# Automation and Labor Market Power 

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#### Abstract

This paper examines the role of automation threat in employers' monopsony power. Using plant-level longitudinal data, I estimate the wage markdowns-wedge between the marginal revenue product of labor and the wage-based on the production approach to quantify employer market power in German manufacturing and how it has changed over time. I find that most manufacturing plants operate in a monopsonistic market, and a worker in a German manufacturer earns 75 cents on each euro generated, on average. Leveraging the estimated wage markdowns and information on industrial robots, I quantify the causal impact of robot penetration on wage markdowns using a shift-share instrumental variable approach and find that robot exposure deepens employers' labor market power. I then examine to what extent workers performing job tasks with different exposure to displacement risks from automation are subject to monopsony power and how automation affects monopsony power over those heterogeneous workers. I show that routine task-performing workers are subject to the lowest degree of monopsony power, while workers performing mostly nonroutine manual tasks are exposed to the highest degree of monopsony power in German manufacturing. I also develop a simple task-based model with heterogeneous firms that characterizes the empirical facts for policy discussion, and predictions from the model similarly suggest that robot adoption enhances wage markdowns.


Keywords: technological change, robot, machines, task displacement, automation threat, monopsony, employer power, markdown, heterogeneous firms, heterogeneous workers JEL Codes: J31, J42, O33

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## 1 Introduction

The idea that employers "exploit" their workers by departing from competition in labor markets is not new in economics. However, research interests in labor market power (equivalently, employer power or monopsony) have been re-established in light of recent empirical evidence. ${ }^{1}$ There is a growing consensus that firms, rather than markets, set wages based on those recent estimates on various measures of labor market power (see Manning (2021), Card (2022), and Ashenfelter et al. (2022) for recent surveys of the literature on monopsony). Due to this growing consensus on monopsonistic wage setting, the current literature on monopsony power has been actively exploring the sources of that power. But many questions about the causes of monopsony power remain unclear (Card, 2022). Hence this paper fills this gap in the literature by highlighting automation or automation threat as a driver of monopsony power. ${ }^{2}$

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. But the impact of automation technologies on employer power in wage negotiation is still understudied, and there are several unanswered questions about the potential role of automation in employers' labor market power. For example, whether robots use deepen labor market power and whether there is any role of displacement threat from automation in employer power. It is also natural to consider the distinction between automation threat and realized adoption of robots when we analyze the role of technology adoption in bargaining power or wage negotiation.

In this paper, I thus explore the role of automation in employers' labor market power, focusing on automation threats. Specifically, I first estimate plant-level wage markdowns using a semi-structural

[^1]control function method and a production function approach to quantify labor market power for German manufacturers and how it has changed over time. I then empirically estimate the causal impact of robot adoption on wage markdowns at the local labor market level. Finally, I construct a model of oligopsony featuring heterogeneous firms with task-based production technologies that operate in a market with Cournot competition to characterize the empirical facts about the relationship between automation and labor market power for policy discussion.

To empirically answer my research question, I quantify the establishment-level degree of monopsony power in the labor market using "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), which measures labor market power or wage markdowns-wedge between a firm's marginal revenue product of labor (MRPL) and the wage that the firm pays to its workers-by accounting for product market power or price markups. This "markdown" equals unity in a perfectly competitive labor market. ${ }^{3}$ The production approach has two main advantages over other measures of monopsony power. ${ }^{4}$ First, it provides an establishment-specific measure of monopsony power that varies over time. It allows me to show how automation "shock" affects the degree of monopsony power at the establishment or local labor market level. Second, this empirical approach is generic and not restricted by any of the different theories of labor market power, such as oligopsony, classic differentiation, and equilibrium search models. ${ }^{5}$

For my empirical analysis, I use an establishment panel survey (IAB Establishment Panel-IAB BP) and novel matched longitudinal employer-employee data (LIAB) from Germany, one of the world's leading countries in robotization and automation (Figure 1). ${ }^{6}$ The detailed firm-level longitudinal dataset (IAB BP) with direct and comprehensive information to estimate production function under labor market imperfection such as labor headcounts ${ }^{7}$ and thus to quantify firm-level

[^2]markups according to De Loecker and Warzynski (2012) enables me to accurately measure the "markdown" using the production approach at the establishment ${ }^{8}$ or firm level over time between 1994 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, which I use to document the facts about the firm's robot adoption to motivate my model features. For my analysis estimating the causal impact of automation, I use industry-level data on the stock of robots obtained from the International Federation of Robotics (IFR) covering more periods since 1993.

I focus on estimating the causal impact of automation on labor market power at the level of local labor markets mainly due to two reasons: (i) firm-level information on robot adoption in the IAB BP data is limited, and (ii) automation threats are more related to the state of automation at some aggregate level such as industry or local labor market levels, rather than at the firm level. First, although German establishment panel data provide the firm's robot adoption at extensive and intensive margins, the information covers only five years between 2014-2018. So it is challenging to make credible and robust inferences about the automation impact using the firm-level measure 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. 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).

This study contributes to several strands of literature. The novel contribution is that I show automation as a significant source of employers' labor market power. First, my work is related to the rich literature that models labor market power. I develop a task-based model of oligopsony with heterogeneous firms, and my model serves as an alternative to benchmark models of monopsony. The model explicitly presents the effects of automation on wage markdowns under firm heterogeneity in the style of Melitz (2003). Relatedly, Leduc and Liu (2022) offer a business cycle model
erase the non-zero true 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.
${ }^{8}$ 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.
with labor market search frictions in which the threat of automation weakens workers' bargaining power in wage negotiations. ${ }^{9,10}$ The model introduced in this paper diverts from their framework in several ways. First, my model embodies two main elements of a firm's automation decisions: (i) robots displace some tasks previously performed by labor in a task-based framework, and (ii) robot adoption is lumpy. Second, my model features markdowns or monopsony power rather than bargaining power. The existing bargaining model does not characterize these features. Hence my work contributes to the literature on labor market power by offering an alternative framework of a simple task-based model that incorporates some key micro facts on a firm's robot adoption derived from the data to characterize the relationship between robot adoption and markdown. By focusing on labor market power, this alternative framework formalizes automation as a source of wage markdowns and labor market concentration and stimulates future works on monopsony power. The model mainly aims to showcase the mechanisms for policy discussions. ${ }^{11}$

Second, my work is related to literature estimating the reduced-form effects of automation, especially on labor market power. I contribute to this literature by providing the first reduced-form evidence on the causal impact of automation on labor market power. Specifically, I estimate the causal effect of robot penetration on labor market power at the local labor market level using a shift-share IV strategy. In the empirical literature investigating the link between automation technologies and labor market power, few recent 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 attempts to understand 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. But, in this paper, I

[^3]find that robot adoption deepens employers' labor market power.
Third, my work is related to a growing literature examining heterogeneity in monopsony power by worker characteristics. I focus on worker heterogeneity by job tasks performed at the workplace, including routine, nonroutine manual, and nonroutine cognitive tasks. I first quantify markdowns for such workers and then estimate the effects of automation on labor market power for them. 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., 2022) using administrative and experimental data. These studies on heterogeneity in labor market power mainly estimate the elasticity of labor supply for different workers as a measure of monopsony power. Although Bachmann et al. (2022) 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. Using these measures, I estimate the heterogeneous effects of robot adoption on monopsony power for workers who vary by their degrees of exposure to displacement risks.

Finally, my work is related to a research agenda analyzing the prevalence and evolution of monopsony power. I find that a worker in a median German manufacturer receives only 85 cents on the marginal euro, which is different from previous estimates for German manufacturing from Mertens (2020), who suggests that the median manufacturer pays a wage higher than the competitive market. I also provide additional distributional estimates and show that a worker in the average plant earns 75 cents on each euro generated. I thus show that median and average German manufacturers operate in an imperfectly competitive labor market. Additionally, I provide the first estimates on the evolution of labor market power in German manufacturing. Using the aggregation method suggested by Yeh et al. (2022), I show that the aggregate markdown in German manufacturing substantially increased between 1994 and 1997 after the German reunification, mainly through a sharp decline in markups. But markdown has decreased since then with some plateau between 2000 and 2008. Despite a weak cross-sectional correlation between labor market concentration measured by Herfindahl-Hirschman Index (HHI) and markdown at the market level (Bassier et al., 2022; Berger et al., 2022; Yeh et al., 2022), my aggregate markdown measure and employment-based HHI present generally similar pattern over time, specifically until 2011.

The rest of the paper proceeds as follows. Section 2 characterizes some facts on a firm's robot adoption. Section 3 presents the theoretical model that formalizes the automation impact on labor market power founded on the main micro facts. Section 4 describes the German data. Section 5 describes the construction of plant-level wage markdowns and discusses the estimated wage markdowns in German manufacturing and its evolution from 1994-2018. Section 6 lays out the local labor market-level analysis on the effects of robot adoption on wage markdowns. Section 7 presents the analysis with heterogeneous workers. Section 8 discusses the main findings and implications.

## 2 Key Facts on Firm Robot Adoption

This section presents four key facts that inform the modeling choices and the empirical analysis. The first two facts relate to the distribution of robots across industries. Most robots and robot adopters concentrate in the manufacturing industry, and robot adopters are rare even within manufacturing. The third fact documents a non-random selection of firms into robot adopters, which informs that more productive firms before automation adopt robots, highlighting the importance of featuring heterogeneous firms in the model. The fourth fact concerns the lumpiness of the number of robots used at the firm, which motivates to model robot adoption as a single machine displacing a particular share of tasks completely.

## Fact 1. Robot adopters are highly concentrated in manufacturing industry.

Figure 2 depicts the share of robot-adopting manufacturers in the total number of robot-adopting firms between 2015 and 2018. The takeaway from the figure is that more than three-quarters of robot adopters are manufacturing plants. This observation is consistent with the automation literature. It justifies the focus of the empirical analysis on the manufacturing industry when investigating the impacts of automation.

## Fact 2. Robot adopters are rare.

Fact 1 above shows that robot users are mainly manufacturing firms. But how prevalent are robot adopters in general and in the manufacturing industry? Table 1 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 nonmanufacturing firms are robot users. Although the manufacturing industry is robot-intensive, as indicated by fact 1 , only $7.19 \%$ of the manufacturing plants were robot users in 2018. Thus robot adoption is relatively rare, even in the manufacturing industry.

## Fact 3. Robot adopters are larger with more employees, especially, in the manufacturing industry.

To further characterize the robot adopters, I estimate the following regression using the 2018 crosssectional sample:

$$
\begin{equation*}
Y_{j k d}=\alpha+\beta \text { Robots Adoption }_{j k d}+\phi_{k}+\varphi_{d}+\varepsilon_{j k d} \tag{1}
\end{equation*}
$$

where $Y_{j k d}$ is a characteristic of firm $j$ in the industry $k$ and district $d$, Robots Adoption ${ }_{j k d}$ is either a dummy variable for robot adoption status that takes the value of 1 if plant $j$ used robots in 2018 and zero otherwise, or the number of robots used by the plant, $\phi_{k}$ and $\varphi_{d}$ are respectively the three-digit industry and district fixed effects. I do not use the sampling weights provided in the data to estimate
equation (1) as the specification already approximates the sample design of the IAB Establishment Panel (region and industry). I have also estimated the same regressions with survey weights, and the qualitative results remain the same. I report only robust standard errors in the baseline regressions shown in Table 2, but clustering by the plants does not change the qualitative implications.

I focus on plant size measured by the number of employees as the plant characteristic $Y_{j k d}$, and Table 2 shows that robot-adopting manufacturers are large (top panel). Here I show the positive relationship between robot adoption and plant size only for manufacturing firms, but the fact also generally holds when I include non-manufacturing plants. As Column (5) of the top panel suggests, the average plant size of the robot adopters is more than three times $\left(e^{1.200} \approx 3.320\right)$ as large as that of the non-adopters. The bottom panel of Table 2 shows the relationship between robotization and plant size on the intensive margin within the robot adopters. As shown in Column (5) of the bottom panel, the association between robot adoption and plant size is positive on the intensive margin.

Numerous studies document this observation using data on industrial robot use among manufacturing firms in different countries, including the U.S. (Acemoglu et al., 2022), Denmark (Humlum, 2019), Spain (Koch et al., 2021), France (Acemoglu et al., 2020; Bonfiglioli et al., 2020), and Germany (Deng et al., 2021).

## Fact 4. Robot adoption is lumpy, especially, in the manufacturing sector.

Figure 3 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 along the distribution. The third takeaway is that robots concentrate amongst robot adopters. This discrete nature of robot adoption motivates the choice in Section 3 to model automation as a lumpy investment.

Recently, a few papers using data on robot adoption among manufacturing firms suggest that robot adoption is lumpy (see, e.g., Humlum, 2019).

## 3 A Simple Model of Automation and Labor Market Power

To formalize how automation impacts labor market power, I propose a task-based model of oligopsony in which firms play an employment-setting game. My model features heterogeneous firms, automation, and wage markdowns.

### 3.1 Setup

The model is general, and the economy can consist of multiple industries. But, based on fact 1 in Section 2 that suggests robot adopters concentrate in the manufacturing sector and for simplicity,

I consider an economy with only one industry, e.g., manufacturing. Recent studies characterizing the robot-adopting firms also consistently suggest that robot adoption is highly skewed towards the largest firms (e.g., Acemoglu et al. (2022) for the U.S., Koch et al. (2021) for Spain, and Deng et al. (2021) for Germany). It is potentially due to fixed costs to automate (Hubmer and Restrepo, 2021). Given this evidence in the literature and fact 3 in Section 2, the model features heterogeneous firms that differ by their productivity in the style of Melitz (2003).

In the industry, there is a finite number of heterogeneous employers $M \in \mathbb{Z}_{+}$that produce an output of $y_{j}=z_{j} x_{j}$, where $z_{j}$ is the firm's $j$ 's productivity and $x_{j}$ is inputs of production. The industry-wide production output is thus $y=\sum_{j} y_{j}$, and the average productivity is $\bar{z}=\sum_{j} z_{j} / M$. Firms pay a fixed cost $f$, which is common across firms, to stay operating in the market. A unit of inputs $x_{j}$ is an assembly of a continuum of tasks $o$ normalized to 1 , i.e., $o \in[0,1]$. To complete a unit of tasks, producers hire workers $l_{j}$ (i.e., labor-only firms) or use human labor $l_{j}$ and robots $r_{j}$, which substitutes labor for some tasks (i.e., semi-automated firms).

Based on fact 4 in Section 2, automation is modeled as lumpy and non-lumpy investments. I consider the lumpiness of robots as a robot having sufficient capacity to completely replace workers in $\theta$ share of tasks (i.e., number of robots at the firm $r_{j}=1$ ). I also allow some firms to have multiple robots, i.e., $r_{j}>1$, and they replace $r_{j} \theta$ share of tasks. The cost of robot adoption is $\rho\left(r_{j}\right)$ per robot where $\rho^{\prime}\left(r_{j}\right)<0$, i.e., a decreasing unit cost of robot adoption. So the total cost of robot adoption is $r_{j} \rho\left(r_{j}\right)$. Given these different automation strategies, there are three groups of firms. First, let $j=1, \ldots, M_{1}$ be the list of single-robot employers who continue to hire workers to complete the remaining $(1-\theta)$ share of tasks per unit output. Second, let $j=M_{1}+1, \ldots, M_{2}$ be the list of multiple-robot adopting firms, and workers complete $\left(1-r_{j} \theta\right)$ share of tasks. Third, let $j=M_{2}+1, \ldots, M$ be the list of labor-only firms where only labor completes all tasks.

Industry-wide labor supply is given by an upward-sloping labor supply schedule $w(l)>0$, where the labor market clearing condition is defined as

$$
l=\sum_{j=1}^{M_{1}} l_{j}+\sum_{j=M_{1}+1}^{M_{2}} l_{j}+\sum_{j=M_{2}+1}^{M} l_{j}=\sum_{j=1}^{M_{1}}(1-\theta) x_{j}+\sum_{j=M_{1}+1}^{M_{2}}\left(1-r_{j} \theta\right) x_{j}+\sum_{j=M_{2}+1}^{M} x_{j} .
$$

Then I denote an inverse of labor supply elasticity as

$$
\begin{equation*}
\varepsilon_{w} \equiv \frac{\partial \ln w(l)}{\partial \ln l} \tag{2}
\end{equation*}
$$

Output price is normalized into a unity, and I assume there is no market power in product market for simplicity without loss of generality and to focus on labor market power in this benchmark model.

