development of AI methods, while Panel 3.A5d is based on keywords associated with the use of AI applications. See Figure 3.A6 for an overview of these distinct keywords. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; own calculations.

Figure 3.A6.: Word clouds of AI skills by category



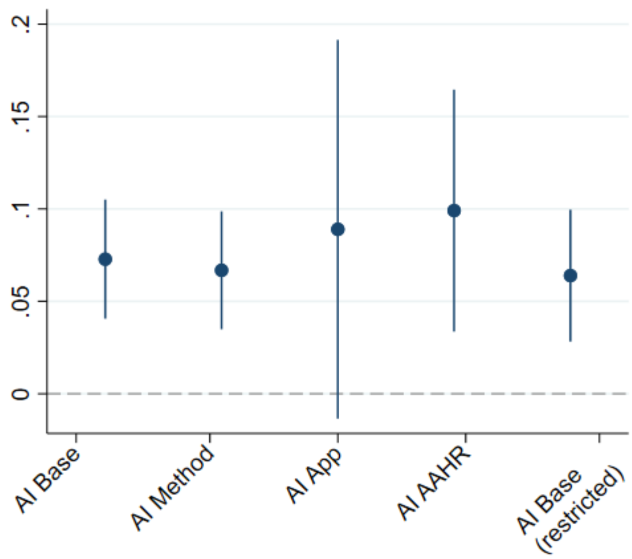
(a) AI Applications



(b) AI Methods

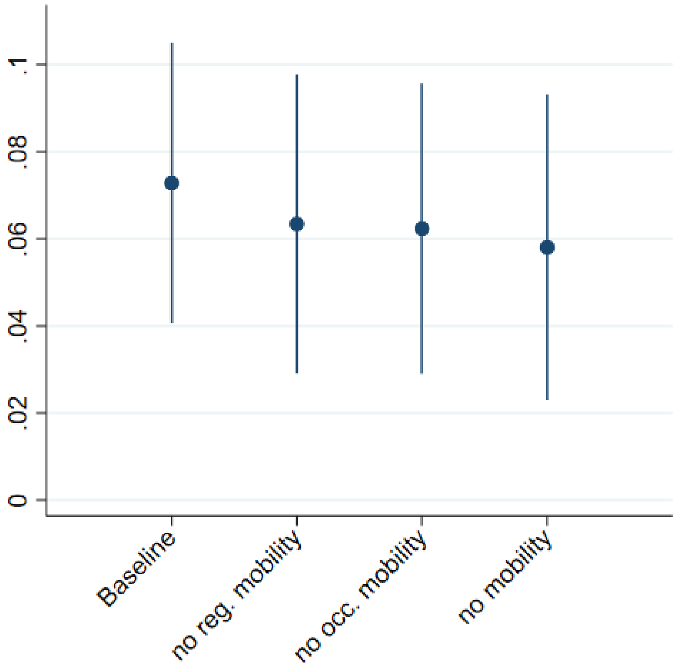
Note: This word cloud comprises keywords that are associated with AI application and AI methods skills. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; own calculations.

Figure 3.A7.: Coefficient plot of AI demand using alternative measures pattern



Note: The figure plots the coefficients of separate regressions using alternative measures of AI exposure as indicated in the figure. All regressions include the same controls and FE (see notes Table 3.2). The vertical lines represent the 95% confidence intervals. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; own calculations.

Figure 3.A8.: Coefficient plot of AI demand by mobility pattern



Note: The figure plots the coefficients of separate regressions but with different sample restrictions based on individuals mobility pattern. All regressions include the same controls and FE (see notes Table 3.2). The vertical lines represent the 95% confidence intervals. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; own calculations.

3.A.2. Tables

Table 3.A1.: Share of AI keywords counts

Rank	AI keywords	Share of counts
0	machine learning	15.02%
1	ki	11.75%
2	ai	9.39%
3	künstliche intelligenz	5.42%
4	chatbot	4.76%
5	artificial intelligence	4.37%
6	autonomes fahren	3.96%
7	spark	3.77%
8	data mining	3.69%
9	ml	3.60%
10	adas	3.40%
11	deep learning	2.63%
12	text mining	2.37%
13	predictive analytics	2.08%
14	computer vision	1.74%
15	maschinelles lernen	1.27%
16	tensorflow	1.24%
17	lidar	1.18%
18	autonomous driving	1.04%
19	machine vision	0.95%
20	ros	0.95%
21	nlp	0.92%
22	natural language processing	0.78%
23	spracherkennung	0.68%
24	new mobility	0.58%
25	ocr	0.55%
26	boosting	0.54%
27	pytorch	0.52%
28	sw design	0.50%
29	remote sensing	0.47%
30	bert	0.47%
31	asr	0.39%
32	neural networks	0.38%
33	keras	0.36%
34	neuronale netze	0.35%
35	adtf	0.34%
36	objekterkennung	0.32%
37	opencv	0.31%
38	reinforcement learning	0.29%
39	v2x	0.29%
40	gan	0.29%
41	structured data	0.29%
42	unstructured data	0.27%

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Table 3.A1 – continued from previous page

Rank	AI keywords	Share of counts
43	transformer	0.24%
44	autonomous systems	0.24%
45	halcon	0.22%
46	cobots	0.19%
47	bilderkennung	0.14%
48	recommender systems	0.13%
49	caffe	0.13%
50	model validation	0.13%
51	flume	0.13%
52	predictive modeling	0.12%
53	abb roboter	0.11%
54	speech recognition	0.10%
55	supervised learning	0.10%
56	gpt	0.09%
57	image recognition	0.09%
58	nlu	0.09%
59	machine translation	0.09%
60	cobot	0.09%
61	sensorfusion	0.08%
62	vit	0.08%
63	motion planning	0.07%
64	data labeling	0.07%
65	neural network	0.07%
66	random forests	0.07%
67	v2v	0.07%
68	object tracking	0.07%
69	unsupervised learning	0.07%
70	electra	0.07%
71	bard	0.06%
72	object detection	0.06%
73	mxnet	0.06%
74	pattern recognition	0.06%
75	text to speech	0.06%
76	texterkennung	0.06%
77	model training	0.06%
78	sw implementation	0.06%
79	v2h	0.05%
80	feedback loop	0.05%
81	roberta	0.05%
82	decision trees	0.05%
83	random forest	0.05%
84	language models	0.05%
85	feature extraction	0.05%
86	elmo	0.05%
87	transfer learning	0.05%
88	dnn	0.05%

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Table 3.A1 – continued from previous page

Rank	AI keywords	Share of counts
89	ros2	0.04%
90	gans	0.04%
91	humanoide roboter	0.04%
92	electromechanical systems	0.04%
93	maschinelle übersetzung	0.04%
94	autonome mobile roboter	0.04%
95	neuronale netzwerke	0.04%
96	federated learning	0.04%
97	gesichtserkennung	0.04%
98	chatgpt	0.04%
99	computervision	0.03%
100	adaptive learning	0.03%
101	text recognition	0.03%
102	torch	0.03%
103	path planning	0.03%
104	support vector machines	0.03%
105	dimensionality reduction	0.03%
106	image segmentation	0.03%
107	mahout	0.03%
108	fahrerlose transportfahrzeuge	0.03%
109	xgboost	0.03%
110	roboterarme	0.03%
111	automl	0.03%
112	automatic speech recognition	0.03%
113	entity recognition	0.03%
114	gradient boosting	0.03%
115	face recognition	0.02%
116	tokenization	0.02%
117	parking assistance	0.02%
118	nmt	0.02%
119	voice recognition	0.02%
120	natürliche sprachverarbeitung	0.02%
121	object recognition	0.02%
122	ai chatbot	0.02%
123	cluster analysis	0.02%
124	robot perception	0.02%
125	object classification	0.02%
126	synthetic data	0.02%
127	robot learning	0.02%
128	nltk	0.02%
129	simultaneous localization and mapping	0.02%
130	v2g	0.02%
131	collaborative robots	0.02%
132	meta learning	0.02%
133	adaptive cruise control	0.02%
134	opennlp	0.02%

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Table 3.A1 – continued from previous page

Rank	AI keywords	Share of counts
135	cntk	0.02%
136	classification algorithms	0.01%
137	image generation	0.01%
138	sentiment analysis	0.01%
139	video generation	0.01%

Table 3.A2.: AI skill demand by occupations (3-digit)

Rank	Occupation (3-digit KLdB 2010)	AI vacancy share
1	Lecturers and researchers at universities and colleges	7.21%
2	Computer science	7.07%
3	Mathematics and statistics	6.85%
4	Software development and programming	6.77%
5	IT-system-analysis, IT-application-consulting	4.97%
6	Technical research and development	4.48%
7	Product and industrial design	4.36%
8	IT-network engineering, IT-coordination/admin	4.28%
9	Technical media design	2.94%
10	Business organisation and strategy	2.69%
11	Physics	2.30%
12	Social sciences	2.27%
13	Theatre, film, television productions	2.10%
14	Laboratory medicine	1.92%
15	Editorial work and journalism	1.78%
16	Advertising and marketing	1.62%
17	Public relations	1.61%
18	Teachers at educational institutions other than schools	1.59%
19	Publishing and media management	1.58%
20	Construction scheduling, supervision, architecture	1.57%
21	Managing directors, executive board members	1.39%
22	Biology	1.36%
23	Event organisation and management	1.22%
24	Human resources management, personnel service	1.20%
25	Legal services, jurisdiction, court officers	1.18%
26	Insurance and financial services	1.15%
27	Media, documentation, information services	1.11%
28	Production planning and scheduling	1.09%
29	Purchasing and sales	1.07%
30	Economics	1.05%
31	Electrical engineering	1.00%
32	Photography, photographic technology	0.94%
33	Geology, geography, meteorology	0.93%
34	Draftspersons, technical designers, model makers	0.87%
35	Environmental protection management and consulting	0.87%
36	Accounting, controlling and auditing	0.85%
37	Plastic- and rubber-making and -processing	0.84%

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Table 3.A2 – continued from previous page

Rank	Occupation (3-digit KLdB 2010)	AI vacancy share
38	Management assistants in transport, logistics	0.84%
39	Chemistry	0.81%
40	Beverage production	0.81%
41	Textile making	0.80%
42	Printing technology, print finishing, book binding	0.77%
43	Pharmacy	0.77%
44	Horsekeeping	0.77%
45	Mechatronics, automation, control technology	0.75%
46	Legislators, senior officials of interest organisations	0.74%
47	Automotive, aeronautic, aerospace, ship building	0.70%
48	Event technology, cinematography, sound engineering	0.66%
49	Machine-building and -operating	0.66%
50	Nutritional advice, health counselling, wellness	0.65%
51	Natural stone, minerals, building materials	0.64%
52	Metal-making	0.63%
53	Office clerks and secretaries	0.62%
54	Public administration	0.61%
55	Technical occupations in medicine, orthopaedic	0.57%
56	Precision mechanics and tool making	0.57%
57	Musicians, singers and conductors	0.51%
58	Surveying and cartography	0.51%
59	Metal constructing and welding	0.50%
60	Technical occupations in railway, aircraft, ships	0.49%
61	Doctors' receptionists and assistants	0.46%
62	Psychology, non-medical psychotherapy	0.45%
63	Production of clothing, textile products	0.44%
64	Interior design, visual marketing, interior decoration	0.44%
65	Hotels	0.44%
66	Building services, waste disposal	0.43%
67	Housekeeping, consumer counselling	0.42%
68	Sales selling drugstore products, pharmaceuticals	0.40%
69	Human medicine and dentistry	0.39%
70	Non-medical therapy, alternative medicine	0.38%
71	Energy technologies	0.36%
72	Driving, flying, sports instructors, educational inst.	0.35%
73	Artisans working with metal	0.35%
74	Tax consultancy	0.34%
75	Physical security, personal protection, fire safety	0.33%
76	Education, social work, pedagogic specialists	0.33%
77	Warehousing, logistics, postal, delivery services	0.33%
78	Driver of vehicles in road traffic	0.32%
79	Interior construction, dry walling, insulation	0.31%
80	Building services engineering	0.30%
81	Farming	0.29%
82	Industrial glass-making and -processing	0.28%
83	Real estate, facility management	0.27%

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Table 3.A2 – continued from previous page

Rank	Occupation (3-digit KLdB 2010)	AI vacancy share
84	Gastronomy occupations	0.27%
85	Cleaning services	0.27%
86	Construction, transportation vehicles, equipment	0.26%
87	Painters, varnishers, plasterers, waterproofing	0.26%
88	Traffic surveillance and control	0.26%
89	Treatment of metal surfaces	0.26%
90	Colour coating and varnishing	0.25%
91	Underground, surface mining, blasting engineering	0.25%
92	Gardening	0.25%
93	Body care	0.23%
94	Wood-working and -processing	0.23%
95	Building construction	0.22%
96	Teachers in schools of general education	0.22%
97	Trading occupations	0.21%
98	Nursing, emergency medical services, obstetrics	0.21%
99	Foodstuffs, confectionery, tobacco production	0.21%
100	Geriatric care	0.21%
101	Metalworking	0.20%
102	Veterinary medicine, non-medical animal health	0.19%
103	Sales (retail) selling clothing, electronics, furniture	0.18%
104	Cooking occupations	0.18%
105	Actors, dancers, athletes, related occupations	0.17%
106	Leather- and fur-making and -processing	0.15%
107	Plumbing, sanitation, heating, air conditioning	0.15%
108	Service occupations in passenger traffic	0.15%
109	Animal husbandry	0.14%
110	Sales (retail) selling books, art, antiques	0.13%
111	Sales in retail trade (without product specialization)	0.12%
112	Civil engineering	0.12%
113	Tourism and the sports (and fitness) industry	0.12%
114	Floristry	0.11%
115	Floor layers	0.10%
116	Forestry, hunting, landscape preservation	0.08%
117	Teachers for specific subjects, vocational training	0.07%
118	Drivers of vehicles in railway traffic	0.06%
119	Paper-making and -processing, packaging	0.05%
120	Sales (retail) selling foodstuffs	0.05%
121	Occupational health, safety admin, public health	0.03%
122	Animal care	0.00%

Table 3.A3.: Wage regressions AI exposure: "Pre-trends"

	Dependent Variable: Log Wages		
	(1)	(2)	(3)
AI Share	0.079***	0.074***	0.032
	(0.022)	(0.022)	(0.020)
Worker FE	✓	✓	✓
Year FE	✓	✓	✓
LMR FE		✓	✓
Occupation FE			✓
AI Share Mean		0.009	
Observations	1,275,961	1,275,961	1,275,958
R^2	0.93	0.93	0.93

Note: All specifications include the following controls: Socioeconomic controls include age, citizenship, education, and gender. Work controls include establishment tenure. Firm controls include establishment size and industry group. AKM effects for the time period 2007-2013. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; own calculations.

Table 3.A4.: First Stage IV regressions AI exposure: Occupation-LMR-level

	Dependent Variable: Log Wages		
	(1)	(2)	(3)
IV:LOOM (Occ-LMR)	0.791***	0.777***	0.631***
	(0.024)	(0.024)	(0.027)
Worker FE	✓	✓	✓
Year FE	✓	✓	✓
LMR FE		✓	✓
Occupation FE			✓
F-statistic (1st stage)	1445.0	1392.3	1010.5
Observations	1,500,688	1,500,688	1,500,688

Note: All specifications include the following controls: Socioeconomic controls include age, citizenship, education, and gender. Work controls include establishment tenure. Firm controls include establishment size and industry group. AKM effects for the time period 2007-2013. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; own calculations.

Table 3.A5.: Wage regressions AI intensity: Occupation-LMR-level

	Dependent Variable: Log Wages		
	(1)	(2)	(3)
AI Intensity	0.027***	0.027***	0.023***
	(0.007)	(0.007)	(0.007)
Worker FE	✓	✓	✓
Year FE	✓	✓	✓
LMR FE		✓	✓
Occupation FE			✓
AI Share Mean		0.009	
Observations	1,500,688	1,500,688	1,500,688
R^2	0.89	0.89	0.89

Note: All specifications include the following controls: Socioeconomic controls include age, citizenship, education, and gender. Work controls include establishment tenure. Firm controls include establishment size and industry group. AKM effects for the time period 2007-2013. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; own calculations.

Table 3.A6.: Wage regressions with flexible interactions

	Dependent Variable: Log Wages					
	(1)	(2)	(3)	(4)	(5)	(6)
AI Share (Occ-LMR)	0.073***	0.057***	0.041***	0.031***	0.025**	0.027**
	(0.016)	(0.014)	(0.013)	(0.012)	(0.011)	(0.011)
LMR X Occupation FE						
LMR X Year FE		✓		✓	✓	✓
Occupation (1-digit) X Year FE			✓	✓		
Occupation (2-digit) X Year FE					✓	
Occupation (3-digit) X Year FE						✓
AI Share (Occ-LMR) Mean			0.009			
Observations	1,500,688	1,500,682	1,500,149	1,500,149	1,500,149	1,500,149
R-squared	0.89	0.89	0.90	0.90	0.90	0.90

Note: All specifications include the following controls: Socioeconomic controls include age, citizenship, education, and gender. Work controls include establishment tenure. Firm controls include establishment size and industry group. AKM effects for the time period 2007-2013. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; own calculations.

Table 3.A7.: Wage regressions in differences over years

	Dependent Variable: Difference Log Wages		
	(1)	(2)	(3)
Δ AI Demand (1 year)	0.051***		
	(0.017)		
Δ AI Demand (2 years)		0.137***	
		(0.030)	
Δ AI Demand (4 years)			0.310***
			(0.059)
Year FE	✓	✓	✓
LMR FE	✓	✓	✓
Occupation FE	✓	✓	✓
Observations	1,126,404	795,358	230,464
R^2	0.019	0.049	0.103

Note: All specifications include the following controls: Socioeconomic controls include age, citizenship, education, and gender. Work controls include establishment tenure. Firm controls include establishment size and industry group. AKM effects for the time period 2007-2013. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; own calculations.

Table 3.A8.: Wage regressions restricted dataset

	Dependent Variable: Log Wages			
	(1)	(2)	(3)	(4)
AI Demand	0.073***	0.078***	0.092***	0.102***
	(0.016)	(0.019)	(0.023)	(0.026)
Baseline	✓			
Balanced Worker Sample		✓		✓
Balanced LMR X Occupation Sample			✓	✓
AI Share Mean	0.009			
Observations	1,500,688	1,099,011	1,383,926	1,013,207
R^2	0.89	0.90	0.89	0.89

Note: All specifications include the following controls: Socioeconomic controls include age, citizenship, education, and gender. Work controls include establishment tenure. Firm controls include establishment size and industry group. AKM effects for the time period 2007-2013. All regressions include worker, year, LMR and occupation (3-digit) fixed effects. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; own calculations.

3.B. Details on OJV Data

3.B.1. NLP Steps

Upon receiving the data from Finbot, we link firm and vacancy information and perform necessary steps to preprocess the textual data, following conventions in the literature (Ash and Hansen, 2023; Gentzkow et al., 2019) In particular, we tokenize the texts, lowercase tokens, and remove special characters. Beyond these basic steps, we enrich the data as follows. First, we assign each vacancy to a specific location, either at the zip code (39% of OJVs), municipality-level (48%), or county-level (10%).[31] Overall, we can assign 97% of job postings to a specific county. Second, we classify job titles according to the German Classification of Occupations 2010 (KldB2010). For this purpose, we use official, codified job titles at the 8-digit level, which are provided by the Federal Employment Agency (BA). Extracting job titles from our vacancies, and comparing their job description with the BA, we can immediately assign job titles to 5-digit occupations for about 60% of vacancies. In a follow-up step, we classify the remaining job titles by annotating a sample of not-yet-classified vacancies.

3.B.2. External Validity

Online job vacancies represent only one of many search channels. Yet, they are by far the most important channel through which firms recruit high-skilled workers (Carrillo-Tudela et al., 2023)—including those required to possess AI-related skills. While the concentration on high-skilled jobs limits the representative nature of our data, it is also particularly suitable to identify AI skills. Nonetheless, the non-representative nature of our data may distort our analysis with unclear implications for the generalizability of our results.

We thus provide extensive external validity on our data quality encompassing comparisons with two sources: (i) the German Job Vacancy Survey (JVS), a representative survey on reported job vacancies, which is carried out by the Institute for Employment Research (IAB)[32], and (ii) the number of workers who are subject to social security contributions (SSC), which we gather from official statistics of the German Federal Employment Agency (FEA). We use the JVS to

[31] About 10% of job postings lack specific working place location information (typically smaller companies operating in one specific region). In such cases, we use the address provided in the imprint as the basis for regional allocation.

