Automation Threat and Labor Market Power

Tsenguunjav Byambasuren*

October 28, 2024
Please click here for the latest version

Abstract

This paper studies the role of automation threat in firms' labor market power. I estimate the wage markdown—the wedge between the marginal revenue product of labor and the wage—to show that firms set wages in German manufacturing, where the labor market is characterized by moderately flexible industry-region, occupation group, and firm-level collective bargaining; the average worker receives 79 cents on the marginal euro. Using the estimated wage markdowns and automation threat proxied by exposure of local labor market regions to industrial robots instrumented by plausibly exogenous shift-share push factors, I find that the automation threat has occupation and region-specific effects on labor market power. Robot exposure increases employer power over routine task-performing workers who face the highest risk of displacement by industrial robots in regions with low union coverage in East Germany, which has spatial frictions and historically weaker worker protections. The key results are consistent with qualitative predictions from the wage bargaining model with heterogeneous workers where employers retain the "right-to-manage" their workforce composition.

Keywords: technological change, task displacement, bargaining power, monopsony, markdown

JEL Codes: J42, O33, J31

*Cornell University. Email: tb497@cornell.edu. I am indebted to my advisors, Nancy Chau, Michèle Belot, Ravi Kanbur, and Arnab Basu, for their invaluable advise, support, and encouragement throughout this project. I am grateful to Justin Bloesch, Wolfgang Dauth, Takuma Habu, Simon Jäger, David Just, Patrick Kline, Shanjun Li, Steffen Müller, Aseem Patel, Evan Riehl, Ayşegül Şahin, Uta Schönberg, Josef Zweimüller, participants at the IZA Summer School in Labor Economics 2023, SOLE Annual Meeting 2024, EEA Annual Meeting 2024, EALE Conference 2024, and seminar participants at Cornell University for their useful comments and helpful conversations. This paper uses confidential data from the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) under the project "The Heterogeneous Effects of Task Displacement and Immigration on Labor Market: Evidence from Germany" (project number FDZ 2253/2254). I thank the staff at the FDZ for their assistance with the German administrative data and for answering my many questions and requests. The data can be obtained by applying to the FDZ. Details on applying for the data set and possibilities for data processing can be found on the FDZ homepage (https://fdz.iab.de/en/startseite-en). I also thank the staff at the Cornell Center for Social Sciences (CCSS) for providing logistical support at the IAB Research Data Center at the CCSS and enabling me to work with the data. All errors are my own.

1 Introduction

Despite the growing consensus that firms, rather than markets, set wages (Berger et al., 2022; Lamadon et al., 2022; Yeh et al., 2022; Felix, 2022), the sources of the firm's labor market power are understudied.[1] In this paper, I first estimate the wage markdowns—wedge between the marginal revenue product of labor and the wage as a measure of firms' labor market power in Germany, where I then quantify the impact of automation threat on wage markdowns emphasizing the job tasks conducted by workers and spatial differences. Germany is an ideal environment to investigate the role of automation threat in employer power as it is one of the leading countries in automation or industrial robots (Acemoglu and Restrepo, 2020; Dauth et al., 2021) and it has a uniquely flexible bargaining system with regional and occupational differences (Jäger et al., 2022). I also develop a wage bargaining model to explore the threat from labor-saving technologies as a determinant of the firm's and workers' bargaining position and employer power in the labor market via its impact on firms' outside options, which cannot be explained by the canonical models of automation like Acemoglu and Restrepo (2018) that characterize the actual automation.

This paper measures the two key indicators to empirically investigate the role of automation threat in labor market power. First, as a measure of monopsony power for German manufacturers, I estimate the plant-level wage markdowns using the "production approach" derived from the duality of the firm's profit maximization and cost minimization problems (Morlacco, 2019; Mertens, 2020; Brooks et al., 2021; Yeh et al., 2022; Delabastita and Rubens, 2023). The "markdown" equals unity in a perfectly competitive labor market. Introducing worker heterogeneity by job tasks performed at the workplace, I also measure the firm's monopsony power over such workers with different exposure to displacement risks and various outside options. German labor market shows regional and occupational differences in employer market power. Second, I measure the automation threat using the local labor market region's exposure to industrial robots. It is crucial to highlight the distinction between the local labor market region's exposure to robots and the actual adoption of robots at the firm, a new salient fact that I document in this paper because the labor market implications of the two shocks could be different and transmit through different channels, as the former indicates a potential event that has not materialized yet but can have real effects and the latter is an event already took place with actual displacement effects. Leveraging these measures, I estimate the causal impact of the German local labor market region's exposure to robots, instrumented by robot exposure in other high-income European countries that introduces variation in robot exposure or automation threat, on wage markdowns aggregated at the local labor market regions.

I leverage an establishment panel survey data (IAB Establishment Panel) and novel matched longitudinal employer-employee data (LIAB) from Germany. The detailed firm-level longitudinal survey data of IAB Establishment Panel with direct and comprehensive information to estimate

[1] Boal and Ransom (1997), Manning (2003), and Ashenfelter et al. (2010) provide comprehensive surveys on monopsony literature over its development stages. For recent literature review on monopsony, see Manning (2021), Card (2022), and Ashenfelter et al. (2022).

production function under labor market imperfection such as labor headcounts and thus to quantify firm-level markups according to De Loecker and Warzynski (2012) enables me to accurately measure “markdown” using production approach at the establishment[2] or firm level over time between 1997 and 2018. The production function is estimated using the semi-structural control function approach offered by Ackerberg et al. (2015). Olley and Pakes (1996) developed the control function approach, which was further refined by Levinsohn and Petrin (2003) and Wooldridge (2009) with different functional forms and specifications. The German establishment panel also contains direct information on the firm’s robot adoption from 2014-2018 that I used to document the main facts about the firm’s robot adoption and compare the actual robot adoption with exposure of local labor markets to robots to guide my analysis. The industry-level data on the stock of robots are obtained from the International Federation of Robotics (IFR), covering more periods since 1993. In this paper, I mainly consider a threat from automation that has not happened yet as an automation threat. However, it is worth noting that there are at least two reasons why automation threats could also exist in robot-adopting firms. First, existing studies on the labor market effects of automation suggest that worker displacement does not occur instantly, and the displacement effect materializes after some periods following an automation shock.[3] Second, the remaining workers after displacement might be subject to a displacement risk in the future, although not replaceable by the current technologies. So, those remaining workers could still be subject to threats from further automation at the current robot-adopting firm. However, it is challenging to isolate the effect of automation threat from that of the actual adoption when exploiting variation from actual adoption. It is also more compelling to think about the threat mechanism from a shock that has not happened yet, which affects labor market outcomes via expectation. For example, Cavounidis et al. (2023) study the effects of threats from automation whose arrival date is uncertain on wages, employment, and age composition of the labor force in occupations through the lens of an overlapping generations model and in the context of teamsters at the dawn of motor trucks in the U.S. early 1900s.

I focus on estimating the causal impact of automation threats on labor market power at the level of local labor markets mainly due to three reasons: (i) firm-level information on robot adoption from the IAB Establishment Panel data is limited, (ii) automation threats are more pertinent to the state of automation at some aggregate level such as industry or local labor markets, rather than at the firm level, and (iii) most of the collective bargaining agreements, particularly regarding wage and salary are made at the aggregate industry-region level in Germany. First, although German establishment panel data provide the firm’s robot adoption at extensive and intensive margins, the

[2]The German data provide employer information at the establishment level, a single production unit, rather than the firms in the legal sense. A potential issue with using establishment as a level of observation is that multiple establishments in a firm could be subject to common shocks and influence each other. However, more than 70% of the establishments in my data are those in a single firm, reflecting the German economy in which a large portion of firms are small and medium enterprises. I, thus, interchangeably use the terms establishment, plant, firm, and employer throughout the paper.

[3]For example, Bessen et al. (forthcoming) show that it takes five years for automation to have displacement effects at the firm in the Netherlands. So, it is likely that workers at automating firms can still be subject to automation threats, especially during the early stages of robot adoption, before they have been displaced from their workplace.

information covers only five years between 2014-2018. So, it is challenging to make credible and robust inferences about the impact of automation threats using firm-level measures due to the lack of statistical power. Second, since my focus in this paper is the effect of automation threats on employers' labor market power, not the impact of realized robot adoption, analysis using firm-level robot adoption is less informative because the industry's or labor market's exposure to robots is more indicative of automation threats. Given these, I leverage local labor market-level analysis to identify the causal impact of automation threat on labor market power.[4] The identification of causal effect relies on a shift-share instrumental variable (IV) design that instruments robot exposure of the local labor market in Germany with robot exposure of the same labor markets in other high-income advanced countries (Acemoglu and Restrepo, 2020; Dauth et al., 2021). Third, the collective bargaining system in Germany is unusually flexible than many of its European neighbors with a more rigid bargaining system as it allows bargaining at various levels, including industry-region, occupation, skill, and experience groups, and even at the firm level in specific instances. However, collective bargaining agreements on wage and salary are usually negotiated at the aggregate level, i.e., industry-region level (Jäger et al., 2022).

This study contributes to several strands of literature in different ways. First, this paper contributes to the literature investigating the labor market effects of automation by empirically showing that automation threat affects employer power. Automation has been found, in a separate strand of literature, as a significant source of changes in wages (e.g., Autor et al., 2003), employment (e.g., Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018, 2019), and wage inequality (e.g., Acemoglu and Restrepo, 2019, 2022). Although these analyses on the labor market effects of automation incorporate monopolistic competition in the product market, they often assume that labor markets are perfectly competitive despite the recent evidence on monopsony power. However, a few papers, such as Chau and Kanbur (2021) and Acemoglu and Restrepo (2023), show that introducing labor market imperfection presents notable differences in the effects of technological progress on employment, wages, and wage inequality. Separate from the labor market effects of the actual event of automation, Cavounidis et al. (2023) show that an automation shock not yet materialized makes younger workers avoid an occupation facing obsolescence, yielding changes in the age structure and employment compression in the occupation and increases the wages of workers entering the occupation via compensating differential. However, the impact of automation technologies, particularly displacement threats from automation which has not happened yet, on employer power in wage negotiation is understudied. There are several unanswered questions about the potential role of automation threat in the wage-setting process and wage negotiation between employers and workers, such as whether there is any role of displacement threat from automation in industrial re-

[4]When using data with richer information on firm-level robot adoption, one can also investigate the threat mechanism by comparing, for example, non-robot adopting firms with robot-adopting firms, with careful consideration of identification problem of anticipation effects (Bessen et al., forthcoming). As discussed above, a threat to be displaced can be present at both types of firms, but it is likely to be more significant at non-robot-adopting firms than at robot-adopting firms.

lations between employers and workers. Therefore, I contribute to this literature by providing the first reduced-form evidence on the causal impact of automation threat or potential robot adoption on labor market power. Specifically, I estimate the causal effect of robot exposure on labor market power at the local labor market level by employing a shift-share IV strategy. In the empirical literature investigating the link between automation technologies and labor market power, a few existing papers estimate the non-causal empirical relationship between the proxy of automation technologies and labor market power. For example, Kirov and Traina (2021) provide one of the earliest estimates on the empirical relationship between automation technologies and monopsony power by estimating a positive relationship between ICT investment and firm-level wedge between marginal revenue product of labor (MRPL) and wage across U.S. manufacturing plants. Mengano (2023), on the other hand, finds that ICT usage plays a minor role in workers' bargaining power across French manufacturing firms. However, this paper provides a causal interpretation for the link between automation threat and employer power and finds that threats from automation grant more power to employers than workers in the labor market.

Second, my work is related to a growing literature examining the prevalence, evolution, and worker heterogeneity of monopsony power. I show that a worker in a median (average) German manufacturer receives only 89 cents (79 cents) on the marginal euro. This markdown estimate is consistent with Bachmann et al. (2022b)'s estimates of labor supply elasticity, which suggest an upward-sloping labor supply curve to an individual firm. Using the aggregation method suggested by Yeh et al. (2022), I also show that the aggregate markdown in German manufacturing has decreased since 1997, with some plateau between 2000 and 2008. A downward trend in aggregate markdowns is consistent with an upward trend in yearly labor supply elasticities (i.e., labor supply curve to an individual firm is becoming flatter) for workers with different routine task intensities, shown by Bachmann et al. (2022b). This aggregate markdown estimate and employment-based labor market concentration measured by the Herfindahl-Hirschman Index (HHI) present generally similar patterns over time, specifically until the Great Recession in 2009, after which markdown presented sharp declines. The sharp decline of wage markdowns in the post-Great Recession periods is strongly consistent with a rise of wages and decline in markdown after the Great Recession (Dustmann et al., 2024), driven by women's wages in the bottom part of the wage distribution, slowing the rise in inequality (Drechsel-Grau et al., 2022). To quantify markdowns for heterogeneous workers, I focus on workers performing different job tasks, including routine, nonroutine manual, and nonroutine cognitive tasks. Some studies show that monopsony power differs by worker characteristics such as gender (Hirsch et al., 2010; Caldwell and Oehlsen, 2022), distaste for commuting (Datta, 2022), and job tasks being performed by the worker (Bachmann et al., 2022b) using administrative and experimental data. These studies mainly estimate the elasticity of labor supply for different workers as a measure of monopsony power. Although Bachmann et al. (2022b) document the heterogeneity in monopsony power for routine, nonroutine manual, and nonroutine cognitive task-performing workers by estimating labor supply elasticity, this study examines the same heterogeneity using a different method, i.e., quantifying markdowns. The estimated markdowns are generally consistent with their estimates of labor supply elasticity for the three types of workers. In particular, routine (nonroutine manual) task-performing workers are subject to the lowest (highest) degree of monopsony power in German manufacturing. Using these measures, I estimate the heterogeneous effects of automation threat on monopsony power for these workers who vary by their degrees of exposure to displacement risks.

Third, this paper contributes to the literature on explaining the changes in workers' and firms' bargaining outcomes and labor market power by offering a simple model of collective bargaining that highlights the role of automation threat in wage-setting. Automation threats could influence workers' and firms' bargaining power by changing firms' outside options.[5] While the classical monopsony model with an upward-sloping labor supply curve does not characterize the firm's outside options, in the proposed wage bargaining model, where the labor supply curve can be upward-sloping, the firm's outside option plays an important role.[6] Focusing on the automation threat channel, Leduc and Liu (2024) provides the first theoretical framework, an extension of the standard Diamond-Mortensen-Pissarides model, showing that automation threat weakens workers' bargaining power.[7] In this paper, I develop a theoretical framework building on the right-to-manage model of wage bargaining by Nickell and Andrews (1983), which better represents the bargaining and industrial relations in Germany where most bargaining between the employer and workers is on wages (Caldwell et al., 2024).[8] Unlike the U.S. and the U.K., collective bargaining in Germany mainly occurs at the industry-region level between the trade union and employers association, mostly concerning wages. Agreements on managerial decisions are co-determined at the firm level (Jäger et al., 2022). Although working conditions such as the number of hours are bargained at the industry-region level, employment is not a bargaining topic in the country, potentially because it is hard to set individual firms' employment levels in sectoral or regional agreements. The employ-

[5] The studies in the literature suggest that one of the sources of change in workers' bargaining power that is potentially caused by the skill-biased technological change is the de-unionization, which could have dampened workers' bargaining power (Acemoglu et al., 2001; Açıkgöz and Kaymak, 2014; Dinlersoz and Greenwood, 2016). Automation threat might affect unionization; however, de-unionization is likely caused by the erosion of union support due to the displacement of union members and higher cost of wage compression from the actual automation. So, the impact of automation threat might not be mediated through the change in unionization.

[6] I employ this static model by assuming that the employer and the workers have perfect information since there will be no actual back-and-forth negotiations at the unique equilibrium of the bargaining game under perfect information (Fudenberg and Tirole, 1983).

[7] Another model that includes both technology adoption and inputs and output market power is also proposed by Rubens (2022), who study the impact of market power on technology adoption, which is the opposite direction of the relationship I investigate in this paper.

[8] The solution to the right-to-manage model is not Pareto-efficient, and thus McDonald and Solow (1981) propose the static model of efficient bargaining procedure where the union and firm simultaneously determine wages and employment, ensuring Pareto efficiency. Although bargaining over wages and employment is Pareto efficient, bargaining over employment is rarely observed. Despite mixed results from various empirical studies testing the predictions of collective bargaining models, empirical evidence consistently suggests two stylized facts: (i) the marginal productivity of labor is not equal to the outside wage, and (ii) employment and bargained wages can be negatively correlated in some contexts. Since these results do not contradict the conclusions of the right-to-manage and those of the insiders-outsiders model without discrimination against entrants (Cahuc et al., 2014, pp. 458-462), I build on the right-to-manage model.

ment is instead left for the firm to decide unilaterally (Hirsch and Schnabel, 2014).[9] The model serves as an alternative framework, which is more *micro* than the existing *macro* or business cycle model, to formalize the empirical evidence provided in this paper. It also offers new insights on the role of bargaining types (separate and joint bargaining between the firm and the union representing different workers) in the interaction between automation threat and bargaining power by featuring heterogeneous workers with displacement risks by automation technologies to a different extent.

The rest of the paper proceeds as follows. Section 2 describes context, data, and background. Section 3 discusses the construction of markdowns and presents the estimates for German manufacturing. Section 4 lays out the empirical strategy to identify the effects of automation threat on wage markdowns, presents the results from the labor market-level analysis, and checks the robustness of the main findings. Section 5 examines the labor market effects at the plant level and explores potential mechanisms. Section 6 presents a wage bargaining model that formalizes the role of automation threat in firms' bargaining process and provides new insights. Finally, Section 7 concludes.

2 Context, Data, and Background

This section first presents the wage-setting system in Germany and its evolution over the study period between the late 1990s and late 2010s. Then, I briefly describe the datasets leveraged for constructing the key variables. Lastly, the section provides some background by documenting key motivating facts that inform the empirical analysis and conceptual framework.

2.1 Context

The German system is based on contracts and mutual agreements under the dual system of collective bargaining and co-determination. Wages, hours, working conditions, and other agreements, usually renegotiated between unions, employer associations, and firms on an annual and biannual basis, are largely regulated by long-lasting sectoral and regional collective bargaining. Agreements on firm-level major and minor or daily managerial decisions are co-determined by employer and workers through representation on corporate boards and works councils. Table 1 summarizes the dual system of employee representation in Germany.

In the remainder of this section, I focus on three salient features relevant to my analysis. First, the collective bargaining coverage in Germany has been eroded since the mid-1980s and the pace of the decentralization accelerated after the mid-1990s (Hassel, 1999). The decline in sectoral bargaining continued between 2000 (48% of establishments and 59% of employment) and 2011 (33% of establishments and 48% of employment). The erosion of collective bargaining agreements generally continued until 2019, indicating that the bargaining system is becoming more flexible

[9] Many studies employ the right-to-manage model to examine various topics related to the German labor market, such as Carruth and Schnabel (1993), Brücker and Jahn (2011), Brücker et al. (2014), Hirsch and Schnabel (2014), and Dwenger et al. (2019).

and is shifting from the industry-region level to the firm level (Jäger et al., 2022). The relatively widespread use of "hardship" and "opening" clauses that have been increasingly common, leading to wage dispersion even with relatively large-scale union agreements (Schneider and Rinne, 2019) could be one of the reasons for the flexible bargaining system in the country.[10] The works council coverage, however, has been relatively stable, potentially due to the 2001 Works Constitution Act aimed to facilitate their formation. This flexible collective bargaining system allowing firms to set wages is unique compared to the more rigid bargaining system of many of its European neighbors. In 2020, the industry-region level bargaining was 43%, while the firm-level bargaining agreements that are mainly to set higher standards for typically very large and highly productive firms than industry-region-level agreements was about 8% (Jäger et al., 2022).

Second, there is a notable regional difference in the collective bargaining coverage. The collective bargaining coverage has been significantly higher in West Germany (68% and 48% of the labor force covered in 1998 and 2018, respectively) than in East Germany (52% and 35% in 1998 and 2018, respectively), indicating more significant worker protection in the West relative to the East. The coverage of works councils has also been higher in West Germany than in West Germany (Jäger et al., 2022). In contrast, in other European countries such as France and Italy, union wages are often bargained at the national level with no regional differences as much as in Germany.

Third, another indication of an unusually flexible collective bargaining system in Germany over my study period is the presence of unions representing different occupation, skill, and experience groups, particularly before 2015. For example, a union confederation of *Deutscher Beamtenbund* (DBB) contains several occupation-specific unions. In 2015, the "unity law" has been passed jointly lobbied by unions and employer associations. Unions argue that they support the law as it narrows the wage inequality between high-skilled and low-skilled workers, and employer associations support the law due to the high demand for wage increases and the threat of strikes from occupation-specific unions representing high-skilled or hard-to-replace workers (Jäger et al., 2022). Workers frequently bargain, driven by managers who actively bargain, and there is heterogeneity in bargaining by different workers (Caldwell et al., 2024). These indicate that high-skilled workers generally have higher bargaining power and are protected by unions more than low-skilled workers, e.g., via occupation-specific unions representing high-skilled workers, especially before the introduction of the unity law. Even with this law undermining the occupation-specific representation, the worker's voice is more likely higher for high-skilled and hard-to-replace workers. The topics in bargaining

[10]There is an active debate about the underlying factors driving these changes in collective bargaining and worker representation trends, and several reasons have been proposed. Studies suggest that the increased intensity of the shift in wage setting from industry or region to the firm during the 1990s is primarily rooted in German reunification. First, the unprecedented de-unionization or decentralization of the wage-setting process is intensified because unions and workers are forced to accept firms' deviations from the union agreements during economic and fiscal difficulties in Germany due to the reunification (Dustmann et al., 2014). Second, opportunities for offshoring to other low-wage central and eastern European countries previously blocked behind the Iron Curtain expand employers' outside options and thus their bargaining power by providing them with cheaper production inputs (Dauth et al., 2014). Third, small and unproductive firms exited the employer associations as they could not keep up with the wage floors set by large and productive firms since the early 1980s (Dustmann et al., 2009).

between occupation-specific unions and employers associations include, for example, specifying wage and salary floors at the industry-region level.

While there is a wide range of union presence and coordination in the country, bargaining can also happen at the firm level and between occupation-specific unions and employer associations. This nuanced environment makes Germany an ideal environment to examine the role of automation threat in labor market power as the automation threat can have heterogeneous effects on regions with different levels of worker protection and workers in occupations subject to various degrees of displacement risk.

2.2 Data

I use four main datasets to construct the key variables, including the automation threat across regions and wage markdowns for heterogeneous workers, and conduct the empirical analysis. The first two datasets are the IAB Establishment Panel survey (IAB-BP) and matched employer-employee data (LIAB) from Germany provided by the Research Data Center (FDZ) of the Federal Employment Agency in the Institute for Employment Research (IAB). The third dataset is the BIBB Establishment survey that reports worker-level representative data on activities or tasks performed at the workplace along with occupation information. I obtain this data from the Federal Institute for Vocational Education and Training (BIBB). These three datasets are mainly used for measuring the wage markdowns for heterogeneous workers. The fourth primary dataset provides the global information on stock of industrial robots across industries in different countries, which I used for approximating the automation threat. The data comes from the International Federation of Robotics (IFR), a widely used data source in the automation literature. Online Appendix A describes these four main datasets in detail. I also use other data sources, including the UN Comtrade and EU KLEMS, to construct shift-share measures on industry-level net exports and ICT investment as additional covariates, described in Section 4.

2.3 Background and Motivating Facts

I present three main facts to provide background and motivate the analysis. The first fact motivates the measure of automation threat using exogenous variation in robot exposure. The second fact establishes the heterogeneity in average real wages across regions to document regional differences in labor market frictions. The third fact concerns the relationship between the wage and union coverage. The last two facts motivate the choice of heterogeneity by regions and union coverage when I estimate the causal impact of robot exposure on wage markdowns in Section 4.3.

Fact 1. Exogenous variation in robot exposure does not predict actual robot adoption. Using nationally representative survey data on realized robot adoption and industry-level information on the stock of robots in other high-income European countries, I document a new fact about the relationship between actual robot adoption in Germany and robot exposure outside of the country.

In doing so, I estimate the following regression:

$$\text{Actual robot adoption}_{dt} = \alpha + \beta \text{Robot exposure shock}_{dt} + \phi_d + \varphi_{st} + \varepsilon_{dt}, \tag{1}$$

where Actual robot adoption$_{dt}$ is the number of robots adopted by German firms aggregated at the local labor market region or district d and expressed as per 1,000 workers in year t between 2014 and 2018, Robot exposure shock$_{dt}$ is the average stock of robots per 1,000 workers in other high-income European countries[11] defined at the same local labor market region level, ϕ_d and φ_{st} are respectively the district and state-by-year fixed effects. Since state-by-year fixed effects are controlled, state and time fixed effects are not necessary. Panel A of Table 2 presents the results, which suggest that exogenous variation in robot exposure from external sources does not predict the actual robot adoption in the country as the correlation is not statistically significant despite the positive coefficient. In panel B, I report the results when I use annual changes in actual robot adoption and robot exposure shock. The relationship between the two is negative and statistically insignificant.[12]

Leveraging the data on the firm's actual robot adoption, I examine the potential reasons why robots stock in other European countries does not predict the actual robot adoption in Germany by characterizing actual robot adoption. I first examine the industry where robots are adopted and find that robot adopters are highly concentrated in the manufacturing industry. Figure 1 depicts the share of robot-adopting manufacturers in the total number of robot-adopting firms, showing that more than three-quarters of robot adopters are manufacturing plants. It justifies the focus of the empirical analysis on the manufacturing industry when investigating the impact of automation threats from industrial robots.

But how prevalent are robot adopters in general and within the manufacturing industry? I then analyze the prevalence of robot adopters, and Table 3 reports the share of robot users across German plants. In 2018, only 1.48% of all surveyed plants, which are representative, used robots. Most of the plants in the survey are non-manufacturing firms, and less than 1% of the non-manufacturing firms are robot users. Although the manufacturing industry is robot-intensive, as indicated above, only 7.19% of the manufacturing plants were robot users in 2018. Thus, robot adoption is relatively rare, even in the manufacturing industry.

To further investigate the robot adoption behavior, Figure 2 shows the distribution of the average number of robots per plant in 2018 within the manufacturing sector. The first takeaway is that many firms in the bottom deciles use only a single robot in their production. The second observation is that the average number of robots used at the firm discretely changes as we move up along the distribution. The third takeaway is that robots are highly concentrated among robot adopters (Deng

[11] The countries are Spain, France, Italy, Norway, Sweden, and UK, which are included in my set of instruments, and I compute the simple arithmetic average of robots stock per 1,000 workers in these countries.

[12] Online Appendix B conducts the robustness checks of the fact on the relationship between actual robot adoption in Germany and average robot exposure in other high-income European countries. Notably, the qualitative findings remain the same.

et al., 2023). This discrete nature of robot adoption suggests that robot adoption is lumpy, especially in the manufacturing sector, which is consistent with data on robot adoption among manufacturing firms in different country contexts (see, e.g., Humlum, 2019).

Fact 2. There is a significant difference in average real wage between East and West Germany districts. Using the German administrative data, Heise and Porzio (2022) show a large wage discount in East Germany compared to West Germany and suggest that East-born workers are less likely to move to districts in the West exhibiting a strong home bias and spatial friction. The suggested wage gap could indicate a presence of labor market power in East Germany, and the spatial friction in the form of home bias is a potential source of firms' wage-setting power as workers' outside option is limited to local districts in the East. Using the LIAB data, I first estimate similar wage regression to show wage heterogeneity between regions:

$$Y_{jt} = \beta \mathbb{I}_{j,East} + \mathbf{X}'_{jt}\delta + \gamma_k + \mu_t + \varepsilon_{jt}, \tag{2}$$

where Y_{jt} is (log) average real daily wage at firm j in year t, $\mathbb{I}_{j,East}$ is a dummy for whether firm j is located in the East, $\mathbf{X}'_{jt}$ is a vector firm-level covariates, including workers' average education, female share, and firm size, and γ_k and μ_t are industry and year fixed effects, respectively. Table 4 presents the results, and the East-West wage gap is estimated at $\beta = -0.199$ (SE: 0.003), which is remarkably similar to Heise and Porzio's (2022) estimate.[13] Figure 3 further shows the wage gap between East and West Germany in each twentiles of the firm size distribution. Consistent with Heise and Porzio (2022), the average real wage paid by the firm increases with firm size in both regions. The real wage discount in East Germany is present for each firm size, which is consistent with imperfect mobility of workers which in turn is conducive to different levels of market power.[14]

Fact 3. Workers less protected by trade unions have lower wages. As discussed in Section 2.1, collective bargaining agreements concerning wage and salary are usually negotiated between unions and employer associations at the industry-region level. I examine the relationship between worker protection and wage by calculating the daily average salary per worker at firms in different quartiles of the union coverage. As shown in Figure 4, the firm's average wage per worker grows as the union coverage increases along its distribution. Controlling for rich sets of fixed effects, Table 5 also shows a positive and statistically significant relationship between union coverage and wage, suggesting that workers protected by trade unions have higher wages.

[13] In Table 4, I include Berlin as part of East Germany. I checked the robustness of these results by excluding Berlin from the sample and found that the results are substantially robust. The results suggest an East-West wage gap of $\beta = -0.226$ (SE: 0.003).

[14] East Germany in Figure 3 includes Berlin, and the relationships and patterns of job ladders remain unchanged when I exclude Berlin from the sample, and the results are available on request.

3 Measuring Markdowns

3.1 Production Approach

I estimate wage markdown, a wedge (or misallocation in the language of Hsieh and Klenow (2009) and Adamopoulos et al. (2022)) between the marginal revenue product of labor (MRPL) and the wage, as a measure of labor market power. I use the production function approach by closely following Yeh et al. (2022) who have shown that the cost minimization problem implies the following expression that measures markdowns accounting for markups:

$$\nu_{jt} = \frac{\theta_{jt}^{L}}{\alpha_{jt}^{L}} \cdot \mu_{jt}^{-1}, \tag{3}$$

where ν_{jt} is the markdown for firm j in year t, $\theta_{jt}^{L} = (\partial F(l_{jt})/\partial l_{jt})(l_{jt}/F(l_{jt}))$ is the output elasticity of labor, $\alpha_{jt}^{L} = W_{jt}(l_{jt})/R_{jt}(l_{jt})$ denotes a firm's labor share of revenue $R_{jt}(l_{jt})$, and $\mu_{jt} = p_{jt}/\lambda_{jt}$ is the firm's price (p_{jt})-cost (λ_{jt}) markup. The markdown equals unity ($\nu_{jt} = 1$) in perfectly competitive labor markets. In labor markets with imperfect competition, on the other hand, employers have market power if $\nu_{jt} > 1$. The markdown less than unity is not intuitive under the profit-maximization assumption, but in practice, it can happen, and it implies that the employer pays wages to its workers higher than their productivity, or it could be a measurement error.

The wage markdown has been quantified by estimating and calculating its components in equation (3). I obtain the output elasticity of labor, θ_{jt}^{L}, from the production function estimation. I estimate production function using "proxy variable" method (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015). Online Appendix C discusses the production function estimation in detail. The firm-level markups are estimated based on the production function estimation as in De Loecker and Warzynski (2012), who show that $\mu_{jt} = \theta_{jt}^{M}(\alpha_{jt}^{M})^{-1}$ where θ_{jt}^{M} is the output elasticity of a variable input M_{jt} other than labor, e.g., material inputs, and α_{jt}^{M} is the share of expenditures on input M_{jt} in total sales revenue. An expenditure on labor as a share of revenue is calculated directly from the data, where labor cost is measured by the total annual wage bill. Table 6 summarizes the main variables used for markdown estimation, estimated total factor productivity (TFP), and average daily wage.

The degree of monopsony power is commonly measured by the wage elasticity of labor supply to the firm using, for example, a method pioneered by Manning (2003), who also has shown that the markdown is proportional to the elasticity of labor supply based on profit maximization problem. The monopsony power can also be indirectly measured by labor market concentration based on the Herfindahl index (Azar et al., 2019). Another indirect or proxy measure of employer power, which is sufficient for measuring the direction of change in employer power, is the number of firms in the market relative to the number of workers. For example, Chau and Kanbur (2021) used the ratio of employers to workers as a measure of employer power. However, estimating markdowns using the production approach has two main advantages over other measures of monopsony power. First, it provides an establishment-specific measure of monopsony power that varies over time. It allows me to show how "shock" in automation threat affects the firms' wage-setting power at the level of establishments or local labor markets. Second, this empirical approach is generic and not restricted to any of the different theories of labor market power, such as oligopsony, classic differentiation, and equilibrium search models to quantify markdowns.[15] Online Appendix D briefly lays out other measures of monopsony power and discusses their linkages with wage markdowns.

3.2 Estimated Markdowns in German Manufacturing Plants

There are two main reasons why I focus on the manufacturing industry in this paper. First, most of the actions in automation or labor-saving technological change happen among manufacturers according to fact 1 in Section 2.3. Second, labor input must satisfy an assumption VI of Yeh et al. (2022), which states that the firm uses labor only for output production, not marketing, hiring, and other purposes.

I present the results of markdown estimation in Table 7. The plant-level estimates clearly show that labor market power in German manufacturing is sizable and larger than unity. The average establishment throughout the period charges a markdown of 1.27–that is, a plant's marginal revenue product of labor is, on average, 27 percent higher than the wage it pays its workers. Alternatively, taking the reciprocal, a markdown of 1.27 implies that a worker receives around 79 cents on the marginal euro generated. Furthermore, I find that labor market power is widespread across manufacturing plants. Half charge a markdown of 1.13 (89 cents on the marginal euro), and the interquartile range is around 0.7.[16,17]

My estimate on median value for wage markdowns is quite different from the previous estimate by Mertens (2020), who suggests that there is no labor market power on the median in the German manufacturing sector (implied wage markdowns $\nu_{it} = 0.88$) using the AFiD-data over the period 2000-2014.[18] However, my estimate on the mean value for wage markdowns is generally consistent

[15] See Boal and Ransom (1997) for a systematic review of these theories of monopsony power.

[16] The sample size for the baseline markdown estimation for all establishments in the sample is larger than that for markdown estimates for establishments in East and West Germany shown in Table 9 where around a quarter of the total number of firms are excluded due to a lack of spatial information. Thus, the markdown was estimated for the remaining three-quarters of firms for which whether they are from East or West Germany is known. Due to this sampling difference, the median and mean estimate for East and West Germany are higher than the baseline estimate of markdowns on the full sample in Table 7. Despite this reduced sample size, the estimated markdowns are relatively stable. In Online Appendix E.1, I check the robustness of my baseline markdown estimates where a common production function was estimated on the full sample by estimating the production function for East and West Germany separately and summarizing the estimated markdowns for all firms. The result shows that overall markdown estimates for Germany are strongly robust.

[17] Online Appendix E.2 shows that my markdown estimates are generally robust to the Cobb-Douglas production function. I discuss my estimates of markups in Online Appendix E.3. In Online Appendix E.4, I show the robustness of the baseline markdown estimates by including the key explanatory variable of interest, robot exposure, in the production function estimation, in the spirit of studies like Brandt et al. (2017).

[18] The difference could be due to different datasets with various samples covering different periods. First, they use administrative data from the statistical office, while we use nationally representative survey data from the Institute for

with Bachmann et al. (2022b)'s findings, suggesting that the German labor market is not perfectly competitive. The market power in an average employer that I have estimated is smaller than that found in other countries, for example, 65 cents in the U.S. (Yeh et al., 2022), 50 cents in Brazil (Felix, 2022), and 71 cents in Colombia (Amodio and De Roux, 2024) earned for each marginal dollar. Overall, I find that both average and median manufacturing plants operate in a market with monopsonistic competition.

I analyze the relationship between markdowns and the firm's idiosyncratic characteristics by focusing on establishment size and productivity to characterize the estimated plant-level markdowns. I thus estimate the markdowns on selected characteristics to investigate the heterogeneity of markdowns.[19] Figure 5 shows that larger (panel (a)) and more productive (panel (b)) firms posit higher markdown on wages in the German manufacturing industry, and these findings are consistent with the results from U.S. manufacturing firms (Yeh et al., 2022). It also provides some credence to my baseline estimate of markdowns.

Markdowns in East and West Germany. Using the same specification as in equation (2), I then examine the heterogeneity in wage markdowns across East and West Germany. The results shown in Table 8 indicates a markdown premium in East Germany, which is relatively small but strongly significant, $\beta = 0.040$ (SE: 0.013).[20] The wage markdown used in Table 8 is estimated based on production function common across regions. However, manufacturing plants from East and West Germany are likely to be different, so I estimate the production function and wage markdowns for sub-samples of East and West German manufacturing separately to summarize the heterogeneity of markdowns by region. Table 9 shows the results, and the median markdown for plants in East Germany is 6.4% higher than that for plants in West Germany. The suggested markdown premium in East Germany from both analyses above is strongly consistent with Bachmann et al. (2022a), who suggest that manufacturing firms in East Germany are smaller and less productive due to higher monopsony power. The median and mean markdowns indicate that labor markets in East Germany are less competitive or are more monopsonistic, potentially due to weaker collective bargaining and works council coverage in East Germany than in West Germany (Jäger et al., 2022).

Similar to the wage-size ladder in East and West Germany shown in Section 2.3, I also investigate the markdown gap between East and West Germany in each twentiles of the firm size (total number of workers) distribution. Figure 6 plots the average firm size against the firms' average wage markdowns for twentiles of the firm size distribution in East and West Germany. Average

Employment Research (IAB). Second, the sample size is quite different: they have 159,673 firm-year observations, while I have 12,794 observations. Third, their sample spans from 2000-2014, while my sample spans between 1998-2018.

[19]Studies in the literature tend to control for firm's age in such regressions, but I exclude age due to limited information on firm's age in the IAB establishment panel. However, the qualitative findings on the relationship between the selected firm characteristics and markdown remain the same even if I include the firm's age, although the sample size substantially drops.

[20]The results are robust to excluding Berlin from the sample. The East-West markdown gap slightly drops to $\beta = 0.036$ (SE: 0.013) when I drop Berlin from the analysis.

wage markdown increases with firm size in West Germany but decreases with firm size in East Germany. The positive relationship between firm size and markdown in West Germany, a more developed region, is consistent with markdown heterogeneity by size in the U.S. (Yeh et al., 2022). The negative relationship between markdown and firm size in East Germany, a relatively underdeveloped region, is similar to that in India (Byambasuren et al., 2024). Leveraging employment shares as a firm size, I also examine the heterogeneity of markdown across East and West German plants. Panels (a) and (b) of Figure 7 show the results in the East and the West, respectively, suggesting similar findings as in Figure 3. The opposite relationship between size and markdown in different regions might be nullifying each other, yielding a weakly positive relationship on the full sample (panel (a) of Figure 5).

Relationship between markdown and union coverage. To examine the heterogeneity in labor market power by trade unions, I provide descriptive evidence on wage markdowns at firms with different union coverage. We expect wage markdown to be lower at firms with high union coverage as unions protect workers from their employers and advocate their interests and demands. As expected, Table 10 shows that markdown is smaller for firms with higher union coverage. The median markdown is almost equal to unity at firms in the top 3 quartiles (Panel A) and top 9 deciles (Panel B) of the union coverage distribution, and markdowns at firms in the first quartile and first decile are noticeably higher than unity. These results are consistent with higher markdown in East Germany, as found above, and weaker worker protection in East Germany via low union coverage, as shown in Jäger et al. (2022).

3.3 Aggregated Markdowns

Thus far, this section focuses on plant-level markdown estimates. Now, I discuss how I construct aggregate markdowns at the local labor market and year level. I aggregate the establishment-level markdowns at the local labor market level using the weighted harmonic mean of micro-level markdowns following Yeh et al. (2022). This method of defining aggregate markdown as a function of micro-level markdowns is similar to that used for aggregating firm productivities in Hsieh and Klenow (2009) and Itskhoki and Moll (2019). One of the advantages of this aggregation method is that we do not need to impose any specific structures in labor and output markets to construct a consistent aggregate measure. Additionally, several studies document that the labor market is local as workers find it costly to search for jobs far from their homes (Manning and Petrongolo, 2017; Marinescu and Rathelot, 2018) and in different occupations and industries that require different sets of skills (Kambourov and Manovskii, 2009). To account for the local nature of labor markets, I use weights based on sales (De Loecker et al., 2020).

In doing so, I first define the *local* labor market. Following Berger et al. (2022), I use an industry-geographical area pair as a local labor market. I focus on three-digit industries (ISIC Rev.4, or equivalently, WZ2008 classification) and states. This results in about 80 sectors within manufacturing and 17 geographical areas.

The aggregate markdowns and markups are defined, respectively, as

$$\mathcal{V}_{klt} = \frac{\left(\sum_{j \in F_t(k,l)} s_{jt} \cdot \frac{\theta^L_{jt}}{\theta^L_{klt}} \cdot (\nu_{jt}\mu_{jt})^{-1}\right)^{-1}}{\left(\sum_{j \in F_t(k,l)} s_{jt} \cdot \frac{\theta^M_{jt}}{\theta^M_{klt}} \cdot \mu^{-1}_{jt}\right)^{-1}}, \tag{4}$$

and

$$\mathcal{M}_{klt} = \left(\sum_{j \in F_t(k,l)} s_{jt} \cdot \frac{\theta^M_{jt}}{\theta^M_{klt}} \cdot \mu^{-1}_{jt}\right)^{-1}, \tag{5}$$

where θ^L_{klt} and θ^M_{klt} are, respectively, the average output elasticities of labor and intermediate materials in the industry k, location l, and year t. Here $s_{jt} = \frac{p_{jt}y_{jt}}{P_{klt}Y_{klt}}$ are sales weights[21] and $F_t(k,l)$ denotes the set of firms in local labor market (k,l).

I further aggregate the markdowns and markups across labor markets using employment weights (Rossi-Hansberg et al., 2021) to examine whether monopsony power in German manufacturing has increased over time. Specifically, I define

$$\mathcal{V}_t = \sum_{k \in K} \sum_{l \in L} \omega_{klt} \mathcal{V}_{klt}, \tag{6}$$

and

$$\mathcal{M}_t = \sum_{k \in K} \sum_{l \in L} \omega_{klt} \mathcal{M}_{klt}, \tag{7}$$

where ω_{klt} is the employment share of labor market (k,l).

Figure 8 illustrates the resulting time trend of aggregate markdowns, $\mathcal{V}_t$, depicting a downward trend since 1997, with some plateau between 2000-2008. The wage markdowns sharply declined since the Great Recession in 2009, consistent with a rise in wages and decline in markdowns since the recession, mainly driven by an increase in wages at the bottom part of the distribution (Drechsel-Grau et al., 2022; Dustmann et al., 2024).

3.4 Comparing Aggregate Markdowns with Labor Market Concentration

To provide additional evidence on the situation of labor market power in Germany, I calculate labor market concentration using the Herfindahl-Hirschmann Index (HHI). Using the matched employer-employee data structure, I construct the HHI for labor markets at the occupation (3-digit KldB

[21] I use sales weights strictly following Yeh et al. (2022), while the plant-level measures can also be aggregated using employment weights. The pattern and interpretation of aggregate measures are the same when the employment weights are employed because the sales and the number of workers are positively correlated, i.e., firms with higher sales employ more workers. The pairwise correlation between the log employment and log sales revenue is 0.9440 (SE: 0.0027, p-value: 0.00). Controlling for firm, year, district-by-year, and industry-by-year, I also find that the coefficient on log revenue in the regression of log employment is 0.3334 (SE: 0.0233).

1988), region, and year level. Using industry as part of the definition of labor markets is not ideal for calculating labor market concentrations. However, I also use sector (3-digit ISIC Rev.4) instead of occupations to be consistent with the markdown measure and compare aggregate markdowns with HHI. Additionally, I apply a range of alternative definitions for profession, industry, and geography for robustness checks. Given that my markdown measure is quantified using the IAB BP data, I also leverage the IAB BP data to calculate the labor market concentration. The HHIs are computed for the entire economy and manufacturing firms since the markdown is estimated only for manufacturing plants.

Given that I have worker-level administrative data matched with their employer, I first count workers at each establishment and then construct the HHI in labor market (o, l) and time t as

$$\mathrm{HHI}_{mt} = \sum_{j=1}^{I} s_{jmt}^2, \tag{8}$$

where s_{jmt}^2 is the market share of firm j in market $m = (o, l)$ as a number between 0 and 100, and o and l denotes occupation and geography index, respectively. In the alternative definition, I calculate (8) for market $m' = (k, l)$ where k is the industry index. A firm's market share in a given market m (or m') and time t is defined as the sum of workers at a given firm in a given market and time divided by the total workers in that market and time. The average HHIs are calculated by weighted average using employment as weights. Formally,

$$\mathrm{HHI}_{lt} = \sum_{o \in O} \omega_{olt} \mathrm{HHI}_{olt} \quad (\text{or } \mathrm{HHI}_{lt} = \sum_{k \in K} \omega_{klt} \mathrm{HHI}_{klt}), \tag{9}$$

and

$$\mathrm{HHI}_{lt} = \sum_{k \in K} \sum_{l \in L} \omega_{klt} \mathrm{HHI}_{klt}. \tag{10}$$

Table 11 shows summary statistics for labor market concentration in Germany for alternative market definitions. In our baseline market definition as a 3-digit KldB 1988 occupation by 141 commuting zones by year, the average overall HHI is 4243. The average HHI implies that the equivalent number of firms recruiting is only 2.4 on average. Looking at percentiles of the HHI beyond the mean, the 75th percentile of HHI is 6250. To put this number into perspective, a market with one firm having 75% of vacancies and another one with 25% yields an HHI of 6,250. 56% of the labor market is highly concentrated (above 2,500), and 16% of the market is moderately concentrated (have an HHI between 1500 and 2,500). The remaining 28% have a low concentration (below 1500 HHI).

Since my focus in this paper is manufacturing plants, I also zoom in on the manufacturing sector in Germany and calculate the HHIs. Table 12 reports the summary statistics for labor market concentration in the manufacturing industry. The main takeaway from the table is that labor market concentration in the manufacturing industry is greater than the country average and, thus, than in the non-manufacturing sector. The average HHI in the manufacturing industry suggests that only 1.7 firms recruit in a local labor market.

Previous studies using only production data, such as Yeh et al. (2022), are constrained in comparing the markdown measure with occupation-based HHIs primarily because such datasets do not have information on vacancies by occupation. Fortunately, our matched data provide a unique opportunity to compare occupation-based and industry-based measures of HHI and aggregate markdowns. From Tables 11-12, we see that HHIs calculated using 3-digit occupations and 3-digit industries are comparable.

To compare the HHIs with my measure of markdowns, I first calculate the bivariate correlation between the HHIs and wage markdowns across local labor markets (three-digit industry-state cells). I find that the cross-sectional correlation between $\mathcal{V}_{klt}$ and HHI_{klt} is weak: across years, this correlation is close to zero, negative sometimes and rarely statistically significant.[22] Despite this weak cross-section correlation, Figure 9 demonstrates that time trends in *aggregate* labor market concentration (HHI_t) and markdowns ($\mathcal{V}_t$) are substantially the same until the Great Recession in 2009. The correlation between aggregate HHI and aggregate markdowns between 1997-2008 is 0.82, and the co-movement of markdowns and labor market concentration over this period is consistent with previous studies (Bassier et al., 2022; Berger et al., 2022; Yeh et al., 2022). However, the two measures have departed from each other since the 2009 Great Recession. As discussed above, aggregate markdowns sharply declined since 2009 because of an increase in wages and the strength of collective bargaining, which cannot be captured by the HHI measure.