### 3.2 Labor Market Power

First, the profit maximization problem of firms that do not automate is simply

$$
\pi_{j}^{0} \equiv \pi^{0}\left(z_{j}\right)=\max _{x_{j}} z_{j} x_{j}-w(l) x_{j}-f
$$

which yields the labor market power:

$$
\begin{equation*}
\sigma_{j}^{0} \equiv \sigma^{0}\left(z_{j}\right) \equiv \frac{z_{j}-w(l)}{w(l)}=\frac{\varepsilon_{w} l_{j}}{l} \tag{3}
\end{equation*}
$$

where $z_{j}$ is the marginal revenue product of labor (MRPL) of firm $j, w(l)$ is the industry-level aggregate wage, and thus $z_{j} / w(l)$ is firm $j$ 's markdown. The term $\varepsilon_{w}$ is the inverse of the labor supply elasticity defined in equation (2), and $l_{j} / l$ is firm $j$ 's employment share in the sector. I take the percentage difference of MRPL from the wage, $\sigma_{j}$, as my measure of employers' labor market power. When $z_{j} / w(l) \rightarrow 1$ or $\sigma \rightarrow 0$, the MRPL equals the wage $w(l)$, as in a competitive equilibrium. In contrast, when $z_{j} / w(l)>1$ or $\sigma=0$, employer $j$ pays their workers less than their MRPL $z_{j}$, i.e., they have labor market power. Because I assume that firms pay the same wage at the industry-level $w(l)$ and more productive firms have higher MRPL $z_{j}$, more productive firms have higher markdowns in equilibrium, which follows from the left-hand side of equation (3), consistent with Berger et al. (2022). Since labor supply elasticity is defined at the industry level and $\partial \sigma_{j}^{0} / \partial l_{j}=\varepsilon_{w} / l>0$, it follows from the right-hand side of equation (3) that larger firms with more workers have higher markdowns in equilibrium. Larger firms are thus more productive in the model.

Second, the profit maximization problem of firms that adopt a single robot is

$$
\pi_{j}^{1} \equiv \pi^{1}\left(z_{j}\right)=\max _{x_{j}} z_{j} x_{j}-(1-\theta) w(l) x_{j}-\rho\left(r_{j}\right)-f
$$

which implies

$$
\begin{equation*}
\sigma_{j}^{1} \equiv \sigma^{1}\left(z_{j}\right) \equiv \frac{z_{j} /(1-\theta)-w(l)}{w(l)}=\frac{\varepsilon_{w} l_{j}}{l} \tag{4}
\end{equation*}
$$

where worker's productivity in a single robot-adopting firm is enhanced by automation, i.e., $z_{j} /(1-$ $\theta)>z_{j}$.

Third, the profit maximization problem of firms that adopt multiple robots is

$$
\pi_{j}^{R} \equiv \pi^{R}\left(z_{j}\right)=\max _{x_{j}} z_{j} x_{j}-\left(1-r_{j} \theta\right) w(l) x_{j}-\rho\left(r_{j}\right) r_{j}-f .
$$

The marginal cost of labor input is declining with automation:

$$
\left(1-r_{j} \theta\right) w(l)\left(1+\varepsilon_{w} l_{j} / l\right)<(1-\theta) w(l)\left(1+\varepsilon_{w} l_{j} / l\right)<w(l)\left(1+\varepsilon_{w} l_{j} / l\right), \quad \text { given } r_{j}>1,
$$

suggesting that firms adopting more robots enjoy strictly lower marginal costs than non-robotadopting firms. It follows that firms with more robots tend to raise their output more readily than less automated firms. Furthermore, the marginal cost of robot adoption decreases with automation for robot-adopting firms:

$$
\rho\left(r_{j}\right)+\rho^{\prime}\left(r_{j}\right) r_{j}<\rho\left(r_{j}\right), \quad \text { given } \rho^{\prime}\left(r_{j}\right)<0 .
$$

The first order condition with respect to labor input $l_{i}$ implies the wage markdown as

$$
\begin{equation*}
\sigma_{j}^{R} \equiv \sigma^{R}\left(z_{j}\right) \equiv \frac{z_{j} /\left(1-r_{j} \theta\right)-w(l)}{w(l)}=\frac{\varepsilon_{w} l_{j}}{l} \tag{5}
\end{equation*}
$$

We see that the productivity effect of automation is critical in assessing the impact of automation on wage markdowns. But there is another component in the labor market power, i.e., labor share $\left(l_{j} / l\right)$, which I investigate below.

### 3.3 Employment, Labor Share, and Labor Market Concentration

The equilibrium profits of the labor-only firm (i.e., $\pi_{j}^{0}$ evaluated at profit-maximizing employment level) can be expressed as a function of labor share $l_{j} / l$ as

$$
\pi_{j}^{0}=w(l) l \varepsilon_{w}\left(l_{j} / l\right)^{2}-f
$$

which is obtained by organizing the terms in the firm's profit function and substituting equation (3) in $\pi_{j}^{0}$ function. Similarly, the equilibrium profits of single-robot firms and multiple-robot firms as a function of labor share $l_{j} / l$ is, respectively

$$
\pi_{j}^{1}=(1-\theta) w(l) l \varepsilon_{w}\left(l_{j} / l\right)^{2}-\rho\left(r_{j}\right)-f
$$

and

$$
\pi_{j}^{R}=\left(1-r_{j} \theta\right) w(l) l \varepsilon_{w}\left(l_{j} / l\right)^{2}-\rho\left(r_{j}\right) r_{j}-f
$$

It follows immediately that the two profit levels are strictly increasing in the square of the respective wage markdowns
$\pi_{j}^{0}=\frac{w(l) l}{\varepsilon_{w}}\left(\sigma_{j}^{0}\right)^{2}-f, \pi_{j}^{1}=\frac{(1-\theta) w(l) l}{\varepsilon_{w}}\left(\sigma_{j}^{1}\right)^{2}-\rho\left(r_{j}\right)-f, \pi_{j}^{R}=\frac{\left(1-r_{j} \theta\right) w(l) l}{\varepsilon_{w}}\left(\sigma_{j}^{R}\right)^{2}-\rho\left(r_{j}\right) r_{j}-f$.

Denote the share of the wage bill in total revenue at the industry level as

$$
s_{L} \equiv \frac{w(l) l}{\sum_{j} z_{j} x_{j}} .
$$

Then the following proposition characterizes the relationship between the industry-level labor share (i.e., the share of the firm's output revenue that goes to labor) and the labor market concentration (measured by Herfindahl-Hirschman index-HHI).

Proposition 1 (Relationship between Labor Share and Labor Market Concentration). The labor share is inversely related to labor market concentration as

$$
H H I_{l}=\sum_{j=1}^{M}\left(\frac{l_{j}}{l}\right)^{2}=\frac{1}{\varepsilon_{w}}\left(\frac{1}{s_{L}}-1\right) .
$$

Refer to the Online Appendix A. 1 for detailed derivation.
It also implies that HHI is a sufficient statistic of the labor share conditional on labor supply elasticity without any need for data on revenue and wages. This result stays the same independent of the automation states of the firm.

### 3.4 Market Equilibrium

I assume a linear functional form for labor supply schedule $w(l)=\alpha+\beta l$, where $\alpha, \beta>0$, to have a closed-form solution. Henceforth, the first-order conditions of the profit maximization problem of single-robot, multiple-robot, and labor-only firms, respectively, are

$$
\begin{gather*}
z_{j}=(1-\theta)\left(\alpha+\beta l+\beta l_{j}\right), \quad j=1, \ldots, M_{1},  \tag{6}\\
z_{j}=\left(1-r_{j} \theta\right)\left(\alpha+\beta l+\beta l_{j}\right), \quad j=M_{1}+1, \ldots, M_{2},  \tag{7}\\
z_{j}=\alpha+\beta l+\beta l_{j}, \quad j=M_{2}+1, \ldots, M . \tag{8}
\end{gather*}
$$

Denote

$$
\bar{z}_{1}=\sum_{j=1}^{M_{1}} \frac{z_{j}}{(1-\theta) M_{1}}, \quad \bar{z}_{2}=\sum_{j=M_{1}+1}^{M_{2}} \frac{z_{j}}{\left(1-r_{j} \theta\right)\left(M_{2}-M_{1}\right)}, \quad \bar{z}_{3}=\sum_{j=M_{2}+1}^{M} \frac{z_{j}}{M-M_{2}}
$$

as the average labor productivity of the single-robot firms $\left(z_{j} /(1-\theta)\right)$, the multiple-robot firms $\left(z_{j} /\left(1-r_{j} \theta\right)\right.$ ), and the labor-only firms $\left(z_{j}\right)$. Also, denote

$$
\begin{equation*}
z^{\theta}=M_{1} \bar{z}_{1}+\left(M_{2}-M_{1}\right) \bar{z}_{2}+\left(M-M_{2}\right) \bar{z}_{3}, \tag{9}
\end{equation*}
$$

and then denote $\bar{z}^{\theta} \equiv z^{\theta} / M$ as the average productivity of the three types of employers under automation. By definition, the average productivity of all firms under automation $\bar{z}^{\theta}$ is strictly greater than the corresponding average when no firms automate $\bar{z}$. Proposition 2 summarizes the market equilibrium.

Proposition 2 (Market Equilibrium). The employment and wages at the equilibrium are

$$
l^{*}=\frac{m}{\beta}\left(z^{\theta}-\alpha(1 / m-1)\right), \quad w\left(l^{*}\right)=m\left(\alpha+z^{\theta}\right)
$$

where $m=1 /(M+1)$.
Refer to the Online Appendix A. 2 for detailed derivation.
The comparative statics from equilibrium employment and the equilibrium wage with respect to productivity $z^{\theta}$ suggests that automation increases both industry-level wage and industry-level employment through productivity effect, given that $\partial l^{*} / \partial z^{\theta}>0$ and $\partial w\left(l^{*}\right) / \partial z^{\theta}>0$.

But how does automation affect the employment of an individual firm $i$ at the equilibrium after accounting for the general equilibrium impacts? Proposition 3 summarizes the nuanced results on the employment impact of automation on individual employers.

Proposition 3 (Employment Impact of Automation for Individual Employers).
3.1. Employment in labor-only firms always decline in automation as $\partial l_{j}^{*} / \partial z^{\theta}=-\frac{m}{\beta}<0$.
3.2. Employment in single-robot firms is higher than that when no firms are automated if and only if productivity $z_{j}$ is sufficiently high, i.e.,

$$
z_{j}>(1-\theta) m_{1} \bar{z}_{1}+\frac{1-\theta}{\theta} m_{2}\left(\bar{z}_{2}-\bar{z}\right)
$$

where $m_{1}=M_{1} /(M+1)$, $m_{2}=\left(M_{2}-M_{1}\right) /(M+1), \bar{z}=\sum_{j=1}^{M} z_{j} / M=\sum_{j=M_{1}+1}^{M_{2}} z_{j} /\left(M_{2}-\right.$ $M_{1}$ ) by construction, and $\bar{z}_{2}>\bar{z}$ by definition.
Refer to the Online Appendix A. 3 for detailed derivation.
Automation has distributional effects across employers. First, the smallest and least productive labor-only firms face higher wages and low employment, which reduce profits. Second, more productive firms that automate have higher labor productivity and hire more workers despite the higher equilibrium wage.

The equilibrium wage markdowns in labor-only, single-robot, and multiple-robot firms are expressed respectively as:

$$
\sigma_{j}^{0}=\frac{z_{j}-w\left(l^{*}\right)}{w\left(l^{*}\right)}, \quad \sigma_{j}^{1}=\frac{z_{j} /(1-\theta)-w\left(l^{*}\right)}{w\left(l^{*}\right)}, \quad \sigma_{j}^{R}=\frac{z_{j} /\left(1-r_{j} \theta\right)-w\left(l^{*}\right)}{w\left(l^{*}\right)} .
$$

Since equilibrium wage increases with automation, wage markdown in labor-only firms unambigu-
ously decreases with automation. But the general equilibrium impact of robot adoption in wage markdown in single- and multiple-robot firms is nuanced. We can show that wage markdowns in automated firms increase with automation, and the increase is higher in multiple-robot firms than single-robot firms due to the higher positive productivity effect.

These produce the following proposition:
Proposition 4 (General Equilibrium Impact of Automation on Wage Markdowns).
4.1. Automation unambiguously reduces the markdown $\sigma_{j}^{0}$ in labor-only firms.
4.2. The equilibrium markdowns in single-robot $\left(\sigma_{j}^{1}\right)$ and multiple-robot firms $\left(\sigma_{j}^{R}\right)$ are greater than markdowns in labor-only firms.
4.3. Markdown in multiple-robot firms is increasingly greater than in single-robot firms as robot adoption intensifies.
Refer to the Online Appendix A. 4 for detailed derivation.
These results taken together suggest that automation has a systematic impact on wage markdowns, although the effect exhibits (i) heterogeneity across firms, which (ii) ranges from a negative effect on all labor-only firms to a positive effect on automated firms with the highest productivity, and (iii) the positive impact of automation on wage markdown in automating firms strengthens as automation intensifies.

In Online Appendix A.5, I extend the benchmark model above with no dynamic patterns of employer exiting or entering the market and where automation shock is exogenous by introducing endogenous exit-entry flows and automation decisions.

## 4 Data

The primary data set is drawn from rich administrative data from Germany provided by the Research Data Center (FDZ) of the Federal Employment Agency in the Institute for Employment Research (IAB). I also use several other supplementary datasets from different sources.

### 4.1 Establishment Data

I use firm-level panel data, IAB Establishment Panel (IAB BP), which covers a large representative sample of establishments to estimate the production function and, thus, wage markdowns in Germany. The longitudinal structure of the IAB BP data enables me to use the control function method, which uses lagged information for identification. The IAB BP data include comprehensive and detailed establishment information necessary for production function estimation, such as annual revenue, number of workers, 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 robots. 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.

For the establishment data, I also extract the district (or kreis) where the plant locates 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 capital stock and impute workers' top-coded wage information and educational attainment recorded in the German administrative data. I relegate details on these imputation procedures to Online Appendix B.1.

### 4.2 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 previous 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 Robots (IFR) since 1993 as the primary measure of automation in my regressions that spans for more periods. Graetz and Michaels (2017) and Graetz and Michaels (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 robots stock is dis-aggregated for 20 manufacturing industries. ${ }^{12}$

I construct the long change in the number of robots and then normalize it by workforce size in the base year. Section 6.1 discusses the construction of this variable in detail, particularly in

[^4]equation (23). I obtain workers count at the industry-by-location level from the BHP extension of the weakly anonymized version of the Sample of Integrated Labour Market Biographies (SIAB), which produces the most reliable results.

### 4.3 Matched Employer-Employee Data

I use the longitudinal version of matched employer-employee data (LIAB) mainly for 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 establishment part of the matched data comes from two sources: IAB Establishment Panel (IAB BP) and Establishment History Panel (BHP). I described how I used the IAB BP dataset above in detail. The BHP data, on the other hand, contain more general information on the industry, location, and total employment for each establishment. Some of the covariates I control in my labor market-level regressions come from the BHP data.

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$\mathrm{BeH})$. The information on employees includes variables such as daily wage and detailed occupation classifications at the 5-digit level from 1975 to 2019. The worker-level data is mainly used for my analysis, where workers are heterogeneous by job tasks performed at the workplace. ${ }^{13}$

### 4.4 Worker-Level Job Tasks

I use worker-level representative cross-sectional data from the Federal Institute for Vocational Training and Training (BIBB)-so-called "BIBB/IAB (and BIBB/BAuA) Employment Surveys"-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 20,000-35,000 individuals in the active labor force. Although there are existing task intensity measures for occupations in other countries like the U.S. (Autor and Dorn, 2013) and the U.S. and Germany are both developed countries, I used this worker-level data from Germany to accurately measure task contents for occupations in the German context because occupational task contents are likely to be different for each country (Caunedo et al., forthcoming). Using the BIBB/IAB and 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, and I use five waves of the survey that match the period of my analysis.

[^5]
## 5 Measuring Markdowns

### 5.1 Theoretical Framework

There are several different but related approaches to measure the monopsony 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, which is upward sloping-in contrast to the horizontal labor supply curve for an individual firm in the perfectly competitive labor market. 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 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 in 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.

In my empirical analysis, I estimate wage markdown, a wedge between the marginal revenue product of labor (MRPL) and the wage, as a measure of labor market power. Below I briefly show the relationship between markdowns and labor supply elasticity to motivate my choice in this paper.