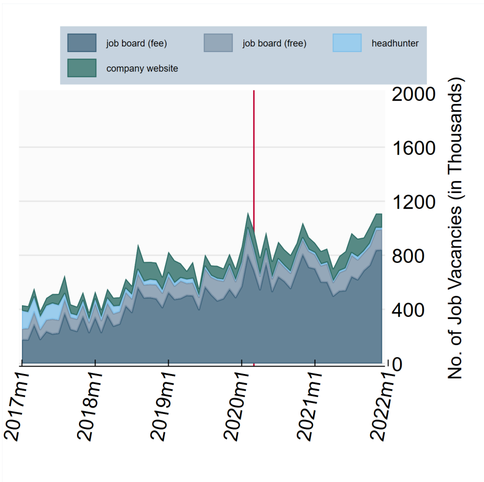
[32] For details on the JVS, see Bossler et al. (2021).

compare broad dynamics in our OJV data with a representative survey on job openings and the information on SSC workers in order to provide more detailed comparison over time, across, occuaptions, and across regions.

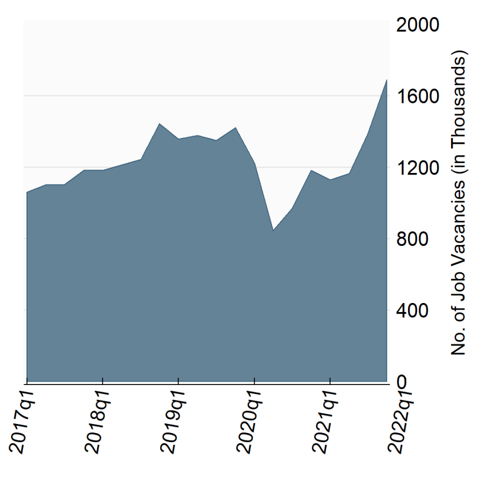
I. Comparison with Job Vacancy Survey

First, we follow common practice in the literature by comparing our OJV data with representative information on vacancies from official sources (Hershbein and Kahn, 2018; Rengers, 2018). Hershbein and Kahn (2018) compare characteristics of the job postings from Lightcast (formerly Burning Glass Technologies) with the Bureau of Labor Statistics' Job Openings and Labor Market Turnover (JOLTS) survey and other data sources for the US at the aggregate level and by industries. Likewise, Rengers (2018) makes similar comparisons for Germany with data from the Federal Employment Agency (BA) and the IAB Job Vacancy Survey. Especially relevant for our purposes, the IAB Job Vacancy Survey is a representative survey and measures the aggregate labor demand and the recruiting behavior of firms in Germany since 1989, making it a well-suited survey for the analysis of recruitment processes (Gürtzgen et al., 2021).

Figure 3.B1.: Number of online job vacancies over time, 2017/01 - 2021/12



(a) OJV data, by source (Inflow)



(b) IAB Vacancy Panel (Stock)

Note: Panel 3.B1a displays the number of online job vacancies that are posted each month in our data, i.e., monthly inflows, broken down by the type of source platform. Panel 3.B1b displays the stock of vacancies firms report to the IAB for each quarter. The values for 2021Q1 onward are estimates as final numbers are not available yet. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; IAB Job Vacancy Panel 2017-2022; own calculations.

Figure 3.B1 demonstrates that our OJV data depicts trends in the number of posted vacancies between 2017 - 2021 that mirror those from the JVS. Panel 3.B1a shows the inflow of OJV over time by source platforms, distinguishing between job boards, headhunters, and company

websites. Notably, the share of OJV originating from job boards has increased from 50% in 2017 to 70% by 2021, illustrating the growing popularity of online job search. In comparison, Panel 3.B1b does not permit such detailed insights, but offers similar insights on the stock of postings at each point in time until 2021. Both data sources display an increasing trend of the number of postings over time, but with a sharp decrease at the beginning of the COVID-19 pandemic in 2020 and a subsequent rebound of postings.

While the stock of vacancies decreased by 40% between 2019Q4 and 2020Q2 based on the IAB Vacancy Panel, the inflows of vacancies in our OJV data decreased by 30% from December 2019 until June 2020. These magnitudes in the drop and subsequent rebound in job vacancies during the pandemic are consistent with previous findings in the literature, such as Australia (Shen and Taska, 2020), Austria (Bamieh and Ziegler, 2020), Sweden (Hensvik et al., 2021), the UK (Arthur, 2021), and the US (Forsythe et al., 2020). Hence, both data sources display similar trends and cyclicality during 2017-21, thereby lending credence to the validity of our OJV data.

II. Comparison with number workers subject to SSC

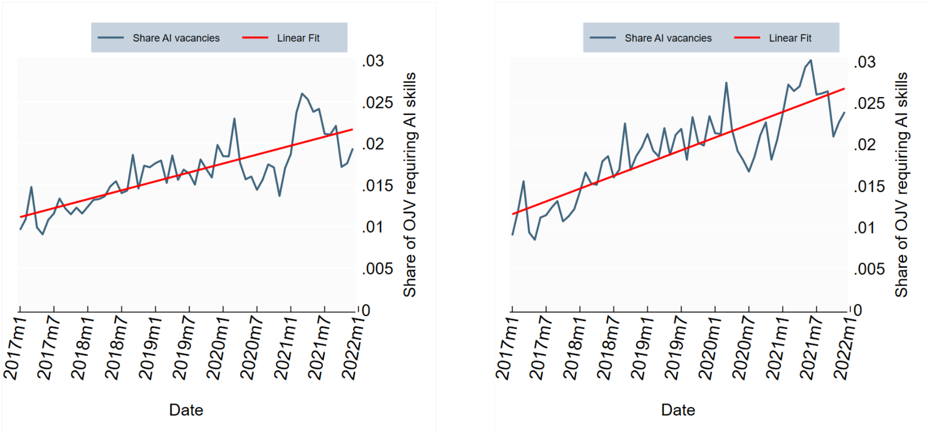
In the second step, we provide additional external validity of our data. Here, we focus on our three stylized facts, i.e. the dimensions along which we exploit variation in demand for AI skills in our main analysis, namely: (i) over time, (ii) across regions, and (iii) across occupations.[33] Our baseline stylized facts are weighted by the number of job postings to account for differential job posting behavior among firms. To assess the extent to which the non-representative nature of our data distorts our results, we reweight our stylized facts, using the LMR-occupation-year level number of SSC workers as weights. For this analysis, we use data from the official statistics of the German Federal Employment Agency (Federal Employment Agency, 2023) on the employment at the occupation-region-year level.

We begin these validation exercises with Figure 3.B2, depicting trends over time. Panel 3.B2a shows the share of AI vacancies between 2017 - 2021 in our baseline specification, weighted by the number of job postings, while Panel 3.B2b illustrates trends over time, weighted by the number of SSC workers. Overall, we find similar trends using either specification. Both panels show a steady increase in demand for AI skills between 2017 and early 2020, followed by COVID-induced slowdown and a subsequent rebound, starting in early 2021. We thus conclude that the

[33]In principle, the JVS would be a viable alternative weighting option. However, the JVS lacks detailed information on job postings by occupations. Similarly, sample size limitations pose a challenge for regional comparisons.

disproportionate number of postings directed at high-skilled workers is unlikely to distort our analysis.

Figure 3.B2.: Number of online job vacancies over time, 2017/01 - 2021/12



(a) Trends in AI Demand: Weighting by number of postings

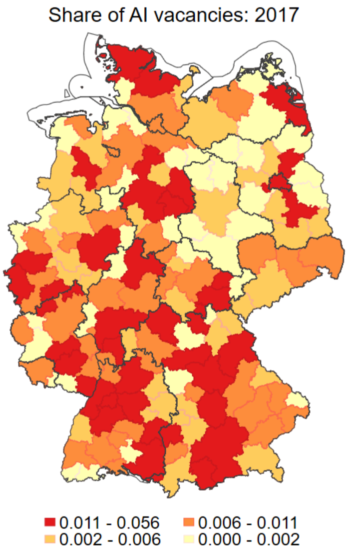
(b) Trends in AI Demand: Weighting by number of SSC workers

Note: Vacancies are defined as an "AI vacancy" if a job posting contains at least one AI-related skill in a given month. Panel 3.B2a displays our baseline AI Skill demand, weighted by the number of postings within a local labor market (occupation-region-year level). Panel 3.B2b displays AI Skill demand, but weighted by the number of workers who are subject to social security contributions to enhance representativativity of the data. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; IAB Job Vacancy Panel 2017-2022; own calculations.

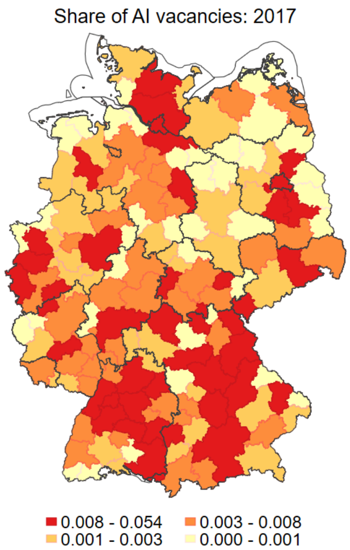
Second, we continue our validation exercise with Figure 3.B3, illustrating the average share of AI vacancies for each of our 141 LMRs in 2017 and 2021. Panel 3.B3a shows the share of AI vacancies in 2017, using the number of jobs postings weights, while Panel 3.B3b depicts the same distribution, but using the number of SSC workers as weights instead. Again, we find both panels provide a similar distribution, depicting a concentration of AI vacancies in the Southern and Western parts of Germany. Similar conclusions carry over to Panels 3.B3c and 3.B3d, in which we display the regional diffusion of AI vacancies in 2021, but using the same class boundaries as in 2017. This descriptive counterfactual also shows similar patterns and underlines the broad regional diffusion of AI demand discussed in the paper.

Third, we complete our validation exercise with Figure 3.B3, illustrating dynamics in AI demand. The horizontal axis displays the baseline AI demand in 2017, while the vertical axis displays the subsequent change in AI demand between 2017 - 2021. The size of the circles clearly shows compositional differences between our OJV data (Panel 3.B4a) and the distribution of SSC workers across occupations (Panel 3.B4b). The large red circles in Panel (Panel 3.B4a) reflect occupations with high AI demand in our OJV data, especially IT-related occupations, and show that these jobs are disproportionately found in our data, compared to the SSC distribution.

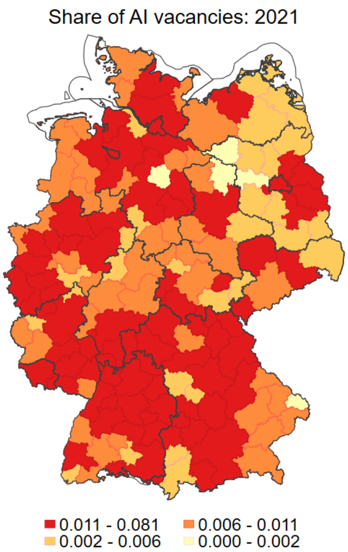
Figure 3.B3.: Demand for AI skills in Germany across local labor markets, 2017-01 - 2021-12



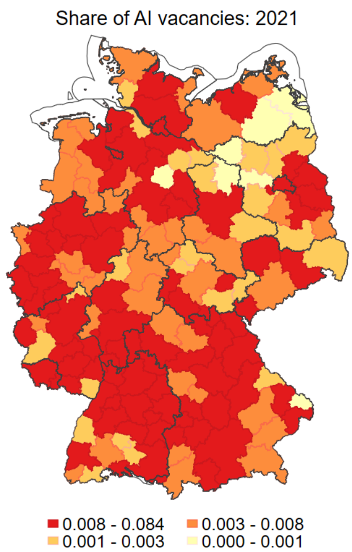
(a) AI demand: 2017 (OJV weights)



(b) AI demand: 2017 (SSC weights)



(c) AI demand: 2021 (OJV weights

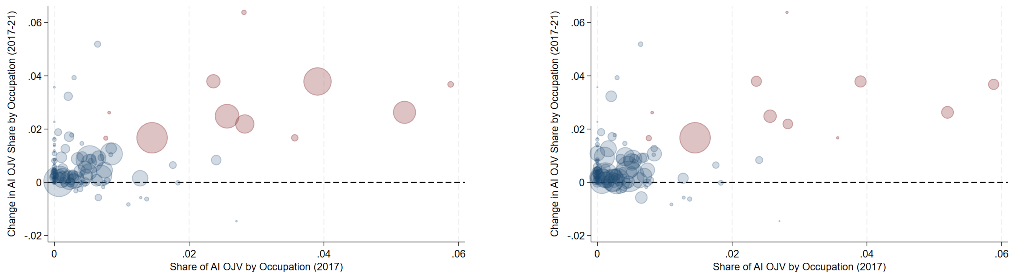


(d) AI demand: 2021 (SSC weights

Note: Local labor markets are assigned into four classes of task intensity. Each class corresponds to quartiles as of 2017 where lowest quartile implies lowest AI demand (yellow) and highest quartile implies highest AI demand (red). Panels 3.B3a and 3.B3c represent our baseline scenario, in which we weight AI skill demand by the number of job postings within a local labor market. In contrast, Panels 3.B3b and 3.B3d use the number of workers who are subject to social security contributions (SSC) as weights to enhance representativeness of the data. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; Official Statistics of the German Federal Employment Agency 2017-2021.

Overall, though, we find similar insights using either the number of postings as weights or the number of SSC workers. Both panels show a positive relationship between baseline AI demand in 2017 and subsequent change between 2017 - 2021, suggesting that occupations with relatively high initial AI demand were also those that have experienced the strongest changes in AI demand ever since.

Figure 3.B4.: Number of online job vacancies over time, 2017/01 - 2021/12



(a) Dynamics in occupational demand for AI skills (OJV weights)

(b) Dynamics in occupational demand for AI skills (SSC weights)

Note: The X-axis displays the share of OJV with AI demand ("AI Vacancies") for 140 3-digit occupations as of 2017. The Y-axis displays the change in AI Vacancies between 2017 - 2021 for each occupation. Panel 3.B4a represents our baseline scenario, in which weight AI skill demand by the number of job postings within a local labor market (occupation-region-year level). In contrast, Panel 3.B4a weights AI skill demand by the number of workers who are subject to social security contributions (SSC) to enhance representativity of the data. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; Official Statistics of the German Federal Employment Agency 2017-2021; own calculation.

III. Takeaways from External Validity

In summary, we have shown that our OJV data captures similar dynamics compared to the representative Job Vacancy Survey. Moreover, our OJV data provides almost identical stylized facts when we reweight our vacancies in order to mimic the distribution of workers who are subject to social security contributions (rather than the number of postings). Overall, we thus conclude that the skewness in our OJV data towards high-skilled worker is unlikely to distort our main results.

Online job vacancies represent only one of many search channels. Yet, they are by far the most important channel through which firms recruit high-skilled workers (Carrillo-Tudela et al., 2023)—including those required to possess AI-related skills. While the concentration on high-skilled jobs limits the representative nature of our data, it is also particularly suitable to identify AI skills. Nonetheless, the non-representative nature of our data may distort our analysis with unclear implications for the generalizability of our results.

We thus provide extensive external validity on our data quality encompassing comparisons with two sources: (i) the German Job Vacancy Survey (JVS), a representative survey on reported job vacancies, which is carried out by the Institute for Employment Research (IAB)[34], and (ii) the

[34]For details on the JVS, see Bossler et al. (2021)

number of workers who are subject to social security (SSC) workers, which we gather from official statistics of the German Federal Employment Agency (FEA). We use the JVS to compare broad dynamics in our OJV data with a representative survey on job openings and the information on SSC workers in order to provide more detailed comparison over time, across, occuaptions, and across regions.

First, we demonstrate our OJV data depicts trends in the number of posted vacancies between 2017 - 2021 that mirror those from the JVS. Specifically, our data depicts an increasing trend of vacancies over time, but with a sharp decrease at the beginning of the COVID-19 pandemic in 2020 and a subsequent rebound of postings.

Second, we show our OJV data captures the diffusion of AI demand in a similar manner when we reweight our stylized facts using the number of SSC workers as weights (rather than the number of job postings). Specifically, we show that both weighing approaches offers almost identical insights on trends in AI demand (i) over time, (ii) across regions, and (iii) across occupations. Our stylized facts are thus robust to either weighting procedure. Overall, we conclude that the skewness in our OJV data towards high-skilled worker is unlikely to distort our main results.

3.B.3. Sample Selection

To focus on high-quality vacancies, we exclude job postings with fewer than 50 and more than 1,000 tokens. Our experience suggests that vacancies outside of this range do not represent standard job advertisements and instead add unnecessary noise to the data. In this context we also drop vacancies posted by temporary employment and large recruitment agencies because these firms typically search for employees with more flexible work schedules and therefore advertise somewhat broader job descriptions and requirements.[35] In addition, firms may advertise hard-to-fill vacancies through temporary work agencies and recruitment agencies. Therefore, excluding vacancies posted by these agencies reduces the likelihood of duplicates in the data. We also omit observations with missing information on either date, location or occupation.

Lastly, in order to focus on ”regular firms”, we restrict our data to vacancies from companies that can be linked to the business register.[36] Specifically, our data includes all firms that are

[35]See Stops et al. (2021) for a detailed discussion on this issue.

[36]The firm-level data includes information about the firm name, the complete address, legal status, industry, original stock and business volume, the number of employees and the formation date.

listed in the German trade register since 1991. About half of the 3,4 Mio. firms in Germany are noncommercial and therefore not listed in the trade register. In addition, firms from the public administration sector are not included.

Applying above filters helps us ensuring high data quality and maintaining comparability with administrative data. Table 3.B1 provides a comprehensive overview of our sample selection, displaying the share of vacancies we lose at each step. Overall, we keep around 13% of all vacancies for our analysis. We lose most vacancies due to removal of postings from temp agencies and restriction to vacancies that cannot be linked to the company registry.

Table 3.B1.: Overview of sample selection summary statistic

Description Reasons for exclusion	Sample Size (%)
Full sample	100
- Temporary work agencies	56.3
- Recruiting agency	55.3
- No firm ID	27.5
- No location	27.5
- Irregular work	23.2
- No occupation code	14.7
- Token restriction [$1000 < X < 50$]	13.2

Note: The table shows the percentage of observations that are dropped from the analysis by applying the filters.
Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; own calculation.

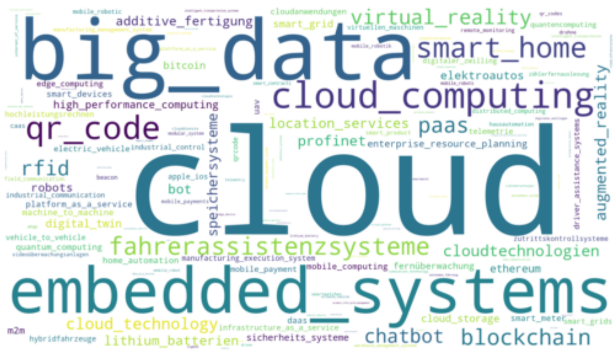
3.C. Details on Construction of “4.0 Measure”

To empirically validate our AI measure, we construct a similar measure, however, using exposure to distinct 4.0 technologies instead. This allows us to test if we actually capture the impact of AI skills —and not any tangent skills associated with related technologies. We collect a broad keyword list of recent digital technologies that are often used alongside AI technologies. We construct this keyword list, using two kind of sources.

First, we extract a comprehensive list of technologies from the European Skills, Competences, Qualifications, and Occupations (ESCO) framework (ESCO (European Skills/Competences, qualifications, and Occupations), 2024). ESCO provides, among others, a harmonized classification of ICT technologies. In this initial step, we collect a list of 905 technologies. However, many of these technologies diffused with the ICT-revolution, starting the late 1970s, and thus do not qualify as 4.0 technology. We thus classify technologies into a “4.0” group, for which we use Chat GPT 4.0 after providing context on the goal of our study and a definition of 4.0 technologies. Despite extensive coverage of ICT-technologies, ESCO lacks information on most recent technologies. In the second step, we thus enrich the list of 4.0 technologies from ESCO by adding further frontier technologies from state-of-the-art literature — especially Kalyani et al. (2023) and Chiarello et al. (2021). Subsequently, we use standard NLP techniques to preprocess our final list of technologies to make it suitable for econometric analysis (Ash and Hansen, 2023; Gentzkow et al., 2019).

In total, we end up with 300 distinct 4.0 technologies in which we exclude any AI-related technologies. These ”4.0 technologies” (Genz et al., 2021) encompass technologies that have been introduced to mass markets in the 2010s and comprise, among others, cloud technologies, virtual reality, and embedded systems. Figure 3.C1 below provides an overview of the most relevant 4.0 technologies.