3.5 Markdowns for Heterogeneous Workers

Now I relax an assumption of homogeneous workers and consider heterogeneous workers with different exposure to displacement risk or automation threat. Workers are divided into groups based on their potential likelihood of being directly affected by labor-saving technologies or automation. Using those worker classifications, I measure markdown for such workers by estimating production functions with heterogeneous labor inputs.

Definition of heterogeneous workers. Using the BIBB/BAuA Employment Surveys and following an approach offered by Antonczyk et al. (2009) and later used by, for example, Bachmann et al. (2022b), I calculate task intensity measure for an individual i as

$$\text{TI}_{ikt} = \frac{\text{number of activities in category } k \text{ performed by } i \text{ at time } t}{\sum_k \text{number of activities in category } k \text{ performed by } i \text{ at time } t}, \tag{11}$$

where $t = \{2006, 2012, 2018\}$, and k indicates routine, nonroutine manual, and nonroutine cogni-

[22] I provide details in Online Appendix E.5.

tive tasks. I generally follow Spitz-Oener (2006) to classify job activities into these three broader task categories k. Then, I aggregate the individual-level task intensity measures at the occupational groups by taking averages of individual task intensities by occupational categories. The population weights in the BIBB datasets are applied to calculate representative aggregate measures. It provides a continuous measure of task intensity for each routine, nonroutine manual, and nonroutine cognitive task category for each 3-digit occupation. For pre-2006 periods, I use the task intensity measure fixed at the 2006 level. Finally, I merge these task intensity measures to the matched employer-employee data by occupation and year combinations.[23]

The BIBB/BAuA Employment Surveys enable me to construct task intensity measures specifically for Germany, while Autor and Dorn (2013)'s measure is constructed for the U.S. context. This feature is critical when determining worker heterogeneity by tasks because tasks performed at different occupations are likely to differ across countries (Caunedo et al., 2023). But, as a robustness check, I use Autor and Dorn (2013)'s static measure of task intensity developed for 1990 U.S. occupations using data from O*NET.

I define workers directly and indirectly affected by automation or robots in different ways based on tasks performed at the workplace and their education level.

Routine, nonroutine cognitive, and nonroutine manual workers: The difference between workers in terms of the risk of being replaced by robots needs to be considered when examining the impacts of actual automation and automation threat on workers because these shocks might have different implications on employers' labor market power given that recent technological change is biased toward replacing routine tasks (Autor et al., 2003; Goos et al., 2014). Depending on the potential risk of displacement and the realized impact of robots, automation threats might have different implications on labor market power for workers who differ in their tasks performed at work. In mechanical terms, automation threat could have differential effects on such workers, given its heterogeneous impacts on their productivity and wages, leading to a differential impact on their markdowns. Due to these nuanced mechanisms, the effects are likely to be highly heterogeneous for workers performing different tasks. Hence, I first examine the heterogeneity by job tasks concentrating on routine, nonroutine cognitive, and nonroutine manual tasks task-performing workers.

I consider that a worker is a routine, nonroutine cognitive, or nonroutine manual worker if the maximum of the three normalized task intensity indices is RTI_{ijt}, NRCTI_{ijt}, or NRMTI_{ijt}, respectively, for worker i at firm j in year t. Note that I added employer index j since I use the linked data for this analysis, and RTI_{ijt}, NRCTI_{ijt}, and NRMTI_{ijt} denote TI_{ikjt} index in equation (11) when task category k is routine, nonroutine cognitive, and nonroutine manual, respectively. These indices are normalized to have mean zero and unit standard deviation.

Defining three types of labor inputs performing different tasks allows more heterogeneity for es-

[23] Although the task intensity measure changes over time, and thus, the same occupation can be classified in different task categories, such instances are not prevalent, given that occupations are grouped into the same category for almost 90% of the time between the study period from 1998 to 2018.

timating the markdown and the impact of automation threat on labor market power. This grouping of workers is similar to that in Bachmann et al. (2022b), who measure monopsony power for such workers by estimating the labor supply elasticity. So, I can also compare my estimates of markdown for these workers with their results. Relatedly, Dodini et al. (2024) calculates the concentration of labor demand for workers performing various job tasks in Norway and shows that labor demand is less concentrated (or more competitive) for routine job tasks than that for nonroutine job tasks, especially in smaller local labor markets. This finding is consistent with my result that routine task-performing workers have the lowest markdown. Table 13 summarizes the employment, labor cost, and daily wage for routine, nonroutine cognitive, and nonroutine manual workers.

High- and low-skilled workers: Although some highly-educated workers perform routine tasks and face automation risks, such as bank tellers, low-education workers are generally subject to automation risks more than high-education workers (Acemoglu et al., 2023). Also, from the perspective of labor market power, the outside employment options for low-education and high-education workers are likely to be different, so markdowns for workers with different educational attainment are expected to be unequal (Yeh et al., 2022). Even if markdowns for such workers are equal, the implication of automation threat on their markdowns could be different. So, I distinguish workers by education categories as (i) low-education: workers without a vocational training degree, and (ii) high-education: workers with a vocational training degree or a degree from a University or a University of the Applied Sciences.

Low- and high-education workers are *not* synonymous for low- and high-skilled workers; however, some studies refer to education as skills (Antonczyk et al., 2009; Yeh et al., 2022) potentially because education level and ability or skills tend to be positively correlated. Hence, this categorization can be considered as a split of low-skilled and high-skilled workers. The impact of automation threat might be more nuanced among workers categorized by skills or education than job tasks if automation in Germany is more consistent with skill-biased technological change. Table 14 presents the descriptive statistics on employment, labor cost, and daily wage for high- and low-skilled workers.

Estimated markdowns for heterogeneous workers. I estimate the production function with heterogeneous labor inputs, then quantify the markdown for those workers. Table 15 shows the estimated plant-level markdowns for heterogeneous workers in the German manufacturing industry who differ by job tasks performed at their workplaces (top panel) and their skills or education level (bottom panel). Heterogeneous workers are included in the production function as separate inputs.

The estimated markdowns for workers who differ by their job tasks performed at the workplace suggest that (i) these workers are also subject to monopsony power in median and average manufacturing plants, and (ii) routine workers are subject to less monopsony power than nonroutine cognitive (NRC) and nonroutine manual (NRM) workers (Panel A of Table 15). These observations are strongly consistent with Bachmann et al. (2022b)'s results. I also find that NRM workers are subject to the highest monopsony power. This result differs from Bachmann et al. (2022b), who suggest NRC workers are subject to the highest degree of monopsony power. Specifically, I find that NRM, NRC, and routine workers receive 50 cents, 62 cents, and 77 cents on each euro generated, respectively, on average. My estimates are generally comparable in magnitude with markdown estimates at the mean implied from their estimated labor supply elasticities for workers who perform NRM ($\nu_{it} = 1.602$ or 62 cents per euro), NRC ($\nu_{it} = 2.043$ or 49 cents per euro), and routine ($\nu_{it} = 1.589$ or 63 cents per euro) tasks in Germany using administrative data on individual labor market histories (SIAB) for the years 1985-2014. My estimates differ from their results mainly for NRM workers, and the difference could be due to four reasons. First, our contexts are different. My estimates are only for the manufacturing industry, while they cover all industries in the country. Second, we use various methods with varying assumptions. I estimate markdown using the production approach, while they estimate labor supply elasticity using Manning (2003)'s method. Third, we leverage different data sets. I leverage the IAB Establishment Panel and the LIAB data to estimate the production function, while they use the Sample of Integrated Labour Market Biographies (SIAB) data. Finally, the period covered in my markdown estimation spans between 1997-2018, while they use periods from 1985-2014.

The estimated markdowns for high-skilled and low-skilled workers show that (i) the two types of workers face monopsony power in median and average manufacturing plants, and (ii) the markdown for low-skilled or low-educated workers is larger than the markdown for high-skilled or high-educated workers (Panel B of Table 15).[24,25] Online Appendix E.7 checks the robustness of markdowns for heterogeneous workers focusing on heterogeneity by job tasks to alternative measures of task contents and shows that the markdown estimates are generally robust.

Trends in aggregate markdowns. I aggregate the plant-level markdowns for heterogeneous workers using equations (4) and (6) similar to the baseline analysis where workers are homogeneous to show how employers' labor market power has changed for different workers in German manufacturing over time. Figure 10 illustrates the trends of aggregate markdowns, $\mathcal{V}_t$, over workers performing routine, nonroutine manual, and nonroutine cognitive tasks. Markdowns for workers performing manual and routine tasks have been decreasing, and the decline is more intensive in magnitude for manual task-performing workers. A downward trend in markdown for routine task-performing workers is strongly consistent with Bachmann et al. (2022b) who show that yearly labor supply elasticity, proportional to the inverse of markdown, has been increasing for workers with mean routine task intensity (RTI). I also find that labor market power for nonroutine cognitive workers has been stable between 1997-2018.

Figure 11 illustrates the time evolution of aggregate markdowns for workers with different skills. The results for low-skilled and high-skilled workers are generally consistent with workers perform-

[24] The distribution of markdowns for workers performing different tasks illustrates that markdowns are highest for manual workers, second-highest for cognitive workers, and lowest for routine workers (Appendix Figure G.1). Markdowns are always relatively higher for low-skilled workers (Appendix Figure G.2).

[25] Online Appendix E.6 examines the determinants of the gap between markdowns for workers performing different tasks using the Blinder-Oaxaca decomposition.

ing various tasks. Specifically, the pattern of employers' labor market power for low-skilled or low-educated workers is downward-sloped, potentially driven by manual workers. The markdown for high-skilled or high-educated workers has been relatively stable between 1997-2018, similar to cognitive workers.

4 Labor Market-Level Analysis

In this section, I describe the empirical strategy I employ to estimate the causal impact of exposure to automation on labor market power at the local labor market level, which relies on a shift-share instrumental variable (IV) design. The section also discusses the identification assumptions.

4.1 Empirical Specification

To investigate the effect of automation threat, proxied by predicted exposure to robots at the local labor markets, on labor market power measured by wage markdowns, I estimate the following equation:

$$\Delta Y_{rt} = \gamma_t + \beta_1 \widehat{\Delta\text{Robots}}_{rt} + \beta_2 \widehat{\Delta\text{Trade}}_{rt} + \beta_3 \widehat{\Delta\text{ICT}}_{rt} + \mathbf{X}'_{rt-1}\delta + \mu_{REG(r)} + \epsilon_{rt}, \tag{12}$$

where ΔY_{rt} is the annual change in one of the labor market outcomes, including markdown, employment, and wage aggregated at the local labor market region r (district or Kreis) in Germany and year $t \in [1998, 2018]$. I define region, not a combination of region and industry, as a local labor market because the data on the stock of industrial robots from the International Federation of Robotics (IFR) is at the industry level for a given country, so that one cannot use the combination of region and industry. Then, the reasons that I prefer to use region instead of industry are two-fold. First, existing studies from the literature examining the labor market effects of robots using the IFR data, such as Dauth et al. (2021) and Acemoglu and Restrepo (2020), used districts or Kreise and commuting zones as the baseline local labor markets in Germany and the U.S., respectively. Second, spatial difference, e.g., between East and West Germany, plays a critical role in labor market dynamics in the German context, as shown in this paper and others like Heise and Porzio (2022).

The annual change in automation threat or local labor market region's "predicted" exposure to robots in Germany $\widehat{\Delta\text{Robots}}_{rt}$ is constructed as

$$\widehat{\Delta\text{Robots}}_{rt} = \sum_k \frac{L_{krt-1}}{L_{rt-1}} \frac{\Delta\text{Robots}_{kt}}{L_{kt-1}}, \tag{13}$$

where L_{kt-1} is the employment in industry k in previous year, L_{krt-1}/L_{rt-1} is the Germany's employment weight of industry k in region r in previous year, and ΔRobots_{kt} is the change in stock of industrial robots in industry k of Germany between the previous and the current year. The research design in this paper exploits substantial variation in industry compositions across local labor markets. This variation further creates variation in exposure to technological change, e.g., industrial robots. However, the robot data for Germany over longer periods, only available from the IFR as described in Section 2.2, are collected only at the industry level. Hence, I follow Acemoglu and Restrepo (2020) and Dauth et al. (2021) and use a shift-share design to allocate each industry's robots stock across kreise or districts according to their shares of the industry's total employment. So, I call this a "predicted" local exposure and denote it with a hat. In my baseline analysis, I use industrial robots in automotive, i.e., $k =$ automotive, because the predicted exposure to robots in all industries fails to satisfy the relevance assumption according to Olea and Pflueger's (2013) weak-instrument test, which is suitable in my setting, although the assumption is satisfied according to the more traditional approach of Stock and Yogo (2005) and Kleibergen and Paap (2006).[26] The automobile is the dominant industry that drives the penetration of manufacturing robots in Europe, including Germany and the U.S. (Figure 12). Thus, the focus on the automotive industry does not sacrifice much variation in industrial robots as most of the variation in robot exposure comes from automotive robots. Despite that, I used the predicted exposure to robots in all industries as a robustness check in my heterogeneity analysis, where the relevance assumption was reasonable. I discuss this identification assumption and the relevant testing approach below.

The terms $\widehat{\Delta\text{Trade}}_{rt}$ and $\widehat{\Delta\text{ICT}}_{rt}$ are the predicted local exposures to net exports and ICT investment, respectively, which was similarly constructed as robot exposure. The annual change in trade exposure, $\widehat{\Delta\text{Trade}}_{rt}$, is measured by the yearly change in German net exports vis-à-vis China and 21 Eastern European countries for every manufacturing industry k using UN Comtrade data, normalized by the employment in the previous year to account for industry size. The annual change in exposure to ICT investment, $\widehat{\Delta\text{ICT}}_{rt}$, is defined by the annual change in real gross fixed capital formation volume per worker for computing and communication equipment using data on installed equipment at the industry level reported in the EU KLEMS database.

The vector X_{rt-1} contains demographic characteristics of the local workforce in the previous period, including the share of females, share of foreigners, share of workers over 50 years old, shares of workers with no educational training, vocational training, and university degree, and shares of workers in broad industry groups. The demographic controls are at the levels of the previous period instead of annual changes to prevent endogenous adjustments on the local labor force after the shock to contaminate the effects of changes in robot exposure or automation threat on changes in markdown. The time fixed effects γ_t controls for time-varying factors common across regions such as nation-wide federal policies and broad region dummies $\mu_{REG(r)}$ indicating if the region r is located in the north, west, south, or east of Germany capture the time-invariant regional differences across the broad regions.

[26] Appendix Table G.1 presents the results from testing the relevance assumption for robots in all industries using the two alternative methods. The instruments are strong enough for robots in all industries under Kleibergen and Paap's (2006) traditional approach; however, they are weak according to Olea and Pflueger's (2013) approach that is more suitable for overidentified models like in this paper.

4.2 Identification and Assumptions

I use variation in predicted robot exposure across industries to identify the causal effect of automation threat on employer power, assuming that some sectors are more likely to adopt industrial robots than others. However, variation in exposure to robots across industries in Germany could be due to differences in industry-level demands. Hence, to address biases resulting from this endogenous distribution of robots across industries and time, I use a shift-share instrumental variable approach that introduces the plausibly exogenous and supply-driven variation in robot exposure. Acemoglu and Restrepo (2020) proposed this strategy for identifying the impacts of automation, which was later used by Dauth et al. (2021) and Acemoglu and Restrepo (2022). In this setting, robot adoptions in other high-income advanced countries introduce the plausibly exogenous and supply-driven variation in predicted robot exposure in Germany, which I consider creates variation in potential robot adoption and thus automation threat.[27] This strategy is similar to the empirical approach of Autor et al. (2013), who investigate the local labor market effects of Chinese import competition in the United States. Specifically, I instrument a variable of predicted exposure to robots in Germany $\Delta\widehat{\text{Robots}}_{rt}$ with non-German exposure variables $\Delta\widehat{\text{Robots}}_{ort}$ that are constructed using data on the contemporaneous industry-level annual change in robot exposure in other high-income European countries:

$$\Delta\widehat{\text{Robots}}_{ort} = \sum_k \frac{L_{krt-j}}{L_{rt-j}} \frac{\Delta\text{Robots}_{okt}}{L_{kt-j}}, \tag{14}$$

where $\Delta\text{Robots}_{okt}$ is the realized stock of robots in industry k on other high-income European countries at year t and employment counts are at the level from the j years prior to the period t. Following the literature, I set $j = 10$ or use employment levels from the prior decade. In all other respects, equations (13) and (14) are the same.

Validity of instruments. For this instrumental variable estimation approach to work, the constructed shift-share instruments must satisfy four main assumptions: (i) relevance, (ii) independence, (iii) exclusion restriction, and (iv) monotonicity. First, there must be a strong correlation between changes in Germany's robot exposure and those in other high-income European countries. To inform the validity of the relevance assumption, Figure 13 depicts the first-stage relationship between the annual changes in exposure to industrial robots in the automotive industry in Germany and six other advanced countries included in the set of instruments. The scatter plots show that the endogenous regressor is strongly associated with the individual IVs, providing some credence to the inclusion restriction. The existing studies suggest that these shift-share instruments satisfy relevance assumption for the U.S. (for example, Acemoglu and Restrepo, 2022) and for Germany (Dauth et al., 2021) based on the traditional test and the popular rule-of-thumb—the F-statistic on the excluded instruments being more than 10 in the first-stage regression (Staiger and Stock, 1997;

[27] The instrument is constructed for each country $c =$ (Spain, France, Italy, Norway, Sweden, and the United Kingdom) as similar to Dauth et al. (2021), and thus I estimate the over-identified model.

Stock and Yogo, 2005; Kleibergen and Paap, 2006). However, Olea and Pflueger (2013) recently proposed a more appropriate test of weak instruments for overidentified models with a single endogenous variable where standard errors are clustered, like in this paper and many other cases in the shift-share literature. Therefore, I check the strength of my instruments using the Montiel Olea-Pflueger weak IV test and show that the endogenous regressor and the instruments are strongly correlated, suggesting a validity of relevance assumption. Section 4.3 presents the results from this formal test.

Second, a shift-share instrumental variable framework I use in this paper yields consistent estimates if the "shifts" or shocks are orthogonal to unobserved factors that determine the outcomes (Borusyak et al., 2022).[28] This condition will hold if shocks to the robot adoption in other high-income European countries are exogenous to changes in local economic conditions in Germany, regardless of whether local exposures to these shocks (i.e., variation in the share component) are endogenous. Given that I estimate an overidentified model in which the number of instruments exceeds the number of endogenous regressors, I can formally test the orthogonality assumption. Employing the overidentifying restrictions test (all IVs are uncorrelated to ϵ_{rt}), I provide evidence on whether the instruments satisfy the orthogonality condition (Sargan, 1958, 1998; Hansen, 1982; Altonji et al., 2005). Third, another assumption that has to be satisfied is the exclusion restriction assumption, which is not directly testable. Following the existing studies that used the same instruments to investigate the employment and wage effects of industrial robots (Acemoglu and Restrepo, 2020; Dauth et al., 2021), I assume that the changes in robot exposure in other high-income European countries considered as instruments affect the labor market outcomes in Germany only through changing the robot exposure in Germany.

Fourth, since I combine multiple instrumental variables (IVs) for a single endogenous variable or a treatment using a two-stage least squares (2SLS) approach, I am required to satisfy the well-known assumption of monotonicity, i.e., the 2SLS estimate is a positively weighted average of local average treatment effects (LATEs), to interpret my IV estimates as causal (Imbens and Angrist, 1994). In my setting, the endogenous variable is the stock of industrial robots in Germany, which I instrument for using robots stock in six other countries. This condition is satisfied if the choice behavior or Germany's robot adoption is effectively homogeneous, while the treatment effects of each instrument are likely heterogeneous in most cases. However, Mogstad et al. (2021) fortunately show that the 2SLS estimates can be a positively weighted average of LATEs under a weaker and verifiable condition of "partial" monotonicity in the case of a binary endogenous variable even if the monotonicity condition is violated. Although the endogenous variable in this paper, the annual change in the stock of robots per 1000 workers, is continuous, I carry out an analysis proposed by Mogstad et al. (2021) to indirectly check the partial monotonicity assumption.

Panel A of Table 16 reports coefficients from regressing $\Delta\widehat{\text{Robots}}_{rt}$ on each instrument sepa-

[28] See Goldsmith-Pinkham et al. (2020) for settings where identification comes from the orthogonality of the "share" component of the shift-share instruments.

rately along with the coefficients from regressing $\Delta\widehat{\text{Robots}}_{o_irt}$ on $\Delta\widehat{\text{Robots}}_{o_jrt}$ where o_i is arbitrarily Spain and $o_j = \{\text{France, Italy, Norway, Sweden, UK}\}$. These models also control for baseline covariates. Column 1 shows that controlling for the covariates (but not the other instruments), the correlation between each instrument and the treatment is positive and statistically significant. It implies that the weights for each complier group must be positive under the partial monotonicity assumption. Similarly, column 2 demonstrates that the partial correlations between the selected pair of instruments from the six instruments are also positive. It also implies that 2SLS weights are positive even if the traditional monotonicity assumption is violated. The joint distribution of the two instruments, thus, is sufficient to yield positive weights. Panel B of Table 16 presents the same results when the treatment and instruments are defined as binary variables, indicating whether the value is above mean because the formal statistical tests proposed by Mogstad et al. (2021) are for binary treatment and binary instruments. The results suggest that the partial monotonicity assumption is satisfied even for binary cases. As the formal tests for positive and negative 2SLS weights were proposed for the case when there are only two instruments, I consider all possible pairs of the six instruments. Consistent with the strong positive correlations in Panel B of Table 16, the null hypothesis of negative weights is strongly rejected ($p = 0.000$), and the null hypothesis of positive weights is not rejected ($p = 1.000$) for all cases (Table 17). These findings provide credence to the validity of the partial monotonicity assumption in my context and allow me to interpret my IV/2SLS estimates as causal.

Statistical inference. I cluster the standard errors at the level of local market regions or Kreise since the variations that I exploit are at the kreis level.[29] Additionally, as pointed out by Adao et al. (2019), conventional standard errors on shift-share explanatory variables such as $\Delta\widehat{\text{Robots}}_{frt}$ might be underestimated because regression residuals are likely to be correlated across regions with similar industry shares. Hence, they propose to compute the standard errors by allowing the correlation amongst error terms within region-industry share groups. I apply their method of calculating cluster-robust variance. In doing so, I closely follow Dauth et al. (2021)'s procedure and similarly use employment shares across industries.

4.3 Results

I first present the baseline results from estimating the effect of robot exposure on employment, wages, and firms' wage-setting power. I then investigate the heterogeneous impacts for workers performing different tasks across regions.

Baseline employment and wage effects. As mentioned earlier, Dauth et al. (2021) estimated the employment and wage impacts of robot exposure in the German manufacturing industry. However, before examining the consequences of robot exposure on labor market power, I study the

[29] I also cluster the standard errors by 50 aggregated labor market regions as a robustness check, and Section 4.4 discusses the results. I am grateful to Wolfgang Dauth for sharing the crosswalk from German Kreise to these aggregate regions.

employment and wage effects in my setting. Since the automation literature suggests that industrial robots, as a routine-biased technological change, have highly differential impacts on labor market conditions for workers performing different tasks, I estimate the employment and wage effects for routine, nonroutine manual, and nonroutine cognitive workers. Panel A of Table 18 presents the employment effects for these heterogeneous workers. Although the point estimates are not statistically significant, the robot exposure reduces the employment of routine workers, increases nonroutine manual workers' employment, and has zero employment effect on nonroutine cognitive workers in manufacturing. These results on employment effects for workers performing different tasks in manufacturing are, in fact, consistent with the results from Dauth et al. (2021), who also found weak employment effects for the same type of workers with generally the same direction of impacts.

As shown in Panel B of Table 18, the wage effects of robot exposure for heterogeneous workers are also not statistically significant. However, the results show that robot exposure increases the wages of routine workers and reduces the nonroutine workers' average daily compensation. The wage-reducing impact for nonroutine cognitive workers is much more significant in magnitude, which would drive the overall wage impact to be negative in manufacturing. Although Dauth et al. (2021) found a statistically significant negative effect on wages in manufacturing, the sign of the wage impact that I estimate is consistent. The subsequent section will examine the employment and wage effects at the plant level.

Baseline markdown effects. Table 19 presents the baseline results obtained from estimating the reduced-form model in equation (12) under four separate specifications wherein more controls are added successively. In panel A, I regress the annual change in aggregate markdowns on the change in robot exposure using ordinary least squares (OLS) between 1998-2018. The result shows that robot exposure is positively associated with employers' labor market power, although the relationship is not statistically significant.[30] In panel B, I estimate the impact of robot exposure on employer power using IV (2SLS) regressions. The effective F-statistic of Olea and Pflueger (2013) is above the threshold of 21 for the case of 10% potential bias and a 5% significance, and it is well above the rule-of-thumb threshold of 10, indicating robot adoptions in other high-income European countries provide significant variation in German robot exposure. Hansen's J-statistic suggests that the excluded IVs are exogenous and valid instruments. The IV estimates are similar in sign and close in magnitude to the OLS counterparts. The results from my preferred specification, shown in column (4), suggest that automation threat increases wage markdowns; however, the impact is not statistically significant in the baseline.

Heterogeneous effects. Since the plants and labor markets in East and West Germany are persistently different (e.g., Bachmann et al., 2022a) and I find that labor market competition is different across East and West German manufacturing plants according to fact 2 in Section 2.3, I first

[30]The positive but not strongly significant association between robot exposure and firms' labor market power is consistent with Mengano (2023) who shows that workers at firms with ICT have lower bargaining power than those at firms without ICT but the relationship is not strongly significant in France.

consider heterogeneity across East and West Germany. Before examining the markdown effect, I investigate the employment and wage effects of robot exposure heterogeneous across regions by estimating the equation (12) on sub-samples of East and West German districts (Table 20). The displacement effect for routine workers is more significant in magnitude in East Germany than in the West, although the effects are not statistically significant (Panel A). The robot exposure reduces the wages of workers performing different tasks in East and West Germany and the wage effects are larger in magnitude in the East; however, these effects are statistically insignificant as well (Panel B).

Then we investigate the markdown effects heterogeneous across East and West Germany. First, Table 21 presents the results for all workers. As shown in the preferred specification in column (4), the impact of robot exposure on wage markdowns is not statistically significant for establishments from both regions. However, the effect is positive for East German firms and negative for West German firms, indicating heterogeneity across space in markdown effects of automation threat.

Second, findings from existing studies in the automation literature suggest that the labor market effects of automation are highly heterogeneous across worker types, and the impact mainly concentrates among routine task-performing workers (e.g., Acemoglu and Restrepo, 2020; Dauth et al., 2021). Thus, I investigate the role of automation threat in firms' wage-setting power for workers performing different tasks, and Table 22 presents the results from the IV (2SLS) regressions. The results indicate that an increase in the labor market's exposure to industrial robots leads to higher wage markdowns over workers performing routine and manual tasks (columns (1) and (2)). In contrast, I find that robot exposure reduces markdowns over nonroutine cognitive workers, i.e., robots might provide power to cognitive workers who are likely to be complementary with robots (column (3)). However, these markdown impacts for workers performing different tasks are generally statistically insignificant.

To further examine the heterogeneous effects of exposure to automation on the labor market, I combine the two dimensions of heterogeneity analyzed above and estimate the regressions for heterogeneous workers in East and West Germany. The estimation results suggest that an increase in robot exposure in the local labor market increases firms' wage-setting power for routine task-performing workers in East Germany (column (1) of Panel A in Table 23). The coefficient estimate is positive, and conventional standard errors suggest that it is statistically significant at the 1% level; however, it is essentially zero when unconventional (or corrected for shift-share design) standard errors are applied. Despite this, the result is intuitive for several reasons. First, workers' outside options in East Germany are more limited than in West Germany as the East is relatively underdeveloped and has fewer and smaller employers (Bachmann et al., 2022a). Second, existing studies such as Heise and Porzio (2022) show that workers in East Germany have a significant home bias that further shrinks workers' outside options. Third, firms in the automotive industry in East Germany might not have industrial robots installed since most of the major car manufacturers are in West Germany, i.e., automation threat is more prevalent in East Germany. The robot exposure does not affect wage markdowns over other workers in East Germany even under conventional standard errors (columns (2) and (3) of Panel A). In the West, as shown in Panel B of Table 23, the point estimates for routine (column (1)), nonroutine manual (column (2)), and nonroutine cognitive (column (3)) workers are relatively smaller than the counterparts in East Germany with the same signs. However, the impacts are still not persistently estimated and generally not statistically significant.

Then, I investigate an additional heterogeneity by union coverage, which plays a central role in the German labor market and presents a significant heterogeneity in wage markdowns according to fact 3 in Section 2.3. Table 24 presents the heterogeneous effects on employment, mainly suggesting displacement effects for routine workers, except in West German districts with high union coverage, and the employment effects are not statistically significant. Table 25 then reports the heterogeneous effects on wages across districts with different union coverage in East and West Germany. The results suggest that the wage effects are more significant in magnitude in the East, consistent with the results above, and the impact in the East is slightly larger for routine workers. However, the wage effects are statistically insignificant, even under the additional heterogeneity by regions.

Table 26 shows the results on the markdown effects. Further splitting the sample of districts around the national median of union coverage reveals that the robot exposure increases markdown for routine workers in local labor markets with low union coverage in East Germany. The effective F-statistic of Olea and Pflueger (2013) is below the threshold of 22 for the case of 10% potential bias and a 5% significance. However, it is above the threshold of 14 for the case of 20% potential bias and a 5% significance and the rule-of-thumb threshold of 10, indicating that the IVs provide plausible variations in the German local labor market's exposure to robots in the automobile industry that can be leveraged to identify a causal effect of robot exposure on wage markdowns for heterogeneous workers in low union districts from East Germany. The effective F-statistics for other sub-samples also suggest that the instruments are sufficiently strong. The estimated effect for such workers is 0.05 and statistically significant at the 1% and 5% significance levels under conventional and unconventional approaches (top left panel). The coefficient estimate for routine workers in low union coverage districts in West Germany has the same sign and is close in magnitude; however, it is not statistically significant (bottom left panel). For routine workers in high union coverage districts in East and West Germany, the coefficient estimates are approximately ten times smaller in magnitude and statistically insignificant (top-right and bottom-right panels).

In addition to the reasonings discussed above for routine workers in East Germany, this result, suggesting that the impact is more significant for districts with low union coverage, is consistent with the descriptive finding in Section 3.2 and findings from existing studies in the same context. For example, Dauth et al. (2021) suggest that the displacement effect is significant for districts with low union coverage, and thus, the displacement or automation threat is expected to be more in such areas.[31] The main findings indicate that, although not strongly significant, there is a pattern

[31] I also estimate the heterogeneous effects of robot exposure on wage markdowns in districts with high and low union coverage for all and heterogeneous workers. The results, available on request, generally suggest that the impacts are not statistically significant until we combine the heterogeneity by East/West, union coverage, and worker types.

of displacement effect on routine workers. The impact of automation threat proxied by the robot exposure on wage markdowns is highly heterogeneous, increasing markdowns over routine workers in districts with weak worker protection in East Germany.

4.4 Robustness Checks

I perform a battery of robustness checks focusing on the heterogeneous effects of robot exposure on labor market power, which is a primary labor market outcome in this paper.

Common production function for East and West Germany. In the baseline heterogeneity analysis by regions, I use wage markdowns based on production function estimated for East and West Germany since the production process and utilization of production inputs can vary across East and West regions. Thus, I check the robustness of my results on the effect of robot exposure on wage markdown using markdowns based on production function commonly estimated for East and West Germany, i.e., on the full sample of German manufacturing firms. Table 27 suggests the findings for heterogeneous workers in East and West districts stay unchanged. The results shown in Table 28 show that my primary finding is highly robust to alternative estimation procedure of wage markdowns, and the markdown effect for routine workers in low union districts from East Germany is more precisely estimated. Similarly to the baseline, the markdown impact of robots is not significant in districts from East Germany with high union coverage and all districts from West Germany, even for routine workers.

Alternative split of union coverage. In the baseline analysis, I split the districts around the national median of union coverage to estimate the heterogeneous effects of robot exposure on markdowns in high and low union districts. Thus, I check the robustness of the results heterogeneous by union coverage using an alternative split, which also informs about which part of the distribution drives the impacts. The effects are concentrated in the bottom part of the distribution, specifically in the bottom eight deciles (Table 29). The effective F-statistic of Olea and Pflueger (2013) slightly suffers and goes below the threshold of 12 for the case of 30% potential bias and a 5% significance. However, the effective F-statistic of 9.4 is not well below the rule-of-thumb threshold of 10 for low union districts in East Germany. So, we can interpret the estimated coefficient as causal. The markdown-increasing impact of robot exposure among workers performing routine tasks in low union districts from East Germany is robust under this alternative split of union coverage (column (1) in Panel A). For West Germany, the effective F-statistic goes down to 6.6 for low union districts, so the estimates are not necessarily causal. However, the estimated effects on markdowns for routine, nonroutine manual, and nonroutine cognitive workers are qualitatively the same as in the baseline (Panel B). I fail to estimate the impacts for districts in the top two deciles of the union coverage distribution because of statistical power issues.

Percentage changes. I use the absolute changes in aggregate markdowns and predicted robot exposures in my baseline analysis. So, I test the robustness of my main findings from the IV regressions in Table 26 by employing percentage changes in the outcome and the key explanatory variables. Table 30 reports the results. The main finding that robot exposure increases markdown for routine workers in districts from East Germany with low union coverage is robust as the estimate is still statistically significant at the 5% level. The markdown effects for groups are generally not statistically significant, the same as the baseline results.

Alternative clusters at the aggregate regions. In my baseline analysis, I clustered the standard errors by districts or kreise at which my treatment variable is defined. As an alternative to this choice of cluster, I use aggregate regions as clusters following Dauth et al. (2021) who clustered the standard errors at the level of 50 aggregate labor market regions. Table 31 presents the 2SLS results for all and heterogeneous workers on the full sample, and the qualitative results are the same as those in Tables 19 and 22. I failed to check the robustness of my results for heterogeneous workers estimated on sub-samples of East and West Germany and districts with high and low union coverage as the number of clusters became too small when I split the sample. However, the results seem to be unaffected by the choice of clusters.

Adding a treatment of robot exposure in other industries. As mentioned in Section 4, I leverage exposure to robots in the automotive industry in my baseline analysis because the instruments were not strong enough according to Olea and Pflueger's (2013) weak IV test when I use robots in all manufacturing industries. Here, I check the robustness of my main findings by adding the local market's exposure to robots in other industries in Germany as an additional treatment variable instrumented by non-automotive robots in other high-income European countries. As shown in Table 32, the impacts of automation exposure on markdowns for routine workers in districts from East and West Germany with different degrees of union coverage are generally robust. However, the statistical significance tends to suffer under the unconventional approach.[32] I find that automotive robots drive the impact since the coefficient estimate on exposure to automotive robots is stronger than the estimate on exposure to other robots in magnitude and statistical significance. This result is consistent with Dauth et al. (2021), who studied the employment and wage effects of robots in Germany. We keep the full set of baseline controls, such as trade shocks and fixed effects, which minimize the omitted variables bias.

Industrial robots in all industries. As discussed earlier, I use robots in the automotive industry in my baseline analysis because the first-stage F-statistic of Olea and Pflueger (2013) was not large enough on the full sample with manufacturing plants from East and West Germany. Despite the failure of this formal test statistic, the first-stage relationship between the annual changes in exposure to industrial robots in all industries for Germany and other high-income European countries is strongly positively associated when estimated on the full sample (Appendix Figure G.3). However, this test statistic changes when I split the sample into East and West Germany, and it is reasonably

[32] In this specification with two endogenous variables, I show Kleibergen and Paap's (2006) statistic to check the relevance of excluded instruments because Olea and Pflueger's (2013) weak IV test is not designed for the case of multiple endogenous variables. The joint F-statistic indicates that the instruments provide plausible variations in robot exposure in Germany that can be leveraged to identify causal effects.

plausible for sub-samples. The effective F-statistic of Olea and Pflueger (2013) is approximately equal to the threshold of 10 for the case of 30% potential bias and a 5% significance for low union districts in East Germany (Panel A of Table 33) and above the threshold of 18 for the case of 10% potential bias and a 5% significance for high union districts in West Germany (Panel B of Table 33). These values are either close to or higher than the rule-of-thumb threshold of 10, after which the weak instrument problem does not appear to affect the validity of conventional t statistics in the case of clustered standard errors (Andrews et al., 2019). The estimation results with alternative endogenous variables and instruments are generally robust, although the statistical significance tends to suffer under the unconventional approach. The effect of robot exposure on wage markdown for routine workers in low union districts from East Germany is positive (column (1) in Panel A). The other results are generally the same as the baseline counterparts.

Alternative group of instruments. In my baseline analysis, I instrument Germany's robot exposure by robot exposure in six other high-income European countries. As discussed earlier, Olea and Pflueger's (2013) weak IV test and a traditional rule-of-thumb test suggest that these six instruments are jointly relevant. Figure 13 also shows a strong correlation between Germany's robot exposure and an individual country's robot exposure for all six countries. However, controlling for other covariates and fixed effects could change the relationship between the endogenous variable and individual instruments. Table 34 thus presents the relationship between instruments and the endogenous variable from the first-stage regression. Although the six instruments jointly satisfy the relevance assumption, the relationships between the endogenous variable and instruments from France and Italy are essentially zero, conditional on baseline covariates and fixed effects. The first-stage relationship for Spain, Norway, Sweden, and the UK is consistently positive and statistically significant at the 1% level (Column (1)), and it also remains the same in a specification including only these four countries (Column (2)). Leveraging robot exposure in Spain, Norway, Sweden, and the UK, Table 35 shows that my main results are remarkably robust to an alternative set of instruments that consist of the four countries.

4.5 On the Mechanism

The heterogeneous effects and robustness checks around those results generally inform the mechanisms through which firms increasingly set their workers' wages below the MRPL in response to an increase in their exposure to robots, i.e., what enables the firms to have wage markdowns over their workers. In addition, information on the number of robots at the firm from the IAB Establishment Panel data enables us to check whether the effects of robot exposure that we identify are the exposure effects or if it also captures the impact of actual robot adoption. In particular, I control actual robot adoption at German manufacturing firms in addition to Germany's robot exposure instrumented by robot exposure in other countries. Since the data on robots used at the firm is available for only five years between 2014 and 2018, I first estimate the baseline IV regression over the same period. Table 36 presents the results. The estimated effects of robot exposure on wage markdowns are not statistically significant in all specifications, except for a negative coefficient estimate for nonroutine manual workers in East German districts with high union coverage, potentially due to a small number of observations and weak statistical power. The relevance test results are also slightly noisy. However, these estimates are helpful to compare with those obtained by including actual robot adoption as an additional control, shown in Table 37. The qualitative and quantitative results generally remain the same, indicating that controlling for actual robot adoption does not affect the impact of robot exposure. The primary mechanism at play is thus the robot exposure.

5 Firm-Level Analysis

Now I switch the focus from local labor market analysis to establishment-level analysis, which complements the previous models. This section first checks the robustness of baseline effects from the local labor market approach by estimating the effects of automation exposure on markdown, employment, and wages at the firm level. Then, I further examine the potential mechanisms through which automation exposure affects labor market power by conducting additional heterogeneity analysis at the granular level.

5.1 Empirical Specification

I use a design that compares the outcomes of manufacturing firms that operate in local labor market regions with varying exposures to automation. Particularly, the estimating equation is

$$\Delta Y_{jt} = \beta \Delta \widehat{\text{Robots}}_{rt} + \mathbf{Z'}_{jt-1}\gamma + \mathbf{X'}_{rt-1}\delta + \phi_j + \mu_{st} + \pi_{kt} + \varepsilon_{jt}, \tag{15}$$

where ΔY_{jt} represents the annual change in one of the outcomes, including markdown, employment, and wage, for firm j in Germany at year $t \in [1998, 2018]$. The term $\Delta \widehat{\text{Robots}}_{rt}$ is the same as in equation (12), the annual change in local labor market's exposure to robots in Germany's automotive industry.[33,34] The vector $\mathbf{Z'}_{jt-1}$ includes firm-level controls, i.e., dummies for six plant size groups based on the number of employees in the previous year.[35] The vector $\mathbf{X'}_{rt-1}$ contains local labor market characteristics included in equation (12) and annual changes in trade exposure and ICT exposure at the labor market level. Leveraging the longitudinal structure of the IAB Establishment Panel data, I control for a rich set of fixed effects at the granular level, including the firm fixed effects ϕ_j, federal state-by-year fixed effects μ_{st}, and two-digit industry-by-year fixed effects π_{kt}. The error term ε_{jt} captures the remaining unobserved, time-varying, and firm-specific factors.

[33] I use robot exposure at the local labor market level, instead of industry's exposure to robots, because the baseline results found in Section 4.3 suggest that the markdown effects are highly heterogeneous across regions particularly, East and West Germany. Thus, I employ the local labor market's exposure to robots to conduct heterogeneity across regions in the firm-level analysis.

[34] I also add robot exposure in other industries for a robustness check of the firm-level results.

[35] Given that information on plant's opening year has many missing observations in the IAB Establishment Panel data, I do not control for plant's age in the regressions.

Heteroskedasticity-robust standard errors are clustered at the district or kreis level.

I consider three main outcomes in specification (15), including (i) plant-level markdowns estimated in Section 3, (ii) log employment or number of employees at the firm obtained from the IAB Establishment Panel data, and (iii) log wage per worker calculated by dividing total wage bill by total number of workers using data from IAB Establishment Panel. The identification strategy is similar to that was used for the local labor market-level analysis, i.e., instrument Germany's robot exposure with robots in other high-income European countries.

5.2 Employment and Wage Effects

To understand the consequences of automation threat on labor market power, I first analyze the employment and wage effects. Table 38 presents the baseline employment effects. As shown in column (1), automation exposure reduces employment; however, the impact is only significant at the 10% level. However, when I estimate the effects on the employment of heterogeneous workers performing different tasks, I find that routine workers have been displaced due to automation exposure, which does not affect the employment of nonroutine manual and nonroutine cognitive workers. These results are strongly consistent with evidence from Dauth et al. (2021), who suggest that automation displaces routine workers in manufacturing with no employment impact on other workers at the individual level in the same context of the German labor market.

Then, I estimate the heterogeneous employment effects by East and West regions, and Table 39 reports the results. The employment effects mainly come from East Germany, where the heterogeneous impacts across workers performing different tasks are more pronounced. In particular, the labor displacement effect for routine workers is still statistically significant at the 1% level, and the displacement effect becomes slightly more significant for nonroutine manual workers. Also, the results show that automation technologies complement nonroutine cognitive workers in East Germany. Like the local labor market-level analysis, I further split the sample of East and West German firms into those residing in districts with different union coverage. The results shown in Table 40 suggest that the displacement effect of routine workers in East Germany concentrates among plants in low-union districts (top-left panel), which is consistent Dauth et al. (2021).

I next study the wage effects of robot exposure. Table 41 presents the results for wage changes. For both cases of homogeneous (column (1)) and heterogeneous (columns (2)-(4)) workers, wages do not respond to changes in the automation exposure. The null wage effects for heterogeneous workers performing different tasks are generally consistent with the results from Dauth et al. (2021). As shown in Table 42, I estimate the heterogeneous effects on average wages by region. The results indicate that the average compensation of heterogeneous workers is not still responsive even when we split the sample into East and West German establishments. Furthermore, I explore the wage effects by conducting additional heterogeneity by union coverage. However, I fail to find a significant impact on average wages in any of the cases, except for a weakly positive impact of robot exposure on wages of nonroutine cognitive workers in low-union districts (see Table 43).

5.3 Markdown Effects

I present the results from estimating the effects of labor market exposure to automation on plant-level wage markdowns to check if the firm-level analysis replicates my baseline results from the local labor market approach. As shown in Panel A of Table 44, the impact of robot exposure on plant-level markdown is positive but not statistically significant for the full sample of Germany (column (1)) and the establishments from East Germany (column (2)). Although the coefficient estimate is statistically insignificant, it is negative for the establishment from West Germany (column (3)). Then, in Panel B of Table 44, I estimate the effect for heterogeneous workers performing different tasks and find that the effects are not significant, although the estimates are positive.

I estimate the markdown effects of automation exposure heterogeneous by region and job tasks, similar to the local market-level analysis. Table 45 shows the results, suggesting that wage markdown over routine workers increases as robot exposure intensifies in East Germany, and the positive effect is statistically significant at the 5% level. For other workers in East Germany and all three types of workers in West Germany, the impact of robot exposure on markdown is essentially zero. All these results are strongly consistent with those from the specification at the local markets, discussed in Section 4.3. Table 46 further investigates the markdown effects heterogeneous across regions with different degrees of union coverage. The robot exposure weakly increases plant-level markdowns over routine workers in low-union districts from East Germany (column (1) in the top-left panel). The markdown effects in all other cells are strongly insignificant.[36]

The empirical evidence from firm-level and labor market-level analyses consistently suggests that exposure to industrial robots leads to lower employment and higher wage markdowns for routine workers. The employment and markdown effects are particularly significant in districts from East Germany with low labor protection. The wages are generally stagnant.

5.4 Potential Mechanisms

The local labor market- and firm-level analyses yield three main results. First, workers performing routine tasks have been displaced by robots since the employment of such workers tends to decline as the local labor market gets more exposed to automotive robots. Second, robot exposure provides labor market power to employers, particularly over routine tasks-performing workers, who are subject to the risk of displacement from industrial robots. Third, this impact is heterogeneous across regions and unions. Thus, I further explore the mechanisms underlying these results by analyzing additional firm-level heterogeneity on markdown effects and discuss other potential channels through which automation exposure might affect employer power. This section also esti-

[36]The plant-level results on employment, wage, and markdown effects of robot exposure are robust to adding a local market's exposure to non-automotive robots in Germany instrumented by non-automotive robots in other high-income European countries as an additional treatment variable. The results from this robustness check are available on request.

mates additional heterogeneous effects that contribute to a better understanding of the labor market and employer power effects of robot exposure using firm-level data.

Unions. Several results in Sections 4.3 and 5 on heterogeneous impacts around unions suggest a potential mechanism. First, most importantly, automation exposure increases markdown over routine workers in districts with low union coverage in East Germany. This result is intuitive as workers are less protected in areas with low union coverage or less worker representation, enabling employers to threaten and intimidate workers in wage negotiation. Put differently, when employers' exposure to alternative sources of labor increases, further improving their outside options, the employer's power or their voice in bargaining with workers. This phenomenon is likely to occur in places where an individual worker bargains their wage with their employer without the unionized force of their fellow workers in the industry, for example, through trade unions. Second, nonroutine workers' markdown decreases and average wage increases, especially for nonroutine cognitive workers, in districts with low union coverage in East Germany. Third, there are no markdown effects at the establishment from West Germany, even under the union coverage heterogeneity.

Displacement threats from potential automation. As suggested by fact 1 in Section 2.3, robot exposure shock from other high-income European countries that I use to introduce variation in Germany's robot exposure does not predict the actual robot adoption in Germany. Thus, the employer power-increasing impact of robot exposure instrumented by plausibly exogenous shift-share factors is not the impact of actual robot adoption, but it could be the impact of robots that have not been realized yet. To further investigate this mechanism, I estimate the relationship between robot exposure predicted from the first-stage regression and actual robot adoption (Table 47). As expected, robot exposure predicted from the first-stage regression is positively correlated with the robot exposure, an outcome in the first-stage regression, and the relationship is highly significant for both automobile and all industrial robots (panel A). However, the robot exposure predicted from the first-stage regression is not associated with the actual robot adoption for any of the automobile and all industrial robots (panel B), confirming that the identified impact is not the effect of actual robot adoption.[37] Therefore, the impact of automation exposure on firms' labor market power that I have identified is likely through the channel of threats from potential automation.

