Supplementary Materials (For Online Publication Only)

Automation Threat and Labor Market Power

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A Data Appendix

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

A.1 Establishment Data

Since the key outcome in this paper is wage markdowns measured using a production function approach, the primary dataset in this paper is the production data. The firm-level production data come from the IAB Establishment Panel (IAB-BP), which covers a large representative sample of establishments in German manufacturing. The longitudinal structure of the IAB-BP data enables me to use the control function method, which uses lagged information for identification to estimate the production function and then wage markdowns. The IAB-BP data includes comprehensive information necessary for production function estimation, such as annual revenue, number of workers or headcount[50], purchase of intermediate materials, and investments.

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

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

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

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

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

A.2 Matched Employer-Employee Data

I use the longitudinal version of matched employer-employee data (LIAB) mainly to construct the control variables, normalize the shock variables, and perform analysis with heterogeneous workers. The LIAB records employment trajectories for each employee who worked at one of the plants in the establishment sample for at least one day over the period. The worker's information in the matched data contains the employment history of each employee with social security records. Specifically, I use data from the Employee History (Beschäftigtenhistorik—BeH). The information on employees includes variables such as daily wage[51] and detailed occupation classifications at the 5-digit level from 1975 to 2019.

The establishment codes in the LIAB match those in the IAB-BP. Thus, for example, I calculate shares of female and foreign workers in the establishment using the LIAB data and merge it with the IAB-BP data to construct the demographic controls included in the regressions. For my analysis allowing for heterogeneous workers, I allocate the plant's total labor cost recorded in the IAB-BP data to workers performing different tasks using the share of each worker's annual earnings in the establishment recorded in the LIAB data. A worker's annual earnings is a multiplication of imputed daily wage and the number of days worked in a given year.[52]

A.3 Worker-Level Job Tasks

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

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

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

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

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

A.4 Industry-Level Robots Stock

The main limitation of information on the firm's robot adoption in the IAB-BP dataset is that a retrospective question was asked only once in 2019 about the firm's use of robots over the five years preceding the survey year from 2014 to 2018. It provides relatively restrictive periods. So, I use industry-year panel data on the stock of industrial robots in 50 countries, including Germany, reported by the International Federation of Robotics (IFR) since 1993 as the primary measure of automation that spans for more periods. Graetz and Michaels (2017, 2018) introduced the use of IFR's robots stock data, which have been later used by Acemoglu and Restrepo (2020) for the U.S. and by Dauth et al. (2021) for Germany. The data come from annual surveys of robot suppliers and cover 90% of the world. The robot stock is disaggregated for 20 manufacturing industries.[53] I predict the local labor market exposure to robots based on the industry-level robots stock using employment weights, and the annual change in the number of robots is normalized by workforce size. In doing these, I use employment counts from the BEH recorded in the matched employer-employee data (LIAB). Section 4.1 discusses the construction of our primary measure of local labor market exposure to robots in more detail, particularly in equation (6).

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

A.5 Construction and Approximation of Some Key Variables

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

Capital stock approximation. I use a *perpetual inventory* method following Mueller (2008, 2017) to compute the stock of capital, one of the key ingredients in the production function estimation. One of the key inputs in using the perpetual inventory approach is industry-specific average economic lives of capital goods, an inverse of depreciation rate, which is obtained from Mueller (2017) at the time-consistent 2-digit industry level for the periods 1993-2014. I merge this information with EP data at the 2-digit industry level, which I generate from the 3-digit industry classification provided in the EP data.[54] 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.[55] Another issue with approximating capital stock is the starting value of the capital stock.

Also Mueller (2008) proposes two approaches to compute the time series of capital stock using either the average replacement investments over the whole sample period (KT) or the first three years (K3) for each firm. I define these two types of capital stock series, following the procedure, and which version of capital stock to use depends on the analysis. The latter performs better than the former when the capital stock has a time trend, as it uses the short-term average as a starting point. However, due to noisy investment data, the capital stock generated in this way, K3, is likely to be misleading. However, the perpetual inventory routine slowly corrects the K3. So, K3 might be less appropriate when using between-firm information and OLS regression. However, it might be more suitable for estimators that use only within-firm information using the GMM method. Since the ACF method of production function estimation uses GMM to estimate production function parameters, I primarily use the capital stock K3 in my analysis despite fewer observations than KT.[56]

Imputation of wages. I observe the nominal daily wage of each worker registered for social security purposes at the firm. Since the wage data comes from social security records, it is generally highly reliable. However, a common challenge of the wage data from the Social Security notifications is that the wage information is recorded only until the Social Security contribution assessment ceiling. If a worker's wage exceeds this upper earnings limit, this value will be entered as her wage, which differs by year and location.[57] Although only about 5% of the observations are subject to

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

[55]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.

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

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

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

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

Office to calculate the real wages.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

C Production Function Estimation

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

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

where y_{jt} is log output, $\mathbf{x}_{jt}$ is a vector of log inputs, both fully variable inputs (e.g., intermediate materials m_{jt}) and not fully variable inputs (e.g., labor l_{jt}[58] and capital k_{jt}). The firm-specific productivity ω_{jt} embeds the constant term. The error term ε_{jt} reflects measurement error in gross outputs y_{jt} defined as revenue deflated by the producer price index for industrial products at the 2-digit industry level.[59] I write the production function in general terms as I estimate the log transformation of the production function $f(\cdot)$ in various functional forms (e.g., Cobb-Douglas and translog) with translog[60] as the primary specification given its flexibility.

