CESifo WORKING PAPERS

9799
2022

June 2022

Can the Labor Demand Curve Explain Job Polarization?

Andreas Peichl, Martin Popp

CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp

An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
· from the CESifo website: https://www.cesifo.org/en/wp

CESifo *Working Paper No. 9799*

Can the Labor Demand Curve Explain Job Polarization?

Abstract

In recent decades, many industrialized economies have witnessed a pattern of job polarization. While shifts in labor demand, namely routinization or offshoring, constitute conventional explanations for job polarization, there is little research on whether shifts in labor supply along the labor demand curve may equally result in job polarization. In this study, we assess the impact of labor supply shifts on job polarization. To this end, we determine unconditional wage elasticities of labor demand from a unique estimation of a profit-maximization model on linked employer-employee data from Germany. Unlike standard practice, we explicitly allow for variations in output and find that negative scale effects matter. Both for a skill- and a novel task-based division of the workforce, our elasticity estimates show that supply shifts from immigration and a decline in collective bargaining successfully explain occupational employment patterns during the 1990s.

JEL-Codes: J230, J310, D220, L600.

Keywords: labor demand, job polarization, skills, tasks.

Andreas Peichl
ifo Institute – Leibniz Institute for Economic Research at the University of Munich / Germany
Poschingerstraße 5
Germany – 81679 Munich
peichl@ifo.de

*Martin Popp**
Institute for Employment Research (IAB)
Regensburger Straße 100
Germany – 90478 Nuremberg
martin.popp@gmx.net

*corresponding author

June 9, 2022
Martin Popp is grateful to the Joint Graduate Program of IAB and FAU Erlangen-Nuremberg (GradAB) for financial support of his research. We particularly thank David Autor, Lutz Bellmann, Mario Bossler, Kerstin Bruckmeier, Katharina Dengler, Andreas Ganzer, Győző Gyöngyösi, Daniel Hamermesh, Christian Merkl, Jannek Mühlhan, and Jürgen Wiemers for helpful discussions and suggestions. We are grateful to Vinzenz Pyka and Tiphaine Wibault for excellent research assistance. Earlier versions of this paper were presented at the Workshop on "Dynamics of Skill Supply and Demand" in Maastricht (ROA), the "Task V" Conference in Bonn (BIBB), the 11th Workshop on Labour Economics in Trier (IAAEU), the 31st EALE Conference in Uppsala (U Uppsala/IFAU), the Workshop on "Vacancies, Hiring and Matching" in Nuremberg (IAB), the 30th Annual EEA Congress (U Rotterdam), and the Verein für Socialpolitik Annual Meeting 2020 (U Cologne) as well as in seminars in Munich (ifo) and Nuremberg (IAB/FAU).

1 Introduction

Job polarization has been documented in many Western countries in recent decades: while low- and high-paid occupations have increased relatively, the employment share of medium-paid occupations has declined (Goos and Manning, 2007).[1] So far, the literature explains this phenomenon solely with shifts in labor demand. On the one hand, technological progress fosters investment in new machines that substitute for routine tasks and are complements to non-routine tasks (Autor, Levy, and Murnane, 2003). On the other hand, globalization has reduced the cost for firms to offshore routine work to low-wage countries (Blinder, 2009). In sum, occupations in the middle of the wage distribution, which predominantly involve routine tasks, lose, whilst jobs at the top or the bottom of the wage distribution, which mostly involve non-routine tasks, gain influence. Numerous studies empirically support the link between labor demand shifts and job polarization (e.g., Acemoglu and Autor, 2011; Goos, Manning, and Salomons, 2009; Autor and Dorn, 2013; Goos, Manning, and Salomons, 2014). This paper is the first to analyze if, in addition to demand shocks, labor supply responses can provide a complementary explanation for job polarization.

We use detailed linked employer-employee data to explore whether labor supply shocks contribute to job polarization in the German manufacturing sector between 1993 and 2016. In a standard supply-demand framework, shifts in labor supply materialize along the negatively sloped labor demand curve. Thus, we require detailed information on the slope of the labor demand curve to disentangle the impact of supply shocks on the polarization pattern. For this purpose, we use a structural labor demand model to estimate unconditional wage elasticities of labor demand (WELD). We then interact these elasticity estimates with observed wage changes to predict counterfactual employment shares for a hypothetical setting in which only labor supply shocks occur. Building on these counterfactual shares, we analyze the role of labor supply and labor demand shifts for job polarization in Germany.

Economic theory argues that the demand for labor falls as wages rise through two channels: negative substitution effects and negative scale effects. In this study, we carry out the first estimation of a profit-maximization model with linked employer-employee (LEE) data to measure the impact of wage rates on labor demand. Although a large number of reduced- and structural-form models provide estimates on this relationship (see, e.g., the meta analysis by Lichter, Peichl, and Siegloch, 2015, as well as our literature review in Appendix A), our

[1] For instance, Autor, Katz, and Kearney (2006) as well as Autor and Dorn (2013) find polarized employment growth in the U.S. for the period 1990-2005. Spitz-Oener (2006) and Dustmann, Ludsteck, and Schönberg (2009) report a similar pattern in Germany for the 1980s and the 1990s. Goos, Manning, and Salomons (2009) show that employment polarized in the majority of European countries between 1993 and 2006 – including Germany, U.K., France, Spain, and the E.U. as a whole.

novel approach allows us to make contributions to the literature on WELDs in four respects.[2] First, the empirical literature pays only little attention to the identification of scale effects. The vast majority of studies focuses on the estimation of conditional WELDs and, thus, assumes a priori that scale effects are absent. We identify two arguments that rationalize the paucity of empirical estimates of unconditional WELDs. On the one hand, reduced-form models, for lack of exogenous wage variation, frequently arrive at positive scale effects that contradict the theory of labor demand.[3] On the other hand, structural-form models usually comply with theory but necessitate rarely available information on producer prices to measure scale effects (e.g., Lopez, 1984; Higgins, 1986; Alam, Omar, and Squires, 2002). Consequently, we instead harness a new linkage possibility and enrich our LEE data with detailed producer price level data to estimate unconditional WELDs within a structural profit-maximization model of labor demand.

Second, available profit-maximization models do not adequately address potential endogeneity in wages and, thus, are likely to provide biased WELDs. Unlike related studies based on aggregate information, we use micro-level data to strengthen the assumption of exogenously given wages (Hamermesh, 1993) and control for establishment fixed effects to eliminate bias from unobserved heterogeneity between employers (Addison, Portugal, and Varejão, 2014). Third, prevailing profit-maximization models do not differentiate between various types of workers and, hence, mask potential heterogeneity in WELDs. We do not view labor as a homogeneous input factor but instead use our rich LEE data to distinguish between workers with different skill levels. Fourth, we go beyond this "skill-based" disaggregation and implement a "task-based" approach (Autor, Levy, and Murnane, 2003). In doing so, we are the first to provide (both conditional and unconditional) wage elasticities of labor demand for workers with different tasks in their job.

In the first part of our analysis, we provide new insights on the effect of higher wages on labor demand. We start by confirming previous findings for Germany, as conditional WELD

[2] See the meta-study by Lichter, Peichl, and Siegloch (2015) for an overview of different approaches to estimate WELDs. Structural models derive elasticities from specific functional forms reflecting the optimization behavior of employers, either by holding output fixed and minimizing a cost function or by maximizing a profit function and allowing output to change. The former approach measures only substitution effects (conditional WELDs) while the latter yields unconditional WELD estimates comprising both substitution and scale effects. In contrast, reduced-form models regress measures of labor demand on wage rates. Models that control for the level of production insulate scale effects and, thus, determine conditional WELDs. For further information, we review the literature in Appendix A, discuss research gaps in more detail and provide a comprehensive overview about structural-form (Table A1) and reduced-form estimates (Table A2) of unconditional WELDs.

[3] See, e.g., Revenga (1997), Slaughter (2001), Amiti and Wei (2006), Harrison and McMillan (2006), Hijzen and Swaim (2010) or Cox et al. (2014). As a result, Lichter, Peichl, and Siegloch (2015) report severe publication bias in reduced-form models and therefore question the credibility of (unconditional) WELD estimates from this literature. In contrast, evidence for publication bias in structural-form studies is much weaker.

estimates by skill exhibit the inverse U-shaped pattern between skills and the substitution effect found in previous work: conditional on output, demand for low- and high-skilled workers is more elastic than for medium-skilled workers (see, e.g., Lichter, Peichl, and Siegloch, 2017).

Next, while all previous structural-form studies for Germany harness a cost-minimization model with given output, we, in contrast, explicitly allow for variations in output and investigate the relevance of scale effects. And they matter: the inverse U-shaped relationship between skills and WELDs turns around and becomes U-shaped.[4] Scale effects turn out to be particularly negative for medium-skilled workers. Hence, unconditional demand for medium-skilled workers (-1.3) is more elastic than the respective demand for low-skilled (-0.9) and high-skilled workers (-0.3). This finding is consistent with the third Hicks-Marshall law of derived demand stating that input factors with a high share in firms' cost also exhibit more negative scale effects.

Finally, we provide the first conditional and unconditional WELD estimates for the task-based approach. Our findings imply that substitution effects are highest for workers with manual non-routine and manual routine tasks. Again, scale effects matter. Overall, unconditional labor demand turns out to be more elastic for manual routine (-1.3) and cognitive routine tasks (-1.5) than for manual non-routine (-1.0), interactive non-routine (-0.8), and analytical non-routine tasks (-1.0).

In the second part of our analysis, we apply the results from the first part to analyze job polarization in Germany. We start by confirming previous findings and document a clear pattern of job polarization in the German manufacturing sector between 1993 and 2016: Whereas the share of medium-paid occupations gradually decreased until 2010, the share of high-paid occupations has been increasing since the turn of the millennium. The share of low-paid employees grew until 2000, before remaining relatively stable for the next decades.[5]

Next, we investigate the role of labor demand versus labor supply shifts for this pattern of job polarization. To do so, we use a supply-demand framework in the tradition of Katz and Murphy (1992).[6] Specifically, we follow Autor, Katz, and Kearney (2008) and regress yearly changes in occupational employment shares on yearly changes in wages per occupation. We find that while conventional demand-based explanations for job polarization apply to the pe-

[4]This result is consistent with the recent finding of Curtis et al., 2022 who analyze the effect of a tax policy called bonus depreciation in the United States on the demand for production workers (using a combination of reduced-form estimates and a calibrated model) and find that the scale effect was responsible for 90 percent of the overall effect of the policy.

[5]These results are consistent with earlier studies on Germany, which also report a polarization of jobs (Spitz-Oener, 2006; Dustmann, Ludsteck, and Schönberg, 2009; Goos, Manning, and Salomons, 2009; Goos, Manning, and Salomons, 2014; Antonczyk, DeLeire, and Fitzenberger, 2018).

[6]In a different context, Borjas (2003) analyzes the labor market impact of immigration by exploiting variation in labor supply shifts due to immigration to the US.

riod from 2000 to 2016, labor supply shocks were the main forces underlying the development of employment shares in the 1990s. Throughout this decade, negative correlations between employment and wage changes point towards strong shifts in labor supply along a stable labor demand curve. In line with this finding, interacting our estimated WELDs with observed wage changes yields counterfactual predictions for employment shares that resemble their factual trends for the period from 1993 and 2000, both for the skill- and the task-based approach. Hence, we infer that aggregate trends during the 1990s, such as the influx of migrants from Eastern Europe after the fall of the Iron Curtain and a rapid decline in the coverage of collective bargaining agreements, shifted labor supply. Moreover, both our slope estimates and counterfactual WELD predictions further indicate that labor supply shocks continued to play a role for low-paid occupations and counterbalanced demand shifts throughout 2000-2016.

The remainder of the paper is structured as follows: Section 2 sketches the theoretical framework, while Section 3 describes the empirical profit-maximization model. Section 4 characterizes the nature of our linked employer-employee data. Sections 5 and 6 show descriptive statistics, resulting elasticity estimates as well as robustness checks for the skill-based and the task-based division of the workforce. Section 7 analyzes whether labor supply shocks along our estimated labor demand curves can contribute to explaining job polarization. Finally, Section 8 concludes.

2 Theoretical Background

A rise in the wage rate will make profit-maximizing firms reduce labor demand for two reasons: substitution effects and scale effects (Sakai, 1974; Hamermesh, 1993).[7] Each effect reflects one of the two optimality considerations that profit-maximizing firms make: whereas the substitution effect relates to cost minimization for a given volume of output, the scale effect is the result of a firm's optimal choice of output. As a consequence, wage elasticities of labor demand can take two forms: conditional on a given output level, or unconditional. Conditional WELDs contain only the substitution effect while unconditional WELDs encompass the total effect of higher wages on labor demand (i.e., the sum of substitution and scale effects). Accordingly, the difference between conditional and unconditional WELDs reflects the scale effect.

Cost minimization requires firms to use the most efficient bundle of inputs to produce a certain level of production. In other words, the marginal rate of technical substitution between any two of the input factors must equal their factor price ratio. Conditional on

[7] Scale effects are sometimes also referred to as "expansion effects" or "output effects" in the literature.

output, wage changes alter factor the price ratios and thus cause firms to adjust their factor input demands – known as the substitution effect. Higher wages render labor relatively more expensive and therefore make firms substitute labor with another input (e.g., more capital) to hold production constant. As a consequence, the theory of labor demand predicts conditional (or constant-output) own-wage elasticities of labor demand to be negative.

Profit maximization, however, not only implies cost minimization given a certain level of output, but also requires firms to choose the level of production optimally. Therefore, wage changes additionally entail scale effects (Nagatani, 1978). Under perfect competition, firms optimize output by equating marginal cost with the product price.[8] Given higher wages, the marginal cost of production rises, thus making firms scale down their output. Hence, the demand for all factors, including labor, declines. Taken together, the own-wage effect on unconditional labor demand is unambiguously negative as both substitution and scale effects point in the same direction (Hamermesh, 1993). Hence, Le Chatelier's principle requires the unconditional (or total) own-wage elasticity of labor demand to exceed (in absolute terms) its conditional counterpart (Samuelson, 1947).[9]

If there is more than one input factor, not only the own-wage, but also the cross-wage elasticity of labor demand matters. For the latter, the sign is ambiguous depending on whether two input factors are substitutes (positive sign) or complements (negative sign). Conditional on output, two inputs represent either "gross substitutes" or "gross complements". When additionally considering scale effects, we differentiate between "net substitutes" or "net complements".

Marshall (1890) and Hicks (1932) identify determinants of the own-wage elasticity of labor demand, meanwhile known as the "Four Hicks-Marshall Laws of Derived Demand".[10] According to the laws, the unconditional wage elasticity of labor demand u_w^L is higher (i.e., more negative/elastic), the higher ...

1. ... the elasticity of substitution σ between labor and other inputs.
2. ... the price elasticity of demand η_P^Y for the final product.
3. ... the labor share s^L in total cost of production (provided that the price elasticity of

[8] With imperfect competition in product markets, firms command price-setting power and equate marginal cost with marginal revenue of production. When facing higher (lower) wages, firms can – at least partly – enforce an increase (a reduction) in product prices that will lower the optimal response in output and, thus, the magnitude of the scale effect.

[9] Throughout the paper, we refer to absolute values when speaking of the magnitude of wage elasticities of labor demand. Consequently, the terms "higher" or "larger" mean "more negative", i.e., a higher (larger) value refers in fact to a lower elasticity.

[10] For more information on the interpretation and derivation of the four Hicks-Marshall laws of derived demand (and especially the third one) see Bronfenbrenner (1961), Hicks (1961), Maurice (1975), Peirson (1988), and Pemberton (1989).

product demand is greater than the elasticity of substitution).

4. ... the price elasticity of supply for other factors in production.

In a framework with perfect competition on factor markets for labor L and capital K, Allen (1938) formulates an intuitively appealing version of the "Fundamental Law of Derived Demand" capturing the first three of these laws:

$$u_w^L \;=\; -\left(1 - s^L\right) \cdot \sigma \;-\; s^L \cdot \eta_P^Y \;<\; 0 \tag{1}$$

The first law of derived demand relates directly to the substitution effect. It stipulates that labor demand is more elastic in wages, the more easily firms substitute labor by capital when holding output constant, operationalized in terms of a higher elasticity of substitution between labor and capital: $\frac{\partial u_w^L}{\partial \sigma} = -\left(1 - s^L\right) < 0$.In contrast, the second law of derived demand refers to the scale effect. The more price-elastic product demand is, the sharper is the decline in output when firms pass on higher wages to consumers in the form of price increases. A higher price elasticity of demand for the final product will therefore result in more negative scale effects: $\frac{\partial u_w^L}{\partial \eta_P^Y} = -s^L < 0$.

The third law of derived demand relates unconditional WELDs to the share of labor in total cost. Marshall (1890) argues that, ceteris paribus, a higher labor share leads to more negative scale effects because wage increases for inputs with a large fraction in total cost will raise marginal cost by more than equivalent increases for smaller groups. Hicks (1932) called this argument the "importance of being unimportant", thus illustrating that small groups can enforce higher wages more effectively than large groups without putting their jobs at risk. Beyond that, he refined the argument by additionally integrating the relationship between the labor share and substitution effects. Vice versa, a higher labor share comes along with less negative substitution effects. In fact, a high labor share implies that workers are a relatively productive input factor that firms are reluctant to dispense with, despite available possibilities of substitution.[11]

In sum, the third law of derived demand features two transmission channels: While a higher share of labor in total cost reduces the size of substitution effects, it involves larger scale effects. Which effect ultimately dominates is an empirical question and depends on the relative magnitude of the elasticity of substitution and the price elasticity of product demand: $\frac{\partial u_w^L}{\partial s^L} = \sigma - \eta_P^Y \gtrless 0$. If consumers substitute more (less) easily than firms, a higher share of labor results in more (less) negative own-wage elasticities of labor demand.