Changes in outside options. Non-robot-adopting manufacturers still hire routine task-performing workers and negotiate wages with them at some point, e.g., at the beginning of employment during hiring or on the job. Labor displacement or intensity of local labor market region's exposure to robots improves non-robot adopting firms' outside options via additional potential workers displaced away from other firms. Put differently, it provides more alternatives for firms to hire and reduces routine workers' layoff options. These changes in employers' and workers' outside options would translate into their bargaining and wage-setting power.

Additionally, as suggested by the empirical results in Sections 4.3 and 5, robot exposure in-

[37] This section zeroes in on robots in the automotive industry, which was the focus of my baseline analysis. However, the results stay the same when I use exposure to robots in all industries as an alternative (Appendix Table G.4).

creases employers' labor market power in East Germany, and (Bachmann et al., 2022a) show that manufacturing firms in East Germany are smaller in size and less productive than West Germany and suggest that it is due to higher monopsony power. Given smaller plants, outside options for workers in East Germany are limited due to few available positions. Workers' job flows biased towards their home region is also significantly large in East Germany (Heise and Porzio, 2022), suggesting a strong home bias in workers' preference. Therefore, it is likely that routine workers' response to automation threats could be more effective in East Germany due to the pre-existing condition of the region.

Heterogeneous effects among firms with different size. The likelihood of robot adoption is higher for larger firms; thus, the displacement thread could be more prevalent. Hence, I estimate the plant-level effects of robot exposure heterogeneous by firm size. Table 48 presents the heterogeneous effects on markdowns for all and heterogeneous workers. Although the coefficient estimates are not statistically significant, the impacts of robot exposure on plant-level markdowns for all workers are positive for small and large firms; however, the magnitude of the estimate is much more significant for large firms than for small firms (Column (1)). The estimated effects for heterogeneous workers in Columns (2)-(4) suggest that the markdown-increasing impact is most significant for routine workers at large firms; however, the estimates are not statistically significant. Table 49 further investigates the heterogeneous effects by firm size on top of the heterogeneity by East and West Germany. The results suggest that robot exposure increases wage markdown for routine workers at large firms in East Germany.[38] Consistent with the markdown effect, I find that robot exposure leads to a decrease in wages at large firms, although the coefficient estimates are not statistically significant (Table 50).

The labor displacement effects for routine workers are intuitively concentrated among large firms that are more likely to adopt robots (Table 51). However, this employment effect is statistically significant in West Germany, where robot adoption is potentially more likely to be realized. The displacement threat, which should not affect employment, might be driving the effects of robot exposure on routine workers' bargaining power in East Germany.

Heterogeneous effects at different periods. As discussed in Section 3.3 and shown in Table 8, aggregate wage markdowns leveled off at a relatively high level until the 2009 Great Recession. After the recession, the aggregate markdown sharply decreased primarily due to wage increases as workers became more mindful of their wages. As presented in Section 2.1, wage inequality presents an upward trend and peaks in the late 2000s (Bossler and Schank, 2023). So, I consider there could be heterogeneity around this period in the effect of robot exposure on markdowns. Table 52 reports the markdown effects of robot exposure in East and West Germany around the late 2000s, suggesting that the effects were concentrated before 2009.[39] Consistent with the changes in workers'

[38] Online Appendix F.1 shows that the heterogeneous effects of robot exposure on plant-level wage markdowns by firm size are strongly robust to alternative definitions of large firms.

[39] Since the task intensity measure used for the classification of routine, nonroutine manual, and nonroutine cognitive

awareness of their wages after the Great Recession and the decline in wage inequality after 2010, the impacts of robot exposure on wages of workers who are complementary or not substitutable are positive in East and West Germany after 2009 (Columns (5) and (6) in the right sub-panel of Table 53).

Another reason that I identify significant markdown effects of robot exposure could be that most of the variations in robot exposure in other high-income Europeans that introduce variations in robot exposure in Germany occurred before 2009 (see panel (b) of Figure 12). The penetration of manufacturing robots in the automobile industry grew until 2008 in European countries other than Germany, while it leveled off and even presented a slight downward trend from then until 2019.

Heterogeneous effects across different industries. To better understand which industries drive the labor market effects of exposure to automation, I estimate the heterogeneous effects by sectors with different intensities in automobile robots. Although I use robots only in the automobile industry, firms in various manufacturing industries in different kreise or counties have varying exposure or intensity to automobile robots because automobile robots are predicted to the local labor market regions based on their employment shares, and thus establishments operate in different industries in those local communities have unequal exposure to automobile robots. The average annual change in district-level automobile robots per 1,000 workers in the country is 0.248 between 1998-2018. I define industries with annual change higher than this national average as industries intensive in automobile robots, i.e., robot-intensive industries. The robot-intensive industries include those that produce (i) food, (ii) beverages, (iii) leather products, (iv) wood products, (v) paper products, (vi) pharmaceuticals, (vii) fabricated metals (excluding machinery and equipment), (viii) machinery and equipment, (ix) motor vehicles, and (x) other manufacturing. The regression results show that the markdown-increasing effects are intuitively more significant in robot-intensive industries in East Germany (Table 54).

I then estimate the employment effects of robot exposure for firms operating in robot-intensive and non-robot-intensive industries. The estimation results, available on request, show that the negative impact on routine workers' employment is statistically significant for firms in the robot-intensive industries. However, the employment effect for routine workers is not statistically significant for plants in industries where automobile robots are not prevalent. These results are intuitive and consistent with the expectation. Then, I add heterogeneity by East and West regions. Table 55 presents the results from these regressions. The employment effect is negative and statistically significant for routine workers employed at plants in both robot-intensive and non-robot-intensive industries in East Germany. The displacement effect, however, is more significant in robot-intensive industries in magnitude and statistical significance.

Firm mobility across regions. The firm's labor market outcomes, like wage markdowns, could

workers did not change until 2012 (see Section 3.5), the results suggesting the effects are mainly concentrated before the 2009 Great Recession reassure that the baseline findings are not affected by the worker classification based on task intensity measure discretely changing over time.

change due to the relocation of the firm in response to changes in the local labor market region's exposure to industrial robots. The estimated impacts of robot exposure could be thus partly due to the changes in the location. Controlling for state-by-year fixed effects accounts for the firm mobility across states or changes that potentially lead firms' move across states over time (Baum-Snow et al., 2024). In addition to state-by-year and firm fixed effects, we can add district fixed effects, and it can capture district-level time-invariant characteristics that attract firms. Online Appendix F.2 checks the robustness of the heterogeneous effects of robot exposure on wage markdowns in East and West Germany by adding district fixed effects, showing that the results are substantially robust.

The district fixed effects are not included in specifications for East and West German districts with different union coverage since the coefficient estimate on predicted robot exposure was dropped when I added the district fixed effects on top of all the other fixed effects and controls. It could indicate that there is not much firm mobility across districts. Thus, it is implausible to consider the results are primarily driven by firm mobility across regions.

6 A Wage Bargaining Model of Automation Threat

The main empirical findings suggest that automation threat, proxied by exposure to industrial robots, increases wage markdown, a measure of monopsony and labor market power, for workers performing routine workers. This markdown impact is particularly significant in East German local labor market regions with low union coverage or weak worker protection.

This section presents a simple conceptual model of wage bargaining. The framework is based on the right-to-manage model of collective bargaining (as proposed by Nickell and Andrews (1983)), where a union and an employer (or employers association) bargain over wages only and then the firm unilaterally chooses an employment level at the bargained wage. The changes in the potential adoption of labor-saving technologies are likely to affect firms' outside options, which feed into the wage negotiation between the employer and workers. So, I offer a bargaining model to characterize the impact of automation threat on firms' labor market power. I do not seek to estimate or calibrate the model; instead, I derive qualitative predictions on hypotheses, some of which I empirically test with German data in the previous sections.

6.1 Setup

Consider a firm that employs two types of workers (routine and nonroutine) to produce an output via the following production function:

$$Q = F(l_L, l_H), \tag{16}$$

where l_L and l_H are the firm's employment of routine and nonroutine labor, respectively. This production function is assumed to be constant returns to scale and thus exhibits diminishing marginal product of labor. I assume that the output market is perfectly competitive (the firm is a price-taker in the output market).

Let $W_L(l_L)$ and $W_H(l_H)$ be the labor supply curve of routine and nonroutine workers, respectively, given the number of workers l_L and l_H. $W_L(l_L)$ and $W_H(l_H)$ are the opportunity cost of working for a firm—a firm must pay at least W_L and W_H for l_L and l_H, but the firm can choose to pay more. Let w_L and w_H be the actual wages paid by the firm to routine and nonroutine workers, respectively. The firm's objective function or the profit function is thus:

$$\pi(w_L, w_H) = Q - w_L l_L - w_H l_H, \tag{17}$$

where the output price is normalized to unity.

Given the heterogeneous workers in the model and the significant role of worker group-specific unions in the German labor market, particularly before the 2015 "unity law",[40] I consider two types of bargaining, including *separate* and *joint* bargaining. I consider each of these two cases below.

Separate bargaining. The firm simultaneously bargains with a union (or unions) representing routine and nonroutine workers separately. The Nash bargaining problem between the firm and the union representing routine and nonroutine workers is:

$$\begin{aligned}
&\underset{w_L}{\text{Max}}\,(Q - w_L l_L - w_H l_H - \bar{\pi}_L)^{\alpha}\,(w_L l_L - W_L(l_L) l_L)^{1-\alpha}\,, \\
&\underset{w_H}{\text{Max}}\,(Q - w_L l_L - w_H l_H - \bar{\pi}_H)^{\beta}\,(w_H l_H - W_H(l_H) l_H)^{1-\beta}\,,
\end{aligned}$$

where α and β are the firm's bargaining strength over routine and nonroutine workers, and $\bar{\pi}_L$ and $\bar{\pi}_H$ are the firm's threat point or the fallback profit for bargaining with routine and nonroutine workers, respectively.

The firm's fallback profit when the firm's agreement with routine workers falls apart, $\bar{\pi}_L$, depends on the number of robots and price of robots as the firm purchases robots as a production input to complete routine jobs in the complete or partial absence of routine workers. The price or rent of robots is denoted by r, and the change in r characterizes the threat of automation. For example, the automation threat increases when the robots become more affordable or in the event of a decrease in the rents of robots. The relationship between the price of robots and the threat point for routine workers is:

$$\frac{\partial \bar{\pi}_L}{\partial r} < 0,$$

since the firm's outside option expands and the threat point increases as the price of robots decreases or automation threat increases.[41] I assume that the firm's threat point for bargaining with

[40] In 2015, the German government passed the "unity law" with support from both unions and employer associations to undermine employers' bargaining with occupation-specific unions.

[41] The production and the fallback profit when the firm does not reach an agreement with routine workers ($Q =$

nonroutine workers $\bar{\pi}_H$ does not directly depend on r because robots are unlikely substitutes for nonroutine workers.

Joint bargaining. The firm jointly bargains with a union representing both types of workers or negotiates with a labor union that maximizes the aggregate utility of routine and nonroutine workers. The Nash bargaining problem is represented by the following maximization problem:

$$\underset{w_L, w_H}{\text{Max}} \left(Q - w_L l_L - w_H l_H - \bar{\pi}_{LH}\right)^{1-\gamma_L-\gamma_H} \left(w_L l_L - W_L(l_L) l_L\right)^{\gamma_L} \left(w_H l_H - W_H(l_H) l_H\right)^{\gamma_H},$$

where γ_L and γ_H are the firm's bargaining strength over routine and nonroutine workers, respectively, and $\bar{\pi}_{LH}$ is the firm's threat point for bargaining with a union representing both types of workers. The impact of r on the threat point for the union maximizing the aggregate utility of routine and nonroutine workers theoretically can be as follows, e.g., depending on the production function (i.e., whether the two types of labor are substitutes or complementary):

$$\begin{cases} \frac{\partial \bar{\pi}_{LH}}{\partial r} > 0 \\ \frac{\partial \bar{\pi}_{LH}}{\partial r} = 0 \\ \frac{\partial \bar{\pi}_{LH}}{\partial r} < 0 \end{cases}$$

where the first case is highly unlikely, and the second case is not supported by the empirical evidence.[42] So, I consider that the firm's fallback profit under joint bargaining $\bar{\pi}_{LH}$ increases when the robot adoption becomes more affordable (or the price of robots r drops).

6.2 Automation Threat and Wage Bargaining

Given the impact of automation threat or the price of robots on the firm's threat point, I derive the effects of threat point on the firm's bargaining outcomes to show the effects of automation threat on bargaining position and wage markdowns. I consider these impacts under the two types of bargaining processes.

Separate bargaining. First, consider the Nash bargaining problem between the firm and routine workers, and the first order condition with respect to w_L yields:

$$w_L l_L = (1-\alpha)(Q - w_H l_H - \bar{\pi}_L) + \alpha W_L(l_L) l_L. \tag{18}$$

Second, the first order condition from the Nash bargaining problem between the firm and non-

$F(l_H, k)$ and $\bar{\pi}_L$, respectively, where k is the number of robots) cannot be zero in either case in which routine and nonroutine workers are substitutes or complements as long as robots can complete routine tasks. Put differently, the impact of automation threat on the firm's fallback profit for bargaining with routine workers $\frac{\partial \bar{\pi}_L}{\partial r}$ is unlikely to be zero, which is supported by the empirical findings.

[42] The firm's threat point under joint bargaining $\bar{\pi}_{LH}$ can be zero if the firm cannot produce anything with only robots and without using any human labor, and thus the $\frac{\partial \bar{\pi}_{LH}}{\partial r}$ can be zero.

routine workers with respect to w_H similarly yields:

$$w_H l_H = (1-\beta)(Q - w_L l_L - \bar{\pi}_H) + \beta W_H(l_H) l_H. \tag{19}$$

Solving (18) and (19), we derive the size of the pie that goes to routine and nonroutine workers, i.e., the bargaining outcomes for routine and nonroutine workers as

$$w_L l_L = \frac{(1-\alpha)(\beta Q + (1-\beta)\bar{\pi}_H - \beta W_H(l_H) l_H - \bar{\pi}_L) + \alpha W_L(l_L) l_L}{1-(1-\alpha)(1-\beta)}, \tag{20}$$

and

$$w_H l_H = \frac{(1-\beta)(\alpha Q + (1-\alpha)\bar{\pi}_L - \alpha W_L(l_L) l_L - \bar{\pi}_H) + \beta W_H(l_H) l_H}{1-(1-\alpha)(1-\beta)}. \tag{21}$$

The comparative statics yield

$$\begin{aligned}
\frac{\partial w_L}{\partial \bar{\pi}_L} &= \frac{\partial Y_L}{\partial \bar{\pi}_L} = -\frac{1-\alpha}{1-(1-\alpha)(1-\beta)} < 0, \\
\frac{\partial w_H}{\partial \bar{\pi}_L} &= \frac{\partial Y_H}{\partial \bar{\pi}_L} = \frac{(1-\alpha)(1-\beta)}{1-(1-\alpha)(1-\beta)} > 0, \\
\frac{\partial (Q - Y_L - Y_H)}{\partial \bar{\pi}_L} &= \frac{\partial Q}{\partial \bar{\pi}_L} - \frac{\partial Y_L}{\partial \bar{\pi}_L} - \frac{\partial Y_H}{\partial \bar{\pi}_L} = \frac{\beta(1-\alpha)}{1-(1-\alpha)(1-\beta)} > 0,
\end{aligned} \tag{22}$$

where $Y_L = w_L l_L$ and $Y_H = w_H l_H$ are the wage income or size of the pie that goes to routine and nonroutine workers, respectively. It gives the following proposition:

Proposition 1. *Suppose that the firm separately bargains with the union(s) representing routine and nonroutine workers.*

1. *w_L and Y_L decrease when $\bar{\pi}_L$ or automation threat increases.*
2. *w_H and Y_H increase when $\bar{\pi}_L$ or automation threat increases.*
3. *An increase in wage and bargaining outcome for nonroutine workers equals $1-\beta$ times a decline in wage and bargaining outcomes for routine workers, where $0 \leq \beta \leq 1$. It indicates an overall decrease in workers' wages and bargaining outcomes.*
4. *The firm profit, $Q - Y_L - Y_H$, increases when $\bar{\pi}_L$ or automation threat increases.*

An increase in automation threat due to an expansion of the potential of automation raises firms' outside options and their fallback profit from negotiation with routine workers, $\bar{\pi}_L$. Given this, the firm can set wages below the marginal product of labor for routine workers and save some profits by reducing labor costs of such workers, Y_L. Nonroutine workers expect this to occur and can request the firm to raise their wages above and beyond their marginal product of labor, which would increase the labor costs of nonroutine workers, Y_H. Separate bargaining, e.g., via worker group-specific unions, can moderate heterogeneous effects of automation threat on the firm's bargaining outcomes over different workers. An increase in nonroutine workers' wage and bargaining outcome equals $1-\beta$ times a decline in routine workers' wage and bargaining outcome, where $0 \leq \beta \leq 1$, indicating an increase in the firm's profit due to automation threat at the expense of routine workers.

However, l_L and l_H are independent of $\bar{\pi}_L$, primarily following the empirical evidence on the insignificant or imprecisely estimated employment effects of robot exposure in German manufacturing according to this and other papers like Dauth et al. (2021), possibly since robot exposure mainly proxies the automation threats rather than actual robot adoption, which could have a more significant impact on employment. Since there is no employment effect of automation threat or $\bar{\pi}_L$ in the model, $\bar{\pi}_L$ also does not affect the marginal product of labor, and it affects the wage markdowns only through its impact on wages. It provides the following proposition:

Proposition 2. *Wage markdowns over routine (nonroutine) workers increase (decrease) when $\bar{\pi}_L$ or automation threat increases.*

Joint bargaining. Now consider that the firm jointly bargains with a union (or unions) representing different types of workers. Suppose a labor union that represents the two types of workers for simplicity, and the results remain the same even if there are multiple unions. In this case of joint bargaining, the union maximizes the aggregate utility of all types of workers. The union, thus, considers both routine and nonroutine workers. Similar to the separate bargaining, the displacement threat of routine workers will also increase in response to the decline in the price of robots. However, this situation will be considered in the bargaining action of the union that also represents the nonroutine workers.

Consider the Nash bargaining problem between the firm and the union representing different types of workers, described above, and the first order conditions with respect to wages of routine and nonroutine workers yield the following, respectively:

$$w_L l_L = \left(\frac{\gamma_L}{1-\gamma_H}\right)(Q - w_H l_H - \bar{\pi}_{LH}) + \left(\frac{1-\gamma_L-\gamma_H}{1-\gamma_H}\right) W_L(l_L) l_L, \tag{23}$$

and

$$w_H l_H = \left(\frac{\gamma_H}{1-\gamma_L}\right)(Q - w_L l_L - \bar{\pi}_{LH}) + \left(\frac{1-\gamma_L-\gamma_H}{1-\gamma_L}\right) W_H(l_H) l_H. \tag{24}$$

Solving (23) and (24), we derive the size of the pie that goes to routine and nonroutine workers, i.e., the bargaining outcomes for such workers as

$$w_L l_L = \gamma_L(Q - \bar{\pi}_{LH} - W_H(l_H) l_H) + (1-\gamma_L) W_L(l_L) l_L, \tag{25}$$

and

$$w_H l_H = \gamma_H(Q - \bar{\pi}_{LH} - W_L(l_L) l_L) + (1-\gamma_H) W_H(l_H) l_H. \tag{26}$$

The comparative statics yield

$$\begin{aligned}
\frac{\partial w_L}{\partial \bar{\pi}_{LH}} &= \frac{\partial Y_L}{\partial \bar{\pi}_{LH}} = -\gamma_L < 0, \\
\frac{\partial w_H}{\partial \bar{\pi}_{LH}} &= \frac{\partial Y_H}{\partial \bar{\pi}_{LH}} = -\gamma_H < 0, \\
\frac{\partial (Q - Y_L - Y_H)}{\partial \bar{\pi}_{LH}} &= \frac{\partial Q}{\partial \bar{\pi}_{LH}} - \frac{\partial Y_L}{\partial \bar{\pi}_{LH}} - \frac{\partial Y_H}{\partial \bar{\pi}_{LH}} = \gamma_L + \gamma_H > 0,
\end{aligned} \tag{27}$$

and provide the following proposition:

Proposition 3. *Suppose that the firm jointly bargains with the union representing routine and non-routine workers.*

1. *w_L and Y_L decrease when $\bar{\pi}_{LH}$ or automation threat increases.*
2. *w_H and Y_H decrease when $\bar{\pi}_{LH}$ or automation threat increases.*
3. *The firm profit, $Q - Y_L - Y_H$, increases when $\bar{\pi}_{LH}$ or automation threat increases.*

Under the joint bargaining between the firm and the union representing all workers, the effects of automation threat on wages and bargaining outcomes of heterogeneous workers are homogeneous, i.e., the impacts are in the same direction for different workers. Given the assumption of no employment effects, we have the following proposition on the markdown impact of automation threat:

Proposition 4. *Wage markdowns over routine and nonroutine workers increase when $\bar{\pi}_{LH}$ or automation threat increases.*

6.3 Discussion

The empirical findings suggest that the causal impact of automation threat on wage markdowns is heterogeneous for workers performing different tasks in German manufacturing. In particular, automation threat increases markdowns over routine workers and reduces markdowns over non-routine workers. The main qualitative predictions from the wage bargaining model developed in this Section consistently show the heterogeneous effects of automation threat on wages, bargaining outcomes, and wage markdowns of different workers under the separate bargaining between the firm and the workers. Due to the data limitation, for example, on union coverage for heterogeneous workers, I cannot directly show whether the heterogeneous effects of automation on labor market power over different workers are mediated through separate bargaining. However, I argue that separate bargaining plays an important role in the impacts I identified in the empirical analysis for several reasons. First, as described in Jäger et al. (2022), the collective bargaining system in Germany is unusually flexible, and some unions are organized at the occupation, skill, and experience group level. A group of workers is likely to avoid jointly bargaining with the employer by teaming up with another group of vulnerable workers, and this behavior could have been one of the reasons for creating occupation-specific unions in the first place. Second, heterogeneous impacts of robot exposure on wage markdowns around the Great Recession suggest that the results are concentrated before 2009, i.e., when the bargaining between the firm and occupation-specific unions was more prevalent. So, joint bargaining is unlikely, especially in the presence of a venue to bargain separately, e.g., through occupation-specific unions, and thus, separate bargaining is plausible.

7 Conclusion

There is growing evidence that the labor market is not perfectly competitive and employers have substantial market power in the labor markets. In this paper, I document that workers earn 79 cents on each marginal euro generated in an average German manufacturing plant. I also find that workers performing nonroutine manual (routine) tasks are subject to the highest (lowest) degree of labor market power in the manufacturing industry. To explore a driving force that gives employers such power in the labor market, I provide empirical evidence on automation threat as a significant source of labor market power. Using administrative and survey data from Germany, I show that exposure to industrial robots equips firms with more power in the labor market over workers in occupations that mainly perform routine tasks. This impact is particularly pronounced in local labor markets with weaker labor protections in East Germany, where the labor market is less competitive and workers have limited outside options. The firm-level analysis also shows that the effect of robot exposure on wage markdowns is concentrated among large firms and those in robot-intensive industries before 2009, in which most of the automation actions took place and worker group-specific unions were more prevalent. These empirical results are generally consistent with qualitative predictions from the wage bargaining model developed in the paper.

This evidence has three critical implications for understanding the wage-setting process in the labor markets. First, workers' mobility and skill sets play a substantial role in setting the wages, given that immobile workers who perform nonroutine cognitive tasks and low-skilled, nonroutine manual task-performing workers are subject to higher markdowns than routine workers. Second, although routine workers have lower markdowns than nonroutine manual and nonroutine cognitive workers, labor-saving technologies biased towards displacing routine tasks provide wage-setting power to employers over workers in occupations performing routine tasks potentially via threats. Third, a potential threat mechanism is more significant in regions where workers have limited outside options potentially due to specific preferences (e.g., home bias) and characteristics of local labor markets (e.g., the strength of trade unions).

This paper made notable contributions to several strands of literature. First, this is the first study to provide a causal interpretation of the effects of automation threat or robot exposure on labor market power. A new empirical fact about the link between actual robot adoption in Germany and robot exposure shock from other high-income European countries suggests that the implication of automation technologies from external sources on labor market power is mainly through automation threats. Second, I investigate the relationship between the task content of jobs and labor market power and examine the effects of automation threat on labor market power for heterogeneous workers performing routine, nonroutine manual, and nonroutine cognitive tasks. Third, the paper also adds to the literature globally measuring the labor market power by providing an estimate of monopsony power in German manufacturing using a dataset that has not been used before in the context. Finally, by developing a simple wage bargaining model incorporating the threat of automation, I formalize the role of automation threat in firms' and workers' bargaining power. The proposed model with heterogeneous workers also provides new insight, suggesting that the bargaining type plays a critical role in the interaction between automation threat and firms' and workers' bargaining outcomes and wage markdowns.

I conclude with some caveats and directions for future research. First, the empirical results on the heterogeneous effects of automation threat on markdowns over different workers and the presence of unions representing specific groups of workers imply the role of the bargaining regime suggested by the theoretical model. However, due to data limitations on union coverage for heterogeneous workers, this paper could not directly test the importance of separate bargaining. So, if the data allows, future research can explicitly examine the role of bargaining regimes. Second, the wage bargaining model proposed in this paper might explain the industrial relations in East Germany better than in West Germany since the impact of automation threat on wage markdowns over routine workers in German manufacturing is more significant in the East, while the effect is essentially zero in the West. As shown in this paper and other papers, the labor market competition and other related conditions are different across East and West Germany, potentially due to the underlying differences across regions, such as differences in workers' pre-existing outside options and preferences. Future research could thus explore a model that can characterize the regional differences in explaining the heterogeneous effects in East and West Germany.

References

Acemoglu, Daron, Philippe Aghion, and Giovanni L. Violante. 2001. "Deunionization, Technical Change and Inequality." In *Carnegie-Rochester Conference Series on Public Policy*. 55(1): 229–264.

Acemoglu, Daron, and David Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings." In *Handbook of Labor Economics*. eds. by Orley Ashenfelter, and David Card: Elsevier, 1043–1171.

Acemoglu, Daron, Hans R. A. Koster, and Ceren Ozgen. 2023. "Robots and Workers: Evidence from the Netherlands." *NBER Working Paper No. 31009*.

Acemoglu, Daron, and Pascual Restrepo. 2018. "The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment." *American Economic Review*, 108(6): 1488–1542.

Acemoglu, Daron, and Pascual Restrepo. 2019. "Automation and New Tasks: How Technology Displaces and Reinstates Labor." *Journal of Economic Perspectives*, 33(2): 3–30.

Acemoglu, Daron, and Pascual Restrepo. 2020. "Robots and Jobs: Evidence from US Labor Markets." *Journal of Political Economy*, 128(6): 2188–2244.

Acemoglu, Daron, and Pascual Restrepo. 2022. "Tasks, Automation, and the Rise in U.S. Wage Inequality." *Econometrica*, 90(5): 1973–2016.

Acemoglu, Daron, and Pascual Restrepo. 2023. "Automation and Rent Dissipation: Implications for Inequality, Productivity, and Welfare." *Working Paper*.

Açıkgöz, Ömer Tuğrul, and Barış Kaymak. 2014. "The Rising Skill Premium and Deunionization." *Journal of Monetary Economics*, 63: 37–50.

Ackerberg, Daniel A., Kevin Caves, and Garth Frazer. 2015. "Identification Properties of Recent Production Function Estimators." *Econometrica*, 83(6): 2411–2451.

Adamopoulos, Tasso, Loren Brandt, Jessica Leight, and Diego Restuccia. 2022. "Misallocation, Selection, and Productivity: A Quantitative Analysis with Panel Data from China." *Econometrica*, 90(3): 1261–1282.

Adao, Rodrigo, Michal Kolesár, and Eduardo Morales. 2019. "Shift-Share Designs: Theory and Inference." *The Quarterly Journal of Economics*, 134(4): 1949–2010.

Altonji, Joseph G., Todd E. Elder, and Christopher R. Taber. 2005. "An Evaluation of Instrumental Variable Strategies for Estimating the Effects of Catholic Schooling." *Journal of Human Resources*, 40(4): 791–821.

Amodio, Francesco, and Nicolas De Roux. 2024. "Measuring Labor Market Power in Developing Countries: Evidence from Colombian Plants." *Journal of Labor Economics*, 42(4): 949–977.

Andrews, Isaiah, James H. Stock, and Liyang Sun. 2019. "Weak Instruments in Instrumental Variables Regression: Theory and Practice." *Annual Review of Economics*, 11 727–753.

Antonczyk, Dirk, Bernd Fitzenberger, and Ute Leuschner. 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.

Ashenfelter, Orley C., Henry Farber, and Michael R. Ransom. 2010. "Labor Market Monopsony." *Journal of Labor Economics*, 28(2): 203–210.

Ashenfelter, Orley, David Card, Henry Farber, and Michael R. Ransom. 2022. "Monopsony in the Labor Market: New Empirical Results and New Public Policies." *Journal of Human Resources*, 57(S): S1–S10.

Autor, David H., and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review*, 103(5): 1553–1597.

Autor, David H., David Dorn, and Gordon H. Hanson. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review*, 103(6): 2121–2168.

Autor, David H., Frank Levy, and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *The Quarterly Journal of Economics*, 118(4): 1279–1333.

Azar, José, Ioana Marinescu, and Marshall Steinbaum. 2019. "Measuring Labor Market Power Two Ways." In *AEA Papers and Proceedings*. 109: 317–321.

Bachmann, Ronald, Gökay Demir, and Hanna Frings. 2022b. "Labor Market Polarization, Job Tasks, and Monopsony Power." *Journal of Human Resources*, 57(S): S11–S49.

Bachmann, Rüdiger, Christian Bayer, Heiko Stüber, and Felix Wellschmied. 2022a. "Monopsony Makes Firms not only Small but also Unproductive: Why East Germany has not Converged." *CEPR Discussion Paper No. DP17302*.

Bassier, Ihsaan, Arindrajit Dube, and Suresh Naidu. 2022. "Monopsony in Movers the Elasticity of Labor Supply to Firm Wage Policies." *Journal of Human Resources*, 57(S): S50–S86.

Baum-Snow, Nathaniel, Nicolas Gendron-Carrier, and Ronni Pavan. 2024. "Local Productivity Spillovers." *American Economic Review*, 114(4): 1030–1069.

Berger, David, Kyle Herkenhoff, and Simon Mongey. 2022. "Labor Market Power." *American Economic Review*, 112(4): 1147–93.

Bessen, James, Maarten Goos, Anna Salomons, and Wiljan van den Berge. forthcoming. "What Happens to Workers at Firms that Automate?" *Review of Economics and Statistics*.

Boal, William M., and Michael R. Ransom. 1997. "Monopsony in the Labor Market." *Journal of Economic Literature*, 35(1): 86–112.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel. 2022. "Quasi-Experimental Shift-Share Research Designs." *The Review of Economic Studies*, 89(1): 181–213.

Bossler, Mario, and Thorsten Schank. 2023. "Wage Inequality in Germany after the Minimum Wage Introduction." *Journal of Labor Economics*, 41(3): 813–857.

Brandt, Loren, Johannes Van Biesebroeck, Luhang Wang, and Yifan Zhang. 2017. "WTO Accession and Performance of Chinese Manufacturing Firms." *American Economic Review*, 107(9): 2784–2820.

Brooks, Wyatt J., Joseph P. Kaboski, Yao Amber Li, and Wei Qian. 2021. "Exploitation of

Labor? Classical Monopsony Power and Labor's Share." *Journal of Development Economics*, 150: 102627.

Brücker, Herbert, Andreas Hauptmann, Elke J. Jahn, and Richard Upward. 2014. "Migration and Imperfect Labor Markets: Theory and Cross-Country Evidence from Denmark, Germany and the UK." *European Economic Review*, 66: 205–225.

Brücker, Herbert, and Elke J. Jahn. 2011. "Migration and Wage-Setting: Reassessing the Labor Market Effects of Migration." *Scandinavian Journal of Economics*, 113(2): 286–317.

Byambasuren, Tsenguunjav, Nancy H. Chau, and Vidhya Soundararajan. 2024. "Public Works Program, Labor Supply, and Monopsony." *Working Paper*.

Cahuc, Pierre, Stéphane Carcillo, and André Zylberberg. 2014. *Labor Economics*. MIT Press.

Caldwell, Sydnee, Ingrid Haegele, and Jörg Heining. 2024. "Bargaining and Inequality in the Labor Market." *Working Paper*.

Caldwell, Sydnee, and Emily Oehlsen. 2022. "Gender, Outside Options, and Labor Supply: Experimental Evidence from the Gig Economy." *Working Paper*.

Card, David. 2022. "Who Set Your Wage?" *American Economic Review*, 112(4): 1075–1090.

Carruth, Alan, and Claus Schnabel. 1993. "The Determination of Contract Wages in West Germany." *The Scandinavian Journal of Economics*, 95(3): 297–310.

Caunedo, Julieta, Elisa Keller, and Yongseok Shin. 2023. "Technology and the Task Content of Jobs across the Development Spectrum." *The World Bank Economic Review*, 37(3): 479–493.

Cavounidis, Costas, Qingyuan Chai, Kevin Lang, and Raghav Malhotra. 2023. "Obsolescence Rents: Teamsters, Truckers, and Impending Innovations." *NBER Working Paper No. 31743*.

Chau, Nancy H., and Ravi Kanbur. 2021. "Employer Power, Labour Saving Technical Change, and Inequality." In *Development, Distribution, and Markets: Festschrift in Honor of Pranab Bardhan*. eds. by Kaushik Basu, Maitreesh Ghatak, Kenneth Kletzer, Sudipto Mundle, and Eric Verhoogen: Oxford University Press, 158–180.

Datta, Nikhil. 2022. "Local Monopsony Power." *Working Paper*.

Dauth, Wolfgang, Sebastian Findeisen, and Jens Suedekum. 2014. "The Rise of the East and the Far East: German Labor Markets and Trade Integration." *Journal of the European Economic Association*, 12(6): 1643–1675.

Dauth, Wolfgang, Sebastian Findeisen, Jens Suedekum, and Nicole Woessner. 2021. "The Adjustment of Labor Markets to Robots." *Journal of the European Economic Association*, 19(6): 3104–3153.

De Loecker, Jan, Jan Eeckhout, and Gabriel Unger. 2020. "The Rise of Market Power and the Macroeconomic Implications." *The Quarterly Journal of Economics*, 135(2): 561–644.

De Loecker, Jan, and Frederic Warzynski. 2012. "Markups and Firm-Level Export Status." *American Economic Review*, 102(6): 2437–2471.

Delabastita, Vincent, and Michael Rubens. 2023. "Colluding Against Workers." *Working Paper*.

Deng, Liuchun, Verena Plümpe, and Jens Stegmaier. 2023. "Robot Adoption at German Plants."

Jahrbücher für Nationalökonomie und Statistik.

Dinlersoz, Emin, and Jeremy Greenwood. 2016. "The Rise and Fall of Unions in the United States." *Journal of Monetary Economics*, 83: 129–146.

Dodini, Samuel, Michael Lovenheim, Kjell Salvanes, and Alexander Willén. 2024. "Monopsony, Job Tasks and Labour Market Concentration." *The Economic Journal*, 134(661): 1914–1949.

Drechsel-Grau, Moritz, Andreas Peichl, Kai D. Schmid, Johannes F. Schmieder, Hannes Walz, and Stefanie Wolter. 2022. "Inequality and Income Dynamics in Germany." *Quantitative Economics*, 13(4): 1593–1635.

Dustmann, Christian, Bernd Fitzenberger, Uta Schönberg, and Alexandra Spitz-Oener. 2014. "From Sick Man of Europe to Economic Superstar: Germany's Resurgent Economy." *Journal of Economic Perspectives*, 28(1): 167–188.

Dustmann, Christian, Carl Gergs, and Uta Schönberg. 2024. "The Evolution of the German Wage Distribution Before and After the Great Recession." *Working Paper*.

Dustmann, Christian, Johannes Ludsteck, and Uta Schönberg. 2009. "Revisiting the German Wage Structure." *The Quarterly Journal of Economics*, 124(2): 843–881.

Dwenger, Nadja, Viktor Steiner, and Pia Rattenhuber. 2019. "Sharing the Burden? Empirical Evidence on Corporate Tax Incidence." *German Economic Review*, 20(4): e107–e140.

Felix, Mayara. 2022. "Trade, Labor Market Concentration, and Wages." *Working Paper*.

Fudenberg, Drew, and Jean Tirole. 1983. "Sequential Bargaining with Incomplete Information." *The Review of Economic Studies*, 50(2): 221–247.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift. 2020. "Bartik Instruments: What, When, Why, and How." *American Economic Review*, 110(8): 2586–2624.

Goos, Maarten, Alan Manning, and Anna Salomons. 2014. "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring." *American Economic Review*, 104(8): 2509–2526.

Hansen, Lars Peter. 1982. "Large Sample Properties of Generalized Method of Moments Estimators." *Econometrica*, 50(4): 1029–1054.

Hassel, Anke. 1999. "The Erosion of the German System of Industrial Relations." *British Journal of Industrial Relations*, 37(3): 483–505.

Heise, Sebastian, and Tommaso Porzio. 2022. "Labor Misallocation Across Firms and Regions." *NBER Working Paper No. 30298*.

Hirsch, Boris, Thorsten Schank, and Claus Schnabel. 2010. "Differences in Labor Supply to Monopsonistic Firms and the Gender Pay Gap: An Empirical Analysis using Linked Employer-Employee Data from Germany." *Journal of Labor Economics*, 28(2): 291–330.

Hirsch, Boris, and Claus Schnabel. 2014. "What can we Learn from Bargaining Models about Union Power? The Decline in Union Power in Germany, 1992–2009." *The Manchester School*, 82(3): 347–362.

Hsieh, Chang-Tai, and Peter J. Klenow. 2009. "Misallocation and Manufacturing TFP in China and India." *The Quarterly Journal of Economics*, 124(4): 1403–1448.

Humlum, Anders. 2019. "Robot Adoption and Labor Market Dynamics." *Working Paper*.

Imbens, Guido W., and Joshua D. Angrist. 1994. "Identification and Estimation of Local Average Treatment Effects." *Econometrica*, 62(2): 467–475.

Itskhoki, Oleg, and Benjamin Moll. 2019. "Optimal Development Policies with Financial Frictions." *Econometrica*, 87(1): 139–173.

Jäger, Simon, Shakked Noy, and Benjamin Schoefer. 2022. "The German Model of Industrial Relations: Balancing Flexibility and Collective Action." *Journal of Economic Perspectives*, 36(4): 53–80.

Kambourov, Gueorgui, and Iourii Manovskii. 2009. "Occupational Specificity of Human Capital." *International Economic Review*, 50(1): 63–115.

Keller, Berndt K., and Anja Kirsch. 2020. "Employment Relations in Germany." In *International and Comparative Employment Relations*. eds. by Russell D. Lansbury, and Greg J. Bamber: Routledge, 179–207.

Kirov, Ivan, and James Traina. 2021. "Labor Market Power and Technological Change in US Manufacturing." *Working Paper*.

Kleibergen, Frank, and Richard Paap. 2006. "Generalized Reduced Rank Tests Using the Singular Value Decomposition." *Journal of Econometrics*, 133(1): 97–126.

Lamadon, Thibaut, Magne Mogstad, and Bradley Setzler. 2022. "Imperfect Competition, Compensating Differentials, and Rent Sharing in the US Labor Market." *American Economic Review*, 112(1): 169–212.

Leduc, Sylvain, and Zheng Liu. 2024. "Automation, Bargaining Power, and Labor Market Fluctuations." *American Economic Journal: Macroeconomics*, 16(4): 311–349.

Levinsohn, James, and Amil Petrin. 2003. "Estimating Production Functions Using Inputs to Control for Unobservables." *The Review of Economic Studies*, 70(2): 317–341.

Manning, Alan. 2003. *Monopsony in Motion: Imperfect Competition in Labor Markets*. Princeton University Press.

Manning, Alan. 2021. "Monopsony in Labor Markets: A Review." *ILR Review*, 74(1): 3–26.

Manning, Alan, and Barbara Petrongolo. 2017. "How Local Are Labor Markets? Evidence from a Spatial Job Search Model." *American Economic Review*, 107(10): 2877–2907.

Marinescu, Ioana, and Roland Rathelot. 2018. "Mismatch Unemployment and the Geography of Job Search." *American Economic Journal: Macroeconomics*, 10(3): 42–70.

McDonald, Ian M., and Robert M. Solow. 1981. "Wage Bargaining and Employment." *The American Economic Review*, 71(5): 896–908.

Mengano, Paolo. 2023. "Trends in Worker Bargaining Power." *Working Paper*.

Mertens, Matthias. 2020. "Labor Market Power and the Distorting Effects of International Trade." *International Journal of Industrial Organization*, 68: 102562.

Mogstad, Magne, Alexander Torgovitsky, and Christopher R. Walters. 2021. "The Causal Interpretation of Two-Stage Least Squares with Multiple Instrumental Variables." *American Economic Review*, 111(11): 3663–3698.

Morlacco, Monica. 2019. "Market Power in Input Markets: Theory and Evidence from French Manufacturing." *Working Paper*.

Nickell, Stephen J., and Martyn Andrews. 1983. "Unions, Real Wages and Employment in Britain 1951-79." *Oxford Economic Papers*, 35: 183–206.

Olea, José Luis Montiel, and Carolin Pflueger. 2013. "A Robust Test for Weak Instruments." *Journal of Business & Economic Statistics*, 31(3): 358–369.

Olley, G. Steven, and Ariel Pakes. 1996. "The Dynamics of Productivity in the Telecommunications Equipment Industry." *Econometrica*, 64(6): 1263–1297.

Rossi-Hansberg, Esteban, Pierre-Daniel Sarte, and Nicholas Trachter. 2021. "Diverging Trends in National and Local Concentration." *NBER Macroeconomics Annual*, 35(1): 115–150.

Rubens, Michael. 2022. "Oligopsony Power and Factor-Biased Technology Adoption." *NBER Working Paper No. 30586*.

Sargan, John D. 1958. "The Estimation of Economic Relationships using Instrumental Variables." *Econometrica*, 26(3): 393–415.

Sargan, John D. 1998. "Estimating using Instrumental Variables." In *Contributions to Econometrics: John Denis Sargan*. New York, NY: Cambridge University Press.

Schneider, Hilmar, and Ulf Rinne. 2019. "The Labor Market in Germany, 2000-2018." *IZA World of Labor*.

Spitz-Oener, Alexandra. 2006. "Technical Change, Job Tasks, and Rising Educational Demands: Looking Outside the Wage Structure." *Journal of Labor Economics*, 24(2): 235–270.

Staiger, Douglas, and James H. Stock. 1997. "Instrumental Variables Regression with Weak Instruments." *Econometrica*, 65(3): 557–586.

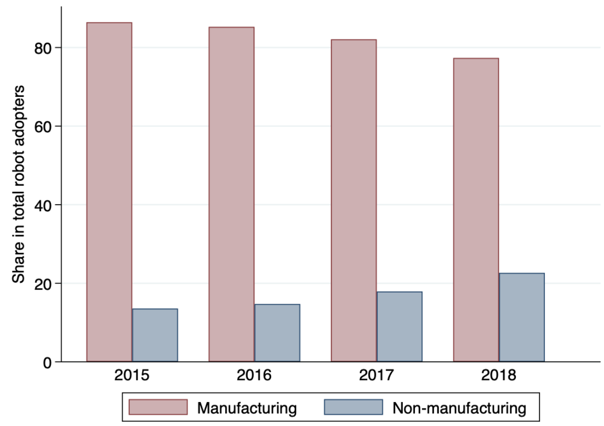
Stock, James H., and Motohiro Yogo. 2005. "Testing for Weak Instruments in Linear IV Regression." In *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*. eds. by Donald W. K. Andrews, and James H. Stock: Cambridge University Press, 80–108.

Wooldridge, Jeffrey M. 2009. "On Estimating Firm-level Production Functions Using Proxy Variables to Control for Unobservables." *Economics Letters*, 104(3): 112–114.

Yeh, Chen, Claudia Macaluso, and Brad Hershbein. 2022. "Monopsony in the US Labor Market." *American Economic Review*, 112(7): 2099–2138.

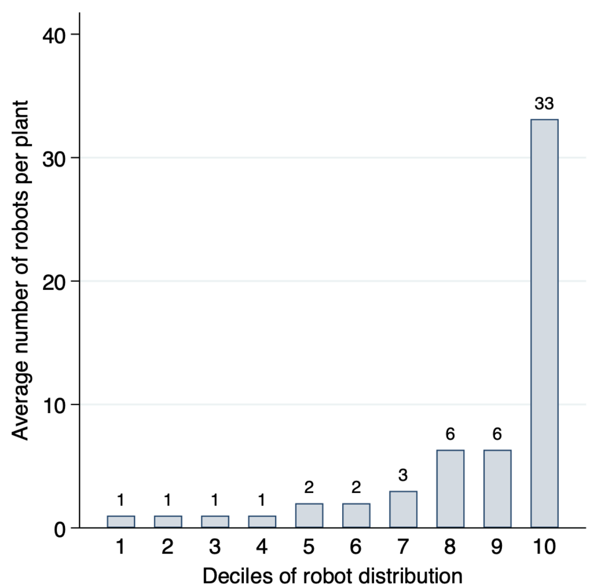
Figures

Figure 1: Robot adopters by industry



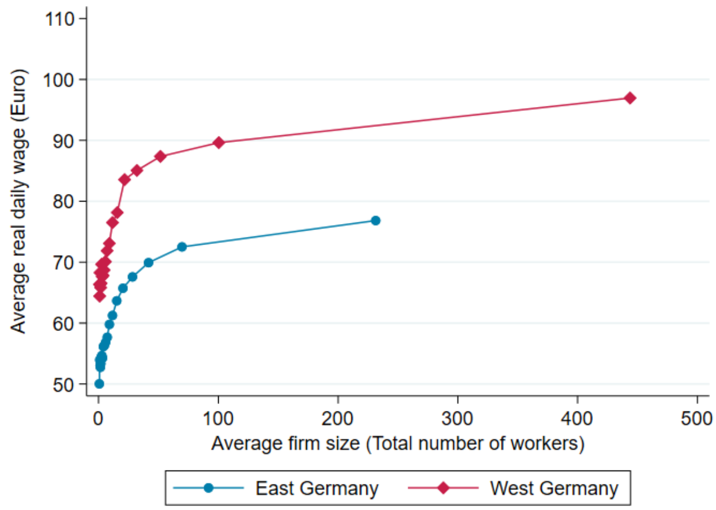
Notes: The figure plots the share of manufacturing and non-manufacturing robot adopters in the total number of robot adopters between 2015-2018 using data from the IAB Establishment Panel (IAB BP). The 2014 data was not presented for compliance with data privacy.