Consider a revenue function $R(l)=(a-b l / 2) l$ 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 $t \in[0, T]$ is the mobility cost, which is assumed to be exogenous at this point, and $\tau \equiv T / L$ where $L$ is a population of workers. The first-order condition for profit maximization problem implies that profits are maximized at an employment level where MRPL, $R_{l}(l)=a-b l$, 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 $w^{\text {so }}$ less than the socially efficient level, $w^{*}$.

The profit maximization problem in the basic monopsony model is

$$
\begin{equation*}
\max _{l \geq 0} R(l)-w^{s}(l) l \tag{10}
\end{equation*}
$$

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

$$
\begin{equation*}
R_{l}(l)=\left(\frac{w_{l}(l) l}{w(l)}+1\right) w(l)=\left(\varepsilon_{S}^{-1}+1\right) w(l) \tag{11}
\end{equation*}
$$

and, thus, the markdown $\nu$, a wedge between the MRPL and the wage, is

$$
\begin{equation*}
\nu \equiv \frac{R_{l}(l)}{w(l)}=\varepsilon_{S}^{-1}+1 \tag{12}
\end{equation*}
$$

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. The markdown equals unity $(\nu=1)$ in perfectly competitive labor markets. In labor markets with imperfect competition, on the other hand, employers have market power if $\nu>1$.

As shown in the optimality condition in equation (12) and in Figure 4, 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 equation (12) as mentioned above, we can measure the degree of monopsony power by estimating the wedge between the (nominal) wage $w^{s o}$ and MRPL $w^{d o}$ on the left-hand side of equation (12), which is expressed by the distance between $w^{s o}$ and $w^{d o}$ in Figure 4. This wedge (or misallocation in the language of Hsieh and Klenow (2009) and Adamopoulos et al. (2022)) between the MRPL and the wage is called "markdown" in the literature. This approach to measuring the monopsony power is often called as "production approach," which I used in this paper.

The main reason I prefer to use the production approach over other measures of monopsony is that methods other than the production function approach do not provide firm- or local labor marketspecific monopsony measure that varies over time. In contrast to other methods, the production approach I use in this paper allows me to estimate the degree of monopsony at the firm and local labor market levels over time, enabling me to investigate the causal impact of automation "shock"robot adoption-on labor market power. Another main advantage of the production approach is that we do not need to take any stance on the source of monopsony power to quantify markdowns.

When applying the production function approach, one can directly take the ratio of MRPL to the nominal wage that the firm pays its workers as in the left-hand side of the equation (12) to compute the markdown. However, the main limitation of this method is that the wage markdown would be
contaminated by the firm's price markup when we do not use physical output. ${ }^{14}$ Thus, we need to consider the firm's markup to measure the markdown more accurately, and I use the production function approach by closely following Yeh et al. (2022). As they have shown, the cost minimization problem implies the following relationship between labor markdown and product markup:

$$
\begin{equation*}
\nu_{j t}=\frac{\theta_{j t}^{L}}{\alpha_{j t}^{L}} \cdot \mu_{j t}^{-1} \tag{13}
\end{equation*}
$$

where $\nu_{j t}$ is the markdown in equation (12) for firm $j$ in year $t, \theta_{j t}^{L}=\left(\partial F\left(l_{j t}\right) / \partial l_{j t}\right)\left(l_{j t} / F\left(l_{j t}\right)\right)$ is the output elasticity of labor $F\left(l_{j t}\right), \mu_{j t}=p_{j t} / \lambda_{j t}$ is the firm's price $\left(p_{j t}\right)$-cost $\left(\lambda_{j t}\right)$ markup, and $\alpha_{j t}^{L}=W_{j t}\left(l_{j t}\right) / R_{j t}\left(l_{j t}\right)$ denotes a firm's labor share of revenue $R_{j t}\left(l_{j t}\right)$. In this paper, I thus use equation (13) to construct the markdown by estimating its components. I obtain the output elasticity of labor, $\theta_{j t}^{L}$, from the production function estimation, which Section 5.2 discusses in detail. The firm-level markups are estimated based on the production function estimation as in De Loecker and Warzynski (2012), who show that $\mu_{j t}=\theta_{j t}^{M}\left(\alpha_{j t}^{M}\right)^{-1}$ where $\theta_{j t}^{M}$ is the output elasticity of a variable input $M_{j t}$ other than labor, e.g., material inputs, and $\alpha_{j t}^{M}$ is the share of expenditures on input $M_{j t}$ in total sales or revenue. An expenditure on labor as a share of revenue is calculated directly from the data, where labor cost is calculated average annual wage bill of a worker multiplied by the total number of workers at the establishment. The section below describes how I estimate the production function, which provides inputs to construct the markdown measure.

Online Appendix C briefly lays out other measures of monopsony power and discusses their linkages with wage markdowns.

### 5.2 Production Function Estimation

I estimate production function using "proxy variable" method (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg et al., 2015). In my production function estimation procedure, I closely follow Yeh et al. (2022) and De Loecker and Warzynski (2012) that rely on assumptions from Ackerberg et al. (2015).
${ }^{14}$ For example, one can calculate the marginal product of labor under Cobb-Douglas production technologies as

$$
\mathrm{MPL}_{j t}=\frac{\partial Y_{j t}}{\partial L_{j t}}=\beta \frac{Y_{j t}}{L_{j t}},
$$

where $\beta$ is the elasticity of output to labor obtained from production function estimation, and $Y_{j t}=A_{j t} K_{j t}^{\alpha} L_{j t}^{\beta}$ and $L_{j t}$ are respectively the firm $j$ 's output and labor input use in year $t$. If we have information on physical outputs and output prices, we can estimate the MPL and compare it with real wages to calculate the markdown. However, output prices that the firm charges its consumers are often absent in the data. So one would observe the nominal output or revenue, a function of output price that includes markups. One can deflate the sales income using industry-specific output prices to approximate the physical outputs. However, it will still include firm-specific markups. Hence, comparing the MPL and wage provides biased estimates on markdowns.

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

$$
\begin{equation*}
y_{j t}=f\left(\mathbf{x}_{j t} ; \boldsymbol{\beta}\right)+\omega_{j t}+\varepsilon_{j t}, \tag{14}
\end{equation*}
$$

where $y_{j t}$ is $\log$ output, $\mathbf{x}_{j t}$ is a vector of $\log$ inputs, both fully variable inputs (e.g., intermediate materials $m_{j t}$ ) and not fully variable inputs (e.g., labor $l_{j t}{ }^{15}$ and capital $k_{j t}$ ). The firm-specific productivity $\omega_{j t}$ embeds the constant term. The error term $\varepsilon_{j t}$ reflects measurement error in gross outputs $y_{j t}$ defined as revenue deflated by producer price index for industrial products at the 2-digit industry level. ${ }^{16}$ 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 trans $\log ^{17}$ as the primary specification given its flexibility.

The main challenge in estimating the firm-level production function in equation (14) 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 use 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). Online Appendix D describes the technical details of the ACF procedure.

Table 3 summarizes the main variables used for markdown estimation, estimated total factor productivity (TFP), average daily wage, and firm-level robot adoption.

[^6]
### 5.3 Estimated Markdowns in German Manufacturing Plants

There are two reasons why I focus on the manufacturing industry in this paper. First, most of the actions in robot adoption happen among manufacturers according to the fact 1 in Section 2. 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 my markdown estimation in Table 4. 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 1.333-that is, a plant's marginal revenue product of labor is, on average, 33 percent higher than the wage it pays its workers. Alternatively, taking the reciprocal, a markdown of 1.333 implies that a worker receives around 75 cents on the marginal euro generated. Furthermore, I find that labor market power is widespread across manufacturing plants. Half charge a markdown of 1.179 ( 85 cents on the marginal euro), and the interquartile range is around 0.7.

My estimate on median value for wage markdowns is quite different from the previous estimate by Mertens (2020), who shows that there is no labor market power on the median in the German manufacturing sector (implied wage markdowns $\nu_{i t}=0.880$ ) using the AFiD-data over the period 2000-2014. My estimate on the mean value for wage markdowns is generally consistent with Bachmann et al. (2022)'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) and 50 cents in Brazil (Felix, 2022) earned for each marginal dollar. Overall, I find that both average and median manufacturing plants operate in a market with monopsonistic competition.

### 5.4 Aggregated Markdowns

This section thus far focuses on plant-level markdown estimates used for firm-level analysis. Now I turn to discuss how I construct aggregate markdowns at the level of local labor markets, which is used for my labor market-level analysis, and at the year level. I aggregate the establishmentlevel 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 define 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

$$
\begin{equation*}
\mathcal{V}_{k l t}=\frac{\left(\sum_{j \in F_{t}(k, l)} s_{j t} \cdot \frac{\theta_{j t}^{L}}{\theta_{k l t}^{L}} \cdot\left(\nu_{j t} \mu_{j t}\right)^{-1}\right)^{-1}}{\left(\sum_{j \in F_{t}(k, l)} s_{j t} \cdot \frac{\theta_{j t}^{M}}{\theta_{k l t}^{M}} \cdot \mu_{j t}^{-1}\right)^{-1}} \tag{15}
\end{equation*}
$$

and

$$
\begin{equation*}
\mathcal{M}_{k l t}=\left(\sum_{j \in F_{t}(k, l)} s_{j t} \cdot \frac{\theta_{j t}^{M}}{\theta_{k l t}^{M}} \cdot \mu_{j t}^{-1}\right)^{-1} \tag{16}
\end{equation*}
$$

where $\theta_{k l t}^{L}$ and $\theta_{k l t}^{M}$ are, respectively, the average output elasticities of labor and intermediate materials in the industry $k$, location $l$, and year $t$. Here $s_{j t}=\frac{p_{j t} y_{j t}}{P_{k l t} Y_{k l t}}$ are sales weights 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

$$
\begin{equation*}
\mathcal{V}_{t}=\sum_{k \in K} \sum_{l \in L} \omega_{k l t} \mathcal{V}_{k l t} \tag{17}
\end{equation*}
$$

and

$$
\begin{equation*}
\mathcal{M}_{t}=\sum_{k \in K} \sum_{l \in L} \omega_{k l t} \mathcal{M}_{k l t} \tag{18}
\end{equation*}
$$

where $\omega_{k l t}$ is the employment share of labor market $(k, l)$.
Figure 5 illustrates the resulting time trend of aggregate markdowns, $\mathcal{V}_{t}$, which has substantially increased between 1994 and 1997, while it has been on a downward trend with some plateau between 2000 and 2008. ${ }^{18}$

### 5.5 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 Herfindahl-Hirschmann Index (HHI). Using the matched employeremployee data structure, I construct the HHI for labor markets at the occupation (3-digit KldB

[^7]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 use 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 use 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 employers, I first count workers at each establishment and then construct the HHI in labor market $(o, l)$ and time $t$ as

$$
\begin{equation*}
\mathrm{HHI}_{m t}=\sum_{j=1}^{I} s_{j m t}^{2}, \tag{19}
\end{equation*}
$$

where $s_{j m t}^{2}$ 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 (19) for market $m^{\prime}=(k, l)$ where $k$ is the industry index. A firm's market share in a given market $m$ (or $m^{\prime}$ ) 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,

$$
\begin{equation*}
\mathrm{HHI}_{l t}=\sum_{o \in O} \omega_{o l t} \mathrm{HHI}_{o l t} \quad\left(\text { or } \mathrm{HHI}_{l t}=\sum_{k \in K} \omega_{k l t} \mathrm{HHI}_{k l t}\right), \tag{20}
\end{equation*}
$$

and

$$
\begin{equation*}
\mathrm{HHI}_{l t}=\sum_{k \in K} \sum_{l \in L} \omega_{k l t} \mathrm{HHI}_{k l t} . \tag{21}
\end{equation*}
$$

Table 5 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 75 th 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 6 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.

Previous studies using only production data, such as Yeh et al. (2022), are constrained in comparing the markdown measure with occupation-based HHIs as 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 5-6, we see that HHIs calculated using 3-digit occupations and 3-digit industries are consistent.

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 $\mathcal{V}_{k l t}$ and $\mathrm{HHI}_{k l t}$ is weak: across years, this correlation is close to zero, negative sometimes and rarely statistically significant. ${ }^{19}$ Despite this weak cross-section correlation, Figure 6 demonstrates that time trends in aggregate labor market concentration $\left(\mathrm{HHI}_{t}\right)$ and markdowns $\left(\mathcal{V}_{t}\right)$ are generally the same, especially before 2011. The correlation between aggregate HHI and aggregate markdowns is 0.17 for the entire period, 1994-2018, while the correlation coefficient between 1994 and 2011 is 0.85 . These observations are generally consistent with previous studies (Bassier et al., 2022; Berger et al., 2022; Yeh et al., 2022).

## 6 Effect of Automation on Labor Market Power

In this section, I estimate the causal impact of automation on labor market power at the local labor market level, relying on a shift-share instrumental variable (IV) approach.

### 6.1 Empirical Specification

To investigate the causal effect of automation shock (measured by predicted exposure to robots at the local labor markets) on local labor market-level markdowns, I estimate the following equation:

$$
\begin{equation*}
\Delta \text { Markdown }_{r}=\alpha+\beta_{1} \Delta \widehat{\operatorname{Robots}}_{r}+\beta_{2} \Delta{\widehat{\operatorname{Trade}_{r}}}_{r}+\beta_{3} \widehat{\Delta \mathrm{ICT}}_{r}+\mathbf{X}_{r}^{\prime} \gamma+\epsilon_{r} \tag{22}
\end{equation*}
$$

where $r$ is the local labor market regions, and $\Delta$ represents the long-difference between $1996^{20}$ and 2018. The term $\Delta$ Markdown $_{r}$ is the change in local markdowns over the period 1996-2018, $\Delta \widehat{\text { Robots }_{r}}$ is the change in the predicted number of robots per worker (as defined in equation (23) below), and ${\widehat{\Delta \text { Trade }_{r}}}_{r}$ and $\widehat{\Delta I C T}_{r}$ are the predicted local exposures to net exports and ICT investment, respectively. The vector $\mathbf{X}^{\prime}{ }_{r}$ contains broad region dummies (i.e., dummies for north, south, east,

[^8]and west regions) and demographic characteristics of the local workforce. The demographic controls include the share of females; the share of foreigners; the share of workers over 50 years old; and the share of workers with no vocational training, vocational training, and university degree. The region dummies and demographic controls are at levels before the start of the shock period instead of changes to prevent endogenous adjustments on the local labor force after the shock to contaminate the effects of changes in robot exposure on changes in markdown.

The key explanatory variable, the change in local labor market's exposure to robots, is constructed as

$$
\begin{equation*}
\Delta{\widehat{\text { Robots }_{r}}}=\sum_{k=1}^{K}\left(\frac{\text { Employment }_{k r}}{\text { Employment }_{r}} \times \frac{\Delta \text { Robots }_{k r}}{\text { Employment }_{k}}\right), \tag{23}
\end{equation*}
$$

where $K=20$. For the construction of trade exposure and exposure to ICT investments, I closely follow Dauth et al. (2021). The change in trade exposure, $\Delta \widehat{\operatorname{Trade}}_{r}$, is measured by an increase in German net exports vis-à-vis China and 21 Eastern European countries from 1996 to 2018 for every manufacturing industry $k$ using UN Comtrade data, normalized by the initial wage bill to account for industry size. The change in exposure to ICT investment, $\widehat{\Delta I C T}_{r}$, is defined by the change in real gross fixed capital formation volume per worker for computing and communication equipment from 1996 to 2018 using data on installed equipment at the industry level reported in the EU KLEMS database.

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 4, 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 counties according to their shares of the industry's total employment. So I call this a "predicted" local exposure and denote it with a hat.

### 6.2 Identification and Assumptions

To identify the effect of robots on wage markdowns, I use variation in predicted robot exposure across industries, assuming that some sectors are more likely to adopt industrial robots than others. But variation in exposure to robots adoption 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 local labor markets 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. ${ }^{21}$ The change in the number of robots in the same set of industries in each other country is normalized and allocated across regions using German's lagged industry-by-region employment counts from 1984.

For this instrumental variable estimation approach to work, the constructed shift-share instruments must satisfy two main assumptions: (i) the inclusion restriction or relevance and (ii) the exclusion restriction. Below I discuss each of these assumptions in my context and then briefly address issues related to statistical inference.