[11] Under perfect competition with a numeraire good, the input share in total cost is equivalent to the production elasticity of the input factor: $s^L = \frac{w \cdot L}{C} = \frac{Y_L \cdot L}{Y}$.

3 Empirical Model

In order to estimate not only substitution effects, but also scale effects, we adopt a profit-maximization model that also incorporates the optimal choice of output, rather than a cost-minimization framework as in previous literature. In each period, we assume firms i to maximize their profits π while operating in perfectly competitive product and factor markets. Firms optimally choose product supply of a single homogeneous output good X^0 that they sell at a given product price w^0. Subject to their technology, firms produce output at minimal cost by combining $M-1$ different labor inputs $X^1, X^2, \ldots, X^{M-1}$ and the capital stock X^M. Factor markets offer labor and capital inputs at given market wages $w^1, w^2, \ldots, w^M$. Within our static framework, we adopt a long-run perspective and presume labor and the stock of capital to be flexible inputs.[12] Following Diewert and Wales (1987), we model technological progress as a quasi-fixed input incorporating a quadratic trend in time t.

Translog Profit Function. Under duality, a profit function suffices to summarize the profit-maximizing conduct of firms (Mundlak, 2001). As is common in the literature, we make use of a Translog profit function (Christensen, Jorgenson, and Lau, 1973), which is a logarithmic second-order Taylor approximation to an arbitrary twice-differentiable profit function. Our single-product, multi-factor Translog profit function exhibits the following log-linear form:

$$
\begin{aligned}
ln\,\pi\,(w^0, \ldots, w^M, t) \;=\; \alpha \;+\; \sum_{m=0}^{M} \beta_m \cdot ln\,w^m \;+\; \frac{1}{2} \cdot \sum_{m=0}^{M} \sum_{n=0}^{M} \beta_{mn} \cdot ln\,w^m \cdot ln\,w^n \\
+\; \gamma \cdot t \;+\; \gamma_t \cdot t^2 \;+\; \sum_{m=0}^{M} \gamma_m \cdot t \cdot ln\,w^m
\end{aligned} \tag{2}
$$

We follow standard practice and impose the regularity conditions of symmetry (3) and homogeneity of degree one in prices (4) on the profit function ($\forall\, m, n = 0, 1, \ldots, M$):

$$\beta_{mn} \overset{!}{=} \beta_{nm} \tag{3}$$

$$\sum_{m=0}^{M} \beta_m \overset{!}{=} 1 \qquad \sum_{m=0}^{M} \beta_{mn} \overset{!}{=} 0 \overset{!}{=} \sum_{n=0}^{M} \beta_{mn} \qquad \sum_{m=0}^{M} \gamma_m \overset{!}{=} 0 \tag{4}$$

[12] We justify the choice of a static labor demand model with the annual frequency of our panel data. As opposed to monthly or quarterly information, adjustment cost necessitating a dynamic model should play only a minor role with yearly data. Note that Lichter, Peichl, and Siegloch (2015) differentiate WELDs according to the time horizon to which they relate. In the short run, dynamic adjustment cost prevent employers from using inputs at their optimal levels. In the medium run, firms adjust the stock of workers and materials, but the stock of capital remains quasi-fixed. In the long run, temporary adjustment costs become negligible, and firms adjust all factors as the fixity of the capital stock no longer holds.

Hotelling's (1932) Lemma states that the derivation of a profit function with respect to product and input prices yields product supply and negative input demand, respectively: $\frac{\partial \pi}{\partial w^0} = X^0$ and $\frac{\partial \pi}{\partial w^m} = -X^m$ ($\forall\, m = 1, 2, \ldots, M$). Applying these identities to the derivative of log profit with respect to the logarithm of product and input prices gives a system of $M + 1$ equations of profit share s ($\forall\, m = 1, 2, \ldots, M$):

$$s^0 \equiv X^0 \cdot \frac{w^0}{\pi} = \frac{\partial \pi}{\partial w^0} \cdot \frac{w^0}{\pi} = \frac{\partial ln\, \pi}{\partial ln\, w^0} = \beta_0 + \sum_{n=0}^{M} \beta_{0n} \cdot ln\, w^n + \gamma_0 \cdot t \tag{5}$$

$$s^m \equiv -X^m \cdot \frac{w^m}{\pi} = \frac{\partial \pi}{\partial w^m} \cdot \frac{w^m}{\pi} = \frac{\partial ln\, \pi}{\partial ln\, w^m} = \beta_m + \sum_{n=0}^{M} \beta_{mn} \cdot ln\, w^n + \gamma_m \cdot t \tag{6}$$

As a novelty among profit-maximization models, we within-transform our micro-level data to eliminate potentially endogenous variation in product or input prices that stems from unobserved time-invariant heterogeneity across establishments. This transformation is equivalent to the inclusion of establishment fixed effects δ^m. Beyond that, our model incorporates year fixed effects ζ^m as well as a random error term ε^m. The associated disturbance vector $\varepsilon = (\varepsilon^0, \varepsilon^1, \ldots, \varepsilon^M)$ is assumed to exhibit a multivariate normal distribution with mean vector of zero and a constant covariance matrix: $\varepsilon \sim N(0, \Sigma)$. However, as profit shares always sum up to one, the error term covariance matrix becomes singular and non-diagonal, thus ruling out the estimation of all share equations as a system. As only M profit shares are linearly independent, we arbitrarily discard the profit share equation for output and normalize all input prices by the product price.[13]

Using panel subscripts i and t to denote the establishment and respective year, we face a final estimation system of M normalized profit share equations ($\forall\, m = 1, 2, \ldots, M$):

$$s^m_{it} = \sum_{n=1}^{M} \beta_{mn} \cdot ln\, \frac{w^n_{it}}{w^0_{it}} + \gamma_m \cdot t + \delta^m_i + \zeta^m_t + \varepsilon^m_{it} \tag{7}$$

We estimate this system of profit share equations using Zellner's (1962) Seemingly Unrelated Regression (SUR), while constraining the parameters to fulfill the symmetry condition (3). We obtain parameters from the discarded profit share equation by means of the constraints from (4). If error terms correlate within establishments across profit shares, SUR is more efficient than equation-wise ordinary least squares (OLS).

Given our SUR estimates and fitted profit shares, we compute unconditional own- and cross-price elasticities u^m_n of product supply and input demand.[14] We follow standard practice

[13] Although it does not matter which equation is dropped under iterative SUR, it is standard in the literature to discard the profit share equation for output.

[14] We obtain fitted profit shares for the discarded output equation as a residual: $\hat{s}^0_{it} = 1 - \sum_{m=1}^{M} \hat{s}^m_{it}$.

and calculate representative elasticities at sample means: $\hat{s}^m = \frac{1}{N}\sum_i \sum_t \hat{s}^m_{it}$.[15] Thus, unconditional own-price elasticities of product supply and input demand take the following form (Sidhu and Baanante, 1981):

$$\hat{u}^m_m = \frac{\partial X^m}{\partial w^m} \cdot \frac{w^m}{X^m} = \hat{s}^m - 1 + \frac{\hat{\beta}_{mm}}{\hat{s}^m} \tag{8}$$

The unconditional cross-price elasticities of product supply and input demand are:

$$\hat{u}^m_n = \frac{\partial X^m}{\partial w^n} \cdot \frac{w^n}{X^m} = \hat{s}^n + \frac{\hat{\beta}_{mn}}{\hat{s}^m} \tag{9}$$

In our single-product and multi-factor model, the matrix of unconditional elasticities reads:

$$\mathbf{\hat{U}} = \left(\begin{array}{c|c} \mathbf{\hat{U}^0_0} & \mathbf{\hat{U}^0_n} \\ \hline \mathbf{\hat{U}^m_0} & \mathbf{\hat{U}^m_n} \end{array} \right) = \left(\begin{array}{c|c|ccc} \hat{u}^0_0 & \hat{u}^0_1 & \cdots & \hat{u}^0_M \\ \hline \hat{u}^1_0 & \hat{u}^1_1 & \cdots & \hat{u}^1_M \\ \vdots & \vdots & \ddots & \vdots \\ \hat{u}^M_0 & \hat{u}^M_1 & \cdots & \hat{u}^M_M \end{array} \right) \tag{10}$$

In the lower right box of $\mathbf{\hat{U}}$, unconditional price elasticities of input demand (including WELDs) describe the total effect of higher factor prices on input demand. Lopez (1984) develops a general method for decomposing these total effects into substitution and scale effects, using only knowledge about the profit function. This procedure eliminates the need for specifying a separate cost-minimization model to measure substitution effects, and no longer requires production to be exogenously given. Higgins (1986) reformulates this decomposition method in terms of elasticities. Applying his formula to our single-product and M-factor profit function, we derive the following matrix of conditional price elasticities c^m_n of product supply and input demand:[16]

$$\mathbf{\hat{C}} = \left(\begin{array}{c|c} \text{N/A} & \text{N/A} \\ \hline \text{N/A} & \mathbf{\hat{U}^m_n} - \mathbf{\hat{U}^m_0}\,(\mathbf{\hat{U}^0_0})^{-1}\,\mathbf{\hat{U}^0_n} \end{array} \right) = \left(\begin{array}{c|ccc} \text{N/A} & & \text{N/A} & \\ \hline & \hat{c}^1_1 & \cdots & \hat{c}^1_M \\ \text{N/A} & \vdots & \ddots & \vdots \\ & \hat{c}^M_1 & \cdots & \hat{c}^M_M \end{array} \right) \tag{11}$$

[15]Note that elasticity estimates vary across establishments as Equations (8) and (9) contain observation-specific profit shares. By inserting sample means into these formulas, our elasticity estimates describe the behavior of a representative establishment. Our estimates are robust to alternative elasticity computations such as calculating the median of the underlying distribution of WELD estimates (see Table C3 and D3).

[16]In a multi-product model, the upper left box in (11) would feature conditional (or input-compensated) price elasticities of product supply, as opposed to conditional (or output-compensated) elasticities of input demand in the lower right box. However, we assume output to be homogeneous and, thus, neglect any substitution effects between different products that arise from revenue maximization given fixed input levels. For the same reason, our estimated unconditional price elasticities of product supply comprise only scale effects.

Conditional price elasticities of input demand appear in the lower right box in $\hat{\mathbf{C}}$ - including a submatrix of $(M-1)^2$ WELDs. We obtain bootstrapped standard errors using 1000 replications.

Input Heterogeneity. Our study represents the first estimation of a profit function that treats labor as a heterogeneous input factor. We estimate our multi-factor Translog profit function for two sets of labor inputs: with a skill-based and a task-based division of the workforce. In the skill-based approach, we differentiate between three types of educational attainment: low-, medium-, and high-skilled workers. Low-skilled workers have not acquired any professional qualification. Instead, medium-skilled workers have completed vocational training whereas high-skilled workers hold a university degree.

In contrast, the task-based approach puts forward that it is the tasks and not the skills that produce goods (Autor, Levy, and Murnane, 2003). However, no study has yet estimated WELDs with respect to different types of tasks – neither conditional nor unconditional. Therefore, we complement our "skill-based" division with a "task-based" division of the workforce and measure unconditional WELDs for five types of tasks. We rely on Spitz-Oener's (2006) distinction of work into task dimensions and assign each worker the task type that is performed most in their occupation.[17] We distinguish workers specializing on manual routine, manual non-routine, cognitive routine, interactive non-routine, or analytical non-routine tasks. Routine and non-routine tasks differ in their susceptibility for automation. Routine tasks can be formulated in terms of rules and, thus, represent a substitute for machines. In contrast, non-routine tasks feature a higher degree of specificity and are not prone to be replaced by technology. Manual tasks are mainly performed by one's hand. While analytical tasks predominantly require workers to think and solve problems, interactive tasks focus on oral and written communication with people. We group together analytical routine and interactive routine tasks and term them "cognitive routine tasks".

4 Data

For our analysis, we us administrative data from the Linked Employer-Employee Dataset (LIAB) of the Institute for Employment Research (IAB) in Germany for the years 1993-2016 (Klosterhuber, Lehnert, and Seth, 2016). The LIAB merges survey data from the IAB Establishment Panel with administrative records on respective employees from the Integrated Employment Biographies (IEB) of the Federal Employment Agency (Müller and Wolter,

[17] Table B1 in the appendix illustrates the division of work into task groups along with exemplary occupations.

2020).

The IEB dataset collects notifications about all workers in Germany that are subject to social security contributions.[18] Among other variables, these administrative records include information on each workers' daily gross wage, qualification, 5-digit occupation, contract type, and whether they work full- or part-time. We impute right-censored gross wages above the upper-earnings limit on social security contributions following Card, Heining, and Kline (2013).[19] To capture a worker's overall cost for the establishment, we sum up gross wages and the employer contribution to social security and obtain a measure of daily labor cost for each employment spell. We assign each worker the task type that is performed most within the corresponding occupation (Dengler, Matthes, and Paulus, 2014).[20] For lack of information on individual hours worked, we restrict our analysis to full-time employees in regular employment.[21] Given all valid employment spells on the 30th of June of each year, we calculate the number of workers and mean daily labor cost per establishment-year combination and input factor and link these variables to the IAB Establishment Panel.

The IAB Establishment Panel is an annual representative survey of German establishments (Ellguth, Kohaut, and Möller, 2014). The term "establishment" refers to an individual plant and is defined as a locally and commercially separate unit where at least one worker subject to social security contributions works.[22] To reflect the universe of German establishments, the random sample is stratified with respect to ten size classes, sixteen industries, and

[18] Self-employed persons, civil servants, and family workers do not enter the IEB data as these groups of workers are exempt from social security contributions.

[19] Card, Heining, and Kline (2013) propose a two-step procedure for the imputation of wages. In a first step, fitted wages from a Tobit regression are used to calculate mean wages per establishment (excluding the observation at hand). In a second step, repeating the regression with this variable as an additional regressor delivers final imputations. Specifically, we adopt Schmucker et al.'s (2018) implementation of this approach and regress log daily wages on age, (square of) log establishment size, share of low-skilled and high-skilled workers within the establishment, share of censored observations excluding the observation at hand as well as dummies for German nationality, workplace in East Germany, one-person establishments, and establishments with more than ten full-time employees. Separate Tobit models are estimated for each interaction of year (24 waves), gender (2 groups), qualification (3 groups), and age (6 groups) whereby the three highest age groups are combined for high-skilled workers.

[20] Dengler, Matthes, and Paulus (2014) harness information from the BERUFENET expert database of the German Federal Employment Agency. The database provides detailed descriptions about 4,000 occupations including their specific requirements. Three independent coders assign requirements to one of the five task dimensions, thus determining the task composition for each 3-digit occupation. For the years 1993-2011, we link 3-digit occupations with main tasks using the German Classification of Occupations 1988 (KldB 1988) whereas, from 2012 onward, the linkage is based on the more recent KldB 2010. The vulnerability of our static linkage (based on 2013) to changes over time is mitigated by the fact that we only look at main tasks and not the task composition per occupation. We are fully aware that our data cannot account for heterogeneity in job tasks among individuals within occupations (Autor, 2013). Nevertheless, the BERUFENET database provides an excellent overview about requirements per occupation and, thus, allows for a reasonable approximation to tasks at the individual level.

[21] Non-regular employment comprises apprentices, workers in marginal part-time employment, and people in partial retirement.

[22] In this study, we use the terms "establishment" and "firm" interchangeably.

the federal states of Germany.[23] The survey is available from 1993 onward, with questions referring to the 30th of June of the respective year.[24] In particular, we retrieve longitudinal information on revenue, investment expenditure, and the 3-digit industry classification from the IAB Establishment Panel.[25] We exploit the investment data to approximate the capital stock using the modified perpetual-inventory method by Müller (2017).[26]

Our structural identification of scale effects requires simultaneous information on product prices. We harness a novel linkage that allows us to enrich our LIAB data with 3-digit producer price levels from the German Federal Statistical Agency (Destatis, 2017). As this linkage is only available for manufacturing, we focus on establishments from this industry throughout the study.[27] To operationalize user cost of capital, we use yearly means of daily twelve-month FIBOR (1993-1998) and EURIBOR (1999-2016) interest rates from the German Bundesbank.

For each observation, we calculate restricted daily profits, which is revenue minus variable cost, as well as product- and input-specific profit shares. We eliminate establishments whose legal form does not imply profit maximization or is unknown. To justify our focus on full-time employees, we further discard establishments with a share of part-time workers of more than 25 percent.[28] We arrive at a final panel of 61,318 establishment-year observations (corresponding to about 91 percent of manufacturing firms in the LIAB data). The dataset includes 12,702 establishments, which we observe, on average, 4.8 times during a span of 24 years. Observed establishments employ a total of 17,442,520 workers, which corresponds to 0.5-1.2 million persons per year or 8-16 percent of overall employment in German manufacturing.

5 Results for the Skill-Based Approach

Descriptive Statistics. We start with analyzing the labor demand curve through the lens of the skill-based approach. Table 1 displays descriptive statistics. On average, establishments

[23] Owing to disproportionate stratification, establishments with a large number of workers, and from small industries or federal states are overrepresented in the final sample.

[24] The IAB Establishment Panel conducts interviews with West German firms since 1993. As of 1996, establishments from East Germany take also part in the survey.

[25] In the IAB Establishment Panel, information on revenue and investment is asked retrospectively. Therefore, we use the waves from 1994 to 2017 and move these variables a year into the past. Industry codes refer to the German Classification of Economic Activities 2008 (WZ 2008) whose first four digits coincides with the NACE Rev. 2 definition. For the years 1993-2007, we impute industry affiliations by applying the heuristic from Eberle et al. (2011) to industry codes for the Classifications of Economic Activities 1993 and 2003.

[26] Division of replacement investment by industry-specific depreciation rates yields a provisional approximation of capital per establishment and year. To mitigate bias from lumpy investment, we use three-year averages of this measure as initial values for the stock of capital per establishment. Given these starting values, we determine subsequent capital stocks via the law of motion using information on net investment, replacement investment, and industry-wide depreciation rates.