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

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

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

[59] 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.

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

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

Recall that firm-specific productivity ω_{jt} unobserved by an econometrician but observed by the firm generates a problem of endogeneity for estimating the above production function. To address this problem, Levinsohn and Petrin (2003) suggest using the demand for intermediate materials[61] m_{jt} as a proxy for productivity, which is given by

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

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

Under the assumption of strict monotonicity that the control function $m_t(\cdot)$ is strictly increasing in ω_{jt}[62], one can invert the equation (C.2) and express the productivity as

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Then, I approximate the productivity in the data as

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

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

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

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

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

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

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

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

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

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

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

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

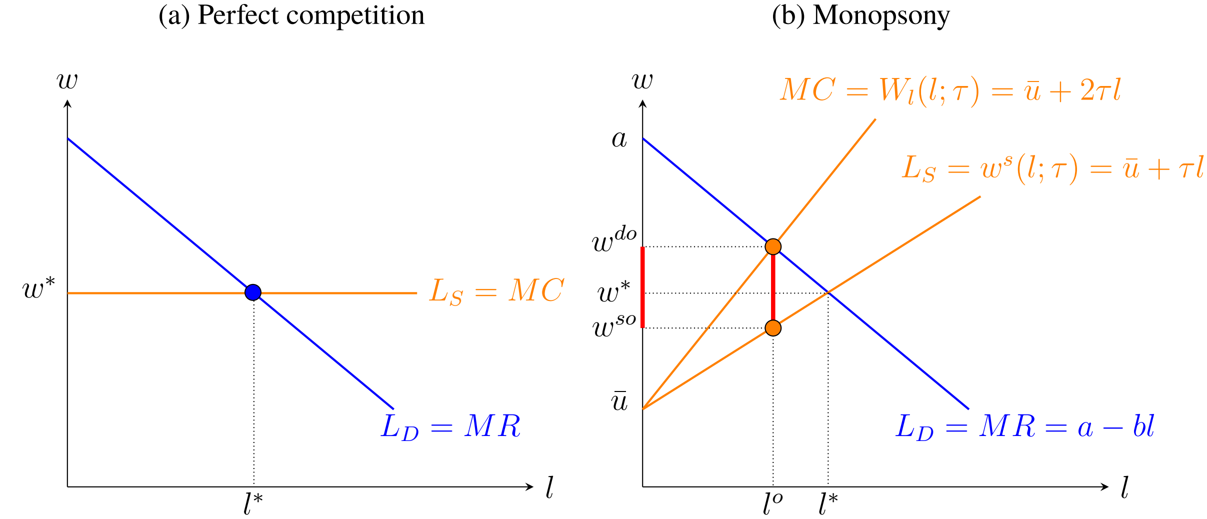
D Overview of Monopsony Measures

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

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

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

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



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

The profit maximization problem in the basic monopsony model is

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

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

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

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

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

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

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

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

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

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

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

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

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

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

E Additional Results on Markdowns

E.1 Robustness of Estimated Markdowns for German Manufacturing

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

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

	Median	Mean	$\text{IQR}_{75\text{-}25}$	SD
Leather and related products	2.185	2.021	1.395	0.748
Wearing apparel	2.014	1.992	1.151	0.699
Furniture	1.704	1.819	1.055	0.705
Wood and wood products (excl. furniture)	1.524	1.629	0.882	0.560
Paper and paper products	1.437	1.447	0.604	0.498
Beverages	1.430	1.488	0.395	0.544
Repair and installation of machinery and equipment	1.320	1.517	0.691	0.646
Other transport equipment	1.319	1.346	0.829	0.507
Rubber and plastics	1.294	1.388	0.586	0.512
Other non-metallic minerals	1.284	1.435	0.754	0.645
Chemicals and chemical products	1.277	1.431	0.855	0.603
Motor vehicles, trailers, and semi-trailers	1.244	1.359	0.731	0.550
Basic pharmaceutical products	1.241	1.313	0.588	0.634
Fabricated metals, excl. machinery and equipment	1.193	1.322	0.666	0.535
Food products	1.179	1.306	0.682	0.563
Electrical equipment	1.154	1.225	0.562	0.481
Machinery and equipment	1.116	1.229	0.551	0.517
Basic metals	1.063	1.172	0.431	0.419
Textiles	1.046	1.238	0.562	0.460
Computer, electronic, and optical products	1.017	1.078	0.583	0.416
Other manufacturing	0.992	1.096	0.465	0.438
Printing and reproduction of recorded media	0.968	1.020	0.395	0.431
Whole sample	**1.200**	**1.331**	**0.726**	**0.569**
Sample size	9,431			

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

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

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

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

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

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

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

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

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

E.2 Markdown Trend under Cobb-Douglas Specification

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

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

Notes: Markdowns are constructed using the IAB Establishment Panel (IAB BP) data from 1997-2018 under the assumption of Cobb-Douglas production and aggregated according to expression (E.1) and (E.3). The employment share of labor market ω_{klt} is based on total number of employees.