Inclusion restriction or relevance: There must be a strong correlation between changes in Germany's robot exposure and those in other high-income European countries. As I show in the next section, the popular rule-of-thumb-the $F$-statistic on the excluded instruments being more than 10 in the first-stage regression-informs the validity of the relevance assumption (Kleibergen and Paap, 2006; Cameron and Miller, 2015). The existing studies show 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).

Exclusion restriction: 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). ${ }^{22}$ This condition will hold if shocks to the robot adoption in other high-income European countries are unrelated 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 overidentifying restrictions test ( $H_{0}$ : all IVs are uncorrelated with $\epsilon_{r}$ ), I cast evidence on whether the instruments satisfy the orthogonality condition (Sargan, 1958, 1998; Hansen, 1982; Altonji et al., 2005).

Statistical inference: I cluster the standard errors by 40 aggregated labor market regions ${ }^{23}$ to allow for heteroskedasticity and serial correlation within clusters. I also cluster the standard errors at the level of local labor markets or kreise, which provides more clusters, to check the robustness of my results. Additionally, as pointed out by Adao et al. (2019), conventional standard errors on shift-share explanatory variables such as $\Delta \widehat{\text { Robots }_{r}}$ 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

[^9]industries.

### 6.3 Results

Table 7 presents the baseline results from estimating reduced-form specification in equation (22) where I regress the long difference in aggregate markdowns between 1996 and 2018 on the long difference in exposure to robots for the same period.

OLS estimates: In panel A of Table 7, I first look at the local labor market-level relationship between wage markdowns and robot exposure using ordinary least squares (OLS) regressions. Column (1) shows results from a specification that controls for broad region dummies and demographic characteristics of the local labor market. The relationship between robot exposure and markdown changes in a kreis is positive. The estimate is statistically significant at the $10 \%$ level when conventional standard errors are applied; however, it becomes statistically insignificant when I correct the standard errors, allowing error terms to be correlated within region-industry share groups.

In Column (2), I include the initial employment shares of nine broad industries instead of the initial employment share of manufacturing workers to control for more detailed industry trends within the manufacturing sector. As a result, the coefficient estimate on robot exposure remains positive and slightly increases in magnitude; however, statistical significance, using conventional or unconventional standard errors, remains the same.

In Column (3), I control for predicted exposure to net exports vis-à-vis China and 21 Eastern European countries, as described in Section 6.1. In Column (4), which is the preferred specification, I add the predicted exposure of local labor markets to ICT equipment. Trade exposure and ICT investment variables have a minor effect on our coefficient of interest. The coefficient estimate and statistical inference are qualitatively unchanged.

IV estimates: Panel B of Table 7 shows the results when the regressions are estimated with IV (2SLS) regressions. The joint $F$-statistic on the excluded instruments is large enough to suggest that robot adoptions in other high-income European countries provide plausible variations in German robot adoption. Hansen's $J$-statistic indicates 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 increases wage markdowns, and the impact is statistically significant at the $5 \%$ level.

## 7 Effects of Automation on Markdowns of Heterogeneous Workers

This section relaxes an assumption of homogeneous workers and considers heterogeneous workers with different exposure to automation risks. To examine the heterogeneous effects of automation or
automation threats, I split workers into several groups based on their potential likelihood of being directly affected by robots. Using those worker classifications, I first measure markdown for such workers by estimating production function with heterogeneous labor inputs and quantifying the heterogeneous effects of robot exposure on labor market power.

### 7.1 Definition of Heterogeneous Workers

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

$$
\begin{equation*}
\mathrm{TI}_{i k t}=\frac{\text { number of activities in category } k \text { performed by } i \text { at time } t}{\sum_{k} \text { number of activities in category } k \text { performed by } i \text { at time } t} \tag{24}
\end{equation*}
$$

where $t=1991$-1992, 1998-1999, 2006, 2012, and 2018, and $k$ indicates routine, nonroutine manual, and nonroutine cognitive 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. Finally, I merge these task intensity measures to the matched employer-employee data by occupation and year combinations.

The main advantage of using the BIBB/IAB and BIBB/BAuA Employment Surveys compared to other measures of tasks intensity, for example, offered by Autor and Dorn (2013), is that the $\mathrm{TI}_{i k t}$ measure varies over time. It allows us to capture the changing nature of the task content of occupations (Edmond and Mongey, 2022). As a robustness check, I use Autor and Dorn (2013)'s static measure of task intensity developed for U.S. occupations using data from O*NET.

I define workers directly and indirectly affected by 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 automation impact on workers because automation 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 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 of robot adoption 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 $\mathrm{RTI}_{i j t}, \mathrm{NRCTI}_{i j t}$, or $\mathrm{NRMTI}_{i j t}$, 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 $\mathrm{RTI}_{i j t}, \mathrm{NRCTI}_{i j t}$, and $\mathrm{NRMTI}_{i j t}$ denote $\mathrm{TI}_{i k j t}$ index in equation (24) 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 estimating the markdown and the impact of robot adoption on labor market power. This grouping of workers is similar to that in Bachmann et al. (2022), 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.

Table 8 summarizes the employment, wage bill, 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 education levels are expected to be unequal (Yeh et al., 2022). Even if markdowns for such workers are equal, the implication of automation on their markdowns could be different. So I distinguish workers by education categories as follows:
low-education: without a vocational training degree,
high-education: with a vocational training degree, or with 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. If robot adoption in Germany is more consistent with skill-biased technological change, automation impact might be more nuanced among workers categorized by skills or education than job tasks.

Table 9 presents the summary statistics on employment, wagebill, and daily wage for high- and
low-skilled workers.

### 7.2 Estimated Markdowns

I estimate the production function similar to equation (14) but with heterogeneous labor inputs, then quantify the markdown for those workers. Table 10 shows the estimated plant-level markdowns for heterogeneous workers in the German manufacturing industry who differ by job tasks performed at their workplaces and their skills or education level.

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 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 10). These observations are strongly consistent with Bachmann et al. (2022)'s results. I also find that NRM workers are the most exploited workers since they are subject to the highest monopsony power. This result differs from Bachmann et al. (2022), who suggest NRC workers are subject to the highest degree of monopsony power. Specifically, I find that NRM, NRC, and routine workers receive 41 cents, 55 cents, and 68 cents on each euro generated, respectively. These estimates are generally comparable in magnitude with Bachmann et al. (2022)'s markdown estimates at the mean implied from their estimated labor supply elasticities for workers who perform NRM ( $\nu_{i t}=1.602$ or 62 cents per euro), NRC ( $\nu_{i t}=2.043$ or 49 cents per euro), and routine ( $\nu_{i t}=1.589$ 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 Bachmann et al. (2022)'s 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 different methods with different assumptions. I estimate markdown using the production approach, while they estimate labor supply elasticity using Manning (2003)'s method. Third, we use different data sets. I use 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 used in my markdown estimation spans between 1994-2018, 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 average manufacturing plants, and (ii) the markdown for lowskilled or low-educated workers is larger than the markdown for high-skilled or high-educated workers (Panel B of Table 10).

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 (Figure 7). Markdowns are always relatively higher for low-skilled workers (Figure 8).

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 differ-
ences 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):

$$
\begin{align*}
& Y^{1}=\beta_{0}^{1}+\sum_{k=1}^{K} \beta_{k}^{1} X_{k}^{1}+\epsilon^{1}  \tag{25}\\
& Y^{2}=\beta_{0}^{2}+\sum_{k=1}^{K} \beta_{k}^{1} X_{k}^{2}+\epsilon^{2}
\end{align*}
$$

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 $\bar{Y}$ and $\left(\bar{X}_{1}, \ldots, \bar{X}_{K}\right)$, as

$$
\begin{equation*}
\bar{Y}^{1}-\bar{Y}^{2}=\underbrace{\left(\beta_{0}^{1}-\beta_{0}^{2}\right)}_{\text {coefficients }}+\underbrace{\sum_{k=1}^{K} \beta_{k}^{2}\left(\bar{X}_{k}^{1}-\bar{X}_{k}^{2}\right)}_{\text {endowments }}+\underbrace{\sum_{k=1}^{K} \bar{X}_{k}^{2}\left(\beta_{k}^{1}-\beta_{k}^{2}\right)}_{\text {coefficients }}+\underbrace{\sum_{k=1}^{K}\left(\bar{X}_{k}^{1}-\bar{X}_{k}^{2}\right)\left(\beta_{k}^{1}-\beta_{k}^{2}\right)}_{\text {interaction }}, \tag{26}
\end{equation*}
$$

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 includes 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 11 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 some worker characteristics. Table 12 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 explain more than onethird of the difference between markdowns for high- and low-skilled workers. ${ }^{24}$

[^10]Trends in aggregate markdowns: I aggregate the plant-level markdowns for heterogeneous workers using equations (15) and (17) similar to my baseline analysis to show how employers' labor market power has changed for different workers in German manufacturing over time. Figure 9 illustrates the resulting time trend of aggregate markdowns, $\mathcal{V}_{t}$, for workers performing different tasks. Markdown for routine task-performing workers has been decreasing since $1998^{25}$ (panel (a)), which is strongly consistent with Bachmann et al. (2022) who show that yearly labor supply elasticity, proportional to the inverse of markdown, has been increasing for workers with mean routine task intensity (RTI). In contrast, labor market power for nonroutine cognitive and nonroutine manual workers is generally upward-sloping from 1998-2018. Note that robot penetration has been continuously increasing during this period. So automation threats might be more prevalent for workers less or not displaceable by current industrial robots as markdowns for NRC and NRM workers have been increasing along with robot penetration.

Figure 10 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 performing various tasks. Specifically, employers' labor market power for low-skilled or low-educated workers has been relatively stable but generally on a downward-sloping pattern. On the contrary, the markdown for high-skilled or high-educated workers is upward-sloped between 1998-2018.

### 7.3 Heterogeneous Effects of Automation

The causal effects of robot exposure on markdown for heterogeneous workers will be estimated generally using equation (22), and I will include the estimation results in the next iteration.

## 8 Discussion

There is growing evidence that the labor market is not perfectly competitive. In this paper, I document that workers earn 75 cents on each marginal euro generated in an average German manufacturing firm. But what gives employers such monopsony power in the labor market? To answer this question, I provide theoretical and empirical evidence on automation or automation threats as a source of labor market power. Using administrative data from Germany, I show that automation

[^11]increases the estimated markdowns for German manufacturers at the local labor market level. This result is consistent with predictions from my model about the effect of labor-saving technologies or robot adoption on markdowns. I also find that monopsony power is highly heterogeneous for workers who perform different job tasks.

This evidence has two critical implications for understanding wage-setting in the labor markets. First, it shows that labor-saving technologies play a significant role in pay-setting. Second, worker's mobility and skill sets also play a substantial role in wage negotiation, given that less mobile workers who perform nonroutine cognitive tasks and low-skilled and nonroutine manual task-performing workers are subject to higher markdowns.

This paper made notable contributions to several strands of literature, and the primary contributions are in monopsony literature. First, my model serves as an alternative framework that incorporates some micro facts of robot adoption to understand the role of robot adoption in wage-setting. Second, this is the first study to provide a causal interpretation of the effects of automation on labor market power. Third, I document the relationship between the task content of jobs and labor market power and examine the causal effects of automation on labor market power for heterogeneous workers performing routine, nonroutine manual, and nonroutine cognitive tasks.

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## Figures

Figure 1: Robot Penetration, 1994-2018


Notes: The figure shows the penetration of robots for selected countries including Germany from 1994-2018 using data on robot stock from the IFR. Europe includes Germany, Finland, 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) obtained from OECD.Stat, except for Germany for which the employment data come from the Establishment History Panel (BHP) data. Only total employment was available for South Korea, so I imputed the dependent employment for South Korea using dependent employment-to-total employment ratio from European countries. Source: IFR, OECD, BHP or BEH, and own calculations.

Figure 2: Robot Adopters by Industry


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

Figure 3: Distribution of Robots (2018, robot adopting plants)


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

Figure 4: A Basic Model of Monopsony


Figure 5: Time Evolution of the Aggregate Markdown, 1994-2018


Notes: Markdowns are constructed using the IAB Establishment Panel (IAB BP) data from 1994-2018 under the assumption of translog production and aggregated according to expressions (15) and (17). The employment share of labor market $\omega_{k l t}$ is based on total number of employees.

Figure 6: Aggregate Markdowns and Local Concentration, 1994-2018


Notes: Based on the IAB Establishment Panel (IAB BP). The solid black line shows the time trend of the aggregate markdown as in equation (17), and the dashed red line shows the time trend of employment-based labor market concentration as in equation (21). The aggregate markdown and local concentration index are normalized relative to their initial value in 1994.

Figure 7: Distributions of Wage Markdowns for NRC, Routine, NRM Workers, 1996-2018


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/IAB and BIBB/BAuA Employment Surveys. The figure depicts the markdown distributions for NRC, routine, and NRM in a given year over the period 1996-2018. NRC, nonroutine cognitive; NRM, nonroutine manual.

Figure 8: Distributions of Wage Markdowns for Workers with Different Skills, 1996-2018













$$
\text { Skilled workers } \quad--- \text { Unskilled workers }
$$

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 1996-2018.

Figure 9: Time Evolution of the Aggregate Markdowns for Workers Performing Different Tasks, 1998-2018


Notes: The figure depicts the time evolution of aggregate markdowns for routine (panel (a)), nonroutine cognitive (panel (b)), and nonroutine manual (panel (c)) workers between 1998 and 2018. Plant-level markdowns are constructed using the IAB Establishment Panel and matched employer-employee (LIAB) data under the assumption of translog production and aggregated according to expressions (15) and (17). The employment share of labor market $\omega_{k l t}$ is based on the total number of employees. The classification of routine, nonroutine cognitive, and nonroutine manual task-performing workers is based on the BIBB/IAB and BIBB/BAuA Employment Surveys.

Figure 10: Time Evolution of the Aggregate Markdowns for Workers with Different Skills, 1998-2018


Notes: The figure plots the time evolution of aggregate markdowns for low-skilled (no vocational training) and highskilled (with at least vocational training) workers between 1998 and 2018. Plant-level markdowns are constructed using the IAB Establishment Panel and matched employer-employee (LIAB) data under the assumption of translog production and aggregated according to expressions (15) and (17). The employment share of labor market $\omega_{k l t}$ is based on the total number of employees.

## Tables

Table 1: 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 (IAB BP) 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 both adopters and non-adopters.

Table 2: Relationship between Robot Adoption and Plant Size

|  | Dependent variable: Log(Employment) |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) | (3) | (4) | (5) |
|  | Panel A. Extensive margin |  |  |  |  |
| Robot use dummy | $\begin{aligned} & 1.647 * * * \\ & (0.081) \end{aligned}$ | $\begin{aligned} & 1.372 * * * \\ & (0.081) \end{aligned}$ | $\begin{aligned} & 1.229^{* * *} \\ & (0.083) \end{aligned}$ | $\begin{aligned} & 1.187 * * * \\ & (0.087) \end{aligned}$ | $\begin{aligned} & 1.200^{* * *} \\ & (0.100) \end{aligned}$ |
| Observations <br> Adjusted $R^{2}$ | $\begin{gathered} 2171 \\ 0.12 \end{gathered}$ | $\begin{aligned} & 1481 \\ & 0.21 \end{aligned}$ | $\begin{aligned} & 1481 \\ & 0.30 \end{aligned}$ | $\begin{aligned} & 1475 \\ & 0.32 \end{aligned}$ | $\begin{aligned} & 1381 \\ & 0.34 \end{aligned}$ |
|  | Panel B. Intensive margin |  |  |  |  |
| Log(Robots) | $\begin{aligned} & 0.305 * * * \\ & (0.058) \end{aligned}$ | $\begin{aligned} & 0.215 * * * \\ & (0.060) \end{aligned}$ | $\begin{aligned} & 0.175 * * * \\ & (0.063) \end{aligned}$ | $\begin{aligned} & 0.194 * * * \\ & (0.067) \end{aligned}$ | $\begin{gathered} 0.265^{* *} \\ (0.116) \end{gathered}$ |
| Observations | 280 | 235 | 233 | 209 | 121 |
| Adjusted $R^{2}$ | 0.07 | 0.16 | 0.19 | 0.23 | 0.18 |
| State FE |  | $\checkmark$ | $\checkmark$ | $\checkmark$ |  |
| Industry FE (2-digit) |  |  | $\checkmark$ |  |  |
| Industry FE (3-digit) |  |  |  | $\checkmark$ | $\checkmark$ |
| District FE |  |  |  |  | $\checkmark$ |

Notes: Based on the IAB Establishment Panel (IAB BP) data. The table reports the coefficient estimates on the dummy variable of robot use (top panel) and the number of robots (in log, bottom panel) used by manufacturing plants in 2018. Sampling weights provided in the data are not applied. The dependent variable is the the number of total employees at the firm (in log). Robust standard errors are reported in parentheses. Significance: ${ }^{*} p<0.10,{ }^{* *} p<0.05$, and *** $p<0.01$.