Figure 2: Distribution of robots (2018, robot adopting plants)



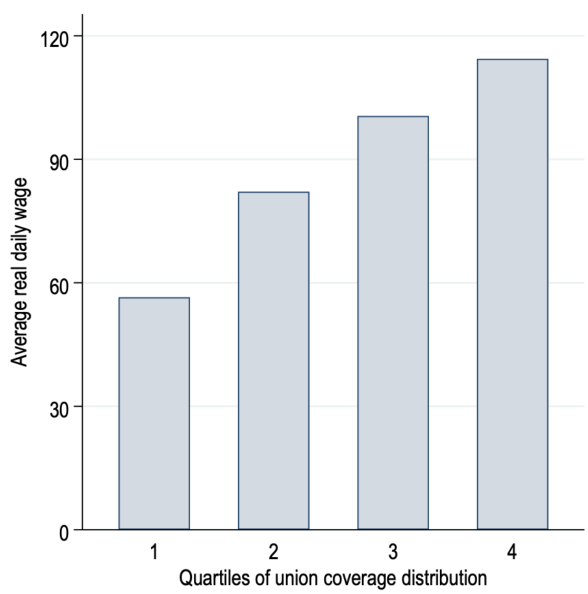
Notes: Based on the IAB Establishment Panel (IAB BP) data. The figures depict the distribution of the average number of robots per manufacturing plant in 2018. Sampling weights provided in the data are applied.

Figure 3: Wage-size ladders



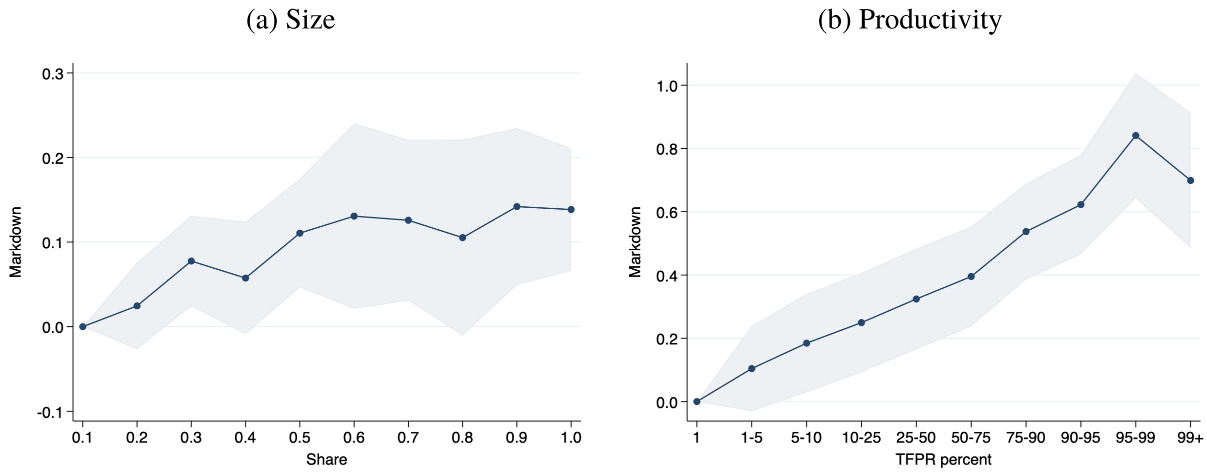
Notes: The figure plots the average number of workers for each twentile of the firm size distribution against the average real daily wage of firms in the twentile, where the wages and size are residualized by industry and year fixed effects.

Figure 4: Average real daily wage along the distribution of union coverage



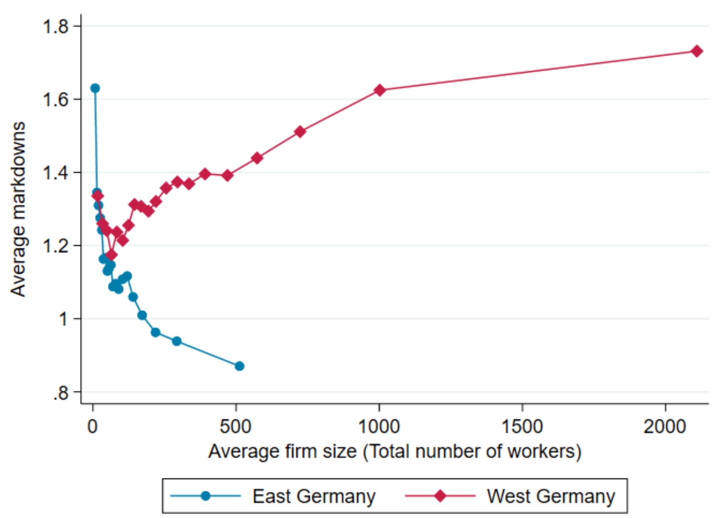
Notes: Based on the IAB Establishment Panel and the matched employer-employee (LIAB) data. The figure show the average real daily wage per worker at the firm in different quartiles of the union coverage. The firm-level union coverage is measured by the share of workers covered by trade unions in total workers using the IAB establishment panel data. The average daily wage per worker at the firm is calculated using the LIAB data.

Figure 5: Relationship between plant-level markdown and firm characteristics



Notes: Based on the IAB Establishment Panel (IAB BP) from 1997-2018. Panel (a) illustrates the point estimates and 95% confidence intervals from estimating plant-level markdowns on size (measured by employment share) indicators. The smallest size indicator is omitted, and coefficients thus reflect deviations relative to this reference group. The plants included in the reference group labeled as "0.1" are those with employment shares $s \in (0, 0.1]$. Other indicator variables are similarly defined. Panel (b) shows the point estimates and 95% confidence intervals from estimating plant-level markdowns on productivity. The first percentile of productivity is omitted, and coefficients thus reflect deviations relative to this reference group. All regressions include dummies for three-digit industry, district, and year fixed effects. Standard errors (SEs) are clustered at the level of three-digit WZ 2008 industries.

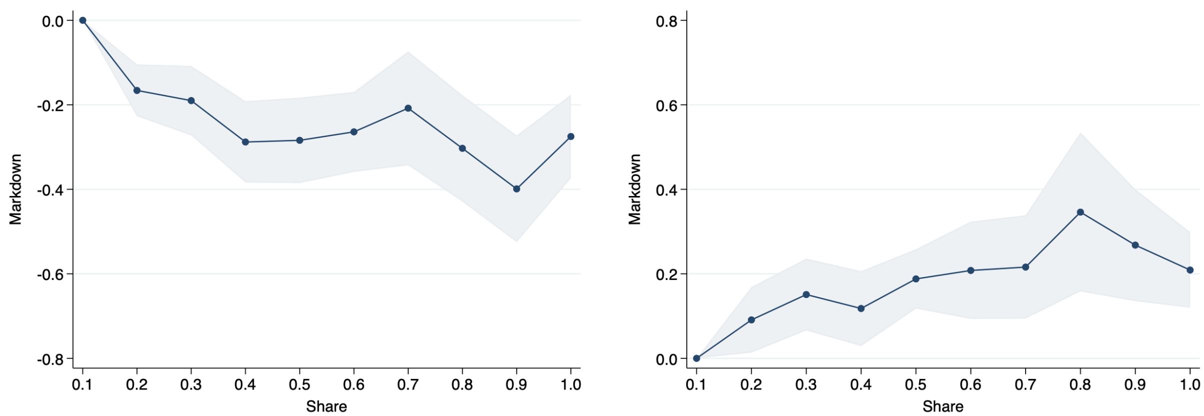
Figure 6: Markdown-size ladders



Notes: The figure plots the average number of workers for each twentile of the firm size distribution against the average wage markdowns in the twentile, where the markdowns and size are residualized by industry and year fixed effects.

Figure 7: Markdown-size relationship in East and West Germany

(a) East Germany (b) West Germany

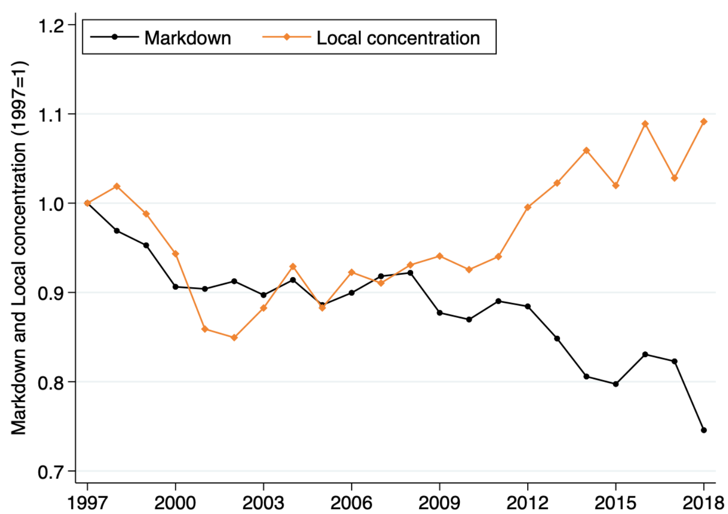


Notes: Based on the IAB Establishment Panel (IAB BP) from 1997-2018. The data on firms' location of operation comes from the LIAB and matched with the IAB BP. The figure plots the point estimates and 95% confidence intervals from estimating plant-level markdowns on size (measured by employment share) indicators in East (panel (a)) and West (panel (b)) Germany. The wage markdowns are estimated separately for East and West German firms, separately. The smallest size indicator is omitted, and coefficients thus reflect deviations relative to this reference group. The plants included in the reference group labeled as "0.1" are those with employment shares $s \in (0, 0.1]$. Other indicator variables are similarly defined. All regressions include dummies for three-digit industry, district, and year fixed effects. Standard errors (SEs) are clustered at the level of three-digit WZ 2008 industries.

Figure 8: Time evolution of the aggregate markdown, 1997-2018

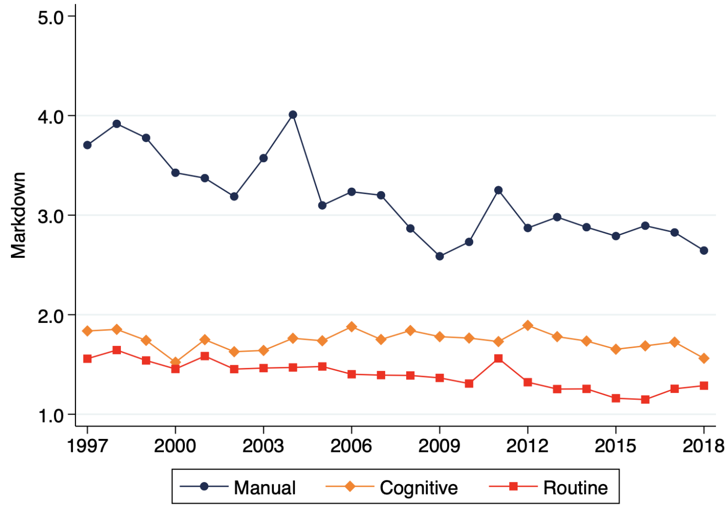
Notes: Markdowns are constructed using the IAB Establishment Panel (IAB BP) data from 1997-2018 under the assumption of translog production and aggregated according to expressions (4) and (6). The employment share of labor market ω_{klt} is based on total number of employees.

Figure 9: Aggregate markdowns and local concentration, 1997-2018



Notes: Based on the IAB Establishment Panel (IAB BP). The solid black line shows the time trend of the aggregate markdown as in equation (6), and the orange line shows the time trend of employment-based labor market concentration as in equation (10). The aggregate markdown and local concentration index are normalized relative to their initial value by 1997.

Figure 10: Time evolution of the aggregate markdowns for workers performing different tasks

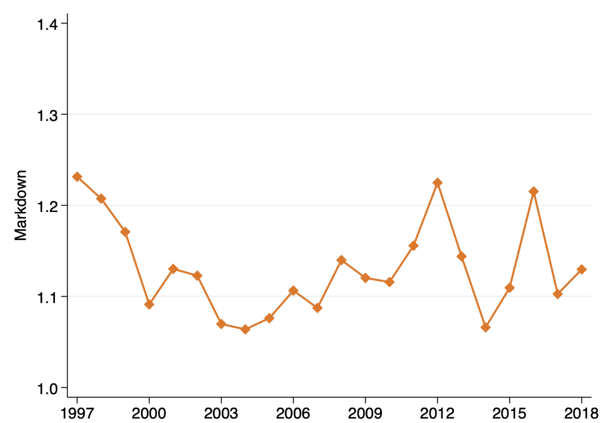


Notes: The figure depicts the time evolution of aggregate markdowns for nonroutine cognitive, routine, and manual workers between 1997 and 2018. Plant-level markdowns are constructed using the IAB Establishment Panel and matched employer-employee (LIAB) data under the assumption of translog production with heterogeneous labor inputs and aggregated according to expressions (4) and (6). The employment share of labor market ω_{klt} is based on the total number of employees. The classification of nonroutine cognitive, routine, and nonroutine manual task-performing workers is based on the BIBB/BAuA Employment Surveys.

Figure 11: Time evolution of the aggregate markdowns for workers with different skills

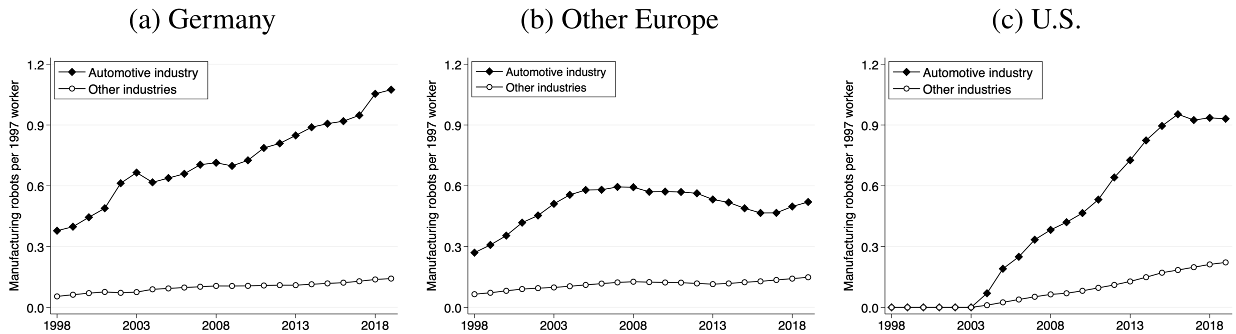
(a) Low-skilled

(b) High-skilled



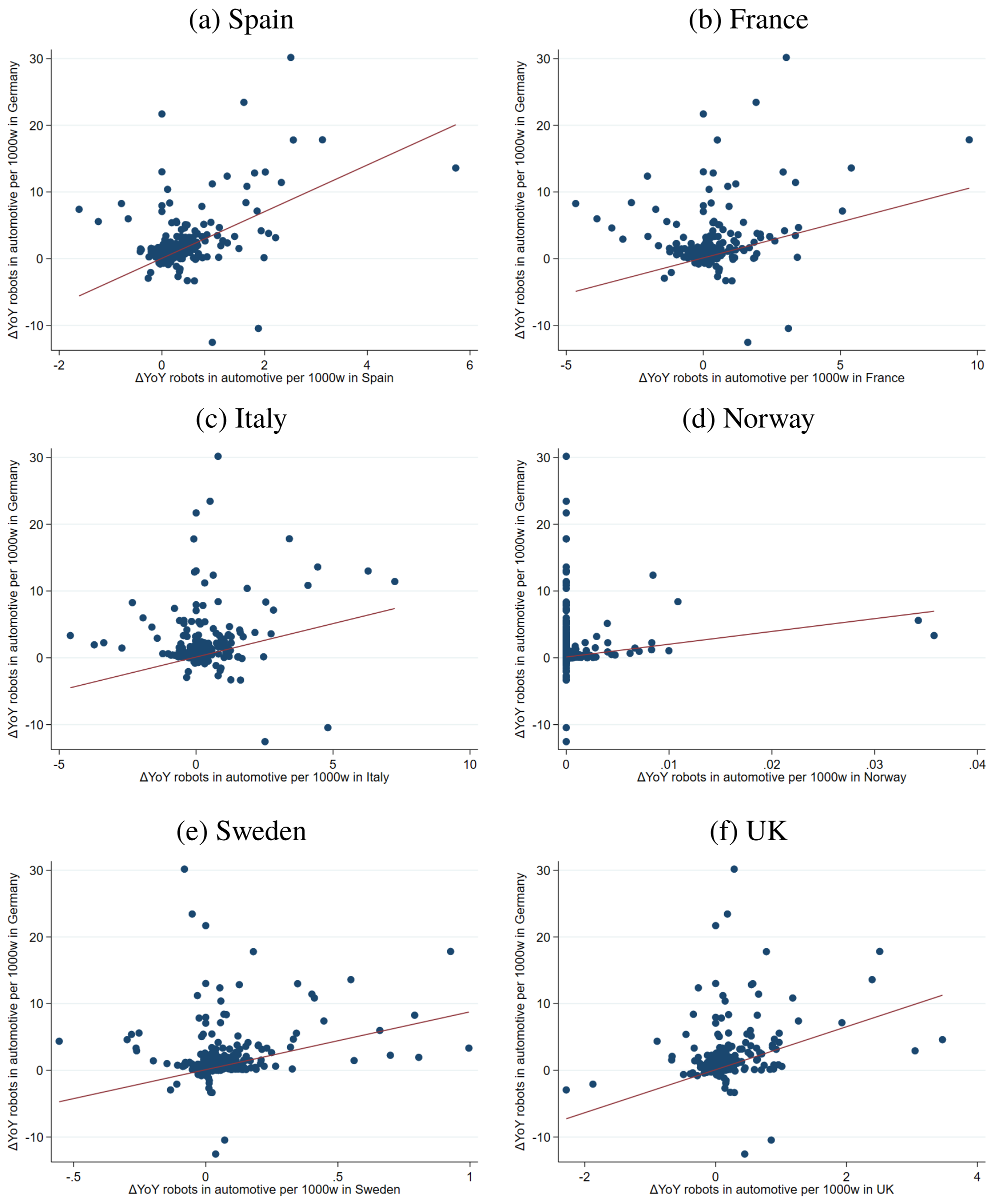
Notes: The figure plots the time evolution of aggregate markdowns for low-skilled workers (no vocational training) and high-skilled workers (with at least vocational training) from 1997-2018. Plant-level markdowns are constructed using the IAB Establishment Panel and matched employer-employee (LIAB) data under the assumption of translog production with heterogeneous labor inputs and aggregated according to expressions (4) and (6). The employment share of labor market ω_{klt} is based on the total number of employees.

Figure 12: Penetration of manufacturing robots in automotive and other industries, 1998-2019



Notes: The figure shows the penetration of manufacturing robots across industries (automotive and other) for selected countries, including Germany, between 1998 and 2019 using data on robot stock from the IFR. Other Europe include France, Italy, Norway, Spain, Sweden, and the United Kingdom. Robot penetration is defined as the robot stock normalized by the dependent employment in full-time equivalents (FTEs) in Germany obtained from the matched employer-employee (LIAB) data.

Figure 13: 2SLS first-stage relationship



Notes: These scatter plots show the first-stage relationship between the annual changes in exposure to industrial robots in the automotive industry for Germany and other high-income European countries between 1998 and 2018.

Tables

Table 1: Two pillars of German industrial relations

	Collective bargaining	Codetermination
Level of negotiation	Industry or region level	Company, establishment, or plant level
Bargaining parties	Unions, employer associations, and firms	Employers and representatives of workers in two forms (representation on corporate boards and works councils)
Negotiation topics	Schedules of minimum requirements for wages, hours, working conditions, entitlements, and promotion criteria for workers in different industries, regions, and occupations, and with different levels of skills and experience.	*Representation on corporate boards*: Major decisions and the appointment, supervision, and dismissal of top corporate management. *Works councils*: Day-to-day managerial decision-making
Negotiation outcomes	Sector-regional level collective agreements	Firm-level agreements

Source: Hassel (1999), Keller and Kirsch (2020), and Jäger et al. (2022)

Table 2: Relationship between actual robot adoption and robot exposure shock

	Dependent variable: Actual robot adoption		
	(1)	(2)	(3)
	Panel A. Robots per 1000 workers		
Robot exposure shock	0.020	0.114	0.072
	(0.020)	(0.181)	(0.173)
Observations	1671	1667	1657
R^2	0.05	0.54	0.56
	Panel B. ΔRobots per 1000 workers		
ΔRobot exposure shock	-0.202	-0.083	-0.206
	(0.164)	(0.288)	(0.282)
Observations	1330	1323	1315
R^2	0.03	0.45	0.47
Year fixed effects	✓	✓	
State fixed effects	✓		
District fixed effects		✓	✓
State-by-Year fixed effects			✓

Notes: The table presents the results from OLS regressions estimating the relationship between actual robot adoption in Germany and average robot exposure in other high-income European countries at the local labor market region level. The sample at the level in panel A covers periods between 2014 and 2018, while the sample in panel B for annual changes covers 2015-2018. The actual robot adoption is measured by aggregating the number of robots adopted by the firm at the district level using sampling weights provided in the IAB Establishment Panel data and expressed as per 1,000 workers. The robot exposure shock into the local labor market regions or districts is measured by the average robots stock in six other European countries (Spain, France, Italy, Norway, Sweden, and UK) "predicted" to districts using employment shares and expressed as per 1,000 workers. The actual robot adoption and robot exposure shock are normalized by the number of workers in the previous period. The relationship in panel A was estimated at the level, while panel B shows the relationship between the annual changes. Standard errors clustered by districts are in parentheses.

Table 3: Share of robot adopters by manufacturing and non-manufacturing in 2018

	Weighted (%)	Unweighted (%)	Number of Surveyed Plants
Manufacturing	7.19	12.48	1,755
Non-manufacturing	0.96	0.92	6,953
Total	1.48	3.25	8,708

Notes: Based on the IAB Establishment Panel data. The second column shows the share of robot adopters in 2018 calculated using survey weights, while the third column reports the share without survey weights. The last column reports the number of surveyed plants, including adopters and non-adopters.

Table 4: Wage gap between East and West Germany

	Dependent variable: Log average real daily wage		
	(1)	(2)	(3)
East dummy	-0.173	-0.153	-0.199
	(0.003)	(0.003)	(0.003)
Observations	207758	207758	207758
R^2	0.04	0.27	0.39
Year fixed effects	✓	✓	✓
Industry fixed effects		✓	✓
Firm characteristics			✓

Notes: The table presents the results from OLS regressions estimating the (log) average real daily wage on a dummy for whether the plant is located in East Germany. The dependent variable, the average real daily wage paid by the firm is constructed using the LIAB data. The industry-fixed effects include dummies for three-digit industries. The firm characteristics include workers' average education, the share of female workers in total workers, and firm size measured by the total number of workers.

Table 5: Relationship between wage and union coverage

	Dependent variable: Log average real daily wage		
	(1)	(2)	(3)
Union coverage	0.347	0.361	0.420
	(0.137)	(0.146)	(0.148)
Observations	11142	8847	8319
R^2	0.86	0.91	0.93
Firm fixed effects	✓	✓	✓
Year fixed effects	✓		
District-by-Year fixed effects		✓	✓
Industry-by-Year fixed effects			✓

Notes: The table presents the results from OLS regressions estimating the relationship between the (log) average real daily wage and union coverage. The firm-level union coverage is measured by the share of workers covered by trade unions in total workers using the IAB Establishment Panel data. The dependent variable, the average real daily wage paid by the firm, is constructed using the LIAB data. The district fixed effects include dummies for kreise. The industry fixed effects include dummies for three-digit industries. The unit of observation is the plant. Standard errors clustered by firms are in parentheses.

Table 6: Summary statistics

	Mean	SD	Min	Max	N
Log TFPR	0.017	0.287	-1.200	1.335	12630
Log revenue	7.548	1.663	3.578	14.243	12806
Log output	7.651	1.654	3.788	14.674	12806
Log capital	7.089	1.695	2.934	14.350	12806
Log labor	3.093	1.240	0.693	8.545	12806
Log material inputs	6.843	1.799	2.945	13.909	12806
Material cost (% revenue)	0.487	0.190	0.020	0.990	12806
Labor cost (% revenue)	0.270	0.131	0.017	1.000	12806
Daily wage (€)	72.11	41.934	1.005	722.534	9966

Notes: The table summarizes the main firm-level characteristics, including revenue productivity (TFPR), sales revenue, production output and inputs, input costs as a share of revenue, and the average daily wage paid to a worker. Variables cover the period 1997-2018 and come from the IAB Establishment Panel except for the daily wage, which comes from the matched employer-employee (LIAB) data. The unit of observation is the firm, and sampling weights are applied.

Table 7: Estimated plant-level markdowns in German manufacturing

	Median	Mean	$IQR_{75\text{-}25}$	SD
Wearing apparel	2.064	2.067	0.871	0.665
Leather and related products	1.669	1.647	0.820	0.493
Beverages	1.616	1.562	0.813	0.651
Wood and wood products (excl. furniture)	1.324	1.555	0.828	0.670
Other transport equipment	1.310	1.326	0.969	0.550
Chemicals and chemical products	1.305	1.451	0.938	0.649
Rubber and plastics	1.291	1.429	0.640	0.549
Other non-metallic minerals	1.290	1.371	0.619	0.585
Furniture	1.279	1.506	0.696	0.616
Textiles	1.254	1.502	0.898	0.783
Paper and paper products	1.234	1.283	0.414	0.371
Basic pharmaceutical products	1.156	1.221	0.568	0.605
Food products	1.145	1.281	0.704	0.559
Repair and installation of machinery and equipment	1.122	1.286	0.708	0.564
Motor vehicles, trailers, and semi-trailers	1.118	1.205	0.568	0.480
Fabricated metals, excl. machinery and equipment	1.107	1.232	0.648	0.529
Machinery and equipment	1.061	1.185	0.482	0.489
Basic metals	1.033	1.194	0.601	0.487
Electrical equipment	1.028	1.078	0.469	0.360
Computer, electronic, and optical products	0.971	1.106	0.546	0.474
Other manufacturing	0.950	1.029	0.491	0.404
Printing and reproduction of recorded media	0.873	0.972	0.470	0.411
Whole sample	**1.129**	**1.271**	**0.670**	**0.565**
Sample size	12,794			

Notes: Markdowns are estimated using the IAB Establishment Panel from 1997-2018 under the assumption of a translog specification for gross output. Each industry group in manufacturing corresponds to the manufacturing categorization of the Federal Statistical Office. The distributional statistics are calculated using sampling weights provided in the data.

Table 8: Markdown gap between East and West Germany

	Dependent variable: Plant-level wage markdowns		
	(1)	(2)	(3)
East dummy	0.045	0.026	0.040
	(0.013)	(0.013)	(0.013)
Observations	9432	9432	9432
R^2	0.02	0.22	0.22
Year fixed effects	✓	✓	✓
Industry fixed effects		✓	✓
Firm characteristics			✓

Notes: The table presents the results from OLS regressions estimating the plant-level wage markdowns on a dummy for whether the plant is located in East Germany. The dependent variable, plant-level wage markdown is estimated using the IAB Establishment Panel data under the translog specification. The industry-fixed effects include dummies for three-digit industries. The firm characteristics include workers' average education, the share of female workers in total workers, and firm size measured by the total number of workers. Regressions are weighted by sampling weights provided in the data.

Table 9: Estimated plant-level markdowns in East/West German manufacturing

	Median	Mean	$\text{IQR}_{75\text{-}25}$	SD	N
East Germany	1.256	1.364	0.687	0.535	4400
West Germany	1.181	1.316	0.702	0.577	4996

Notes: Markdowns for East and West German manufacturing establishments are estimated using the IAB Establishment Panel from 1997-2018 under the assumption of a translog specification for gross output. The production function and markdowns are separately estimated for East and West German plants. The distributional statistics are calculated using sampling weights provided in the data.

Table 10: Estimated plant-level markdowns for firms with different union coverage in German manufacturing

	Median	Mean	SD	Min	Max	N
	Panel A. Union coverage quartiles					
First quartile	1.163	1.308	0.597	0.111	3.656	3229
Top 3 quartiles	1.089	1.206	0.500	0.018	3.641	9577
	Panel B. Union coverage deciles					
First decile	1.258	1.407	0.645	0.416	3.656	1321
Top 9 deciles	1.072	1.178	0.483	0.018	3.641	11485

Notes: Markdowns are estimated using the IAB Establishment Panel and the linked employer-employee (LIAB) data from 1997-2018 under the assumption of a translog specification for gross output. The sample was divided into quartiles (panel A) and deciles (panel B) of the firm's union coverage. The distributional statistics are calculated using sampling weights provided in the data.

Table 11: Summary statistics for labor market concentration – All industries – 2018
(for different market definitions)

	Mean	Min	Max	25th Pctile	75th Pctile	fraction moderately concentrated	fraction highly concentrated
	Panel A. By Occupation × Region						
Baseline geographical definition: 141 CZs							
HHI (By 3-digit KldB 1988)	4243	34	10000	1357	6250	0.16	0.56
Alternative occupational definition:							
HHI (By 3-digit KldB 2010)	3472	31	10000	950	5000	0.17	0.45
HHI (By 2-digit KldB 1988)	2980	40	10000	779	4286	0.18	0.39
HHI (By 2-digit KldB 2010)	1784	37	10000	446	2081	0.14	0.21
HHI (By 1-digit Blossfeld)	961	25	10000	277	1094	0.09	0.08
Alternative geographical definition:							
HHI (By Kreis)	5246	37	10000	2000	10000	0.15	0.68
HHI (By 258 CZs)	4869	37	10000	1765	10000	0.15	0.64
HHI (By 42 regions)	2916	27	10000	698	4075	0.17	0.37
HHI (By Federal state)	2257	10	10000	422	3001	0.13	0.29
	Panel B. By Industry × Region						
Baseline geographical definition: 141 CZs							
HHI (By 3-digit ISIC Rev.4)	4557	30	10000	1528	7812	0.15	0.61
Alternative industrial definition:							
HHI (By 2-digit ISIC Rev.4)	3365	26	10000	885	5000	0.16	0.45
Alternative geographical definition:							
HHI (By Kreis)	5552	43	10000	2356	10000	0.14	0.72
HHI (By 258 CZs)	5178	34	10000	2000	10000	0.15	0.68
HHI (By 42 regions)	3398	24	10000	797	5000	0.15	0.46
HHI (By Federal state)	2837	8	10000	562	4043	0.14	0.38

Notes: Based on data from the Employee History (BeH). The table shows summary statistics for the labor market Herfindahl-Hirschman Index (HHI) under various market definitions using German matched employer-employee (LIAB) data from the Federal Employment Agency. In the top panel, the baseline is calculated using 141 commuting zones (CZs) for the geographic market definition and 3-digit KldB 1988 codes for the occupational market definition. In the bottom panel, I use industry instead of occupation in the definition of labor market. The baseline is calculated using 141 CZs for the geographic market definition and 3-digit ISIC Rev.4 (WZ2008) industry codes for the industrial market definition. The calculation under alternative market definitions is done by changing the baseline along one dimension. Note that regions are a cluster of kreis (or counties in the U.S.), and there are 42 regions in Germany.

Table 12: Summary statistics for labor market concentration – Manufacturing – 2018 (for different market definitions)

	Mean	Min	Max	25th Pctile	75th Pctile	fraction moderately concentrated	fraction highly concentrated
	Panel A. By Occupation × Region						
Baseline geographical definition: 141 CZs							
HHI (By 3-digit KldB 1988)	5800	204	10000	2638	10000	0.13	0.76
Alternative occupational definition:							
HHI (By 3-digit KldB 2010)	5285	145	10000	2200	10000	0.15	0.70
HHI (By 2-digit KldB 1988)	4907	183	10000	2000	8828	0.17	0.66
HHI (By 2-digit KldB 2010)	4022	177	10000	1429	5547	0.18	0.55
HHI (By 1-digit Blossfeld)	2871	150	10000	909	3863	0.18	0.38
Alternative geographical definition:							
HHI (By Kreis)	6747	313	10000	3750	10000	0.10	0.86
HHI (By 258 CZs)	6327	253	10000	3333	10000	0.12	0.82
HHI (By 42 regions)	4814	75	10000	1724	9260	0.16	0.63
HHI (By Federal state	4152	75	10000	1250	6250	0.16	0.54
	Panel B. By Industry × Region						
Baseline geographical definition: 141 CZs							
HHI (By 3-digit ISIC Rev.4)	6003	198	10000	3061	10000	0.11	0.80
Alternative industrial definition:							
HHI (By 2-digit ISIC Rev.4)	4328	162	10000	1746	6250	0.18	0.62
Alternative geographical definition:							
HHI (By Kreis)	7103	284	10000	4400	10000	0.07	0.91
HHI (By 258 CZs)	6645	310	10000	3750	10000	0.09	0.86
HHI (By 42 regions)	4721	113	10000	1911	7278	0.15	0.66
HHI (By Federal state)	4021	69	10000	1511	5702	0.18	0.57

Notes: Based on data from the Employee History (BeH). The table shows summary statistics for the labor market Herfindahl-Hirschman Index (HHI) for the manufacturing sector under various market definitions using German matched employer-employee (LIAB) data from the Federal Employment Agency. In the top panel, the baseline is calculated using 141 commuting zones (CZs) for the geographic market definition and 3-digit KldB 1988 codes for the occupational market definition. In the bottom panel, I use industry instead of occupation in the definition of labor market. The baseline is calculated using 141 CZs for the geographic market definition and 3-digit ISIC Rev.4 (WZ2008) industry codes for the industrial market definition. The calculation under alternative market definitions is done by changing the baseline along one dimension. Note that regions are a cluster of kreis (or counties in the U.S.), and there are 42 regions in Germany.

Table 13: Summary statistics (NRC, routine, NRM workers)

	NRC			Routine			NRM		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Log labor	2.298	1.473	7346	2.905	1.423	8686	1.941	1.436	5229
Labor cost (% revenue)	0.072	0.095	9849	0.158	0.123	9849	0.032	0.077	9849
Daily wage (€)	88.91	57.85	7336	74.25	39.76	8678	67.98	40.83	5225

Notes: The table summarizes the employment, labor cost, and daily wages for workers performing different tasks between 1997-2018. The classification of workers is based on task intensity measures constructed using the BIBB/BAuA Employment surveys. Employment and wage bill information comes from the IAB Establishment Panel, while daily wage comes from the matched employer-employee (LIAB) data. The unit of observation is the firm, and sampling weights are applied. NRC, nonroutine cognitive; NRM, nonroutine manual.

Table 14: Summary statistics (high-skilled and low-skilled workers)

	High-skilled			Low-skilled		
	Mean	SD	N	Mean	SD	N
Log labor	3.221	1.355	9563	1.979	1.483	6165
Labor cost (% revenue)	0.230	0.131	9957	0.032	0.073	9957
Daily wage (€)	78.83	43.53	9552	44.54	32.00	6157

Notes: The table summarizes the employment, labor cost, and daily wages for workers with different skills between 1997-2018. High-skilled workers have vocational training and university degrees, whereas low-skilled workers have no vocational training. Employment and wage bill information comes from the IAB Establishment Panel, while daily wage comes from the matched employer-employee (LIAB) data. The unit of observation is the firm, and sampling weights are applied.

Table 15: Estimated plant-level markdowns for heterogeneous workers in German manufacturing

	Median	Mean	$\text{IQR}_{75\text{-}25}$	SD	N
	Panel A. NRC, routine, and NRM workers				
Routine workers	1.153	1.291	0.669	0.623	3178
Nonroutine cognitive (NRC) workers	1.356	1.613	0.880	0.904	3178
Nonroutine manual (NRM) workers	1.492	1.985	1.508	1.645	3178
	Panel B. High-skilled and low-skilled workers				
High-skilled workers	1.108	1.246	0.592	0.527	4223
Low-skilled workers	1.610	2.198	1.731	2.015	4223

Notes: Markdowns are estimated using the IAB Establishment Panel and the linked employer-employee (LIAB) data from 1997-2018 under the assumption of a translog specification for gross output with heterogeneous labor inputs. Labor inputs of production are heterogeneous by tasks performed at the workplace (panel A) and skill or education level (panel B). In the top panel, I group workers based on task intensity measures constructed using the BIBB/BAuA Employment Surveys. The distributional statistics are calculated using sampling weights provided in the data.

Table 16: Testing for positive 2SLS weights

	Germany's exposure to robots (1)	Spain's exposure to robots (2)
	Panel A. Continuous treatment and continuous instruments	
France's exposure to robots	1.010	0.385
	(0.281)	(0.033)
Italy's exposure to robots	0.913	0.348
	(0.226)	(0.071)
Norway's exposure to robots	149.839	14.775
	(43.861)	(4.265)
Sweden's exposure to robots	7.669	1.654
	(1.104)	(0.477)
UK's exposure to robots	2.928	0.694
	(0.323)	(0.192)
Spain's exposure to robots	3.285	1.000
	(0.232)	—
	Panel B. Binary treatment and binary instruments	
France's exposure to robots	0.546	0.763
	(0.044)	(0.029)
Italy's exposure to robots	0.547	0.712
	(0.045)	(0.029)
Norway's exposure to robots	0.412	0.411
	(0.057)	(0.060)
Sweden's exposure to robots	0.592	0.637
	(0.047)	(0.031)
UK's exposure to robots	0.618	0.699
	(0.045)	(0.023)
Spain's exposure to robots	0.650	1.000
	(0.042)	—

Notes: The table displays regressions of the variable listed in each column on the variable listed on each row. In panel A, treatment and instrumental variables are continuous, i.e., annual change in robots per 1,000 workers. In panel B, treatment and instrumental variables are defined as binary variables, specifically, taking a value of 1 if the annual change in robots per 1,000 workers is above the mean and 0 otherwise. All models control for covariates. Standard errors clustered at the district level are in parentheses.

Table 17: Formal test for partial monotonicity

	p-value: positive weights (1)	p-value: negative weights (2)
	Panel A. Exposure to robots in Spain and another country	
France's exposure to robots	1.000	0.000
Italy's exposure to robots	1.000	0.000
Norway's exposure to robots	1.000	0.000
Sweden's exposure to robots	1.000	0.000
UK's exposure to robots	1.000	0.000
	Panel B. Exposure to robots in France and another country	
Italy's exposure to robots	1.000	0.000
Norway's exposure to robots	1.000	0.000
Sweden's exposure to robots	1.000	0.000
UK's exposure to robots	1.000	0.000
	Panel C. Exposure to robots in Italy and another country	
Norway's exposure to robots	1.000	0.000
Sweden's exposure to robots	1.000	0.000
UK's exposure to robots	1.000	0.000
	Panel D. Exposure to robots in Norway and in another country	
Sweden's exposure to robots	1.000	0.000
UK's exposure to robots	1.000	0.000
	Panel E. Exposure to robots in Sweden and in another country	
UK's exposure to robots	1.000	0.000

Notes: The table presents the results from a formal test for partial monotonicity according to Mogstad et al. (2021). The p-value in column (1) comes from a test of the null hypothesis that the 2SLS weights are all positive, and the p-value in column (2) comes from a test of the null hypothesis that at least one weight is negative.

Table 18: Effect of robot exposure on employment and wages of heterogeneous workers in manufacturing industry

	Dependent variable: Annual log difference in employment and wage		
	Routine	Nonroutine manual	Nonroutine cognitive
	(1)	(2)	(3)
	Panel A. Employment		
ΔPredicted robot exposure	-0.0026	0.0014	-0.0000
	(0.0021)	(0.0022)	(0.0023)
	[0.1069]	[0.0403]	[0.0953]
Montiel Olea-Pflueger weak IV test			
Effective F-statistic ($\alpha = 5\%$)	133.163	133.163	133.163
Critical value 2SLS ($\tau = 10\%$)	19.510	19.511	19.511
Hansen's J-stat p-value	0.608	0.637	0.223
	Panel B. Wages		
ΔPredicted robot exposure	0.0001	-0.0002	-0.0020
	(0.0011)	(0.0006)	(0.0018)
	[0.0261]	[0.0156]	[0.0218]
Montiel Olea-Pflueger weak IV test			
Effective F-statistic ($\alpha = 5\%$)	133.163	133.163	133.163
Critical value 2SLS ($\tau = 10\%$)	19.510	19.510	19.511
Hansen's J-stat p-value	0.717	0.257	0.243

Notes: $N = 4599$ local labor market regions-by-year (district-by-year). The table presents the IV (2SLS) results from estimating the annual log difference in employment (number of workers, Panel A) and log difference in wages (average daily wage, Panel B) of heterogeneous workers on the annual change in predicted exposure to robots in the automotive industry per 1,000 workers between 1998 and 2018. The key explanatory variable is the annual change in the German local labor market's exposure to robots in the automotive industry instrumented by installations of automotive robots in other high-income European countries. The dependent variable in Panels A and B is the annual log difference in the number of workers and average daily wage, respectively, of routine (column (1)), nonroutine manual (column (2)), and nonroutine cognitive (column (3)) workers. All specifications control for constant, broad region dummies, time fixed effects, and demographic characteristics of districts or kreise in the previous period. The broad region dummies indicate if the region is located in the north, west, south, or east of Germany. The demographic controls are constructed using the matched employer-employee data (LIAB) and include the share of females, the share of foreigners, the share of workers over 50 years old, the shares of workers with no vocational training, vocational training, and university degree, and employment shares across broad industries (agriculture, food products, consumer goods, industrial goods, capital goods, construction, consumer-related services, business-related services, and public sector). Exposure to net exports and ICT equipment is measured by the annual change in German net exports vis-à-vis China and 21 Eastern European countries (in 1,000 euros per worker) and by the annual change in German ICT equipment (in 1,000 euros per worker), respectively. Standard errors clustered at the level of local labor markets or districts are in parentheses. Shift-share standard errors are in brackets.

Table 19: Robot exposure and wage markdowns

	Dependent variable: Annual change in aggregate markdowns			
	(1)	(2)	(3)	(4)
	Panel A. OLS			
ΔPredicted robot exposure	0.0012	0.0007	0.0007	0.0007
	(0.0029)	(0.0031)	(0.0031)	(0.0031)
	[0.0006]	[0.0010]	[0.0010]	[0.0010]
	Panel B. 2SLS			
ΔPredicted robot exposure	0.0007	-0.0000	0.0000	0.0001
	(0.0032)	(0.0035)	(0.0035)	(0.0035)
	[0.0180]	[0.0164]	[0.0242]	[0.0038]
Montiel Olea-Pflueger weak IV test				
Effective F-statistic ($\alpha = 5\%$)	43.973	46.212	46.225	46.251
Critical value 2SLS ($\tau = 10\%$)	21.230	21.309	21.308	21.314
Hansen's J-stat p-value	0.360	0.359	0.358	0.358
Year fixed effects	✓	✓	✓	✓
Broad region dummies	✓	✓	✓	✓
Demographics	✓	✓	✓	✓
Manufacturing share	✓			
Broad industry shares		✓	✓	✓
ΔNet exports in 1,000 euros per worker			✓	✓
ΔICT equipment in 1,000 euros per worker				✓

Notes: $N = 4599$ local labor market regions-by-year (district-by-year). Panel A presents the OLS results from estimating the annual change in aggregate markdowns on the annual change in predicted exposure to robots in the automotive industry per 1,000 workers between 1998 and 2018. Panel B reports results from the 2SLS IV regressions where the German local labor market's exposure to robots in the automotive industry is instrumented by installations of automotive robots in other high-income European countries. All specifications control for constant, broad region dummies, year fixed effects, and demographic characteristics of districts or kreise in the previous period. The broad region dummies indicate if the region is located in the north, west, south, or east of Germany. The demographic controls are constructed using the matched employer-employee data (LIAB) and include the share of females, the share of foreigners, the share of workers over 50 years old, the shares of workers with no vocational training, vocational training, and university degree, and employment shares across industries. The manufacturing share represents the employment share of manufacturing workers in total employment. Broad industry shares are the shares of workers in nine broad industry groups (agriculture, food products, consumer goods, industrial goods, capital goods, construction, consumer-related services, business-related services, and public sector). Exposure to net exports and ICT equipment is measured by the annual change in German net exports vis-à-vis China and 21 Eastern European countries (in 1,000 euros per worker) and by the annual change in German ICT equipment (in 1,000 euros per worker), respectively. Standard errors clustered at the level of local labor markets or districts are in parentheses. Shift-share standard errors are in brackets.

Table 20: Heterogeneous effects of robot exposure on employment and wages of heterogeneous workers in East and West Germany

	Dependent variable: Annual log difference in employment and wage					
	East Germany			West Germany		
	Routine	NRM	NRC	Routine	NRM	NRC
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Employment					
ΔPredicted robot exposure	-0.008	0.021	0.023	-0.001	0.002	-0.000
	(0.007)	(0.009)	(0.010)	(0.002)	(0.002)	(0.002)
	[0.052]	[0.018]	[0.040]	[0.052]	[0.018]	[0.040]
Montiel Olea-Pflueger weak IV test						
Effective F-statistic ($\alpha = 5\%$)	75.92	75.92	75.92	125.38	125.38	125.38
Critical value 2SLS ($\tau = 10\%$)	23.04	23.04	23.04	20.14	20.14	20.14
Hansen's J-stat p-value	0.93	0.87	0.77	0.48	0.70	0.27
Observations	1596	1596	1596	6048	6048	6048
	Panel B. Wages					
ΔPredicted robot exposure	-0.004	-0.005	-0.010	0.000	-0.000	-0.0015
	(0.003)	(0.002)	(0.004)	(0.001)	(0.001)	(0.002)
	[0.006]	[0.005]	[0.009]	[0.006]	[0.005]	[0.009]
Montiel Olea-Pflueger weak IV test						
Effective F-statistic ($\alpha = 5\%$)	75.92	75.92	75.92	125.38	125.38	125.38
Critical value 2SLS ($\tau = 10\%$)	23.04	23.04	23.04	20.14	20.14	20.14
Hansen's J-stat p-value	0.73	0.78	0.67	0.70	0.05	0.26
Observations	1596	1596	1596	6048	6048	6048

Notes: Panels A and B present the IV (2SLS) results from estimating the annual log difference in employment (number of workers) and log difference in wages (average daily wage) of heterogeneous workers, respectively, on the annual change in predicted exposure to robots in the automotive industry per 1,000 workers between 1998 and 2018. The key explanatory variable is the annual change in the local labor market's exposure to robots in the automotive industry instrumented by installations of automotive robots in other high-income European countries. In Panels A and B, the sample in the left and right sub-panels consists of districts from East and West Germany, respectively. All specifications control for constant, year fixed effects, and demographic characteristics of districts or kreise in the previous period. The demographic controls are constructed using the matched employer-employee data (LIAB) and include the share of females, the share of foreigners, the share of workers over 50 years old, the shares of workers with no vocational training, vocational training, and university degree, and employment shares across industries. Broad industry shares are the shares of workers in nine broad industry groups (agriculture, food products, consumer goods, industrial goods, capital goods, construction, consumer-related services, business-related services, and public sector). Exposure to net exports and ICT equipment is measured by the annual change in German net exports vis-à-vis China and 21 Eastern European countries (in 1,000 euros per worker) and by the annual change in German ICT equipment (in 1,000 euros per worker), respectively. Unit of observation: local labor market region (kreis or district). Standard errors clustered at the local labor market level are in parentheses. Shift-share standard errors are in brackets.