Figure 3.C1.: Word clouds of 4.0 technologies (excluding AI)



Note: This word cloud comprises keywords that are associated with other 4.0 technologies, except AI. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; own calculation.

4. Hunting for Talent: How Firms Respond to Labor Shortages*

Abstract: Over the past decade, developed countries have been experiencing increasing labor shortages. Using data from online job vacancies, I examine whether firms adjust their skill requirements in response to changes in labor market tightness. My main finding is that the tightening of the labor market is associated with a reduction in firms' skill requirements in terms of education. This occurs through two mechanisms: First, firms shift demand from higher-skilled to lower-skilled workers, and second, they increase the flexibility of educational requirements for middle- and low-skilled positions. This is accompanied by an increase in the provision of training by firms for medium-skilled workers, suggesting internal skill development. In a complementary analysis, however, I find mixed results with regard to experience requirements. The heterogeneity analysis reveals significant variation across occupations and firms, with adjustments concentrated in less complex and routine occupations and in firms with high vacancy rates. These findings have significant policy implications, as lowering skill requirements may increase the mismatch of new hires.

*I am grateful for comments from Ronald Bachmann, Andreas Lichter, Eduard Storm, Julia Bredtmann, Matias Cortes, Thomas Bauer and participants at various RWI seminars for helpful comments.

4.1. Introduction

The past decade has seen a notable rise in skills shortages reported by firms in many developed countries (Peichl et al., 2022). While there was a temporary decline due to the Covid19 pandemic, this was followed by an even more pronounced increase in the tightness of the labor market.[1] In Germany, labor market tightness, defined as the ratio of vacancies per job seeker, increased strongly between 2011 and 2023 and more than doubled from 0.21 to 0.56 (Bossler and Popp, 2023). Demographic change, coupled with the retirement of the baby boomer generation, will contribute to a further tightening of the labor market (Fuchs and Weyh, 2018; Peichl et al., 2022).[2]

While further tightening of the labor market poses recruitment challenges for firms, firms may also contribute through unattractive job offers and inadequate recruitment efforts (Cappelli, 2015). As competition for talent increases, firms can improve their chances of attracting skilled workers by either increasing the number of vacancies or by intensifying their recruitment intensity per vacancy (Davis et al., 2013; Gavazza et al., 2018; Leduc and Liu, 2020). Narrowly defined, recruitment intensity includes the time and cost invested in filling a position. More broadly it can also include other aspects of recruitment behavior that reflect the increased effort firms are making to fill a position (Abraham et al., 2020). Thus, Modestino et al. (2016) interpret the reduction of requirements for education and experience in response to tightening labor markets as an increase in hiring intensity.

In this paper, I investigate whether firms adjust their job requirements in response to changes in labor market tightness. First, I analyze whether firms adjust their skill requirements specified in online job vacancies. I focus on educational skill requirements. However, I also consider the role of experience in a complementary analysis. Second, I examine whether firms respond by adopting alternative recruitment strategies. In this context, I examine firms' flexibility in skill requirements and the provision of benefits to certain skill groups to improve the attractiveness of the job. Third, I study the heterogeneity of the effect across occupational skill levels, task groups, and firm types.

For the analysis, I use data on the near universe of online job vacancies (OJV) for Germany

[1] For a discussion of the reasons for the sharp increase in labor market tightness after the Covid19 pandemic, see (Causa et al., 2022; Duval et al., 2022; Kiss et al., 2022).

[2] According to projections for Germany, the potential labour force will shrink by 7.5 million people by 2035, a reduction of 16 per cent (Klinger and Fuchs, 2020).

for the period 2017 to 2023. The OJV data provide real-time data on firms' labor demand at a detailed regional and occupational level. Since the data contain the raw job description, I use natural language processing methods[3] to extract skill requirements. To construct a measure of labor market tightness, I use data on registered vacancies for job seekers from the official statistics of the German Federal Employment Agency. The data are aggregated and linked at the level of commuting zones, occupations, and years. Thus, I take into account the importance of the regional and occupational dimensions in identifying labor shortages (Peichl et al., 2022).

In a first step, I analyze the relationship between firms' skill requirements and labor market tightness using a fixed-effects model. I include various fixed effects and interaction terms to account for differences in the level of labor market tightness across local labor markets and to control for region- and occupation-specific trends. To mitigate endogeneity and reverse causality concerns, I use a leave-one-out instrument: I instrument vacancies and jobseekers in an occupation in a commuting zone with the average number of vacancies and jobseekers in all other commuting zones. While I do not claim full exogeneity of this instrument, I argue that this instrument mitigates the influence of local confounding factors.

In a second step, I test for the adoption of two alternative hiring strategies: increasing the flexibility of skill requirements and providing benefits to certain skill groups. Since firms have the option of listing either a single skill, multiple skills, or no skills at all, I distinguish between these options in my analysis. Thus, my main measure of firms' flexibility in skill requirements is the specification of multiple skills in a job advertisement. However, I consider the demand for career changers as another proxy for skill flexibility. With regard to benefits, I focus on the role of training, as firms may use training to complement skill adjustments, and remote work, as it allows firms to broaden their applicant pool. Therefore, I construct indicators that capture the combined occurrence of a benefit and a skill requirement in a job advertisement.

The empirical analysis is guided by hypotheses derived from the macro literature linking labor market tightness and hiring standards.[4] The first hypothesis posits that firms respond to increasing labor market tightness by lowering their skill requirements. My results support this hypothesis. According to the preferred OLS specification, an increase in local labor market

[3]Natural language processing is the set of methods and techniques used to transform text into data. See Gentzkow et al. (2019) for an introduction.

[4]see (Baydur, 2017; Carrillo-Tudela et al., 2023a; Gavazza et al., 2018; Lochner et al., 2021; Mongey and Violante, 2019)

tightness from the 25th to the 75th percentile[5] is associated with a 0.6 and 0.17 percentage point increase in the share of medium and low education vacancies, respectively, and a 0.15 percentage point decrease in the share of high education vacancies. Instrumental variable estimation results confirm the pattern of these results, even with larger estimates. Moreover, the results are robust to a number of robustness checks.

To gain a clearer understanding of the adjustment of skill requirements, I focus on two mechanisms: Firms can either shift their demand from high-skilled to low-skilled workers or they can increase the flexibility of their skill requirements. I find evidence for both adjustment mechanisms: First, firms shift their demand from high-skilled to low-skilled workers. Within occupations, this is reflected in a shift in demand toward less complex jobs.[6] Second, when hiring medium- and low-skilled workers, firms increase the flexibility of their educational skill requirements. In doing so, firms adjust their ideal candidate profile and signal that they are open to low-skilled applicants, thereby improving job opportunities for low-skilled jobseekers.

Based on the theoretical framework, my second hypothesis is that firms increase their training supply in response to increasing labor market tightness, especially for medium- and low-skilled workers. Indeed, I can show that firms increase their training supply in response to an increase in labor market tightness, but only in combination with the demand for medium-skilled workers. This suggests that companies are providing additional training to address potential skill gaps.

In a complementary analysis, I also carry out the analysis with regard to experience requirements. However, the evidence on the adjustment of experience requirements is mixed. While I find a slight decrease in the share of high experience vacancies, suggesting a reduction in skill requirements, I find an even larger decrease in the share of low experience vacancies. Moreover, this is accompanied by an increasing share of vacancies requiring no experience at all.

Finally, the heterogeneity analysis reveals two findings: First, adjustments in skill requirements tend to occur mainly in skilled and routine occupations, which are the less complex occupations. Second, I find that adjustments are stronger in firms with a higher job vacancy to employment ratio (job vacancy rate). This result shows that these firms are particularly affected by labor shortages and have more difficulties finding suitable candidates.

[5] The values of labor market tightness at the 25th and 75th percentiles of the distribution are 0.33 and 1.18, respectively.

[6] The fifth digit of the German occupational classification indicates the complexity of the occupation. For the purposes of analysis, I distinguish between skilled workers on the one hand and experts and specialists on the other.

The findings have important policy implications. First, the results provide evidence that firms adjust their hiring efforts in response to labor market conditions. This is important for the design of policies targeting job search and skill development, as the intended effects of policies may be mitigated by a change in firms' recruiting behavior. Second, lowering skill requirements can be a source of skill mismatch if new hires do not have the skills required for the job, with potentially adverse effects on firm-level productivity (McGowan and Andrews, 2015).

My research contributes to several strands of the literature. First, it is closely related to studies using online job vacancy data to study changes in skill requirements in response to changes in the unemployment rate. Evidence for the US shows that negative employment shocks, such as the Great Recession, led to an increased demand for higher skilled workers and acted as an accelerator for the restructuring of production processes (Hershbein and Kahn, 2018; Modestino et al., 2020). However, Modestino et al. (2016) show that the decline in unemployment in the aftermath of the financial crisis was associated with a reduction in skill requirements.

By focusing on the case of Germany, my paper adds to these studies twofold. First, German firms may adopt different strategies due to differences in labor market institutions and lower turnover rates (Jung and Kuhn, 2014), but also due to the importance of the dual education system (Haasler, 2020) and the prevalence of occupational licensing (Koumenta and Pagliero, 2017). Second, I also test for the adoption of alternative recruitment strategies. To the best of my knowledge, this is the first study to examine whether firms are increasingly welcoming applications from career changers or whether they are broadening their skill requirements as a result of increasing labor market tightness.

Second, my research relates to the growing body of literature examining the role of recruiting intensity in the search and matching process. Davis et al. (2013) were the first to show that variation in recruiting intensity can explain heterogeneity in the number of hires per vacancy across establishments. Moreover, studies have shown that recruiting intensity is procyclical and increases with labor market tightness at the macroeconomic (Gavazza et al., 2018; Leduc and Liu, 2020; Mongey and Violante, 2019) and at the establishment level (Forsythe and Weinstein, 2021). In addition, firms adjust their hiring standards in response to changes in labor market conditions (Carrillo-Tudela et al., 2023a; Chugh and Merkl, 2016; Lochner et al., 2021). The OJV data provide me with information on the profile and skills of the ideal candidate and allows me to look into the "black box" of the recruitment process of firms. In addition, I can study short-term responses to changes in labor market tightness.

Third, I add to the expanding literature on firms' responses to labor shortages. While there is evidence of a negative effect of labor shortages on firms' employment growth (Bossler and Popp, 2024; Stevens, 2007), there is some indication of a positive wage effect for certain groups of workers, particularly high-skilled and STEM workers (Brunow et al., 2022; Burstedde and Schüler, 2020). My contribution to this literature is twofold: First, I focus on the adjustment of firms' recruitment standards in response to changes in labor market tightness. Second, the availability of OJV data allows for the analysis of recent trends. Thus, the data also capture the variation in tightness over the Covid19 period.

Fourth, I contribute to research that highlights the importance of wording in OJV and direct outreach to specific groups to encourage their applications[7]. I contribute to this literature by examining job advertisements that target specific skill groups and career changers, assuming that firms are aware of the importance of language in job advertisements.

The paper is organized as follows. In Section 4.2, I discuss the underlying theoretical framework and derive hypotheses to guide the empirical analysis. In Sections 4.3 and 4.4, I describe the data and provide descriptive evidence on skill requirements and labor market tightness. In Section 4.5, I discuss the empirical strategy and present the results in Section 4.6. Finally, I conclude in Section 4.7.

4.2. Theoretical Framework

In this section, I outline the theoretical framework underlying the understanding of firms' responses to labor market tightness. According to the Standard Search and Matching (SSM) model (Pissarides, 2000), the complex process by which firms and workers meet can be described by a matching technology that provides the number of matches at any point in time (Mortensen and Pissarides, 1999; Pissarides, 2000). In the SSM model, the number of matches depends on the number of vacancies and the number of unemployed, but the model can be extended to include on-the-job search. Then, labor market tightness is described by the ratio of vacancies to job seekers (Dolado et al., 2009; Postel-Vinay and Robin, 2002). According to the standard SSM model, the job finding rate is proportional to the tightness of the labor market, while the

[7]see Burn et al. (2022a,b); Del Carpio and Fujiwara (2023); Flory et al. (2021)

job-filling rate is inversely related to it.

In particular, my paper relates to papers introducing recruitment intensity and standards into the matching model. Given that vacancy creation is costly, Leduc and Liu (2020) argue that firms adjust not only vacancies but also recruitment intensity in response to aggregate shocks. Since the vacancy rate is negatively related to tightness, firms must exert more effort to hire a given number of workers in tighter labor markets (Landais et al., 2018). For the U.S. in the period before and after the financial crisis, Davis et al. (2013) identify significant differences in job-filling rates across establishments. In particular, the authors find that establishments with stronger employment growth have higher job fill rates. They explain this finding by heterogeneity in recruiting intensity, such that firms with greater recruiting intensity fill their open positions faster. The procyclical nature of recruiting intensity, demonstrated by Gavazza et al. (2018); Mongey and Violante (2019), reveals that firms increase (decrease) their hiring efforts in tight (slack) labor markets.

One aspect of hiring intensity is the adjustment of hiring standards. While the SSM model assumes homogeneous workers, firms decide not only on the number of hires but also on the type of workers they want to hire (Baydur, 2017; Merkl and Van Rens, 2019). Assuming that higher-skilled workers are more attractive due to lower training costs, firms decide on a number of hires and set a threshold for training costs. Only workers whose required training costs are below the threshold are hired (Chugh and Merkl, 2016; Lochner et al., 2021). Lochner et al. (2021) show that companies that decide to hire a larger number of employees set a lower threshold and are less selective in their hiring. Moreover, as firms hire more workers in good economic times, hiring standards adjust over the business cycle (Lochner et al., 2021) which can explain significant variation in regional matching efficiency (Carrillo-Tudela et al., 2023a).

For the analysis, I measure hiring standards based on skill requirements reported in online job vacancy data. Furthermore, I construct a measure of labor market tightness using data on registered vacancies and job seekers from the German Federal Employment Agency.[8]. Both variables are aggregated at the level of commuting zones, occupations (3-digit level of the German classification of occupations) and year.

According to the theoretical framework, a tightening of the labor market will increase competition among firms for qualified candidates, making it more difficult for firms to attract candidates

[8]For details on the data and construction of the labor market tightness measure, see section 4.3.

who meet their desired criteria. As a result, firms adjust their hiring standards to account for the limited availability of qualified candidates (Carrillo-Tudela et al., 2023a; Lochner et al., 2021). Consequently, firms lower their requirements in response to increased labor market tightness. This relationship is summarized in Hypothesis 1:

- *Hypothesis 1:* Firms lower their skill requirements in response to increasing labor market tightness.

One way to lower skill requirements is to shift demand from higher-skilled to lower-skilled workers. Another way that firms can lower their skill requirements is by broadening their criteria for suitable candidates. Instead of strictly requiring several years of work experience and a certain level of education, firms may be more open to considering candidates with less experience or less education. Correspondingly, firms can maintain their demand for higher-skilled workers while also targeting middle- and low-skilled workers through the same job posting. The following two hypotheses summarize the relationship:

- *Hypothesis 1A:* Firms reduce their demand for highly skilled workers in terms of experience and education in response to increasing labor market tightness, while increasing their demand for workers with medium or even low levels of education and experience.
- *Hypothesis 1B:* Firms increase their flexibility regarding skill requirements in response to increasing labor market tightness.

In addition, Chugh and Merkl (2016) and Lochner et al. (2021) assume that the hiring of lower-skilled workers is associated with higher training costs to fill skill gaps. Accordingly, firms that lower their hiring standards will need to invest more resources in training and development programs in order to upgrade or retrain workers who may not initially meet all of the desired criteria. Therefore, I test whether there is an increase in firms advertising the provision of training for specific skill groups, especially for medium- and low-skilled workers. This relationship is formulated in Hypothesis 2.

- *Hypothesis 2*: An increase in labor market tightness is associated with increased provision of on-the-job training by firms, especially for medium- and low-skilled workers.

Moreover, compensation packages can also influence the attractiveness of a job (Davis et al., 2013). In this context, I focus in particular on the role of remote work as the pandemic created a "push" in supply (Alipour et al., 2021). Remote work allows for longer commuting distances, thereby expanding the geographic area from which a firm can recruit (Coskun et al., 2024). Thus, I examine whether firms use remote work to expand their applicant pool in order to deal with labor shortages.

4.3. Data

4.3.1. Online Job Vacancy Data

Data Processing

Online Job Vacancy (OJV) data provides real-time information on firms' labor demand, specifically in terms of tasks, required skills, and benefits. The data allow researchers to study current labor demand as well as firms' responses to economic conditions. While online job postings do not capture total labor demand, they are one of the most important recruitment channels for firms, especially for matching more productive firms with higher-skilled workers (Carrillo-Tudela et al., 2023b). They also play a critical role in connecting companies with workers, although they do not provide information about the actual hiring decision.

I use the near universe of online job postings for Germany for the period 2017 to 2023. The job listings are collected by Palturai GmbH/Finbot AG[9], which scrapes job listings from job boards, company websites, headhunters, and temporary work agencies. Finbot AG performs some basic cleaning procedures, remove duplicates from the same source (i.e. sources from the same URL address) and extract metadata such as job title and company name. I received various data packages, including the raw job description, information about the company, and the source of the job posting.

Although I obtain the data from a commercial data provider, the data have two advantages over other OJV data commonly used in economic research. First, I have access to the original text of the job ad, not just the extracted skills, which gives me more control over the data generation process. Second, Finbot merges the OJV data with data from the German Business Register.[10] The link is available for about 60% of the job offers and provides additional information about

[9]Finbot AG is a subsidiary of Palturai GmbH, based in Hofheim, Germany, and provides customized company, people, and job listing data and market analysis.

[10]The dataset is based on information from the German Business Register and includes all firms that have been listed in the German Business Register since 1991. About half of the 3.4 million firms in Germany are non-commercial and therefore not listed in the business register. In addition, enterprises in the public administration sector are not included.

the company, including location, industry and employee size. One limitation of the data is that it does not vary over time.

After receiving the data, I perform further cleaning and preprocessing steps, following the convention in the literature (Gentzkow et al., 2019). In particular, I tokenize the job description text of each vacancy, convert words to lowercase and remove special characters. I also assign each job to a specific location, preferably at the postal code level (90% of OJV), and classify the job titles according to the German Classification of Occupations 2010 (60% of OJV).[11]

Identification of Skills

I use a keyword approach to identify skill requirements, demand for career changers, and benefits in the OJV data. For work education and experience, I distinguish three levels: low, medium, and high.[12] In addition, I look for terms that explicitly state that the hiring company is open to hiring people interested in changing careers. To capture the provision of benefits, I look for terms that describe remote work and training. Table 4.1 provides an overview of the classification, see section 4.B for a full list of keywords including their translations.

Table 4.1.: Classification keywords

Keyword	Job Postings that look for
Low education	Lower secondary education
Medium education	Secondary education or an apprenticeship
High education	At least tertiary education or equivalent
Low experience	Junior positions and those explicitly aimed at graduates, as well as those that require (almost) no experience
Medium experience	Some initial experience, between two and four years
High experience	Managerial positions and those requiring several years of experience (more than 4 years)
Career changer	Job ads specifically targeting career changers
Remote work	Provision of remote work
Training	Provision of training and further education opportunities

I run an algorithm that loops over all job postings, counts whether a keyword occurs in a

[11] The main reason for not being able to assign a job title is either that it is too general or that there is no specific title at all. Therefore, I believe that this limitation does not affect the validity of the results.

[12] In German job postings, the level of experience is often described in terms such as "keine Berufserfahrung" or "mehrjährige Berufserfahrung" instead of explicitly stating the number of years. So the measure is not simply continuous.

job posting, and stores this information as metadata to a vacancy. The categorization is not exclusive, as a company may specify different education or experience requirements within the same job posting. To measure skill flexibility, I count the combined occurrence of two skills, as well as the occurrence of only one skill in a job posting. Figures 4.B2, 4.B1 and4.B3 show the word clouds for the different target groups and for career changers, remote work and training. The size of the words reflects the importance of each word in the vacancy data.

Final Dataset

In constructing the final dataset, I apply several sample restrictions in order to maintain a high quality of the data and to achieve comparability with data from the official statistics of the Federal Employment Agency.

First, I exclude vacancies advertised by temporary employment and recruitment agencies. Since firms use these agencies to advertise positions that are hard to fill, it is uncertain whether these jobs had already been advertised by the firm itself. Second, I restrict the sample to jobs that are subject to social insurance contributions, and exclude job postings for interns, students, apprentices, short-term helpers, and marginal jobs. Since my outcome skill demand is defined at the intersection of LMR, occupation, and year, I drop postings with missing information on any of these dimensions. Furthermore, I restrict my sample to those job advertisements that can be linked to the business register. After applying all the filters, the initial dataset is reduced to 15% vacancies. Table 4.A1 provides an overview of the filters applied to the data, and the portion of the data that is excluded in each step.