Table 3: Summary Statistics

|  | Mean | SD | Min | Max | Obs. |
| :--- | ---: | ---: | ---: | ---: | ---: |
| Log TFPR | 0.015 | 0.289 | -1.218 | 1.327 | 13007 |
| Log revenue | 7.552 | 1.663 | 3.578 | 14.243 | 13187 |
| Log output | 7.660 | 1.653 | 3.788 | 14.674 | 13187 |
| Log capital | 7.114 | 1.686 | 2.934 | 14.403 | 13187 |
| Log labor | 3.103 | 1.241 | 0.693 | 8.596 | 13187 |
| Log material inputs | 6.848 | 1.796 | 2.945 | 13.915 | 13187 |
| Material cost (\% revenue) | 0.485 | 0.190 | 0.020 | 0.990 | 13187 |
| Labor cost (\% revenue) | 0.270 | 0.130 | 0.015 | 1.000 | 13187 |
| Daily wage ( $€$ ) | 7.854 | 41.839 | 1.005 | 722.534 | 10252 |
| Firm’s robot adoption status (dummy, \% firms) | 0.084 | 0.278 | 0 | 1 | 1289 |
| Number of robots at the firm | 0.487 | 3.717 | 0 | 100 | 1289 |

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, average daily wage paid to a worker, and robot adoption. Variables cover the period 1994-2018 and come from the IAB Establishment Panel (IAB BP) except for the daily wage, which come from the matched employer-employee (LIAB) data. The unit of observation is the firm, and sampling weights are applied.

Table 4: Estimated Plant-level Markdowns in German Manufacturing

| Industry group | Median | Mean | $\mathrm{IQR}_{75-25}$ | SD |
| :--- | :---: | :---: | :---: | :---: |
| Wearing apparel | 2.131 | 2.144 | 0.716 | 0.670 |
| Leather and related products | 1.950 | 1.834 | 1.027 | 0.614 |
| Beverages | 1.644 | 1.535 | 0.757 | 0.578 |
| Other transport equipment | 1.397 | 1.409 | 0.928 | 0.597 |
| Chemicals and chemical products | 1.387 | 1.559 | 0.926 | 0.679 |
| Rubber and plastics | 1.370 | 1.490 | 0.696 | 0.561 |
| Furniture | 1.367 | 1.567 | 0.677 | 0.670 |
| Other non-metallic minerals | 1.323 | 1.429 | 0.686 | 0.610 |
| Wood and wood products (excl. furniture) | 1.322 | 1.589 | 0.847 | 0.701 |
| Paper and paper products | 1.278 | 1.350 | 0.411 | 0.382 |
| Basic pharmaceutical products | 1.266 | 1.334 | 0.705 | 0.580 |
| Textiles | 1.260 | 1.520 | 1.073 | 0.816 |
| Food products | 1.217 | 1.350 | 0.725 | 0.599 |
| Repair and installation of machinery and equipment | 1.175 | 1.376 | 0.756 | 0.623 |
| Motor vehicles, trailers, and semi-trailers | 1.153 | 1.251 | 0.580 | 0.503 |
| Fabricated metals, excl. machinery and equipment | 1.141 | 1.286 | 0.674 | 0.565 |
| Basic metals | 1.136 | 1.297 | 0.730 | 0.533 |
| Machinery and equipment | 1.103 | 1.268 | 0.501 | 0.581 |
| Electrical equipment | 1.091 | 1.140 | 0.457 | 0.391 |
| Computer, electronic, and optical products | 1.003 | 1.139 | 0.554 | 0.505 |
| Other manufacturing | 0.990 | 1.078 | 0.514 | 0.431 |
| Printing and reproduction of recorded media | 0.895 | 1.032 | 0.482 | 0.468 |
| Whole sample | $\mathbf{1 . 1 7 9}$ | $\mathbf{1 . 3 3 3}$ | $\mathbf{0 . 7 0 8}$ | $\mathbf{0 . 6 0 4}$ |
| Sample size | 13,175 |  |  |  |

Notes: Markdowns are estimated using the IAB Establishment Panel (IAB BP) from 1994-2018 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 5: Summary Statistics for Labor Market Concentration - All Industries - 2018
(for different market definitions)

|  | Mean | Min | Max | $\begin{aligned} & \text { 25th } \\ & \text { Pctile } \end{aligned}$ | 75th <br> Pctile | fraction moderately concentrated | fraction highly concentrated |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Panel A. By Occupation $\times$ Region |  |  |  |  |  |  |
| Baseline geographical definition: 141 CZs |  |  |  |  |  |  |  |
| 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 $\times$ 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 labor market Herfindahl-Hirschman Index (HHI) under various market definitions, for the year 2018 using German matched employer-employee (longitudinal 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 total of 42 regions in Germany.

Table 6: Summary Statistics for Labor Market Concentration - Manufacturing - 2018 (for different market definitions)

|  | Mean | Min | Max | $\begin{gathered} \text { 25th } \\ \text { Pctile } \end{gathered}$ | 75th <br> Pctile | fraction moderately concentrated | fraction highly concentrated |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Panel A. By Occupation $\times$ Region |  |  |  |  |  |  |
| Baseline geographical definition: 141 CZs |  |  |  |  |  |  |  |
| 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 $\times$ 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 labor market Herfindahl-Hirschman Index (HHI) for manufacturing sector under various market definitions, for the year 2018 using German matched employer-employee (longitudinal 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 total of 42 regions in Germany.

Table 7: Labor Market-Level Effect of Robots on Markdowns: Long Difference

|  | Dependent variable: <br> Change in aggregate markdowns, 1996-2018 |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
|  | (1) | (2) | (3) | (4) |
|  | Panel A. OLS |  |  |  |
| Exposure to robots | $\begin{gathered} 0.0024^{*} \\ (0.0013) \\ {[0.0018]} \end{gathered}$ |  |  |  |
| $R^{2}$ | 0.060 | 0.117 | 0.140 | 0.143 |
|  | Panel B. 2SLS |  |  |  |
| Exposure to robots | $\begin{aligned} & 0.0039 * *[* *] \\ & (0.0019) \\ & {[0.0018]} \end{aligned}$ | $\begin{aligned} & 0.0050 * *[* *] \\ & (0.0023) \\ & {[0.0021]} \end{aligned}$ | $\begin{aligned} & 0.0046^{* *[* *]} \\ & (0.0020) \\ & {[0.0018]} \end{aligned}$ | $\begin{aligned} & 0.0045^{* *[* *]} \\ & (0.0020) \\ & {[0.0018]} \end{aligned}$ |
| First-stage $F$-stat on IVs | 297.327 | 433.903 | 413.489 | 389.774 |
| Hansen's $J$-stat $p$-value | 0.664 | 0.446 | 0.502 | 0.526 |
| $R^{2}$ | 0.055 | 0.110 | 0.133 | 0.137 |
| Broad region dummies | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |
| Demographics | $\checkmark$ | $\checkmark$ | $\checkmark$ | $\checkmark$ |
| Manufacturing share | $\checkmark$ |  |  |  |
| Broad industry shares |  | $\checkmark$ | $\checkmark$ | $\checkmark$ |
| Exposure to net exports |  |  | $\checkmark$ | $\checkmark$ |
| Exposure to ICT equipment |  |  |  | $\checkmark$ |

Notes: $N=212$ local labor market regions (Landkreise und kreisfreie Staedte). Panel A presents the OLS results from estimating the long difference in aggregate markdowns on the long difference in predicted robot exposure per 1000 workers between 1996 and 2018. Panel B reports results from the 2SLS IV regressions where German robot exposure is instrumented with robot installations across industries in other high-income countries. All specifications control for constant, broad region dummies and demographic characteristics of kreise or counties in the pre-shock period. The broad region dummies indicate if the region is located in the north, west, south, or east of Germany. The demographic controls constructed using the IAB Establishment Panel and the matched data include the share of females; the share of foreigners; the share of workers over 50 years old; and the shares of workers with no vocational training, vocational training, and university degree, measured in the base year 1996. Employment shares across industries are based on BHP and BeH data and measured in 1994. 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 long difference in German net exports vis-à-vis China and 21 Eastern European countries (in 1000 euros per worker) and by the long difference in German ICT equipment (in euros per worker), respectively, between 1996 and 2018. Standard errors clustered at the level of 40 aggregate labor market regions are in parentheses. Shift-share standard errors and statistical significance stars based on them are in brackets. Significance: $* p<0.10, * * p<0.05$, and $* * * p<0.01$.

Table 8: Summary Statistics (NRC, Routine, NRM Workers)

|  | NRC |  |  | Routine |  |  | NRM |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Mean | SD | N | Mean | SD | N | Mean | SD | N |
| Log labor | 2.381 | 1.540 | 7509 | 2.847 | 1.403 | 7331 | 2.535 | 1.579 | 5782 |
| Labor cost (\% revenue) | 0.070 | 0.097 | 10168 | 0.104 | 0.115 | 10168 | 0.088 | 0.137 | 10168 |
| Daily wage (€) | 91.923 | 58.648 | 7498 | 73.180 | 36.563 | 7325 | 67.223 | 39.545 | 5776 |

Notes: The table summarizes the employment, wagebill, and daily wages for workers performing different tasks over the period 1994-2018. The classification of workers is based on task intensity measures constructed using the BIBB/IAB (1991-1992 and 1998-1999) and BIBB/BAuA Employment surveys (2006, 2012, and 2018). Employment and wagebill information come from the IAB Establishment Panel (IAB BP) while daily wage comes from the matched employeremployee (LIAB) data. The unit of observation is the firm, and sampling weights are applied. NRC, nonroutine cognitive; NRM, nonroutine manual.

Table 9: Summary Statistics (High-skilled and Low-skilled Workers)

|  | High-skilled |  |  | Low-skilled |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Mean | SD | N | Mean | SD | N |
| Log labor | 3.247 | 1.36 | 9837 | 2.013 | 1.501 | 6345 |
| Labor cost (\% revenue) | 0.23 | 0.131 | 10243 | 0.032 | 0.073 | 10243 |
| Daily wage ( $€$ ) | 79.522 | 43.428 | 9826 | 45.024 | 32.069 | 6336 |

Notes: The table summarizes the employment, wage bill, and daily wages for workers with different skills over the period 1994-2018. High-skilled workers are those with vocational training and university degrees, whereas low-skilled workers are those without vocational training. Employment and wage bill information come from the IAB Establishment Panel (IAB BP) while daily wage comes from the matched employer-employee (LIAB) data. The unit of observation is the firm, and sampling weights are applied.

Table 10: Estimated Plant-level Markdowns for Heterogeneous Workers in German
Manufacturing

|  | Median | Mean | $\mathrm{IQR}_{75-25}$ | SD | N |
| :---: | :---: | :---: | :---: | :---: | :---: |
|  | Panel A. NRC, Routine, and NRM workers |  |  |  |  |
| Routine workers | 1.054 | 1.472 | 1.204 | 1.189 | 2029 |
| Non-routine cognitive (NRC) workers | 1.633 | 1.811 | 0.940 | 0.920 | 2029 |
| Non-routine manual (NRM) workers | 1.508 | 2.448 | 1.791 | 2.810 | 2029 |
|  | Panel B. High-skilled and Low-skilled workers |  |  |  |  |
| High-skilled workers | 1.088 | 1.242 | 0.628 | 0.573 | 4290 |
| Low-skilled workers | 1.565 | 2.074 | 1.627 | 1.816 | 4290 |

Notes: Markdowns are estimated using the IAB Establishment Panel (IAB BP) and the linked employer-employee (LIAB) data 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 top panel, I group workers based on task intensity measures constructed using the BIBB/IAB and BIBB/BAuA Employment Surveys. The distributional statistics are calculated using sampling weights provided in the data.

Table 11: Difference between Markdown for Workers Performing Different Tasks Explained by Observables and Job Tasks

|  | NRC, Routine, and NRM |  |  |
| :--- | :---: | :---: | :---: |
|  | NRM(1) - NRC(2) <br> gap in explanatory <br> variables | NRM(1) - Routine(2) <br> gap in explanatory <br> variables | NRC(1) - Routine(2) <br> gap in explanatory <br> variables |
| Group 1 | $1.6842(0.0478)$ | $1.6842(0.0478)$ | $1.6944(0.0182)$ |
| Group 2 | $1.6944(0.0182)$ | $1.5840(0.0244)$ | $1.5840(0.0244)$ |
| Difference $(1-2)$ | $-0.0103(0.0512)$ | $0.1002(0.0537)$ | $0.1104(0.0305)$ |
| Endowments | $0.0331(0.0353)$ | $0.0158(0.0107)$ | $0.0803(0.0445)$ |
| Coefficients | $0.3736(0.1181)$ | $0.0889(0.0532)$ | $0.1501(0.0415)$ |
| Interaction | $-0.4170(0.1147)$ | $-0.0045(0.0226)$ | $-0.1200(0.0533)$ |

Notes: The table presents results from the Blinder-Oaxaca decomposition of wage markdowns for heterogeneous workers performing different job tasks over the 1994-2018. 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 degree). The standard errors are in parentheses. NRC, nonroutine cognitive; NRM, nonroutine manual.

Table 12: Difference between Markdown for High-skilled and Low-skilled Workers Explained by Observables and Skills

| Variables | Low-skilled workers' wage markdown equation; <br> Low-skilled - High-skilled gap in explanatory variables |
| :--- | :---: |
| Low-skilled workers | $2.6921(0.0336)$ |
| High-skilled workers | $1.0922(0.0065)$ |
| Difference (Low-skilled - High-skilled) | $1.6000(0.0342)$ |
| Endowments | $-0.1370(0.0133)$ |
| Coefficients | $1.0866(0.0609)$ |
| Interaction | $0.6504(0.0541)$ |

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 the 1994-2018. 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.

# Online Appendix (For Online Publication Only) 

## Automation and Labor Market Power

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## A Theory Appendix

## A. 1 Derivation of Proposition 1

Using the expression of share of wage bill in total revenue at the industry level, we obtain

$$
\begin{equation*}
\frac{1}{s_{L}}-1=\frac{\sum_{j} z_{j} x_{j}-w(l) l}{w(l) l}=\frac{\sum_{j}\left(z_{j}-w(l)\right) l_{j}}{w(l) l} . \tag{A.1}
\end{equation*}
$$

The wage markdown in equation (3) can be rewritten as

$$
\frac{z_{j}-w(l)}{w(l)} \frac{l_{j}}{l}=\varepsilon_{w}\left(\frac{l_{j}}{l}\right)^{2}
$$

Taking the sum of above expression over firms in the industry, we get

$$
\begin{equation*}
\frac{\sum_{j}\left(z_{j}-w(l)\right) l_{j}}{w(l) l}=\varepsilon_{w} \sum_{j}\left(\frac{l_{j}}{l}\right)^{2} . \tag{A.2}
\end{equation*}
$$

Plugging (A.1) and expression of HHI into (A.2) yields

$$
H H I_{l}=\frac{1}{\varepsilon_{w}}\left(\frac{1}{s_{L}}-1\right) .
$$

## A. 2 Derivation of Proposition 2

By rearranging the terms, simply rewrite the expression of $z^{\theta}$ as

$$
z^{\theta}=\sum_{j=1}^{M_{1}} \frac{z_{j}}{1-\theta}+\sum_{j=M_{1}+1}^{M_{2}} \frac{z_{j}}{1-r_{i} \theta}+\sum_{j=M_{2}+1}^{M} z_{j},
$$

and substituting $z_{j}$ expressions from the first order conditions in (6)-(8) into above, we obtain

$$
z^{\theta}=(\alpha+\beta l) M+\beta l .
$$

By rearranging the term of this expression, we obtain the equilibrium employment as

$$
l^{*}=\frac{m}{\beta}\left(z^{\theta}-\alpha(1 / m-1)\right)
$$

where $m=1 /(M+1)$.
The equilibrium wage follows as

$$
w\left(l^{*}\right)=\alpha+\beta l^{*}=m\left(\alpha+z^{\theta}\right) .
$$

## A. 3 Derivation of Proposition 3

Substituting the industry-level equilibrium employment shown in Proposition 2 into first order conditions in (6)-(8), the equilibrium employment in individual firm $j$ that adopts single and multiple robots is defined respectively as

$$
\begin{equation*}
l_{j}^{*}=\frac{1}{\beta}\left(z_{j} /(1-\theta)-m z^{\theta}-\alpha m\right), \quad j=1, \ldots, M_{1} \tag{A.3}
\end{equation*}
$$

and

$$
\begin{equation*}
l_{j}^{*}=\frac{1}{\beta}\left(z_{j} /\left(1-r_{j} \theta\right)-m z^{\theta}-\alpha m\right), \quad j=M_{1}+1, \ldots, M_{2} . \tag{A.4}
\end{equation*}
$$

The equilibrium employment in labor-only firms, on the other hand, is

$$
\begin{equation*}
l_{j}^{*}=\frac{1}{\beta}\left(z_{j}-m z^{\theta}-\alpha m\right), \quad j=M_{2}+1, \ldots, M \tag{A.5}
\end{equation*}
$$

From (A.5) above, result (i) in Proposition 3 is immediate, i.e., $\partial l_{j}^{*} / \partial z^{\theta}=-m / \beta<0$ for laboronly employers.