Table 21: Heterogeneous effects of robot exposure on wage markdowns in East and West Germany

	Dependent variable: Annual change in aggregate markdowns			
	(1)	(2)	(3)	(4)
	Panel A. East Germany			
ΔPredicted robot exposure	0.004	0.004	0.004	0.005
	(0.003)	(0.003)	(0.003)	(0.003)
	[0.227]	[0.117]	[0.048]	[0.013]
Observations	1449	1449	1449	1449
Montiel Olea-Pflueger weak IV test				
Effective F-statistic ($\alpha = 5\%$)	1211.06	73.26	70.98	71.08
Critical value 2SLS ($\tau = 10\%$)	22.27	23.04	23.04	23.04
Hansen's J-stat p-value	0.65	0.62	0.61	0.60
	Panel B. West Germany			
ΔPredicted robot exposure	-0.004	-0.005	-0.005	-0.005
	(0.005)	(0.005)	(0.005)	(0.005)
	[0.008]	[0.156]	[0.020]	[0.004]
Observations	3150	3150	3150	3150
Montiel Olea-Pflueger weak IV test				
Effective F-statistic ($\alpha = 5\%$)	77.86	86.32	86.30	86.86
Critical value 2SLS ($\tau = 10\%$)	22.82	22.69	22.69	22.69
Hansen's J-stat p-value	0.33	0.32	0.32	0.32
Year fixed effects	✓	✓	✓	✓
Demographics	✓	✓	✓	✓
Manufacturing share	✓			
Broad industry shares		✓	✓	✓
ΔNet exports in 1,000 euros per worker			✓	✓
ΔICT equipment in 1,000 euros per worker				✓

Notes: Panels A and B present the IV (2SLS) results from estimating the annual change in aggregate markdowns in East and West Germany, respectively, on the annual change in predicted exposure to robots in the automotive industry per 1,000 workers between 1998 and 2018. The key explanatory variable is the annual change in the local labor market's exposure to robots in the automotive industry instrumented by installations of automotive robots in other high-income European countries. The dependent variable in Panels A and B is the annual change in aggregate markdowns where production function is estimated on the sub-sample consisting of manufacturing establishments from East and West Germany, respectively. All specifications control for constant, year fixed effects, and demographic characteristics of districts or kreise in the previous period. The broad region dummies indicate if the region is located in the north, west, south, or east of Germany. The demographic controls are constructed using the matched employer-employee data (LIAB) and include the share of females, the share of foreigners, the share of workers over 50 years old, the shares of workers with no vocational training, vocational training, and university degree, and employment shares across industries. The manufacturing share represents the employment share of manufacturing workers in total employment. Broad industry shares are the shares of workers in nine broad industry groups (agriculture, food products, consumer goods, industrial goods, capital goods, construction, consumer-related services, business-related services, and public sector). Exposure to net exports and ICT equipment is measured by the annual change in German net exports vis-à-vis China and 21 Eastern European countries (in 1,000 euros per worker) and by the annual change in German ICT equipment (in 1,000 euros per worker), respectively. Unit of observation: local labor market region (kreis or district). Standard errors clustered at the local labor market level are in parentheses. Shift-share standard errors are in brackets.

Table 22: Effect of robot exposure on wage markdowns for heterogeneous workers

	Dependent variable: Annual change in aggregate markdowns		
	Routine	Nonroutine manual	Nonroutine cognitive
	(1)	(2)	(3)
ΔPredicted robot exposure	0.009	0.007	-0.004
	(0.006)	(0.007)	(0.005)
	[0.004]	[0.010]	[0.006]
Montiel Olea-Pflueger weak IV test			
Effective F-statistic ($\alpha = 5\%$)	46.25	46.25	46.25
Critical value 2SLS ($\tau = 10\%$)	21.31	21.31	21.31
Hansen's J-stat p-value	0.25	0.25	0.56
R^2	0.02	0.01	0.01

Notes: $N = 4599$ local labor market regions-by-year (district-by-year). The table presents the IV (2SLS) results from estimating the annual change in aggregate markdowns for heterogeneous workers on the annual change in predicted exposure to robots in the automotive industry per 1,000 workers between 1998 and 2018. The key explanatory variable is the annual change in the German local labor market's exposure to robots in the automotive industry instrumented by installations of automotive robots in other high-income European countries. The dependent variable is the annual change in aggregate markdowns for routine (column (1)), nonroutine manual (column (2)), and nonroutine cognitive (column (3)) workers. All specifications control for constant, broad region dummies, time fixed effects, and demographic characteristics of districts or kreise in the previous period. The broad region dummies indicate if the region is located in the north, west, south, or east of Germany. The demographic controls are constructed using the matched employer-employee data (LIAB) and include the share of females, the share of foreigners, the share of workers over 50 years old, the shares of workers with no vocational training, vocational training, and university degree, and employment shares across broad industries (agriculture, food products, consumer goods, industrial goods, capital goods, construction, consumer-related services, business-related services, and public sector). Exposure to net exports and ICT equipment is measured by the annual change in German net exports vis-à-vis China and 21 Eastern European countries (in 1,000 euros per worker) and by the annual change in German ICT equipment (in 1,000 euros per worker), respectively. Standard errors clustered at the level of local labor markets or districts are in parentheses. Shift-share standard errors are in brackets.

Table 23: Heterogeneous effects of robot exposure on wage markdowns for heterogeneous workers in East and West Germany

	Dependent variable: Annual change in aggregate markdowns		
	Routine	Nonroutine manual	Nonroutine cognitive
	(1)	(2)	(3)
	Panel A. East Germany		
ΔPredicted robot exposure	0.013	0.022	-0.007
	(0.003)	(0.015)	(0.004)
	[0.039]	[0.168]	[0.060]
Montiel Olea-Pflueger weak IV test			
Effective F-statistic ($\alpha = 5\%$)	71.08	71.08	71.08
Critical value 2SLS ($\tau = 10\%$)	23.04	23.04	23.04
Hansen's J-stat p-value	0.51	0.77	0.51
Observations	1449	1449	1449
R^2	0.02	0.02	0.02
	Panel B. West Germany		
ΔPredicted robot exposure	0.010	0.006	-0.006
	(0.008)	(0.013)	(0.004)
	[0.005]	[0.029]	[0.010]
Montiel Olea-Pflueger weak IV test			
Effective F-statistic ($\alpha = 5\%$)	86.86	86.86	86.86
Critical value 2SLS ($\tau = 10\%$)	22.69	22.69	22.69
Hansen's J-stat p-value	0.56	0.57	0.50
Observations	3150	3150	3150
R^2	0.01	0.01	0.01

Notes: Panels A and B present the IV (2SLS) results from estimating the annual change in aggregate markdowns for heterogeneous workers in East and West Germany, respectively, on the annual change in predicted exposure to robots in the automotive industry per 1,000 workers between 1998 and 2018. The key explanatory variable is the annual change in the local labor market's exposure to robots in the automotive industry instrumented by installations of automotive robots in other high-income European countries. The dependent variable in Panels A and B is the annual change in aggregate markdowns for routine (column (1)), nonroutine manual (column (2)), and nonroutine cognitive (column (3)) workers where production function with heterogeneous workers is estimated on the sub-sample consisting of manufacturing establishments from East and West Germany, respectively. All specifications control for constant, time fixed effects, and demographic characteristics of districts or kreise in the previous period. The demographic controls are constructed using the matched employer-employee data (LIAB) and include the share of females, the share of foreigners, the share of workers over 50 years old, the shares of workers with no vocational training, vocational training, and university degree, and employment shares across broad industries (agriculture, food products, consumer goods, industrial goods, capital goods, construction, consumer-related services, business-related services, and public sector). Exposure to net exports and ICT equipment is measured by the annual change in German net exports vis-à-vis China and 21 Eastern European countries (in 1,000 euros per worker) and by the annual change in German ICT equipment (in 1,000 euros per worker), respectively. Unit of observation: local labor market region (kreis or district). Standard errors clustered at the local labor market level are in parentheses. Shift-share standard errors are in brackets.

Table 24: Heterogeneous effects of robot exposure on employment of heterogeneous workers in districts from East and West Germany with different union coverage

	Dependent variable: Annual log difference in employment					
	Below the median			Above the median		
	Routine (1)	NRM (2)	NRC (3)	Routine (4)	NRM (5)	NRC (6)
	Panel A. East Germany					
ΔPredicted robot exposure	-0.015	0.030	-0.009	-0.009	0.014	0.031
	(0.020)	(0.015)	(0.032)	(0.009)	(0.011)	(0.013)
	[0.052]	[0.018]	[0.040]	[0.052]	[0.018]	[0.040]
Montiel Olea-Pflueger weak IV test						
Effective F-statistic ($\alpha = 5\%$)	15.72	15.72	15.72	271.20	271.20	271.20
Critical value 2SLS ($\tau = 10\%$)	21.82	21.82	21.82	22.31	22.31	22.31
Critical value 2SLS ($\tau = 20\%$)	14.10	14.10	14.10	14.43	14.43	14.43
Critical value 2SLS ($\tau = 30\%$)	11.21	11.21	11.21	11.49	11.49	11.49
Hansen's J-stat p-value	0.51	0.96	0.39	0.81	0.84	0.78
Observations	589	589	589	1007	1007	1007
	Panel B. West Germany					
ΔPredicted robot exposure	-0.001	-0.003	-0.001	0.002	0.010	-0.001
	(0.003)	(0.003)	(0.003)	(0.007)	(0.004)	(0.008)
	[0.052]	[0.018]	[0.040]	[0.052]	[0.018]	[0.040]
Montiel Olea-Pflueger weak IV test						
Effective F-statistic ($\alpha = 5\%$)	67.81	67.81	67.81	8.95	8.95	8.95
Critical value 2SLS ($\tau = 10\%$)	21.48	21.48	21.48	22.56	22.56	22.56
Critical value 2SLS ($\tau = 20\%$)	13.80	13.80	13.80	14.63	14.63	14.63
Critical value 2SLS ($\tau = 30\%$)	10.94	10.94	10.94	11.66	11.66	11.66
Hansen's J-stat p-value	0.66	0.43	0.79	0.41	0.41	0.30
Observations	3241	3241	3241	2807	2807	2807

Notes: Panels A and B present the IV (2SLS) results from estimating the annual log difference in employment (number of workers) of heterogeneous workers in East and West Germany, respectively, on the annual change in predicted exposure to robots in the automotive industry per 1,000 workers between 1998 and 2018. The key explanatory variable is the annual change in the local labor market region's exposure to robots in the automotive industry instrumented by installations of automotive robots in other high-income European countries. In Panels A and B, the sample in the left and right sub-panels consists of districts with union coverage below and above the national median, respectively. All specifications control for constant, year fixed effects, and demographic characteristics of districts or kreise in the previous period. The demographic controls are constructed using the matched employer-employee data (LIAB) and include the share of females, the share of foreigners, the share of workers over 50 years old, the shares of workers with no vocational training, vocational training, and university degree, and employment shares across industries. Broad industry shares are the shares of workers in nine broad industry groups (agriculture, food products, consumer goods, industrial goods, capital goods, construction, consumer-related services, business-related services, and public sector). Exposure to net exports and ICT equipment is measured by the annual change in German net exports vis-à-vis China and 21 Eastern European countries (in 1,000 euros per worker) and by the annual change in German ICT equipment (in 1,000 euros per worker), respectively. Unit of observation: local labor market region (kreis or district). Standard errors clustered at the local labor market level are in parentheses. Shift-share standard errors are in brackets.

Table 25: Heterogeneous effects of robot exposure on wages of heterogeneous workers in districts from East and West Germany with different union coverage

	Dependent variable: Annual log difference in wages					
	Below the median			Above the median		
	Routine (1)	NRM (2)	NRC (3)	Routine (4)	NRM (5)	NRC (6)
	Panel A. East Germany					
ΔPredicted robot exposure	-0.005	-0.006	-0.006	-0.005	-0.007	-0.010
	(0.009)	(0.004)	(0.017)	(0.005)	(0.003)	(0.004)
	[0.006]	[0.005]	[0.009]	[0.006]	[0.005]	[0.009]
Montiel Olea-Pflueger weak IV test						
Effective F-statistic ($\alpha = 5\%$)	15.72	15.72	15.72	271.20	271.20	271.20
Critical value 2SLS ($\tau = 10\%$)	21.82	21.83	21.82	22.31	22.31	22.31
Critical value 2SLS ($\tau = 20\%$)	14.10	14.10	14.10	14.43	14.43	14.43
Critical value 2SLS ($\tau = 30\%$)	11.21	11.21	11.21	11.49	11.49	11.49
Hansen's J-stat p-value	0.35	0.65	0.29	0.85	0.86	0.83
Observations	589	589	589	1007	1007	1007
	Panel B. West Germany					
ΔPredicted robot exposure	0.000	-0.000	0.000	-0.001	0.001	-0.009
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.004)
	[0.006]	[0.005]	[0.009]	[0.006]	[0.005]	[0.009]
Montiel Olea-Pflueger weak IV test						
Effective F-statistic ($\alpha = 5\%$)	67.81	67.81	67.81	8.95	8.95	8.95
Critical value 2SLS ($\tau = 10\%$)	21.48	21.48	21.48	22.56	22.56	22.56
Critical value 2SLS ($\tau = 20\%$)	13.80	13.80	13.80	14.63	14.63	14.63
Critical value 2SLS ($\tau = 30\%$)	10.94	10.94	10.94	11.66	11.66	11.66
Hansen's J-stat p-value	0.42	0.18	0.55	0.27	0.41	0.47
Observations	3241	3241	3241	2807	2807	2807

Notes: Panels A and B present the IV (2SLS) results from estimating the annual log difference in wages (average daily wage) of heterogeneous workers in East and West Germany, respectively, on the annual change in predicted exposure to robots in the automotive industry per 1,000 workers between 1998 and 2018. The key explanatory variable is the annual change in the local labor market region's exposure to robots in the automotive industry instrumented by installations of automotive robots in other high-income European countries. In Panels A and B, the sample in the left and right sub-panels consists of districts with union coverage below and above the national median, respectively. All specifications control for constant, year fixed effects, and demographic characteristics of districts or kreise in the previous period. The demographic controls are constructed using the matched employer-employee data (LIAB) and include the share of females, the share of foreigners, the share of workers over 50 years old, the shares of workers with no vocational training, vocational training, and university degree, and employment shares across industries. Broad industry shares are the shares of workers in nine broad industry groups (agriculture, food products, consumer goods, industrial goods, capital goods, construction, consumer-related services, business-related services, and public sector). Exposure to net exports and ICT equipment is measured by the annual change in German net exports vis-à-vis China and 21 Eastern European countries (in 1,000 euros per worker) and by the annual change in German ICT equipment (in 1,000 euros per worker), respectively. Unit of observation: local labor market region (kreis or district). Standard errors clustered at the local labor market level are in parentheses. Shift-share standard errors are in brackets.

Table 26: Heterogeneous effects of robot exposure on wage markdowns for heterogeneous workers in districts from East and West Germany with different union coverage

	Dependent variable: Annual change in aggregate markdowns					
	Below the median			Above the median		
	Routine (1)	NRM (2)	NRC (3)	Routine (4)	NRM (5)	NRC (6)
	Panel A. East Germany					
ΔPredicted robot exposure	0.052	0.082	0.009	0.004	-0.005	-0.013
	(0.010)	(0.032)	(0.007)	(0.003)	(0.025)	(0.004)
	[0.024]	[0.082]	[0.021]	[0.048]	[0.185]	[0.030]
Montiel Olea-Pflueger weak IV test						
Effective F-statistic ($\alpha = 5\%$)	14.94	14.94	14.94	256.97	256.97	256.97
Critical value 2SLS ($\tau = 10\%$)	21.99	21.98	21.98	22.34	22.34	22.34
Critical value 2SLS ($\tau = 20\%$)	14.23	14.23	14.23	14.46	14.46	14.46
Hansen's J-stat p-value	0.72	0.89	0.85	0.58	0.72	0.64
Observations	527	527	527	922	922	922
	Panel B. West Germany					
ΔPredicted robot exposure	0.032	0.077	-0.001	0.007	-0.003	-0.006
	(0.021)	(0.077)	(0.013)	(0.003)	(0.013)	(0.005)
	[0.057]	[0.170]	[0.056]	[0.007]	[0.040]	[0.014]
Montiel Olea-Pflueger weak IV test						
Effective F-statistic ($\alpha = 5\%$)	13.53	13.53	13.53	33.50	33.50	33.50
Critical value 2SLS ($\tau = 10\%$)	21.11	21.11	21.11	22.37	22.37	22.37
Critical value 2SLS ($\tau = 20\%$)	13.51	13.51	13.51	14.48	14.48	14.48
Hansen's J-stat p-value	0.68	0.83	0.42	0.56	0.57	0.71
Observations	1660	1660	1660	1490	1490	1490

Notes: The left and right sub-panels of Panel A present the IV (2SLS) results from estimating the annual change in aggregate markdowns for heterogeneous workers in districts from East Germany with union coverage below and above the national median, respectively, on the annual change in predicted exposure to robots in the automotive industry per 1,000 workers between 1998 and 2018. Panel B's left and right sub-panels report the counterparts for districts from West Germany. The union coverage of the district is measured by the share of workers covered by unions in total workers in the district. The sample in the left and right sub-panel of Panel A consists of districts from East Germany whose union coverage is below and above the national median, respectively. The sample in the left and right sub-panel of Panel B consists of districts from West Germany whose union coverage is below and above the national median, respectively. The key explanatory variable is the annual change in the local labor market's exposure to robots in the automotive industry instrumented by installations of automotive robots in other high-income European countries. The dependent variable in Panels A and B is the annual change in aggregate markdowns for routine (column (1)), nonroutine manual (column (2)), and nonroutine cognitive (column (3)) workers where production function with heterogeneous workers is estimated on the sub-sample consisting of manufacturing establishments from East and West Germany, respectively. All specifications control for constant, time fixed effects, and demographic characteristics of districts or kreise in the previous period. The demographic controls are constructed using the matched employer-employee data (LIAB) and include the share of females, the share of foreigners, the share of workers over 50 years old, the shares of workers with no vocational training, vocational training, and university degree, and employment shares across broad industries (agriculture, food products, consumer goods, industrial goods, capital goods, construction, consumer-related services, business-related services, and public sector). Exposure to net exports and ICT equipment is measured by the annual change in German net exports vis-à-vis China and 21 Eastern European countries (in 1,000 euros per worker) and by the annual change in German ICT equipment (in 1,000 euros per worker), respectively. Unit of observation: local labor market region (kreis or district). Standard errors clustered at the local labor market level are in parentheses. Shift-share standard errors are in brackets. NRC, nonroutine cognitive; NRM, nonroutine manual.

Table 27: Robustness: Heterogeneous effects of robot exposure on wage markdowns for heterogeneous workers in East and West Germany
(production function estimated on the full sample)

	Dependent variable: Annual change in aggregate markdowns		
	Routine (1)	Nonroutine manual (2)	Nonroutine cognitive (3)
	Panel A. East Germany		
ΔPredicted robot exposure	0.024	0.035	-0.015
	(0.008)	(0.011)	(0.006)
	[0.024]	[0.053]	[0.020]
Montiel Olea-Pflueger weak IV test			
Effective F-statistic ($\alpha = 5\%$)	71.08	71.08	71.08
Critical value 2SLS ($\tau = 10\%$)	23.04	23.04	23.04
Hansen's J-stat p-value	0.56	0.81	0.52
Observations	1449	1449	1449
R^2	0.03	0.03	0.02
	Panel B. West Germany		
ΔPredicted robot exposure	0.005	0.000	-0.003
	(0.003)	(0.008)	(0.003)
	[0.005]	[0.022]	[0.009]
Montiel Olea-Pflueger weak IV test			
Effective F-statistic ($\alpha = 5\%$)	86.86	86.86	86.86
Critical value 2SLS ($\tau = 10\%$)	22.69	22.69	22.69
Hansen's J-stat p-value	0.36	0.43	0.68
Observations	3150	3150	3150
R^2	0.02	0.01	0.01

Notes: Panels A and B present the IV (2SLS) results from estimating the annual change in aggregate markdowns for heterogeneous workers in East and West Germany, respectively, on the annual change in predicted exposure to robots in the automotive industry per 1,000 workers between 1998 and 2018. The key explanatory variable is the annual change in the local labor market's exposure to robots in the automotive industry instrumented by installations of automotive robots in other high-income European countries. The dependent variable in Panels A and B is the annual change in aggregate markdowns for routine (column (1)), nonroutine manual (column (2)), and nonroutine cognitive (column (3)) workers at manufacturing establishments from East and West Germany, respectively, where production function with heterogeneous workers is estimated on the full sample. All specifications control for constant, time fixed effects, and demographic characteristics of districts or kreise in the previous period. The demographic controls are constructed using the matched employer-employee data (LIAB) and include the share of females, the share of foreigners, the share of workers over 50 years old, the shares of workers with no vocational training, vocational training, and university degree, and employment shares across broad industries (agriculture, food products, consumer goods, industrial goods, capital goods, construction, consumer-related services, business-related services, and public sector). Exposure to net exports and ICT equipment is measured by the annual change in German net exports vis-à-vis China and 21 Eastern European countries (in 1,000 euros per worker) and by the annual change in German ICT equipment (in 1,000 euros per worker), respectively. Unit of observation: local labor market region (kreis or district). Standard errors clustered at the local labor market level are in parentheses. Shift-share standard errors are in brackets.

Table 28: Robustness: Heterogeneous effects of robot exposure on wage markdowns for heterogeneous workers in districts from East and West Germany with different union coverage (production function estimated on the full sample)

	Dependent variable: Annual change in aggregate markdowns					
	Below the median			Above the median		
	Routine	NRM	NRC	Routine	NRM	NRC
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. East Germany					
ΔPredicted robot exposure	0.109	0.086	0.050	0.000	0.010	-0.036
	(0.029)	(0.037)	(0.015)	(0.005)	(0.015)	(0.007)
	[0.026]	[0.071]	[0.028]	[0.072]	[0.153]	[0.085]
Montiel Olea-Pflueger weak IV test						
Effective F-statistic ($\alpha = 5\%$)	14.94	14.94	14.94	256.97	256.97	256.97
Critical value 2SLS ($\tau = 10\%$)	21.98	21.98	21.99	22.34	22.34	22.34
Critical value 2SLS ($\tau = 20\%$)	14.23	14.23	14.23	14.46	14.46	14.46
Hansen's J-stat p-value	0.48	0.77	0.91	0.70	0.91	0.42
Observations	527	527	527	922	922	922
	Panel B. West Germany					
ΔPredicted robot exposure	0.005	-0.000	0.001	0.005	0.009	-0.005
	(0.008)	(0.024)	(0.008)	(0.002)	(0.006)	(0.003)
	[0.031]	[0.078]	[0.062]	[0.011]	[0.021]	[0.012]
Montiel Olea-Pflueger weak IV test						
Effective F-statistic ($\alpha = 5\%$)	13.53	13.53	13.53	33.50	33.50	33.50
Critical value 2SLS ($\tau = 10\%$)	21.11	21.11	21.11	22.37	22.37	22.37
Critical value 2SLS ($\tau = 20\%$)	13.51	13.51	13.51	14.48	14.48	14.48
Hansen's J-stat p-value	0.36	0.38	0.59	0.86	0.54	0.69
Observations	1660	1660	1660	1490	1490	1490

Notes: The left and right sub-panels of Panel A present the IV (2SLS) results from estimating the annual change in aggregate markdowns for heterogeneous workers in districts from East Germany with union coverage below and above the national median, respectively, on the annual change in predicted exposure to robots in the automotive industry per 1,000 workers between 1998 and 2018. Panel B's left and right sub-panels report the counterparts for districts from West Germany. The union coverage of the district is measured by the share of workers covered by unions in total workers in the district. The sample in the left and right sub-panel of Panel A consists of districts from East Germany whose union coverage is below and above the national median, respectively. The sample in the left and right sub-panel of Panel B consists of districts from West Germany whose union coverage is below and above the national median, respectively. The key explanatory variable is the annual change in the local labor market's exposure to robots in the automotive industry instrumented by installations of automotive robots in other high-income European countries. The dependent variable in Panels A and B is the annual change in aggregate markdowns for routine (column (1)), nonroutine manual (column (2)), and nonroutine cognitive (column (3)) workers at manufacturing establishments from East and West Germany, respectively, where production function with heterogeneous workers is estimated on the full sample. All specifications control for constant, time fixed effects, and demographic characteristics of districts or kreise in the previous period. The demographic controls are constructed using the matched employer-employee data (LIAB) and include the share of females, the share of foreigners, the share of workers over 50 years old, the shares of workers with no vocational training, vocational training, and university degree, and employment shares across broad industries (agriculture, food products, consumer goods, industrial goods, capital goods, construction, consumer-related services, business-related services, and public sector). Exposure to net exports and ICT equipment is measured by the annual change in German net exports vis-à-vis China and 21 Eastern European countries (in 1,000 euros per worker) and by the annual change in German ICT equipment (in 1,000 euros per worker), respectively. Unit of observation: local labor market region (kreis or district). Standard errors clustered at the local labor market level are in parentheses. Shift-share standard errors are in brackets. NRC, nonroutine cognitive; NRM, nonroutine manual.

Table 29: Robustness: Heterogeneous effects of robot exposure on wage markdowns for heterogeneous workers in districts from East/West Germany with different union coverage (alternative split of union coverage)

	Dependent variable: Annual change in aggregate markdowns		
	Routine	Nonroutine manual	Nonroutine cognitive
	(1)	(2)	(3)
	Panel A. East Germany		
ΔPredicted robot exposure	0.023	0.059	-0.026
	(0.006)	(0.030)	(0.005)
	[0.008]	[0.029]	[0.008]
Montiel Olea-Pflueger weak IV test			
Effective F-statistic ($\alpha = 5\%$)	9.40	9.40	9.40
Critical value 2SLS ($\tau = 10\%$)	22.84	22.84	22.84
Critical value 2SLS ($\tau = 20\%$)	14.85	14.85	14.85
Critical value 2SLS ($\tau = 30\%$)	11.85	11.85	11.85
Hansen's J-stat p-value	0.34	0.76	0.75
Observations	1238	1238	1238
	Panel B. West Germany		
ΔPredicted robot exposure	0.014	0.010	-0.016
	(0.010)	(0.023)	(0.024)
	[0.133]	[0.306]	[0.150]
Montiel Olea-Pflueger weak IV test			
Effective F-statistic ($\alpha = 5\%$)	6.59	6.59	6.59
Critical value 2SLS ($\tau = 10\%$)	22.85	22.85	22.85
Critical value 2SLS ($\tau = 20\%$)	14.86	14.86	14.86
Critical value 2SLS ($\tau = 30\%$)	11.86	11.86	11.86
Hansen's J-stat p-value	0.36	0.34	0.46
Observations	2590	2590	2590

Notes: Panels A and B present the IV (2SLS) results from estimating the annual change in aggregate markdowns for heterogeneous workers in districts from East and West Germany, respectively, with union coverage in the bottom eight deciles of the distribution on the annual change in predicted exposure to robots in the automotive industry per 1,000 workers between 1998 and 2018. The union coverage of the district is measured by the share of workers covered by unions in total workers in the district. The key explanatory variable is the annual change in the local labor market's exposure to robots in the automotive industry instrumented by installations of automotive robots in other high-income European countries. The dependent variable in Panels A and B is the annual change in aggregate markdowns for routine (column (1)), nonroutine manual (column (2)), and nonroutine cognitive (column (3)) workers where production function with heterogeneous workers is estimated on the sub-sample consisting of manufacturing establishments from East and West Germany, respectively. All specifications control for constant, time fixed effects, and demographic characteristics of districts or kreise in the previous period. The demographic controls are constructed using the matched employer-employee data (LIAB) and include the share of females, the share of foreigners, the share of workers over 50 years old, the shares of workers with no vocational training, vocational training, and university degree, and employment shares across broad industries (agriculture, food products, consumer goods, industrial goods, capital goods, construction, consumer-related services, business-related services, and public sector). Exposure to net exports and ICT equipment is measured by the annual change in German net exports vis-à-vis China and 21 Eastern European countries (in 1,000 euros per worker) and by the annual change in German ICT equipment (in 1,000 euros per worker), respectively. Unit of observation: local labor market region (kreis or district). Standard errors clustered at the local labor market level are in parentheses. Shift-share standard errors are in brackets.

Table 30: Robustness: Heterogeneous effects of robot exposure on wage markdowns for heterogeneous workers in districts from East and West Germany with different union coverage (percent changes)

	Dependent variable: Annual change in aggregate markdowns					
	Below the median			Above the median		
	Routine (1)	NRM (2)	NRC (3)	Routine (4)	NRM (5)	NRC (6)
	Panel A. East Germany					
ΔPredicted robot exposure	14.908	27.304	2.607	0.274	5.273	-7.025
	(4.249)	(12.314)	(2.643)	(1.238)	(6.369)	(1.485)
	[7.588]	[14.185]	[7.431]	[15.674]	[26.129]	[14.982]
Montiel Olea-Pflueger weak IV test						
Effective F-statistic ($\alpha = 5\%$)	5.04	5.04	5.04	243.88	243.88	243.88
Critical value 2SLS ($\tau = 10\%$)	22.29	22.29	22.29	21.66	21.66	21.66
Critical value 2SLS ($\tau = 20\%$)	14.44	14.44	14.44	13.93	13.93	13.93
Critical value 2SLS ($\tau = 30\%$)	11.49	11.49	11.49	11.05	11.05	11.05
Hansen's J-stat p-value	0.71	0.76	0.83	0.53	0.46	0.74
Observations	527	527	527	922	922	922
	Panel B. West Germany					
ΔPredicted robot exposure	7.224	5.281	0.656	0.964	0.020	-0.660
	(3.926)	(5.406)	(1.463)	(0.433)	(2.172)	(0.878)
	[14.955]	[22.188]	[9.452]	[2.129]	[5.986]	[2.145]
Montiel Olea-Pflueger weak IV test						
Effective F-statistic ($\alpha = 5\%$)	18.10	18.10	18.10	44.67	44.67	44.67
Critical value 2SLS ($\tau = 10\%$)	19.73	19.73	19.73	22.45	22.45	22.45
Critical value 2SLS ($\tau = 20\%$)	12.48	12.48	12.48	14.55	14.55	14.55
Critical value 2SLS ($\tau = 30\%$)	9.81	9.81	9.81	11.58	11.58	11.58
Hansen's J-stat p-value	0.71	0.77	0.26	0.77	0.90	0.74
Observations	1660	1660	1660	1490	1490	1490

Notes: The table checks the robustness of IV (2SLS) results by using percent changes in aggregate markdowns for heterogeneous workers and predicted exposure to robots in the automotive industry per 1,000 workers. The sample in the left and right sub-panel of Panel A consists of districts from East Germany whose union coverage is below and above the national median, respectively. The sample in the left and right sub-panel of Panel B consists of districts from West Germany whose union coverage is below and above the national median, respectively. The dependent variable in Panels A and B is the annual percent change in aggregate markdowns for routine (column (1)), nonroutine manual (column (2)), and nonroutine cognitive (column (3)) workers where production function with heterogeneous workers is estimated on the sub-sample consisting of manufacturing establishments from East and West Germany, respectively. The key explanatory variable is the annual percent change in the local labor market's exposure to robots in the automotive industry instrumented by installations of automotive robots in other high-income European countries. All specifications include the full set of baseline control variables. Standard errors clustered at the local labor market level are in parentheses. Shift-share standard errors are in brackets. NRC, nonroutine cognitive; NRM, nonroutine manual.

Table 31: Robustness: Effect of robot exposure on wage markdowns
(alternative clusters at the aggregate regions)

	Dependent variable: Annual change in aggregate markdowns			
	All workers	Heterogeneous workers		
		Routine	NRM	NRC
	(1)	(2)	(3)	(4)
ΔPredicted robot exposure	0.000	0.009	0.007	-0.004
	(0.003)	(0.006)	(0.010)	(0.004)
	[0.004]	[0.004]	[0.010]	[0.006]
Montiel Olea-Pflueger weak IV test				
Effective F-statistic ($\alpha = 5\%$)	43.00	43.00	43.00	43.00
Critical value 2SLS ($\tau = 10\%$)	21.56	21.56	21.56	21.56
Hansen's J-stat p-value	0.50	0.15	0.18	0.44

Notes: $N = 4599$ local labor market regions-by-year (district-by-year). The table checks the robustness of the IV (2SLS) results from estimating the effect of robot exposure on aggregate wage markdowns for all workers (column (1)) and heterogeneous workers (columns (2)-(4)) by using 50 aggregate regions to cluster the standard errors. The key explanatory variable is the annual change in the German local labor market's exposure to robots in the automotive industry instrumented by installations of automotive robots in other high-income European countries. The dependent variable is the annual change in aggregate markdowns for all (column (1)), routine (column (2)), nonroutine manual (column (3)), and nonroutine cognitive (column (4)) workers. All specifications control for constant, broad region dummies, time fixed effects, and the full set of baseline control variables. Standard errors clustered by the 50 aggregate regions are in parentheses. Shift-share standard errors are in brackets. NRC, nonroutine cognitive; NRM, nonroutine manual.

Table 32: Robustness: Heterogeneous effects of robot exposure on wage markdowns for heterogeneous workers in districts from East and West Germany with different union coverage (robots in automobile and other industries)

	Dependent variable: Annual change in aggregate markdowns					
	Below the median			Above the median		
	Routine	NRM	NRC	Routine	NRM	NRC
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. East Germany					
ΔPredicted robot exposure	0.058	0.069	0.005	0.007	-0.011	-0.011
(*automobile industry*)	(0.009)	(0.034)	(0.008)	(0.004)	(0.024)	(0.006)
	[0.068]	[0.237]	[0.059]	[0.044]	[0.158]	[0.056]
Kleibergen-Paap weak ID test	32.35	32.35	32.35	83.73	83.73	83.73
Hansen's J-stat p-value	0.94	0.86	0.85	0.64	0.58	0.49
Observations	527	527	527	922	922	922
	Panel B. West Germany					
ΔPredicted robot exposure	0.033	0.077	-0.002	0.006	-0.000	-0.006
(*automobile industry*)	(0.021)	(0.077)	(0.013)	(0.003)	(0.012)	(0.005)
	[0.089]	[1.231]	[0.095]	[0.005]	[0.017]	[0.003]
Kleibergen-Paap weak ID test	14.55	14.55	14.55	20.33	20.33	20.33
Hansen's J-stat p-value	0.90	0.79	0.54	0.71	0.33	0.91
Observations	1660	1660	1660	1490	1490	1490

Notes: The table checks the robustness of IV (2SLS) results by adding a treatment variable of annual change in the local labor market's exposure to non-automotive robots instrumented by non-automotive robots in other high-income European countries. The sample in the left and right sub-panel of Panel A consists of districts from East Germany whose union coverage is below and above the national median, respectively. The sample in the left and right sub-panel of Panel B consists of districts from West Germany whose union coverage is below and above the national median, respectively. The dependent variable in Panels A and B is the annual change in aggregate markdowns for routine (column (1)), nonroutine manual (column (2)), and nonroutine cognitive (column (3)) workers where production function with heterogeneous workers is estimated on the sub-sample consisting of manufacturing establishments from East and West Germany, respectively. The key explanatory variable is the annual change in the local labor market's exposure to robots in the automotive industry instrumented by installations of automotive robots in other high-income European countries. All specifications include the full set of baseline control variables. Standard errors clustered at the local labor market level are in parentheses. Shift-share standard errors are in brackets. NRC, nonroutine cognitive; NRM, nonroutine manual.

Table 33: Robustness: Heterogeneous effects of robot exposure on wage markdowns for heterogeneous workers in districts from East/West Germany with different union coverage (robots in all industries)

	Dependent variable: Annual change in aggregate markdowns		
	Routine (1)	Nonroutine manual (2)	Nonroutine cognitive (3)
	Panel A. East Germany		
ΔPredicted robot exposure	0.0065	0.0012	0.0001
	(0.0032)	(0.0090)	(0.0025)
	[0.0063]	[0.0275]	[0.0062]
Montiel Olea-Pflueger weak IV test			
Effective F-statistic ($\alpha = 5\%$)	9.852	9.852	9.852
Critical value 2SLS ($\tau = 10\%$)	20.162	20.147	20.146
Critical value 2SLS ($\tau = 20\%$)	12.877	12.868	12.868
Critical value 2SLS ($\tau = 30\%$)	10.171	10.165	10.165
Hansen's J-stat p-value	0.757	0.321	0.427
Observations	1238	1238	1238
	Panel B. West Germany		
ΔPredicted robot exposure	-0.0014	0.0042	0.0002
	(0.0008)	(0.0026)	(0.0011)
	[0.0085]	[0.0244]	[0.0097]
Montiel Olea-Pflueger weak IV test			
Effective F-statistic ($\alpha = 5\%$)	35.041	35.041	35.041
Critical value 2SLS ($\tau = 10\%$)	17.560	17.561	17.562
Hansen's J-stat p-value	0.389	0.123	0.807
Observations	2590	2590	2590

Notes: The table checks the robustness of IV (2SLS) results on the heterogeneous effect of robot exposure on wage markdowns for heterogeneous workers in districts from East and West Germany with different union coverage by using total robots in all industries instead of automotive robots as in the baseline analysis. Panels A and B contain East and West German districts in the bottom eight deciles of union coverage distribution, respectively. The dependent variable in Panels A and B is the annual change in aggregate markdowns for routine (column (1)), nonroutine manual (column (2)), and nonroutine cognitive (column (3)) workers where production function with heterogeneous workers is estimated on the sub-sample consisting of manufacturing establishments from East and West Germany, respectively. The key explanatory variable is the annual change in the local labor market's exposure to robots in all industries instrumented by installations of robots in other high-income European countries. All specifications include the full set of baseline control variables. Standard errors clustered at the local labor market level are in parentheses. Shift-share standard errors are in brackets. NRC, nonroutine cognitive; NRM, nonroutine manual.

Table 34: First-stage regression

	Dependent variable: ΔPredicted robot exposure in Germany	
	(1)	(2)
ΔPredicted robot exposure in Spain	3.187	2.709
	(0.250)	(0.198)
ΔPredicted robot exposure in Norway	102.651	118.352
	(27.469)	(29.974)
ΔPredicted robot exposure in Sweden	2.244	2.612
	(0.251)	(0.276)
ΔPredicted robot exposure in UK	0.827	0.778
	(0.169)	(0.240)
ΔPredicted robot exposure in France	-0.381	
	(0.357)	
ΔPredicted robot exposure in Italy	-0.007	
	(0.247)	
Observations	4599	4599
R^2	0.39	0.38

Notes: The table presents the OLS coefficients from first-stage regressions. The dependent variable is the annual change in predicted robot exposure in Germany, and the main explanatory variables are the annual change in predicted robot exposure in six (Column (1)) and four (Column (2)) other high-income European countries. All specifications control for constant, time fixed effects, broad region dummies, and demographic characteristics of districts or kreise in the base period.

Table 35: Robustness: Heterogeneous effects of robot exposure on wage markdowns for heterogeneous workers in districts from East and West Germany with different union coverage (alternative group of instruments)

	Dependent variable: Annual change in aggregate markdowns					
	Below the median			Above the median		
	Routine	NRM	NRC	Routine	NRM	NRC
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. East Germany					
ΔPredicted robot exposure	0.052	0.082	0.009	0.009	-0.012	-0.020
	(0.010)	(0.032)	(0.007)	(0.004)	(0.027)	(0.006)
	[0.023]	[0.078]	[0.021]	[0.046]	[0.174]	[0.028]
Montiel Olea-Pflueger weak IV test						
Effective F-statistic ($\alpha = 5\%$)	16.57	16.57	16.57	203.81	203.81	203.81
Critical value 2SLS ($\tau = 10\%$)	22.35	22.34	22.34	22.93	22.93	22.93
Critical value 2SLS ($\tau = 20\%$)	14.53	14.52	14.52	14.92	14.92	14.92
Hansen's J-stat p-value	0.70	0.75	0.77	0.46	0.70	0.33
Observations	527	527	527	922	922	922
	Panel B. West Germany					
ΔPredicted robot exposure	0.034	0.077	-0.004	0.006	-0.011	-0.001
	(0.021)	(0.075)	(0.014)	(0.003)	(0.019)	(0.006)
	[0.065]	[0.188]	[0.064]	[0.008]	[0.046]	[0.016]
Montiel Olea-Pflueger weak IV test						
Effective F-statistic ($\alpha = 5\%$)	22.84	22.84	22.84	56.73	56.73	56.73
Critical value 2SLS ($\tau = 10\%$)	21.10	21.10	21.10	22.27	22.27	22.27
Critical value 2SLS ($\tau = 20\%$)	13.53	13.53	13.53	14.42	14.42	14.42
Hansen's J-stat p-value	0.83	0.62	0.24	0.27	0.30	0.47
Observations	1660	1660	1660	1490	1490	1490

Notes: The table checks the robustness of IV (2SLS) results using an alternative set of instruments that consist of the annual changes of predicted exposure to automotive robots in Spain, Norway, Sweden, and the UK. The sample in the left and right sub-panel of Panel A consists of districts from East Germany whose union coverage is below and above the national median, respectively. The sample in the left and right sub-panel of Panel B consists of districts from West Germany whose union coverage is below and above the national median, respectively. The dependent variable in Panels A and B is the annual change in aggregate markdowns for routine (column (1)), nonroutine manual (column (2)), and nonroutine cognitive (column (3)) workers where production function with heterogeneous workers is estimated on the sub-sample consisting of manufacturing establishments from East and West Germany, respectively. All specifications include the full set of baseline control variables. Standard errors clustered at the local labor market level are in parentheses. Shift-share standard errors are in brackets. NRC, nonroutine cognitive; NRM, nonroutine manual.

Table 36: Heterogeneous effects of robot exposure on wage markdowns for heterogeneous workers in districts from East and West Germany with different union coverage (2014-2018)

	Dependent variable: Annual change in aggregate markdowns					
	Below the median			Above the median		
	Routine (1)	NRM (2)	NRC (3)	Routine (4)	NRM (5)	NRC (6)
	Panel A. East Germany					
ΔPredicted robot exposure	0.001	-0.095	0.065	-0.001	-0.039	-0.001
	(0.052)	(0.222)	(0.060)	(0.004)	(0.017)	(0.004)
Montiel Olea-Pflueger weak IV test						
Effective F-statistic ($\alpha = 5\%$)	7.24	0.93	5.72	2877.77	106.25	4763.26
Critical value 2SLS ($\tau = 10\%$)	21.83	20.39	21.97	20.53	22.34	18.85
Critical value 2SLS ($\tau = 20\%$)	14.06	12.98	14.17	13.22	14.47	11.96
Critical value 2SLS ($\tau = 30\%$)	11.17	10.24	11.26	10.50	11.52	9.41
Hansen's J-stat p-value	0.58	0.65	0.47	0.67	0.51	0.74
Observations	77	77	77	199	199	199
	Panel B. West Germany					
ΔPredicted robot exposure	-0.005	0.015	-0.011	0.007	0.009	0.011
	(0.009)	(0.020)	(0.025)	(0.007)	(0.013)	(0.015)
Montiel Olea-Pflueger weak IV test						
Effective F-statistic ($\alpha = 5\%$)	451.84	173.79	5.52	78.35	76.05	78.09
Critical value 2SLS ($\tau = 10\%$)	18.97	20.86	22.51	22.37	21.87	22.34
Critical value 2SLS ($\tau = 20\%$)	12.15	13.42	14.60	14.53	14.21	14.51
Critical value 2SLS ($\tau = 30\%$)	9.62	10.64	11.63	11.59	11.33	11.57
Hansen's J-stat p-value	0.51	0.26	0.41	0.37	0.67	0.32
Observations	303	303	303	289	289	289

Notes: The table presents the results from estimating the specifications in Table 26 on the sample between 2014 and 2018. NRC, nonroutine cognitive; NRM, nonroutine manual.

Table 37: Heterogeneous effects of robot exposure on wage markdowns for heterogeneous workers in districts from East and West Germany with different union coverage (controlling for actual robot adoption)

	Dependent variable: Annual change in aggregate markdowns					
	Below the median			Above the median		
	Routine	NRM	NRC	Routine	NRM	NRC
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. East Germany					
ΔPredicted robot exposure	0.002	-0.091	0.065	-0.002	-0.040	0.001
	(0.054)	(0.224)	(0.060)	(0.004)	(0.017)	(0.004)
Montiel Olea-Pflueger weak IV test						
Effective F-statistic ($\alpha = 5\%$)	7.13	0.90	5.59	2619.67	113.18	4437.34
Critical value 2SLS ($\tau = 10\%$)	21.80	20.34	21.94	20.61	22.37	18.80
Critical value 2SLS ($\tau = 20\%$)	14.05	12.94	14.15	13.28	14.49	11.92
Critical value 2SLS ($\tau = 30\%$)	11.15	10.21	11.24	10.54	11.54	9.38
Hansen's J-stat p-value	0.60	0.64	0.50	0.67	0.60	0.67
Observations	77	77	77	199	199	199
	Panel B. West Germany					
ΔPredicted robot exposure	-0.005	0.015	-0.011	0.006	0.006	0.010
	(0.009)	(0.020)	(0.025)	(0.006)	(0.011)	(0.014)
Montiel Olea-Pflueger weak IV test						
Effective F-statistic ($\alpha = 5\%$)	447.10	172.66	5.50	78.35	75.83	78.10
Critical value 2SLS ($\tau = 10\%$)	18.95	20.85	22.51	22.39	21.96	22.36
Critical value 2SLS ($\tau = 20\%$)	12.14	13.41	14.60	14.54	14.26	14.52
Critical value 2SLS ($\tau = 30\%$)	9.61	10.63	11.63	11.60	11.37	11.58
Hansen's J-stat p-value	0.50	0.22	0.41	0.36	0.67	0.32
Observations	303	303	303	289	289	289

Notes: The table presents the effects of robot exposure on wage markdowns using a regression where the district-level actual robot adoption (number of robots adopted at the firm aggregated at the district level, expressed per 1,000 workers) has been added to a specification in Table 36. NRC, nonroutine cognitive; NRM, nonroutine manual.

Table 38: Plant-level effects of robot exposure on employment

	Dependent variable: Annual % change in plant-level employment			
	All workers	Heterogeneous workers		
		Routine	NRM	NRC
	(1)	(2)	(3)	(4)
ΔPredicted robot exposure	-0.008	-0.020	-0.009	0.012
	(0.005)	(0.007)	(0.013)	(0.008)
Observations	7623	7623	7623	7623

Notes: Column (1) presents the results from estimating the annual percentage change in employment at the plant on the annual change in the local labor market's predicted exposure to robots in the automotive industry per 1,000 workers between 1998 and 2018 using the IV (2SLS) regressions. Columns (2)-(4) report the effects of automation exposure on the employment of heterogeneous workers performing different tasks, and the dependent variable is the annual percentage change in the number of routine workers (column (2)), nonroutine manual–NRM workers (column (3)), and nonroutine cognitive–NRC workers (column (4)). All specifications control for constant, six plant size groups based on the number of employees at the establishment in the previous year, and demographic characteristics of districts or kreise in the previous year. The demographic controls are constructed using the matched employer-employee data (LIAB) and include the share of females, the share of foreigners, the share of workers over 50 years old, the shares of workers with no vocational training, vocational training, and university degree, and employment shares across broad industries (agriculture, food products, consumer goods, industrial goods, capital goods, construction, consumer-related services, business-related services, and public sector). The local labor market characteristics also contain the annual changes in exposure to net exports and ICT equipment. The firm, state-by-year, and industry-by-year fixed effects are also controlled in each specification. Standard errors clustered at the level of local labor markets or districts are in parentheses.