For the purposes of this paper, I also exclude vacancies for unskilled helpers, as indicated by the fifth digit of the German Occupational Classification (Federal Employment Agency, 2021)[13], and drop occupations in the armed forces and occupations in agriculture, fishing, and forestry.[14] The final dataset includes 11.6 million observations for the period 2017 to 2013. To put the numbers in perspective: According to the IAB vacancy survey, there were 1.75 million open vacancies in Germany in the first quarter of 2023 (Kubis, 2023). By comparison, I measure an inflow of 888 thousand new vacancies in the OJV data from Palturai GmbH/Finbot AG in the

[13]I exclude helper positions for the following reasons: first, unskilled helpers are not included in the Federal Employment Agency's analysis of skill shortages because they are not considered skilled workers; second, online job advertisements are biased toward skilled workers, and thus unskilled helpers are underrepresented in our data; and third, job advertisements for unskilled helpers tend to be shorter and contain less information about the tasks and skills required, making it more difficult to study skill demand and changes for this group.

[14]Following the procedure in the in the official statistics, I combine the occupations health care (813) and elderly care (821).

same period. However, not all vacancies are posted online. In addition, I exclude vacancies for helper positions. Therefore, the number of vacancies in my sample is likely to be smaller.

The dataset is aggregated to a combination of labor market region, occupation, and year - the definition of local labor markets in this paper. This is consistent with evidence highlighting the importance of regional labor markets and occupations as key determinants of local labor market tightness (Peichl et al., 2022). For the definition of labor market regions (LMR), I use the definition of commuting zones by Kosfeld and Werner (2012). For occupations, I follow the standard practice of the Federal Employment Agency in analyzing labor shortages by categorizing occupations at the three-digit level according to the German classification system (BA, 2020).

The final dataset presents the total number of vacancies within the labor market region-occupation cell within the respective year. The numbers are an inflow-based measure and capture the total inflow of job postings during the respective year. Finally, I construct a balanced dataset that includes only those local labor market-occupation cells with at least five postings in each year between 2017 and 2023. The final sample includes 133 occupations, 141 labor markets, and 7,847 labor market-occupation cells. For the heterogeneity analysis, I create datasets at a more disaggregated level. On the one hand, I further disaggregate the data by occupational skill level. On the other hand, I further disaggregate the data by firm type (vacancy rate and industry).

For each skill S^i, skill demand is defined accordingly:

$$s^i_{olt} = \frac{S^i_{olt}}{OJV_{olt}} \tag{4.1}$$

where s^i_{olt} is a ratio that measures the share of online job vacancies with skill requirement S^i within a local labor market l, occupation o and year t relative to the total number of online job vacancies (OJV) within that cell.

4.3.2. Federal Employment Agency Data

To measure labor market tightness, I use data from the official statistics of the German Federal Employment Agency (FEA) on the number of registered vacancies and the number of registered job seekers for the period 2017 to 2023. The FEA data represent a moving average of the stock of vacancies and jobseekers between January 1st and December 31st of each year. Thus, the data is a measure of average supply and demand over the year, rather than a snapshot at one point in time. In addition, the annual aggregation allows for analysis at a more disaggregated regional and occupational level. The dataset does not include vacancies for marginal employment and those posted by temporary employment agencies.

Since firms are not required to report their vacancies to the Federal Employment Agency, the registered vacancies from the FEA do not capture the full labor demand in the German labor market. The comparison with the IAB Vacancy Survey, which is a representative survey of German firms (IAB, 2023), shows that reporting differs according to the occupational level of an occupation. Reporting is highest among helpers and professionals, but lower among experts and specialists. Neglecting these differences in reporting would introduce a significant bias into the measurement. To obtain a representative dataset, I follow the standard approach and weight the data from the FEA with data on reporting rates from the IAB job vacancy survey (Bossler and Popp, 2023; Burstedde et al., 2020).

Jobseekers, on the other hand, are obliged to register with the public employment agency if they wish to receive unemployment benefits. Therefore, the registered jobseekers should include all jobseekers currently available in the labor market. It should be noted, however, that there are limitations. First, the measure does not take into account graduates and people in training who could potentially enter the labor market. Second, it also includes workers who registered as jobseekers in anticipation of a possible contract expiry but received a contract extension. Jobseekers are allocated to an occupation on the basis of their preferred target occupation. In addition, I use the data from the FEA on the employment in each of the LMR occupation year cells. I use this data to weight each of the LMR occupation year cells in the analysis.

For the analysis, local labor market tightness is defined along two dimensions: the regional (Kosfeld and Werner, 2012) and the 3-digit occupational level of the German Classification of Occupations (KldB 2010). For the heterogeneity analysis, I further disaggregate the data by skill level. Therefore, I look at two groups: one is professionals and the other is experts and specialists.[15] Accordingly, labor market tightness is defined as follows:

$$\theta_{olt} = \frac{V_{olt}}{JS_{olt}} \tag{4.2}$$

[15] As unskilled helpers are not included in the analysis (Burstedde et al., 2020).

where θ_{olt} is defined as the ratio of vacancies V to job seekers JS within an occupation-LMR-year cell.

4.3.3. Occupational Panel

For additional information at the occupational level, I use data from the German Occupational Panel provided by the IAB, which is available for the years 2012 and 2018 (Grienberger et al., 2023). It provides information on the task content of occupations based on BERUFENET, which allows the classification of occupations into task groups. I use this data to group occupations into three different task groups (routine, non-routine manual, and non-routine cognitive) based on the highest task intensity. I use the 2016 measure of task intensity to avoid reverse causality.

4.4. Descriptives

In this section, I first present descriptive statistics and trends for my outcome variable, skill demand. I then examine the key explanatory variable, labor market tightness, and its variation over time, across LMRs, and occupations.

4.4.1. Skill Requirements in OJV Data

The main interest of this paper is the adjustment of skill requirements in online job postings. From 2017 to 2023, the total number of job postings in the OJV data increases significantly, from about 775,000 job postings in 2017 to about 2.5 million job postings in 2023 (see Table 4.2). I create a balanced dataset of LMR occupation cells, totaling 7,847 cells per year, as described in Section 3. The average number of job postings per cell more than triples, from an average of 99 postings to 315 postings. Although at a lower average level, this also applies to the median number of postings. However, the standard deviations of the job postings increase from 302 to 683.

When it comes to skill requirements, companies are much more likely to list education than experience requirements (see Table 4.2). In 2017, only 36% of job postings did not mention any educational requirements, which decreases to 28% by 2023. Given a education requirement, most postings require at least a medium or high level of education (see Table 4.2). However,

Table 4.2.: Summary statistics

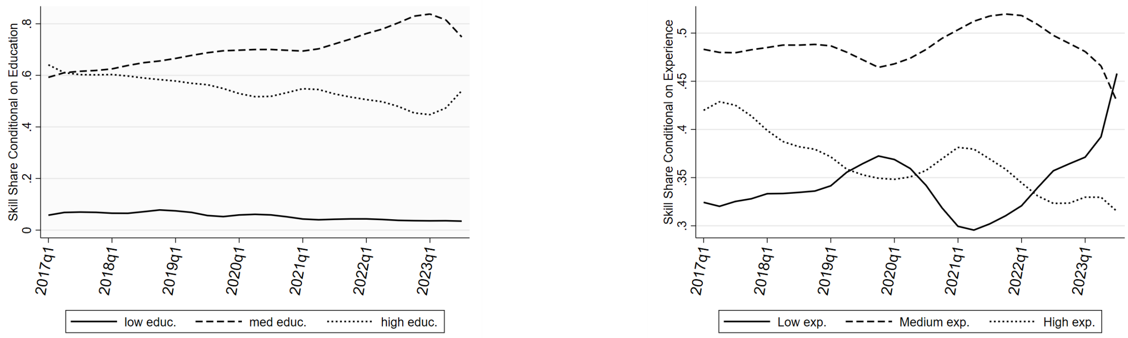
	2017	**2019**	**2023**
OJV data			
Total job postings	774,010	1,153,887	2,473,463
Number LMR-occupation cells	7,847	7,847	7,847
Median job postings	27	48	119
Mean job postings	99	147	315
Std. job postings	302	404	683
Skill Demand (in %)			
No education	36.0	34.3	28.0
Low education	4.3	4.8	2.6
Medium education	39.7	46.1	59.5
High education	38.6	35.6	32.9
No experience	65.6	66.9	68.1
Low experience	11.7	12.6	13.3
Medium experience	17.4	16.1	15.1
High experience	13.4	10.3	9.5
Career Changer	2.0	2.8	5.8
Remote work	3.6	6.6	23.4
Training	16.8	19.8	24.1
Labour market tightness (FEA data)			
Number of vacancies	964,169	1,219,784	1,397,952
Number of job seekers	1,959,635	1,732,431	1,534,115
Labour tightness	0.49	0.7	0.91

Notes: The sample is restricted to LMR-occupation cells with at least 5 postings in every year. Local labor market regions (LMR) are defined at the commuting zone level following Kosfeld and Werner (2012). Occupations are classified using KldB2010 at the 3-digit level. The skill shares are constructed using OJV data as described in section 4.5. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

the limited demand for workers with lower levels of education (only 4%) is also due to the absence of helper positions. Figure 4.1 shows the trend in the share of vacancies with educational requirements, conditional on any educational requirement. While vacancies with medium education requirements increased, those with high education requirements decreased, with the trend reversing only in 2023. Because job postings can include either no, a single, or multiple educational skill requirements, the numbers in the graph are greater than one. In the analysis, I distinguish between three types of skill demand: overall skill demand, singular skill demand (focusing on a single skill), and combined skill demand (including different skill requirements).

In terms of experience, 65% of job postings did not mention any experience requirement in 2017. Figure 4.1 shows the trend in experience requirements, conditional on at least one experience requirement. Job postings requiring medium experience (2-4 years) are the most common, followed by high and then low. Over time, however, there is a strong variation in the

Figure 4.1.: Trend in skill demand



(a) Education (b) Experience

Notes: The figures shows the share of vacancies with education (experience) requirement relative to the number of vacancies with at least one education (experience) requirement by quarter over the years. Each LMR-occupation-year cell is weighted by the FEA employment data in that cell. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

share of vacancies with experience requirements.[16]

As outlined in *Hypothesis 1B* in section 4.2, firms can also lower their recruiting standards by increasing their flexibility with regard to skill requirements. Therefore, I take a closer look at singular and combined skill demand within a job posting. Figures 4.2 and 4.3 show the share of job vacancies with singular (on the diagonal) and combined (below the diagonal) skill demand. With respect to education, Figure 4.2 shows that singular demand for high education has decreased significantly, while the singular demand for medium education has increased. Moreover, the combined demand for medium and high education is quite common (24% in 2017 and 29% in 2023). By comparison, the combined demand for experience is less common.

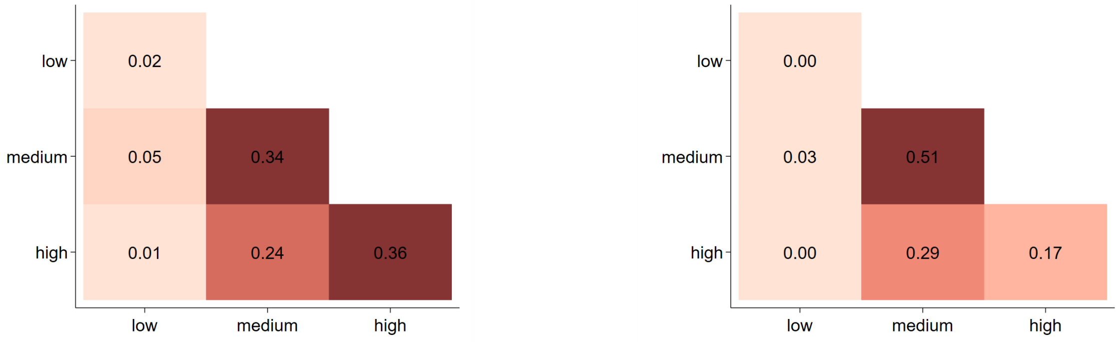
Targeting career changers is an alternative mechanism for reducing experience requirements. The demand for career changers remained relatively low until 2019, when it started to increase from only 2% to 5.8% (see Figure 4.A1). However, there is significant heterogeneity across occupations.[17] In addition, firms may either offer training to signal the importance of skills development and to fill skills gaps (*Hypothesis 2*) or provide remote work to attract candidates from a wider geographical area. Table 4.2 shows that the share of vacancies offering training increased from 16.8% to 24.1%, and the share of vacancies offering remote work increased sharply

[16]Compared to the figures reported by Modestino et al. (2016) for the United States in 2014, the share of jobs with education requirements is higher while the demand for experience requirements is similar. One reason for the difference is the exclusion of unskilled helpers from my sample. Another is the higher share of licensed occupations and the importance of vocational education in Germany.

[17]In 2017, demand for career changers was common for only a few occupations, such as transportation occupations (Table 4.A2). Between 2017 and 2023, the demand for career changers increases for many occupations, especially sales occupations, but also passenger transport service occupations and cleaning occupations (see Table 4.A3).

from 3.6% in 2017 to 24.1% in 2023 (see figure 4.A2 for an illustration of the trends over the years.).

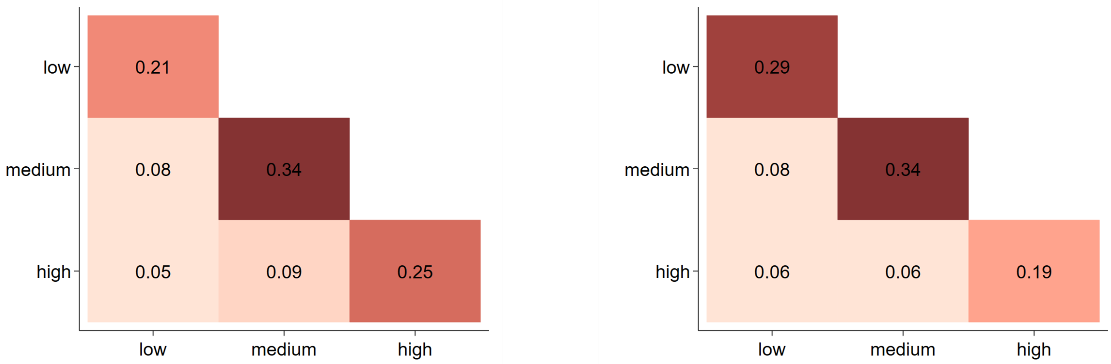
Figure 4.2.: Singular and combined demand for educational skills



(a) 2017 (b) 2023

Notes: The shares are relative to the number of vacancies with a least one education requirements and add up to one. The numbers indicate the share of vacancies with one single skill (diagonal) and the combination of two skills (lower diagonal). Each LMR-occupation-year cell is weighted by the FEA employment data in that cell. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

Figure 4.3.: Singular and combined demand for experience skills



(a) 2017 (b) 2023

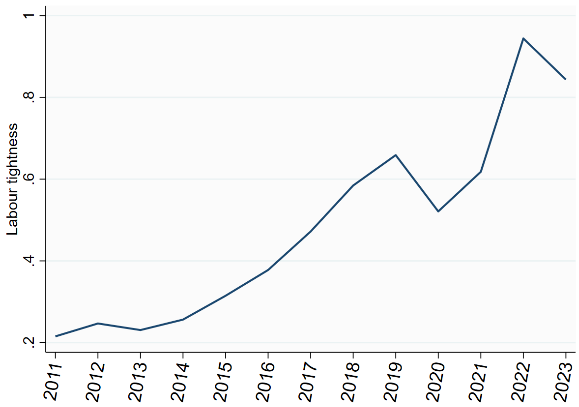
Notes: The shares are relative to the number of vacancies with a least one experience requirements and add up to one. The numbers indicate the share of vacancies with one single skill (diagonal) and the combination of two skills (lower diagonal). Each LMR-occupation-year cell is weighted by the FEA employment data in that cell. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

4.4.2. Labor Market Tightness

For the analysis, I consider the variation in labor market tightness over time, across local labor markets and occupations. In this section, I will examine these three dimensions in more detail.

From 2017 to 2023, the average labor market tightness increased from 0.49 to 0.91 vacancies

Figure 4.4.: Trend labour market tightness 2011-2023



Notes: Labor market tightness defined as the ratio of job vacancies to jobseekers. Source: FEA data 2017-2023; own calculations.

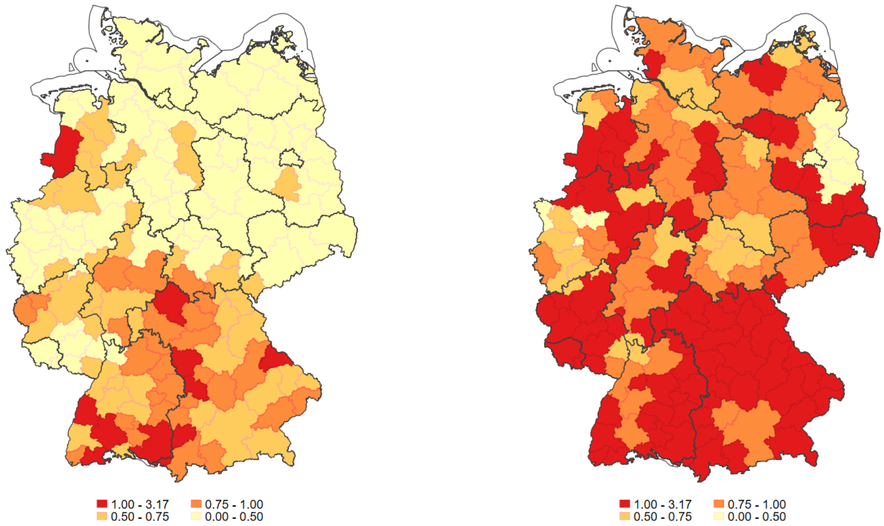
per job seekers (see Table 4.2).[18] As shown in Figure 4.4, labor market tightness remained fairly constant between 2011 and 2013 and increased steadily from 2013 to 2019. The outbreak of the Covid19 pandemic led to a temporary decrease in labor market tightness, with a strong rebound effect in the post-pandemic period, exceeding pre-2019 levels. Firms' labor demand, as measured by the evolution of vacancies over time, has been the main determinant of the increase in labor market tightness (see Figure 4.A4). However, this trend has been exacerbated by a concurrent decline in the number of job seekers (see Figure 4.A5).

Previously, labor shortages were considered to be limited to specific regions and occupations (Burstedde and Risius, 2017; Czepek et al., 2015). However, they are now recognized as a widespread challenge affecting almost all regions and occupations (Peichl et al., 2022). This shift is illustrated in Figure 4.5, which shows average labor market tightness across regions. In 2017, the southern states of Germany, particularly Baden-Württemberg and Bavaria, were most affected by labor market tightness. Moreover, few labor market regions had average labor market tightness greater than one, indicating more than one vacancy per jobseeker. By comparison, with average labor market tightness scores below 0.5 vacancy per job seeker, the labor markets in the northern, western, and eastern parts of Germany were relatively slack.

As can be derived from the dark red colors in the Figure 4.5, the picture changes significantly between the years 2017 and 2013. The average tightness of the labor market continued to increase in the southern states, but also in all regions of Germany, with only a few exceptions. Regions less affected by labor market tightness include metropolitan areas such as the Rhineland

[18] Although there are differences between occupational skill levels (see Figure 4.A3), the movement in labor market tightness remains broadly parallel for professional occupations and expert and specialist occupations.

Figure 4.5.: Regional variation in labor market tightness 2017 and 2023



(a) 2017 (b) 2023

Notes: Labor market tightness is measured as the ratio of vacancies to jobseekers. The color represent categories in labor market tightness based on Bundesagentur für Arbeit (2023). Labor market regions defined following Kosfeld and Werner (2012). Source: FEA data 2017-2023; own calculations.

in the west and Berlin in the northeast, as well as very rural areas close to the Polish border.

At the occupational level, some occupations were already experiencing notable labor market tightness in 2017. Occupations with the highest labor market tightness in 2017 include those in transportation and construction, health care, and craft occupations, as well as occupations that will be increasingly in demand as a result of technological and environmental changes, such as occupations in energy and information technology and automation (see Figure 4.A4). These occupations already had average labor market tightness scores above one in 2017. Several of the aforementioned occupations experience further tightening between 2017 and 2023. In addition, the increase in tightness was particularly strong for tax accountants and for engineering occupations, especially civil and electrical engineering (see Table 4.A5). In all of these occupations, the increase in tightness was greater than 100 percentage point. [19]

[19] Despite known labor shortages, health care occupations are not among the occupations experiencing the largest increases in labor market tightness. However, this is consistent with reports from healthcare professionals that recruitment channels other than online job postings are becoming increasingly important. These channels include recruiting through personal contacts or using social media as a platform (Senghaas and Struck, 2023).