[27] Such a linkage is possible because the German Classification of Products (GP 2009) is designed to overlap with the German Classification of Economic Activities (WZ 2008) for the manufacturing industry.

[28] In this way, we reduce the average share of part-time workers in total employment to 4.0 percent.

earn a daily restricted profit of around 510,000 Euro.[29] The German manufacturing sector is characterized by a particularly high share of medium-skilled workers in employment. Between 1993 and 2016, the average establishment from the manufacturing industry employs 31 low-skilled, 210 medium-skilled, and 42 high-skilled full-time workers. Establishments maintain an average capital stock worth about 90 million Euro. Whilst the averages of the mean daily labor cost differ only slightly between low-skilled (89.6 Euro) and medium-skilled workers (95.8 Euro), high-skilled workers generate considerably higher daily labor costs in the amount of 160.1 Euro. The average interest rate is 2.7 percentage points.

Overall, expenditure for medium-skilled labor dominate firms' wage bill with a mean share in restricted cost of 67.3 percent (see Table C1).[30] This property holds for the vast majority of establishments: at the 10th percentile, medium-skilled workers still feature a cost share of 49.1 percent. We identify two explanations for the high use of medium-skilled workers in German manufacturing. On the one hand, Germany's well-known dual training system provides integrated education in vocational schools and firms, rendering vocational training attractive to both workers and employers. On the other hand, the fact that the average medium-skilled worker receives only half the wage of high-skilled workers, while earning only little more than low-skilled workers, is supposed to stimulate labor demand.

Using the panel structure of the LIAB, we decompose variation in our measure of nominal revenues into variation between and within establishments. At around one third, a substantial part of variation in revenue comes from changes within establishments over time. To the extent that prices remain relatively stable throughout the period of study, this variation points to output changes within establishments over time, reflecting a potential materialization of scale effects. We view this finding as empirical support for our decision to use a profit-maximization model in which firms can adjust output.

Conditional WELDs. Table 2 depicts estimates for conditional price elasticities of input demand based on our Translog profit function for the skill-based approach.[31] Conditional own-wage elasticities of labor demand turn out to be negative, thus mirroring negative substitution effects. Our estimates show that the demand for medium-skilled workers (-0.23) is

[29] At first glance, this figure might seem quite high. However, we report restricted profits in a sense that we neglect expenditure for part-time workers, workers with a non-regular contract, and other input factors such as materials or energy. Moreover, the mean value is affected by outliers at the top of the profit distribution.

[30] This stylized fact mechanically results in profit shares for medium-skilled workers that are more negative than profit shares for low-skilled workers, high-skilled workers, and the capital stock. As our system of equations features profit shares as dependent variables, we report descriptive statistics for profit instead of cost shares in Table 1. However, as cost shares can be more easily interpreted than profit shares, we further report means and selected percentiles of cost shares in the appendix.

[31] Underlying SUR estimates for the system of four normalized profit share equations can be found in Table C2 in the appendix.

Table 1: Descriptive Statistics for Skill-Based Approach

		Mean	P50	Stand. Dev.	Mini-mum	Maxi-mum	Obser-vations
	Profit	5.1e05	7.5e04	3.7e06	43.63	1.5e08	16,636
Quantity	Output	2.5e05	1.8e04	2.5e06	26.54	1.6e08	45,442
	Low-Skilled W.	31.17	1	136.1	0	6,238	61,318
	Med.-Skilled W.	209.8	38	1011	0	44,664	61,318
	High-Skilled W.	41.57	3	308.3	0	17,826	61,318
	Capital Stock	9.0e07	7.5e06	7.8e08	486.1	3.5e10	30,603
Price	Output	0.988	0.980	0.264	0.419	6.010	56,217
	Low-Skilled W.	89.63	88.22	29.67	0.933	352.8	36,434
	Med.-Skilled W.	95.78	93.05	34.73	0.036	524.4	60,831
	High-Skilled W.	160.1	158.3	61.80	3.476	1233	44,204
	Capital Stock	0.027	0.023	0.016	0.000	0.065	61,318
Profit Share	Output	1.446	1.336	1.604	1.006	174.8	16,636
	Low-Skilled W.	-0.038	-0.017	0.127	-13.21	0.000	16,636
	Med.-Skilled W.	-0.292	-0.222	0.639	-47.51	-0.002	16,636
	High-Skilled W.	-0.076	-0.039	0.392	-28.49	0.000	16,636
	Capital Stock	-0.039	-0.017	0.752	-95.52	0.000	16,636

NOTE. — The table shows descriptive statistics for the skill-based approach. All statistics reflect establishment-year observations. Restricted profits (in Euro and per day) originate from data on output, inputs, and their specific prices. Output refers to the daily mean of yearly revenues (expressed in Euro). The workforce is divided into three groups with different levels of educational attainment: low-skilled, medium-skilled, and high-skilled workers. Labor inputs denote the number of full-time employees with a regular contract on June 30 in the respective year. Capital stock (in Euro) is approximated by means of the modified perpetual-inventory method from Müller (2017). Output prices relate to yearly producer price levels with base year 2010. Prices for labor inputs refer to the establishment-specific mean of individual labor cost on June 30 in the respective year. User cost of capital (in percentage points / 100) represent yearly means of daily twelve-month FIBOR (1993-1998) and EURIBOR (1999-2016) interest rates. Profit shares are the quotient of product- or input-specific revenues/costs and total profits. P50 = Median. Stand. Dev. = Standard Deviation. W. = Workers. Sources: LIAB + Destatis, 1993-2016.

less elastic than the demand for low- (-0.77) and high-skilled workers (-0.33), conditional on output.[32] Given their large cost shares, the small substitution effects for medium-skilled workers are in line with the third Hicks-Marshall law of derived demand. Our results corroborate the so-called "inverse U-shaped pattern" between skills and substitution effects, as put forward by earlier studies for Germany using cost minimization models (e.g., Fitzenberger and Franz, 1998; Peichl and Siegloch, 2012; Cox et al., 2014; Lichter, Peichl, and Siegloch, 2017). For capital demand, we find an insignificant own-price elasticity of -0.57. Significantly positive cross-wage elasticities suggest that low- and medium-skilled workers represent mutual net substitutes. Conditional on output, substitution and complementarity relations do not appear to be pronounced for other input pairs as their conditional cross-price elasticities show insignificant values.

[32]Numerous LIAB studies for Germany find an insignificant value for the conditional own-wage elasticity of labor demand for high skilled workers, such as Bellmann, Bender, and Schank (1999), Addison et al. (2008), or Lichter, Peichl, and Siegloch (2017). We attribute this insignificance to top-coding of wages at the social

Unconditional WELDs and Scale Effects. Unlike prior studies with LEE data (see Appendix A for details), the estimation of a profit function allows us to measure not only the substitution effects, but also the total effects of higher wages on the demand for labor. Table 3 illustrates the matrix of unconditional elasticity estimates, which, compared to the conditional WELD matrix, also contains scale effects. In contrast to the majority of reduced-form estimates in the literature, our WELD estimates are consistent with the theoretical proposition that scale effects are negative.[33] However, the size of scale effects varies across inputs. For low- (-0.90) and high-skilled workers (-0.33), unconditional own-wage elasticities of labor demand turn out to be only slightly more negative than their conditional counterparts, thus indicating minor scale effects. In contrast, medium-skilled workers exhibit large scale effects. For this group, the unconditional own-wage elasticity increases (in absolute terms) from -0.23 to -1.40. Crucially, by virtue of scale effects, the well-known inverse U-shaped pattern between skills and the own-wage elasticity of labor demand turns around and becomes U-shaped (see Figure C1).

Again, the third Hicks-Marshall law of derived demand can shed light on the markedly negative scale effect of medium-skilled workers. Given their high share in total cost, wage increases translate into more pronounced output reductions for medium-skilled workers than for any other factor.[34] For this reason, employers reduce their labor demand to a larger extent relative to a setting where wage rates of less cost-intensive inputs rise. In our analysis, the scale effect for medium-skilled workers is large enough to overcompensate their relatively low substitution effect. Apart from that, the unconditional own-price elasticity of capital demand amounts to -0.67. Low-skilled workers and the capital stock represent mutual gross complements. In line with production theory, we also recover a significantly positive price elasticity of product supply of 0.36.

Sensitivity and Heterogeneity. We conduct several checks to evaluate the sensitivity and heterogeneity of our estimates. Table C3 illustrates own-price elasticities from these checks. In sum, our robustness checks buttress that highly negative scale effects turn around the inverse U-shaped pattern between skills and substitution effects. Specifically, our WELD estimates are robust to computing elasticities at the median (instead of elasticities at the mean), to integrating the Translog profit function itself into the equation system, to discarding year

security contribution ceiling.

[33] In line with our argumentation in Section 1, estimation of a reduced-form model with our LIAB data yields positive scale effects for each input factor.

[34] Elasticities in the first row from Table 3 illustrate that output is reduced most when medium-skilled workers become more expensive.

Table 2: Conditional WELDs for Skill-Based Approach

Price Quantity	Output	Low-Skilled Workers	Medium-Skilled Workers	High-Skilled Workers	Capital Stock
Output	N/A	N/A	N/A	N/A	N/A
Low-Skilled Workers	N/A	**-0.774*** (0.049)**	0.786*** (0.229)	0.211 (0.189)	-0.224 (0.147)
Medium-Skilled Workers	N/A	0.095*** (0.028)	**-0.232* (0.134)**	0.055 (0.145)	0.082 (0.058)
High-Skilled Workers	N/A	0.096 (0.084)	0.208 (0.525)	**-0.330 (0.592)**	0.026 (0.102)
Capital Stock	N/A	-0.248 (0.160)	0.751 (0.523)	0.063 (0.245)	**-0.566 (0.435)**

NOTE. — The table displays estimates of conditional WELDs for the skill-based approach. Elasticities are evaluated at sample means and fitted values. Bootstrapped standard errors are in parentheses. The number of Bootstrap samples is 1,000. Own-price elasticities are shown in bold type. Conditional WELDs incorporate only substitution effects as they relate to cost minimization given fixed output. Conditional WELDs were derived from the matrix of unconditional WELDs by means of the decomposition method from Lopez (1984) and Higgins (1986). The number of observations is 14,830. N/A = Not Available. * = p<0.10. ** = p<0.05. *** = p<0.01. Sources: LIAB + Destatis, 1993-2016.

Table 3: Unconditional WELDs for Skill-Based Approach

Quantity \ Price	Output	Low-Skilled Workers	Medium-Skilled Workers	High-Skilled Workers	Capital Stock
Output	**0.359*** (0.063)**	-0.033*** (0.004)	-0.288*** (0.028)	-0.009 (0.054)	-0.029*** (0.003)
Low-Skilled Workers	1.392*** (0.147)	**-0.902*** (0.046)**	-0.333** (0.152)	0.177 (0.139)	-0.335** (0.159)
Medium-Skilled Workers	1.455*** (0.134)	-0.040** (0.018)	**-1.401*** (0.139)**	0.020 (0.121)	-0.034 (0.063)
High-Skilled Workers	0.166 (1.012)	0.081 (0.062)	0.075 (0.451)	**-0.334 (0.449)**	0.013 (0.144)
Capital Stock	1.325*** (0.146)	-0.370** (0.172)	-0.313 (0.573)	0.031 (0.343)	**-0.672 (0.443)**

Note. — The table displays estimates of unconditional WELDs for the skill-based approach. Elasticities are evaluated at sample means and fitted values. Bootstrapped standard errors are in parentheses. The number of Bootstrap samples is 1,000. Own-price elasticities are shown in bold type. Unconditional WELDs incorporate both substitution and scale effects as they relate to profit maximization with flexible output. The number of observations is 14,830. * = p<0.10. ** = p<0.05. *** = p<0.01. Sources: LIAB + Destatis, 1993-2016.

fixed effects, and to including dummy variables for the stratification variables of the IAB Establishment Panel (industry, size class, and federal state). Using median instead of mean wages merely alters the own-wage elasticities of the demand for high-skilled workers, where we observe positive but still insignificant values. Alternative measures for the stock of capital and user cost of capital do not affect the pattern of our WELD estimates.[35]

We do not find marked differences in terms of elasticities between West and East German establishments. On average, large establishments (i.e., with more than two hundred full-time employees) and those establishments that follow a collective wage agreement at the firm or industry level feature more negative substitution effects for high-skilled workers than small establishments or those without a collective agreement. For the years 2010-2016, we can restrict our sample to firms facing medium or high competitive pressure. WELD estimates deviate only slightly from the elasticities that refer to the overall 2010-2016 sample. We view the latter result as evidence that our identifying assumption of perfect competition (without the possibility of firms adjusting prices or wages) does not bias our results.[36]

6 Results for the Task-Based Approach

Descriptive Statistics. In addition to WELDs by skills, and for the first time in the literature, we provide wage elasticities of labor demand for different types of tasks. Table 4 illustrates descriptive statistics for the task-based approach. Establishments achieve a mean restricted profit of 850,000 Euro per day.[37] In German manufacturing, the average establishment employs about 100 full-time workers each who mainly perform manual routine and cognitive routine tasks, respectively. Demand for workers with a focus on analytical non-routine tasks or manual non-routine tasks is lower whereas workers that predominantly carry out interactive non-routine tasks are rare. Average labor costs per day turn out to be higher for analytical non-routine (146.8 Euro) and interactive non-routine tasks (144.6 Euro) than for workers executing cognitive routine tasks (107.3 Euro), manual non-routine (92.0 Euro), or manual routine tasks (91.5 Euro). While jobs with manual routine, cognitive routine, and analytical non-routine tasks each cover about twenty-five percent of total cost (see Table D1),

[35] Given the modified perpetual-inventory method from (Müller, 2017), our alternative measure for the capital stock uses complete instead of three-year averages of approximated capital as starting values for the law of motion. The alternative measure for user cost of capital refers to three-month FIBOR (1993-1998) and EURIBOR (1999-2016) instead of twelve-month interest rates from the German Bundesbank.

[36] In a meta-study on minimum wages, Lemos (2008) finds evidence that wage increases translate into price increases but only to a limited extent.

[37] Our reported profits for the task-based approach exceed those reported for the skill-based approach. The difference is likely driven by selection given that we are only able to calculate profits for establishments that employ at least one worker from all three skill or five task types, respectively. Hence, establishments that enter the task-based approach are on average larger and, thus, should feature higher restricted profits than establishments from the skill-based approach.

Table 4: Descriptive Statistics for Task-Based Approach

		Mean	P50	Stand. Dev.	Mini-mum	Maxi-mum	Obser-vations
	Profit	8.5e05	1.4e05	5.1e06	958.5	1.5e08	8,642
Quantity	Output	2.5e05	1.8e04	2.5e06	26.54	1.6e08	45,442
	Man. R. Task	94.84	15	402.4	0	17,190	61,318
	Man. N.-R. Task	18.19	1	90.53	0	3,503	61,318
	Cogn. R. Task	102.1	11	554.2	0	27,549	61,318
	Inter. N.-R. Task	3.931	0	25.57	0	1,328	61,318
	An. N.-R. Task	58.99	6	439.7	0	23,531	61,318
	Capital Stock	9.0e07	7.5e06	7.8e08	486.1	3.5e10	30,603
Price	Output	0.988	0.980	0.264	0.419	6.010	56,217
	Man. R. Task	91.53	88.77	31.26	0.107	1290	52,897
	Man. N.-R. Task	91.95	88.83	35.83	1.465	912.8	35,526
	Cogn. R. Task	107.3	105.2	40.30	0.036	580.7	52,372
	Inter. N.-R. Task	144.6	143.8	69.14	1.689	708.7	21,503
	An. N.-R. Task	146.8	145.7	50.40	0.119	1233	46,230
	Capital Stock	0.027	0.023	0.016	0.000	0.065	61,318
Profit Share	Output	1.411	1.312	1.643	1.007	139.9	8,642
	Man. R. Task	-0.112	-0.072	0.197	-10.52	0.000	8,642
	Man. N.-R. Task	-0.021	-0.009	0.047	-1.865	0.000	8,642
	Cogn. R. Task	-0.129	-0.082	0.379	-18.59	0.000	8,642
	Inter. N.-R. Task	-0.015	-0.005	0.039	-1.386	0.000	8,642
	An. N.-R. Task	-0.091	-0.062	0.413	-33.02	0.000	8,642
	Capital Stock	-0.043	-0.018	0.826	-76.44	0.000	8,642

NOTE. — The table shows descriptive statistics for the task-based approach. All statistics reflect establishment-year observations. Restricted profits (in Euro and per day) originate from data on output, inputs, and their specific prices. Output refers to the daily mean of yearly revenues (expressed in Euro). The workforce is divided into five groups with different main tasks: manual non-routine, manual routine, cognitive routine, interactive non-routine, and analytical non-routine tasks. Labor inputs denote the number of full-time employees with a regular contract on June 30 in the respective year. Capital stock (in Euro) is approximated by means of the modified perpetual-inventory method from Müller (2017). Output prices relate to yearly producer price levels with base year 2010. Prices for labor inputs refer to the establishment-specific mean of individual labor cost on June 30 in the respective year. User cost of capital (in percentage points / 100) represent yearly means of daily twelve-month FIBOR (1993-1998) and EURIBOR (1999-2016) interest rates. Profit shares are the quotient of product- and input-specific revenues/costs and total profits. An. = Analytical. Cogn. = Cognitive. Inter. = Interactive. Man. = Manual. N.-R. = Non-Routine. P50 = Median. R. = Routine. Stand. Dev. = Standard Deviation. Sources: LIAB + Destatis, 1993-2016.

the remaining quarter is split among the other inputs. By construction, prices and quantities for both output and capital stock do not deviate from the skill-based approach.