To show result (ii), we need to find equilibrium employment for individual employers when no firms automate. The profit maximization problem when no firms automate is

$$
\max _{x_{j}} z_{j} x_{j}-w(l) x_{j}-f,
$$

and the first order condition implies

$$
\begin{equation*}
z_{j}=\alpha+\beta l_{j}+\beta l \tag{A.6}
\end{equation*}
$$

Denote $\bar{z}=\sum_{j=1}^{M} z_{j} / M$ and $z=M \bar{z}$. Using these, we find

$$
z=\sum_{j=1}^{M} z_{j}=(\alpha+\beta l) M+\beta l
$$

and further derive the equilibrium industry-level employment as

$$
l^{*}=\frac{m}{\beta}(z-\alpha(1 / m-1)) .
$$

By substituting this into the first order condition in (A.6) and rearranging the terms, the equilibrium employment for individual employers when no firms automate is defined as

$$
l_{j}^{*}=\frac{1}{\beta}\left(z_{j}-m z-\alpha m\right)
$$

Now we write employment in single-robot adopting firms to be higher than when no firms are automated as follows to find necessary and sufficient condition of such situation:

$$
\frac{1}{\beta}\left(z_{j} /(1-\theta)-m z^{\theta}-\alpha m\right)>\frac{1}{\beta}\left(z_{j}-m z-\alpha m\right),
$$

which further reduces into

$$
\frac{\theta}{(1-\theta)} z_{j}>m\left(z^{\theta}-z\right)
$$

Breaking down and then rearranging the terms we can finally reach the following expression:

$$
z_{j}>(1-\theta) m_{1} \bar{z}_{1}+\frac{1-\theta}{\theta} m_{2}\left(\bar{z}_{2}-\bar{z}\right)
$$

where $m_{1}=M_{1} /(M+1)$, $m_{2}=\left(M_{2}-M_{1}\right) /(M+1)$, and $\bar{z}=\sum_{j}^{M} z_{j} / M=\sum_{j=M_{1}+1}^{M_{2}} z_{j} /\left(M_{2}-\right.$ $M_{1}$ ) by construction. Here $\bar{z}_{2}>\bar{z}$ by definition due to productivity-enhancing impact of automation, so every term on the right hand side is positive.

## A. 4 Derivation of Proposition 4

The result in Proposition 4.1 is straightforward because automation increases equilibrium wage with no impact on productivity of labor-only firms, leading to drop in equilibrium wage markdowns in such firms.

To show result in Proposition 4.2, note that the equilibrium markdown increases with automa-
tion if and only if

$$
\frac{z_{j} /(1-\theta)-w\left(l^{1}\right)}{w\left(l^{1}\right)}>\frac{z_{j}-w\left(l^{0}\right)}{w\left(l^{0}\right)} \quad \text { and } \quad \frac{z_{j} /\left(1-r_{j} \theta\right)-w\left(l^{R}\right)}{w\left(l^{R}\right)}>\frac{z_{j}-w\left(l^{0}\right)}{w\left(l^{0}\right)}
$$

where $l^{0}$ is the equilibrium employment when no firms automate, $l^{1}$ is the equilibrium employment when some firms adopt single robot and others do not automate, and $l^{R}$ is the equilibrium employment when some firms adopt multiple robots, some adopt single robot, and others do not automate. Above inequalities require, respectively

$$
\begin{equation*}
\frac{1}{1-\theta}>\frac{w\left(l^{1}\right)}{w\left(l^{0}\right)} \Leftrightarrow \alpha+\sum_{j=1}^{M} z_{j}>\alpha(1-\theta)+\sum_{j=1}^{M_{1}} z_{j}+\sum_{j=M_{1}+1}^{M}(1-\theta) z_{j}, \tag{A.7}
\end{equation*}
$$

and

$$
\begin{align*}
& \frac{1}{1-r_{j} \theta}>\frac{w\left(l^{R}\right)}{w\left(l^{0}\right)} \Leftrightarrow \\
& \alpha+\sum_{j=1}^{M} z_{j}>\alpha\left(1-r_{j} \theta\right)+\sum_{j=1}^{M_{1}}\left(\frac{1-r_{j} \theta}{1-\theta}\right) z_{j}+\sum_{j=M_{1}+1}^{M_{2}} z_{j}+\sum_{j=M_{2}+1}^{M}\left(1-r_{j} \theta\right) z_{j}, \tag{A.8}
\end{align*}
$$

to be satisfied.
I first examine the relationship in (A.7). It is easy to show that the equilibrium wage when no firms automate $\left(w\left(l^{0}\right)\right)$ and when some firms adopt only single machine and others do not automate $\left(w\left(l^{1}\right)\right)$ as below by solving the profit maximization problem in the two regimes:

$$
w\left(l^{0}\right)=m(\alpha+z), \quad w\left(l^{1}\right)=m\left(\alpha+z_{1}^{\theta}\right),
$$

where

$$
z=\sum_{j=1}^{M} z_{j}, z_{1}^{\theta}=M_{1} \bar{z}_{1}+\left(M-M_{1}\right) \bar{z}_{2}, \bar{z}_{1}=\sum_{j=1}^{M_{1}} \frac{z_{j}}{(1-\theta) M_{1}}, \bar{z}_{2}=\sum_{j=M_{1}+1}^{M} \frac{z_{j}}{M-M_{1}},
$$

where $M_{1}$ is the list of firms that adopt single machine, and $M-M_{1}$ is the list of non-automation firms. Using the expressions of equilibrium wages in the two regimes above, we can easily find result in (A.7). If we further terminate the sum and rearrange the terms, the following inequality is immediate

$$
\sum_{j=M_{1}+1}^{M} z_{j}>-\alpha
$$

which is always true. So the equilibrium markdown in an industry with single-robot and labor-only firms is always greater than that in an industry with no robot-adopting firms.

Now I turn to the relationship in (A.9). Similarly solving the profit maximization problem under two regimes: (i) no firms automate, and (ii) some firms adopt single machine, some adopt multiple machines, and others do not automate, provides the following equilibrium wages under the two regimes, respectively,

$$
w\left(l^{0}\right)=m(\alpha+z), \quad w\left(l^{R}\right)=m\left(\alpha+z_{R}^{\theta}\right)
$$

where $z_{R}^{\theta} \equiv z^{\theta}$ as in (9), and other expressions are same as above. Again, using these equilibrium wage equations, the result in (A.9) is immediate. Rearranging the terms yield the following inequality:

$$
\sum_{j=1}^{M_{1}}\left(\frac{1-1 / r_{j}}{1-\theta}\right) z_{j}-\sum_{j=M_{2}+1}^{M} z_{j}>-\alpha
$$

which is also always true for $r_{j}>1, \theta>0$, and $\alpha>0$.
Finally, I will derive the result in Proposition 4.3. The equilibrium markdown in multiple-robot firms $\left(\sigma_{i}^{R}\right)$ is greater than that in single-robot firms $\left(\sigma_{i}^{1}\right)$ if and only if

$$
\frac{z_{j} /\left(1-r_{j} \theta\right)-w\left(l^{R}\right)}{w\left(l^{R}\right)}>\frac{z_{j} /(1-\theta)-w\left(l^{1}\right)}{w\left(l^{1}\right)}
$$

which would further require

$$
\begin{align*}
& \frac{1-\theta}{1-r_{j} \theta}>\frac{w\left(l^{R}\right)}{w\left(l^{1}\right)} \Leftrightarrow \\
& -\theta \alpha+\sum_{j=1}^{M_{1}} z_{j}+\sum_{j=M_{1}+1}^{M}(1-\theta) z_{j}>-\alpha r_{j} \theta+\sum_{j=1}^{M_{1}}\left(\frac{1-r_{j} \theta}{1-\theta}\right)+\sum_{j=M_{1}+1}^{M_{2}} z_{j}+\sum_{j=M_{2}+1}^{M}\left(1-r_{j} \theta\right) z_{j} \tag{A.9}
\end{align*}
$$

to hold. Rearranging the terms show that multiple-robot firms have greater equilibrium markdown than single-robot firms if

$$
\sum_{j=1}^{M_{1}} \frac{z_{j}}{1-\theta}-\sum_{j=M_{1}+1}^{M_{2}} \frac{z_{j}}{r_{j}-1}+\sum_{j=M_{2}+1}^{M} z_{j}+\alpha>0
$$

It is easy to see that above inequality tends to always hold as robot adoption intensifies or $r_{i}>1$ increases.

## A. 5 Extension: Endogenous Exit-Entry and Endogenous Automation

Consider that firms can exit the market endogenously following the automation shock, and the subsequent change in market structure affects the wage markdowns among surviving firms. Recall
that the equilibrium profits of labor-only firms is

$$
\pi_{j}^{0}=z_{j} l_{j}^{*}-w\left(l^{*}\right) l_{j}^{*}-f>(\leq) 0 \Leftrightarrow\left(\frac{l_{j}^{*}}{l^{*}}\right)^{2}>(\leq) \frac{1}{\varepsilon_{w}} \frac{f}{w\left(l^{*}\right) l^{*}}
$$

So the firms to exit the market first subsequent to automation shock are the least productive laboronly firms as they have the smallest labor shares. Highly productive automating firms operate in the market since they have large labor shares and large labor market power. A reduction in the number of firms operate in the industry due to automation shock attenuates the reduction in wage markdown among the labor-only firms with low productivity, but magnifies the rise in wage markdown among high productive firms.

Finally, suppose that automation decision is endogenous as opposed to exogenous automation shock in the benchmark model. Since profit of single robot-adopting firm is

$$
\pi_{j}^{1}=z_{j} l_{j} /(1-\theta)-w(l) l_{j}-\rho\left(r_{j}\right)-f
$$

the most productive firms among single-robot firms disproportionately benefit from automation through the productivity effect $1 /(1-\theta)$. Because high productive firms have higher labor share $l_{j} / l$ and thus higher wage markdown $\varepsilon_{w} l_{j} / l$, firms with high ex-ante wage markdowns are more likely to find automation more profitable among single-machine firms.

For multiple-robot firms, employer profit is

$$
\pi_{j}^{R}=z_{j} l_{j} /\left(1-r_{j} \theta\right)-w(l) l_{j}-\rho\left(r_{j}\right) r_{j}-f,
$$

and the derivative with respect to $r_{j}$ yields

$$
\theta z_{j} l_{j} /\left(1-r_{j} \theta\right)^{2}-\left(\eta_{j}+1\right) \rho\left(r_{j}\right),
$$

where $\eta_{j}=\rho^{\prime}\left(r_{j}\right) r_{j} / \rho\left(r_{j}\right)$ is the elasticity of robot adoption cost with respect to number of robots used at the firm, which is assumed to be constant. I assume that marginal cost of adopting an incremental robots decreases, i.e., $\rho^{\prime}\left(r_{j}\right)<0$, so that $\eta_{j}<0$. Similar to single-robot firms, the most productive firms among multiple-robot firms benefit from automation through productivity effect $1 /\left(1-r_{j} \theta\right)$, but how much those most productive firms benefit from automation depends on the elasticity $\eta_{j}$. To be specific, additional robot increases the profits of multiple-robot firms if $\eta_{j}<-1$, and decreases the profits if $-1 \geq \eta_{j}<0$.

## B Data Appendix

## B. 1 Imputations

This section 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.

## B.1.1 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. ${ }^{26}$ 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. ${ }^{27}$ 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 earlier 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. ${ }^{28}$

[^12]
## B.1.2 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 recorded as her wage, which differs by year and location. ${ }^{29}$ Although only about $5 \%$ of the observations are subject to 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 used 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.

## B.1.3 Imputation of Educational Attainments

I use the information on workers' educational attainment to impute the right-censored wages. But 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.

## C Overview of Monopsony Measures

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:

$$
\begin{equation*}
\varepsilon_{N w}=\varepsilon_{R w}-\varepsilon_{q w}, \tag{С.1}
\end{equation*}
$$

where $\varepsilon_{N w}$ is the wage elasticity of labor supply to the firm, $\varepsilon_{R w}$ is the wage elasticity of the share of recruits hired from employment, and $\varepsilon_{q w}$, 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 key role.

The classical monopsony in static settings has also been recently revived, and Card et al. (2018)

[^13]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:
\[

$$
\begin{equation*}
\frac{1}{\varepsilon_{j}}=\frac{1-s_{j}}{\varepsilon} \tag{C.2}
\end{equation*}
$$

\]

where $s_{j}$ is the market share of the firm, and $\varepsilon$ is the inverse of the elasticity of labor supply faced by the firm as the labor supply is given by $n_{j}=\varepsilon^{-1}\left(w_{j}-b_{j}\right)$ 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 5 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 (C.2). 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.

## D Details of Production Function Estimation

Recall that I estimate the following production function in the log form,

$$
\begin{equation*}
y_{j t}=f\left(\mathbf{v}_{j t}, \mathbf{k}_{j t} ; \boldsymbol{\beta}\right)+\omega_{j t}+\varepsilon_{j t}, \tag{D.1}
\end{equation*}
$$

where $\mathbf{v}_{j t}$ is the $\log$ of fully flexible inputs $\mathbf{V}_{j t}, \mathbf{k}_{j t}$ is the $\log$ of non-fully flexible or fixed inputs $\mathbf{K}_{j t}$, and $f\left(\mathbf{v}_{j t}, \mathbf{k}_{j t} ; \boldsymbol{\beta}\right)=\ln \left(F\left(\mathbf{V}_{j t}, \mathbf{K}_{j t} ; \boldsymbol{\beta}\right)\right)$.