Table 39: Plant-level effects of robot exposure on employment of heterogeneous workers in East and West Germany

	Dependent variable: Annual % change in plant-level employment		
	Routine (1)	Nonroutine manual (2)	Nonroutine cognitive (3)
	Panel A. East Germany		
ΔPredicted robot exposure	-0.016	-0.013	0.022
	(0.004)	(0.006)	(0.006)
Observations	3649	3649	3649
	Panel B. West Germany		
ΔPredicted robot exposure	-0.001	-0.017	0.006
	(0.008)	(0.014)	(0.008)
Observations	3823	3823	3823
Firm characteristics	✓	✓	✓
Regional demographics	✓	✓	✓
Firm fixed effects	✓	✓	✓
State-by-Year fixed effects	✓	✓	✓
Industry-by-Year fixed effects	✓	✓	✓

Notes: Panel A presents the results from estimating the annual percentage change in employment at the plant on the annual change in the local labor market's predicted exposure to robots in the automotive industry per 1,000 workers in East Germany between 1998 and 2018 using the IV (2SLS) regressions. Panel B reports the results from the 2SLS IV regressions for West Germany. In both panels, the dependent variable is the annual percentage change in plant-level employment of routine (column (1)), nonroutine manual (column (2)), and nonroutine cognitive (column (3)) workers. All specifications include the same set of controls and fixed effects as in Table 38. Standard errors clustered at the level of local labor markets or districts are in parentheses.

Table 40: Plant-level effects of robot exposure on employment of heterogeneous workers in districts from East and West Germany with different union coverage

	Dependent variable: Annual % change in plant-level employment					
	Bottom 8 deciles			Top 2 deciles		
	Routine (1)	NRM (2)	NRC (3)	Routine (4)	NRM (5)	NRC (6)
	Panel A. East Germany					
ΔPredicted robot exposure	-0.012	-0.012	0.005	-0.013	-0.023	0.076
	(0.006)	(0.007)	(0.008)	(0.015)	(0.028)	(0.024)
Observations	3149	3149	3149	224	224	224
	Panel B. West Germany					
ΔPredicted robot exposure	0.008	0.001	-0.015	-0.008	0.000	0.003
	(0.009)	(0.014)	(0.017)	(0.006)	(0.004)	(0.004)
Observations	3273	3273	3273	182	182	182
Firm characteristics	✓	✓	✓	✓	✓	✓
Regional demographics	✓	✓	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓	✓	✓
State-by-Year fixed effects	✓	✓	✓	✓	✓	✓
Industry-by-Year fixed effects	✓	✓	✓	✓	✓	✓

Notes: The left sub-panel of Panel A presents the results from estimating the annual percentage change in employment at the plant on the annual change in the local labor market's predicted exposure to robots in the automotive industry per 1,000 workers in districts from East Germany whose union coverage is in the bottom eight deciles of the distribution in the previous period between 1998 and 2018 using the IV (2SLS) regressions. The right sub-panel of Panel A reports the results from the IV (2SLS) regressions for plants in districts from East Germany with high union coverage (i.e., districts in the top two deciles of the distribution of district-level union coverage). Panel B's left and right sub-panels show the corresponding results for West Germany. In all panels, the dependent variable is the annual percentage change in plant-level employment of routine workers (columns (1) and (4)), nonroutine manual–NRM workers (columns (2) and (5)), and nonroutine cognitive–NRC workers (columns (3) and (6)). All specifications include the same set of controls and fixed effects as in Table 38. Standard errors clustered at the level of local labor markets or districts are in parentheses.

Table 41: Plant-level effects of robot exposure on wages

	Dependent variable: Annual % change in plant-level average wage			
	All workers	Heterogeneous workers		
		Routine	NRM	NRC
	(1)	(2)	(3)	(4)
ΔPredicted robot exposure	0.002	0.008	-0.006	0.012
	(0.007)	(0.010)	(0.006)	(0.013)
Observations	7623	7623	7623	7623

Notes: Column (1) presents the results from estimating the annual percentage change in average wage at the plant on the annual change in the local labor market's predicted exposure to robots in the automotive industry per 1,000 workers between 1998 and 2018 using the IV (2SLS) regressions. Columns (2)-(4) report the effects of automation exposure on the average wage of heterogeneous workers performing different tasks, and the dependent variable is the annual percentage change in the average wage of routine workers (column (2)), nonroutine manual–NRM workers (column (3)), and nonroutine cognitive–NRC workers (column (4)). All specifications control for constant, six plant size groups based on the number of employees at the establishment in the previous year, and demographic characteristics of districts or kreise in the previous year. The demographic controls are constructed using the matched employer-employee data (LIAB) and include the share of females, the share of foreigners, the share of workers over 50 years old, the shares of workers with no vocational training, vocational training, and university degree, and employment shares across broad industries (agriculture, food products, consumer goods, industrial goods, capital goods, construction, consumer-related services, business-related services, and public sector). The local labor market characteristics also contain the annual changes in exposure to net exports and ICT equipment. The firm, state-by-year, and industry-by-year fixed effects are also controlled in each specification. Standard errors clustered at the level of local labor markets or districts are in parentheses.

Table 42: Plant-level effects of robot exposure on wages of heterogeneous workers in East and West Germany

	Dependent variable: Annual % change in plant-level average wage		
	Routine	Nonroutine manual	Nonroutine cognitive
	(1)	(2)	(3)
	Panel A. East Germany		
ΔPredicted robot exposure	-0.005	-0.001	-0.006
	(0.003)	(0.004)	(0.007)
Observations	3649	3649	3649
	Panel B. West Germany		
ΔPredicted robot exposure	-0.005	0.013	0.016
	(0.010)	(0.015)	(0.015)
Observations	3823	3823	3823
Firm characteristics	✓	✓	✓
Regional demographics	✓	✓	✓
Firm fixed effects	✓	✓	✓
State-by-Year fixed effects	✓	✓	✓
Industry-by-Year fixed effects	✓	✓	✓

Notes: Panel A presents the results from estimating the annual percentage change in average wage at the plant on the annual change in the local labor market's predicted exposure to robots in the automotive industry per 1,000 workers in East Germany between 1998 and 2018 using the IV (2SLS) regressions. Panel B reports the results from the 2SLS IV regressions for West Germany. In both panels, the dependent variable is the annual percentage change in the average wage of routine (column (1)), nonroutine manual (column (2)), and nonroutine cognitive (column (3)) workers. All specifications include the same set of controls and fixed effects as in Table 41. Standard errors clustered at the level of local labor markets or districts are in parentheses.

Table 43: Plant-level effects of robot exposure on wages of heterogeneous workers in districts from East and West Germany with different union coverage

	Dependent variable: Annual % change in plant-level average wage					
	Bottom 8 deciles			Top 2 deciles		
	Routine (1)	NRM (2)	NRC (3)	Routine (4)	NRM (5)	NRC (6)
	Panel A. East Germany					
ΔPredicted robot exposure	-0.001	-0.004	0.011	-0.011	0.009	-0.025
	(0.007)	(0.005)	(0.007)	(0.018)	(0.025)	(0.018)
Observations	3149	3149	3149	224	224	224
	Panel B. West Germany					
ΔPredicted robot exposure	-0.002	-0.005	0.035	0.001	-0.003	0.015
	(0.020)	(0.012)	(0.016)	(0.006)	(0.003)	(0.011)
Observations	3273	3273	3273	182	182	182
Firm characteristics	✓	✓	✓	✓	✓	✓
Regional demographics	✓	✓	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓	✓	✓
State-by-Year fixed effects	✓	✓	✓	✓	✓	✓
Industry-by-Year fixed effects	✓	✓	✓	✓	✓	✓

Notes: The left sub-panel of Panel A presents the results from estimating the annual percentage change in average wage at the plant on the annual change in the local labor market's predicted exposure to robots in the automotive industry per 1,000 workers in districts from East Germany whose union coverage is in the bottom eight deciles of the distribution in the previous period between 1998 and 2018 using the IV (2SLS) regressions. The right sub-panel of Panel A reports the results from the IV (2SLS) regressions for plants in districts from East Germany with high union coverage (i.e., districts in the top two deciles of the distribution of district-level union coverage). Panel B's left and right sub-panels show the corresponding results for West Germany. In all panels, the dependent variable is the annual percentage change in the average wage of routine workers (columns (1) and (4)), nonroutine manual–NRM workers (columns (2) and (5)), and nonroutine cognitive–NRC workers (columns (3) and (6)). All specifications include the same set of controls and fixed effects as in Table 41. Standard errors clustered at the level of local labor markets or districts are in parentheses.

Table 44: Plant-level effects of robot exposure on wage markdowns

	Panel A. All workers		
	Germany	East Germany	West Germany
	(1)	(2)	(3)
ΔPredicted robot exposure	0.009	0.009	-0.007
	(0.010)	(0.006)	(0.010)
Observations	7623	3649	3823
	Panel B. Heterogeneous workers		
	Routine	Nonroutine manual	Nonroutine cognitive
	(1)	(2)	(3)
ΔPredicted robot exposure	0.007	0.012	0.001
	(0.007)	(0.008)	(0.009)
Observations	7623	7623	7623
Firm characteristics	✓	✓	✓
Regional demographics	✓	✓	✓
Firm fixed effects	✓	✓	✓
State-by-Year fixed effects	✓	✓	✓
Industry-by-Year fixed effects	✓	✓	✓

Notes: Panel A presents the results from estimating the annual change in plant-level markdowns on the annual change in the local labor market's predicted exposure to robots in the automotive industry per 1,000 workers between 1998 and 2018 using the IV (2SLS) regressions. In column (1) of Panel A, the sample consists of all firms in the IAB Establishment Panel for which wage markdowns have been estimated. The sample in columns (2) and (3) of Panel A consists of plants from East and West Germany, respectively. Panel B reports the effects of automation exposure on plant-level markdowns for heterogeneous workers performing different tasks, and the dependent variable is the annual change in plant-level markdowns for routine (column (1)), nonroutine manual (column (2)), and nonroutine cognitive (column (3)) workers. All specifications control for constant, six plant size groups based on the number of employees at the establishment in the previous year, and demographic characteristics of districts or kreise in the previous year. The demographic controls are constructed using the matched employer-employee data (LIAB) and include the share of females, the share of foreigners, the share of workers over 50 years old, the shares of workers with no vocational training, vocational training, and university degree, and employment shares across broad industries (agriculture, food products, consumer goods, industrial goods, capital goods, construction, consumer-related services, business-related services, and public sector). The local labor market characteristics also contain the annual changes in exposure to net exports and ICT equipment. The firm, state-by-year, and industry-by-year fixed effects are also controlled in each specification. Standard errors clustered at the level of local labor markets or districts are in parentheses.

Table 45: Plant-level effects of robot exposure on wage markdowns for heterogeneous workers in East and West Germany

	Dependent variable: Annual change in plant-level markdowns		
	Routine	Nonroutine manual	Nonroutine cognitive
	(1)	(2)	(3)
	Panel A. East Germany		
ΔPredicted robot exposure	0.012	-0.002	0.002
	(0.005)	(0.009)	(0.008)
Observations	3649	3649	3649
	Panel B. West Germany		
ΔPredicted robot exposure	-0.002	0.013	-0.005
	(0.004)	(0.014)	(0.006)
Observations	3823	3823	3823
Firm characteristics	✓	✓	✓
Regional demographics	✓	✓	✓
Firm fixed effects	✓	✓	✓
State-by-Year fixed effects	✓	✓	✓
Industry-by-Year fixed effects	✓	✓	✓

Notes: Panel A presents the results from estimating the annual change in plant-level markdowns on the annual change in the local labor market's predicted exposure to robots in the automotive industry per 1,000 workers in East Germany between 1998 and 2018 using the 2SLS IV regressions. Panel B reports the results from the IV (2SLS) regressions for West Germany. In both panels, the dependent variable is the annual change in plant-level markdowns for routine (column (1)), nonroutine manual (column (2)), and nonroutine cognitive (column (3)) workers. All specifications control for constant, six plant size groups based on the number of employees at the establishment in the previous year, and demographic characteristics of districts or kreise in the previous year. The demographic controls are constructed using the matched employer-employee data (LIAB) and include the share of females, the share of foreigners, the share of workers over 50 years old, the shares of workers with no vocational training, vocational training, and university degree, and employment shares across broad industries (agriculture, food products, consumer goods, industrial goods, capital goods, construction, consumer-related services, business-related services, and public sector). The local labor market characteristics also contain the annual changes in exposure to net exports and ICT equipment. The firm, state-by-year, and industry-by-year fixed effects are also controlled in each specification. Standard errors clustered at the level of local labor markets or districts are in parentheses.

Table 46: Plant-level effects of robot exposure on wage markdowns for heterogeneous workers in districts from East and West Germany with different union coverage

	Dependent variable: Annual change in plant-level markdowns					
	Bottom 8 deciles			Top 2 deciles		
	Routine (1)	NRM (2)	NRC (3)	Routine (4)	NRM (5)	NRC (6)
	Panel A. East Germany					
ΔPredicted robot exposure	0.018	0.004	-0.004	-0.037	-0.004	0.004
	(0.010)	(0.008)	(0.007)	(0.044)	(0.054)	(0.049)
Observations	3149	3149	3149	224	224	224
	Panel B. West Germany					
ΔPredicted robot exposure	0.000	0.000	-0.004	-0.001	-0.002	-0.000
	(0.011)	(0.022)	(0.011)	(0.002)	(0.003)	(0.003)
Observations	3273	3273	3273	182	182	182
Firm characteristics	✓	✓	✓	✓	✓	✓
Regional demographics	✓	✓	✓	✓	✓	✓
Firm fixed effects	✓	✓	✓	✓	✓	✓
State-by-Year fixed effects	✓	✓	✓	✓	✓	✓
Industry-by-Year fixed effects	✓	✓	✓	✓	✓	✓

Notes: The left sub-panel of Panel A presents the results from estimating the annual change in plant-level markdowns on the annual change in the local labor market's predicted exposure to robots in the automotive industry per 1,000 workers in districts from East Germany whose union coverage is in the bottom eight deciles of the distribution in the previous period between 1998 and 2018 using the IV (2SLS) regressions. The right sub-panel of Panel A reports the results from the IV (2SLS) regressions for plants in districts from East Germany with high union coverage (i.e., districts in the top two deciles of the distribution of district-level union coverage). Panel B's left and right sub-panels show the corresponding results for West Germany. In all panels, the dependent variable is the annual change in plant-level markdowns for routine workers (columns (1) and (4)), nonroutine manual–NRM workers (columns (2) and (5)), and nonroutine cognitive–NRC workers (columns (3) and (6)). All specifications include the same set of controls and fixed effects as in Table 45. Standard errors clustered at the level of local labor markets or districts are in parentheses.

Table 47: Relationship between robot exposure, robot exposure predicted from the first stage of 2SLS, and actual robot adoption

	Automobile robots			All industrial robots		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Dependent variable: ΔRobot exposure					
ΔRobot exposure predicted from the first-stage	0.589	0.288	0.278	0.630	0.350	0.362
	(0.068)	(0.080)	(0.077)	(0.054)	(0.063)	(0.063)
Observations	1023	1021	1011	1023	1021	1011
R^2	0.42	0.64	0.68	0.41	0.77	0.80
	Panel B. Dependent variable: ΔActual robot adoption					
ΔRobot exposure predicted from the first-stage	0.388	-0.046	-0.116	0.013	-0.035	-0.051
	(0.308)	(0.113)	(0.178)	(0.074)	(0.060)	(0.057)
Observations	815	811	803	815	811	803
R^2	0.04	0.36	0.42	0.04	0.49	0.52
Year fixed effects	✓	✓		✓	✓	
State fixed effects	✓			✓		
District fixed effects		✓	✓		✓	✓
State-by-Year fixed effects			✓			✓

Notes: The table presents the results from OLS regressions estimating the relationship between the annual change in the local labor market's exposure to robots in the automotive industry (left panel) and all industries (right panel) predicted from the first stage of the IV (2SLS) estimation and the annual change in robot exposure defined by the equation (13) (top panel) and annual change in actual robot adoption (bottom panel) in Germany between 2015 and 2018. The first-stage regression controls for instruments and covariates in equation (12). The actual robot adoption is measured by aggregating the number of robots adopted by the firm at the district level using sampling weights provided in the IAB Establishment Panel data and expressed as per 1,000 workers. Standard errors clustered by districts are in parentheses.

Table 48: Heterogeneous effects of robot exposure on plant-level markdowns by firm size

	Dependent variable: Annual change in plant-level markdowns			
	All workers	Heterogeneous workers		
		Routine	NRM	NRC
	(1)	(2)	(3)	(4)
	Panel A. Small firms			
ΔPredicted robot exposure	0.001	-0.000	0.020	-0.002
	(0.008)	(0.008)	(0.011)	(0.012)
Observations	4833	4833	4833	4833
	Panel A. Large firms			
ΔPredicted robot exposure	0.015	0.015	0.008	-0.003
	(0.020)	(0.021)	(0.015)	(0.010)
Observations	3714	3714	3714	3714

Notes: The table presents the results from estimating the annual change in plant-level markdowns on the annual change in the local labor market's predicted exposure to robots in the automotive industry per 1,000 workers for small (top panel) and large (bottom panel) firms between 1998 and 2018 using the IV (2SLS) regressions. Small firms are those in the bottom 7 deciles of the size distribution in the previous period, while large firms are plants in the top 3 deciles. Column (1) shows the effects for all workers. Columns (2)-(4) report the effects of automation exposure on the markdowns over heterogeneous workers performing different tasks, and the dependent variable is the annual change in the markdowns over routine workers (column (2)), nonroutine manual–NRM workers (column (3)), and nonroutine cognitive–NRC workers (column (4)). All specifications control for constant and demographic characteristics of districts or kreise in the previous year. The demographic controls are constructed using the matched employer-employee data (LIAB) and include the share of females, the share of foreigners, the share of workers over 50 years old, the shares of workers with no vocational training, vocational training, and university degree, and employment shares across broad industries (agriculture, food products, consumer goods, industrial goods, capital goods, construction, consumer-related services, business-related services, and public sector). The local labor market characteristics also contain the annual changes in exposure to net exports and ICT equipment. The firm, state-by-year, and industry-by-year fixed effects are also controlled in each specification. Standard errors clustered at the level of local labor markets or districts are in parentheses.

Table 49: Plant-level effects of robot exposure on wage markdowns for heterogeneous workers at small and large firms in East and West Germany

	Dependent variable: Annual change in plant-level markdowns					
	Small firms			Large firms		
	Routine (1)	NRM (2)	NRC (3)	Routine (4)	NRM (5)	NRC (6)
	Panel A. East Germany					
ΔPredicted robot exposure	-0.003	0.001	0.005	0.047	-0.021	-0.018
	(0.006)	(0.012)	(0.010)	(0.013)	(0.045)	(0.021)
Observations	2879	2879	2879	925	925	925
	Panel B. West Germany					
ΔPredicted robot exposure	-0.004	0.001	-0.013	0.005	0.022	0.002
	(0.008)	(0.014)	(0.013)	(0.009)	(0.018)	(0.010)
Observations	1754	1754	1754	2589	2589	2589

Notes: The left sub-panel of Panel A presents the results from estimating the annual change in markdowns of small firms on the annual change in the local labor market's predicted exposure to robots in the automotive industry per 1,000 workers in districts from East Germany between 1998 and 2018 using the IV (2SLS) regressions. The right sub-panel of Panel A reports the results from the IV (2SLS) regressions for large plants in districts from East Germany. Small firms are those in the bottom 7 deciles of the size distribution in the previous period, while large firms are plants in the top 3 deciles. Panel B's left and right sub-panels show the corresponding results for West Germany. In all panels, the dependent variable is the annual change in plant-level markdowns for routine workers (columns (1) and (4)), nonroutine manual–NRM workers (columns (2) and (5)), and nonroutine cognitive–NRC workers (columns (3) and (6)). All specifications include the same set of controls and fixed effects as in Table 45, except for plant size dummies. Standard errors clustered at the level of local labor markets or districts are in parentheses.

Table 50: Plant-level effects of robot exposure on wages of heterogeneous workers at small and large firms in East and West Germany

	Dependent variable: Annual % change in plant-level average wage					
	Small firms			Large firms		
	Routine (1)	NRM (2)	NRC (3)	Routine (4)	NRM (5)	NRC (6)
	Panel A. East Germany					
ΔPredicted robot exposure	0.002	0.004	0.001	-0.005	-0.005	-0.008
	(0.004)	(0.005)	(0.008)	(0.014)	(0.011)	(0.011)
Observations	2879	2879	2879	925	925	925
	Panel B. West Germany					
ΔPredicted robot exposure	-0.011	0.025	-0.001	-0.002	-0.006	0.009
	(0.010)	(0.022)	(0.010)	(0.016)	(0.006)	(0.015)
Observations	1754	1754	1754	2589	2589	2589

Notes: The left sub-panel of Panel A presents the results from estimating the annual percentage change in average wage at small firms on the annual change in the local labor market's predicted exposure to robots in the automotive industry per 1,000 workers in districts from East Germany between 1998 and 2018 using the IV (2SLS) regressions. The right sub-panel of Panel A reports the results from the IV (2SLS) regressions for large plants in districts from East Germany. Small firms are those in the bottom 7 deciles of the size distribution in the previous period, while large firms are plants in the top 3 deciles. Panel B's left and right sub-panels show the corresponding results for West Germany. In all panels, the dependent variable is the annual percentage change in the average wage of routine workers (columns (1) and (4)), nonroutine manual–NRM workers (columns (2) and (5)), and nonroutine cognitive–NRC workers (columns (3) and (6)). All specifications include the same set of controls and fixed effects as in Table 49. Standard errors clustered at the level of local labor markets or districts are in parentheses.

Table 51: Plant-level effects of robot exposure on employment of heterogeneous workers at small and large firms in East and West Germany

	Dependent variable: Annual % change in plant-level employment					
	Small firms			Large firms		
	Routine (1)	NRM (2)	NRC (3)	Routine (4)	NRM (5)	NRC (6)
	Panel A. East Germany					
ΔPredicted robot exposure	-0.008	-0.014	0.020	-0.009	0.001	0.012
	(0.005)	(0.007)	(0.008)	(0.014)	(0.015)	(0.013)
Observations	2879	2879	2879	925	925	925
	Panel B. West Germany					
ΔPredicted robot exposure	0.016	-0.022	-0.001	-0.017	0.002	0.027
	(0.010)	(0.020)	(0.007)	(0.007)	(0.010)	(0.013)
Observations	1754	1754	1754	2589	2589	2589

Notes: The left sub-panel of Panel A presents the results from estimating the annual percentage change in employment at small firms on the annual change in the local labor market's predicted exposure to robots in the automotive industry per 1,000 workers in districts from East Germany between 1998 and 2018 using the IV (2SLS) regressions. The right sub-panel of Panel A reports the results from the IV (2SLS) regressions for large plants in districts from East Germany. Small firms are those in the bottom 7 deciles of the size distribution in the previous period, while large firms are plants in the top 3 deciles. Panel B's left and right sub-panels show the corresponding results for West Germany. In all panels, the dependent variable is the annual percentage change in plant-level employment of routine workers (columns (1) and (4)), nonroutine manual–NRM workers (columns (2) and (5)), and nonroutine cognitive–NRC workers (columns (3) and (6)). All specifications include the same set of controls and fixed effects as in Table 49. Standard errors clustered at the level of local labor markets or districts are in parentheses.

Table 52: Plant-level effects of robot exposure on wage markdowns for heterogeneous workers in East and West Germany around the Great Recession

	Dependent variable: Annual change in plant-level markdowns					
	Before Great Recession			After Great Recession		
	Routine (1)	NRM (2)	NRC (3)	Routine (4)	NRM (5)	NRC (6)
	Panel A. East Germany					
ΔPredicted robot exposure	0.007	0.011	0.007	0.004	-0.005	-0.002
	(0.002)	(0.007)	(0.003)	(0.005)	(0.011)	(0.008)
Observations	2127	2127	2127	1427	1427	1427
	Panel B. West Germany					
ΔPredicted robot exposure	-0.004	-0.001	-0.007	-0.005	0.021	-0.0056
	(0.004)	(0.009)	(0.007)	(0.009)	(0.025)	(0.009)
Observations	2363	2363	2363	1365	1365	1365

Notes: The left sub-panel of Panel A presents the results from estimating the annual change in plant-level markdowns on the annual change in the local labor market's predicted exposure to robots in the automotive industry per 1,000 workers in districts from East Germany between 1998 and 2008, i.e., before the Great Recession, using the IV (2SLS) regressions. The right sub-panel of Panel A reports the results from the IV (2SLS) regressions in districts from East Germany between 2009 and 2018, i.e., after the recession. Panel B's left and right sub-panels show the corresponding results for West Germany. In all panels, the dependent variable is the annual change in plant-level markdowns for routine workers (columns (1) and (4)), nonroutine manual–NRM workers (columns (2) and (5)), and nonroutine cognitive–NRC workers (columns (3) and (6)). All specifications include the same set of controls and fixed effects as in Table 45. Standard errors clustered at the level of local labor markets or districts are in parentheses.

Table 53: Plant-level effects of robot exposure on wages of heterogeneous workers in East and West Germany around the Great Recession

	Dependent variable: Annual % change in plant-level average wage					
	Before Great Recession			After Great Recession		
	Routine	NRM	NRC	Routine	NRM	NRC
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. East Germany					
ΔPredicted robot exposure	-0.002	-0.005	0.007	-0.001	0.010	0.011
	(0.003)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)
Observations	2127	2127	2127	1427	1427	1427
	Panel B. West Germany					
ΔPredicted robot exposure	-0.007	0.000	0.012	-0.022	0.017	0.025
	(0.006)	(0.004)	(0.012)	(0.017)	(0.018)	(0.018)
Observations	2363	2363	2363	1365	1365	1365

Notes: The left sub-panel of Panel A presents the results from estimating the annual percentage change in average wage on the annual change in the local labor market's predicted exposure to robots in the automotive industry per 1,000 workers in districts from East Germany between 1998 and 2008, i.e., before the Great Recession, using the IV (2SLS) regressions. The right sub-panel of Panel A reports the results from the IV (2SLS) regressions in districts from East Germany between 2009 and 2018, i.e., after the recession. Panel B's left and right sub-panels show the corresponding results for West Germany. In all panels, the dependent variable is the annual percentage change in the average wage of routine workers (columns (1) and (4)), nonroutine manual–NRM workers (columns (2) and (5)), and nonroutine cognitive–NRC workers (columns (3) and (6)). All specifications include the same set of controls and fixed effects as in Table 45. Standard errors clustered at the level of local labor markets or districts are in parentheses.

Table 54: Plant-level effects of robot exposure on wage markdowns for heterogeneous workers across industries in East and West Germany

	Dependent variable: Annual change in plant-level markdowns					
	Robot-intensive industries			Non-robot-intensive industries		
	Routine (1)	NRM (2)	NRC (3)	Routine (4)	NRM (5)	NRC (6)
	Panel A. East Germany					
ΔPredicted robot exposure	0.019	0.013	0.023	-0.011	-0.008	-0.034
	(0.006)	(0.011)	(0.012)	(0.016)	(0.021)	(0.017)
Observations	1911	1911	1911	1725	1725	1725
	Panel B. West Germany					
ΔPredicted robot exposure	-0.002	0.013	-0.009	0.121	0.128	-0.118
	(0.005)	(0.016)	(0.007)	(0.150)	(0.334)	(0.176)
Observations	2132	2132	2132	1629	1629	1629

Notes: The left sub-panel of Panel A presents the results from estimating the annual change in plant-level markdowns on the annual change in the local labor market's predicted exposure to robots in the automotive industry per 1,000 workers in districts from East Germany between 1998 and 2018 using the IV (2SLS) regressions for plants in industries where automobile robots are intensive, i.e., robot-intensive industries. The right sub-panel of Panel A reports the results from the IV (2SLS) regressions for non-robot-intensive industries in districts from East Germany. Panel B's left and right sub-panels show the corresponding results for West Germany. In all panels, the dependent variable is the annual change in plant-level markdowns for routine workers (columns (1) and (4)), nonroutine manual–NRM workers (columns (2) and (5)), and nonroutine cognitive–NRC workers (columns (3) and (6)). All specifications include the same set of controls and fixed effects as in Table 45. Standard errors clustered at the level of local labor markets or districts are in parentheses.

Table 55: Plant-level effects of robot exposure on employment of heterogeneous workers across industries in East and West Germany

	Dependent variable: Annual percentage change in plant-level employment					
	Robot-intensive industries			Non-robot-intensive industries		
	Routine (1)	NRM (2)	NRC (3)	Routine (4)	NRM (5)	NRC (6)
	Panel A. East Germany					
ΔPredicted robot exposure	-0.022	-0.004	0.027	-0.019	-0.014	0.003
	(0.006)	(0.009)	(0.010)	(0.009)	(0.022)	(0.012)
Observations	1911	1911	1911	1725	1725	1725
	Panel B. West Germany					
ΔPredicted robot exposure	-0.001	-0.015	0.004	0.032	-0.264	0.158
	(0.008)	(0.011)	(0.009)	(0.204)	(0.293)	(0.168)
Observations	2132	2132	2132	1629	1629	1629

Notes: The left sub-panel of Panel A presents the results from estimating the annual percentage change in plant-level employment on the annual change in the local labor market's predicted exposure to robots in the automotive industry per 1,000 workers in districts from East Germany between 1998 and 2018 using the IV (2SLS) regressions for plants in industries where automobile robots are intensive, i.e., robot-intensive industries. The right sub-panel of Panel A reports the results from the IV (2SLS) regressions for non-robot-intensive industries in districts from East Germany. Panel B's left and right sub-panels show the corresponding results for West Germany. In all panels, the dependent variable is the annual percentage change in plant-level employment of routine workers (columns (1) and (4)), nonroutine manual–NRM workers (columns (2) and (5)), and nonroutine cognitive–NRC workers (columns (3) and (6)). All specifications include the same set of controls and fixed effects as in Table 54. Standard errors clustered at the level of local labor markets or districts are in parentheses.

Supplementary Materials (For Online Publication Only)

Automation Threat and Labor Market Power

Tsenguunjav Byambasuren

October 28, 2024

A Data Appendix **S1**
A.1 Establishment Data S1
A.2 Matched Employer-Employee Data S2
A.3 Worker-Level Job Tasks S2
A.4 Industry-Level Robots Stock S3
A.5 Construction and Approximation of Some Key Variables S4

B Robustness of the Relationship between Actual Robot Adoption and Robot Exposure Shock **S6**

C Production Function Estimation **S10**

D Overview of Monopsony Measures **S14**

E Additional Results on Markdowns **S17**
E.1 Robustness of Estimated Markdowns for German Manufacturing S17
E.2 Markdown Trend under Cobb-Douglas Specification S19
E.3 Markups S20
E.4 Markdown Estimation Controlling for Robot Exposure S22
E.5 Cross-Sectional Correlation between Aggregate Markdown and Labor Market Concentration S23
E.6 Explaining the Markdown Gap at the Mean S24
E.7 Robustness of Markdowns for Heterogeneous Workers S26

F Additional Results on Firm-Level Effects **S30**
F.1 Robustness of Heterogeneous Effects by Firm Size S30
F.2 Additional Robustness of Firm-Level Results S31

G Additional Figures and Tables **S32**
G.1 Additional Figures S32
G.2 Additional Tables S35

A Data Appendix

This appendix first describes the four main datasets used for measuring the key variables and conducting the empirical analysis. Then I discuss the construction and approximation of some variables, including capital stock, wage, and education.

A.1 Establishment Data

Since the key outcome in this paper is wage markdowns measured using a production function approach, the primary dataset in this paper is the production data. The firm-level production data come from the IAB Establishment Panel (IAB-BP), which covers a large representative sample of establishments in German manufacturing. The longitudinal structure of the IAB-BP data enables me to use the control function method, which uses lagged information for identification to estimate the production function and then wage markdowns. The IAB-BP data includes comprehensive information necessary for production function estimation, such as annual revenue, number of workers or headcount[43], purchase of intermediate materials, and investments.

A unique feature of the IAB-BP data is that it is the first data with direct information on robot use. Other studies mostly use indirect or proxy measures of robot adoption such as imports of robots and automation technologies (Humlum, 2019; Acemoglu et al., 2020; Barth et al., 2020; Bonfiglioli et al., 2020; Domini et al., 2021), ICT investment or usage (Kirov and Traina, 2021; Mengano, 2023), and investment in and costs of automation technologies (Aghion et al., 2020; Bessen et al., forthcoming). An exception to this unique feature of my data on automation is the Spanish administrative data, used by Koch et al. (2021), which reports direct information on robots but only on the extensive margin. But the IAB BP survey data also provide information on the firm's robot use on the intensive margin (number of robots used by the firm), providing greater flexibility and enabling me to offer new insights and facts about the firm's robot adoption in comparison with aggregate-level information on robots and robot exposure.

For the establishment data, I also extract the district (or *kreis*) where the plant is located from the Establishment History Panel (BHP), which contains more general information on the industry, location, and total employment for each establishment. Using the unique establishment identifier, I merge this dataset with the IAB BP and the matched data to import the district information. So, regions in this paper will be at the district level unless otherwise noted. To estimate the production function and thus quantify markdown using the production approach, I approximate the firm's cap-

[43] Some studies such as De Loecker et al. (2016), Yeh et al. (2022), Bau and Matray (2023), and Lochner and Schulz (2024) use the total wage bill as a proxy measure of labor; however, compensation of employees is less representative of physical labor inputs than labor headcounts at the firm with wage-setting power where workers are underpaid and thus the labor cost underestimates the labor inputs and introduces measurement error in markdown estimates. Although the estimated effect of automation threat on markdown will be consistent even in the presence of this measurement error in the dependent variable, which will be captured in the error term, the measurement error might erase the non-zero causal effect. Hence, it is ideal to use headcounts as labor inputs in estimating production function and markdown under the relaxation of perfectly competitive labor market assumption.

ital stock, and the details on the procedure are provided below.

The IAB establishment panel survey began in 1993 with only West German plants included, and plants from East Germany have been covered since 1996 (https://iab.de/en/the-iab/surveys/the-iab-establishment-panel/). Therefore, I consider the sample of firm-level data spanning the periods 1996-2018 to construct the nationally representative estimate of markdowns and estimate the impact automation threats on labor market power in Germany.

A.2 Matched Employer-Employee Data

I use the longitudinal version of matched employer-employee data (LIAB) mainly to construct the control variables, normalize the shock variables, and perform analysis with heterogeneous workers. The LIAB records employment trajectories for each employee who worked at one of the plants in the establishment sample for at least one day over the period. The worker's information in the matched data contains the employment history of each employee with social security records. Specifically, I use data from the Employee History (Beschäftigtenhistorik—BeH). The information on employees includes variables such as daily wage[44] and detailed occupation classifications at the 5-digit level from 1975 to 2019.

The establishment codes in the LIAB match those in the IAB-BP. Thus, for example, I calculate shares of female and foreign workers in the establishment using the LIAB data and merge it with the IAB-BP data to construct the demographic controls included in the regressions. For my analysis allowing for heterogeneous workers, I allocate the plant's total labor cost recorded in the IAB-BP data to workers performing different tasks using the share of each worker's annual earnings in the establishment recorded in the LIAB data. A worker's annual earnings is a multiplication of imputed daily wage and the number of days worked in a given year.[45]

A.3 Worker-Level Job Tasks

In this paper, I highlight worker heterogeneity based on the risks of displacement from labor-saving automation technologies, including differences in tasks performed by the worker and the worker's skill level measured by educational attainment. I focus on worker heterogeneity by task differences since recent technological change is more biased towards routine tasks. I use three waves of worker-level representative cross-sectional data from the Federal Institute for Vocational Training and Training (BIBB)–so-called "BIBB/BAuA Employment Surveys (2006, 2012, and 2018)"–for my analysis in which workers differ by their job tasks performed at their workplaces. This data contains information on occupational skill requirements or qualifications and working conditions in Germany for around 20,000 individuals in the active labor force. Although there are existing task

[44]Following the literature, I impute workers' top-coded wage information and educational attainment recorded in the German administrative data. I provide details on these imputation procedures below.

[45]The LIAB records parallel episodes if an individual simultaneously does multiple jobs. I restrict the data to the highest-paying job of an employee as the main episode following the literature, e.g., Dauth et al. (2021).

intensity measures for occupations in other countries like the U.S. (Autor and Dorn, 2013) and the U.S. and Germany are similarly advanced countries, I used this worker-level data from Germany to accurately measure task contents for occupations in the German context because occupational task contents can differ across different countries (Caunedo et al., 2023).

Using the BIBB/BAuA Employment Surveys, I categorize activities that employees perform at the workplace into routine, nonroutine manual, and nonroutine cognitive tasks to group workers into categories that differ by their exposure to automation technologies. The BIBB Employment Survey has been collected every 6-7 years since 1979, but I use three waves that employ the German Classification of Occupations 2010 (KldB 2010). The earlier surveys–so-called "BIBB/IAB Employment Surveys (1985-1986, 1991-1992, and 1998-1999)" employ the KldB 1998. Using the KldB 2010 occupation classifications, I merge the task intensity measures aggregated at the 3-digit occupation level in the BIBB/BAuA surveys to the LIAB data by occupation. For years before 2006, I used the fixed task intensity measure for 2006.

A.4 Industry-Level Robots Stock

The main limitation of information on the firm's robot adoption in the IAB-BP dataset is that a retrospective question was asked only once in 2019 about the firm's use of robots over the five years preceding the survey year from 2014 to 2018. It provides relatively restrictive periods. So, I use industry-year panel data on the stock of industrial robots in 50 countries, including Germany, reported by the International Federation of Robotics (IFR) since 1993 as the primary measure of automation that spans for more periods. Graetz and Michaels (2017, 2018) introduced the use of IFR's robots stock data, which have been later used by Acemoglu and Restrepo (2020) for the U.S. and by Dauth et al. (2021) for Germany. The data come from annual surveys of robot suppliers and cover 90% of the world. The robot stock is disaggregated for 20 manufacturing industries.[46] I predict the local labor market exposure to robots based on the industry-level robots stock using employment weights, and the annual change in the number of robots is normalized by workforce size. In doing these, I use employment counts from the BEH recorded in the matched employer-employee data (LIAB). Section 4.1 discusses the construction of our primary measure of local labor market exposure to robots in more detail, particularly in equation (13).

[46] Following Graetz and Michaels (2017, 2018) and Dauth et al. (2021), I drop the IFR industries: all other manufacturing, all other non-manufacturing, and unspecified. It does not significantly affect the representativeness of the data as these three groups of industries only account for 5% of the total stock of robots in Germany. I also ignore agriculture, mining, electricity/gas/water supply, construction, and education to be consistent with my markdown estimation, performed for only manufacturing plants. The establishments in non-manufacturing industrial sectors reported in the IAB-BP data are too few. Thus, the estimated markdowns are noisy. I exclude non-industrial sectors in the markdown estimation and in this paper mainly because information on production prices is not available for those industries. So, I cannot deflate sales revenue, capital, and intermediate materials for non-industrial plants.

A.5 Construction and Approximation of Some Key Variables

I first describes how I approximate the capital stock in the IAB Establishment Panel. I then explain how I impute education records and top-coded wage information in the worker-level German administrative data.

Capital stock approximation. I use a *perpetual inventory* method following Mueller (2008, 2017) to compute the stock of capital, one of the key ingredients in the production function estimation. One of the key inputs in using the perpetual inventory approach is industry-specific average economic lives of capital goods, an inverse of depreciation rate, which is obtained from Mueller (2017) at the time-consistent 2-digit industry level for the periods 1993-2014. I merge this information with EP data at the 2-digit industry level, which I generate from the 3-digit industry classification provided in the EP data.[47] Given that the economic lives information is provided up to 2014 while my analysis spans until 2018, I extrapolate economic lives for four years between 2014-2018 by (i) keeping it constant and the 2014 level and (ii) using 3-year moving average.[48] Another issue with approximating capital stock is the starting value of the capital stock.

Also Mueller (2008) proposes two approaches to compute the time series of capital stock using either the average replacement investments over the whole sample period (KT) or the first three years (K3) for each firm. I define these two types of capital stock series, following the procedure, and which version of capital stock to use depends on the analysis. The latter performs better than the former when the capital stock has a time trend, as it uses the short-term average as a starting point. However, due to noisy investment data, the capital stock generated in this way, K3, is likely to be misleading. However, the perpetual inventory routine slowly corrects the K3. So, K3 might be less appropriate when using between-firm information and OLS regression. However, it might be more suitable for estimators that use only within-firm information using the GMM method. Since the ACF method of production function estimation uses GMM to estimate production function parameters, I primarily use the capital stock K3 in my analysis despite fewer observations than KT.[49]

Imputation of wages. I observe the nominal daily wage of each worker registered for social security purposes at the firm. Since the wage data comes from social security records, it is generally highly reliable. However, a common challenge of the wage data from the Social Security notifications is that the wage information is recorded only until the Social Security contribution assessment ceiling. If a worker's wage exceeds this upper earnings limit, this value will be entered as her wage, which differs by year and location.[50] Although only about 5% of the observations are subject to

[47] Federal employment agency reports the time-consistent classification of economic activities at different aggregation levels.

[48] Since the average economic lives have been substantially stable over the years from 1993 to 2014 with small variance, an extrapolation for four years is not expected to affect the results in any economically meaningful way. Also, there is no record of any events that might have changed the dynamic pattern of the average economic lives of capital goods. The results from production function estimation using these two different capital stocks are extremely similar.

[49] I also use KT in my production function estimation as a robustness check and find that estimates on production function parameters remain the same.

[50] The nominal wages and the assessment ceilings are deflated by the consumer price index from the Federal Statistical

this top-coding procedure, this censorship affects some groups of workers, e.g., high-skilled male workers above certain ages in regular full-time employment. To address this censoring problem, I use a two-step imputation procedure proposed by Dustmann et al. (2009), widely employed in the literature, e.g., by Card et al. (2013). First, I run a series of Tobit wage regressions—fit separately by year, East and West Germany, and three educational groups—on worker characteristics, including gender, age range, and tenure.

Imputation of educational attainments. I use the information on workers' educational attainment to impute the right-censored wages. However, the highest level of workers' educational attainment in the German administrative data is inconsistent over time. For example, the educational attainment of an individual with a university degree is recorded as an apprenticeship even if the individual has a university degree but did an apprenticeship later on. Following Fitzenberger et al. (2005), I correct such inconsistent developments in educational attainment.

Office to calculate the real wages.

B Robustness of the Relationship between Actual Robot Adoption and Robot Exposure Shock

To check the robustness of Fact 1 in Section 2.3, this appendix first examines the relationship between actual robot adoption and robot exposure shock in the automotive industry (Table B.1).

Table B.1: Relationship between actual robot adoption and robot exposure shock in automotive industry

	Dependent variable: Actual robot adoption		
	(1)	(2)	(3)
	Panel A. Robots in automotive per 1000 workers		
External exposure to robots in automotive	0.214	1.079	1.138
	(0.170)	(1.712)	(1.648)
Observations	1671	1667	1657
R^2	0.03	0.44	0.47
	Panel B. ΔRobots in automotive per 1000 workers		
ΔExternal exposure to robots in automotive	-0.030	-0.141	-0.257
	(0.075)	(0.092)	(0.205)
Observations	1330	1323	1315
R^2	0.03	0.39	0.43
Year fixed effects	✓	✓	
State fixed effects	✓		
District fixed effects		✓	✓
State-by-Year fixed effects			✓

Notes: The table presents the results from OLS regressions estimating the relationship between actual robot adoption in Germany and average robot exposure in the automotive industry in other high-income European countries at the local labor market region level. The sample at the level in panel A covers periods between 2014 and 2018, while the sample in panel B for annual changes covers 2015-2018. The actual robot adoption is measured by aggregating the number of robots adopted by the firm in the automotive industry at the district level using sampling weights provided in the IAB Establishment Panel data and expressed as per 1,000 workers. The robot exposure shock into the local labor market regions or districts is measured by the robots stock in the automotive industry in six other European countries (Spain, France, Italy, Norway, Sweden, and UK) "predicted" to the district using employment shares and expressed as per 1,000 workers. The actual robot adoption and robot exposure are normalized by the number of workers in the previous period. In panel A, the relationship was estimated at the level, while panel B shows the relationship between the annual changes. Standard errors clustered by districts are in parentheses.

Second, I estimate the relationship between actual robot adoption and robot exposure shock for all industries and automobile industries separately for East and West Germany (Tables B.2 and B.3).

Table B.2: Relationship between actual robot adoption and robot exposure shock in East Germany

	Dependent variable: Actual robot adoption					
	All industries			Automobile industry		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Robots per 1000 workers					
Robot exposure shock	0.213	0.492	0.373	2.302	4.253	4.605
	(0.087)	(0.844)	(0.867)	(3.448)	(6.332)	(6.315)
Observations	356	356	356	356	356	356
R^2	0.14	0.49	0.53	0.05	0.51	0.54
	Panel B. ΔRobots per 1000 workers					
ΔRobot exposure shock	0.209	1.166	1.130	6.724	2.904	7.905
	(0.858)	(1.737)	(1.720)	(7.407)	(3.614)	(5.873)
Observations	283	282	282	283	282	282
R^2	0.05	0.32	0.34	0.04	0.34	0.39
Year fixed effects	✓	✓		✓	✓	
State fixed effects	✓			✓		
District fixed effects		✓	✓		✓	✓
State-by-Year fixed effects			✓			✓

Notes: The table presents the results from OLS regressions estimating the relationship between actual robot adoption and average robot exposure in other high-income European countries at the local labor market region level in East Germany for industrial robots in all industries (left sub-panel) and automobile industry (right sub-panel). The sample at the level in panel A covers periods between 2014 and 2018, while the sample in panel B for annual changes covers 2015-2018. The actual robot adoption is measured by aggregating the number of robots adopted by the firm at the district level using sampling weights provided in the IAB Establishment Panel data and expressed as per 1,000 workers. The robot exposure shock into the local labor market regions or districts is measured by the robots stock at the industry level in six other European countries (Spain, France, Italy, Norway, Sweden, and UK) "predicted" to districts using employment shares and expressed as per 1,000 workers. The actual robot adoption and robot exposure shock are normalized by the number of workers in the previous period. The relationship in panel A was estimated at the level, while panel B shows the relationship between the annual changes. Standard errors clustered by districts are in parentheses.

Table B.3: Relationship between actual robot adoption and robot exposure shock in West Germany

	Dependent variable: Actual robot adoption					
	All industries			Automobile industry		
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Robots per 1000 workers					
Robot exposure shock	-0.014	-0.001	0.007	0.136	-0.221	-0.279
	(0.015)	(0.089)	(0.091)	(0.125)	(0.357)	(0.348)
Observations	1315	1311	1301	1315	1311	1301
R^2	0.03	0.55	0.56	0.02	0.35	0.39
	Panel B. ΔRobots per 1000 workers					
ΔRobot exposure shock	-0.249	-0.234	-0.374	-0.055	-0.154	-0.295
	(0.152)	(0.224)	(0.235)	(0.079)	(0.107)	(0.207)
Observations	1047	1041	1033	1047	1041	1033
R^2	0.02	0.50	0.51	0.01	0.43	0.46
Year fixed effects	✓	✓		✓	✓	
State fixed effects	✓			✓		
District fixed effects		✓	✓		✓	✓
State-by-Year fixed effects			✓			✓

Notes: The table presents the results from OLS regressions estimating the relationship between actual robot adoption and average robot exposure in other high-income European countries at the local labor market region level in West Germany for industrial robots in all industries (left sub-panel) and automobile industry (right sub-panel). The sample at the level in panel A covers periods between 2014 and 2018, while the sample in panel B for annual changes covers 2015-2018. The actual robot adoption is measured by aggregating the number of robots adopted by the firm at the district level using sampling weights provided in the IAB Establishment Panel data and expressed as per 1,000 workers. The robot exposure shock into the local labor market regions or districts is measured by the robots stock at the industry level in six other European countries (Spain, France, Italy, Norway, Sweden, and UK) "predicted" to districts using employment shares and expressed as per 1,000 workers. The actual robot adoption and robot exposure shock are normalized by the number of workers in the previous period. The relationship in panel A was estimated at the level, while panel B shows the relationship between the annual changes. Standard errors clustered by districts are in parentheses.