Conditional WELDs. Table 5 displays conditional price elasticities of input demand that stem from estimating the system of profit share equations for the task-based approach.[38] Estimated own-wage elasticities of labor demand are significantly smaller than zero and thus in line with the theoretical prediction that substitution effects are negative. Conditional labor

[38]The underlying SUR estimates for the system of six normalized profit share equations are shown in Table D2 in the appendix.

demand is more elastic for manual routine (-0.98) than for manual non-routine tasks (-0.83). Cognitive routine tasks (-0.86) are slightly more substitutable than interactive non-routine (-0.77) and analytical non-routine tasks (-0.73). Obviously, the magnitude of substitution effects tends to be more negative for routine than for non-routine tasks. This result is intuitively appealing as non-routine tasks should be less easily substitutable than routine tasks.[39] Cross-price elasticities imply that jobs with an emphasis on manual routine, cognitive routine, and analytical non-routine tasks reflect net substitutes. Moreover, the capital stock is a net substitute for interactive and analytical non-routine tasks whereas it serves as a net complement for manual non-routine tasks.

Unconditional WELDs and Scale Effects. Table 6 displays the estimated matrix of unconditional elasticities for the task-based approach. In line with theory, we find negative scale effects for all inputs. Hence, a cost-minimization model with given production would underestimate total own-wage responses in labor demand.[40] Figure D1 illustrates the estimated set of own-wage elasticities of labor demand for different types of tasks (in ascending order of average daily labor costs). Manual non-routine and interactive non-routine tasks show hardly discernible scale effects, thus featuring unconditional own-wage elasticities of -0.97 and -0.81. By virtue of high fractions in total cost, the remaining task dimensions exhibit more pronounced scale effects. The own-wage elasticity of the demand for analytical non-routine tasks falls to -0.97. We report the most negative total effects for cognitive routine (-1.48) and manual routine tasks (-1.32). Overall, demand for routine tasks is more elastic than for non-routine tasks. Manual non-routine tasks represent mutual gross complements to the capital stock. Other than the demand for tasks, the unconditional own-price elasticity of capital demand is not significantly smaller than zero. The price elasticity of supply is 0.41, reflecting a positively sloped product supply curve.

Sensitivity and Heterogeneity. Table D3 displays results from robustness checks for the task-based approach. Again, the tests generally support the baseline pattern. With the profit function included in the estimation system, manual routine and cognitive routine tasks still feature more negative total effects than manual non-routine, interactive non-routine, and analytical non-routine tasks. The general WELD pattern is robust to calculating elasticities at the median of observations, excluding year fixed effects, controlling for stratification variables,

[39] Autor, Levy, and Murnane (2003, p. 1280) characterize routine tasks as those with a "limited and well-defined" set of activities. Therefore, routine tasks imply a high ease of substitution.

[40] Also with the task-based approach, applying reduced-form models to our LIAB data produces positive scale effects for each input factor.

Table 5: Conditional WELDs for Task-Based Approach

Quantity \ Price	Output	Manual Routine Task	Manual Non-Routine Task	Cognitive Routine Task	Interactive Non-Routine Task	Analytical Non-Routine Task	Capital Stock
Output	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Manual Routine Task	N/A	**-0.975***** **(0.117)**	0.056 (0.055)	0.682*** (0.143)	0.027 (0.040)	0.204** (0.081)	0.007 (0.082)
Manual Non-Routine Task	N/A	0.288 (0.284)	**-0.833***** **(0.127)**	0.614* (0.334)	0.042 (0.077)	0.265 (0.240)	-0.376* (0.224)
Cognitive Routine Task	N/A	0.603*** (0.119)	0.105* (0.056)	**-0.857***** **(0.165)**	0.018 (0.055)	0.179** (0.085)	-0.048 (0.117)
Interactive Non-Routine Task	N/A	0.193 (0.291)	0.059 (0.107)	0.146 (0.449)	**-0.769***** **(0.110)**	0.065 (0.212)	0.306** (0.146)
Analytical Non-Routine Task	N/A	0.254** (0.102)	0.064 (0.058)	0.253** (0.119)	0.011 (0.036)	**-0.726***** **(0.141)**	0.143** (0.062)
Capital Stock	N/A	0.026 (0.283)	-0.255* (0.151)	-0.189 (0.457)	0.149** (0.069)	0.402** (0.170)	**-0.133** **(0.335)**

NOTE. — The table displays estimates of conditional WELDs for the task-based approach. Elasticities are evaluated at sample means and fitted values. Bootstrapped standard errors are in parentheses. The number of Bootstrap samples is 1,000. Own-price elasticities are shown in bold type. Conditional WELDs incorporate only substitution effects as they relate to cost minimization given fixed output. Conditional WELDs were derived from the matrix of unconditional WELDs by means of the decomposition method from Lopez (1984) and Higgins (1986). The number of observations is 7,482. N/A = Not Available. * = p<0.10. ** = p<0.05. *** = p<0.01. Sources: LIAB + Destatis 1993-2016.

Table 6: Unconditional WELDs for Task-Based Approach

Quantity \ Price	Output	Manual Routine Task	Manual Non-Routine Task	Cognitive Routine Task	Interactive Non-Routine Task	Analytical Non-Routine Task	Capital Stock
Output	**0.405***** **(0.047)**	-0.103*** (0.008)	-0.029*** (0.003)	-0.148*** (0.034)	-0.013*** (0.002)	-0.078*** (0.010)	-0.033*** (0.003)
Manual Routine Task	1.339*** (0.089)	**-1.317***** **(0.116)**	-0.040 (0.057)	0.191 (0.130)	-0.016 (0.038)	-0.054 (0.083)	-0.102 (0.079)
Manual Non-Routine Task	1.949*** (0.176)	-0.209 (0.293)	**-0.972***** **(0.126)**	-0.100 (0.297)	-0.020 (0.076)	-0.112 (0.242)	-0.536** (0.222)
Cognitive Routine Task	1.702*** (0.343)	0.169 (0.114)	-0.017 (0.051)	**-1.481***** **(0.294)**	-0.036 (0.059)	-0.149 (0.111)	-0.187 (0.120)
Interactive Non-Routine Task	1.206*** (0.159)	-0.114 (0.276)	-0.028 (0.106)	-0.296 (0.484)	**-0.808***** **(0.106)**	-0.168 (0.204)	0.207 (0.149)
Analytical Non-Routine Task	1.265*** (0.151)	-0.068 (0.103)	-0.027 (0.058)	-0.211 (0.161)	-0.029 (0.035)	**-0.970***** **(0.147)**	0.040 (0.063)
Capital Stock	1.507*** (0.142)	-0.358 (0.279)	-0.362** (0.149)	-0.742 (0.467)	0.101 (0.070)	0.111 (0.176)	**-0.256** **(0.344)**

NOTE. — The table displays estimates of unconditional WELDs for the task-based approach. Elasticities are evaluated at sample means and fitted values. Bootstrapped standard errors are in parentheses. The number of Bootstrap samples is 1,000. Own-price elasticities are shown in bold type. Unconditional WELDs incorporate both substitution and scale effects as they relate to profit maximization with flexible output. The number of observations is 7,482. * = p<0.10. ** = p<0.05. *** = p<0.01. Sources: LIAB + Destatis, 1993-2016.

or using our alternative measures for wages, capital, and interest rates.

We report particularly strong substitution effects for the demand for cognitive routine tasks in large and West German establishments. Establishments bound to a collective bargaining agreement tend to show more elastic reactions in labor demand, apart from analytical non-routine tasks. Limiting the sample to establishments with medium or high competitive pressure hardly alters the results from 2010 to 2016.

7 Discussion of Results and Link to Job Polarization

In this section, we make use of our WELD estimates from the previous sections to evaluate whether shocks to labor supply can explain employment changes in German manufacturing between 1993 and 2016.

Employment Trends. To do so, we start by showing the observed employment trends in our data. Following the polarization literature, we assign each 3-digit occupation a quantile rank according to its average daily labor cost in the base year 2000. Given this ranking, we classify jobs into three equally-sized groups: low-paid occupations (quantile rank: 0-0.33), medium-paid occupations (quantile rank: 0.33-0.67), and high-paid occupations (quantile rank: 0.67-1). We plot changes in log employment shares between 1993 and 2016 (multiplied by 100) against quantile ranks and apply a kernel-weighted local polynomial smoothing regression to this scatterplot.[41] Figure 1 shows the results. Building on the shape of the fitted regression curve, we document a clear pattern of job polarization in German manufacturing between 1993 and 2016: employment shares of low- and high-paid workers increased while the share of occupations in the middle of the wage distribution decreased.[42] Our results are consistent with earlier studies on Germany, which also report a polarization of jobs (Spitz-Oener, 2006; Dustmann, Ludsteck, and Schönberg, 2009; Goos, Manning, and Salomons, 2009; Goos, Manning, and Salomons, 2014; Antonczyk, DeLeire, and Fitzenberger, 2018).[43]

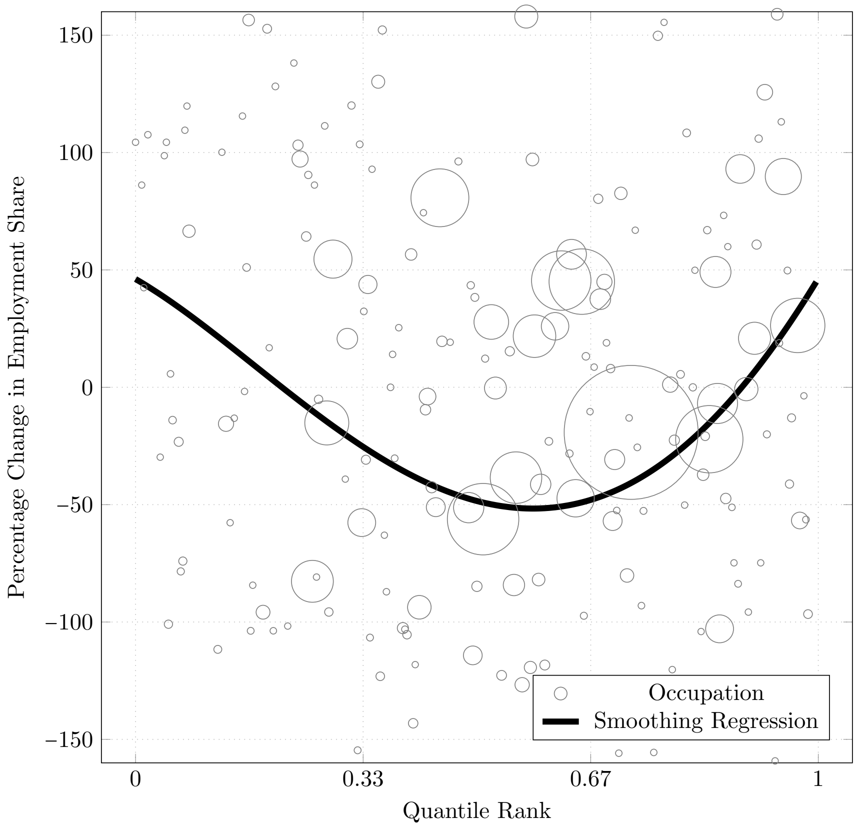
Next, Figure 2 displays the development of employment shares of low-, medium-, and high-paid workers that underlie the polarization pattern from Figure 1. In the 1990s, the share of low-paid occupations grew whereas medium- and high-paid jobs lost little. After the turn of the millennium, the share of medium-paid occupations continued to decline while

[41] The employment shares per KldB 1988 occupation in 2016 are based on crosswalks from the KldB 2010 occupation variable.

[42] This finding is not a result of parameterizing our smoothing regression but can also be seen in Figure E1 where we plot percentage changes in employment shares for five occupational quintiles and detect a similar pattern.

[43] For identical periods, polarization patterns from this study and from the literature may differ owing to other base years, different smoothing techniques, and the focus on the manufacturing industry in this study.

Figure 1: Smoothed Changes in Occupational Employment Share



NOTE: — The figure depicts changes in log employment shares (multiplied by 100) for 3-digit KldB 1988 occupations in German manufacturing. Each occupation holds a quantile rank given its mean daily labor cost in the year 2000. The size of each marker is proportional to occupational employment in the year 2000. Building on this pattern, we a employ kernel-weighted local polynomial smoothing regression with degree 3, a bandwidth of 0.8, and employment in 2000 as regression weight. The graphs are truncated at ±150 % for better illustration. KldB = German Classification of Occupations. Source: LIAB, 1993-2016.

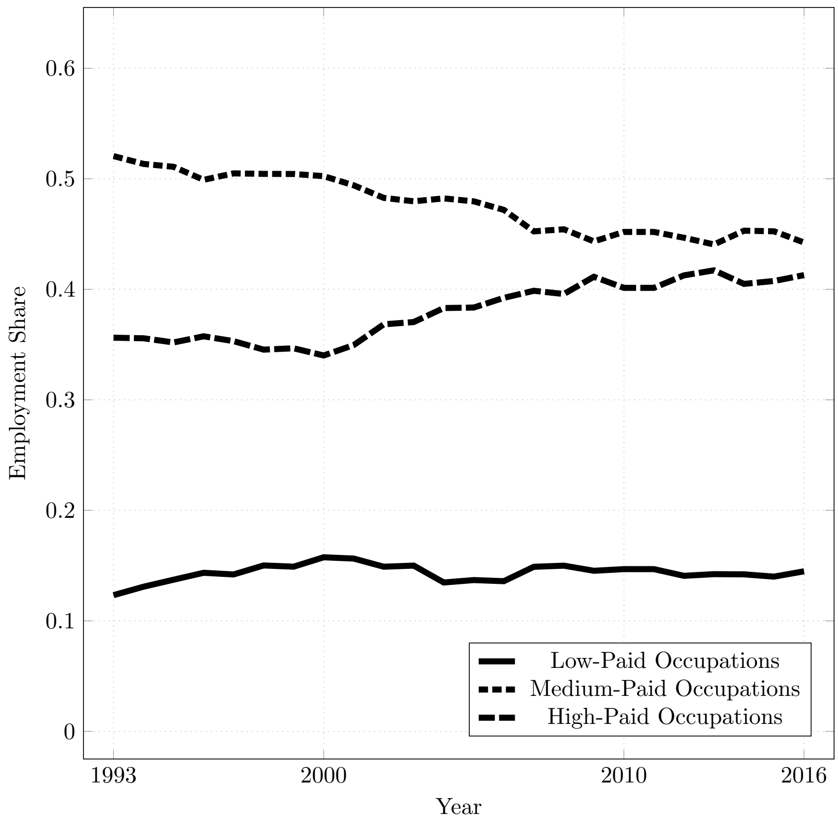
high-paid professions gained influence. Between 2000 and 2016, the share of low-paid jobs remained relatively stable.[44,45]

In general, shifts in labor supply or in labor demand, or a mixture of both forces, may explain the job polarization pattern in German manufacturing. The polarization literature puts forward two reasons that uniformly reflect shifts affecting the labor demand curve (Acemoglu and Autor, 2011; Goos, Manning, and Salomons, 2009; Goos, Manning, and Salomons, 2014). First, the routinization hypothesis from Autor, Levy, and Murnane (2003) states that technological progress has fostered the introduction of new machines that substitute for routine tasks and are complements to non-routine tasks. On the one hand, jobs in the middle of the wage distribution that predominantly involve routine tasks lose. On the other hand, jobs

[44] The occupation variable in the IEB data features a structural break between the years 2010 and 2011. To rule out misleading artefacts due to this break in Figure 2, we assume away any employment changes that happened between these two years.

[45] Additionally, the panels of Figure E2 and E3 display smoothing regressions and employment changes per occupational quintile separately for the years 1993-2016, 1993-2000, 2000-2010, and 2010-2016.

Figure 2: Occupational Employment Shares over Time



NOTE. — The figure illustrates the development of occupational group's employment shares between 1993 and 2016 in German manufacturing. We divide 3-digit KldB 1988 occupations into three equally-sized occupational groups according to their mean daily labor cost in the year 2000: low-paid occupations (quantile rank: 0-0.33), medium-paid occupations (quantile rank: 0.33-0.67), and high-paid occupations (quantile rank: 0.67-1). Due to a structural break in the occupation variable, we eliminate potentially spurious changes between 2010 and 2011. KldB = German Classification of Occupations. Source: LIAB, 1993-2016.

at the top or the bottom of the wage distribution that imply non-routine tasks win. Second, globalization has lowered the cost for firms to offshore routine work to low-wage countries (Blinder, 2009).

Correlation Analysis. In order to disentangle whether labor supply or labor demand shocks have shaped the observed job polarization pattern, we use a simple supply-demand framework in the tradition of Katz and Murphy (1992). Specifically, we follow Autor, Katz, and Kearney (2008) and estimate the following equation via ordinary least squares:

$$\Delta e_{ot} = \mu + \rho \cdot \Delta w_{ot} + \varepsilon_{ot} \tag{12}$$

In detail, we regress yearly changes in occupational employment shares e on a constant as well as on yearly changes in wages w per occupation o. The sign of the slope estimate ρ indicates whether shifts in labor demand or shifts in labor supply dominate. While a positive value reflects demand-side movements on a stable and rising labor supply curve, a negative sign points to labor supply shifts along the falling labor demand curve.

Table 7 reports the set of slope estimates. For the years 1993-2016, we report a positive value of 0.08 (t-value: 2.05). However, looking at the entire sample conceals major differences between the underlying decades.[46] For 1993-2000, we obtain a significant slope estimate of -0.97 (t-value: 12.92), suggesting that employment and wages are negatively correlated. Estimating Equation (12) separately for low-, medium- and high-paid occupations shows that this insight also holds true along the entire distribution of occupations.[47] Hence, we reason that labor supply shocks were the main force behind employment shifts in German manufacturing in the 1990s, with movements that predominantly took place along the negatively sloped labor demand curve. The intervals from 2000 to 2010 and between 2010 and 2016 feature significantly positive slope estimates of 0.31 (t-value: 6.51) and 0.70 (t-value: 7.51), respectively. Significantly positive correlations for medium- and high-paid workers signal that shifts in labor demand between 2000 and 2016 shaped employment patterns. From Figure 2, we can infer that these labor demand shocks along the labor supply curve favored jobs at the top to the detriment of workers in the middle of the distribution. In contrast, slope estimates for low-paid workers turn out to be insignificant for both intervals. Hence, for low-paid workers between 2000 and 2016, shifts in the supply of low-paid workers have balanced out co-existing labor demand shocks.