Firm-specific productivity $\omega_{j t}$ 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 ${ }^{30} m_{j t}$ as a proxy for productivity, which is given by

$$
\begin{equation*}
m_{j t}=m_{t}\left(\omega_{j t} ; \mathbf{k}_{j t}, \mathbf{c}_{j t}\right) \tag{D.2}
\end{equation*}
$$

where $\mathbf{c}_{j t}$ 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 $\omega_{j t}{ }^{31}$, one can invert equation (D.2) and express the productivity as

$$
\begin{equation*}
\omega_{j t}=m_{t}^{-1}\left(m_{j t} ; \mathbf{k}_{j t}, \mathbf{c}_{j t}\right)=g_{t}\left(m_{j t} ; \mathbf{k}_{j t}, \mathbf{c}_{j t}\right) \tag{D.3}
\end{equation*}
$$

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

$$
\begin{align*}
y_{j t} & =f\left(\mathbf{v}_{j t}, \mathbf{k}_{j t} ; \boldsymbol{\beta}\right)+g_{t}\left(m_{j t} ; \mathbf{k}_{j t}, \mathbf{c}_{j t}\right)+\varepsilon_{j t} \\
& =\Phi_{t}\left(\mathbf{v}_{j t}, \mathbf{k}_{j t}, \mathbf{c}_{j t}\right)+\varepsilon_{j t}  \tag{D.4}\\
& =\phi_{j t}+\varepsilon_{j t} .
\end{align*}
$$

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 $\mathbf{v}_{j t}=m_{j t}, \mathbf{k}_{j t}=\left(k_{j t}, l_{j t}\right)^{\prime}$, and $\mathbf{c}_{j t}$ contains additional controls, the firm fixed effects and year fixed effects. Equation (D.4) is the first-stage estimation. The first stage is performed by OLS regression of $y_{j t}$ on third-degree polynomial in $\tilde{\mathbf{x}}_{j t}=\left(k_{j t}, l_{j t}, m_{j t}\right)^{\prime}$ with interaction terms and $\mathbf{c}_{j t}$ to obtain $\hat{\phi}_{j t}$. For translog production technology, we have

$$
\begin{equation*}
\mathbf{x}_{j t}=\left(k_{j t}, l_{j t}, m_{j t}, k_{j t} l_{j t}, k_{j t} m_{j t}, l_{j t} m_{j t}, k_{j t}^{2}, l_{j t}^{2}, m_{j t}^{2}\right)^{\prime} \tag{D.5}
\end{equation*}
$$

Similar to OP and LP models, the ACF model assumes that the firm's information set at $t, I_{j t}$, includes current and past productivity shocks $\left\{\omega_{j \tau}\right\}_{\tau=0}^{t}$ but does not include future productivity shocks $\left\{\omega_{j \tau}\right\}_{\tau=t+1}^{\infty}$. Hence, the transitory shocks $\varepsilon_{j t}$ satisfy $\mathbb{E}\left(\varepsilon_{j t} \mid I_{j t}\right)=0$. Under this assumption,

[^14]the first-stage moment condition is
\[

$$
\begin{equation*}
\mathbb{E}\left(\varepsilon_{j t} \mid I_{j t}\right)=\mathbb{E}\left[y_{j t}-\phi_{j t} \mid I_{j t}\right]=0 . \tag{D.6}
\end{equation*}
$$

\]

In the first stage of ACF, none of the parameters will be estimated, but it generates an estimate $\hat{\phi}_{j t}$ 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,

$$
\begin{equation*}
p\left(\omega_{i t+1} \mid I_{j t}\right)=p\left(\omega_{j t+1} \mid \omega_{j t}\right) \tag{D.7}
\end{equation*}
$$

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

$$
\begin{equation*}
\omega_{j t}=\mathbb{E}\left(\omega_{j t} \mid I_{j t-1}\right)+\xi_{j t}=\mathbb{E}\left(\omega_{j t} \mid \omega_{j t-1}\right)+\xi_{j t}=h\left(\omega_{j t-1}\right)+\xi_{j t}, \tag{D.8}
\end{equation*}
$$

where $\mathbb{E}\left(\xi_{j t} \mid I_{j t-1}\right)=0$. Substituting this into production function in (D.1), we get

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

where the second line follows from the definition of $\phi_{t-1}$.
Since $\mathbb{E}\left(\xi_{j t} \mid I_{j t-1}\right)=0$ and $\mathbb{E}\left(\varepsilon_{j t} \mid I_{j t}\right)=0$ (which also implies $\mathbb{E}\left(\varepsilon_{j t} \mid I_{j t-1}\right)=0$ ), the second stage of ACF estimation procedure uses the following moment condition:

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

where $\phi_{t-1}$ is replaced by its estimate from the first stage. Wooldridge (2009) pointed out that the functions $\phi_{t}$ 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

$$
\begin{equation*}
\omega_{j t}=s_{t}\left(\omega_{j t-1}\right)+\xi_{j t} \tag{D.11}
\end{equation*}
$$

Then I approximate the productivity in the data as

$$
\begin{equation*}
\omega_{j t}(\boldsymbol{\beta})=\hat{\phi}_{j t}-f\left(\mathbf{x}_{j t} ; \boldsymbol{\beta}\right) . \tag{D.12}
\end{equation*}
$$

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

$$
\begin{align*}
\omega_{j t}(\boldsymbol{\beta}) & =\Omega_{j t-1}(\boldsymbol{\beta})^{\prime} \rho(\boldsymbol{\beta})+\xi_{j t} \\
& =\sum_{p=0}^{\mathcal{P}} \rho_{p} \omega_{j t-1}^{p}(\boldsymbol{\beta})+\xi_{j t} . \tag{D.13}
\end{align*}
$$

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

$$
\begin{equation*}
\xi_{j t}=\omega_{j t}(\boldsymbol{\beta})-\Omega_{j t-1}(\boldsymbol{\beta})^{\prime} \hat{\rho}(\boldsymbol{\beta}), \tag{D.14}
\end{equation*}
$$

where $\hat{\rho}(\boldsymbol{\beta})=\left(\left\{\hat{\rho}_{p}\right\}_{p=1}^{\mathcal{P}}\right)^{\prime}$ is obtained by regressing $\Omega_{j t-1}(\boldsymbol{\beta})$ on $\omega_{j t}(\boldsymbol{\beta})$ 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 $\mathbf{z}_{j t} \in \mathbb{R}^{Z}$ as the vector that contains one-period lagged values of every polynomial term in $f\left(\mathbf{x}_{j t} ; \boldsymbol{\beta}\right)$ including $l_{j t}$ and $m_{j t}$ but capital at the current period $k_{j t}$. Thus, the system of second stage moment conditions for GMM estimation to identify $\boldsymbol{\beta} \in \mathbb{R}^{Z}$ is defined as

$$
\begin{equation*}
\mathbb{E}\left(\xi_{j t}(\boldsymbol{\beta}) \mathbf{z}_{j t}\right)=\mathbf{0}_{Z \times 1} \tag{D.15}
\end{equation*}
$$

Now I briefly discuss assumptions behind the moment conditions. First, labor input $l_{j t}$ 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, $l_{j t}$ 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. Assumption that labor is chosen after time $t-1$ implies that $l_{j t}$ is correlated with $\xi_{j t}$.

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

$$
\begin{equation*}
k_{j t}=\kappa\left(k_{j t-1}, i_{j t-1}\right), \tag{D.16}
\end{equation*}
$$

where investment $i_{j t-1}$ 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 $k_{j t-1}$ and $i_{j t-1}$. So it is safe to assume that $k_{j t}$ is orthogonal to $\xi_{j t}+\varepsilon_{j t}$. 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.

## E Additional Results on Markdowns

## E. 1 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. Appendix 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, 1994-2018


Notes: Markdowns are constructed using the IAB Establishment Panel (IAB BP) data from 1994-2018 under the assumption of Cobb-Douglas production and aggregated according to expression (15) and (17). The employment share of labor market $\omega_{k l t}$ is based on total number of employees.

## E. 2 Markups

Appendix Table E. 1 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 30 percent ( 24 percent) of market power at the plant-year level at the mean (median). In contrast to markdowns, variations of markups across and within industry groups are significantly smaller than variations of markdowns. The IQR and standard deviation of markups are 19.7 percent.

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 (13). 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).

Table E.1: Estimated Plant-level Markups in German Manufacturing

| Industry group | Median | Mean | $\mathrm{IQR}_{75}-25$ | SD |
| :--- | :---: | :---: | :---: | :---: |
| Wearing apparel | 1.403 | 1.427 | 0.276 | 0.235 |
| Leather and related products | 1.335 | 1.366 | 0.231 | 0.197 |
| Beverages | 1.331 | 1.434 | 0.316 | 0.348 |
| Other transport equipment | 1.316 | 1.391 | 0.298 | 0.238 |
| Chemicals and chemical products | 1.312 | 1.350 | 0.177 | 0.161 |
| Rubber and plastics | 1.301 | 1.339 | 0.287 | 0.221 |
| Furniture | 1.258 | 1.306 | 0.173 | 0.199 |
| Other non-metallic minerals | 1.223 | 1.231 | 0.101 | 0.075 |
| Wood and wood products (excl. furniture) | 1.221 | 1.235 | 0.160 | 0.131 |
| Paper and paper products | 1.221 | 1.264 | 0.156 | 0.141 |
| Basic pharmaceutical products | 1.217 | 1.332 | 0.216 | 0.265 |
| Textiles | 1.214 | 1.273 | 0.260 | 0.149 |
| Food products | 1.214 | 1.257 | 0.111 | 0.180 |
| Repair and installation of machinery and equipment | 1.212 | 1.260 | 0.151 | 0.168 |
| Motor vehicles, trailers, and semi-trailers | 1.206 | 1.252 | 0.053 | 0.127 |
| Fabricated metals, excl. machinery and equipment | 1.186 | 1.215 | 0.109 | 0.108 |
| Basic metals | 1.185 | 1.196 | 0.129 | 0.100 |
| Machinery and equipment | 1.176 | 1.209 | 0.108 | 0.118 |
| Electrical equipment | 1.166 | 1.182 | 0.035 | 0.069 |
| Computer, electronic, and optical products | 1.166 | 1.255 | 0.241 | 0.200 |
| Other manufacturing | 1.160 | 1.203 | 0.083 | 0.160 |
| Printing and reproduction of recorded media | 1.137 | 1.202 | 0.112 | 0.163 |
| Whole sample | $\mathbf{1 . 2 4 3}$ | $\mathbf{1 . 2 9 9}$ | $\mathbf{0 . 1 9 7}$ | $\mathbf{0 . 1 9 7}$ |
| Sample size | 13,175 |  |  |  |

Notes: Markups are estimated using the IAB Establishment Panel (IAB BP) data from 1994-2018 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.

Appendix Figure E. 2 presents the time series for the aggregate markup. The markup is aggregated at the market level according to equation (16). Then, we 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 biased.

This bias will not contaminate the markdowns. While we should take the markup estimates cautiously, a trend in aggregate markups could be informative. I find that the markup trend in German manufacturing is not monotonic. The markup sharply declined between 1994 and 1998. But it has been increasing since 1999. The markup level has not reached back its 1994 level yet by 2018.

Figure E.2: Time Evolution of Employment-Weighted Markups across German Manufacturing Plants from 1994 to 2018


Notes: Markups are constructed using the IAB Establishment Panel (IAB BP) data from 1994-2018 under the assumption of translog production and aggregated according to expressions (16) and (18). The employment share of labor market $\omega_{j l t}$ is based on total number of employees.

## E. 3 Cross-Sectional Correlation between Aggregate Markdown and Labor Market Concentration

Appendix Table E. 2 presents the cross-sectional correlation (across labor markets-a combination of 3-digit industries and federal states) between the aggregate markdown $\mathcal{V}_{k l t}$ and labor market concentration $\mathrm{HHI}_{k l t}$. 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 0.04 , which is close to zero (second column).

To check the robustness of my baseline employment HHI measure calculated using IAB BP data, I compute the same index according to equation (19) based on the matched data (LIAB). The cross-section correlation between the two HHIs is strong, positive, and statistically significant at
the $1 \%$ level most of the time (third column). Across years and on average, the correlation between aggregate markdown and LIAB-based HHI is mostly positive but sometimes statistically significant (fourth column).

Table E.2: Correlation between Employment HHIs and Aggregate Markdowns across Local Labor Markets

| Year | $\rho\left(\mathcal{V}_{j l t}, \mathrm{HHI}_{j l t}^{I A B-B P}\right)$ | $\rho\left(\mathrm{HHI}_{j l t}^{\text {IAB-BP }}, \mathrm{HHI}_{j l t}^{L I A B}\right)$ | $\rho\left(\mathcal{V}_{j l t}, \mathrm{HHI}_{j l t}^{L I A B}\right)$ |
| :---: | :---: | :---: | :---: |
| 1994 | 0.2391 | 0.3946 | -0.0756 |
| 1996 | -0.0162 | $0.1818^{* *}$ | 0.0212 |
| 1998 | $0.1797^{* * *}$ | $0.1436^{* *}$ | $0.1800^{* * *}$ |
| 2000 | 0.0573 | $0.1486^{* *}$ | $0.1019^{*}$ |
| 2002 | $0.0914^{*}$ | $0.2113^{* * *}$ | 0.0719 |
| 2004 | 0.0666 | $0.2029^{* * *}$ | $0.1131^{* *}$ |
| 2006 | 0.0338 | $0.2266^{* * *}$ | $0.1084^{* *}$ |
| 2008 | -0.0089 | $0.2412^{* * *}$ | $0.1189^{* *}$ |
| 2010 | -0.0147 | $0.3284^{* * *}$ | 0.0260 |
| 2012 | 0.0405 | $0.2669^{* * *}$ | $0.1555^{* * *}$ |
| 2014 | -0.0180 | $0.2230^{* * *}$ | 0.0308 |
| 2016 | -0.0063 | $0.1379^{* *}$ | 0.0501 |
| 2018 | 0.0349 | $0.2607^{* * *}$ | 0.1087 |
| Average | $\mathbf{0 . 0 3 8 8}$ *** | $\mathbf{0 . 2 1 6 0 * * *}$ | $\mathbf{0 . 0 8 9 1}$ |

Notes: Markdowns are estimated using the IAB Establishment Panel (IAB BP) data from 1994-2018 under the assumption of a translog specification for gross output. The cross-market correlations are calculated at the 3-digit ISIC-state level every other year. Aggregate markdowns are calculated according to equation (15) whereas labor market concentration $\mathrm{HHI}_{k l t}$ is calculated according to equation (19) using either IAB BP and matched employer-employee (LIAB) data, which are highlighted in the superscript. Significance: ${ }^{*} p<0.10, * * p<0.05$, and ${ }^{* * *} p<0.01$.

## F Robustness Checks

## F. 1 Robustness of Automation Effects on Markdown of Heterogeneous Workers Performing Different Tasks

## F.1.1 Classification of Workers

This appendix performs the robustness check of my results on the effects of automation on markdowns for heterogeneous workers performing different job tasks at their workplaces using an alternative measure of task intensity. In my baseline analysis, I define heterogeneous workers performing different tasks based on task intensity measures constructed using Germany's BIBB/IAB and BIBB/BAuA Employment Surveys and an approach by Antonczyk et al. (2009). But, in this appendix, I check the robustness of my results with heterogeneous workers performing different tasks to the
use of alternative task intensity measures proposed by Autor and Dorn (2013). ${ }^{32}$
Since Autor and Dorn (2013) create their measures of task content or task inputs for each occupation in the U.S. using $\mathrm{O}^{*}$ NET data, the values of the indices could be different from the values of indices constructed using the German dataset of BIBB/IAB and BIBB/BAuA Employment Surveys. However, it is reasonable to consider that these two different 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. ${ }^{33}$ After that, using crosswalks obtained from the Institute for Structural Research (IBS), ${ }^{34}$ 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). ${ }^{35}$ 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 $T_{o, 1980}^{A}, T_{o, 1980}^{R}$, and $T_{o, 1980}^{M}$, respectively, before merging with the matched data. But after matching these with the linked data (LIAB), I denote them as $T_{i j t}^{A}, T_{i j t}^{R}$, or $T_{i j t}^{M}$ 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 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 $T_{i j t}^{A}, T_{i j t}^{R}$, or $T_{i j t}^{M}$, respectively.

Appendix Table F. 1 summarizes the employment, wage bill, and daily wage for abstract, routine, and manual workers.

[^15]Table F.1: Summary Statistics (Abstract, Routine, and Manual Workers)

|  | Abstract |  |  | Routine |  |  | Manual |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Mean | SD | N | Mean | SD | N | Mean | SD | N |
| Log labor | 2.610 | 1.403 | 6923 | 2.873 | 1.461 | 8396 | 2.335 | 1.375 | 6653 |
| Labor cost (\% revenue) | 0.067 | 0.102 | 10002 | 0.126 | 0.122 | 10002 | 0.068 | 0.102 | 10002 |
| Daily wage ( $€$ ) | 116.015 | 70.590 | 6920 | 74.741 | 36.667 | 8387 | 66.442 | 45.058 | 6646 |

Notes: The table summarizes the employment, wagebill, and daily wages for abstract, routine, and manual workers over the period 1994-2018. The classification of workers is based on Autor and Dorn (2013)'s task content/inputs measures. Employment and wagebill information come from the IAB Establishment Panel (IAB BP) while daily wage comes from the matched employer-employee (LIAB) data. The unit of observation is the firm, and sampling weights are applied.

## F.1.2 Estimated Markdowns

Appendix Table F. 2 presents the estimated plant-level markdowns, which are strongly consistent with my baseline results. Specifically, routine workers are subject to the lowest monopsony power, while manual workers are subject to the highest labor market power on average.

Table F.2: Estimated Plant-level Markdowns for Workers Performing Different Job Tasks in German Manufacturing (based on Autor-Dorn measure)

|  | Median | Mean | $\mathrm{IQR}_{75-25}$ | SD | N |
| :--- | :---: | :---: | :---: | :---: | :---: |
| Routine workers | 1.015 | 1.121 | 0.630 | 0.526 | 3790 |
| Abstract workers | 1.129 | 1.386 | 0.990 | 0.922 | 3790 |
| Manual workers | 1.549 | 1.962 | 1.144 | 1.567 | 3790 |

Notes: Markdowns are estimated using the IAB Establishment Panel (IAB BP) and the linked employer-employee (LIAB) data 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 Appendix Figure F.1, is generally the same for nonroutine cognitive, routine, and nonroutine manual workers in the baseline analysis.