4.5. Empirical Methodology

4.5.1. Fixed Effect Model

To examine the effect of labor market tightness on skill demand, I first estimate the following fixed-effects model that exploits variation across local labor markets, occupations, and time:

$$s^i_{olt} = \alpha + \beta\theta_{olt} + \phi_{ol} + \delta_t + \rho_{lt} + \gamma_{ot} + e_{olt} \tag{4.3}$$

where s_{olt} is the outcome variable skill demand at the occupation, LMR, year level. I estimate a separate regression for each skill S^i. The main explanatory variable is labor market tightness at the occupation, LMR, year level as defined in eq. 4.2.

To account for unobserved factors, I include a set of fixed effects to control for unobserved factors: First, to account for level differences in labor market tightness and skill demand across LMR occupation cells —the unit of my panel dataset —I include $LMR \times occupation$ (3-digit) FE (ϕ_{ol}). Since my sample is fully balanced across years, this is conceptually equivalent to running a first-difference regression. Second, I include year FE (δ_t) to control for year-specific shocks, such as the Covid19 pandemic. In addition, I include fully flexible time trends: First, I add $LMR \times year$ FE to capture regional demand shocks; second, I include $occupation(2-digit) \times year$ to control for occupation-specific time trends. I use occupation trends at the 2-digit level rather than the 3-digit level to allow for some variation among similar occupations. In the preferred specification of the model, the effect of labor market tightness on skill demand is identified using variation over time within an LMR occupation cell, while also controlling for regional and occupational trends.

4.5.2. Identification

The above specification captures the reduced-form effect of labor market tightness on firms' skill requirements. One concern is that there are other factors that are correlated with both skill requirements and labor market tightness. Potential confounders can be either short-run, such as the Covid19 pandemic, which affected the entire economy but with different effects across regions (Ben Yahmed et al., 2022; Hamann et al., 2023), or long-run, such as the impact of technological progress, which influences skill requirements (Deming and Kahn, 2018; Langer and Wiederhold, 2023) and labor demand (Acemoglu and Restrepo, 2018). Another concern is the potential reverse causality of skill requirements on labor market tightness. For example, technology adoption is associated with skill upgrading and requires workforce training (Gathmann et al., 2023).

First, to reduce the potential influence of confounding factors, I include year fixed-effects and flexible occupational and regional time trends. These interactions capture variations within occupational groups and regions over the years that could be associated with short-term confounding factors. I note, however, that these interactions cannot completely rule out the potential impact of other confounding factors. For this reason, the results should be interpreted with caution. Second, to mitigate concerns about reverse causality, I use a leave-one-out instrument commonly used in the industrial organization literature[20]. In particular, I follow Bossler and Popp (2024) and instrument vacancies and job seekers with the average values in the same occupation in all other LMR within the same year. Therefore, I assume that local vacancies and local jobseekers can be decomposed into a national trend and a local residual. The leave-one-out instrument is defined as follows:

$$I_{olt}^{V} = \sum_{k \neq l} V_{okt} \quad (4.4) \qquad\qquad I_{olt}^{JS} = \sum_{k \neq l} JS_{okt} \quad (4.5)$$

Under the assumption that local decisions to upgrade skills do not significantly affect the national level of vacancies and job seekers, I can mitigate concerns about reverse causality. Moreover, I show that the results are robust to the use of lagged labor market tightness rather than contemporaneous tightness, further mitigating these concerns (see section 4.6.3).

In addition, to establish validity, an instrument must meet the criteria of relevance and exclusion. In this context, the trend in local labor market tightness is defined as a composite measure that includes both national trends and local demand factors. Since local labor market tightness is influenced by national economic conditions, policies, and population demographics, national trends in labor market tightness are relevant to local labor market conditions. To maintain the exclusion restriction, the national trend in job seekers and vacancies must be uncorrelated with the error term in the baseline estimation. While the instrument effectively mitigates the influence of local factors, it is difficult to claim complete exogeneity. There may be national-level trends that affect skill requirements in ways other than through labor market tightness.

[20] For a discussion see (Azar et al., 2022; Qiu and Sojourner, 2023; Rinz, 2024)

However, I argue that this effect is smaller than the effect of local labor market tightness on skill requirements. Thus, while the effect cannot be definitively considered causal, the use of this instrument allows for a closer approximation of causality.

4.6. Results

In this section, I present the results of the OLS and IV estimation of labor market tightness on skill demand. I start by presenting the baseline results, followed by an analysis of alternative adjustment mechanisms. I then test the validity of the OLS results using an IV approach before moving on to examine heterogeneity across occupations, firms, and industries. In section 4.6.1 I focus on the results for education requirements, while in section 4.6.2 I examine the effects on experience requirements. In section 4.6.3, I present the results of the robustness checks.

4.6.1. Education

OLS Results

First, I present the results on the educational skill requirements. Estimates of the OLS specification of labor market tightness on the demand for educational attainment are reported in Table 4.3 Panel A. In the preferred specification, I account for year-specific shocks and include fully flexible time trends across 2-digit occupations and LMR regions.[21] For ease of interpretation, the coefficient is standardized with a mean of zero and a standard deviation of one. Thus, the estimated coefficient represents an increase in labor market tightness of one standard deviation, which is equal to 1.1 in my sample.

For overall skill demand, I find a significant positive relationship between labor market tightness and the share of vacancies with medium and low educational skill requirements. The results indicate that a one standard deviation increase in labor market tightness is associated with a 0.77 percentage point increase in the demand for medium education and a 0.23 percentage point increase in the demand for low education. Conversely, an increase in labor market tightness is associated with a 0.2 percentage point decrease in the share of vacancies with high education requirements. In addition, the share of vacancies with no educational requirement is also

[21] Results for the specification with less fixed-effects are reported in Table 4.A6.

Table 4.3.: Regression of labor market tightness on educational skill demand

	(1) low educ.	(2) med. educ	(3) high educ	(4) no educ
Panel A: Overall Skill Demand				
LM Tightness	0.228***	0.767***	-0.206**	-0.543***
	(0.060)	(0.119)	(0.079)	(0.104)
Panel B: Singular Skill Demand				
LM Tightness	0.034	0.542***	-0.253***	-0.543**
	(0.025)	(0.110)	(0.059)	(0.104)
LMR × Occupation FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
LMR × Year FE	yes	yes	yes	yes
Occupation (2d) × Year FE	yes	yes	yes	yes
Observations	54,929	54,929	54,929	54,929

Notes: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustering at the LMR level. Labor market tightness is standardized with mean of zero and standard deviation of one. Each coefficient in the table presents the result of a separate regression. Regression is weighted using employment in LMR-occupation-year cell. The outcome variable is skill demand, the share of OJV in each LMR-occupation-year cell with skill requirement S. Alternative specifications are reported in Table 4.A7. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

decreasing, as shown in column (4) of Table 4.3.

To illustrate the results, an increase in labor market tightness from the 25th to the 75th percentile, equivalent to a difference of 0.87, is associated with a 0.60 percentage point increase in the share of vacancies with medium education, a 0.17 percentage point increase in the share of vacancies with low education, and a 0.15 percentage point decrease in the share of vacancies with high education.[22] The results provide support for *Hypothesis 1* outlined in section 4.2, which posits that firms reduce their educational requirements in response to an increase in labor market tightness. In addition, the results are in line with the findings of Modestino et al. (2016, 2020), who show that firms adjust their skill requirements in response to labor market conditions.

In a next step, I examine whether firms adjust their skill requirements by either reallocating their demand from high-skilled to less-skilled workers (*Hypothesis 1A*) or by increasing the flexibility of their skill requirements (*Hypothesis 1B*). To test *Hypothesis 1A*, I re-estimate the baseline regression using a measure of singular skill demand that captures the share of job postings that target a single skill group. In comparison, the baseline captures overall skill

[22]Calculation details: The reported coefficients correspond to a one standard deviation increase in labor market tightness, which is 1.1 in my sample. The difference between the 25th (0.33) and 75th percentiles (1.18) is 0.85. Thus, the skill adjustment associated with moving from the 25th to the 75th percentile is $0.85/1.1 \times \beta$.

Table 4.4.: Regression of labor market tightness on educational skill demand: flexibility in skill requirements

	(1) low & medium	(2) medium & high	(3) share skilled worker
LM Tightness	0.199***	0.052	0.201***
	(0.053)	(0.069)	(0.069)
LMR X Occupation FE	yes	yes	yes
Year FE	yes	yes	yes
LMR X Year FE	yes	yes	yes
Occupation (2d) X Year FE	yes	yes	yes
Observations	54,929	54,929	54,929

Notes: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustering at the LMR level. Labor market tightness is standardized with mean of zero and standard deviation of one. Each coefficient in the table presents the result of a separate regression. Regression is weighted using employment in LMR-occupation-year cell. Alternative specifications are reported in Table 4.A7. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

demand, as firms can target multiple skill groups within a job posting. The results in Table 4.3 Panel B confirm the findings of a positive relationship with medium and a negative relationship with high educational requirements. However, the coefficient for low education is no longer significant and smaller.

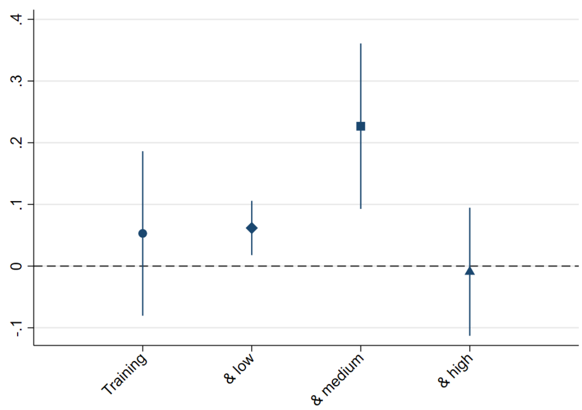
To test *Hypothesis 1B*, I create a measure that captures the combined occurrence of low & medium and medium & high education requirements within a job posting. Table 4.4 reports the results regarding the flexibility of skill demand. The results indicate that an increase in labor market tightness (by one standard deviation) is associated with a 0.2 percentage point increase in the combined demand for low- and medium-educated workers. However, the results do not show a significant increase in the combined demand for medium and highly educated individuals. The results suggest that the increase in the combined demand for low-educated workers was due to an increase in the flexibility of skill requirements in the recruitment of medium- and low-skilled workers. In addition, firms can lower average hiring standards within occupation groups by shifting their demand from experts and specialists to skilled workers. The results in column (3) indicate that firms increase their demand for skilled workers relative to experts and specialists in response to increased labor market tightness.

The results support the hypothesis that firms lower their educational skill requirements in response to increased labor market tightness. First, there is a shift in demand from highly educated to medium educated workers in support of *Hypothesis 1A*. An underlying mechanism is the shift in demand from professionals and specialists to skilled workers. I will examine the heterogeneity across occupations in more detail in section 4.6.1. Second, the increase in the combined demand for low- and medium-skilled workers implies, in line with *Hypothesis 1B*, increased flexibility in educational requirements for firms recruiting medium- and low-skilled workers. Overall, the results are consistent with those of Modestino et al. (2016) and Modestino et al. (2020), suggesting that firms adjust their hiring strategies and hiring intensity in response to labor market dynamics.

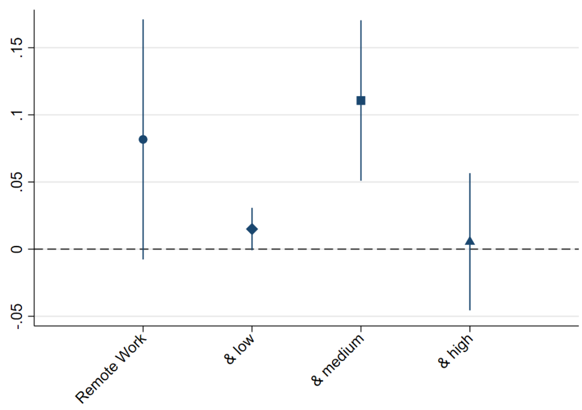
Alternative Adjustment Mechanisms

As discussed in section 4.5, firms may also resort to alternative adjustment mechanisms. First, firms may provide training to compensate for potential skill gaps resulting from a reduction in hiring standards. Second, firms can maintain their skill requirements while broadening their candidate pool by offering remote work. This allows them to attract talent from a wider geographic area. For the analysis, I use a measure that captures the combined supply of either training or remote work and the demand for a particular skill group.

Figure 4.6.: Coefficient plots of labor market tightness on educational skill demand and benefits



(a) Training and educational skills



(b) Remote work and educational skills

Notes: Each point estimate represents the coefficient from a separate regression. Vertical lines represent 95% confidence intervals. Standard errors are clustered at the LMR level. The outcome variable is the share of OJV that provides benefit (training/remote work) and states the specific skill requirement. The regression includes $LMR \times$ *occupation* FE, year FE, and interactions for LMR, year, and occupation year. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

Figure 4.6 plots the estimated coefficient of the regression of labor market tightness on the share of vacancies offering training (remote work) in combination with the demand for a specific skill group. First, a one standard deviation increase in labor market tightness is associated with a 0.23 percentage point increase in the share of vacancies offering training in combination with the demand for medium-skilled workers. By comparison, the relationship is weaker for low-skilled and insignificant for high-skilled workers. This finding implies that firms use training as a complementary measure to lowering hiring standards.

Second, for remote work, I only find a positive and significant relationship between labor market tightness and the provision of remote work in combination with the demand for medium-skilled workers. Notably, there is no significant relationship between labor market tightness and the provision of remote work for higher skilled workers. In general, the results do not suggest that the provision of remote work is used in occupations and regions that are more exposed to labor market tightness.

IV Results

To reduce endogeneity concerns (see section 4.5 for a discussion), I instrument the local labor market tightness in an occupation with the average labor market tightness for the same occupation in all other commuting zones.[23] The results of the IV regression are reported in Table 4.5 and confirm the positive relationship between labor market tightness and the demand for medium and low education, and the negative relationship between labor market tightness and the demand for high education. However, the IV regression estimates are significantly larger. A one standard deviation increase in labor market tightness is associated with a 5.9 percentage point increase in the demand for medium education and a 1.0 percentage point increase in the demand for low education. In addition, a one standard deviation increase in labor market tightness is associated with a 1.3 percentage point decrease in the demand for high education. Moreover, the negative relationship between the increase in labor market tightness and the decrease in the share of vacancies with no education requirement is confirmed.

The difference between the IV and OLS estimates suggests the presence of confounding variables. On the one hand, the smaller OLS estimates suggest that local confounding factors moderate labor market tightness and skill demand, thereby biasing the OLS estimates downward. On the other hand, the larger IV estimates compared to OLS could also result from national confounding factors. As discussed in section 4.5, the instrument helps to mitigate the influence

[23] As an alternative, I also create a leave-one-out instrument at the state level. The coefficients are slightly larger and the corresponding F-statistic is 114.5.

Table 4.5.: IV Regression of labor market tightness on educational skill demand

	(1)	(2)	(3)	(4)
	low educ.	med. educ	high educ	no educ
Overall Skill Demand				
LM Tightness	1.024***	5.956***	-1.300***	-4.123***
	(0.145)	(0.473)	(0.291)	(0.333)
LMR × Occupation FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
LMR × Year FE	yes	yes	yes	yes
Occupation (2d) × Year FE	yes	yes	yes	yes
Observations	54,929	54,929	54,929	54,929

Notes: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustering at the LMR level. Labor market tightness is standardized with mean of zero and standard deviation of one. Each coefficient in the table presents the result of a separate regression. Regression is weighted using employment in LMR-occupation-year cell. The outcome variable skill demand is instrumented using the average labor market tightness across all other LMRs within the same occupation. The F-statistic of the first stage is 117.05. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

of local confounding, but the impact of national confounding cannot be completely ruled out. In addition, the leave-one-out instrument reduces the impact of outliers and converges the estimate to the national mean. Furthermore, the estimate increases as the instrument mitigates the impact of outliers, causing the labor market tightness value to converge towards the national average.

Heterogeneity

The baseline results may mask significant heterogeneity across occupations, firm types and industries. To gain deeper insights into the underlying mechanisms, I re-estimate the baseline regression for different occupational skill levels, by task group, firm type and industry.

Occupational Skill Level

First, I examine heterogeneity across occupational skill levels. The OJV and FEA data allow me to construct a dataset at the intersection of LMR, occupation, year, and skill level. The occupational skill level of the German occupational classification indicates the complexity of the job and is therefore correlated with skill requirements. As discussed in section 4.6.1, an increase in labor market tightness is associated with an increase in the share of vacancies for skilled relative to expert and specialist occupations. Conducting the analysis by skill level allows me to analyze whether the decline in educational requirements described in section 4.6.1 reflect only a shift to skilled occupations, or whether adjustments are also taking place within occupational skill levels. [24]

Table 4.6 reports the regression results by occupational skill level. The results show that adjustments in skill requirements are concentrated within skilled occupations. Within skilled occupations, an increase in labor market tightness by one standard deviation is associated with a 0.56 percentage point increase in the share of jobs with medium skill requirements. However, the significant relationship between the tightness of the labor market and the share of vacancies with high skill requirements observed in the baseline specification is no longer significant. This can be attributed in part to the shift in demand from experts and specialists to skilled occupations described in section 4.6.1. The lack of skill adjustment in more complex occupations is due to minimum occupational requirements and occupational licensing designed to prevent skill decline.

Table 4.6.: Regression of labor market tightness on educational skill demand by occupational skill group

	(1) low educ.	(2) med. educ	(3) high educ	(4) no educ
Skilled Workers				
LM Tightness	0.116	0.556***	0.122	-0.416***
	(0.071)	(0.118)	(0.104)	(0.119)
Observations	36,057	36,057	36,057	36,057
Experts & Specialists				
LM Tightness	0.026*	0.030	-0.078	-0.043
	(0.013)	(0.139)	(0.095)	(0.099)
Observations	32,886	32,886	32,886	32,886
LMR X Occupation FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
LMR X Year	yes	yes	yes	yes
Occupation (2d) X Year FE	yes	yes	yes	yes

Notes: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustering at the LMR level. Each coefficient in the table presents the result of a separate regression. Separate regression by skill level. See notes to Table 4.3. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

[24] The results are the same when I run a pooled regression including fixed effects for LMR, occupation, and skill level along with skill level fixed effects.

Occupational Task Groups

Second, I consider heterogeneity across occupational task groups. The task framework characterizes occupations as bundles of tasks (Acemoglu and Autor, 2011; Autor et al., 2003). The task composition of an occupation can be a proxy for job complexity. Thus, it can serve as an indicator of the ease with which employers can lower hiring standards. Following the literature, I categorize occupations (3-digit) into three distinct task groups based on the predominant task within an occupation: routine, non-routine manual (NRM), and non-routine cognitive (NRC). As the baseline model includes occupation fixed effects, I cannot add additional task group fixed effects. Therefore, I split the sample by task group.

Table 4.7.: Regression of labor market tightness on educational skill demand by task group

	(1) low educ.	(2) med. educ	(3) high educ	(4) no educ
Routine occupations				
LM Tightness	0.345***	1.166***	-0.624***	-0.795***
	(0.114)	(0.192)	(0.133)	(0.156)
Observations	29,526	29,526	29,526	29,526
NRM occupations				
LM Tightness	-0.056	-0.100	0.113	0.030
	(0.124)	(0.255)	(0.182)	(0.246)
Observations	6,909	6,909	6,909	6,909
NRC occupations				
LM Tightness	0.065	-0.150	0.181*	0.041
	(0.045)	(0.111)	(0.102)	(0.125)
Observations	18,438	18,438	18,438	18,438
LMR X Occupation FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
LMR X Year	yes	yes	yes	yes
Occupation (2d) X Year FE	yes	yes	yes	yes

Notes: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustering at the LMR level. Each coefficient in the table presents the result of a separate regression. Separate regression by task group. See notes to Table 4.3. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

Table 4.7 shows that the reduction in education requirements occurs within routine occupations. For routine occupations, a one standard deviation increase in labor market tightness is associated with an increase in the demand for medium (+1.17 pp) and low (+0.34 pp) educated workers and a decrease in the demand for highly educated workers (-0.62 pp). In addition, a one standard deviation increase in labor market tightness is associated with a 0.8 percentage point decrease in the share of vacancies with no educational requirement. Conversely, I find that a one standard deviation increase in labor market tightness is associated with an increase in the share of vacancies with high education requirements for non-routine cognitive occupations. However, I do not find a significant relationship between labor market tightness and skill demand for non-routine manual occupations.[25] The results are consistent with the results by occupational skill level. The likelihood of skill adjustment is lower in more complex occupations. This is the case for expert and specialist occupations and non-routine cognitive occupations. However, routine and skilled occupations, which on average have lower skill requirements, are more likely to experience a reduction in education requirements.