E.3 Markups

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

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

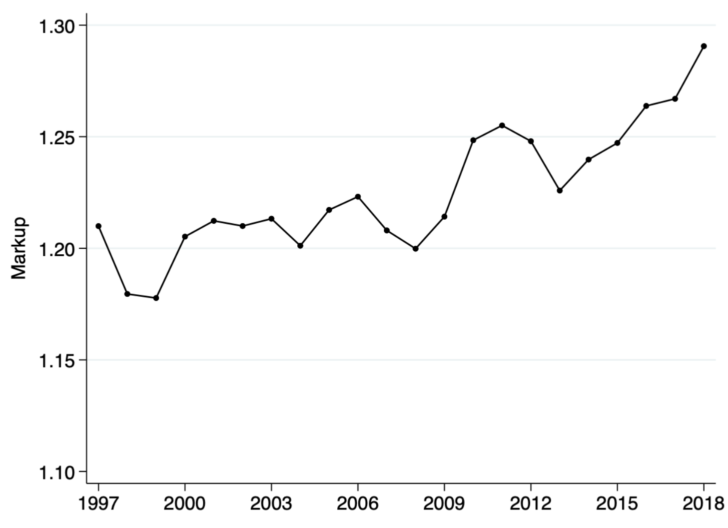
Figure E.2 presents the time series for the aggregate markup. The markup is aggregated at the market level according to equation (E.2). Then, I aggregate markups across markets through employment weights. As briefly discussed above, firm-level markups estimated using deflated revenues instead of physical outputs are biased, and thus, the aggregate markups are also biased. While we should take the markup estimates cautiously, a trend in aggregate markups could be informative. The markup in German manufacturing has been monotonically increasing since 1997 until 2018.

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

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

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

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



Notes: Markups are constructed using the IAB Establishment Panel data from 1997-2018 under the assumption of translog production and aggregated according to expressions (E.2) and (E.4). The employment share of labor market ω_{jlt} is based on total number of employees.

E.4 Markdown Estimation Controlling for Robot Exposure

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

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

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

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

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

E.5 Markdown and Markup Aggregation

The aggregate markdowns and markups are defined, respectively, as

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

and

$$\mathcal{M}_{klt} = \left(\sum_{j \in F_t(k,l)} s_{jt} \cdot \frac{\theta^M_{jt}}{\theta^M_{klt}} \cdot \mu^{-1}_{jt}\right)^{-1}, \tag{E.2}$$

where θ_{klt}^{L} and θ_{klt}^{M} are, respectively, the average output elasticities of labor and intermediate materials in the industry k, location l, and year t. Here $s_{jt} = \frac{p_{jt}y_{jt}}{P_{klt}Y_{klt}}$ are sales weights[63] and $F_t(k,l)$ denotes the set of firms in local labor market (k,l).

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

$$\mathcal{V}_t = \sum_{k \in K} \sum_{l \in L} \omega_{klt} \mathcal{V}_{klt}, \tag{E.3}$$

and

$$\mathcal{M}_t = \sum_{k \in K} \sum_{l \in L} \omega_{klt} \mathcal{M}_{klt}, \tag{E.4}$$

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

E.6 Measuring Labor Market Concentration

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

$$\text{HHI}_{mt} = \sum_{j=1}^{I} s_{jmt}^2, \tag{E.5}$$

where s_{jmt}^2 is the market share of firm j in market $m = (o,l)$ as a number between 0 and 100, and o and l denotes occupation and geography index, respectively. In the alternative definition, I calculate (E.5) for market $m' = (k,l)$ where k is the industry index. A firm's market share in a given market m (or m') and time t is defined as the sum of workers at a given firm in a given market and time divided by the total workers in that market and time. The average HHIs are calculated by weighted average using employment as weights. Formally,

$$\text{HHI}_{lt} = \sum_{o \in O} \omega_{olt} \text{HHI}_{olt} \quad (\text{or } \text{HHI}_{lt} = \sum_{k \in K} \omega_{klt} \text{HHI}_{klt}), \tag{E.6}$$

and

$$\text{HHI}_{lt} = \sum_{k \in K} \sum_{l \in L} \omega_{klt} \text{HHI}_{klt}. \tag{E.7}$$

[63] I use sales weights strictly following Yeh et al. (2022), while the plant-level measures can also be aggregated using employment weights. The pattern and interpretation of aggregate measures are the same when the employment weights are employed because the sales and the number of workers are positively correlated, i.e., firms with higher sales employ more workers. The pairwise correlation between the log employment and log sales revenue is 0.944 (SE: 0.003, p-value: 0.00). Controlling for firm, year, district-by-year, and industry-by-year, I also find that the coefficient on log revenue in the regression of log employment is 0.333 (SE: 0.023).

E.7 Cross-Sectional Correlation between Markdown and Labor Market Concentration

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

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

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

Notes: Markdowns are estimated using the IAB Establishment Panel (IAB BP) data from 1997-2018 under the assumption of a translog specification for gross output. The cross-market correlations are calculated at the 3-digit ISIC-state level for every other year. Aggregate markdowns are calculated according to equation (E.1) whereas labor market concentration HHI_{klt} is calculated according to equation (E.5) using either IAB BP and matched employer-employee (LIAB) data, which are highlighted in the superscript. Significance: $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$.