Table 7: Regressions of Employment Changes on Wage Changes

	Low-Paid Occupations	Medium-Paid Occupations	High-Paid Occupations	All Occupations
1993-2016	-0.244*** (0.067)	0.313*** (0.079)	0.326*** (0.066)	0.082** (0.040)
1993-2000	-1.174*** (0.133)	-0.960*** (0.131)	-0.697*** (0.127)	-0.969*** (0.075)
2000-2010	0.050 (0.075)	0.669*** (0.089)	0.502*** (0.084)	0.306*** (0.047)
2010-2016	0.251 (0.171)	0.949*** (0.190)	0.864*** (0.135)	0.698*** (0.093)

NOTE. — The table shows slope estimates from regressions of yearly occupational changes in log employment share on yearly occupational changes in log average daily wages and a constant. Standard errors are in parentheses. We divide 3-digit KldB 1988 occupations into three equally-sized occupational groups based on their mean daily labor cost in the year 2000: low-paid occupations (quantile rank: 0-0.33), medium-paid occupations (quantile rank: 0.33-0.67), and high-paid occupations (quantile rank: 0.67-1). KldB = German Classification of Occupations. * = p<0.10. ** = p<0.05. *** = p<0.01. Source: LIAB, 1993-2016.

[46] In Tables E1 and E2 we check the sensitivity with respect to the grouping of years and find similar results on smaller and longer intervals (± 1-2 years) as well as on rolling samples of six years.

[47] For the 1990s, Dustmann, Ludsteck, and Schönberg (2009) also report negative correlations between employment and wage changes below the median. However, the authors do not restrict their analysis to the manufacturing industry.

Counterfactual WELD Simulation. We use our WELD estimates to cross-validate and more rigorously assess whether labor supply shocks can explain parts of the polarization pattern. In a simple demand-supply framework with pure shocks to labor supply, employment effects depend on the product of wage changes and the slope of the labor demand curve. While we track wages in our data, our estimated WELD estimates directly entail the slope of the labor demand curve. For both the skill- and the task-based approach, we interact observed price changes per input with our estimated matrix of unconditional price elasticities of input demand and product supply. Building on this, we construct counterfactual trends in employment shares for the occupational groups g of low-, medium- and high-paid workers ($\forall\, g = 1, 2, 3$ and $\forall\, t = 1994, \ldots, 2016$):

$$\hat{e}_t^g = \frac{\hat{X}_t^g}{\hat{X}_t} = \frac{\hat{X}_{t-1}^g + \sum_{m=1}^{M-1} \sum_{n=0}^{M} \hat{X}_{t-1}^{gm} \cdot \frac{\partial w_t^{gm}}{w_{t-1}^{gm}} \cdot \hat{u}_n^m}{\hat{X}_{t-1} + \sum_{g=1}^{3} \sum_{m=1}^{M-1} \sum_{n=0}^{M} \hat{X}_{t-1}^{gm} \cdot \frac{\partial w_t^m}{w_t^m} \cdot \hat{u}_n^m} \quad \text{with } \hat{X}_{1993}^{gm} = X_{1993}^{gm} \tag{13}$$

Our simulation yields counterfactual employment shares for a hypothetical setting in which, by assumption, employment changes occur solely through shifts in labor supply along a stable labor demand curve. Crucially, these counterfactual shares should provide a reasonable fit to factual employment shares for those occupations and periods where a negative slope estimate ρ indicates a dominance of labor supply shocks over labor demand shocks. Given our slope estimates from (12), we expect a good approximation for all three occupational groups in the 1990s and, to a lesser degree, also for low-paid occupations throughout 2000-2016.

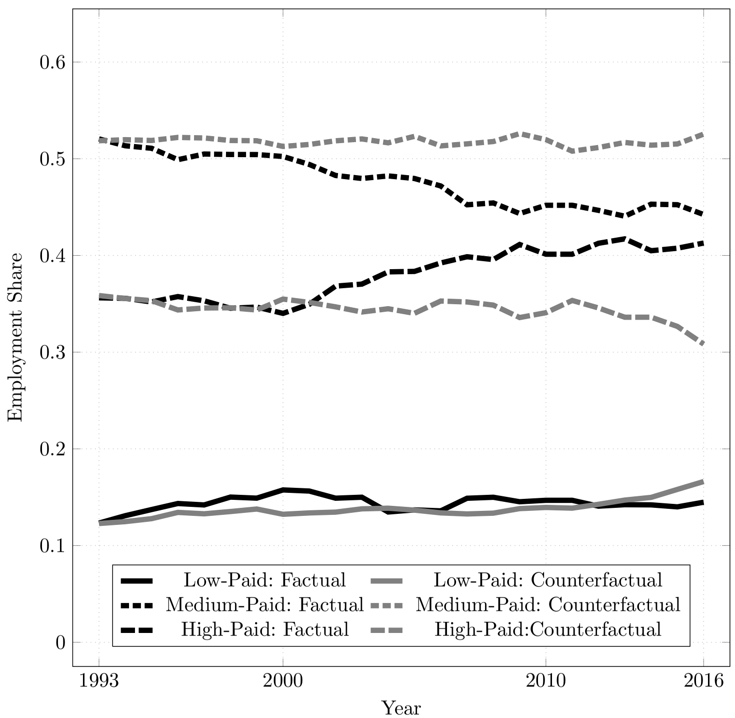
Figure 3 compares our counterfactual WELD simulations from (13) with factual employment shares, both for the skill- and the task-based approach. For ease of interpretation, we illustrate the underlying composition of workers within low-, medium- and high-paid occupations in Table E3 and display relative wage changes for five occupational quintiles in Figure E4.[48] As expected from the negative correlations, predictions from both the skill- and the task-based approach provide a good fit to factual trends for the 1990s, thus corroborating our hypothesis that labor supply shocks shaped employment changes in this decade. Demand for low-paid occupations was increasing in the 1990s due to lower wage growth and a higher share of workers with less negative own-wage elasticities of labor demand, relative to medium-paid occupations. At the same time, medium- and high-paid occupations lost employment share due to pronounced wage growth and a relatively high fraction of workers in tasks with large scale effects, respectively.[49] Moreover, throughout 2000-2016, our counterfactual prediction

[48] See Teulings (1995) for a theoretical model on the mapping between skills and tasks.

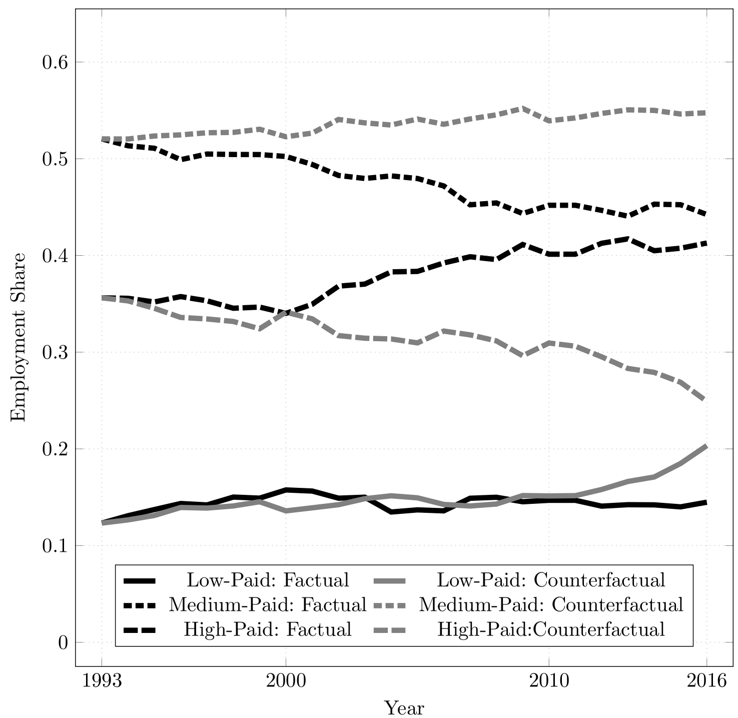
[49] We suspect the imputation for right-censored wages to cause the slightly worse fit for high-paid occupations during the 1990s.

Figure 3: Factual vs. Counterfactual Trends in Employment Shares

(a) Skill-Based Approach



(b) Task-Based Approach



Note. — The figure illustrates the development of occupational group's employment shares between 1993 and 2016 in German manufacturing. We divide 3-digit KldB 1988 occupations into three equally-sized occupational groups according to their mean daily labor cost in the year 2000: low-paid occupations (quantile rank: 0-0.33), medium-paid occupations (quantile rank: 0.33-0.67), and high-paid occupations (quantile rank: 0.67-1). The simulation of counterfactual trends interacts observed changes in labor cost per input with the estimated matrix of unconditional elasticities. KldB = German Classification of Occupations. Sources: LIAB + Destatis, 1993-2016.

for low-skilled occupations does not deviate much from its factual trend. This result fits well to the corresponding slope estimates of zero indicating that both demand and supply shifts were operating. In contrast, our simulation cannot explain the trends in employment shares for medium- and high-paid occupations from 2000 onward. However, this failure is entirely consistent with our finding of strongly positive slope estimates for both groups, suggesting that, instead, shifts in labor demand along the labor supply curve were dominating for these groups. We therefore suspect conventional demand-based explanations, such as routinization or offshoring, to shape the pattern in the 2000s and 2010s.[50]

Aggregate Trends and Events. In a last step, we further substantiate our reasoning in favor of labor supply shocks in German manufacturing by showing that observed aggregate trends and episodic events indeed affected labor supply in the relevant occupation-by-decade combinations. In line with Dustmann, Ludsteck, and Schönberg (2009), we suspect two different events to have shifted labor supply along the labor demand curve during the 1990s. First, the fall of the Iron Curtain and the subsequent reunification of Germany led to a large influx of migrants from Eastern Europe.[51] Figure E5 shows that Germany, as a consequence, experienced a net inflow of 3.2 million people during the 1990s. As a result, the workforce in Germany grew by about 2 million workers, or 5 percent, until 2000. In fact, many of these immigrants were low-skilled (Glitz, 2012). The sharp increase in labor supply increased competition among low-skilled workers and led to wage moderation for this group (see Figure E4, Panel b).

Second, in the 1990s, German labor markets experienced a rapid decline in the coverage of collective bargaining agreements.[52] Figure E6 displays the coverage of collective bargaining agreements in German manufacturing from 1993 onward. Until 2000, the share of West German establishments committed to such an agreement fell from 95 to 70 percent. In East Germany, the fraction plummeted from 68 to 35 percent between 1996 and 2000. In the same decade, the share of covered workers dropped by 8 (West Germany) and 21 percentage points (East Germany), respectively. Card, Heining, and Kline (2013) as well as Goldschmidt and Schmieder (2017) argue that this decline was sparked by the decision of worker unions to claim West German wages in East German establishments soon after reunification and de-

[50] One can view our simulation for medium- and high-paid occupations during the 2000s as hypothetical trends if routinization and offshoring did not occur.

[51] See Borjas (2003) for an analysis of the labor market impact of immigration in the US.

[52] In Germany, firms can take part in collective bargaining in two ways. On the one hand, firms can join an employer association and thereby agree to recognizing union wages that are negotiated at the regional or industry level. On the other hand, firms can enter into direct negotiations with the union. In both cases, collective bargaining agreements usually apply for the entire workforce, regardless whether employees are union members or not.

spite a large gap in productivity. Consequently, East German establishments left collective agreements and caused West German establishments to follow them. At the same time, high unemployment rates and the new threat of moving production to Eastern Europe hindered work councils and unions to oppose these decisions. Dustmann et al. (2014) report that the resulting loss of wage growth was particularly large for low-paid workers.

In line with patterns in both immigration and collective bargaining, Dustmann, Ludsteck, and Schönberg (2009) show that relative wage premiums of low-skilled workers declined relatively to medium- and high-skilled workers throughout the 1990s. In sum, we argue that the co-existence of relatively low wage growth (from supply shifts) and relatively low wage elasticities of labor demand for low-paid workers, compared to medium- and high-paid occupations, can successfully explain relative growth in employment of low-paid occupations during the 1990s.

Both our slope estimates and counterfactual WELD predictions further indicate that labor supply shocks continued to play a role for low-paid occupations and counterbalanced demand shifts throughout 2000-2016. Importantly, between 2003 and 2005, the German government enacted a series of far-reaching labor market reforms (known as “Hartz laws”) targeting a reduction in unemployment.[53] As of January 1, 2005, the final Hartz IV reform sought to increase labor supply by introducing sanctions for unemployed persons refusing job offers as well as cutting benefits for long-term unemployed. As a result, Hartz IV weakened the bargaining position of low-paid workers who are particularly vulnerable to becoming unemployed, thereby contributing to only modest wage growth at the bottom of the distribution during the 2000s (see Figure E4, Panel c).

Additionally, Figure E6 shows that, albeit at a lower pace, the decline in collective bargaining in German manufacturing sustained after 2000.[54] As a result of lower-tail inequality (see, e.g., Drechsel-Grau et al., 2022, for a detailed analysis of inequality in Germany), Germany, for the first time in its history, introduced a nation-wide minimum wage in 2015. The

[53]See Bradley and Kügler (2019) or Krause and Uhlig (2012) for a detailed discussion of the Hartz reforms. Burda and Seele (2020) detect negative correlations between wage and employment changes, which the authors also attribute to labor supply shocks caused by the Hartz reforms. However, their analysis differs from ours in many respects. While the authors analyze around one hundred age-by-gender-by-region(-by-qualification) cells for intervals of five years, we investigate yearly changes for 3-digit occupations. Moreover, we focus on full-time employment in the manufacturing sector based on administrative data instead of survey data. Furthermore, we consider heterogeneity of workers and report correlations separately for the bottom, middle and top of the wage distribution instead of showing only pooled correlations for the entire wage distribution.

[54]Despite low wage growth due to positive supply shocks and favorable demand shocks from routinization, the smoothing regression in Figure E2 Panel a displays a reduction in employment shares for low-paid occupations between 2000 and 2010. Given that our study only refers to regular workers, we rationalize this finding by the fact that the Hartz II reform rendered the use of marginal employment more attractive for employers. First, Hartz II strongly increased the tax exemption threshold for mini jobs. Second, the upper limit of 15 working hours per week for workers in marginal employment was discarded.

minimum wage was set at 8.50 Euro per hour and lead to strong wage growth at the lower tail of the distribution (see Figure E4, Panel d).[55] Moreover, net migration into Germany receded after the turn of the millennium but, since 2010, has risen again in the wake of the European migrant crisis (see Figure E5).

8 Conclusion

This paper sheds new light on the relationship between wages and the demand for labor. Our study entails a unique estimation of a profit-maximization model with linked employer-employee data for the German manufacturing sector. While previous cost-minimization studies merely analyze substitution effects given a fixed level of production, we draw on a more general profit-maximization model to explicitly allow for commonly neglected scale effects. In fact, the elasticity estimates show that scale effects matter. Consequently, conditional wage elasticities, the conventional outcome from models of labor demand, systematically underestimate the overall employment response of firms to wage changes. We can corroborate the inverse U-shaped pattern between skills and substitution effects, put forward by a series of earlier cost-minimization studies for Germany. However, with the inclusion of scale effects, this pattern turns around and becomes U-shaped, suggesting that labor demand for medium-skilled workers is more elastic than for low- and high-skilled workers. We complement our skill-based approach with a task-based approach and, for the first time in the literature, determine wage elasticities of labor demand for different types of tasks. We observe that substitution effects turn out to be more negative for routine than for non-routine tasks. Including scale effects, unconditional labor demand is most elastic for manual routine, cognitive routine, and analytical non-routine tasks.

For the years 1993 to 2016, we observe a distinct polarization of jobs in German manufacturing. While the share of low-paid occupations increases in the 1990s, high-paid occupations gain momentum from 2000 onward. In the 1990s and 2000s, the share of medium-paid jobs exhibits a gradual decline. However, while the international literature argues that shifts in labor demand, like routinization or offshoring, cause a polarization of jobs, we find that labor

[55] Bossler and Gerner (2020) attribute a disemployment effect of 45,000 up to 68,000 workers to the 2015 minimum wage introduction. In a related study, Caliendo et al. (2018) identify an employment loss of 78,000 regular workers. Finally, Dustmann et al. (2022) document substantial reallocation effects of the minimum wage that are hidden behind close to zero aggregate employment effects. Using our unconditional WELD estimates, a simple simulation of the minimum wage introduction yields an estimated decline in employment by 15,700 (skill-based approach) and 17,000 regular full-time workers (task-based approach) for the German manufacturing industry (see Table E4). In both approaches, about two thirds of the decline in employment relate to East Germany. In light of the German minimum wage literature, our simulation results feature a reasonable magnitude given that the manufacturing sector accounts for about one fourth of total employment in Germany.

supply shocks played an equally important role in shaping the pattern in German manufacturing. A regression analysis à la Katz and Murphy (1992) suggests that labor supply shifted for low-, medium- and high-paid occupations during the 1990s and, to a lesser degree, for low-paid occupations throughout 2000-2016. Given our unconditional WELD estimates, a simple simulation of counterfactual employment trends provides a satisfactory fit to factual development for the same occupation-decade combinations, thus cross-validating that indeed supply shifts took place along a relatively stable labor demand curve. Furthermore, our results are consistent with contemporary events that shifted labor supply: a large influx of migrants from Eastern Europe after the fall of the Iron Curtain, the reduction of collective bargaining agreements since Germany's reunification, and, with special reference to low-paid workers, the Hartz reforms as well as the 2015 introduction of a statutory minimum wage.