Firm Characteristics

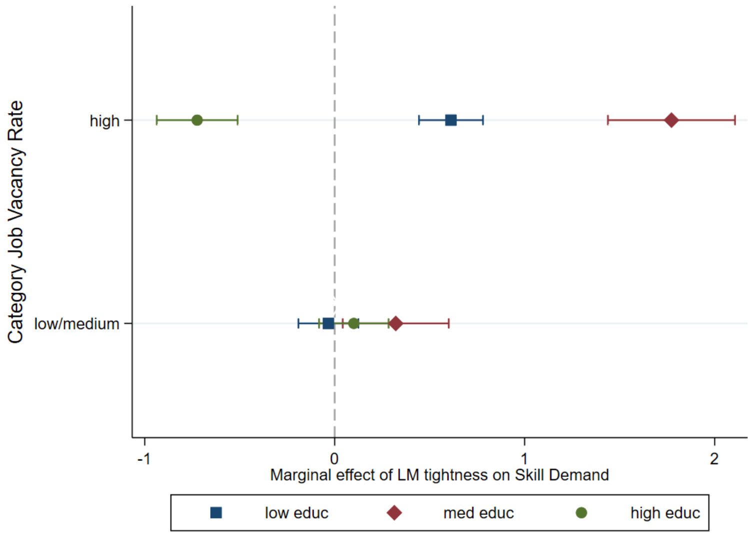
As Davis et al. (2013) show, there is considerable variation in matching efficiency across establishments. Lowering hiring standards is one way of influencing this. Hence, I examine the heterogeneity in educational skill adjustments across firms. I focus on the role of vacancy rates and industry heterogeneity. I use data from the German Business Register to further disaggregate the OJV dataset by firm type. This allows me to construct the outcome variable, skill demand, at this level. However, the data on labor market tightness do not vary by firm type. This implies that all hiring firms face the same labor market tightness in a given occupation in a labor market. Therefore, I pool the data and include an interaction term between tightness and firm type as well as a fixed effect for firm type.

Studies show that growing firms are less selective, while larger firms grow more slowly and therefore increase their hiring standards (Baydur, 2017; Carrillo-Tudela et al., 2023a). Therefore, I test whether firms with a higher demand for labor lower their educational requirements more than firms with a lower demand for labor. To do so, I proxy labor demand with the job vacancy rate, which I construct by relating the average number of job postings to initial employment at the firm level.[26] I distinguish between firms with a high vacancy rate and those with a low vacancy rate. The assignment is based on the quartiles of the vacancy rate distribution: high

[25]It should be noted that the OJV data are biased toward the demand for higher-skilled applicants, and therefore the demand for non-routine manual occupations is underrepresented in the online vacancy data (Carrillo-Tudela et al., 2023b).

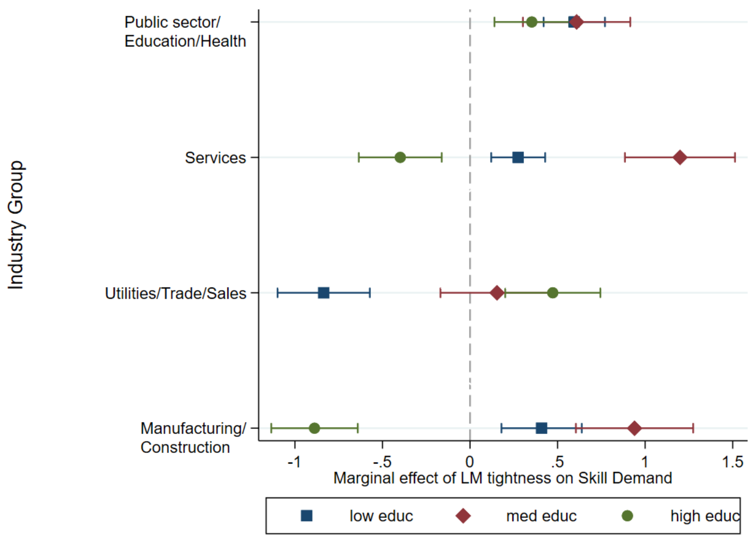
[26]Employment data come from the business register and are fixed over time, so they are not affected by the number of postings and hires during the analysis period. In addition, the number of employees is only reported in ranges in the business register. As a solution, I estimate the number of employees using the midpoint of each range.

Figure 4.7.: Marginal effect of labor market tightness on educational skill demand by job vacancy rate



Notes: Marginal effect of LM tightness on skill demand by job vacancy rate category. The vertical lines present 95% confidence intervals. Standard errors are clustered at the LMR level. Job vacancy rate is defined as the ratio of job vacancies relative to initial employment. Separate regression by skill. The outcome variable is the share of OJV skill requirement. The regression includes $LMR \times occupation$ FE, year FE, and interactions for LMR, year, and occupation year. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

Figure 4.8.: Marginal effect of labor market tightness on educational skill demand by industry group



Notes: Marginal effects of LM tightness on skill demand by industry group. The vertical lines present 95% confidence intervals. Standard errors are clustered at the LMR level. Separate regression by skill. The outcome variable is the share of OJV skill requirement. The regression includes $LMR \times occupation$ FE, year FE, and interactions for LMR, year, and occupation year. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

(>4th quartile percentile) and medium to low (<4th quartile).[27]

[27] The vacancy rate distribution is calculated conditional on having any vacancy. The 75th percentile value is 0.2.

Figure 4.7 shows the marginal effects of labor market tightness on skill demand by vacancy rate category. Firms with a high job vacancy rate drive the adjustment in skill requirements. For these firms, a one standard deviation increase in labor market tightness is associated with an increase in the share of vacancies with medium (+1.6 pp) and low (+0.5 pp) education requirements, but a 0.6 percentage point decrease in the share of vacancies with high education requirements. In contrast, for firms with lower vacancy rates, there is no systematic relationship between labor market tightness and hiring standards.

Second, the analysis by industry group reveals significant heterogeneity (Figure 4.8). The decline in skill requirements takes place within services and within manufacturing and construction. This finding is consistent with that of Davis et al. (2013), who documented substantial variation in vacancy yields across industries. Differences in occupational structure and skill requirements are potential factors contributing to this variation.

4.6.2. Experience

OLS Results

To complement the results for the education requirements, I perform the same analysis for the experience requirements. Table 4.3 Panel A shows mixed evidence for the effect of labor market tightness on experience requirements. While a one standard deviation increase in labor market tightness is associated with a 0.09 percentage point decrease in the share of vacancies with high experience requirements, it is also associated with a 0.23 percentage point decrease in the share of vacancies with low experience requirements. This is accompanied by an increase in the share of vacancies with no experience requirements. The pattern of results remains the same when using singular instead of total skill requirements (see Table 4.3 Panel B). I also test for flexibility in experience requirements (*Hypothesis 1B*): First, I find that the combined demand for different levels of experience does not play a role (see Table 4.A8). Second, I find no evidence that firms increase the flexibility of experience requirements by targeting career changers (see Table 4.A8 column (3)).

Overall, the results indicate a decline in the importance of experience requirements as the labor market tightens, as evidenced by an increase in the number of vacancies with no experience requirements. This is accompanied by a decrease in demand for workers with low experience

Table 4.8.: Regression of labor market tightness on the demand for experience skills

	(1) low exp.	(2) med. exp.	(3) high exp.	(4) no exp.
Panel A: Overall Skill Demand				
LM Tightness	-0.229***	0.058	-0.092*	0.197**
	(0.054)	(0.060)	(0.050)	(0.089)
Panel B: Singular Skill Demand				
LM Tightness	-0.161***	0.094	-0.061	0.197**
	(0.044)	(0.060)	(0.041)	(0.089)
LMR × Occupation FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
LMR × Year FE	yes	yes	yes	yes
Occupation (2d) × Year FE	yes	yes	yes	yes
Observations	54,929	54,929	54,929	54,929

Notes: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustering at the LMR level. Labor market tightness is standardized with mean of zero and standard deviation of one. Each coefficient in the table presents the result of a separate regression. Regression is weighted using employment in LMR-occupation-year cell. The outcome variable is skill demand, the share of OJV in each LMR-occupation-year cell with skill requirement S. Alternative specification are reported in Table 4.A7. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

requirements and a slight decrease for those with high experience requirements. However, these results do not support *Hypotheses 1A* and *1B* outlined in section 4.2, suggesting that firms reduce skill requirements or increase the flexibility of skill requirements in response to tighter labor markets.

In addition, I examine the use of alternative adjustment mechanisms in the form of training provision and remote work. Consistent with the results on educational requirements, Figure 4.A6 shows that an increase in labor market tightness is associated with an increase in the provision of training for medium-experienced workers. The results support *Hypothesis 2* in section 4.2, which posits that firms offer training, particularly for medium-skilled workers, in response to increasing labor market tightness. However, the results do not suggest a significant increase in the supply of remote work in response to increasing labor market tightness.

IV Results

In order to mitigate endogeneity concerns, I run an instrumental variable regression using a leave-one-out instrument. The results of the estimation are reported in Table 4.9. The results confirm the pattern of the baseline results. However, the coefficients are significantly larger. The results suggest that a one standard deviation increase in labor market tightness is associated with a decrease in the share of vacancies with low (-1.1 percentage points) and high (-0.7 percentage points) experience requirements. In addition, the estimated coefficient on medium experience becomes significant, indicating that a one standard deviation increase in tightness is associated with a 0.37 increase in the demand for workers with medium experience. The IV estimation confirms the negative relationship between an increase in labor market tightness and a decrease in the share of vacancies with no experience requirements.

Table 4.9.: IV Regression of labor market tightness on the demand for experience skills

	(1)	(2)	(3)	(4)
	low exp.	med. exp.	high exp.	no exp.
Overall Skill Demand				
LM Tightness	-1.076***	0.374**	-0.742***	1.067***
	(0.168)	(0.161)	(0.155)	(0.241)
LMR × Occupation FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
LMR × Year FE	yes	yes	yes	yes
Occupation (2d) × Year FE	yes	yes	yes	yes
Observations	54,929	54,929	54,929	54,929

Notes: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustering at the LMR level. Labor market tightness is standardized with mean of zero and standard deviation of one. Each coefficient in the table presents the result of a separate regression. Regression is weighted using employment in LMR-occupation-year cell. The outcome variable skill demand is instrumented using the average labor market tightness across all other LMRs within the same occupation. The F-statistic of the first stage is 117.05. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

Heterogeneity

As for education, I also analyze heterogeneity across occupational skill levels, task groups, firm types, and industries. Consistent with the findings on education, adjustments in skill requirements occur mainly within skilled and routine occupations (see Tables 4.A10 and 4.A10). Within these occupational groups, an increase in labor market tightness is associated with an overall decrease in the share of jobs requiring any experience requirement and a decrease in the share of jobs requiring little experience. However, for experts and specialists, the share of vacancies with experience requirements increases in response to increasing labor market tightness, but with no effect on any particular experience group.

I also consider heterogeneity in the effect across firm types and by industry. First, the reduction in experience requirements in response to an increase in labor market tightness is concentrated in firms with a high job vacancy rate and in the service sector (see Figure 4.A7 and 4.A8). This is consistent with the findings for education, which show that skill adjustment is concentrated in firms with high vacancy rates and in services. In contrast to the findings for education, I find no evidence of skill adjustment in manufacturing and construction.

4.6.3. Robustness

In order to test the strength and reliability of the results presented in the previous sections, I conduct several robustness checks. On the one hand, I address possible model misspecification and, on the other hand, I analyze the role of Covid19 and compositional changes in the dataset over time.

To address misspecification concerns, I perform the following checks: First, to strengthen the robustness of the results, I estimate a model using changes in labor market tightness and skill requirements instead of levels. This approach is similar to the methodology of Modestino et al. (2020) and Hershbein and Kahn (2018), who analyze changes in skill requirements after the US Great Recession. The results presented in Table 4.A11 are very consistent with the baseline results. They confirm that the increase in labor market tightness is associated with firms lowering their educational requirements.

Second, to mitigate concerns about reverse causality from skill requirements to labor market tightness, I estimate the model using lagged labor market tightness (see Table 4.A12). The results confirm those of the baseline analysis. Third, I examine potential nonlinearity in the relationship between labor market tightness and skill demand by including squared labor market tightness in the model (see Table 4.A13). The results support a linear relationship.

Given that my analysis period includes the years of the Covid19 pandemic, there is some concern that the pandemic may have biased the results. As discussed in section 4.4, the pandemic initially caused a brief decrease in labor market tightness, followed by a sharp increase. Table 4.A14 presents results excluding the years 2020 and 2021. However, excluding these years does not significantly change the results. Furthermore, I can rule out that my results are driven by extreme values (Table 4.A15). To account for this, I top-code labor market tightness at the 95th percentile.

In a final step, I test for the contribution of compositional changes in the dataset. To do this, I follow two approaches. First, I restrict the sample to firms that have already posted job vacancies in 2017 (Table 4.A16). Second, I restrict the sample to those firms that post job vacancies in each year between 2017 and 2023 (Table 4.A17). While this approach reduces concerns about sample selection, it shifts the composition of the dataset towards firms that post more frequently, which are most likely to be larger firms. The results confirm the pattern of the baseline results. In particular, the results confirm that an increase in labor market tightness is associated with an increase in the share of vacancies with medium and low educational requirements and a decrease in the share of vacancies targeted at workers with low experience. Qualitatively similar but less significant results are obtained for high levels of experience and education.

4.7. Conclusion

Labor market tightness has increased strongly in Germany over the past decade, posing a recruitment challenge for firms. In this paper, I analyze whether firms respond to a tightening labor market by adjusting their skill requirements in terms of education, but also experience. For the analysis, I combine data from the near universe of online job postings and data from the German Federal Employment Agency for the period 2017-2023.

My key finding is that firms lower their educational requirements in response to tightening labor markets. According to the preferred OLS specification, an increase in local labor market tightness from the 25th to the 75th percentile of the distribution is associated with a 0.60 and 0.17 percentage point increase in the share of vacancies requiring medium and low levels of education, respectively, while the share of high-education vacancies decreases by 0.15 percentage points. I find evidence for two underlying mechanisms: First, a demand shift from higher- to lower-skilled workers, and second, greater flexibility in educational skill requirements for the hiring of medium- and low-skilled workers.

My second finding is that an increase in labor market tightness is correlated with increased provision of on-the-job training for medium-skilled workers. This suggests that in addition to lowering skill requirements, firms complement this adjustment by offering additional training to fill potential skill gaps. The heterogeneity analysis reveals notable differences across occupations, with skill adjustment occurring in less complex, routine occupations. This points to the role of occupational licensing and minimum entry requirements in more complex, non-routine occupations, limiting the scope for skill adjustment. Moreover, I find that the decline in hiring standards is driven by firms with high labor demand, indicating that they are particularly affected by labor shortages.

In a complementary analysis, I also examine the adjustment of experience requirements. However, the results regarding experience are mixed. The results suggest an overall decrease in experience requirements, accompanied by a decrease in the share of low and a slight decrease in the share of high experience vacancies.

Overall, the results show that firms adjust their skill requirements in response to changes in labor market tightness, and even suggest that firms increasingly provide training for medium-skilled workers. These findings have important policy implications, as they imply that policies targeting job search and skill development will also affect firms' hiring efforts, thereby shaping the intended outcomes of such policies.

Reducing skill requirements benefits low-skilled workers by improving their job opportunities and access to on-the-job training, but it can also exacerbate skill mismatches and potentially hinder firm productivity (McGowan and Andrews, 2015). However, measuring the actual skills mismatch is challenging and requires comprehensive data on both worker skills and job requirements (Perry et al., 2014). The integration of these data sources is a promising avenue for potential research to address this issue.

While OJV data provide useful insights into a firms' recruitment processes, there is a difference between skill adjustments in vacancies and changes in actual hiring practices. Although beyond the scope of this paper, the impact of the labor shortage on the skill level of the actual new hires remains an interesting question for future research. In addition, there is evidence of a shift from degree-based to skills-based hiring for the US (Fuller et al., 2024). While I do not observe an increase in vacancies with no college degree, I do observe a shift from college degrees to vocational degrees. Therefore, the analysis of skills-based recruitment, especially in the context of labor shortages and technological change, would appear to be an interesting area for future research.

Bibliography

Abraham, K. G., Haltiwanger, J. C., and Rendell, L. E. (2020). How tight is the us labor market? *Brookings Papers on Economic Activity*, 2020(1):97–165.

Acemoglu, D. and Autor, D. H. (2011). Skills, tasks and technologies: Implications for employment and earnings. In Card, D. and Ashenfelter, O., editors, *Handbook of Labor Economics*, pages 1043–1171. Elsevier.

Acemoglu, D. and Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review*, 108(6):1488–1542.

Alipour, J.-V., Langer, C., and O'Kane, L. (2021). Is working from home here to stay? A look at 35 million job ads. *CESifo Forum*, 22(6).

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, 118(4):1279–1333.

Azar, J., Marinescu, I., and Steinbaum, M. (2022). Labor market concentration. *Journal of Human Resources*, 57(S):S167–S199.

BA (2020). Grundlagen: Methodenbericht – Engpassanalyse – Methodische Weiterentwicklung. Technical report, German Federal Employment Agency. Accessed: 2023-08-14.

Baydur, I. (2017). Worker selection, hiring, and vacancies. *American Economic Journal: Macroeconomics*, 9(1):88–127.

Ben Yahmed, S., Berlingieri, F., and Brüll, E. (2022). Adjustments of local labour markets to the COVID-19 crisis: The role of digitalisation and working-from-home. ZEW Discussion Paper No. 22-031, ZEW-Centre for European Economic Research.

Bossler, M. and Popp, M. (2023). Arbeitsmarktanspannung aus beruflicher und regionaler Sicht: Die steigende Knappheit an Arbeitskräften bremst das Beschäftigungswachstum. IAB-Kurzbericht No. 12/2023, IAB - Institute for Employment Research.

Bossler, M. and Popp, M. (2024). Labor demand on a tight leash. IZA-Discussion Paper No. 16837, IZA-Institute of Labor Economics.

Brunow, S., Lösch, S., and Okhrin, O. (2022). Labor market tightness and individual wage growth: Evidence from Germany. *Journal for Labour Market Research*, 56(1):16.

Bundesagentur für Arbeit (2023). Fachkräfteengpassanalyse 2022. Technical report, German Federal Employment Agency.

Burn, I., Button, P., Corella, L. M., and Neumark, D. (2022a). Does ageist language in job ads predict age discrimination in hiring? *Journal of Labor Economics*, 40(3):613–667.

Burn, I., Firoozi, D., Ladd, D., and Neumark, D. (2022b). Help really wanted? The impact of age stereotypes in job ads on applications from older workers. NBER Working Paper No. 30287, National Bureau of Economic Research.

Burstedde, A., Flake, R., Jansen, A., Malin, L., Risius, P., Seyda, S., Schirner, S., and Werner, D. (2020). Die Messung des Fachkräftemangels. Methodik und Ergebnisse aus der IW-Fachkräftedatenbank zur Bestimmung von Engpassberufen und zur Berechnung von Fachkräftelücken und anderen Indikatoren. IW-Report No. 59, IW - Institut der deutschen Wirtschaft e.V.

Burstedde, A. and Risius, P. (2017). Fachkräfteengpässe in Unternehmen: Regionale Fachkräftesituation und Mobilität. KoFa-Studie No. 2, IW - Institut der deutschen Wirtschaft e.V.

Burstedde, A. and Schüler, R. M. (2020). Reagieren Löhne in Deutschland auf den Fachkräftemangel? *IW-Trends-Vierteljahresschrift zur empirischen Wirtschaftsforschung*, 47(4):45–66.

Cappelli, P. H. (2015). Skill gaps, skill shortages, and skill mismatches: Evidence and arguments for the United States. *ILR review*, 68(2):251–290.

Carrillo-Tudela, C., Gartner, H., and Kaas, L. (2023a). Recruitment policies, job-filling rates, and matching efficiency. *Journal of the European Economic Association*, 21(6):2413–2459.

Carrillo-Tudela, C., Kaas, L., and Lochner, B. (2023b). Matching through search channels. Discussion Paper 16583, IZA - Institute of Labor Economics.

Causa, O., Abendschein, M., Luu, N., Soldani, E., and Soriolo, C. (2022). The post-COVID-19 rise in labour shortages. OECD Economics Department Working Papers No. 1721, OECD.