To check the robustness of my baseline employment HHI measure calculated using IAB BP data, I compute the same index according to equation (E.5) based on the matched employer-employee data (LIAB). The cross-section correlation between the two HHIs is strong, positive, and almost always statistically significant at the 1% level (third column). Across years and on average, the correlation between aggregate markdown and LIAB-based HHI is mostly positive but rarely statistically significant (fourth column), consistent with the results in the second column.

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

$$\begin{aligned} Y^1 &= \beta_0^1 + \sum_{k=1}^{K} \beta_k^1 X_k^1 + \epsilon^1, \\ Y^2 &= \beta_0^2 + \sum_{k=1}^{K} \beta_k^1 X_k^2 + \epsilon^2, \end{aligned} \tag{E.8}$$

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

$$\overline{Y}^1 - \overline{Y}^2 = \underbrace{(\beta_0^1 - \beta_0^2)}_{\text{coefficients}} + \underbrace{\sum_{k=1}^{K} \beta_k^2 (\overline{X}_k^1 - \overline{X}_k^2)}_{\text{endowments}} + \underbrace{\sum_{k=1}^{K} \overline{X}_k^2 (\beta_k^1 - \beta_k^2)}_{\text{coefficients}} + \underbrace{\sum_{k=1}^{K} (\overline{X}_k^1 - \overline{X}_k^2)(\beta_k^1 - \beta_k^2)}_{\text{interaction}}, \tag{E.9}$$

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

Table E.7 presents results from the Blinder-Oaxaca decomposition on the contribution of worker characteristics to the gap in markdowns due to job task differences. The result suggests that unobserved task differences explain a substantial part of the difference between markdowns for workers performing different tasks after accounting for various worker characteristics. Table E.8 presents results from the Blinder-Oaxaca decomposition on the contribution of worker characteristics to the skill gap in markdowns. The result shows that unobserved skill differences account for more than two-thirds of the difference between markdowns for high- and low-skilled workers.[64]

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

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

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

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

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

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

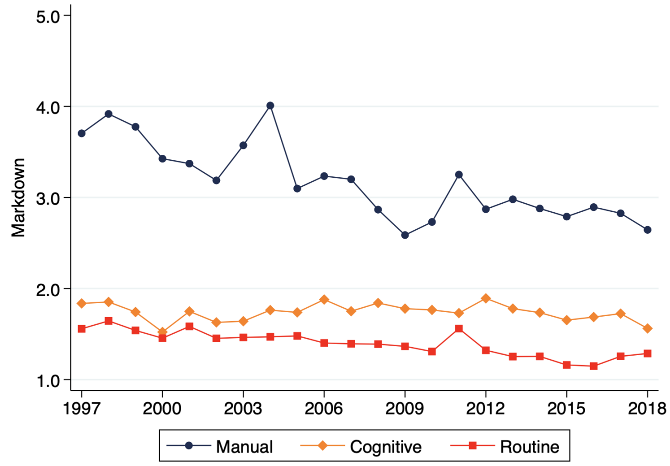
Notes: The table presents results from the Blinder-Oaxaca decomposition of wage markdowns for high-skilled (with at least vocational training) and low-skilled (without vocational training) workers over 1997-2018. The explanatory variables include workers' average age and worker composition of the group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

E.9 Trends in Aggregate Markdowns for Heterogeneous Workers

I aggregate the plant-level markdowns for heterogeneous workers using equations (E.1) and (E.3) similar to the baseline analysis where workers are homogeneous to show how employers' labor market power has changed for different workers in German manufacturing over time. Figure E.3 illustrates the trends of aggregate markdowns, $\mathcal{V}_t$, over workers performing routine, nonroutine manual, and nonroutine cognitive tasks. Markdowns for workers performing manual and routine tasks have been decreasing, and the decline is more intensive in magnitude for manual task-performing workers.[65] Labor market power for nonroutine cognitive workers has been stable between 1997-2018.

[65] A downward trend in markdown for routine workers is strongly consistent with Bachmann et al. (2022b) who show that labor supply elasticity, proportional to the inverse of markdown, has been increasing for routine workers.

Figure E.3: Time evolution of the aggregate markdowns for workers performing different tasks

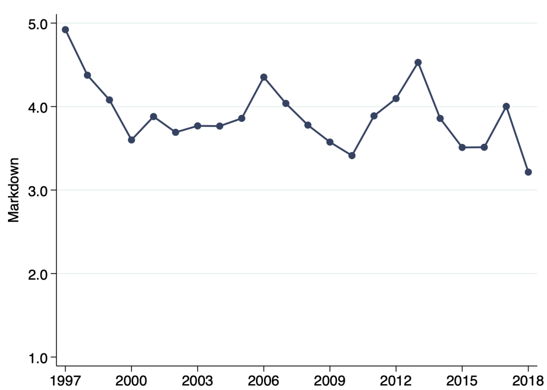


Notes: The figure depicts the time evolution of aggregate markdowns for nonroutine cognitive, routine, and manual workers between 1997 and 2018. Plant-level markdowns are constructed using the IAB Establishment Panel and matched employer-employee (LIAB) data under the assumption of translog production with heterogeneous labor inputs and aggregated according to expressions (E.1) and (E.3). The employment share of labor market ω_{klt} is based on the total number of employees. The classification of nonroutine cognitive, routine, and nonroutine manual task-performing workers is based on the BIBB/BAuA Employment Surveys.