Our results have important policy implications. In the presence of rigid wages above the equilibrium level, it is the demand for labor that falls short and thus creates unemployment. Therefore, the optimal minimum wage is a function of the wage elasticity of labor demand (Lee and Saez, 2012). A simple simulation using our WELD estimate yields a disemployment effect of around 16,000 full-time regular workers in German manufacturing following the introduction of a nation-wide minimum wage of 8.50 Euro per hour in 2015. In a right-to-manage framework, the threat of reducing labor demand sets an upper limit on wage claims of unions (Nickell and Andrews, 1983). Our unconditional WELDs therefore recommend unions to demand the lowest nominal wage increases for workers with medium skills and routine tasks whereas conditional estimates from the literature would endorse the contrary. Wage elasticities of labor demand also impinge on the incidence of taxes on labor income. In this context, the existence of scale effects implies that deadweight losses are higher than previously expected, with employers bearing an increased fraction of this burden. Moreover, calibration of various economic models requires knowledge about the size of labor demand elasticities.

In terms of future research, it would be instructive to harness less aggregated information on producer price levels (e.g., at the regional or establishment level). Beyond that, worker-level information on job requirements would help to identify variation in tasks within occupations. Finally, as dynamics are difficult to integrate in a profit-maximization model, our analysis is limited to static labor demand. However, formation of scale effects does not necessarily need to kick in immediately as changes in production take time. Any such refinements can help to better identify unconditional wage elasticities of labor demand and, hence, allow for a more sophisticated evaluation of labor supply shifts along a stable labor demand curve.

References

Acemoglu, D. and Autor, D. H. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In: *Handbook of Labor Economics: Vol. 4B*, ed. by Ashenfelter, O. C. and Card, D., Amsterdam: North Holland, pp. 1043–1171.

Addison, J. T., Bellmann, L., Schank, T., and Teixeira, P. (2008). The Demand for Labor: An Analysis Using Matched Employer–Employee Data from the German LIAB. Will the High Unskilled Worker Own-Wage Elasticity Please Stand Up? *Journal for Labour Market Research* 29 (2), pp. 114–137.

Addison, J. T., Portugal, P., and Varejão, J. (2014). Labor Demand Research: Toward a Better Match between Better Theory and Better Data. *Labour Economics* 30, pp. 4–11.

Alam, M. F., Omar, I. H., and Squires, D. (2002). Sustainable Fisheries Development in the Tropics: Trawlers and Licence Limitation in Malaysia. *Applied Economics* 34 (3), pp. 325–337.

Allen, R. G. (1938). *Mathematical Analysis for Economists*. London: Macmillan.

Amiti, M. and Wei, S.-J. (2006). *Service Offshoring and Productivity: Evidence from the United States*. Centre for Economic Policy Research, CEPR Discussion Paper 5475.

Antonczyk, D., DeLeire, T., and Fitzenberger, B. (2018). Polarization and Rising Wage Inequality: Comparing the U.S. and Germany. *Econometrics* 6 (2), pp. 1–33.

Autor, D. and Dorn, D. (2013). The Growth of Low-Skill Service Jobs and the Polarization of the U.S. Labor Market. *American Economic Review* 103 (5), pp. 1553–1597.

Autor, D. H. (2013). The 'Task Approach' to Labor Markets: An Overview. *Journal of Labour Market Research* 46 (3), pp. 185–199.

Autor, D. H., Katz, L. F., and Kearney, M. S. (2006). The Polarization of the U.S. Labor Market. *American Economic Review* 96 (2), pp. 189–194.

Autor, D. H., Katz, L. F., and Kearney, M. S. (2008). Trends in U.S. Wage Inequality: Revising the Revisionists. *Review of Economics and Statistics* 90 (2), pp. 300–323.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *Quarterly Journal of Economics* 118 (4), pp. 1279–1333.

Bellmann, L., Bender, S., and Schank, T. (1999). Flexibility of Firms' Labor Demand: Substitutability or Complementarity. *Journal of Economics and Statistics* 219 (1-2), pp. 109–126.

Blinder, A. S. (2009). Offshoring: Big Deal, or Business as Usual? In: *Offshoring of American Jobs: What Response from U.S. Economic Policy*, ed. by Friedman, B., Cambridge: MIT Press, pp. 19–60.

Borjas, G. J. (2003). The Labor Demand Curve is Downward Sloping: Reexamining the Impact of Immigration on the Labor Market. *Quarterly Journal of Economics* 118 (4), pp. 1335–1374.

Bossler, M. and Gerner, H.-D. (2020). Employment Effects of the New German Minimum Wage: Evidence from Establishment-Level Micro Data. *Industrial and Labor Relations Review* 73 (5), pp. 1070–1094.

Bradley, J. and Kügler, A. (2019). Labor Market Reforms: An Evaluation of the Hartz Policies in Germany. *European Economic Review* 113, pp. 108–135.

Bronfenbrenner, M. (1961). Notes on the Elasticity of Derived Demand. *Oxford Economic Papers* 13 (3), pp. 254–261.

Burda, M. C. and Seele, S. (2020). Reevaluating the German Labor Market Miracle. *German Economic Review* 21 (2), pp. 139–179.

Caliendo, M., Fedorets, A., Preuss, M., Schröder, C., and Wittbrodt, L. (2018). The Short-Run Employment Effects of the German Minimum Wage Reform. *Labour Economics* 53, pp. 46–62.

Card, D., Heining, J., and Kline, P. (2013). Workplace Heterogeneity and the Rise of West German Wage Inequality. *Quarterly Journal of Economics* 128 (3), pp. 967–1015.

Christensen, L. R., Jorgenson, D. W., and Lau, L. J. (1973). Transcendental Logarithmic Production Frontiers. *Review of Economics and Statistics* 55 (1), pp. 28–45.

Cox, M., Peichl, A., Pestel, N., and Siegloch, S. (2014). Labor Demand Effects of Rising Electricity Prices: Evidence for Germany. *Energy Policy* 75, pp. 266–277.

Curtis, E. M., Garret, D. G., Ohrn, E. C., Roberts, K. A., and Suárez Serrato, J. C. (2022). *Capital Investment and Labor Demand*. National Bureau of Economic Research, NBER Working Paper 29485.

Dengler, K., Matthes, B., and Paulus, W. (2014). *Occupational Tasks in the German Labour Market: An Alternative Measurement on the Basis of an Expert Database*. Institute for Employment Research, FDZ Method Report Series 12/2014.

Destatis (2017). *Preise: Index der Erzeugerpreise gewerblicher Produkte (Inlandsabsatz) nach dem Güterverzeichnis für Produktionsstatistiken, Ausgabe 2009 (GP-2009).*

Diewert, W. E. and Wales, T. J. (1987). Flexible Functional Forms and Global Curvature Conditions. *Econometrica* 55 (1), pp. 43–68.

Drechsel-Grau, M., Peichl, A., Schmieder, J., Schmid, K. D., Walz, H., and Wolter, S. (2022). Inequality and Income Dynamics in Germany. *Quantitative Economics*, forthcoming.

Dustmann, C., Fitzenberger, B., Schönberg, U., and Spitz-Oener, A. (2014). From Sick Man of Europe to Economic Superstar: Germany's Resurgent Economy. *Journal of Economic Perspectives* 28 (1), pp. 167–188.

Dustmann, C., Lindner, A., Schönberg, U., Umkehrer, M., and vom Berge, P. (2022). Reallocation Effects of the Minimum Wage. *Quarterly Journal of Economics* 137 (1), pp. 267–328.

Dustmann, C., Ludsteck, J., and Schönberg, U. (2009). Revisiting the German Wage Structure. *Quarterly Journal of Economics* 124 (2), pp. 843–881.

Eberle, J., Jacobebbinghaus, P., Ludsteck, J., and Witter, J. (2011). *Generation of Time-Consistent Industry Codes in the Face of Classication Changes: Simple Heuristic Based on the Establishment History Panel (BHP).* Institute for Employment Research, FDZ Method Report Series 05/2011.

Ellguth, P., Kohaut, S., and Möller, I. (2014). The IAB Establishment Panel: Methodological Essentials and Data Quality. *Journal of Labour Market Research* 47 (1-2), pp. 27–41.

Fitzenberger, B. and Franz, W. (1998). Flexibilität der qualifikatorischen Lohnstruktur und Lastverteilung der Arbeitslosigkeit: Eine ökonometrische Analyse für Westdeutschland. In: *Verteilungsprobleme der Gegenwart: Diagnose und Therapie*, ed. by Gahlen, B., Hesse, H., and Ramser, H. J., Tübingen: Mohr Siebeck, pp. 47–79.

Glitz, A. (2012). The Labor Market Impact of Immigration: A Quasi-Experiment Exploiting Immigrant Location Rules in Germany. *Journal of Labor Economics* 30 (1), pp. 175–213.

Goldschmidt, D. and Schmieder, J. F. (2017). The Rise of Domestic Outsourcing and the Evolution of the German Wage Structure. *Quarterly Journal of Economics* 132 (3), pp. 1165–1217.

Goos, M. and Manning, A. (2007). Lousy and Lovely Jobs: The Rising Polarization of Work in Britain. *Review of Economics and Statistics* 89 (1), pp. 118–133.

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

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

Hamermesh, D. S. (1993). *Labor Demand*. Princeton: Princeton University Press.

Harrison, A. E. and McMillan, M. S. (2006). *Outsourcing Jobs? Multinationals and U.S. Employment*. National Bureau of Economic Research, NBER Working Paper 12372.

Hicks, J. R. (1932). *Theory of Wages*. London: Macmillan.

Hicks, J. T. (1961). Marshall's Third Rule: A Further Comment. *Oxford Economic Papers* 13 (3), pp. 262–265.

Higgins, J. (1986). Input Demand and Output Supply on Irish Farms: A Micro-Economic Approach. *European Review of Agricultural Economics* 13 (4), pp. 477–493.

Hijzen, A. and Swaim, P. (2010). Offshoring, Labour Market Institutions and the Elasticity of Labour Demand. *European Economic Review* 54 (8), pp. 1016–1034.

Hotelling, H. (1932). Edgeworth's Taxation Paradox and the Nature of Demand and Supply Functions. *Journal of Political Economy* 40 (5), pp. 577–616.

Katz, L. F. and Murphy, K. M. (1992). Changes in Relative Wages, 1963-1987: Supply and Demand Factors. *Quarterly Journal of Economics* 107 (1), pp. 35–78.

Klosterhuber, W., Lehnert, P., and Seth, S. (2016). *Linked-Employer-Employee Data from the IAB: LIAB Cross-Sectional Model 2 1993-2014 (LIAB QM2 9314)*. Institute for Employment Research, FDZ Data Report Series 05/2016.

Krause, M. U. and Uhlig, H. (2012). Transitions in the German Labor Market: Structure and Crisis. *Journal of Monetary Economics* 59 (1), pp. 64–79.

Lee, D. and Saez, E. (2012). Optimal Minimum Wage Policy in Competitive Labor Markets. *Journal of Public Economics* 96 (9-10), pp. 739–749.

Lemos, S. (2008). A Survey of the Effects of the Minimum Wage on Prices. *Journal of Economic Surveys* 22 (1), pp. 187–212.

Lichter, A., Peichl, A., and Siegloch, S. (2015). The Own-Wage Elasticity of Labor Demand: A Meta-Regression Analysis. *European Economic Review* 80, pp. 94–119.

Lichter, A., Peichl, A., and Siegloch, S. (2017). Exporting and Labour Demand: Micro-Level Evidence from Germany. *Canadian Journal of Economics* 50 (4), pp. 1161–1189.

Lopez, R. E. (1984). Estimating Substitution and Expansion Effects Using a Profit Function Framework. *American Journal of Agricultural Economics* 66 (3), pp. 358–367.

Marshall, A. (1890). *Principles of Economics*. London: Macmillan.

Maurice, S. C. (1975). On the Importance of Being Unimportant: An Analysis of the Paradox in Marshall's Third Rule of Derived Demand. *Economica* 42 (168), pp. 385–393.

Müller, D. and Wolter, S. (2020). German Labour Market Data: Data Provision and Access for the International Scientific Community. *German Economic Review* 21 (3), pp. 313–333.

Müller, S. (2017). *Capital Stock Approximation with the Perpetual Inventory Method: An Update*. Institute for Employment Research, FDZ Method Report Series 05/2017.

Mundlak, Y. (2001). Production and Supply. In: *Handbook of Agricultural Economics: Vol. 1A*, ed. by Gardner, B. and Rausser, G., Amsterdam: North Holland, pp. 3–85.

Nagatani, K. (1978). Substitution and Scale Effects in Factor Demands. *Canadian Journal of Economics* 11 (3), pp. 521–527.

Nickell, S. and Andrews, M. (1983). Unions, Real Wages and Employment in Britain 1951-79. *Oxford Economic Papers* 35 (Supplement), pp. 183–206.

Peichl, A. and Siegloch, S. (2012). Accounting for Labor Demand Effects in Structural Labor Supply Models. *Labour Economics* 19, pp. 129–138.

Peirson, J. (1988). The Importance of Being Unimportant: Marshall's Third Rule of Derived Demand. *Scottish Journal of Political Economy* 36 (4), pp. 396–405.

Pemberton, J. (1989). Marshall's Rules for Derived Demand: A Critique and a Generalisation. *Scottish Journal of Political Economy* 36 (4), pp. 396–405.

Revenga, A. (1997). Employment and Wage Effects of Trade Liberalization: The Case of Mexican Manufacturing. *Journal of Labor Economics* 15 (S3), pp. 20–43.

Sakai, Y. (1974). Substitution and Expansion Effects in Production Theory: The Case of Joint Production. *Journal of Economic Theory* 9 (3), pp. 255–274.

Samuelson, P. A. (1947). *The Foundations of Economic Analysis*. Cambridge: Harvard University Press.

Schmucker, A., Eberle, J., Ganzer, A., Stegmaier, J., and Umkehrer, M. (2018). *Establishment History Panel 1975-2016*. Institute for Employment Research, FDZ Data Report Series 01/2018.

Sidhu, S. S. and Baanante, C. A. (1981). Estimating Farm-Level Input Demand and Wheat Supply in the Indian Punjab Using a Translog Profit Function. *American Journal of Agricultural Economics* 63 (2), pp. 237–246.

Slaughter, M. J. (2001). International Trade and Labor-Demand Elasticities. *Journal of International Economics* 54 (1), pp. 27–56.

Spitz-Oener, A. (2006). Technical Change, Job Tasks, and Rising Educational Demands. *Journal of Labor Economics* 24 (2), pp. 235–270.

Teulings, C. (1995). The Wage Distribution in a Model of the Assignment of Skills to Jobs. *Journal of Political Economy* 103 (2), pp. 280–315.

Zellner, A. (1962). An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias. *Journal of the American Statistical Association* 57 (298), pp. 348–368.

Online Appendix

A Appendix: Literature Review

A large empirical literature has estimated wage elasticities of labor demand, either with a focus on WELDs or as a by-product of research on firms.[56] This literature builds on two different methodological strategies: structural- and reduced-form models (Lichter, Peichl, and Siegloch, 2015). Importantly, both techniques differ in their identification of substitution and scale effects.

Reduced-form models follow theory loosely. Such models simply regress measures of labor demand on wage rates and control variables. In a log-linear model, the estimated wage coefficient directly represents the wage elasticity of labor demand. Reduced-form models that control for the level of production insulate scale effects and, thus, determine conditional WELDs as output is kept constant (Hamermesh, 1993). On the contrary, excluding the output variable from the set of controls results in the estimation of unconditional WELDs.

Structural-form models strongly relate to labor demand theory. These models derive elasticities from specific functional forms of dual functions that reflect optimization behavior of employers. Cost functions mirror the conduct of minimizing cost given a fixed volume of production (Addison, Portugal, and Varejão, 2014). Thus, holding output fixed, the identification of parameters from a cost function yields conditional WELDs. In contrast, profit functions relate to the concept of profit maximization which incorporates not only cost minimization given a fixed output but also choosing the level of output optimally. As a consequence, identification of a profit function yields unconditional WELD estimates comprising both substitution and scale effects. To measure WELDs, parameter estimates must be inserted into WELD formulas that depend on specification of the underlying cost or profit function. Despite the profusion of WELD estimates, we argue that our empirical analysis adds to the literature on WELDs in four respects.

First, empirical knowledge on scale effects is limited. The majority of reduced- and structural-form studies focuses on the estimation of conditional WELDs, thereby measuring only substitution effects and assuming that scale effects are zero. For lack of exogenous variation in wages, reduced-form models frequently arrive at positive scale effects that contradict labor demand theory (e.g., Revenga, 1997; Slaughter, 2001; Amiti and Wei, 2006; Harrison and McMillan, 2006; Hijzen and Swaim, 2010; Cox et al., 2014).[57] Beyond, Lichter,

[56] The meta-study of Lichter, Peichl, and Siegloch (2015) comprises 151 empirical studies on WELDs for the secondary and tertiary sector.

[57] The theoretical prediction that scale effects are negative is based on two assumptions that are likely to hold in reality. On the one hand, higher (lower) wages must translate into higher (lower) marginal cost of

Peichl, and Siegloch (2015) argue that the mere inclusion of an output variable does not suffice to decompose the overall relationship into substitution and scale effects. The failure to produce negative scale effects might well explain why the majority of reduced-form studies only report conditional WELD estimates. In line with our conjecture, Lichter, Peichl, and Siegloch (2015) detect severe publication bias in reduced-form models and therefore question the credibility of WELD estimates from this branch of the literature. In Table A2, we provide an overview of reduced-form models that estimate unconditional WELDs. For the reasons given, we refrain from estimating reduced-form models but instead follow a structural approach in our study.

Structural-form models explicitly model the conceptual difference between profit maximization and cost minimization and, hence, better comply with the theoretical prediction that scale effects are negative (e.g., Lopez, 1984; Higgins, 1986; Alam, Omar, and Squires, 2002). Accordingly, Lichter, Peichl, and Siegloch (2015) find that publication bias is much weaker in structural models than in reduced-form models. Nevertheless, the vast majority of structural-form studies does not refer to profit but to cost functions and, thus, assumes scale effects to be absent. The reason is that cost-minimization models, unlike profit-maximization models, do not necessitate information on producer prices that are hardly available. Until now, the limited number of profit-maximization models mainly applies to the primary sector where economy-wide price level information on single agricultural products (e.g., rice or wheat) is easily available. Although in modern economies the secondary and tertiary sector account for a much higher fraction in GDP, a total of only nine studies make use of a structural model to determine unconditional WELDs for these two sectors. Table A1 reviews these articles. Contrary to these studies, we use a unique combination of rich LEE data and detailed information on producer price levels to measure scale effects within a profit-maximization model.