Chugh, S. K. and Merkl, C. (2016). Efficiency and labor market dynamics in a model of labor selection. *International Economic Review*, 57(4):1371–1404.

Coskun, S., Dauth, W., Gartner, H., Stops, M., and Weber, E. (2024). Working from home increases work-home distances. IZA Discussion Paper No. 16855, IZA - Institute of Labor Economics.

Czepek, J., Dummert, S., Kubis, A., Leber, U., Müller, A., and Stegmaier, J. (2015). Betriebe im Wettbewerb um Arbeitskräfte: Bedarf, Engpässe und Rekrutierungsprozesse in Deutschland. IAB-Bibliothek No. 352, IAB - Institute for Employment Research.

Davis, S. J., Faberman, R. J., and Haltiwanger, J. C. (2013). The establishment-level behavior of vacancies and hiring. *The Quarterly Journal of Economics*, 128(2):581–622.

Del Carpio, L. and Fujiwara, T. (2023). Do gender-neutral job ads promote diversity? Experimental evidence from Latin America's tech sector. NBER Discussion Paper No. 31314, National Bureau of Economic Research.

Deming, D. and Kahn, L. B. (2018). Skill requirements across firms and labor markets: Evidence from job postings for professionals. *Journal of Labor Economics*, 36(S1):S337–S369.

Dolado, J. J., Jansen, M., and Jimeno, J. F. (2009). On-the-job search in a matching model with heterogeneous jobs and workers. *The Economic Journal*, 119(534):200–228.

Duval, M. R. A., Duval, R., Ji, Y., Li, L., Oikonomou, M., Pizzinelli, C., Shibata, M. I., Sozzi, A., and Tavares, M. M. (2022). Labor market tightness in advanced economies. IMF Staff Discussion Notes No. 2022/001, International Monetary Fund.

Federal Employment Agency (2021). Klassifikation der Berufe 2010–überarbeitete Fassung 2020 Band 1: Systematischer und alphabetischer Teil mit Erläuterungen. Technical report, German Federal Employment Agency (BA).

Flory, J. A., Leibbrandt, A., Rott, C., and Stoddard, O. (2021). Increasing workplace diversity: Evidence from a recruiting experiment at a fortune 500 company. *Journal of Human Resources*, 56(1):73–92.

Forsythe, E. and Weinstein, R. (2021). Recruiting intensity, hires, and vacancies: Evidence from firm-level data. IZA Discussion Paper No. 14138, IZA - Institute of Labor Economics.

Fuchs, M. and Weyh, A. (2018). Demografischer Wandel und Arbeitsmarkt. *Blätter der Wohlfahrtspflege (BdW)*, 165(2):50–53.

Fuller, J. B., Sigelman, M., and Martin, A. (2024). Skills-based hiring: The long road from pronouncements to practice.

Gathmann, C., Kagerl, C., Pohlan, L., and Roth, D. (2023). The pandemic push: Digital technologies and workforce adjustments. IZA Discussion Paper 16062, IZA - Institute of Labor Economics.

Gavazza, A., Mongey, S., and Violante, G. L. (2018). Aggregate recruiting intensity. *American Economic Review*, 108(8):2088–2127.

Gentzkow, M., Kelly, B., and Taddy, M. (2019). Text as data. *Journal of Economic Literature*, 57(3):535–574.

Grienberger, K., Janser, M., and Lehmer, F. (2023). The occupational panel for germany. *Jahrbücher für Nationalökonomie und Statistik*, 243(6):711–724.

Haasler, S. R. (2020). The german system of vocational education and training: challenges of gender, academisation and the integration of low-achieving youth. *Transfer: European Review of Labour and Research*, 26(1):57–71.

Hamann, S., Niebuhr, A., Roth, D., and Sieglen, G. (2023). How does the COVID-19 pandemic affect regional labour markets and why do large cities suffer most? IAB - Discussion Paper No. 3/2023, IAB - Institute for Employment Research.

Hershbein, B. and Kahn, L. B. (2018). Do recessions accelerate routine-biased technological change? Evidence from vacancy postings. *American Economic Review*, 108(7):1737–1772.

IAB (2023). Aktuelle Ergebnisse - IAB Stellenerhebung. `https://iab.de/das-iab/befragungen/iab-stellenerhebung/aktuelle-ergebnisse/`. Accessed: 2023-10-18.

Jung, P. and Kuhn, M. (2014). Labour market institutions and worker flows: Comparing Germany and the US. *The Economic Journal*, 124(581):1317–1342.

Kiss, Á., Morandini, M. C., Turrini, A., and Vandeplas, A. (2022). Slack and tightness: Making sense of post COVID-19 labour market developments in the EU. European Commission Discussion Papers No. 178, European Commission.

Klinger, S. and Fuchs, J. (2020). Wie sich der demografische Wandel auf den deutschen Arbeitsmarkt auswirkt. In *IAB-Forum, IAB-Institute for Employment Research*.

Kosfeld, R. and Werner, A. (2012). Deutsche arbeitsmarktregionen: Neuabgrenzung nach den kreisgebietsreformen 2007–2011. *Spatial Research and Planning*, 70(1).

Koumenta, M. and Pagliero, M. (2017). Measuring prevalence and labour market impacts of occupational regulation in the Eu. Final report, European Commission.

Kubis, A. (2023). IAB-Stellenerhebung 1/2023: 1,75 Millionen offene Stellen am Arbeitsmarkt. `https://www.iab-forum.de/iab-stellenerhebung-1-2023-175-millionen-offene-stellen-am-arbeitsmarkt/`. accessed: 2024-05-18.

Landais, C., Michaillat, P., and Saez, E. (2018). A macroeconomic approach to optimal unemployment insurance: Theory. *American Economic Journal: Economic Policy*, 10(2):152–181.

Langer, C. and Wiederhold, S. (2023). The value of early-career skills. CESifo Working Paper 10288, CESifo.

Leduc, S. and Liu, Z. (2020). The weak job recovery in a macro model of search and recruiting intensity. *American Economic Journal: Macroeconomics*, 12(1):310–343.

Lochner, B., Merkl, C., Stüber, H., and Gürtzgen, N. (2021). Recruiting intensity and hiring practices: Cross-sectional and time-series evidence. *Labour Economics*, 68:101939.

McGowan, M. A. and Andrews, D. (2015). Skill mismatch and public policy in oecd countries. OECD Economics Department Working Papers 1210, OECD.

Merkl, C. and Van Rens, T. (2019). Selective hiring and welfare analysis in labor market models. *Labour Economics*, 57:117–130.

Modestino, A. S., Shoag, D., and Ballance, J. (2016). Downskilling: Changes in employer skill requirements over the business cycle. *Labour Economics*, 41:333–347.

Modestino, A. S., Shoag, D., and Ballance, J. (2020). Upskilling: Do employers demand greater skill when workers are plentiful? *The Review of Economics and Statistics*, 102(4):793–805.

Mongey, S. and Violante, G. L. (2019). Macro recruiting intensity from micro data. NBER Discussion Paper 26231, National Bureau of Economic Research.

Mortensen, D. T. and Pissarides, C. A. (1999). New developments in models of search in the labor market. *Handbook of labor economics*, 3:2567–2627.

Peichl, A., Sauer, S., and Wohlrabe, K. (2022). Fachkräftemangel in Deutschland und Europa–Historie, Status quo und was getan werden muss. *ifo Schnelldienst*, 75(10):70–75.

Perry, A., Wiederhold, S., and Ackermann-Piek, D. (2014). How can skill mismatch be measured? new approaches with piaac. *methods, data, analyses*, 8(2):38.

Pissarides, C. A. (2000). *Equilibrium unemployment theory.* MIT press.

Postel-Vinay, F. and Robin, J.-M. (2002). Equilibrium wage dispersion with worker and employer heterogeneity. *Econometrica*, 70(6):2295–2350.

Qiu, Y. and Sojourner, A. (2023). Labor-market concentration and labor compensation. *ILR Review*, 76(3):475–503.

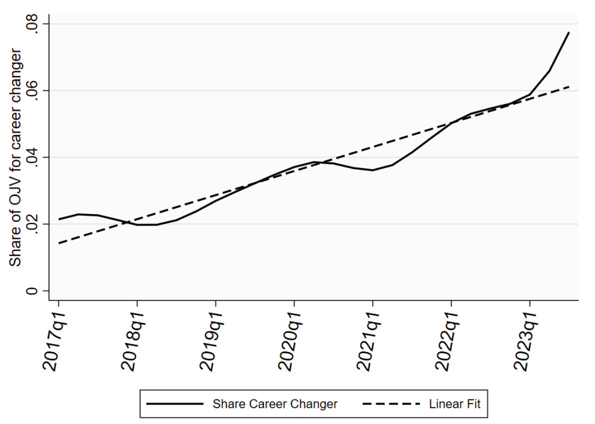
Rinz, K. (2024). Labor market concentration, earnings, and inequality. *Journal of Human Resources*, 59(S). Published online before print October 12, 2020.

Senghaas, M. and Struck, O. (2023). Arbeits-und Personalsituation in der Alten- und Krankenpflege: Wie beurteilen Beschäftigte und Führungskräfte Belastungsfaktoren, Ressourcen und Handlungsmöglichkeiten? IAB-Forschungsbericht No. 8/2023, IAB - Institute for Employment Research.

Stevens, P. A. (2007). Skill shortages and firms' employment behaviour. *Labour Economics*, 14(2):231–249.

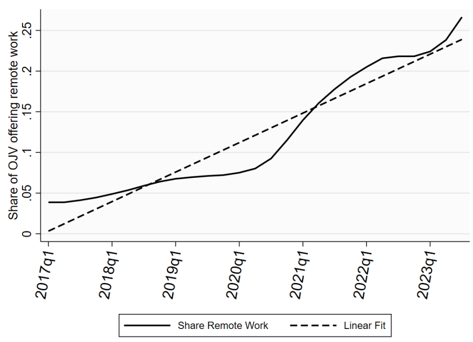
4.A. Additional Figures and Tables

Figure 4.A1.: Trend demand career changers

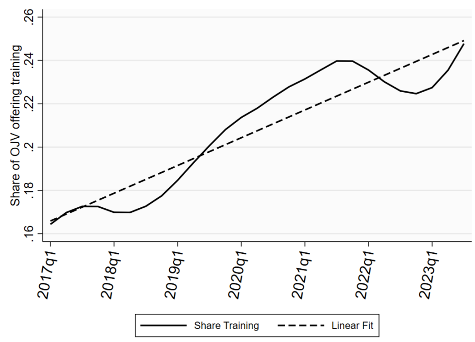


Notes: The figures shows the share of vacancies with demand for career changers by quarter over the years. Each LMR-occupation-year cell is weighted by the FEA employment data in that cell. Source: Source: Palturai GmbH/Finbot AG (OJV data) 2017-2021; FEA data 2017-2013; own calculations.

Figure 4.A2.: Trend remote work and training



(a) Remote work



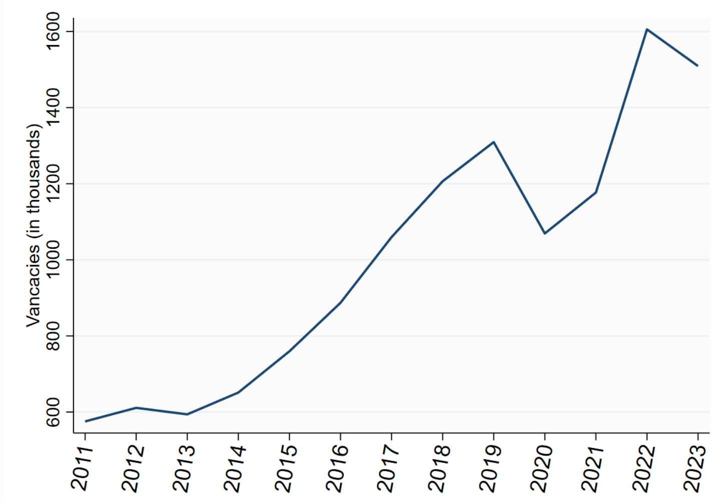
(b) Training

Notes: The figures shows the share of vacancies that offer remote work or training by quarter over the years. Each LMR-occupation-year cell is weighted by the FEA employment data in that cell. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

Figure 4.A3.: Trend in labor market tightness 2011-2023 by occupational skill level

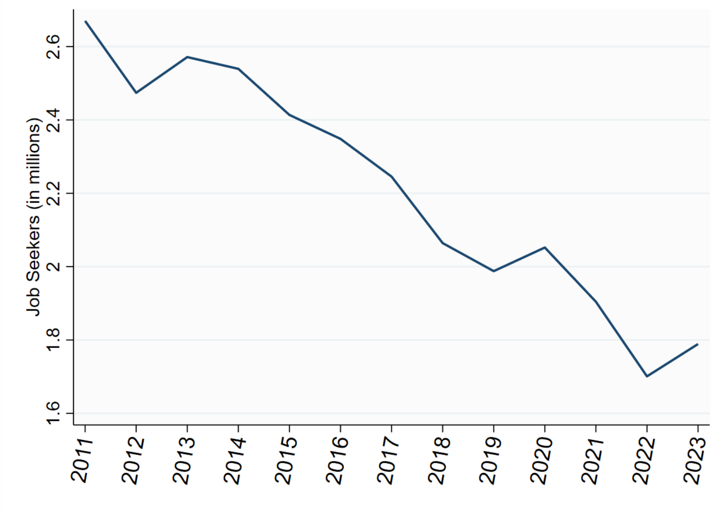
Notes: Labor market tightness is the ratio of vacancies to jobseekers by skill level as indicated by the fifth digit of the occupational classification. Source: FEA data 2011-2023; own calculations.

Figure 4.A4.: Trend in vacancies 2011-2023



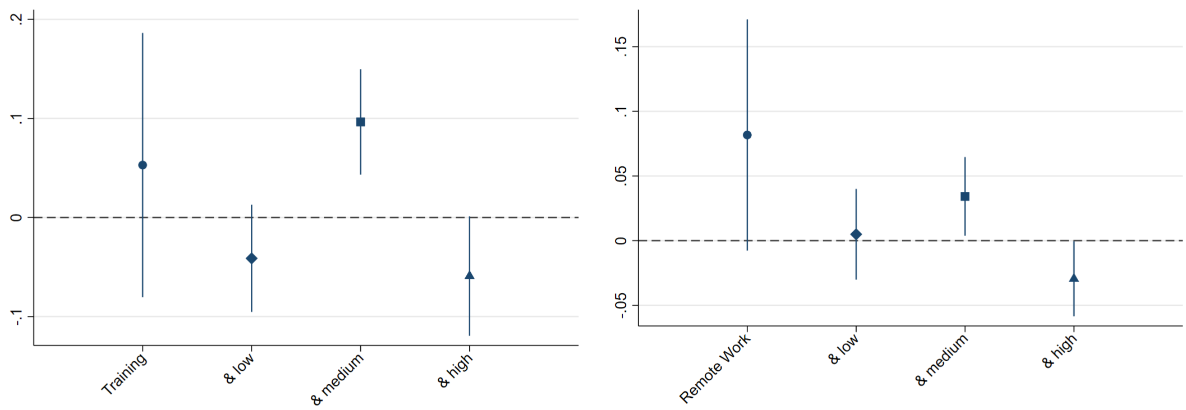
Source: FEA data 2011-2023; own calculations.

Figure 4.A5.: Trend in job seekers 2011-2023



Source: FEA data 2011-2023; own calculations.

Figure 4.A6.: Coefficient plots of labor market tightness on experience skill demand and benefits

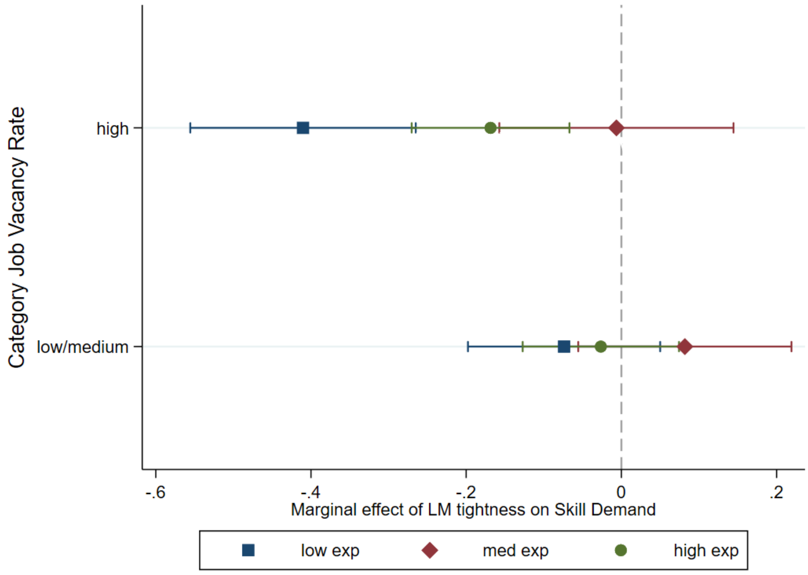


(a) Training and experience skills

(b) Remote Work and experience skills

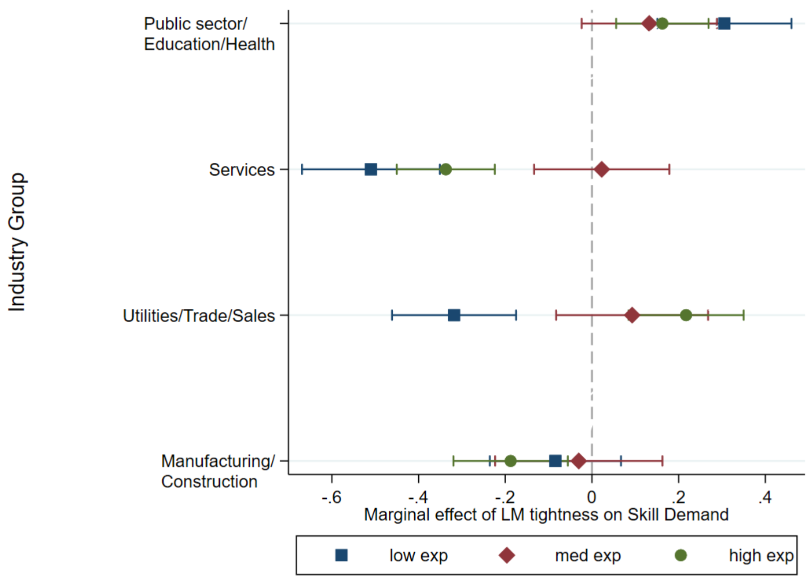
Notes: Each point estimate represents the coefficient from a separate regression. Vertical lines represent 95% confidence intervals. Standard errors are clustered at the LMR level. The outcome variable is the share of OJV that provides benefit (training/remote work) and states the specific skill requirement. The regression includes $LMR \times$ *occupation* FE, year FE, and interactions for LMR, year, and occupation year. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

Figure 4.A7.: Marginal effect of labor market tightness on experience skill demand by job vacancy rate



Notes: Marginal effect of LM tightness on skill demand by job vacancy rate category. The vertical lines present 95% confidence intervals. Standard errors are clustered at the LMR level. Job vacancy rate is defined as the ratio of job vacancies relative to initial employment. Separate regression by skill. The outcome variable is the share of OJV skill requirement. The regression includes $LMR \times occupation$ FE, year FE, and interactions for LMR, year, and occupation year. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

Figure 4.A8.: Marginal effect of labor market tightness on experience skill demand by industry group



Notes: Marginal effects of LM tightness on skill demand by job vacancy rate category. The vertical lines present 95% confidence intervals. Standard errors are clustered at the LMR level. Separate regression by skill. The outcome variable is the share of OJV skill requirement. The regression includes $LMR \times occupation$ FE, year FE, and interactions for LMR, year, and occupation year. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

Table 4.A1.: Sample selection OJV data

Description	Sample Size (%)
Full sample	100
- Temporary work agencies	56.3
- Recruiting agency	55.3
- No firm ID	27.5
- No location	27.5
- No irregular work	23.2
- No occupation code	14.7
- Token restriction [$1000 < X < 50$]	13.2

Note: The table shows the percentage of observations that are dropped from the analysis when the filters are applied. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; own calculations.

Table 4.A2.: Demand for career changer in 2017

Occupational title (KldB2010 3-digit)	(in %)
522: Vehicle guidance in rail transport	40.5
515: Monitoring and control of transport operations	36.6
512: Monitoring and maintenance of transport infrastructure	23.2
291: Beveridge production	17.1
623: Food sales	9.0
621: Sales (without product specialization)	8.1
514: Service staff in passenger transportation	6.9
914: Economics	6.1
211: Mining, open-cast mining and blasting technology	5.9
711: Manager	5.7

Notes: Demand for career changer is the share of vacancies targeting career changers relative to all vacancy postings in 2017. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; own calculations.