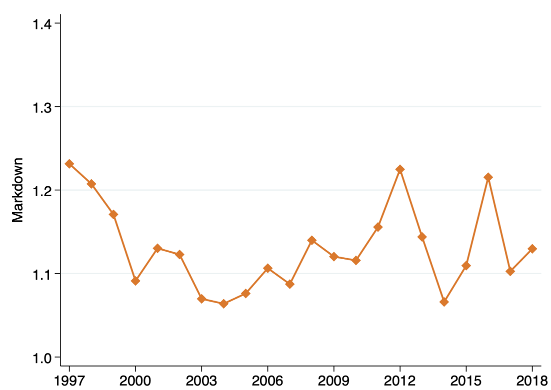
Figure E.4 illustrates the time evolution of aggregate markdowns for workers with different skills. The results for low-skilled and high-skilled workers are generally consistent with workers performing various tasks. Specifically, the pattern of employers' labor market power for low-skilled or low-educated workers is downward-sloped, potentially driven by manual workers. The markdown for high-skilled or high-educated workers has been relatively stable between 1997-2018, similar to cognitive workers.

Figure E.4: Time evolution of the aggregate markdowns for workers with different skills

(a) Low-skilled



(b) High-skilled



Notes: The figure plots the time evolution of aggregate markdowns for low-skilled workers (no vocational training) and high-skilled workers (with at least vocational training) from 1997-2018. Plant-level markdowns are constructed under the assumption of translog production with heterogeneous labor inputs and aggregated according to expressions (E.1) and (E.3). The employment share of labor market ω_{klt} is based on the total number of employees.

E.10 Robustness of Markdowns for Heterogeneous Workers

In my baseline analysis, I define heterogeneous workers performing different tasks based on task intensity measures constructed using Germany's BIBB/BAuA Employment Surveys and an approach by Antonczyk et al. (2009). But this appendix checks the robustness of my results on markdowns for heterogeneous workers performing different tasks to the use of alternative task intensity measures proposed by Autor and Dorn (2013).[66]

Classification of workers. Since Autor and Dorn (2013) create their measures of task content or task inputs for each occupation in the U.S. using O*NET data, the values of the indices could be different from the values of indices constructed using the German dataset of BIBB/BAuA Employment Surveys. However, it is reasonable to consider that these two measures are comparable. Specifically, they build three measures of abstract, routine, and manual task inputs for their constructed version of 3-digit 1990 U.S. Census occupations (`occ1990dd`). I match them with German administrative data through Germany's 5-digit KldB 2010 occupation classifications based on several crosswalks. First, I obtain Autor and Dorn (2013)'s version of 3-digit 1990 U.S. Census occupations matched with 3-digit 2000 U.S. Census occupations (`occ2000`) from Acemoglu and Autor (2011)'s data appendix of task measure construction. Then, I match that with the 6-digit 2000 Standard Occupational Classification (SOC) via 3-digit 2000 U.S. Census occupations using their crosswalks.[67] After that, using crosswalks obtained from the Institute for Structural Research (IBS),[68] 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).[69] After all these crosswalks, I have Autor and Dorn (2013)'s three measures for abstract, routine, and manual task inputs merged to Germany's linked employer-employee data at the 5-digit occupations level.

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

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

[67] 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`

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

[69] 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`.

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^A_{ijt}, T^R_{ijt}, or T^M_{ijt}, respectively. Table E.9 summarizes the employment, wage bill, and daily wage for abstract, routine, and manual workers.

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

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

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

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

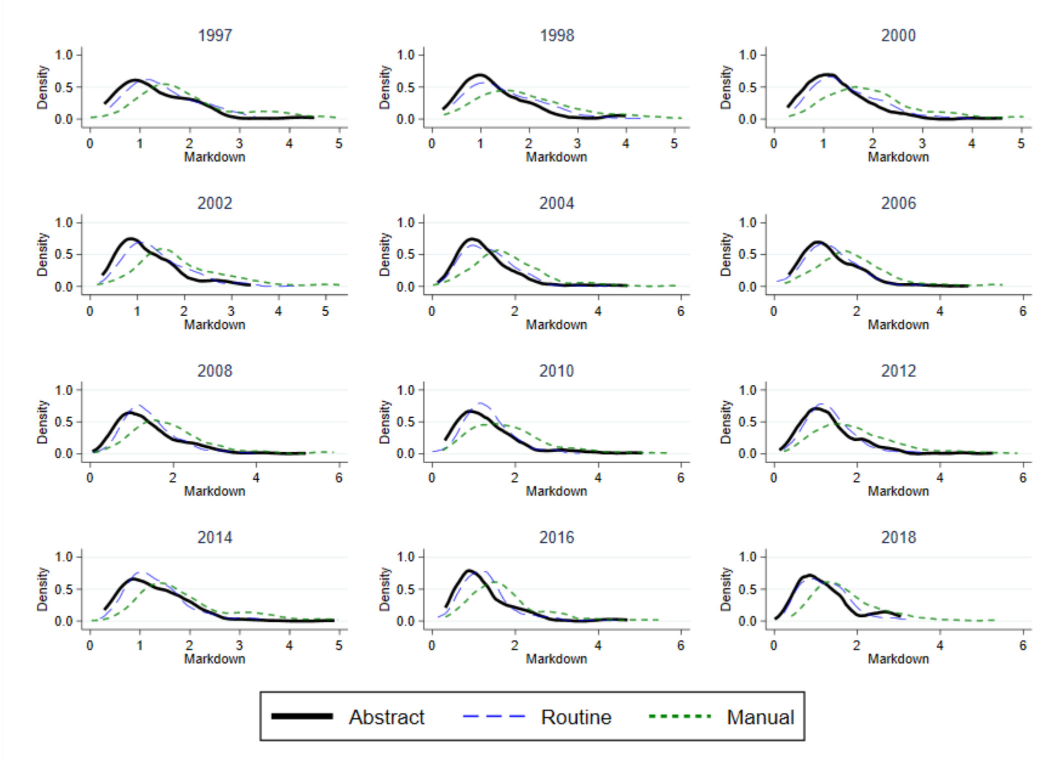
Table E.10: Estimated plant-level markdowns for workers performing routine, abstract, and manual job tasks in German manufacturing