Second, existing profit-maximization models do not address potential endogeneity in wages and thus are prone to arriving at biased WELD estimates. The majority of studies for the primary sector and all nine studies for the secondary and tertiary sector rely on aggregate data. WELD estimations without instrumental variables, however, should ideally harness micro-level information for two reasons (Senses, 2010). On the one hand, the assumption that wages exhibit exogenous variation becomes more plausible when using data at the firm or establishment level (Hamermesh, 1993). For, under perfect competition, single firms are not powerful enough to affect market-level input prices via their labor demand. Unlike

production that make firms decrease (increase) production. On the other hand, labor inputs must be normal goods in a sense that lower (higher) output also necessitates less (more) labor in the production process. Against this background, we argue that reduced-form models are more likely to not adequately describe the output decision than that their positive scale effects reflect reality.

entire industries, these units face a horizontally sloped labor supply curve that is perfectly elastic in the wage rate. Hence, by using micro-level information on firms, wage changes trace out the labor demand curve. The interaction of labor demand and labor supply shifts, however, causes industry-level studies to suffer from simultaneity bias and, thus, renders their wage rates endogenous. On the other hand, micro-level information relates to the level at which personnel decisions take place and, thus, reveal the concentration of workers on employers. Industry-level or more aggregate data, however, mask fluctuations in employment between employers and therefore lead to downward biased WELD estimates for the level of the firm.[58] Being aware of both problems with aggregate data, we utilize an adequate unit of observation and estimate our profit-maximization model at the level of establishments.

Beyond, no study from the entire literature on profit-maximization models uses longitudinal variation in panel data to account for unobserved heterogeneity at the micro level. But, the labor demand curve of an industry is the horizontal sum of firm-specific labor demand within this industry. To measure representative elasticities at the firm level, WELD estimations should therefore build solely on variation within and not (additionally) on variation between firms. Ideally, fixed effect estimators are utilized to extract within-firm variation from panel data. Simultaneously, these estimators also control for unobserved time-invariant firm heterogeneity and thus eliminate a further source of endogeneity in input and output prices (Addison, Portugal, and Varejão, 2014).[59] Consequently, the large number of cross-sectional studies merely investigates differences between firms and is furthermore prone to endogenous wages. Existing time-series analyses are hardly better since despite harnessing variation over time, they only refer to aggregate data.. We take advantage of the longitudinal character of our LEE data and thus both measure adjustments within establishments and control for unobserved heterogeneity.

Third, Hamermesh (1993) emphasizes the need for a fine division of the workforce into meaningful groups when estimating wage elasticities of labor demand. In the optimum case, inputs reflect groups with similar productive characteristics. Existing profit-maximization models, however, do not adequately treat labor as a heterogeneous input factor.[60] Instead, available profit-maximization models estimate homogeneous WELDs and therefore cannot account for heterogeneous adjustment in labor demand. The paucity of heterogeneous estimates for unconditional WELDs comes from a lack of adequate data. In addition to data on

[58] Some empirical studies even harness region- or economy-wide data.

[59] For example, unobserved heterogeneity in firm-level labor demand can comprise time-invariant effects of talented managers, locational advantages, or market niches (Blien, Kirchhof, and Ludewig, 2006).

[60] There are only few exceptions. Some agricultural studies differentiate between family and non-family workers. For the secondary sector, Woodland (1977) distinguishes workers in blue- and white-collar jobs.

producer prices, WELD estimates for different types of labor necessitate information on heterogeneity in both firms and workers that conventional data products do generally not reflect (Haltiwanger et al., 1998). Hamermesh (1999) and Addison, Portugal, and Varejão (2014) argue that the study of labor demand should utilize linked employer-employee data.[61] LEE data deliver simultaneous information on firms and their respective workers. By aggregating individual information on workers, they allow researchers to generate firm-level information on employment and wage levels for different labor inputs. As the first to overcome this gap, we use a profit-maximization model to measure scale effects for workers with different skills. More precisely, we divide the workforce into low-, medium-, and high-skilled workers and look whether unconditional WELDs vary across these groups.

Fourth, the task-based approach puts forward that it is the tasks and not the skills that produce goods (Autor, Levy, and Murnane, 2003). Acemoglu and Autor (2011, p. 1045) define a task as "a unit of work activity that produces output" while skill represents "a worker's endowment of capabilities for performing various tasks". Skills do not directly produce goods. Instead, skills are applied to tasks which generate output. In a setting where the assignment of skills to certain tasks persists, the distinction between both terms is redundant. However, both terms are no longer congruent when the relationship between skills and tasks is subject to change, e.g., for economic or technological reasons. Surprisingly, an estimation of WELDs with tasks as inputs – no matter if conditional or unconditional, or if derived from a reduced- or structural models – is not available in the literature. The use of rich LEE data enables us to close the missing link between WELDs the task-based approach. We therefore complement our "skill-based" division of the workforce with a "task-based" division of labor and estimate unconditional WELDs for manual non-routine, manual routine, cognitive routine, interactive non-routine, and analytical non-routine tasks.

Apart from the international literature on WELDs, our empirical framework constitutes the first estimation of a profit-maximization model for Germany. Recent cost-minimization studies for Germany reach the unanimous conclusion that there is an inverse U-shaped relationship between skills and conditional WELDs: conditional labor demand is more elastic for low- and high-skilled workers than for medium-skilled workers. The grey lines in Figure C1 illustrate this pattern. Peichl and Siegloch (2012) propose an iterative demand-supply link to improve supply-based labor market simulations. To calibrate their model, the authors estimate a Translog cost function with German LEE information for the years 1996-2007. Conditional WELD estimates suggest that establishments reduce their labor demand more strongly

[61] See Abowd and Kramarz (1999) for an overview about existing linked employer-employee datasets.

with wage increases for low- (-1.1) and high-skilled workers (-0.6) compared to medium-skilled workers (-0.4). For the period 2003-2007, Cox et al. (2014) examine the impact of rising electricity prices on labor demand in the German manufacturing sector. Conditional WELDs stem from a Translog cost function with energy as a separate input factor. Although estimations take place at the industry level, the set of conditional own-wage elasticities exhibits an extreme version inverse U-shaped pattern: an increase in wage rates by 1 percent leads on average to a decrease in conditional demand for low-, medium-, and high-skilled workers of 1.6, 0.6, and 1.5 percent. Lichter, Peichl, and Siegloch (2017) analyze how an establishment's export behavior affects the wage elasticity of labor demand. Evidence from a Generalized Leontief cost function and LEE data shows that the inverse U-shaped relationship holds for non-exporting establishment between 1996 and 2008. Exporting establishments feature a similar pattern but with a conditional WELD for high-skilled workers that is slightly smaller than for medium-skilled workers. With the estimation of cost functions, however, the studies have in common that they can only measure substitution effects. Instead, we go one step further and estimate a profit function to also account for scale effects. In our analysis, we argue that the overall relationship between skills and unconditional WELDs is different from the familiar pattern. When including scale effects, the inverse U-shaped pattern turns around and becomes U-shaped.

Table A1: Unconditional WELD Estimates from Structural-Form Models

	Scale Effect	Workforce	Fixed Effects	Data	Unit	Country	Year
Woodland (1977)	N/A	collar	no	time series	industry	Canada	1947-1970
Segerson and Mount (1985)	N/A	homogeneous	no	time series	industry	USA	1961-1977
Deno (1988)	N/A	homogeneous	no	panel	region	USA	1970-1978
Kim (1988)	negative	homogeneous	no	time series	industry	USA	1948-1971
Kintis and Panas (1988)	N/A	homogeneous	no	time series	industry	Greece	1963-1980
Crihfield and Panggabean (1996)	N/A	homogeneous	no	cross section	area	USA	1963/72/82
Klein and Kyle (1997)	N/A	homogeneous	no	panel	industry	USA	1971-1982
Lee and Ma (2001)	N/A	homogeneous	no	time series	industry	USA	1950-1987
Koebel and Laisney (2016)	negative	homogeneous	yes	time series	industry	USA	1949-2011
This Paper	negative	skill/task	yes	panel	firm	Germany	1993-2016

NOTE. — The table includes empirical studies that employ structural-form models to estimate unconditional wage elasticities of labor demand. For reasons of parsimony, we exclude the vast number of studies that refer solely to the primary sector which involves farming, fishing, and mining (NACE 2008 Classification: A-B). To identify scale effects, the study must estimate both conditional and unconditional WELDs. NACE = Statistical Nomenclature of Economic Activities in the European Community. N/A = Not Available. Source: Own illustration.

Table A2: Unconditional WELD Estimates from Reduced-Form Models

	Scale Effect	Workforce	Fixed Effects	Data	Unit	Country	Year
Kirkpatrick (1982)	N/A	homogeneous	no	time series	industry	Germany	1960-1979
Symons and Layard (1984)	N/A	homogeneous	no	time series	industry	G7 $\setminus$ {Italy}	1956-1980
Faini and Schiantarelli (1985)	(negative)	homogeneous	yes	panel	industry	Italy	1970-1979
Mairesse and Dormont (1985)	N/A	homogeneous	yes	panel	firm	FRA/GER/USA	1970-1979
Heise (1987)	N/A	homogeneous	no	time series	industry	Germany	1968-1983
Wadhwani (1987)	N/A	homogeneous	no	time series	industry	UK	1962-1981
Burgess (1988)	N/A	homogeneous	no	time series	industry	UK	1963-1982
Pencavel and Holmlund (1988)	N/A	homogeneous	no	time series	industry	Sweden	1951-1983
Begg et al. (1989)	N/A	homogeneous	no	time series	economy	GER/JAP/UK	1953-1986
Nickell and Symons (1990)	N/A	homogeneous	no	time series	industry	USA	1962-1984
Wadhwani and Wall (1990)	N/A	homogeneous	yes	panel	industry	UK	1974-1982
Arellano and Bond (1991)	N/A	homogeneous	yes/no	panel	firm	UK	1979-1984
Blanchflower, Millward, and Oswald (1991)	N/A	homogeneous	no	cross section	firm	UK	1984
Revenga (1997)	(positive)	homogeneous	yes/no	panel	firm/industry	Mexico	1984-1990
van Reenen (1997)	N/A	homogeneous	yes	panel	firm	UK	1976-1982
Krishna, Mitra, and Chinoy (2001)	N/A	gender/overtime	yes	panel	firm	Turkey	1983-1986
Slaughter (2001)	positive	collar	yes	panel	industry	USA	1961-1991
Lewis and MacDonald (2002)	(negative)	homogeneous	no	time series	economy	Australia	1959-1998

NOTE. — The table includes empirical studies that employ reduced-form models to estimate unconditional wage elasticities of labor demand. For reasons of parsimony, we exclude the vast number of studies that refer solely to the primary sector which involves farming, fishing, and mining (NACE 2008 Classification: A-B). To identify scale effects, the study must estimate both conditional and unconditional WELDs. Parentheses around the sign of the scale effect signal that conditional and unconditional WELDs are not directly comparable within the respective study. FRA = France. GER = Germany. JAP = Japan. NACE = Statistical Nomenclature of Economic Activities in the European Community. N/A = Not Available. Source: Own illustration.

Table A2: Unconditional WELD Estimates from Reduced-Form Models (Cont.)

	Scale Effect	Workforce	Fixed Effects	Data	Unit	Country	Year
Addison and Teixeira (2005)	(positive)	homogeneous	yes	panel	firm	Germany	1993-2001
Addison and Teixeira (2005)	(negative)	homogeneous	yes	panel	firm	Portugal	1990-1997
Amiti and Wei (2005)	differing	homogeneous	yes	panel	industry	UK	1995-2001
Arnone et al. (2005)	differing	homogeneous	yes	panel	firm	Belgium	1998-2002
Fajnzylber and Maloney (2005)	N/A	skill/collar	yes	panel	firm	CHL/COL/MEX	1977-1995
Amiti and Wei (2006)	positive	homogeneous	yes	panel	industry	USA	1992-2000
Harrison and McMillan (2006)	positive	homogeneous	yes	panel	firm	USA	1982-1999
Aguilar and Rendon (2008)	N/A	homogeneous	no	cross section	firm	Peru	2004
Haouas and Yagoubib (2008)	N/A	homogeneous	yes/no	panel	industry	Tunisia	1971-1996
Aguilar and Rendon (2010)	N/A	collar	no	cross section	firm	Peru	2004
Hijzen and Swaim (2010)	positive	homogeneous	yes	panel	industry	OECD	1980-2002
Ayala (2012)	negative	homogeneous	yes	panel	industry	Colombia	1974-2009
Mitra and Shin (2012)	N/A	homogeneous	yes/no	panel	firm	South Korea	2002-2008
Sala and Trivin (2013)	differing	homogeneous	yes	cross section	industry/region	Spain	1964-2007
Cox et al. (2014)	(positive)	skill/collar	yes	panel	industry	Germany	2003-2007
Lichter, Peichl, and Siegloch (2017)	(differing)	skill	yes	panel	firm	Germany	1996-2008
Beaudry, Green, and Sand (2018)	N/A	skill	yes	panel	industry/region	USA	1970-2014
Kölling (2018)	N/A	skill	yes	panel	firm	Germany	2001-2014

NOTE. — The table includes empirical studies that employ reduced-form models to estimate unconditional wage elasticities of labor demand. For reasons of parsimony, we exclude the vast number of studies that refer solely to the primary sector which involves farming, fishing, and mining. To identify scale effects, the study must estimate both conditional and unconditional WELDs (NACE 2008 Classification: A-B). Parentheses around the sign of the scale effect signal that conditional and unconditional WELDs are not directly comparable within the respective study. CHL = Chile. COL = Columbia. MEX = Mexico. NACE = Statistical Nomenclature of Economic Activities in the European Community. N/A = Not Available. OECD = Organization for Economic Co-operation and Development. Source: Own illustration.

B Appendix: Empirical Model

Table B1: Task-Based Division of Workforce

		Non-Routine	Routine
Manual		animal keeper, athlete, cook, florist, lumberman, mason, masseur, waiter	baker, brewer, butcher, farmer, metalworker, tailor, shoemaker
Cognitive	Interactive	advisor, innkeeper, interpreter, pastor, sales agent, social worker	accountant, broker, cashier, clerk, inspector, mechanist
	Analytical	architect, chemist, dentist, economist, engineer, judge, manager	

Note. — The table shows exemplary occupations for the five task dimensions of the task-based approach. Routine and non-routine tasks differ in their susceptibility for automation. Routine tasks can be formulated in terms of rules and, thus, represent a substitute for machines. In contrast, non-routine tasks feature a higher degree of specificity and are not prone to be replaced by technology. Manual tasks are mainly performed by one's hand. While analytical tasks predominantly require workers to think and solve problems, interactive tasks focus on oral and written communication with people. We group together analytical routine and interactive routine tasks and term them "cognitive routine tasks". Sources: Spitz-Oener (2006) + Dengler, Matthes, and Paulus (2014).

C Appendix: Skill-Based Approach

Table C1: Cost Shares for Skill-Based Approach

		Mean	P5	P10	P25	P50	P75	P90	P95	Observations
Cost Sh.	Low-Skilled W.	0.087	0.005	0.009	0.020	0.054	0.127	0.212	0.272	20,008
	Med.-Skilled W.	0.673	0.412	0.491	0.590	0.689	0.777	0.841	0.873	20,008
	High-Skilled W.	0.162	0.025	0.038	0.069	0.126	0.215	0.327	0.429	20,008
	Capital Stock	0.079	0.002	0.006	0.021	0.053	0.104	0.179	0.241	20,008

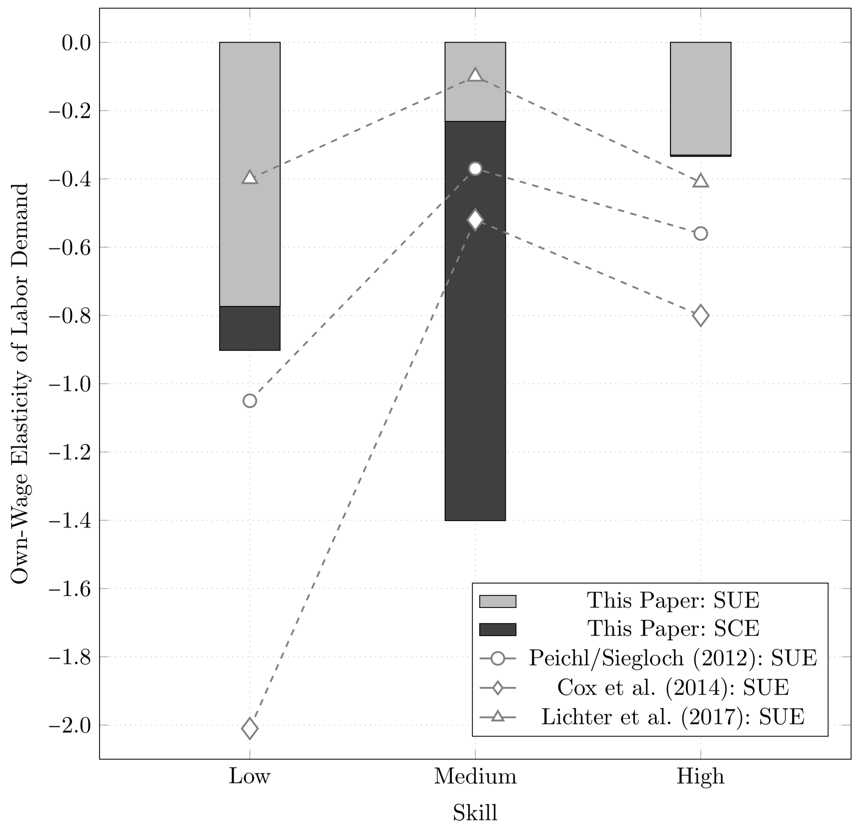
NOTE. — The table displays means and selected percentiles of cost shares for different types of skills. Cost shares are the ratio of input-specific costs to overall restricted costs of an establishment. Dev. = Deviation. PX = Xth Percentile. Sh. = Share. W. = Workers. Source: LIAB, 1993-2016.