Appendix Table F. 3 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 shows that unobserved task differences explain a significant part of the overall differential between markdowns for workers performing different job tasks after accounting for worker's observable characteristics. Appendix Table G. 3 reports the detailed results from the Blinder-Oaxaca decomposition analysis.

Figure F.1: Distributions of Wage Markdowns for Abstract, Routine, Manual Workers, 1996-2018



2002



2008






$\square$

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 1996-2018.

Table F.3: Difference between Markdown for Workers Performing Different Tasks Explained by Observables and Job Tasks (Autor-Dorn)

|  | Abstract, routine, and manual workers |  |  |  |
| :--- | :---: | :---: | :---: | :---: |
|  | Manual(1)-Abstract(2) <br> gap in explanatory <br> variables | Manual(1)-Routine(2) <br> gap in explanatory <br> variables | Abstract(1) - Routine(2) <br> gap in explanatory <br> variables |  |
| Group 1 | $1.9210(0.0194)$ | $1.9210(0.0194)$ | $1.4287(0.0142)$ |  |
| Group 2 | $1.4287(0.0142)$ | $1.2661(0.0087)$ | $1.2661(0.0087)$ |  |
| Difference $(1-2)$ | $0.4923(0.0240)$ | $0.6550(0.0213)$ | $0.1626(0.0167)$ |  |
| Endowments | $-0.0206(0.0155)$ | $-0.0151(0.0062)$ | $-0.1368(0.0256)$ |  |
| Coefficients | $0.2292(0.0431)$ | $0.6329(0.0234)$ | $0.1414(0.0235)$ |  |
| Interaction | $0.2837(0.0404)$ | $0.0372(0.0152)$ | $0.1580(0.0305)$ |  |

Notes: The table presents results from the Blinder-Oaxaca decomposition of wage markdowns for heterogeneous workers performing different job tasks over the 1994-2018. 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 degree). The standard errors are in parentheses.

## G Additional Figures and Tables

Table G.1: Difference between Markdown for Workers Performing Different Tasks Explained by Observables and Job Tasks

|  | NRC, Routine, and NRM |  |  |
| :---: | :---: | :---: | :---: |
|  | NRM(1) - NRC(2) <br> gap in explanatory variables | NRM(1) - Routine(2) <br> gap in explanatory variables | NRC(1) - Routine(2) <br> gap in explanatory variables |
| Overall |  |  |  |
| Group 1 | 1.6842 (0.0478) | 1.6842 (0.0478) | 1.6944 (0.0182) |
| Group 2 | 1.6944 (0.0182) | 1.5840 (0.0244) | 1.5840 (0.0244) |
| Difference (1-2) | -0.0103 (0.0512) | 0.1002 (0.0537) | 0.1104 (0.0305) |
| Endowments | 0.0331 (0.0353) | 0.0158 (0.0107) | 0.0803 (0.0445) |
| Coefficients | 0.3736 (0.1181) | 0.0889 (0.0532) | 0.1501 (0.0415) |
| Interaction | -0.4170 (0.1147) | -0.0045 (0.0226) | -0.1200 (0.0533) |
| Endowments |  |  |  |
| Share of female workers | -0.0804 (0.0162) | -0.0007 (0.0012) | 0.0134 (0.0189) |
| Share of workers with vocational training | 0.0029 (0.0318) | -0.0031 (0.0039) | 0.0653 (0.0233) |
| Share of workers with university degree | 0.2109 (0.0539) | 0.0030 (0.0074) | -0.0204 (0.0509) |
| Share of immigrant workers | -0.0793 (0.0178) | -0.0057 (0.0036) | 0.0163 (0.0079) |
| Share of part-time workers | -0.0007 (0.0024) | 0.0081 (0.0056) | 0.0219 (0.0063) |
| Age | -0.0203 (0.0085) | 0.0143 (0.0059) | -0.0161 (0.0062) |
| Coefficients |  |  |  |
| Share of female workers | -0.1733 (0.0806) | -0.0185 (0.0462) | 0.0761 (0.0291) |
| Share of workers with vocational training | -0.5031 (0.2100) | -0.2368 (0.2316) | 0.3772 (0.2112) |
| Share of workers with university degree | 0.4997 (0.1449) | 0.0637 (0.0324) | -0.0461 (0.0196) |
| Share of immigrant workers | 0.0117 (0.0085) | -0.0283 (0.0217) | -0.0634 (0.0216) |
| Share of part-time workers | 0.2783 (0.0311) | 0.1470 (0.0243) | -0.0518 (0.0167) |
| Age | -1.4057 (0.3577) | -0.5175 (0.3668) | 0.8449 (0.2294) |
| Intercept | 1.6660 (0.3614) | 0.6792 (0.3545) | -0.9868 (0.2808) |
| Interaction |  |  |  |
| Share of female workers | 0.0825 (0.0386) | 0.0008 (0.0021) | 0.0633 (0.0243) |
| Share of workers with vocational training | -0.1162 (0.0490) | -0.0020 (0.0032) | -0.0681 (0.0383) |
| Share of workers with university degree | -0.4467 (0.1297) | -0.0330 (0.0173) | -0.1636 (0.0693) |
| Share of immigrant workers | 0.0317 (0.0233) | -0.0067 (0.0057) | 0.0423 (0.0147) |
| Share of part-time workers | -0.0500 (0.0194) | 0.0218 (0.0144) | -0.0207 (0.0073) |
| Age | 0.0817 (0.0222) | 0.0146 (0.0108) | 0.0269 (0.0081) |

Notes: The table presents results from the Blinder-Oaxaca decomposition of wage markdowns for heterogeneous workers performing different job tasks over the 1994-2018. 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 degree). NRC, nonroutine cognitive; NRM, nonroutine manual. The standard errors are in parentheses.

Table G.2: Difference between Markdown for High-skilled and Low-skilled Workers Explained by Observables and Skills

| Variables | Low-skilled workers' wage markdown equation; <br> Low-skilled - High-skilled gap in explanatory variables |
| :--- | :---: |
| Overall |  |
| Low-skilled workers | $2.6921(0.0336)$ |
| High-skilled workers | $1.0922(0.0065)$ |
| Difference (Low-skilled - High-skilled) | $1.6000(0.0342)$ |
| Endowments | $-0.1370(0.0133)$ |
| Coefficients | $1.0866(0.0609)$ |
| Interaction | $0.6504(0.0541)$ |
| Endowments |  |
| Share of female workers | $0.0032(0.0011)$ |
| Share of workers performing cognitive tasks | $0.0172(0.0040)$ |
| Share of workers performing manual tasks | $-0.0010(0.0010)$ |
| Share of immigrant workers | $-0.0085(0.0050)$ |
| Share of part-time workers | $0.0003(0.0004)$ |
| Age | $-0.1482(0.0124)$ |
| Coefficients |  |
| Share of female workers | $-0.0462(0.0304)$ |
| Share of workers performing cognitive tasks | $0.1316(0.0424)$ |
| Share of workers performing manual tasks | $-0.0344(0.0175)$ |
| Share of immigrant workers | $-0.0208(0.0073)$ |
| Share of part-time workers | $0.0539(0.0159)$ |
| Age | $-2.8633(0.1587)$ |
| Intercept | $3.8658(0.1249)$ |
| Interaction |  |
| Share of female workers | $-0.0040(0.0028)$ |
| Share of workers performing cognitive tasks | $-0.053(0.0172)$ |
| Share of workers performing manual tasks | $-0.0075(0.0040)$ |
| Share of immigrant workers | $-0.0369(0.0130)$ |
| Share of part-time workers | $0.0016(0.0022)$ |
| Age | $0.7501(0.0432)$ |

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 the 1994-2018. 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.3: Difference between Markdown for Workers Performing Different Tasks Explained by Observables and Job Tasks (Autor-Dorn)

|  | Abstract, routine, and manual workers |  |  |
| :--- | :---: | :---: | :---: |
|  | $\begin{array}{c}\text { Manual(1) - Abstract(2) } \\ \text { gap in explanatory } \\ \text { variables }\end{array}$ | $\begin{array}{c}\text { Manual(1)-Routine(2) } \\ \text { gap in explanatory } \\ \text { variables }\end{array}$ | $\begin{array}{c}\text { Abstract(1)-Routine(2) } \\ \text { gap in explanatory }\end{array}$ |
|  |  |  |  |
| variables |  |  |  |$]$

Notes: The table presents results from the Blinder-Oaxaca decomposition of wage markdowns for heterogeneous workers performing different job tasks over the 1994-2018. 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 degree). NRC, nonroutine cognitive; NRM, nonroutine manual. The standard errors are in parentheses.

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[^1]:    ${ }^{1}$ Despite the renewed interest in monopsony power, the term "monopsony" dates back to Robinson (1969). Boal and Ransom (1997), Manning (2003), and Ashenfelter et al. (2010) provide comprehensive surveys on monopsony literature over its development stages.
    ${ }^{2}$ One might consider why automation threats should affect wage negotiation while automation should have already displaced the replaceable workers, and the remaining workers who are not or less replaceable by automation technologies should not be subject to automation threats. But there are at least two reasons why automation threats could still exist in the robot-adopting firms or local labor markets. 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. 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. Second, the remaining workers might be subject to a displacement risk in the future, although not replaceable by the current technologies. So those remaining workers could be the ones who are subject to automation threats.

[^2]:    ${ }^{3}$ Yeh et al. (2022) quantify the plant-level markdowns in the U.S. manufacturing industry using the "production approach" based on data from the U.S. Census and find an average markdown of 1.53 over the period 1976-2014, implying that a worker earns only 65 cents on each dollar generated.
    ${ }^{4}$ 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 borrowed from Industrial Organization (IO) literature (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.
    ${ }^{5}$ See Boal and Ransom (1997) for a systematic review of these theories of monopsony power.
    ${ }^{6}$ Germany is one of the leading countries in the world in terms of the stock of industrial robots per worker (Acemoglu and Restrepo, 2020; Dauth et al., 2021). It indicates that Germany is an ideal environment to examine the impact of automation on monopsony power.
    ${ }^{7}$ Some studies such as De Loecker et al. (2016), Yeh et al. (2022), Bau and Matray (2023), and Lochner and Schulz (forthcoming) 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 or exploited and thus the labor cost underestimates the labor inputs and introduces measurement error in markdown estimates. Although the estimated effect of automation 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

[^3]:    ${ }^{9}$ In this paper, I focus on monopsony rather than bargaining power, which is based on outside options of each of the two agents (employer and worker) involved in wage bargaining or negotiation. From a technical perspective, monopsony and bargaining power are distinct; however, researchers sometimes use them to interpret the same phenomenon. For example, a clear difference in addition to the role of the outside option is that monopsony involves one employer (or multiple employers in the recent view of the monopsony) and a group of workers. However, bargaining power is about negotiations between one employer and one worker. See Manning (2021)'s footnote 1 for motivation of the differences.
    ${ }^{10}$ Relatedly, Arnoud (2018) documents that automation threat is associated with lower workers' bargaining power. The author approximated workers' bargaining power using an observed wage; however, the observed compensation is not fully informative about employees' bargaining power relative to employers. This challenge in measuring bargaining power has been one of the limitations of investigating the determinants of employer's bargaining power. But recent developments in the literature made progress in measuring bargaining power and outside options. For example, Caldwell and Harmon (2019) estimate workers' bargaining power for different skill groups by analyzing how Danish workers' wages respond to changes in the information of their outside options, i.e., the basis of workers' bargaining power. Caldwell and Danieli (2022) also develop an index of outside options based on workers' commuting costs, preferences, and skills. Additionally, Jäger et al. (2022) directly measure workers' outside option by asking workers' expected wage change if forced to leave their current employer in a survey.
    ${ }^{11}$ 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.

[^4]:    ${ }^{12}$ 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 the revenue.

[^5]:    ${ }^{13}$ The dataset 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, Dauth et al. (2021), for example.

[^6]:    ${ }^{15}$ 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 (forthcoming) argue that wage bills better capture heterogeneous labor inputs as it accounts 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.
    ${ }^{16}$ 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.
    ${ }^{17}$ The output elasticities of labor and intermediate materials are calculated by $\theta_{j t}^{L}=\hat{\beta}_{l}+\hat{\beta}_{k l} k_{j t}+\hat{\beta}_{l m} m_{j t}+2 \hat{\beta}_{l l} l_{j t}$ and $\theta_{j t}^{M}=\hat{\beta}_{m}+\hat{\beta}_{k m} k_{j t}+\hat{\beta}_{l m} l_{j t}+2 \hat{\beta}_{m m} m_{j t}$, respectively. Here $\hat{\beta}_{l}$ and $\hat{\beta}_{m}$ are parameter estimates on labor and intermediate materials, $\hat{\beta}_{l l}$ and $\hat{\beta}_{m m}$ are parameter estimates on quadratic terms, $\hat{\beta}_{k l}, \hat{\beta}_{l m}, \hat{\beta}_{k m}, \hat{\beta}_{l m}$ are the parameter estimate on cross term, and $l$ and $m$ are respectively log labor and log intermediate materials.

[^7]:    ${ }^{18}$ Online Appendix E. 1 shows that my markdown estimates are generally robust to the Cobb-Douglas production function. I discuss my estimates of markups in Online Appendix E.2.

[^8]:    ${ }^{19}$ I provide details in Online Appendix E.3.
    ${ }^{20}$ The aggregate markdown measure, robot penetration, and other controls span from 1994 to 2018; however, I use 1996 instead of 1994 as the beginning period because aggregate markdowns are calculated for a few local labor markets (or kreise) and even a few establishments in 1994 and 1995. So I consider the periods between 1996 and 2018 to cover more representative local labor markets and provide more robust estimates.

[^9]:    ${ }^{21}$ The instrument is constructed for each country $c=$ (Spain, Finland, France, Italy, Norway, Sweden, and the United Kingdom) as similar to Dauth et al. (2021), and thus I estimate the over-identified model.
    ${ }^{22}$ See Goldsmith-Pinkham et al. (2020) for settings where identification comes from the orthogonality of the "share" component of the shift-share instruments.
    ${ }^{23}$ I am grateful to Wolfgang Dauth for sharing the crosswalk from German kreise to 50 aggregate regions. Out of these 50 regions, the wage markdowns are estimated for 40 local labor markets due to data availability.

[^10]:    ${ }^{24}$ Appendix Figures G. 1 and G. 2 show the detailed results from the Blinder-Oaxaca decomposition for task and skill

[^11]:    differences, respectively.
    ${ }^{25}$ There are several reasons that I show the time evolution of aggregate markdowns under worker heterogeneity. Although the plant-level estimates for heterogeneous workers are available from 1994-2018, the aggregate numbers are censored for 1994 and 1995, given that the markdowns are estimated for too few firms (less than 20) for each period. I omitted 1996 and 1997 because estimates were too noisy for some groups of workers, potentially due to several reasons. First, during the mid-1990s, there might be some left-over impacts of economic transformations in Germany that happened in the early 1990s, such as the German reunification. Second, similar to 1994-1995, the underlying establishments in which aggregate markdowns are based were also relatively small, which might also be contributing to noisy estimates. Therefore, to provide a more robust inference about trends of labor market power for heterogeneous workers, I focus on periods since 1998.

[^12]:    ${ }^{26}$ Federal employment agency reports the time-consistent classification of economic activities at different aggregation levels.
    ${ }^{27}$ 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.
    ${ }^{28}$ I also use KT in my production function estimation as a robustness check and find that estimates on production function parameters remain the same.

[^13]:    ${ }^{29}$ The nominal wages and the assessment ceilings are deflated by the consumer price index from the Federal Statistical Office to calculate the real wages.

[^14]:    ${ }^{30}$ 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, $i_{j t}$, rather than intermediate inputs, $m_{j t}$, 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 $i_{j t}$ and $l_{j t}$. Hence, the ACF method primarily uses intermediate inputs as a proxy variable.
    ${ }^{31}$ 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.

[^15]:    ${ }^{32}$ I obtained Autor and Dorn (2013)'s occupational task measures from David Dorn's website: https://www.ddorn.net/data.htm\#Occupational\%20Tasks
    ${ }^{33}$ 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
    ${ }^{34}$ https://ibs.org.pl/app/uploads/2016/04/onetsoc_to_isco_cws_ibs_en1.pdf
    ${ }^{35}$ 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.