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

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

The distribution of markdowns for abstract, routine, and manual workers, plotted in Figure E.5, is generally the same for nonroutine cognitive, routine, and nonroutine manual workers in the baseline analysis.

Figure E.5: Distributions of wage markdowns for abstract, routine, manual workers



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

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

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

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

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

F Additional Results on Firm-Level Effects

F.1 Robustness of Heterogeneous Effects by Firm Size

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

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

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

Notes: The table presents the results from estimating the annual change in plant-level markdowns on the annual change in the local labor market's predicted exposure to robots in the automotive industry per 1,000 workers for large firms between 1998 and 2018 using the IV (2SLS) regressions under various definition of large firms. In Panels A-D, large firms are defined as those in the top 2 quintiles, top tercile, top quartile, and above the median of the firm size distribution, respectively. Columns (1)-(3) report the effects of automation exposure on the markdowns over heterogeneous workers performing different tasks, and the dependent variable is the annual change in the markdowns over routine workers (column (1)), nonroutine manual–NRM workers (column (2)), and nonroutine cognitive–NRC workers (column (3)). All specifications include the same set of controls and fixed effects as in Table 46. Standard errors clustered at the level of local labor markets or districts are in parentheses.

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

F.2 Additional Robustness of Firm-Level Results

The firm location can vary across the regions over time potentially due to the firm mobility across districts or a firm can have multiple plants in different places with the same firm identification. So, we can control for district fixed effects in addition to the firm fixed effects. Table F.2 shows the robustness of IV (2SLS) estimates in Table 43 by adding district or kreis fixed effects. The results from this robustness check are qualitatively and almost quantitatively similar to the baseline results.

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

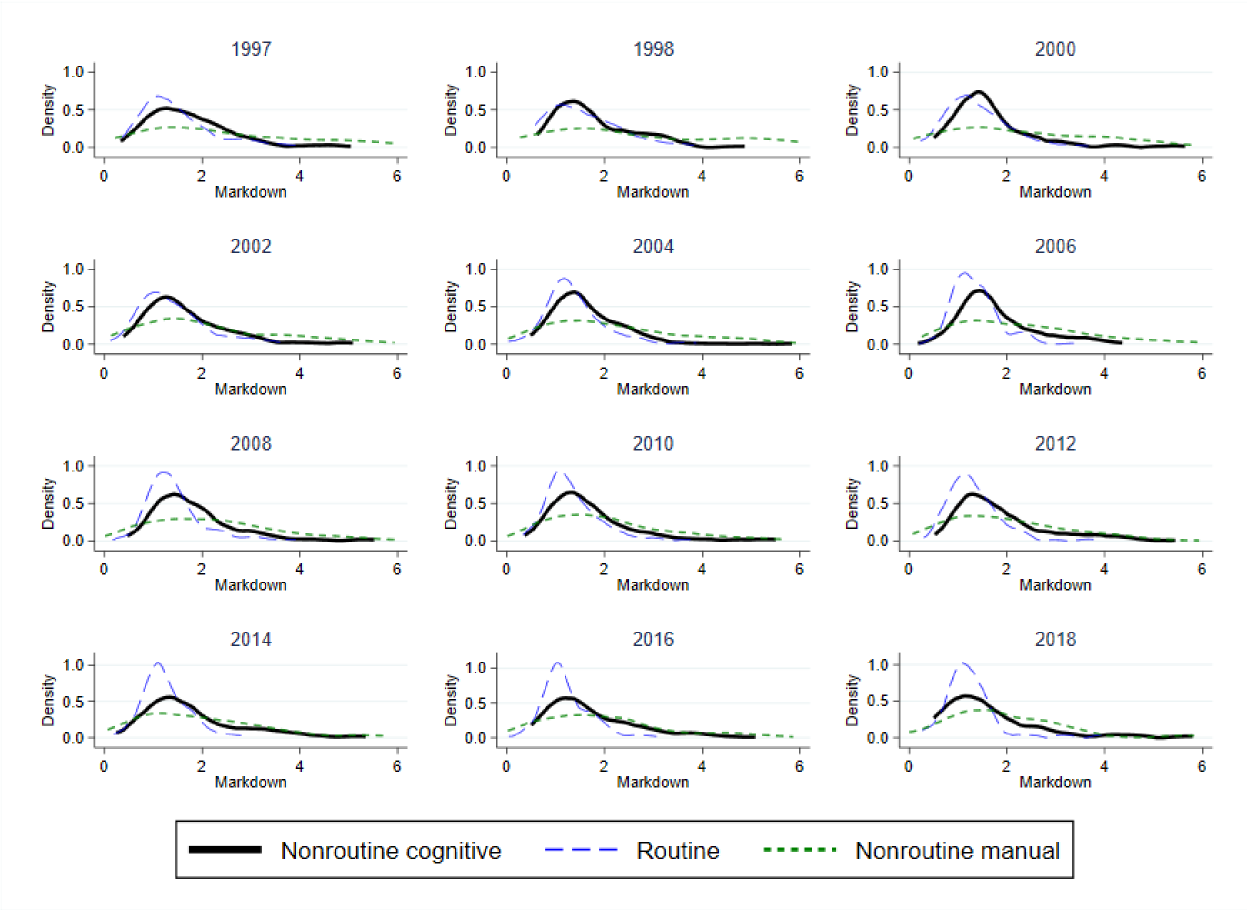
	Dependent variable: Annual change in plant-level markdowns		
	Routine (1)	Nonroutine manual (2)	Nonroutine cognitive (3)
	Panel A. East Germany		
ΔPredicted robot exposure	0.011	-0.003	0.003
	(0.005)	(0.009)	(0.008)
Observations	3649	3649	3649
	Panel B. West Germany		
ΔPredicted robot exposure	-0.002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