Table 4.A3.: Change demand for career changer: 2017-2023

Occupational title (KldB2010 3-digit)	(in pp)
Occupational Group (3-digit) 623: Food Sales	36.4
514: Service staff in passenger transportation	30.3
824: Funeral services	25.1
233: Photo technology and photography	21.2
541: Cleaning	17.0
621: Sales (without product specialization)	16.9
612: Trade	16.3
513: Warehousing, post and delivery, goods handling	14.7
292: Food and luxury food production	13.2
622: Sales textiles, electronics, vehicles and hardware	13.1

Notes: Demand for career changer is the share of vacancies targeting career changers relative to all vacancy postings in 2017. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; own calculations.

Table 4.A4.: Labor market tightness 2017: Top 10 occupations

Occupational title (KldB2010 3-digit)	Labor Market Tightness
522: Conductor rail transport	2.73
813: Healthcare and nursing	2.28
342: Plumbing, sanitation, heating and air conditioning	2.28
817: Non-medical therapy and medical treatment	2.03
825: Medical, orthopaedic and rehabilitation technology	1.92
261: Mechatronics and automation technology	1.81
262: Energy technology	1.73
311: Construction planning and supervision, architecture	1.56
431: Information technology	1.53
512: Monitoring/maintenance transportation infrastructure	1.48

Notes: Labour market tightness is defined as the ratio of registered vacancies to job seekers. Source: FEA data 2017-2023; own calculations.

Table 4.A5.: Change labor market tightness 2017-2023: Top 10 occupations

Occupational Title	Δ Labor Tightness
723: Conductor rail transport	2.44
723: Tax consultancy	2.37
261: Mechatronics and automation technology	1.89
515: Monitoring and control of traffic operations	1.69
322: Civil engineering	1.68
263: Electrical engineering	1.27
262: Energy technology	1.27
312: Surveying and cartography	1.13
342: Plumbing, sanitation, heating and air conditioning	1.05
732: Administration	1.07

Notes: Labour market tightness is defined as the ratio of registered vacancies to job seekers. Source: FEA data 2017-2023; own calculations.

Table 4.A6.: Regression of labor market tightness on educational skill demand

	(1)	(2)	(3)
Demand low education			
LM Tightness	0.242***	0.442***	0.228***
	(0.075)	(0.073)	(0.060)
Demand medium education			
LM Tightness	0.618***	0.514***	0.767***
	(0.137)	(0.108)	(0.119)
Demand high education			
LM Tightness	0.059	0.067	-0.206**
	(0.087)	(0.077)	(0.079)
Demand no education			
LM Tightness	-0.644***	-0.646***	-0.543***
	(0.121)	(0.118)	(0.104)
LMR X Occupation FE	yes	yes	yes
Year FE	yes	yes	yes
LMR X Year	no	yes	yes
Occupation (2d) X Year FE	no	no	yes
Observations	54,929	54,929	54,929

Notes: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each coefficient in the table presents the result of a separate regression. The outcome variable is skill demand, the share of OJV in each LMR-occupation-year cell with skill requirement S as indicated in the left column. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

Table 4.A7.: Regression of labor market tightness on demand for experience skills

	(1)	(2)	(3)
Demand low experience			
LM Tightness	-0.027	-0.047	-0.229***
	(0.046)	(0.052)	(0.054)
Demand medium experience			
LM Tightness	-0.046	-0.012	0.058
	(0.051)	(0.053)	(0.060)
Demand high experience			
LM Tightness	-0.122***	-0.197***	-0.092*
	(0.045)	(0.048)	(0.049)
Demand no experience			
LM Tightness	0.255***	0.305***	0.197**
	(0.083)	(0.087)	(0.089)
LMR X Occupation FE	yes	yes	yes
Year FE	yes	yes	yes
LMR X Year	no	yes	yes
Occupation (2d) X Year FE	no	no	yes
Observations	54,929	54,929	54,929

Notes: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each coefficient in the table presents the result of a separate regression. The outcome variable is skill demand, the share of OJV in each LMR-occupation-year cell with skill requirement S as indicated in the left column. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

Table 4.A8.: Regression of labor market tightness on the demand for experience skills: flexibility in skill requirements

	(1) low & medium	(2) medium & high	(3) career changer
LM Tightness	-0.035**	0.003	-0.070
	(0.016)	(0.015)	(0.061)
LMR X Occupation FE	yes	yes	yes
Year FE	yes	yes	yes
LMR X Year FE	yes	yes	yes
Occupation (2d) X Year FE	yes	yes	yes
Observations	54,929	54,929	54,929

Notes: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Clustering at the LMR level. Labor market tightness is standardized with mean of zero and standard deviation of one. Each coefficient in the table presents the result of a separate regression. Regression is weighted using employment in LMR-occupation-year cell. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

Table 4.A9.: Regression of labor market tightness on the demand for experience skills by occupational skill group

	(1) low exp.	(2) med. exp.	(3) high exp.	(4) no exp.
Skilled Workers				
LM Tightness	-0.243***	-0.006	-0.019	0.228**
	(0.066)	(0.066)	(0.048)	(0.095)
Observations	36,057	36,057	36,057	36,057
Experts & Specialists				
LM Tightness	0.063	0.078	0.034	-0.199**
	(0.063)	(0.056)	(0.050)	(0.079)
Observations	32,886	32,886	32,886	32,886
LMR X Occupation FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
LMR X Year	yes	yes	yes	yes
Occupation (2d) X Year FE	yes	yes	yes	yes

Notes: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each coefficient in the table presents the result of a separate regression. Separate regression by skill level. See notes to Table 4.8. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

Table 4.A10.: Regression of labor market tightness on the demand for experience skills by task group

	(1) low exp.	(2) med. exp.	(3) high exp.	(4) no exp.
Routine occupations				
LM Tightness	-0.514***	0.087	-0.088	0.384***
	(0.087)	(0.101)	(0.071)	(0.117)
Observations	29,526	29,526	29,526	29,526
NRM occupations				
LM Tightness	-0.042	0.000	-0.095	0.075
	(0.119)	(0.129)	(0.107)	(0.212)
Observations	6,909	6,909	6,909	6,909
NRC occupations				
LM Tightness	-0.019	-0.025	0.011	-0.045
	(0.092)	(0.074)	(0.055)	(0.128)
Observations	18,438	18,438	18,438	18,438
LMR X Occupation FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
LMR X Year	yes	yes	yes	yes
Occupation (2d) X Year FE	yes	yes	yes	yes

Notes: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each coefficient in the table presents the result of a separate regression. Separate regression by task group. See notes to Table 4.8. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

Table 4.A11.: Regression of change in labor market tightness on change in skill demand

	Experience			Education		
	low	med.	high	low	med.	high
Change LM Tightness	-0.386***	-0.076	-0.208 **	0.310***	0.887***	-0.365**
	(0.122)	(0.110)	(0.092)	(0.097)	(0.229)	(0.158)
LMR X Occ FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
LMR X Year	yes	yes	yes	yes	yes	yes
Occ (2d) X Year FE	yes	yes	yes	yes	yes	yes
Observations	7,847	7,847	7,847	7,847	7,847	7,847

Notes: Standard errors in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Each coefficients presents the estimate of a separate regression. Outcome is the change in LM tightness between 2017 and 2023. In addition, I include controls for skill levels in baseline year. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

Table 4.A12.: Regression of lagged labor market tightness on skill demand

	Experience			Education		
	low	med.	high	low	med.	high
L1.Tightness	-0.097*	0.052	-0.134**	0.162***	0.572***	-0.269***
	(0.054)	(0.060)	(0.054)	(0.052)	(0.123)	(0.097)
LMR X Occ FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
LMR X Year	yes	yes	yes	yes	yes	yes
Occ (2d) X Year FE	yes	yes	yes	yes	yes	yes
Observations	54,929	54,929	54,929	54,929	54,929	54,929

Notes: See Table 4.3. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

Table 4.A13.: Regression with squared labor market tightness

	Experience			Education		
	low	med.	high	low	med.	high
LM Tightness	-0.267***	0.008	-0.190**	0.327***	1.057***	-0.503***
	(0.085)	(0.094)	(0.077)	(0.098)	(0.163)	(0.122)
$(LM\ Tightness)^2$	0.005	0.007	0.014**	-0.014*	-0.041***	0.042***
	(0.006)	(0.007)	(0.006)	(0.008)	(0.014)	(0.012)
LMR X Occ FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
LMR X Year	yes	yes	yes	yes	yes	yes
Occ (2d) X Year FE	yes	yes	yes	yes	yes	yes
Observations	54,929	54,929	54,929	54,929	54,929	54,929

Notes: See Table 4.3. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

Table 4.A14.: Regression without years of Covid19 pandemic

	Experience			Education		
	low	med.	high	low	med.	high
LM Tightness	-0.194***	0.050	-0.083*	0.348***	0.897***	-0.233**
	(0.069)	(0.072)	(0.048)	(0.078)	(0.146)	(0.093)
LMR X Occ FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
LMR X Year	yes	yes	yes	yes	yes	yes
Occ (2d) X Year FE	yes	yes	yes	yes	yes	yes
Observations	39,235	39,235	39,235	39,235	39,235	39,235

Notes: For the analysis the years of the Covid19 pandemic (2020 and 2021) are excluded. See Table 4.3. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

Table 4.A15.: Regression top-coded labor market tightness

	Experience			Education		
	low	med.	high	low	med.	high
LM Tightness	-0.227***	0.063	-0.113**	0.259***	0.856***	-0.271***
	(0.062)	(0.070)	(0.054)	(0.068)	(0.128)	(0.087)
LMR X Occ FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
LMR X Year	yes	yes	yes	yes	yes	yes
Occ (2d) X Year FE	yes	yes	yes	yes	yes	yes
Observations	54,929	54,929	54,929	54,929	54,929	54,929

Notes: LM Tightness is top-coded at the 95 percentile. See Table 4.3. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

Table 4.A16.: Regression sample conditional on posting firms in 2017

	Experience			Education		
	low	med.	high	low	med.	high
LM Tightness	-0.260***	0.122	-0.054	0.218***	0.750***	-0.111
	(0.069)	(0.075)	(0.052)	(0.066)	(0.130)	(0.095)
LMR X Occ FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
LMR X Year	yes	yes	yes	yes	yes	yes
Occ (2d) X Year FE	yes	yes	yes	yes	yes	yes
Observations	54,927	54,927	54,927	54,927	54,927	54,927

Notes: See Table 4.3. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

Table 4.A17.: Regression balanced firm sample

	Experience			Education		
	low	med.	high	low	med.	high
LM Tightness	-0.311***	0.020	0.045	0.244***	0.551***	-0.041
	(0.092)	(0.093)	(0.060)	(0.074)	(0.135)	(0.107)
LMR X Occ FE	yes	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
LMR X Year	yes	yes	yes	yes	yes	yes
Occ (2d) X Year FE	yes	yes	yes	yes	yes	yes
Observations	54,873	54,873	54,873	54,873	54,873	54,873

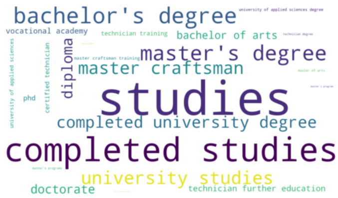
Notes: See Table 4.3. Source: Palturai GmbH/Finbot AG (OJV data) 2017-2023; FEA data 2017-2023; own calculations.

4.B. Word Clouds and Keyword Lists

Figure 4.B1.: Word clouds education groups

(a) Low Education

(b) Medium Education



(c) High Education

Figure 4.B2.: Word clouds experience groups

(a) Low Experience

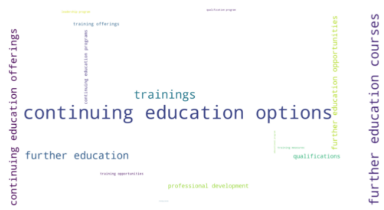
(b) Medium Experience

(c) High Experience

Figure 4.B3.: Word clouds career changer, remote work and training

(a) Career changer

(b) Remote work



(c) Training

Table 4.B1.: German keyword list and English translation: low experience

German	**English**
absolventen	graduates
berufsanfaenger	beginner
berufsanfänger	beginner
berufseinsteiger	career starter
berufseinsteiger_gerne	career starters welcome
berufseinsteiger_willkommen	career starters welcome
berufseinstieg	career entry
berufserfahrung_kein_muss	no experience required
berufserfahrung_keine	no experience required
berufserfahrung_ohne	no experience required
einsteigerposition	entry-level position
einstiegsposition	entry-level position
hochschulabsolvent	university graduate
junior	junior
nachwuchs	young talent
nachwuchskraft	young talent
neueinsteiger	newcomer
unerfahrene_willkommen	inexperienced welcome

Table 4.B2.: German keyword list and English translation: medium experience

German	**English**
berufserfahrung_2_jahre	2 years of professional experience
berufserfahrung_3_jahre	3 years of professional experience
berufserfahrung_drei_jahre	3 years of professional experience
berufserfahrung_dreijährige	3 years of professional experience
berufserfahrung_einschlägige	relevant professional experience
berufserfahrung_erste	first professional experience
berufserfahrung_im_bereich	professional experience in the field
berufserfahrung_vergleichbare_position	comparable position experience
berufserfahrung_zwei_jahre	2 years of professional experience
berufserfahrung_zweijährige	2 years of professional experience
erfahrung_2_jahre	2 years of experience
erfahrung_3_jahre	3 years of experience
erfahrung_drei_jahre	3 years of experience
erfahrung_dreijährige	3 years of experience
erfahrung_einschlägige	relevant experience
erfahrung_erste	first experience
erfahrung_praktische	practical experience
erfahrung_zwei_jahre	2 years of experience
erfahrung_zweijährige	2 years of experience
experience_2_years	2 years of experience
experience_3_years	3 years of experience
praxiserfahrung_angemessene	appropriate practical experience
praxiserfahrung_in_bereichen	practical experience in areas

Table 4.B3.: German keyword list and English translation: high experience

German	**English**
10_years_experience	10 years experience
4_years_experience	4 years experience
5_years_experience	5 years experience
6_years_experience	6 years experience
8_years_experience	8 years experience
berufserfahren	experienced
berufserfahrener	experienced
berufserfahrung_10_jahre	10 years of professional experience
berufserfahrung_5_jahre	5 years of professional experience
berufserfahrung_6_jahre	6 years of professional experience
berufserfahrung_7_jahre	7 years of professional experience
berufserfahrung_8_jahre	8 years of professional experience
berufserfahrung_acht_jahre	8 years of professional experience
berufserfahrung_fünf_jahre	5 years of professional experience
berufserfahrung_langjährig	long-term professional experience
berufserfahrung_sechs_jahre	6 years of professional experience
berufserfahrung_sieben_jahre	7 years of professional experience
berufserfahrung_umfassende	comprehensive professional experience
berufserfahrung_viele_jahre	many years of professional experience
berufserfahrung_vier_jahre	4 years of professional experience
berufserfahrung_zehn_jahre	10 years of professional experience
erfahrung_10_jahre	10 years of experience
erfahrung_4_jahre	4 years of experience
erfahrung_5_jahre	5 years of experience
erfahrung_6_jahre	6 years of experience
erfahrung_8_jahre	8 years of experience
erfahrung_fundierte	solid experience
erfahrung_fünf_jahre	5 years of experience
erfahrung_langjährig	long-term experience
erfahrung_langjährige	long-term experience
erfahrung_mehrjährige	multi-year experience
erfahrung_sechs_jahre	6 years of experience
erfahrung_vier_jahre	4 years of experience
erfahrung_zehn_jahre	10 years of experience
fachkraft_erfahrene	experienced professional
fachkraft_mit_berufserfahrung	professional with work experience
mitarbeiter_erfahrener	experienced employee
mitarbeiter_mit_berufserfahrung	employee with work experience
senior	senior
tätigkeit_langjährige	long-term activity
tätigkeit_mehrjährige	multi-year activity
vertriebserfahrung_mehrjährige	multi-year sales experience

Table 4.B4.: German keyword list and English translation: low education

German	**English**
berufsbildungsreife	vocational maturity
berufsreife	vocational maturity
berufsvorbereitungsjahr	pre-vocational year
fachoberschulreife	technical college entrance qualification
hauptschulabschluss	secondary school leaving certificate
mittlere_reife	intermediate maturity
mittlerer_abschluss	intermediate certificate
mittlerer_bildungsabschluss	intermediate educational qualification
mittlerer_schulabschluss	intermediate school leaving certificate
ohne_schulabschluss	without school leaving certificate
qualifizierter_sekundarabschluss_i	qualified secondary school leaving certificate I
realschulabschluss	secondary school leaving certificate

Table 4.B5.: German keyword list and English translation: medium education

German	**English**
abitur	secondary school diploma (Abitur)
allgemeine_hochschulreife	general university entrance qualification
ausbildung	apprenticeship
ausbildung_abgeschlossene	completed apprenticeship
ausbildung_abgeschlossene_technische	completed technical apprenticeship
ausbildung_technische	technical training
berufsausbildung_technische	technical vocational training
berufsgrundbildungsjahr	basic vocational training year
berufsqualifizierender_abschluss	vocational qualification
fachabi	technical college entrance qualification
fachabitur	technical college entrance qualification
fachhochschulreife	university of applied sciences entrance qualification
fachoberschulreife	technical college entrance qualification
gymnasialabschluss	secondary school diploma
hochschulreife	university entrance qualification
hochschulzugangsberechtigung	university entrance qualification
lehrausbildung	apprenticeship training

Table 4.B6.: German keyword list and English translation: high education

German	**English**
abgeschlossenes_hochschulstudium	completed university degree
abgeschlossenes_studium	completed studies
bachelor	bachelor's degree
bachelor_degree	bachelor's degree
bachelor_of_arts	bachelor of arts
bachelorabschluss	bachelor's degree
berufsakademie	vocational academy
completed_studies	completed studies
diplom	diploma
doktorat	doctorate
fachhochschulabschluss	university of applied sciences degree
fachhochschule	university of applied sciences
hochschulstudium	university studies
magister_artium	master of arts
master	master's degree
master_degree	master's degree
master_of_arts	master of arts
masterabschluss	master's degree
masterstudiengang	master's program
masterstudiengänge	master's programs
meister	master craftsman
meisterausbildung	master craftsman training
phd	phd
promotion	doctorate
promotionsstudium	doctoral studies
studium	studies
techniker_geprüfte	certified technician
techniker_geprüfter	certified technician
techniker_weiterbildung	technician further education
technikerabschluss	technician degree
technikerausbildung	technician training
verwaltungsfachhochschule	administration university of applied sciences

Table 4.B7.: German keyword list and English translation: career changer

German	**English**
berufswechsel	career change
fachfremd	non-specialist
quereinsteig	career change
quereinsteiger	career changer
quereinstieg	career change
seiteneinsteiger	lateral entrant
seiteneinstieg	lateral entry
wiedereinstieg	return to work
wiedereinstiegsprogramm	returnship program

Table 4.B8.: German keyword list and English translation: remote work

German	English
arbeit_von_zu_hause	work from home
arbeiten_von_zu_hause	work from home
arbeitsplatz_zu_hause	home office
heimarbeit	homeworking
home_office	home office
homeoffice	home office
mobilarbeit	mobile work
mobile_arbeit	mobile work
mobiler_arbeit	mobile work
mobiles_arbeiten	mobile working
remote	remote
remote_work	remote work
telearbeit	telecommuting
zu_hause	at home
zu_hause_arbeiten	work at home

Table 4.B9.: German keyword list and English translation: training

German	English
ausbildungsmöglichkeiten	training opportunities
berufliche_weiterentwicklung	professional development
bildungsprogramm	educational program
fortbildung	further education
fortbildungen	further education courses
fortbildungsinitiativen	further education initiatives
fortbildungsmöglichkeiten	further education opportunities
führungskräfteprogramm	leadership program
qualifizierungen	qualifications
qualifizierungsprogramm	qualification program
schulungsangebot	training offerings
schulungsangebote	training offerings

Eidesstattliche Versicherung

Ich, Frau M.Sc. Myrielle Gonschor, versichere an Eides statt, dass die vorliegende Dissertation von mir selbstständig und ohne unzulässige fremde Hilfe unter Beachtung der „Grundsätze zur Sicherung guter wissenschaftlicher Praxis an der Heinrich-Heine-Universität Düsseldorf" erstellt worden ist.

Essen, der 24. Mai 2024

M. Gonschor

Unterschrift