Third, I conduct the robustness by estimating the relationship between firm-level actual robot adoption and district-level robot exposure shock as follows:

$$\text{Actual robot adoption}_{jdt} = \alpha + \beta \text{Robot exposure shock}_{dt} + \phi_j + \mu_{kt} + \varphi_{st} + \varepsilon_{jdt}, \tag{B.1}$$

where Actual robot adoption$_{jdt}$ is the number of robots used by the firm j in district d per 1,000 workers in year t, ϕ_j is the firm fixed effects, μ_{kt} is the industry-by-year fixed effects, and all other terms are the same as those in equation (1). Table B.4 presents the estimation results, showing that the relationship between firm-level actual robot adoption and district-level robot exposure shock is essentially zero. It suggests that the baseline findings in Section 2.3 are substantially robust.

Table B.4: Relationship between firm-level actual robot adoption and district-level robot exposure shock

	Dependent variable: Firm-level actual robot adoption			
	(1)	(2)	(3)	(4)
	Panel A. Robots per 1000 workers			
Robot exposure shock	0.047	0.065	0.068	0.114
	(0.029)	(0.152)	(0.153)	(0.195)
Observations	6442	6418	6418	6215
R^2	0.02	0.17	0.18	0.75
	Panel B. ΔRobots per 1000 workers			
ΔRobot exposure shock	0.034	-0.148	-0.169	-0.160
	(0.060)	(0.104)	(0.104)	(0.128)
Observations	5275	5256	5256	5050
R^2	0.01	0.11	0.12	0.46
	Panel C. ΔRobots per 1000 workers			
ΔRobot exposure predicted from the first-stage	0.008	-0.029	-0.028	-0.025
	(0.017)	(0.024)	(0.024)	(0.029)
Observations	4616	4606	4606	4433
R^2	0.01	0.10	0.10	0.46
Year fixed effects	✓	✓		
State fixed effects	✓			
District fixed effects		✓	✓	
State-by-Year fixed effects			✓	✓
Firm fixed effects				✓

Notes: The table presents the results from OLS regressions estimating the relationship between the firm-level actual robot adoption and district-level robot exposure shock. The sample at the level in panel A covers periods between 2014 and 2018, while the sample in panels B and C for annual changes covers 2015-2018. The firm-level actual robot adoption is measured by the number of robots adopted by the firm per 1,000 workers. The robot exposure shock in panels A and B is measured by the average robot stock in all industries in other high-income European countries (Spain, France, Italy, Norway, Sweden, and UK) "predicted" to districts using employment shares and expressed as per 1,000 workers. The district's exposure to robots in panel C is predicted from the first stage of the IV (2SLS) regression. The actual robot adoption and robot exposure are normalized by the number of workers in the previous period. Standard errors clustered by districts are in parentheses.

C Production Function Estimation

I bring the data to the following production function to estimate parameters $\boldsymbol{\beta}$:

$$y_{jt} = f(\mathbf{x}_{jt}; \boldsymbol{\beta}) + \omega_{jt} + \varepsilon_{jt}, \tag{C.1}$$

where y_{jt} is log output, $\mathbf{x}_{jt}$ is a vector of log inputs, both fully variable inputs (e.g., intermediate materials m_{jt}) and not fully variable inputs (e.g., labor l_{jt}[51] and capital k_{jt}). The firm-specific productivity ω_{jt} embeds the constant term. The error term ε_{jt} reflects measurement error in gross outputs y_{jt} defined as revenue deflated by the producer price index for industrial products at the 2-digit industry level.[52] I write the production function in general terms as I estimate the log transformation of the production function $f(\cdot)$ in various functional forms (e.g., Cobb-Douglas and translog) with translog[53] as the primary specification given its flexibility.

The main challenge in estimating the firm-level production function in equation (C.1) is the classical problem of endogeneity of inputs, i.e., input demand is likely to be correlated with unobservables, particularly the firm's productivity. To address this challenge and provide a consistent estimate of production function parameters, I rely on the refined control function approach proposed by Ackerberg et al. (2015) (ACF). The ACF method is designed for value-added production functions, and Gandhi et al. (2020) suggest that we cannot accurately identify gross output production function parameters using the ACF approach without further assumptions. Hence, our data that reports the firm's revenue and purchases of intermediate materials enable me to employ the ACF approach. The identification strategy behind the control function method of ACF (also Olley and Pakes (1996) and Levinsohn and Petrin (2003)) relies on the assumption that firms dynamically optimize their decisions in discrete times. The intuition behind identifying consistent estimators using control function or "proxy variable" methods can be thought through the logic of IV estimators (Wooldridge, 2009; Yeh et al., 2022).

Let's separate a vector of log inputs $\mathbf{x}_{jt}$ into $\mathbf{v}_{jt}$ (log of fully flexible inputs $\mathbf{V}_{jt}$) and $\mathbf{k}_{jt}$ (log of non-fully flexible or fixed inputs $\mathbf{K}_{jt}$). Thus, the production function can be denoted as

[51] In this paper, I use the number of workers as a labor input, while one can approximate the labor by wage bills. For example, Lochner and Schulz (2024) argue that wage bills better capture heterogeneous labor inputs as they account for workers' ability differences. The use of wage bills generally addresses ability differences of workers as, for example, high-skilled labor inputs cost more, and wage bills will reflect it. However, wage bills will be a biased measure of labor input for labor markets with imperfect competition because wage bills undervalue productivity when an employer has some monopsony power to pay less to its workers than wages in competitive markets. Hence, in our setting with imperfect competition in the labor market, it is better to use the headcount of employees as a labor input.

[52] I obtained the producer price index (PPI) from the Federal Statistical Office of Germany. The PPI is only available for industrial products in the mining, agriculture, and manufacturing sectors, which is another reason I focus on the manufacturing industry in this study. I calculate the annual average PPI by averaging monthly PPIs.

[53] The output elasticities of labor and intermediate materials are calculated as $\theta^L_{jt} = \hat{\beta}_l + \hat{\beta}_{kl}k_{jt} + \hat{\beta}_{lm}m_{jt} + 2\hat{\beta}_{ll}l_{jt}$ and $\theta^M_{jt} = \hat{\beta}_m + \hat{\beta}_{km}k_{jt} + \hat{\beta}_{lm}l_{jt} + 2\hat{\beta}_{mm}m_{jt}$, respectively. Here $\hat{\beta}_l$ and $\hat{\beta}_m$ are parameter estimates on labor and intermediate materials, $\hat{\beta}_{ll}$ and $\hat{\beta}_{mm}$ are parameter estimates on quadratic terms, $\hat{\beta}_{kl}$, $\hat{\beta}_{lm}$, $\hat{\beta}_{km}$, $\hat{\beta}_{lm}$ are parameter estimates on cross terms, and l and m are, respectively, log labor and log intermediate materials.

$f(\mathbf{x}_{jt};\boldsymbol{\beta}) = f(\mathbf{v}_{jt}, \mathbf{k}_{jt};\boldsymbol{\beta}) = \ln(F(\mathbf{V}_{jt}, \mathbf{K}_{jt};\boldsymbol{\beta}))$.

Recall that firm-specific productivity ω_{jt} unobserved by an econometrician but observed by the firm generates a problem of endogeneity for estimating the above production function. To address this problem, Levinsohn and Petrin (2003) suggest using the demand for intermediate materials[54] m_{jt} as a proxy for productivity, which is given by

$$m_{jt} = m_t(\omega_{jt}; \mathbf{k}_{jt}, \mathbf{c}_{jt}), \tag{C.2}$$

where $\mathbf{c}_{jt}$ denotes a vector of any additional factors that affect a firm's demand for material inputs, such as input prices.

Under the assumption of strict monotonicity that the control function $m_t(\cdot)$ is strictly increasing in ω_{jt}[55], one can invert the equation (C.2) and express the productivity as

$$\omega_{jt} = m_t^{-1}(m_{jt}; \mathbf{k}_{jt}, \mathbf{c}_{jt}) = g_t(m_{jt}; \mathbf{k}_{jt}, \mathbf{c}_{jt}). \tag{C.3}$$

Substituting equation (C.3) into the production function in (C.1), we obtain the production as a function of only observables

$$\begin{aligned} y_{jt} &= f(\mathbf{v}_{jt}, \mathbf{k}_{jt}; \boldsymbol{\beta}) + g_t(m_{jt}; \mathbf{k}_{jt}, \mathbf{c}_{jt}) + \varepsilon_{jt} \\ &= \Phi_t(\mathbf{v}_{jt}, \mathbf{k}_{jt}, \mathbf{c}_{jt}) + \varepsilon_{jt} \\ &= \phi_{jt} + \varepsilon_{jt}. \end{aligned} \tag{C.4}$$

I implement the ACF procedure to estimate the production function, which adopts a two-stage procedure where each stage uses a different moment condition. To perform the procedure, I take $\mathbf{v}_{jt} = m_{jt}$, $\mathbf{k}_{jt} = (k_{jt}, l_{jt})'$, and $\mathbf{c}_{jt}$ contains additional controls, the firm fixed effects and year fixed effects. Equation (C.4) is the first-stage estimation. The first stage is performed by OLS regression of y_{jt} on third-degree polynomial in $\tilde{\mathbf{x}}_{jt} = (k_{jt}, l_{jt}, m_{jt})'$ with interaction terms and $\mathbf{c}_{jt}$ to obtain $\hat{\phi}_{jt}$. For translog production technology, we have

$$\mathbf{x}_{jt} = (k_{jt}, l_{jt}, m_{jt}, k_{jt}l_{jt}, k_{jt}m_{jt}, l_{jt}m_{jt}, k_{jt}^2, l_{jt}^2, m_{jt}^2)'. \tag{C.5}$$

Similar to OP and LP models, the ACF model assumes that the firm's information set at t, I_{jt},

[54] The control function approach is also called as "proxy variable" method as it uses the intermediate inputs (in cases of ACF and LP) or investment (in case of OP) as a proxy variable. Investments, i_{jt}, rather than intermediate inputs, m_{jt}, can also be used as the proxy variable in the ACF procedure; however, one would lose the ability to allow serially correlated, unobserved, firm-specific input price shocks to i_{jt} and l_{jt}. Hence, the ACF method primarily uses intermediate inputs as a proxy variable.

[55] Intuitively, the strict monotonicity assumption implies that more productive firms use more intermediate materials, which is plausible. Another advantage of proxying a firm's productivity at time t with its materials purchase at period t is that intermediate inputs purchased in period t are likely to be mainly used in production at time t. Although firms can store some materials for future production, this is likely relatively small.

includes current and past productivity shocks $\{\omega_{j\tau}\}_{\tau=0}^{t}$ but does not include future productivity shocks $\{\omega_{j\tau}\}_{\tau=t+1}^{\infty}$. Hence, the transitory shocks ε_{jt} satisfy $\mathbb{E}(\varepsilon_{jt}|I_{jt}) = 0$. Under this assumption, the first-stage moment condition is

$$\mathbb{E}(\varepsilon_{jt}|I_{jt}) = \mathbb{E}[y_{jt} - \phi_{jt}|I_{jt}] = 0. \tag{C.6}$$

In the first stage of ACF, none of the parameters will be estimated, but it generates an estimate $\hat{\phi}_{jt}$ using the above moment condition. Now, we turn to the second-stage estimation. The firm productivity is assumed to evolve according to the following distribution, known to the firm,

$$p(\omega_{it+1}|I_{jt}) = p(\omega_{jt+1}|\omega_{jt}), \tag{C.7}$$

which is stochastically increasing in ω_{jt}. Using this assumption on the evolution of productivity shocks and information set above, one can decompose ω_{jt} into its conditional expectation at $t-1$ and an innovation term, i.e.,

$$\omega_{jt} = \mathbb{E}(\omega_{jt}|I_{jt-1}) + \xi_{jt} = \mathbb{E}(\omega_{jt}|\omega_{jt-1}) + \xi_{jt} = h(\omega_{jt-1}) + \xi_{jt}, \tag{C.8}$$

where $\mathbb{E}(\xi_{jt}|I_{jt-1}) = 0$. Substituting this into production function in (C.1), we get

$$\begin{aligned} y_{jt} &= f(\mathbf{x}_{jt};\boldsymbol{\beta}) + h(\omega_{jt-1}) + \xi_{jt} + \varepsilon_{jt} \\ &= f(\mathbf{x}_{jt};\boldsymbol{\beta}) + h\left[\phi_{t-1} - f(\mathbf{x}_{jt-1};\boldsymbol{\beta})\right] + \xi_{jt} + \varepsilon_{jt}, \end{aligned} \tag{C.9}$$

where the second line follows from the definition of ϕ_{t-1}.

Since $\mathbb{E}(\xi_{jt}|I_{jt-1}) = 0$ and $\mathbb{E}(\varepsilon_{jt}|I_{jt}) = 0$ (which also implies $\mathbb{E}(\varepsilon_{jt}|I_{jt-1}) = 0$), the second stage of ACF estimation procedure uses the following moment condition:

$$\begin{aligned} &\mathbb{E}(\xi_{jt} + \varepsilon_{jt}|I_{jt-1}) \\ &\quad = \mathbb{E}[y_{jt} - f(\mathbf{x}_{jt};\boldsymbol{\beta}) - h\left(\hat{\phi}_{t-1} - f(\mathbf{x}_{jt-1};\boldsymbol{\beta})\right)|I_{jt-1}] = 0, \end{aligned} \tag{C.10}$$

where ϕ_{t-1} is replaced by its estimate from the first stage. Wooldridge (2009) pointed out that the functions ϕ_t and h can be thought of as IV estimators. Additionally, Yeh et al. (2022) discuss how the identification of the ACF estimator can be interpreted through the logic of an IV estimator. We transform conditional moments into unconditional moments for actual estimation. To illustrate the second-stage moment conditions, suppose that the productivity process is defined as

$$\omega_{jt} = s_t(\omega_{jt-1}) + \xi_{jt}. \tag{C.11}$$

Then, I approximate the productivity in the data as

$$\omega_{jt}(\boldsymbol{\beta}) = \hat{\phi}_{jt} - f(\mathbf{x}_{jt};\boldsymbol{\beta}). \tag{C.12}$$

Then, I approximate $s_t(\cdot)$ with $\mathcal{P}^{\text{th}}$-order polynomial in its arguments

$$\begin{aligned}\omega_{jt}(\boldsymbol{\beta}) &= \Omega_{jt-1}(\boldsymbol{\beta})'\rho(\boldsymbol{\beta}) + \xi_{jt} \\ &= \sum_{p=0}^{\mathcal{P}} \rho_p \omega_{jt-1}^p(\boldsymbol{\beta}) + \xi_{jt}.\end{aligned} \tag{C.13}$$

Thus, the innovations to productivity are constructed as a function $\boldsymbol{\beta}$ as

$$\xi_{jt} = \omega_{jt}(\boldsymbol{\beta}) - \Omega_{jt-1}(\boldsymbol{\beta})'\hat{\rho}(\boldsymbol{\beta}), \tag{C.14}$$

where $\hat{\rho}(\boldsymbol{\beta}) = (\{\hat{\rho}_p\}_{p=1}^{\mathcal{P}})'$ is obtained by regressing $\Omega_{jt-1}(\boldsymbol{\beta})$ on $\omega_{jt}(\boldsymbol{\beta})$ with OLS, and I set $\mathcal{P} = 3$ following De Loecker and Warzynski (2012) and Yeh et al. (2022).

Following De Loecker and Warzynski (2012) and Yeh et al. (2022), I define the instrument $\mathbf{z}_{jt} \in \mathbb{R}^Z$ as the vector that contains one-period lagged values of every polynomial term in $f(\mathbf{x}_{jt}; \boldsymbol{\beta})$ including l_{jt} and m_{jt} but capital at the current period k_{jt}. Thus, the system of second-stage moment conditions for GMM estimation to identify $\boldsymbol{\beta} \in \mathbb{R}^Z$ is defined as

$$\mathbb{E}(\xi_{jt}(\boldsymbol{\beta})\mathbf{z}_{jt}) = \mathbf{0}_{Z\times 1}. \tag{C.15}$$

Now, I briefly discuss assumptions behind the moment conditions. First, labor input l_{jt} is assumed to be chosen at period t, $t-1$, or somewhere between the two periods at $t-b$ where $0 < b < 1$. It allows labor to have some dynamic pattern and addresses the fact that labor inputs are more flexible than capital. Given some adjustment costs and other frictions in the labor market, for example, due to labor contracts, l_{jt} is modeled to be chosen at $t-b$, not all the points between t and $t-1$. In this sense, labor is not a perfectly variable input in the ACF, which is a weaker assumption than the OP in which labor is perfectly variable. The assumption that labor is chosen after time $t-1$ implies that l_{jt} is correlated with ξ_{jt}.

Second, the capital k_{jt} is assumed to be accumulated according to the following form:

$$k_{jt} = \kappa(k_{jt-1}, i_{jt-1}), \tag{C.16}$$

where investment i_{jt-1} is chosen in period $t-1$. Thus, we assume that the firm's choice of capital at time t is predetermined in period $t-1$ with choices of k_{jt-1} and i_{jt-1}. So it is safe to assume that k_{jt} is orthogonal to $\xi_{jt} + \varepsilon_{jt}$. For other terms in the "instrument", they all take their one-period lagged values, which must be orthogonal to the current period innovations (except for capital investment) because firms cannot observe their idiosyncratic shocks in the future.

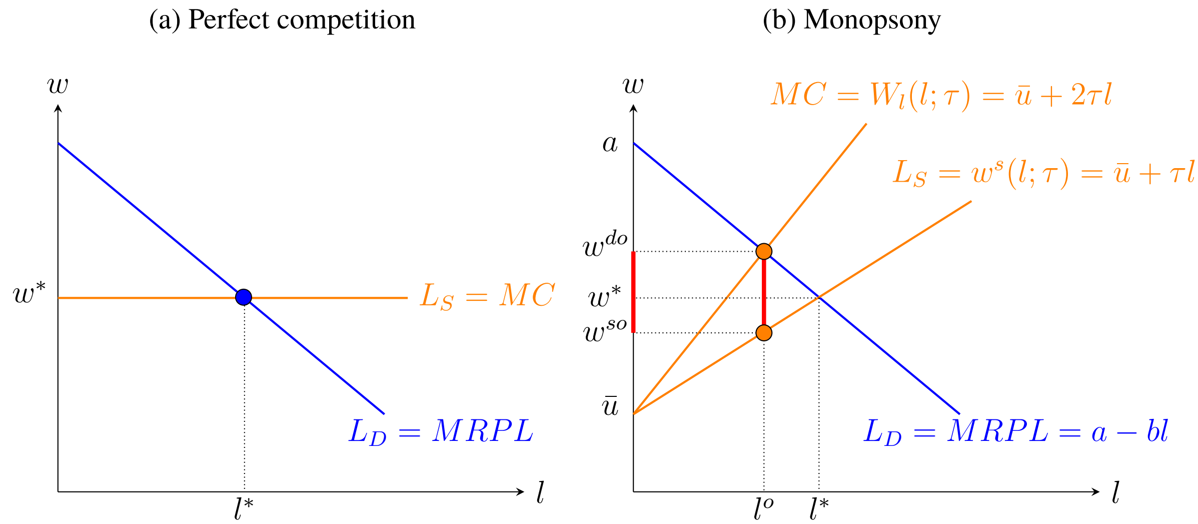
D Overview of Monopsony Measures

There are several different but related approaches to measuring employer power (see Manning, 2021, for a recent survey on measures of monopsony). The choice of method to use depends on the objectives of the analysis, the framework under consideration, and the data available to the researcher. In the traditional model, the labor market has a single buyer. Since there is only one buyer, that buyer faces the entire market's labor supply curve, upward sloping—in contrast to the horizontal labor supply curve for an individual firm in the perfectly competitive labor market with many employers. In the early stage of the literature, monopsony power has been measured as "potential monopsony power" in the language of Bronfenbrenner (1956) by estimating wage elasticity of labor supply to the firm under the assumption of an isolated labor market with a single firm. We rarely use the traditional model with this assumption because, in practice, it is unlikely that there is only one employer in the labor market.

The literature suggests several sources of upward-sloping labor supply curve to an individual firm in the presence of other firms. As reviewed by Boal and Ransom (1997) and later summarized by Naidu and Posner (2022), they include (i) collusion and Cournot competition among firms, (ii) workers' heterogeneous preferences for firms, (iii) the presence of workers' moving costs to change employers, (iv) search friction, and (v) efficiency wages at large firms. The labor supply elasticity still can be functional to quantify the labor market power; however, there are other measures, such as job separation rate, if models of job search (Burdett and Mortensen, 1998) are used to interpret the source of monopsony power.

This appendix first briefly shows the relationship between markdowns and labor supply elasticity using a simple model with an arbitrary functional form assumption. Consider a revenue function $R(l) = (a - bl/2)l$ and the associated profits $R(l) - W(l)$ where $W(l) = w^s(l)l$ denotes total labor cost. An inverse labor supply function is given by $w^s(l) = \bar{u} + \tau l$ where $\bar{u}$ is the constant utility when a worker does not work, and $\tau \in [0, T]$ is the mobility cost or travel cost for the worker, which is assumed to be exogenous at this point, and $\tau \equiv T/L$ where L is a population of workers. It is worth noting that, in this model for illustration, I use mobility cost τ as the source of the upward-sloping labor supply curve, i.e., the labor supply curve to an individual firm will be a horizontal line $w^s(l) = \bar{u}$ if we shut down the mobility cost or set $\tau = 0$. Figure D.1 shows the labor market equilibrium under perfect (panel (a)) and imperfect (panel (b)) competition. The first-order condition for profit maximization problem implies that profits are maximized at an employment level where the marginal revenue product of labor (MRPL), $R_l(l) = a - bl$, generated to the firm equals the marginal cost of labor, $W_l(l) = \bar{u} + 2\tau l$. Since the marginal cost of labor exceeds the wage, l^o number of workers will be hired by the firm, which is less than the socially efficient amount l^*. The firm pays a wage of w^{so} less than the socially efficient level, w^*.

Figure D.1: Individual firm's labor market equilibrium



Notes: Panel (a) depicts the labor market equilibrium for an individual firm under perfect competition, while panel (b) illustrates a basic model of monopsony.

The profit maximization problem in the basic monopsony model is

$$\max_{l \geq 0} R(l) - w^s(l)l, \tag{D.1}$$

where I ignore the index of firm i and time t for notational simplicity at the moment. The first-order condition of this maximization problem is

$$R_l(l) = \left(\frac{w_l(l)l}{w(l)} + 1\right) w(l) = \left(\varepsilon_S^{-1} + 1\right) w(l), \tag{D.2}$$

and, thus, the markdown ν, a wedge between the MRPL and the wage, is

$$\nu \equiv \frac{R_l(l)}{w(l)} = \varepsilon_S^{-1} + 1 \tag{D.3}$$

where $R_l(l) = \frac{\partial R(l)}{\partial l}$ is the MRPL, $w(l)$ is the wage, and $\varepsilon_S = \frac{\partial l}{\partial w(l)} \frac{w(l)}{l}$ is the elasticity of labor supply.

As shown by the optimality condition in equation (D.3) and Figure D.1b, the wedge between the MRPL and the monopsony wage is directly linked to the wage elasticity of labor supply to an individual firm. In addition to measuring the monopsony by estimating the elasticity of labor supply on the right-hand side of (D.3) as mentioned above, we can compute the degree of monopsony power by estimating the wedge between the (nominal) wage w^{so} and MRPL w^{do} on the left-hand side of (D.3), which is expressed by the distance between w^{so} and w^{do} in Figure D.1b.

Second, I review other methods of measuring monopsony power, starting with different variants of labor supply elasticity. In a dynamic setting, a measure of monopsony based on a model pioneered by Manning (2003) indirectly quantifies the wage elasticity to the firm by estimating its two components using the following steady-state relationship:

$$\varepsilon_{Nw} = \varepsilon_{Rw} - \varepsilon_{qw}, \tag{D.4}$$

where ε_{Nw} is the wage elasticity of labor supply to the firm, ε_{Rw} is the wage elasticity of the share of recruits hired from employment, and ε_{qw}, is the wage elasticity of workers' separation decisions to either employment or unemployment. Manning (2021) calls this a "modern" monopsony in which labor market frictions play a critical role.

The classical monopsony in static settings has also been recently revived, and Card et al. (2018) argue that the labor supply curve that an individual firm faces would be imperfectly elastic due to idiosyncratic non-wage amenities offered by firms even if there are a small number of firms in the labor market. The idea here is that a wage decline, for example, does not necessarily lead all existing workers to leave because some might still like their idiosyncratic non-wage aspects. In this strand, the wage elasticity of the labor supply curve to an individual firm j is derived as:

$$\frac{1}{\varepsilon_j} = \frac{1 - s_j}{\varepsilon} \tag{D.5}$$

where s_j is the market share of the firm, and ε is the inverse of the elasticity of labor supply faced by the firm as the labor supply is given by $n_j = \varepsilon^{-1}(w_j - b_j)$ where n_j is log employment, w_j is log wage, and b_j is a labor supply shifter. Manning (2021) calls this as a "new classical" monopsony in which non-wage amenities play in key role.

The measures of monopsony described above and in Section 3 are derived from theories. But there are also some measures borrowed from other fields of economics. For example, one can use concentration ratios for vacancies and employment using the Herfindahl index borrowed from Industrial Organization (IO) literature (Azar et al., 2019). Relatedly, perfectly elastic labor supply (or $\varepsilon \approx 0$) implies perfect competition in the labor market, which is consistent with the monopsony model, if a firm j's market share is small (or $s_j \approx 0$) according to equation (D.5). One could also use the number of employers in the labor market relative to the number of workers as a measure of (inverse) employer power or monopsony. In particular, if the ratio of employers to workers is lower, employer power is higher. Intuitively, the wage elasticity of labor supply positively relates to the number of firms in the market since workers' quit rate and labor supply elasticity would be higher in a market with more employers or vacancies. For example, Chau and Kanbur (2021) used this measure to analytically examine the impact of monopsony power on wage inequality in a labor market with search frictions.

E Additional Results on Markdowns

E.1 Robustness of Estimated Markdowns for German Manufacturing

In this paper, I show that estimated markdowns for East and West Germany are higher in the East than in the West. In this appendix, I check the robustness of my baseline markdown estimates for German manufacturing by pooling the markdowns estimated separately for East and West Germany. The country-level median and average markdowns in Table E.1 are highly similar to those in Table 7. The markdown distribution across industries within manufacturing is also consistent with my baseline estimates.

Table E.1: Estimated plant-level markdowns in German manufacturing

	Median	Mean	$IQR_{75\text{-}25}$	SD
Leather and related products	2.185	2.021	1.395	0.748
Wearing apparel	2.014	1.992	1.151	0.699
Furniture	1.704	1.819	1.055	0.705
Wood and wood products (excl. furniture)	1.524	1.629	0.882	0.56
Paper and paper products	1.437	1.447	0.604	0.498
Beverages	1.43	1.488	0.395	0.544
Repair and installation of machinery and equipment	1.32	1.517	0.691	0.646
Other transport equipment	1.319	1.346	0.829	0.507
Rubber and plastics	1.294	1.388	0.586	0.512
Other non-metallic minerals	1.284	1.435	0.754	0.645
Chemicals and chemical products	1.277	1.431	0.855	0.603
Motor vehicles, trailers, and semi-trailers	1.244	1.359	0.731	0.55
Basic pharmaceutical products	1.241	1.313	0.588	0.634
Fabricated metals, excl. machinery and equipment	1.193	1.322	0.666	0.535
Food products	1.179	1.306	0.682	0.563
Electrical equipment	1.154	1.225	0.562	0.481
Machinery and equipment	1.116	1.229	0.551	0.517
Basic metals	1.063	1.172	0.431	0.419
Textiles	1.046	1.238	0.562	0.46
Computer, electronic, and optical products	1.017	1.078	0.583	0.416
Other manufacturing	0.992	1.096	0.465	0.438
Printing and reproduction of recorded media	0.968	1.02	0.395	0.431
Whole sample	**1.200**	**1.331**	**0.726**	**0.569**
Sample size	9,431			

Notes: Markdowns are estimated for East and West German establishments separately using the IAB Establishment Panel from 1997-2018 under the assumption of a translog specification for gross output. The plant-level markdowns estimated separately for East and West German establishments are pooled to calculate the nationally representative estimate. Each industry group in manufacturing corresponds to the manufacturing categorization of the Federal Statistical Office. The distributional statistics are calculated using sampling weights provided in the data. Industries of wearing apparel and leather and related products are censored in this table because industry-specific markdowns were estimated for less than 20 establishments in these two industry groups, and thus the number of observations slightly declined.

To further analyze the production technologies in East and West Germany and compare them with that estimated on the full sample, Table E.2 presents production parameters and output elasticities estimated on different samples. Despite some differences in production parameters across East and West Germany, I find that output elasticities separately estimated for East/West Germany are comparable to those estimated on a nationally representative sample covering the entire country. Thus, using the same production function for East and West German manufacturing firms as I did in my baseline markdown estimation is reasonable.

Table E.2: Components of markdown estimates under translog function

	Full sample (Germany)	East Germany	West Germany
	(1)	(2)	(3)
	Panel A. Production parameters		
β_k	0.146	0.155	0.202
β_l	0.723	0.823	0.656
β_m	0.260	0.140	0.253
β_{kl}	0.036	0.033	0.064
β_{km}	-0.039	-0.038	-0.051
β_{lm}	-0.133	-0.133	-0.143
β_{k^2}	0.006	0.005	0.001
β_{l^2}	0.052	0.037	0.043
β_{m^2}	0.075	0.083	0.083
	Panel B. Elasticities		
θ_l	0.383 (0.118)	0.369 (0.122)	0.395 (0.122)
θ_m	0.604 (0.128)	0.609 (0.136)	0.586 (0.136)

Notes: Panel A presents production function parameters estimated on the full sample (Column 1), sub-sample of East German establishments (Column 2), and sub-sample of West German firms (Column 3) using the IAB Establishment Panel data in 1997-2018 under translog specification. In Panel B, I show the mean value of output elasticities estimated on different samples, and standard errors are in parenthesis. The elasticities are calculated using sampling weights provided in the data.

The literature usually estimates industry-specific production function to account for heterogeneity in production across industries (e.g., Yeh et al., 2022; Brooks et al., 2021). However, in my baseline analysis, I estimate a production function common across sectors, mainly because the number of manufacturing firms in the primary firm-level data is relatively small, although the survey is nationally representative. Estimating the production function for each two-digit industry provides noisier markdown estimates than the baseline markdowns, as shown in Table E.3. Therefore, I prefer to employ production functions similar across industry groups in my baseline analysis, which provides more stable results. However, the overall markdowns are generally consistent with my baseline markdowns in median and average manufacturers.

Table E.3: Estimated plant-level markdowns in German manufacturing (industry-specific)

Industry Group	Median	Mean	$IQR_{75\text{-}25}$	SD
Furniture	5.261	6.178	3.359	3.134
Other non-metallic minerals	5.064	6.231	4.275	3.133
Repair and installation of machinery and equipment	3.024	3.948	3.233	2.406
Other manufacturing	2.604	2.986	1.737	1.713
Textiles	2.523	3.141	2.106	2.061
Paper and paper products	1.909	2.168	1.980	1.165
Wood and wood products (excl. furniture)	1.507	1.981	1.842	1.543
Fabricated metals, excl. machinery and equipment	1.481	1.677	0.797	0.902
Rubber and plastics	1.376	1.652	0.691	1.412
Motor vehicles, trailers, and semi-trailers	1.331	1.605	0.729	1.083
Beverages	1.317	1.771	1.327	1.461
Machinery and equipment	1.307	1.360	0.507	0.484
Food products	1.052	1.230	0.701	0.622
Basic metals	1.050	1.119	0.722	0.538
Chemicals and chemical products	1.047	1.142	0.750	0.562
Other transport equipment	1.027	1.190	0.544	0.638
Computer, electronic, and optical products	0.985	1.219	0.680	1.318
Electrical equipment	0.942	1.005	0.868	0.664
Printing and reproduction of recorded media	0.803	0.879	0.581	0.574
Basic pharmaceutical products	0.623	0.693	0.691	0.647
Whole sample	**1.413**	**2.111**	**1.321**	**2.125**
Sample size	12,588			

Notes: Markdowns are estimated separately for each two-digit industry group using the IAB Establishment Panel from 1997-2018 under the assumption of a translog specification for gross output. Each industry group in manufacturing corresponds to the manufacturing categorization of the Federal Statistical Office. The distributional statistics are calculated using sampling weights provided in the data.

E.2 Markdown Trend under Cobb-Douglas Specification

As an alternative to my baseline choice of the functional form of the production function, translog, I estimate the production function and thus markdowns using Cobb-Douglas specification. Figure E.1 illustrates the time trend of aggregate markdowns. The result suggests that my estimates are not entirely but generally robust to this different functional form.

Figure E.1: Time evolution of aggregate markdowns under Cobb-Douglas specification

Notes: Markdowns are constructed using the IAB Establishment Panel (IAB BP) data from 1997-2018 under the assumption of Cobb-Douglas production and aggregated according to expression (4) and (6). The employment share of labor market ω_{klt} is based on total number of employees.

E.3 Markups

Table E.4 reports the estimates for markups. The summary statistics are provided for each industry group. The results indicate a presence of market power in output markets: producers have about 31 percent (26 percent) of market power at the plant-year level at the mean (median). Compared to the markdowns, variations of markups across and within industry groups are relatively smaller than variations of markdowns. The IQR and standard deviation of markups are 19.3 and 18.7 percent, respectively.

Although these estimates of markups are informative, they are subject to bias because physical outputs are proxied by revenues deflated by 2-digit industry-level prices (Klette and Griliches, 1996; Bond et al., 2021). So, one should take these markup estimates as lower bounds for market power in output markets. Fortunately, our estimates of markdown, which is my main focus in this paper, are still valid with these estimates of markups as the bias cancels out in the equation (3). So, the markdowns estimated using deflated revenues are not subject to Bond et al. (2021)'s critique when the markups are used to obtain estimates for markdowns. A formal proof can be found in Online Appendix O.6 of Yeh et al. (2022).

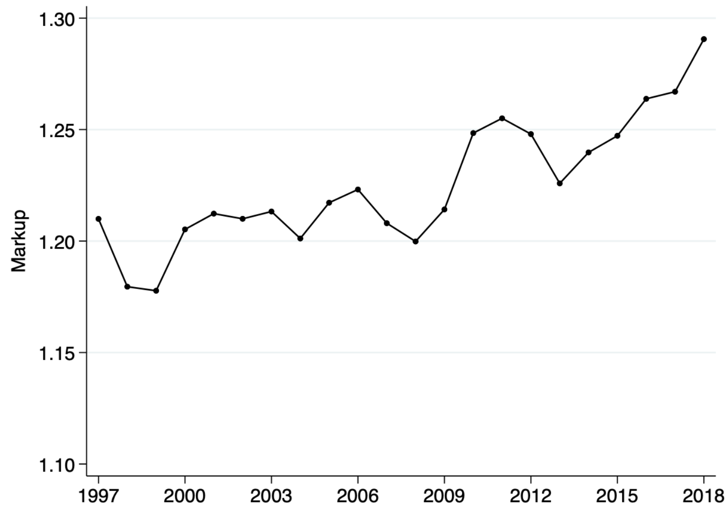
Figure E.2 presents the time series for the aggregate markup. The markup is aggregated at the market level according to equation (5). Then, I aggregate markups across markets through employment weights. As briefly discussed above, firm-level markups estimated using deflated revenues instead of physical outputs are biased, and thus, the aggregate markups are also biased. This bias will not contaminate the markdowns. While we should take the markup estimates cautiously, a trend in aggregate markups could be informative. The markup trend in German manufacturing has been monotonically increasing since 1997 until 2018.

Table E.4: Estimated plant-level markups in German manufacturing

Industry Group	Median	Mean	$IQR_{75\text{-}25}$	SD
Printing and reproduction of recorded media	1.422	1.435	0.250	0.214
Food products	1.357	1.381	0.244	0.184
Other manufacturing	1.342	1.372	0.179	0.158
Computer, electronic, and optical products	1.334	1.398	0.314	0.223
Beverages	1.333	1.417	0.324	0.322
Basic pharmaceutical products	1.284	1.312	0.241	0.147
Textiles	1.281	1.335	0.281	0.205
Fabricated metals, excl. machinery and equipment	1.276	1.317	0.167	0.190
Furniture	1.243	1.250	0.098	0.076
Wood and wood products (excl. furniture)	1.237	1.335	0.228	0.253
Paper and paper products	1.237	1.248	0.162	0.127
Other non-metallic minerals	1.235	1.274	0.173	0.143
Motor vehicles, trailers, and semi-trailers	1.226	1.270	0.116	0.172
Repair and installation of machinery and equipment	1.223	1.269	0.057	0.122
Machinery and equipment	1.218	1.256	0.123	0.151
Rubber and plastics	1.205	1.231	0.109	0.103
Basic metals	1.199	1.211	0.133	0.100
Electrical equipment	1.196	1.226	0.110	0.114
Other transport equipment	1.185	1.271	0.251	0.190
Leather and related products	1.182	1.197	0.035	0.066
Chemicals and chemical products	1.176	1.216	0.107	0.141
Wearing apparel	1.162	1.206	0.055	0.151
Whole sample	**1.258**	**1.310**	**0.193**	**0.187**
Sample size	12,794			

Notes: Markups are estimated using the IAB Establishment Panel data from 1997-2018 under the assumption of a translog specification for gross output. Each industry group in manufacturing corresponds to the manufacturing categorization of the Federal Statistical Office. The distributional statistics are calculated using sampling weights provided in the data.

Figure E.2: Time Evolution of Markups across German Manufacturing Plants



Notes: Markups are constructed using the IAB Establishment Panel data from 1997-2018 under the assumption of translog production and aggregated according to expressions (5) and (7). The employment share of labor market ω_{jlt} is based on total number of employees.

E.4 Markdown Estimation Controlling for Robot Exposure

The studies estimating the production function and markups using the production approach tend to include the key explanatory variable of interest in the production function. For example, Brandt et al. (2017) include their measure of trade liberalization in the estimation of production parameters to examine the effects of trade liberalization in China on markups and productivity of Chinese manufacturing firms. In this appendix, I similarly include the measure of exposure to industrial robots in the production function estimation and check the robustness of the baseline markdown estimates. Table E.5 compares the markdown estimates from this analysis with the baseline measure, showing that the estimated markdown remains the same when including Germany's exposure to industrial robots in the production function estimation.

Table E.5: Estimated plant-level markdowns with and without robot exposure in the production function estimation

	Mean	SD	Min	Max	N
Baseline measure (without robot exposure)	1.271	0.565	0.018	3.656	12,806
Alternative measure (with robot exposure)	1.279	0.532	0.002	3.390	9,564

Notes: Markdowns are estimated using the IAB Establishment Panel from 1997-2018 under the assumption of a translog specification for gross output. The distributional statistics are calculated using sampling weights provided in the data.

To further illustrate the similarity between the two markdown measures, I regress the baseline measure on the alternative measure conditional on plant and year fixed effects and find a coefficient of 0.993 (SE: 0.000, p-value: 0.00). Although the two measures are almost identical, I use the baseline markdown measure estimated without robot exposure in the production function estimation as it is estimated for 30% more observations than the alternative measure.

E.5 Cross-Sectional Correlation between Aggregate Markdown and Labor Market Concentration

Table E.6 presents the cross-sectional correlation (across labor markets–a combination of 3-digit industries and federal states) between the aggregate markdown $\mathcal{V}_{klt}$ and labor market concentration HHI_{klt}. The correlation between aggregate markdown and labor market concentration calculated using the same dataset (IAB Establishment Panel–IAB BP) is positive and statistically significant at the 1% level on average; however, the correlation coefficient is 0.02, which is close to zero (second column).

Table E.6: Correlation between employment HHIs and aggregate markdowns across local labor markets

Year	$\rho(\mathcal{V}_{jlt}, \text{HHI}_{jlt}^{\textit{IAB-BP}})$	$\rho(\text{HHI}_{jlt}^{\textit{IAB-BP}}, \text{HHI}_{jlt}^{\textit{LIAB}})$	$\rho(\mathcal{V}_{jlt}, \text{HHI}_{jlt}^{\textit{LIAB}})$
1998	0.156**	0.143**	0.203***
2000	0.045	0.149**	0.129**
2002	0.085*	0.213***	0.056
2004	0.055	0.203***	0.103**
2006	0.011	0.220***	0.085*
2008	-0.021	0.237***	0.074
2010	-0.042	0.330***	0.038
2012	0.026	0.266***	0.131**
2014	-0.028	0.223***	0.020
2016	-0.014	0.138**	0.045
2018	0.072	0.258***	0.122
Average	**0.024****	**0.215*****	**0.081*****

Notes: Markdowns are estimated using the IAB Establishment Panel (IAB BP) data from 1997-2018 under the assumption of a translog specification for gross output. The cross-market correlations are calculated at the 3-digit ISIC-state level for every other year. Aggregate markdowns are calculated according to equation (4) whereas labor market concentration HHI_{klt} is calculated according to equation (8) using either IAB BP and matched employer-employee (LIAB) data, which are highlighted in the superscript. Significance: $^*p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

To check the robustness of my baseline employment HHI measure calculated using IAB BP data, I compute the same index according to equation (8) based on the matched employer-employee data (LIAB). The cross-section correlation between the two HHIs is strong, positive, and almost always statistically significant at the 1% level (third column). Across years and on average, the correlation between aggregate markdown and LIAB-based HHI is mostly positive but rarely statistically significant (fourth column), consistent with the results in the second column.

E.6 Explaining the Markdown Gap at the Mean

Using a traditional but widely-used descriptive method of Blinder-Oaxaca decomposition (Oaxaca, 1973; Blinder, 1973), I decompose the differences in wage markdowns across these heterogeneous workers into a component accounted for by differences in observed characteristics and unexplained or unobserved differences. The following equation of Blinder-Oaxaca decomposition estimates the separate OLS regressions of markdown for heterogeneous workers (types 1 and 2) for firm j at year t (the j and t subscripts are suppressed to simplify the notation):

$$\begin{aligned} Y^1 &= \beta_0^1 + \sum_{k=1}^{K} \beta_k^1 X_k^1 + \epsilon^1, \\ Y^2 &= \beta_0^2 + \sum_{k=1}^{K} \beta_k^1 X_k^2 + \epsilon^2, \end{aligned} \tag{E.1}$$

where Y is the markdown, which is explained by K variables $(X_1, \ldots, X_K)$ in the linear regression model. For example, type 1 workers are low-skilled, and type 2 workers are high-skilled workers under skill heterogeneity. Given that the OLS with a constant term produces residuals with a zero mean, the wage markdown differential across different workers is expressed, using means $\overline{Y}$ and $(\overline{X}_1, \ldots, \overline{X}_K)$, as

$$\overline{Y}^1 - \overline{Y}^2 = \underbrace{(\beta_0^1 - \beta_0^2)}_{\text{coefficients}} + \underbrace{\sum_{k=1}^{K} \beta_k^2 (\overline{X}_k^1 - \overline{X}_k^2)}_{\text{endowments}} + \underbrace{\sum_{k=1}^{K} \overline{X}_k^2 (\beta_k^1 - \beta_k^2)}_{\text{coefficients}} + \underbrace{\sum_{k=1}^{K} (\overline{X}_k^1 - \overline{X}_k^2)(\beta_k^1 - \beta_k^2)}_{\text{interaction}}, \tag{E.2}$$

where the first term captures the difference in intercepts. The second term identifies the impact of skill or task differences in the explanatory variables evaluated using the type 2 worker coefficients (explained component). This component is also known as the "endowment effect". The third term is the unexplained differential and represents the impact of the skill or job tasks (unexplained component), also known as the "coefficients effect". The fourth term is a component involving an interaction due to the simultaneous effect of differences in endowments and components. The Blinder-Oaxaca decomposition method combines the first and the third terms into the unexplained component since they similarly denote differences between the two groups that cannot be explained by the observed covariates.

Table E.7 presents results from the Blinder-Oaxaca decomposition on the contribution of worker characteristics to the gap in markdowns due to job task differences. The result suggests that unobserved task differences explain a substantial part of the difference between markdowns for workers performing different tasks after accounting for various worker characteristics. Table E.8 presents results from the Blinder-Oaxaca decomposition on the contribution of worker characteristics to the skill gap in markdowns. The result shows that unobserved skill differences account for more than two-thirds of the difference between markdowns for high- and low-skilled workers.[56]

Table E.7: Difference between markdown for workers performing NRC, routine, and NRM tasks explained by observables and job tasks

	NRM(1) - NRC(2) gap in explanatory variables	NRM(1) - Routine(2) gap in explanatory variables	NRC(1) - Routine(2) gap in explanatory variables
Group 1	2.384 (0.029)	2.384 (0.029)	1.752 (0.015)
Group 2	1.752 (0.015)	1.366 (0.010)	1.366 (0.010)
Difference (1 - 2)	0.632 (0.032)	1.018 (0.030)	0.386 (0.018)
Endowments	-0.149 (0.030)	-0.016 (0.007)	0.114 (0.024)
Coefficients	0.530 (0.072)	1.064 (0.033)	0.253 (0.032)
Interaction	0.251 (0.072)	-0.030 (0.016)	0.019 (0.036)

Notes: The table presents results from the Blinder-Oaxaca decomposition of wage markdowns for heterogeneous workers performing different job tasks over 1997-2018. The explanatory variables include workers' average age and worker composition of the group (shares of female, part-time, immigrant workers, and workers with vocational training and university degrees). The standard errors are in parentheses. NRC, nonroutine cognitive; NRM, nonroutine manual.

Table E.8: Difference between markdown for high-skilled and low-skilled workers explained by observables and skills

	Low-skilled workers' wage markdown equation; Low-skilled - High-skilled gap in explanatory variables
Low-skilled workers	3.043 (0.040)
High-skilled workers	1.174 (0.006)
Difference (low-skilled - high-skilled)	1.868 (0.040)
Endowments	-0.081 (0.014)
Coefficients	1.323 (0.076)
Interaction	0.627 (0.068)

Notes: The table presents results from the Blinder-Oaxaca decomposition of wage markdowns for high-skilled (with at least vocational training) and low-skilled (without vocational training) workers over 1997-2018. The explanatory variables include workers' average age and worker composition of the group (shares of female, part-time, immigrant workers, and workers performing nonroutine cognitive and nonroutine manual tasks). The standard errors are in parentheses.

[56] Appendix Figures G.2 and G.3 show the detailed results from the Blinder-Oaxaca decomposition for task and skill differences, respectively.