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

G Additional Figures and Tables

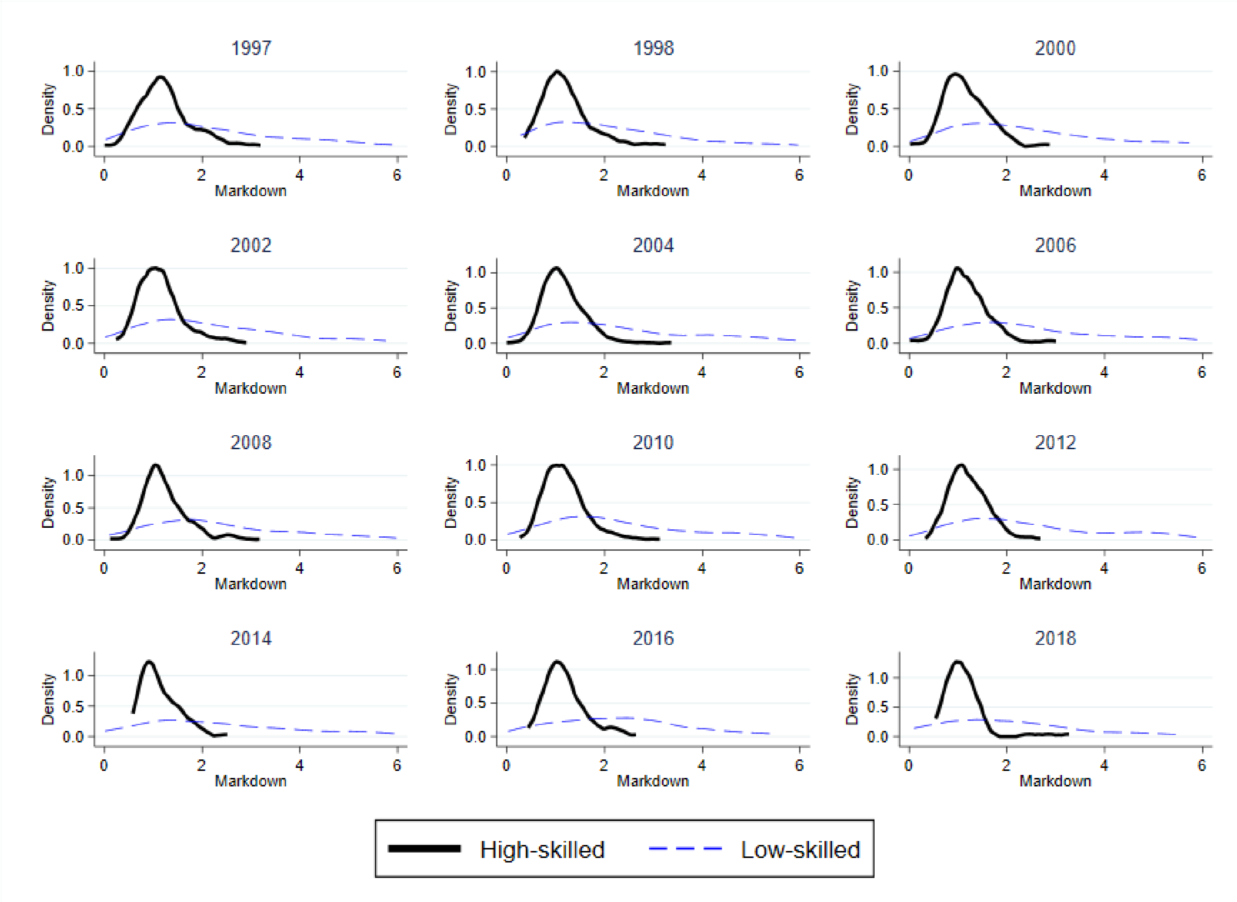
G.1 Additional Figures

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



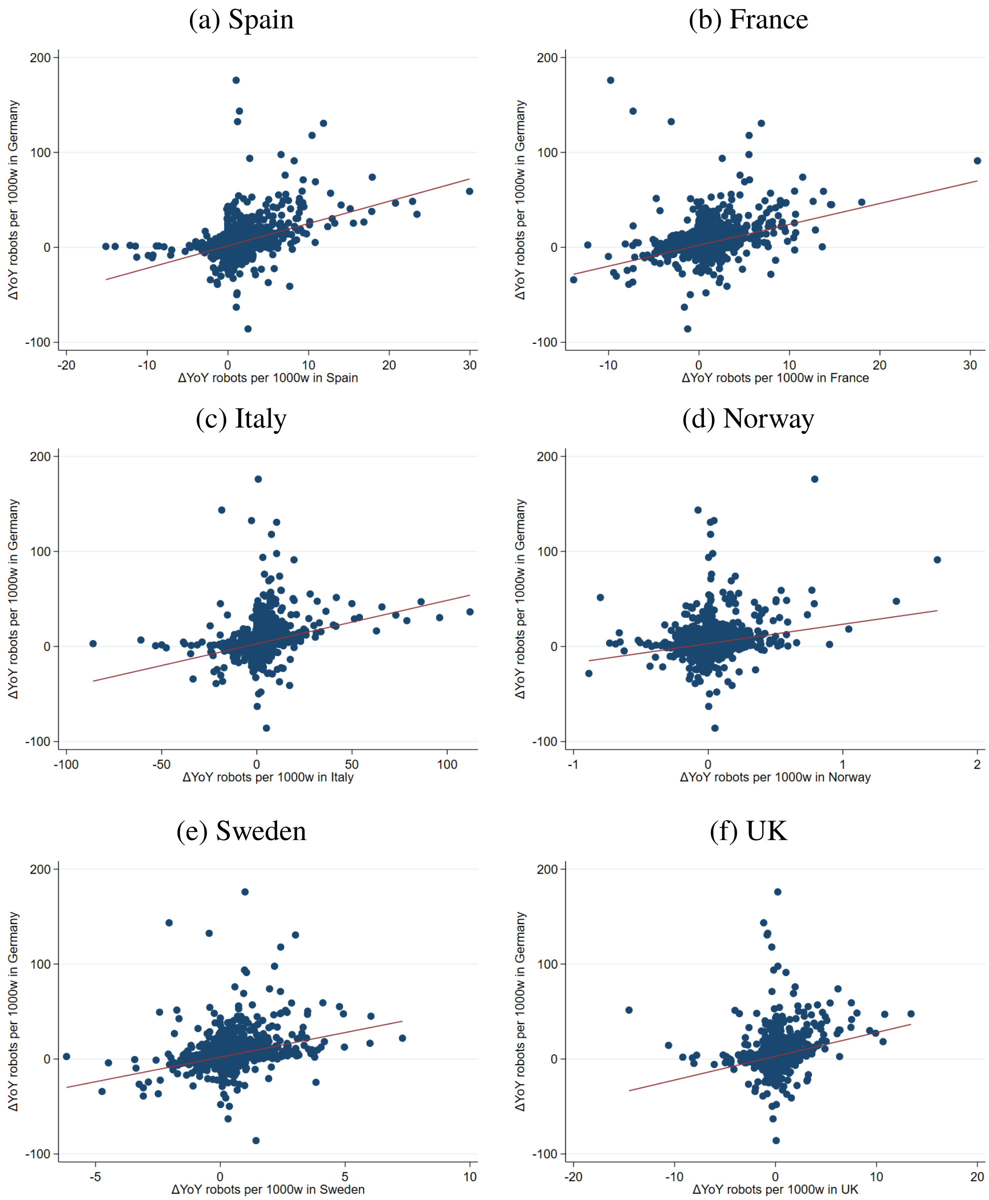
Notes: Based on the IAB Establishment Panel and matched employer-employee (LIAB) data. The classification of nonroutine cognitive, routine, and nonroutine manual task-performing workers is based on the BIBB/BAuA Employment Surveys. The figure depicts the markdown distributions for NRC, routine, and NRM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

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



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

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



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

G.2 Additional Tables

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

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

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

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

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

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

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

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

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

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

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

Notes: The table presents the results from OLS regressions estimating the relationship between the annual change in robot exposure predicted from the first stage of the 2SLS estimation and annual change in robot exposure defined by equation (6) (top panel) and annual change in actual robot adoption (bottom panel) in Germany between 2015 and 2018. In this table, robots in all industries are considered. The first-stage regression controls for instruments and covariates in equation (5). The actual robot adoption is measured by aggregating the number of robots adopted by the firm at the district level using sampling weights provided in the IAB Establishment Panel data and expressed as per 1,000 workers. Standard errors clustered by districts are in parentheses. Significance: *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$.

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

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

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

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