E.7 Robustness of Markdowns for Heterogeneous Workers

In my baseline analysis, I define heterogeneous workers performing different tasks based on task intensity measures constructed using Germany's BIBB/BAuA Employment Surveys and an approach by Antonczyk et al. (2009). But this appendix checks the robustness of my results on markdowns for heterogeneous workers performing different tasks to the use of alternative task intensity measures proposed by Autor and Dorn (2013).[57]

Classification of workers. Since Autor and Dorn (2013) create their measures of task content or task inputs for each occupation in the U.S. using O*NET data, the values of the indices could be different from the values of indices constructed using the German dataset of BIBB/BAuA Employment Surveys. However, it is reasonable to consider that these two measures are comparable. Specifically, they build three measures of abstract, routine, and manual task inputs for their constructed version of 3-digit 1990 U.S. Census occupations (`occ1990dd`). I match them with German administrative data through Germany's 5-digit KldB 2010 occupation classifications based on several crosswalks. First, I obtain Autor and Dorn (2013)'s version of 3-digit 1990 U.S. Census occupations matched with 3-digit 2000 U.S. Census occupations (`occ2000`) from Acemoglu and Autor (2011)'s data appendix of task measure construction. Then, I match that with the 6-digit 2000 Standard Occupational Classification (SOC) via 3-digit 2000 U.S. Census occupations using their crosswalks.[58] After that, using crosswalks obtained from the Institute for Structural Research (IBS),[59] I matched the `occ1990dd` to the 6-digit 2010 SOC and then to the 4-digit 2008 International Standard Classification of Occupations (ISCO-08). Finally, I match it with the 5-digit German Klassifikation der Berufe 2010 (KldB 2010) via 4-digit ISCO-08 using a crosswalk obtained from Germany's Federal Employment Agency (Bundesagentur für Arbeit).[60] After all these crosswalks, I have Autor and Dorn (2013)'s three measures for abstract, routine, and manual task inputs merged to Germany's linked employer-employee data at the 5-digit occupations level.

The three indices for abstract, routine, and manual task inputs in each occupation o in 1980, which are scaled between zero and ten, are denoted as $T^A_{o,1980}$, $T^R_{o,1980}$, and $T^M_{o,1980}$, respectively, before merging with the matched data. But after matching these with the linked data (LIAB), I denote them as T^A_{ijt}, T^R_{ijt}, or T^M_{ijt} although the values are the same across worker i, firm j, and year t within an occupation o. Since I have an individual index i, I drop the occupation index o. Then, following

[57] I obtained Autor and Dorn (2013)'s occupational task measures from David Dorn's website: https://www.ddorn.net/data.htm#Occupational%20Tasks

[58] The data files of task measure construction and the crosswalks are available on David Autor's website: `https://economics.mit.edu/people/faculty/david-h-autor/data-archive`

[59] `https://ibs.org.pl/app/uploads/2016/04/onetsoc_to_isco_cws_ibs_en1.pdf`

[60] The crosswalk between 4-digit ISCO-08 and 5-digit KldB 2010 can be downloaded from `https://statistik.arbeitsagentur.de/DE/Statischer-Content/Grundlagen/Klassifikationen/Klassifikation-der-Berufe/KldB2010-Fassung2020/Arbeitsmittel/Generische-Publikationen/Umsteigeschluessel-KLDB2020-ISCO08.xlsx`.

Acemoglu et al. (2023), I normalize these three measures to have mean zero and unit standard deviation. Using these indices, I determine whether a worker i at firm j in year t is an abstract, routine, or manual worker if the maximum of the three normalized tasks inputs measure is T^{A}_{ijt}, T^{R}_{ijt}, or T^{M}_{ijt}, respectively.

Table E.9 summarizes the employment, wage bill, and daily wage for abstract, routine, and manual workers.

Table E.9: Summary statistics (abstract, routine, and manual workers)

	Abstract			Routine			Manual		
	Mean	SD	N	Mean	SD	N	Mean	SD	N
Log labor	2.553	1.393	6659	2.828	1.450	8142	2.364	1.379	6607
Labor cost (% revenue)	0.066	0.100	9718	0.126	0.122	9718	0.071	0.103	9718
Daily wage (€)	115.9	71.60	6657	74.67	37.91	8132	66.85	45.74	6602

Notes: The table summarizes the employment, labor cost, and daily wages for abstract, routine, and manual workers over the period 1997-2018. The classification of workers is based on Autor and Dorn (2013)'s task content/inputs measures. Employment and wage bill information comes from the IAB Establishment Panel while daily wage comes from the matched employer-employee (LIAB) data. The unit of observation is the firm, and sampling weights are applied.

Estimated markdowns for heterogeneous workers. Table E.10 presents the estimated plant-level markdowns for heterogeneous workers, generally consistent with my baseline results. Specifically, routine workers are subject to the lowest degree of monopsony power, while manual workers are subject to the highest labor market power on average. Markdown for manual workers is also the highest in the median firm; however, abstract workers have slightly lower markdown than routine workers, a different result from the baseline. This difference could be due to contextual differences and resulting differences in task contents for occupations.

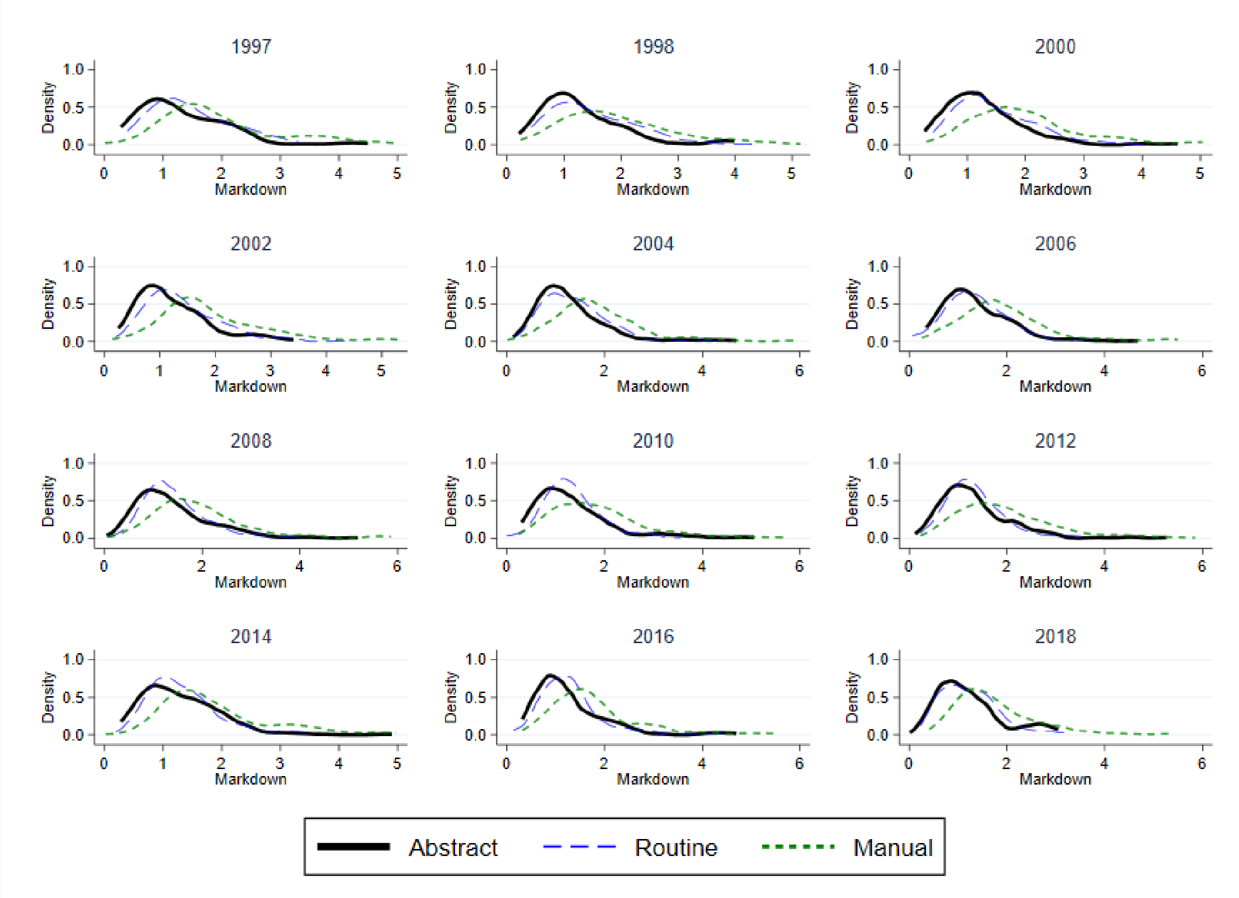
Table E.10: Estimated plant-level markdowns for workers performing routine, abstract, and manual job tasks in German manufacturing

	Median	Mean	$\text{IQR}_{75\text{-}25}$	SD	N
Routine workers	1.075	1.185	0.656	0.566	3779
Abstract workers	1.069	1.280	0.866	0.807	3779
Manual workers	1.634	2.310	1.355	2.354	3779

Notes: Markdowns are estimated using the IAB Establishment Panel and the linked employer-employee (LIAB) data in 1997-2018 under the assumption of a translog specification for gross output with heterogeneous labor inputs. Labor inputs of production are heterogeneous by tasks performed at the workplace. I classify workers based on Autor and Dorn (2013)'s task contents measures. The distributional statistics are calculated using sampling weights provided in the data.

The distribution of markdowns for abstract, routine, and manual workers, plotted in Figure E.3, is generally the same for nonroutine cognitive, routine, and nonroutine manual workers in the baseline analysis.

Figure E.3: Distributions of wage markdowns for abstract, routine, manual workers



Notes: Based on the IAB Establishment Panel and matched employer-employee (LIAB) data. The classification of abstract, routine, and manual task-performing workers is based on Autor and Dorn (2013)'s task contents measures. The figure depicts the markdown distributions for abstract, routine, and manual workers every other year from 1997-2018.

Table E.11 presents results from the Blinder-Oaxaca decomposition on the contribution of worker characteristics to the gap in markdowns due to task differences. The result shows that unobserved task differences explain a significant part of the overall differential between markdowns for workers performing different tasks after accounting for workers' observable characteristics. Table G.5 reports the detailed results from the Blinder-Oaxaca decomposition analysis.

Table E.11: Difference between markdown for workers performing abstract, routine, and manual tasks explained by observables and job tasks

	Manual(1) - Abstract(2) gap in explanatory variables	Manual(1) - Routine(2) gap in explanatory variables	Abstract(1) - Routine(2) gap in explanatory variables
Group 1	2.063 (0.023)	2.063 (0.023)	1.324 (0.012)
Group 2	1.324 (0.012)	1.375 (0.010)	1.375 (0.010)
Difference (1 - 2)	0.739 (0.025)	0.689 (0.025)	-0.050 (0.015)
Endowments	0.021 (0.012)	-0.042 (0.007)	-0.175 (0.028)
Coefficients	0.495 (0.045)	0.685 (0.027)	-0.034 (0.020)
Interaction	0.223 (0.041)	0.046 (0.018)	0.159 (0.031)

Notes: The table presents results from the Blinder-Oaxaca decomposition of wage markdowns for heterogeneous workers performing different job tasks over 1997-2018. The classification of workers performing different tasks is based on Autor and Dorn (2013)'s task contents measures. The explanatory variables include workers' average age and worker composition of the group (shares of female, part-time, immigrant workers, and workers with vocational training and university degrees). The standard errors are in parentheses.

F Additional Results on Firm-Level Effects

F.1 Robustness of Heterogeneous Effects by Firm Size

In Section 5.4, I define firms in the top 3 deciles of the firm size distribution as large firms and show that markdown effects of robot exposure concentrate among such firms. This section, however, checks the robustness of that result using alternative definitions of large firms based on different parts of the firm size distribution.

Table F.1: Robustness: Plant-level effects of robot exposure on wage markdowns for heterogeneous workers at large firms in East Germany (different parts of the firm size distribution)

	Dependent variable: Annual change in plant-level markdowns		
	Routine (1)	Nonroutine manual (2)	Nonroutine cognitive (3)
	Panel A. Top 2 quintiles		
ΔPredicted robot exposure	0.044	0.024	0.006
	(0.010)	(0.023)	(0.022)
Observations	1428	1428	1428
	Panel B. Top tercile		
ΔPredicted robot exposure	0.135	0.043	-0.009
	(0.052)	(0.060)	(0.036)
Observations	652	652	652
	Panel C. Top quartile		
ΔPredicted robot exposure	0.101	-0.042	-0.021
	(0.049)	(0.085)	(0.048)
Observations	338	338	338
	Panel D. Above median		
ΔPredicted robot exposure	0.025	0.003	-0.007
	(0.014)	(0.023)	(0.023)
Observations	1413	1413	1413

Notes: The table presents the results from estimating the annual change in plant-level markdowns on the annual change in the local labor market's predicted exposure to robots in the automotive industry per 1,000 workers for large firms between 1998 and 2018 using the IV (2SLS) regressions under various definition of large firms. In Panels A-D, large firms are defined as those in the top 2 quintiles, top tercile, top quartile, and above the median of the firm size distribution, respectively. Columns (1)-(3) report the effects of automation exposure on the markdowns over heterogeneous workers performing different tasks, and the dependent variable is the annual change in the markdowns over routine workers (column (1)), nonroutine manual–NRM workers (column (2)), and nonroutine cognitive–NRC workers (column (3)). All specifications include the same set of controls and fixed effects as in Table 48. Standard errors clustered at the level of local labor markets or districts are in parentheses.

Table F.1 shows that the baseline effects heterogeneous by firm size are remarkably robust to various definitions of large firms where the impacts are concentrated.

F.2 Additional Robustness of Firm-Level Results

The firm location can vary across the regions over time potentially due to the firm mobility across districts or a firm can have multiple plants in different places with the same firm identification. So, we can control for district fixed effects in addition to the firm fixed effects. Table F.2 shows the robustness of IV (2SLS) estimates in Table 45 by adding district or kreis fixed effects. The results from this robustness check are qualitatively and almost quantitatively similar to the baseline results.

Table F.2: Robustness: Plant-level effects of robot exposure on wage markdowns for heterogeneous workers in East and West Germany (controlling for district fixed effects)

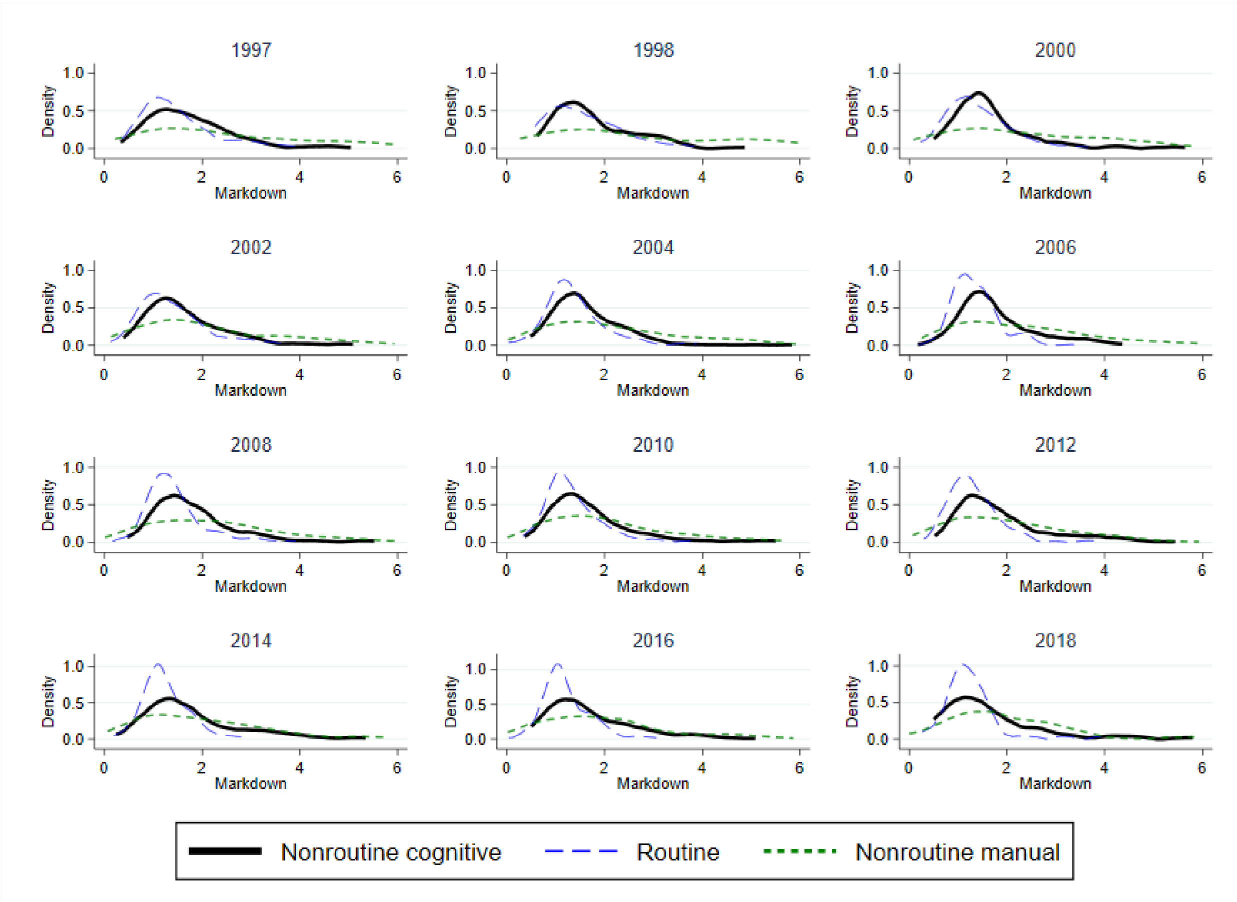
	Dependent variable: Annual change in plant-level markdowns		
	Routine (1)	Nonroutine manual (2)	Nonroutine cognitive (3)
	Panel A. East Germany		
ΔPredicted robot exposure	0.011 (0.005)	-0.003 (0.009)	0.003 (0.008)
Observations	3649	3649	3649
	Panel B. West Germany		
ΔPredicted robot exposure	-0.002 (0.004)	0.013 (0.014)	-0.005 (0.006)
Observations	3823	3823	3823

Notes: Panel A presents the results from estimating the annual change in plant-level markdowns on the annual change in the local labor market's predicted exposure to robots in the automotive industry per 1,000 workers in East Germany between 1998 and 2018 using the 2SLS IV regressions. Panel B reports the results from the IV (2SLS) regressions for West Germany. In both panels, the dependent variable is the annual change in plant-level markdowns for routine (column (1)), nonroutine manual (column (2)), and nonroutine cognitive (column (3)) workers. All specifications control for constant, six plant size groups based on the number of employees at the establishment in the previous year, and demographic characteristics of districts or kreise in the previous year. The demographic controls are constructed using the matched employer-employee data (LIAB) and include the share of females, the share of foreigners, the share of workers over 50 years old, the shares of workers with no vocational training, vocational training, and university degree, and employment shares across broad industries (agriculture, food products, consumer goods, industrial goods, capital goods, construction, consumer-related services, business-related services, and public sector). The local labor market characteristics also contain the annual changes in exposure to net exports and ICT equipment. The firm, district, state-by-year, and industry-by-year fixed effects are also controlled in each specification. Standard errors clustered at the level of local labor markets or districts are in parentheses.

G Additional Figures and Tables

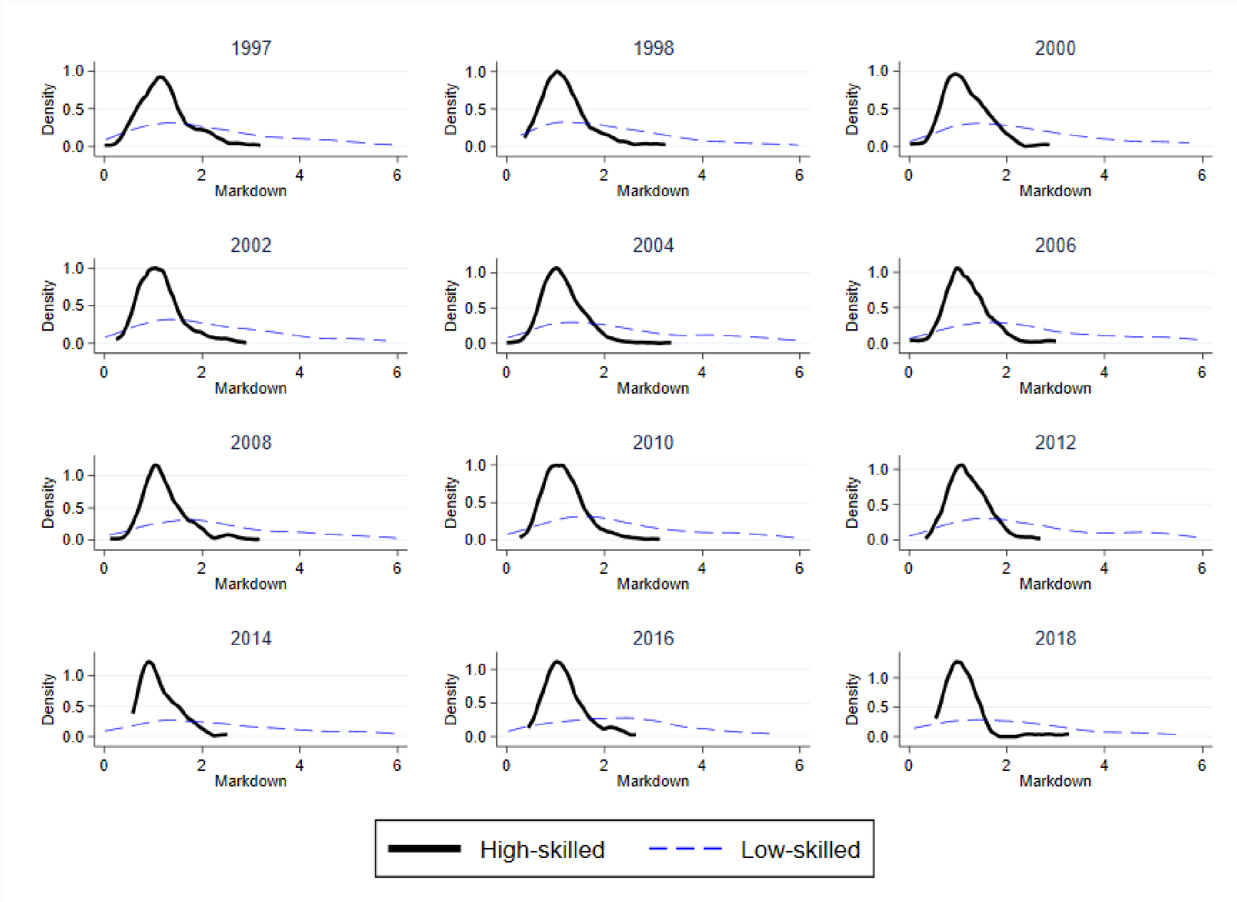
G.1 Additional Figures

Figure G.1: Distributions of wage markdowns for NRC, routine, NRM workers



Notes: Based on the IAB Establishment Panel and matched employer-employee (LIAB) data. The classification of nonroutine cognitive, routine, and nonroutine manual task-performing workers is based on the BIBB/BAuA Employment Surveys. The figure depicts the markdown distributions for NRC, routine, and NRM in a given year over the period 1997-2018. NRC, nonroutine cognitive; NRM, nonroutine manual.

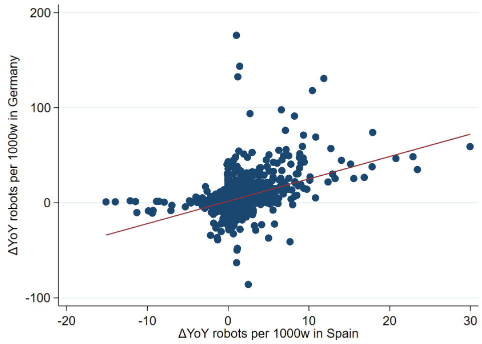
Figure G.2: Distributions of wage markdowns for workers with different skills



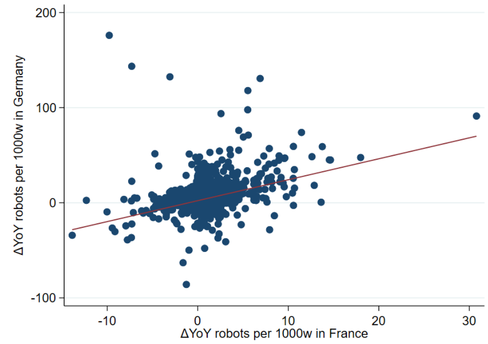
Notes: Based on the IAB Establishment Panel and matched employer-employee (LIAB) data. The figure depicts the markdown distributions for high-skilled (with at least vocational training) and low-skilled (no vocational training) workers every other year from 1997-2018.

Figure G.3: 2SLS first-stage relationship (robots in all industries)

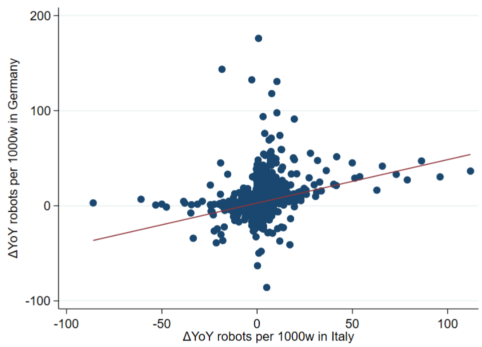
(a) Spain



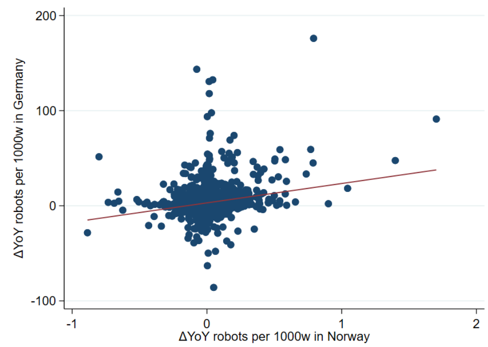
(b) France



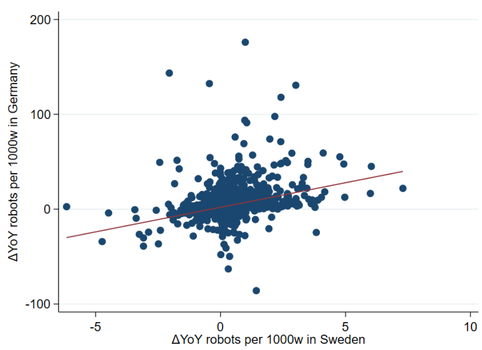
(c) Italy



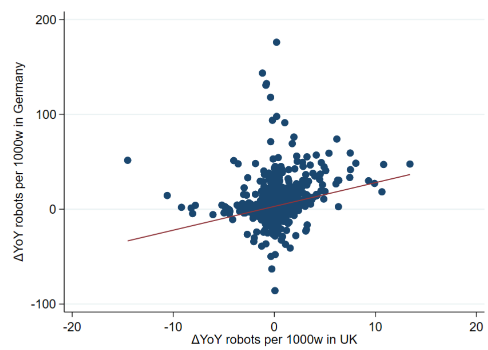
(d) Norway



(e) Sweden



(f) UK



Notes: These scatter plots show the first-stage relationship between the annual changes in exposure to industrial robots in all industries for Germany and other high-income European countries between 1998 and 2018.

G.2 Additional Tables

Table G.1: Test of relevance assumption for robots in all industries

	Dependent variable: Annual change in aggregate markdowns			
	(1)	(2)	(3)	(4)
ΔPredicted robot exposure	-0.0003	-0.0004	-0.0004	-0.0004
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Montiel Olea-Pflueger weak IV test				
Effective F-statistic ($\alpha = 5\%$)	4.835	4.854	4.860	4.852
Critical value 2SLS ($\tau = 10\%$)	22.393	22.492	22.492	22.492
Critical value 2SLS ($\tau = 20\%$)	14.527	14.602	14.602	14.602
Critical value 2SLS ($\tau = 30\%$)	11.579	11.644	11.644	11.644
Kleibergen-Paap weak ID test	45.668	56.181	56.424	56.503
Hansen's J-stat p-value	0.832	0.779	0.776	0.778
Year fixed effects	✓	✓	✓	✓
Broad region dummies	✓	✓	✓	✓
Demographics	✓	✓	✓	✓
Manufacturing share	✓			
Broad industry shares		✓	✓	✓
ΔNet exports in 1,000 euros per worker			✓	✓
ΔICT equipment in 1,000 euros per worker				✓

Notes: $N = 4599$ local labor market regions-by-year (district-by-year). The table presents results from the IV (2SLS) regressions where the German local labor market's exposure robots in all industries are instrumented by installations of all robots in other high-income European countries. The table also tests the inclusion restriction or relevance assumption in this case using Olea and Pflueger's (2013) and Kleibergen and Paap's (2006) weak IV tests. All specifications control for constant, broad region dummies, year fixed effects, and demographic characteristics of districts or kreise in the previous period. The broad region dummies indicate if the region is located in the north, west, south, or east of Germany. The demographic controls are constructed using the matched employer-employee data (LIAB) and include the share of females, the share of foreigners, the share of workers over 50 years old, the shares of workers with no vocational training, vocational training, and university degree, and employment shares across industries. The manufacturing share represents the employment share of manufacturing workers in total employment. Broad industry shares are the shares of workers in nine broad industry groups (agriculture, food products, consumer goods, industrial goods, capital goods, construction, consumer-related services, business-related services, and public sector). Exposure to net exports and ICT equipment is measured by the annual change in German net exports vis-à-vis China and 21 Eastern European countries (in 1,000 euros per worker) and by the annual change in German ICT equipment (in 1,000 euros per worker), respectively. Standard errors clustered at the level of local labor markets or districts are in parentheses.

Table G.2: Difference between markdown for workers performing NRC, routine, and NRM tasks explained by observables and job tasks (detailed)

	NRM(1) - NRC(2) gap in explanatory variables	NRM(1) - Routine(2) gap in explanatory variables	NRC(1) - Routine(2) gap in explanatory variables
Overall			
Group 1	2.384 (0.029)	2.384 (0.029)	1.752 (0.015)
Group 2	1.752 (0.015)	1.366 (0.010)	1.366 (0.010)
Difference (1 - 2)	0.632 (0.032)	1.018 (0.030)	0.386 (0.018)
Endowments	-0.149 (0.030)	-0.016 (0.007)	0.114 (0.024)
Coefficients	0.530 (0.072)	1.064 (0.033)	0.253 (0.032)
Interaction	0.251 (0.072)	-0.030 (0.016)	0.019 (0.036)
Endowments			
Share of female workers	-0.232 (0.020)	-0.008 (0.002)	0.104 (0.014)
Share of workers with vocational training	-0.085 (0.034)	-0.012 (0.004)	0.045 (0.012)
Share of workers with university degree	0.192 (0.044)	0.008 (0.003)	-0.063 (0.025)
Share of immigrant workers	-0.016 (0.008)	0.003 (0.002)	0.021 (0.004)
Share of part-time workers	-0.002 (0.002)	0.011 (0.003)	0.015 (0.005)
Age	-0.006 (0.004)	-0.017 (0.005)	-0.008 (0.003)
Coefficients			
Share of female workers	-0.435 (0.062)	-0.101 (0.024)	0.080 (0.016)
Share of workers with vocational training	-0.411 (0.159)	-0.621 (0.150)	-0.116 (0.155)
Share of workers with university degree	-0.117 (0.094)	-0.063 (0.021)	-0.035 (0.015)
Share of immigrant workers	0.020 (0.007)	0.059 (0.013)	0.003 (0.015)
Share of part-time workers	0.055 (0.021)	0.022 (0.012)	-0.009 (0.009)
Age	-0.732 (0.216)	-0.620 (0.193)	0.091 (0.139)
Intercept	2.149 (0.268)	2.387 (0.226)	0.238 (0.187)
Interaction			
Share of female workers	0.273 (0.039)	0.010 (0.004)	0.113 (0.023)
Share of workers with vocational training	-0.120 (0.047)	-0.032 (0.008)	0.022 (0.029)
Share of workers with university degree	0.099 (0.080)	0.024 (0.008)	-0.109 (0.047)
Share of immigrant workers	0.031 (0.011)	-0.005 (0.003)	-0.002 (0.010)
Share of part-time workers	-0.007 (0.003)	0.012 (0.007)	-0.007 (0.007)
Age	-0.024 (0.008)	-0.040 (0.013)	0.003 (0.004)

Notes: The table presents results from the Blinder-Oaxaca decomposition of wage markdowns for heterogeneous workers performing different job tasks over 1997-2018. The explanatory variables include workers' average age and worker composition of the group (shares of female, part-time, immigrant workers, and workers with vocational training and university degrees). NRC, nonroutine cognitive; NRM, nonroutine manual. The standard errors are in parentheses.

Table G.3: Difference between markdown for high-skilled and low-skilled workers explained by observables and skills (detailed)

	Low-skilled workers' wage markdown equation; Low-skilled - High-skilled gap in explanatory variables
Overall	
Low-skilled workers	3.043 (0.040)
High-skilled workers	1.174 (0.006)
Difference (Low-skilled - High-skilled)	1.868 (0.040)
Endowments	-0.081 (0.014)
Coefficients	1.323 (0.076)
Interaction	0.627 (0.068)
Endowments	
Share of female workers	0.003 (0.001)
Share of workers performing cognitive tasks	0.006 (0.004)
Share of workers performing manual tasks	0.003 (0.001)
Share of immigrant workers	-0.011 (0.005)
Share of part-time workers	0.000 (0.000)
Age	-0.081 (0.012)
Coefficients	
Share of female workers	-0.072 (0.037)
Share of workers performing cognitive tasks	0.157 (0.047)
Share of workers performing manual tasks	0.015 (0.017)
Share of immigrant workers	-0.027 (0.008)
Share of part-time workers	0.053 (0.019)
Age	-2.860 (0.191)
Intercept	4.056 (0.142)
Interaction	
Share of female workers	-0.006 (0.004)
Share of workers performing cognitive tasks	-0.074 (0.022)
Share of workers performing manual tasks	0.003 (0.004)
Share of immigrant workers	-0.047 (0.015)
Share of part-time workers	0.003 (0.002)
Age	0.749 (0.051)

Notes: The table presents results from the Blinder-Oaxaca decomposition of wage markdowns for high-skilled (with at least vocational training) and low-skilled (without vocational training) workers over 1997-2018. The explanatory variables include workers' average age and worker composition of the group (shares of female, part-time, immigrant workers, and workers performing nonroutine cognitive and nonroutine manual tasks). The standard errors are in parentheses.

Table G.4: Relationship between robot exposure, robot exposure predicted from the first stage of 2SLS, and actual robot adoption

	(1)	(2)	(3)
	Panel A. Dependent variable: ΔRobot exposure		
Robot exposure predicted from the first-stage	0.630	0.350	0.362
	(0.054)	(0.063)	(0.063)
Observations	1023	1021	1011
R^2	0.41	0.77	0.80
	Panel B. Dependent variable: ΔActual robot adoption		
ΔRobot exposure predicted from the first-stage	0.013	-0.035	-0.051
	(0.074)	(0.060)	(0.057)
Observations	815	811	803
R^2	0.04	0.49	0.52
Year fixed effects	✓	✓	
State fixed effects	✓		
District fixed effects		✓	✓
State-by-Year fixed effects			✓

Notes: The table presents the results from OLS regressions estimating the relationship between the annual change in robot exposure predicted from the first stage of the 2SLS estimation and annual change in robot exposure defined by equation (13) (top panel) and annual change in actual robot adoption (bottom panel) in Germany between 2015 and 2018. In this table, robots in all industries are considered. The first-stage regression controls for instruments and covariates in equation (12). The actual robot adoption is measured by aggregating the number of robots adopted by the firm at the district level using sampling weights provided in the IAB Establishment Panel data and expressed as per 1,000 workers. Standard errors clustered by districts are in parentheses. Significance: $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$.

Table G.5: Difference between markdown for workers performing abstract, routine, and manual tasks explained by observables and job tasks (detailed)

	Manual(1) - Abstract(2) gap in explanatory variables	Manual(1) - Routine(2) gap in explanatory variables	Abstract(1) - Routine(2) gap in explanatory variables
Overall			
Group 1	2.063 (0.023)	2.063 (0.023)	1.324 (0.012)
Group 2	1.324 (0.012)	1.375 (0.010)	1.375 (0.010)
Difference (1 - 2)	0.739 (0.025)	0.689 (0.025)	-0.050 (0.015)
Endowments	0.021 (0.012)	-0.042 (0.007)	-0.175 (0.028)
Coefficients	0.495 (0.045)	0.685 (0.027)	-0.034 (0.020)
Interaction	0.223 (0.041)	0.046 (0.018)	0.159 (0.031)
Endowments			
Share of female workers	0.000 (0.001)	-0.019 (0.005)	-0.020 (0.005)
Share of workers with vocational training	-0.035 (0.028)	0.004 (0.002)	0.114 (0.019)
Share of workers with university degree	0.052 (0.034)	-0.014 (0.003)	-0.245 (0.034)
Share of immigrant workers	-0.009 (0.003)	0.001 (0.001)	0.003 (0.003)
Share of part-time workers	0.012 (0.007)	0.000 (0.003)	0.000 (0.002)
Age	0.001 (0.002)	-0.015 (0.003)	-0.026 (0.004)
Coefficients			
Share of female workers	0.090 (0.018)	0.115 (0.030)	-0.037 (0.019)
Share of workers with vocational training	-0.705 (0.100)	-0.752 (0.122)	0.257 (0.116)
Share of workers with university degree	-0.523 (0.079)	-0.053 (0.014)	0.043 (0.011)
Share of immigrant workers	-0.031 (0.006)	-0.085 (0.012)	-0.021 (0.009)
Share of part-time workers	0.097 (0.009)	0.162 (0.012)	0.015 (0.010)
Age	-0.508 (0.165)	0.072 (0.154)	0.558 (0.109)
Intercept	2.075 (0.185)	1.226 (0.170)	-0.848 (0.144)
Interaction			
Share of female workers	0.006 (0.003)	-0.043 (0.011)	0.015 (0.008)
Share of workers with vocational training	-0.293 (0.042)	0.008 (0.004)	-0.078 (0.035)
Share of workers with university degree	0.404 (0.061)	-0.013 (0.004)	0.190 (0.050)
Share of immigrant workers	-0.022 (0.005)	0.015 (0.004)	0.011 (0.005)
Share of part-time workers	0.120 (0.012)	0.078 (0.010)	-0.005 (0.003)
Age	0.009 (0.003)	0.002 (0.004)	0.025 (0.005)

Notes: The table presents results from the Blinder-Oaxaca decomposition of wage markdowns for heterogeneous workers performing different job tasks over 1997-2018. The classification of workers performing different tasks is based on Autor and Dorn (2013)'s task contents measures. The explanatory variables include workers' average age and worker composition of the group (shares of female, part-time, immigrant workers, and workers with vocational training and university degrees). NRC, nonroutine cognitive; NRM, nonroutine manual. The standard errors are in parentheses.

References

Acemoglu, Daron, and David Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings." In *Handbook of Labor Economics*. eds. by Orley Ashenfelter, and David Card: Elsevier, 1043–1171.

Acemoglu, Daron, Hans R. A. Koster, and Ceren Ozgen. 2023. "Robots and Workers: Evidence from the Netherlands." *NBER Working Paper No. 31009*.

Acemoglu, Daron, Claire Lelarge, and Pascual Restrepo. 2020. "Competing with Robots: Firm-Level Evidence from France." In *AEA Papers and Proceedings*. 110: 383–388.

Acemoglu, Daron, and Pascual Restrepo. 2020. "Robots and Jobs: Evidence from US Labor Markets." *Journal of Political Economy*, 128(6): 2188–2244.

Ackerberg, Daniel A., Kevin Caves, and Garth Frazer. 2015. "Identification Properties of Recent Production Function Estimators." *Econometrica*, 83(6): 2411–2451.

Aghion, Philippe, Céline Antonin, Simon Bunel, and Xavier Jaravel. 2020. "What Are the Labor and Product Market Effects of Automation? New Evidence from France." *CEPR Discussion Paper No. 14443*.

Antonczyk, Dirk, Bernd Fitzenberger, and Ute Leuschner. 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.

Autor, David H., and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review*, 103(5): 1553–1597.

Azar, José, Ioana Marinescu, and Marshall Steinbaum. 2019. "Measuring Labor Market Power Two Ways." In *AEA Papers and Proceedings*. 109: 317–321.

Barth, Erling, Marianne Roed, Pål Schøne, and Janis Umblijs. 2020. "How Robots Change Within-Firm Wage Inequality." *IZA Discussion Paper No. 13605*.

Bau, Natalie, and Adrien Matray. 2023. "Misallocation and Capital Market Integration: Evidence from India." *Econometrica*, 91(1): 67–106.

Bessen, James, Maarten Goos, Anna Salomons, and Wiljan van den Berge. forthcoming. "What Happens to Workers at Firms that Automate?" *Review of Economics and Statistics*.

Blinder, Alan S. 1973. "Wage Discrimination: Reduced Form and Structural Estimates." *Journal of Human Resources*, 8(4): 436–455.

Boal, William M., and Michael R. Ransom. 1997. "Monopsony in the Labor Market." *Journal of Economic Literature*, 35(1): 86–112.

Bond, Steve, Arshia Hashemi, Greg Kaplan, and Piotr Zoch. 2021. "Some Unpleasant Markup Arithmetic: Production Function Elasticities and Their Estimation from Production Data." *Journal of Monetary Economics*, 121: 1–14.

Bonfiglioli, Alessandra, Rosario Crinò, Harald Fadinger, and Gino Gancia. 2020. "Robot Imports and Firm-Level Outcomes." *CEPR Discussion Paper No. DP14593*.

Brandt, Loren, Johannes Van Biesebroeck, Luhang Wang, and Yifan Zhang. 2017. "WTO Accession and Performance of Chinese Manufacturing Firms." *American Economic Review*, 107(9): 2784–2820.

Bronfenbrenner, Martin. 1956. "Potential Monopsony in Labor Markets." *ILR Review*, 9(4): 577–588.

Brooks, Wyatt J., Joseph P. Kaboski, Yao Amber Li, and Wei Qian. 2021. "Exploitation of Labor? Classical Monopsony Power and Labor's Share." *Journal of Development Economics*, 150: 102627.

Burdett, Kenneth, and Dale T. Mortensen. 1998. "Wage Differentials, Employer Size, and Unemployment." *International Economic Review*, 39(2): 257–273.

Card, David, Jörg Heining, and Patrick Kline. 2013. "Workplace Heterogeneity and the Rise of West German Wage Inequality." *The Quarterly Journal of Economics*, 128(3): 967–1015.

Card, David, Ana Rute Cardoso, Joerg Heining, and Patrick Kline. 2018. "Firms and Labor Market Inequality: Evidence and Some Theory." *Journal of Labor Economics*, 36(S1): S13–S70.

Caunedo, Julieta, Elisa Keller, and Yongseok Shin. 2023. "Technology and the Task Content of Jobs across the Development Spectrum." *The World Bank Economic Review*, 37(3): 479–493.

Chau, Nancy H., and Ravi Kanbur. 2021. "Employer Power, Labour Saving Technical Change, and Inequality." In *Development, Distribution, and Markets: Festschrift in Honor of Pranab Bardhan*. eds. by Kaushik Basu, Maitreesh Ghatak, Kenneth Kletzer, Sudipto Mundle, and Eric Verhoogen: Oxford University Press, 158–180.

Dauth, Wolfgang, Sebastian Findeisen, Jens Suedekum, and Nicole Woessner. 2021. "The Adjustment of Labor Markets to Robots." *Journal of the European Economic Association*, 19(6): 3104–3153.

De Loecker, Jan, Pinelopi K. Goldberg, Amit K. Khandelwal, and Nina Pavcnik. 2016. "Prices, Markups, and Trade Reform." *Econometrica*, 84(2): 445–510.

De Loecker, Jan, and Frederic Warzynski. 2012. "Markups and Firm-Level Export Status." *American Economic Review*, 102(6): 2437–2471.

Domini, Giacomo, Marco Grazzi, Daniele Moschella, and Tania Treibich. 2021. "Threats and Opportunities in the Digital Era: Automation Spikes and Employment Dynamics." *Research Policy*, 50(7): 104137.

Dustmann, Christian, Johannes Ludsteck, and Uta Schönberg. 2009. "Revisiting the German Wage Structure." *The Quarterly Journal of Economics*, 124(2): 843–881.

Fitzenberger, Bernd, Aderonke Osikominu, and Robert Völter. 2005. "Imputation Rules to Improve the Education Variable in the IAB Employment Subsample." *ZEW Discussion Paper No. 05-10*.

Gandhi, Amit, Salvador Navarro, and David A. Rivers. 2020. "On the Identification of Gross Output Production Functions." *Journal of Political Economy*, 128(8): 2973–3016.

Graetz, Georg, and Guy Michaels. 2017. "Is Modern Technology Responsible for Jobless Recoveries?" *American Economic Review: Papers & Proceedings*, 107(5): 168–173.

Graetz, Georg, and Guy Michaels. 2018. "Robots at Work." *Review of Economics and Statistics*, 100(5): 753–768.

Humlum, Anders. 2019. "Robot Adoption and Labor Market Dynamics." *Working Paper*.

Kirov, Ivan, and James Traina. 2021. "Labor Market Power and Technological Change in US Manufacturing." *Working Paper*.

Kleibergen, Frank, and Richard Paap. 2006. "Generalized Reduced Rank Tests Using the Singular Value Decomposition." *Journal of Econometrics*, 133(1): 97–126.

Klette, Tor Jakob, and Zvi Griliches. 1996. "The Inconsistency of Common Scale Estimators when Output Prices Are Unobserved and Endogenous." *Journal of Applied Econometrics*, 11(4): 343–361.

Koch, Michael, Ilya Manuylov, and Marcel Smolka. 2021. "Robots and Firms." *The Economic Journal*, 131(638): 2553–2584.

Levinsohn, James, and Amil Petrin. 2003. "Estimating Production Functions Using Inputs to Control for Unobservables." *The Review of Economic Studies*, 70(2): 317–341.

Lochner, Benjamin, and Bastian Schulz. 2024. "Firm Productivity, Wages, and Sorting." *Journal of Labor Economics*, 42(1): 85–119.

Manning, Alan. 2003. *Monopsony in Motion: Imperfect Competition in Labor Markets*. Princeton University Press.

Manning, Alan. 2021. "Monopsony in Labor Markets: A Review." *ILR Review*, 74(1): 3–26.

Mengano, Paolo. 2023. "Trends in Worker Bargaining Power." *Working Paper*.

Mueller, Steffen. 2008. "Capital Stock Approximation using Firm Level Panel Data." *Jahrbücher für Nationalökonomie und Statistik*, 228(4): 357–371.

Mueller, Steffen. 2017. "Capital Stock Approximation with the Perpetual Inventory Method: An Update." *FDZ-Methodenreport 05/2017*.

Naidu, Suresh, and Eric A. Posner. 2022. "Labor Monopsony and the Limits of the Law." *Journal of Human Resources*, 57(S): S284–S323.

Oaxaca, Ronald. 1973. "Male-Female Wage Differentials in Urban Labor Markets." *International Economic Review*, 14(3): 693–709.

Olea, José Luis Montiel, and Carolin Pflueger. 2013. "A Robust Test for Weak Instruments." *Journal of Business & Economic Statistics*, 31(3): 358–369.

Olley, G. Steven, and Ariel Pakes. 1996. "The Dynamics of Productivity in the Telecommunications Equipment Industry." *Econometrica*, 64(6): 1263–1297.

Wooldridge, Jeffrey M. 2009. "On Estimating Firm-level Production Functions Using Proxy Variables to Control for Unobservables." *Economics Letters*, 104(3): 112–114.

Yeh, Chen, Claudia Macaluso, and Brad Hershbein. 2022. "Monopsony in the US Labor Market." *American Economic Review*, 112(7): 2099–2138.