Table C2: SUR Estimation for Skill-Based Approach

Profit Share	Low-Skilled Workers s^1	Medium-Skilled Workers s^2	High-Skilled Workers s^3	Capital Stock s^K
$ln\,\frac{w^1}{w^0}$	-0.0045** (0.0020)	0.0017 (0.0047)	-0.0085*** (0.0028)	0.0103** (0.0044)
$ln\,\frac{w^2}{w^0}$	0.0017 (0.0047)	0.0336 (0.0271)	-0.0266* (0.0144)	0.0010 (0.0157)
$ln\,\frac{w^3}{w^0}$	-0.0085*** (0.0028)	-0.0266* (0.0144)	-0.0553*** (0.0131)	-0.0032 (0.0076)
$ln\,\frac{w^4}{w^0}$	0.0103** (0.0044)	0.0010 (0.0157)	-0.0032 (0.0076)	-0.0110 (0.0186)
t	0.0134** (0.0063)	0.0401 (0.0525)	0.0089 (0.0322)	0.0260* (0.0154)
Establishment FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	14,830	14,830	14,830	14,830
χ^2 (p Value)	330.1*** (0.000)	88.41*** (0.000)	66.64*** (0.000)	269.3*** (0.000)

NOTE. — The table displays results from an iterative seemingly unrelated regression on system of four profit share equations for the skill-based approach. Standard errors are in parentheses. We within-transformed the data prior to the estimation. Regulatory conditions apply through imposition of linear homogeneity in prices and symmetry. The bottom row provides χ^2 tests for joint significance of the set of independent variables. FE = Fixed Effects. SUR = Seemingly Unrelated Regression. * = p<0.10. ** = p<0.05. *** = p<0.01. Sources: LIAB + Destatis, 1993-2016.

Figure C1: Own-Wage Elasticities of Labor Demand by Skill



NOTE. — The figure compares estimated relationships between own-wage elasticities of labor demand and skills for Germany. Workers with low education neither completed vocational training nor hold a university degree. Medium-skilled workers passed vocational training while high-skilled workers (also) graduated from a university. Bars represent estimates originating from this study, and markers describe estimates from related studies. Substitution effects are highlighted in grey whereas scale effects are illustrated in black. SCE = Scale Effect. SUE = Substitution Effect. Sources: LIAB + Destatis, 1993-2016.

Table C3: Robustness Checks for Skill-Based Approach

		Output	Low-Skilled Workers	Medium-Skilled Workers	High-Skilled Workers	Capital Stock
Baseline	Cond.	N/A	-0.77	-0.23	-0.33	-0.57
	Uncond.	0.36	-0.90	-1.40	-0.33	-0.67
At Median of Observations	Cond.	N/A	-0.68	-0.21	0.38	-0.35
	Uncond.	0.28	-0.76	-1.38	0.29	-0.41
With Profit Function	Cond.	N/A	-0.78	-0.24	-0.10	-0.61
	Uncond.	0.27	-0.91	-1.28	-0.12	-0.70
Without Year FE	Cond.	N/A	-0.82	-0.23	-0.32	-0.86
	Uncond.	0.37	-0.94	-1.38	-0.33	-1.01
With Stratification Variables	Cond.	N/A	-0.79	-0.21	-0.30	-0.59
	Uncond.	0.35	-0.92	-1.39	-0.30	-0.69
Median Wages	Cond.	N/A	-0.77	-0.07	0.25	-0.24
	Uncond.	0.32	-0.90	-1.29	0.24	-0.36
Alternative Capital Stock	Cond.	N/A	-0.75	-0.16	-0.25	0.69
	Uncond.	0.39	-0.88	-1.42	-0.26	0.62
Alternative User Cost of Capital	Cond.	N/A	-0.79	-0.21	-0.33	-0.53
	Uncond.	0.35	-0.92	-1.39	-0.33	-0.63
West Germany	Cond.	N/A	-0.73	-0.16	-0.24	-0.46
	Uncond.	0.36	-0.90	-1.44	-0.26	-0.56
East Germany	Cond.	N/A	-0.67	-0.14	-0.33	-0.13
	Uncond.	0.35	-0.72	-1.12	-0.42	-0.23
Small Establishments	Cond.	N/A	-0.82	-0.04	0.46	0.00
	Uncond.	0.28	-0.98	-1.35	0.25	-0.13
Large Establishments	Cond.	N/A	-0.90	-0.21	-0.76	-0.60
	Uncond.	0.46	-0.98	-1.30	-1.14	-0.69
Without Wage Agreement	Cond.	N/A	-0.82	0.28	2.12	-0.16
	Uncond.	0.20	-0.98	-1.51	0.72	-0.35
With Wage Agreement	Cond.	N/A	-0.85	-0.39	-0.50	-1.21
	Uncond.	0.43	-0.95	-1.41	-0.77	-1.31
2010-2016	Cond.	N/A	-0.85	-0.04	0.44	-2.15
	Uncond.	0.30	-0.98	-1.37	0.43	-2.25
Medium or High Competition	Cond.	N/A	-0.86	-0.03	0.57	-3.09
	Uncond.	0.30	-1.02	-1.40	0.54	-3.21

Note. — The table illustrates robustness checks for the skill-based approach. For reasons of parsimony, we focus on own-wage (own-price) elasticities of labor demand (product supply). The alternative capital measure uses full-sample instead of three-year averages of approximated capital as starting values for the law of motion. Instead of twelve-month rates, our alternative measure for user cost of capital refers to three-month FIBOR (1993-1998) and EURIBOR (1999-2016) interest rates. Stratification variables include industry, size class, and federal state. The sample of establishments from East Germany refers to 1996-2016. We use the threshold of 200 full-time employees to divide employers into small and large firms. Establishments with a wage agreement abide by a collective agreement at the firm or industry level. The sample of establishments with medium or high competitive pressure refers to 2010-2016. Cond. = Conditional. FE = Fixed Effects. Uncond. = Unconditional. Sources: LIAB + Destatis, 1993-2016.

D Appendix: Task-Based Approach

Table D1: Cost Shares for Task-Based Approach

		Mean	P5	P10	P25	P50	P75	P90	P95	Obser-vations
Cost Share	Man. R. Task	0.279	0.023	0.041	0.114	0.257	0.422	0.551	0.605	10,396
	Man. N.-R. Task	0.061	0.004	0.007	0.014	0.029	0.062	0.158	0.255	10,396
	Cogn. R. Task	0.309	0.089	0.118	0.179	0.278	0.425	0.536	0.615	10,396
	Inter. N.-R. Task	0.040	0.001	0.002	0.005	0.015	0.043	0.099	0.163	10,396
	An. N.-R. Task	0.225	0.065	0.094	0.142	0.209	0.292	0.379	0.435	10,396
	Capital Stock	0.085	0.004	0.009	0.028	0.060	0.113	0.187	0.247	10,396

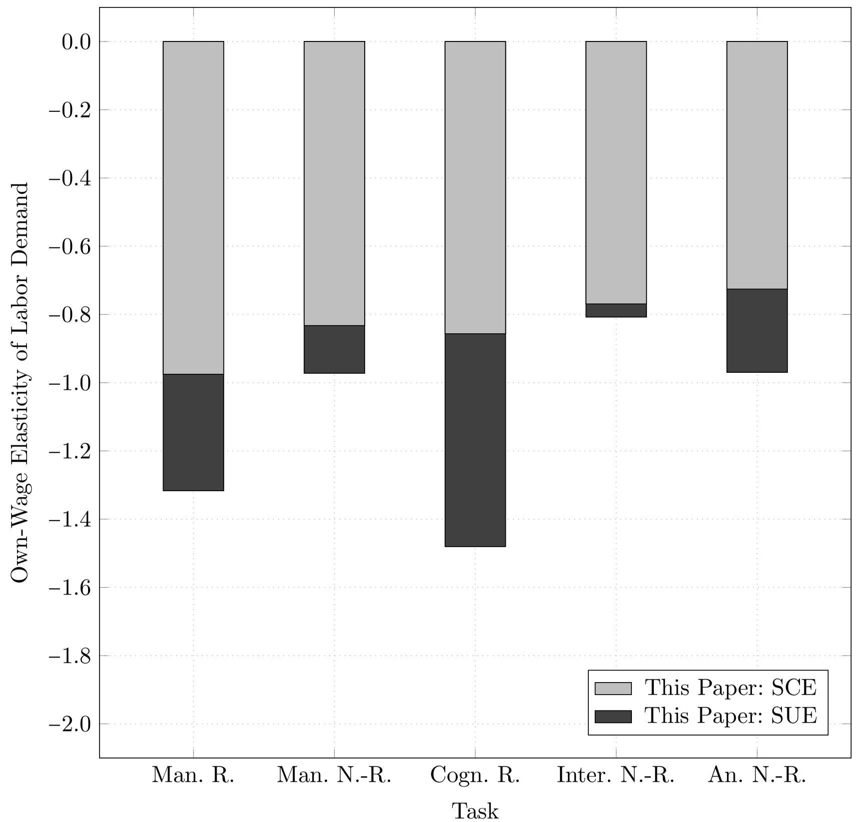
Note. — The table displays means and selected percentiles of cost shares for different types of tasks. An. = Analytical. Cogn. = Cognitive. Dev. = Deviation. Inter. = Interactive. Man. = Manual. N.-R. = Non-Routine. PX = Xth Percentile. R. = Routine. Source: LIAB, 1993-2016.

Table D2: SUR Estimation for Task-Based Approach

Profit Share	Manual Routine Task s^1	Manual Non-Routine Task s^2	Cognitive Routine Task s^3	Interactive Non-Routine Task s^4	Analytical Non-Routine Task s^5	Capital Stock s^6
$ln\,\frac{w^1}{w^0}$	0.0223*** (0.0079)	0.0021 (0.0024)	-0.0330*** (0.0092)	0.0001 (0.0018)	-0.0032 (0.0062)	0.0076 (0.0049)
$ln\,\frac{w^2}{w^0}$	0.0021 (0.0024)	-0.0010 (0.0016)	-0.0004 (0.0029)	0.0001 (0.0008)	0.0005 (0.0022)	0.0104*** (0.0024)
$ln\,\frac{w^3}{w^0}$	-0.0330*** (0.0092)	-0.0004 (0.0029)	0.0433** (0.0206)	0.0026 (0.0023)	0.0077 (0.0114)	0.0188*** (0.0057)
$ln\,\frac{w^4}{w^0}$	0.0001 (0.0018)	0.0001 (0.0008)	0.0026 (0.0023)	-0.0031*** (0.0009)	0.0012 (0.0017)	-0.0035** (0.0016)
$ln\,\frac{w^5}{w^0}$	-0.0032 (0.0062)	0.0005 (0.0022)	0.0077 (0.0114)	0.0012 (0.0017)	-0.0098 (0.0093)	-0.0059 (0.0044)
$ln\,\frac{w^6}{w^0}$	0.0076 (0.0049)	0.0104*** (0.0024)	0.0188*** (0.0057)	-0.0035** (0.0016)	-0.0059 (0.0044)	-0.0234*** (0.0072)
t	0.0260** (0.0110)	0.0073** (0.0029)	0.0291 (0.0302)	-0.0004 (0.0020)	0.0170 (0.0178)	0.0285*** (0.0066)
Establishment FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,482	7,482	7,482	7,482	7,482	7,482
χ^2 (p Value)	155.9*** (0.000)	316.4*** (0.000)	87.18*** (0.000)	64.85*** (0.000)	82.15*** (0.000)	583.4*** (0.000)

NOTE. — The table displays results from an iterative seemingly unrelated regression on system of six profit share equations for the task-based approach. Standard errors are in parentheses. We within-transformed the data prior to the estimation. Regulatory conditions apply through imposition of linear homogeneity in prices and symmetry. The bottom row provides χ^2 tests for joint significance of the set of independent variables. FE = Fixed Effects. SUR = Seemingly Unrelated Regression. * = p<0.10. ** = p<0.05. *** = p<0.01. Sources: LIAB + Destatis, 1993-2016.

Figure D1: Own-Wage Elasticities of Labor Demand by Task



Note. — The figure contrasts estimated relationships between own-wage elasticities of labor demand and tasks for Germany. Routine tasks can be formulated in terms of rules and, thus, represent a substitute for machines. In contrast, non-routine tasks feature a higher degree of specificity and are not prone to be replaced by technology. Manual tasks are mainly performed by one's hand. While analytical tasks predominantly require workers to think and solve problems, interactive tasks focus on oral and written communication with people. We group together analytical routine and interactive routine tasks and term them . Substitution effects are highlighted in grey whereas scale effects are illustrated in black. SCE = Scale Effect. SUE = Substitution Effect. Sources: LIAB + Destatis, 1993-2016.

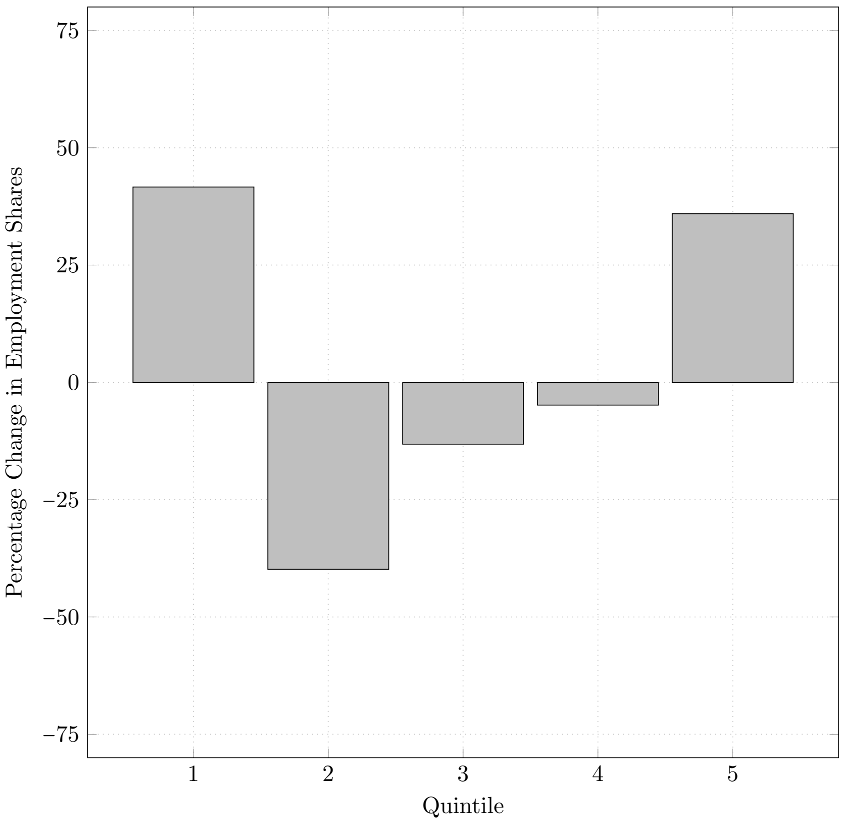
Table D3: Robustness Checks for Task-Based Approach

		Output	Man. R. Task	Man. N.-R. Task	Cogn. R. Task	Inter. N.-R. Task	An. N.-R. Task	Cap. Stock
Baseline	Cond.	N/A	-0.97	-0.83	-0.86	-0.77	-0.73	-0.13
	Uncond.	0.41	-1.32	-0.97	-1.48	-0.81	-0.97	-0.26
At Median of Observations	Cond.	N/A	-1.13	-0.77	-1.03	-0.46	-0.72	0.33
	Uncond.	0.34	-1.39	-0.91	-1.62	-0.47	-0.91	0.23
With Profit Function	Cond.	N/A	-0.94	-0.80	-0.84	-0.76	-0.69	-0.14
	Uncond.	0.26	-1.28	-0.95	-1.14	-0.80	-0.79	-0.21
Without Year FE	Cond.	N/A	-0.98	-0.85	-0.89	-0.74	-0.69	-0.88
	Uncond.	0.40	-1.34	-0.97	-1.41	-0.78	-0.98	-1.01
With Stratification Variables	Cond.	N/A	-0.99	-0.84	-0.87	-0.77	-0.72	-0.05
	Uncond.	0.40	-1.33	-0.98	-1.51	-0.81	-0.96	-0.17
Median Wages	Cond.	N/A	-0.97	-0.83	-0.86	-0.77	-0.73	-0.13
	Uncond.	0.41	-1.32	-0.97	-1.48	-0.81	-0.97	-0.26
Alternative Capital Stock	Cond.	N/A	-0.98	-0.75	-0.75	-0.73	-0.77	0.37
	Uncond.	0.46	-1.35	-0.89	-1.46	-0.77	-1.02	0.27
Alternative User Cost of Capital	Cond.	N/A	-0.97	-0.83	-0.84	-0.77	-0.71	-0.17
	Uncond.	0.40	-1.31	-0.97	-1.47	-0.81	-0.96	-0.29
West Germany	Cond.	N/A	-1.19	-0.92	-1.07	-0.64	-0.54	-0.10
	Uncond.	0.41	-1.51	-1.08	-1.81	-0.68	-0.75	-0.20
East Germany	Cond.	N/A	-0.45	-0.71	-0.56	-0.97	-0.98	-0.18
	Uncond.	0.38	-0.85	-0.81	-1.00	-1.02	-1.25	-0.34
Small Establishments	Cond.	N/A	-0.64	-0.80	-0.82	-0.69	-0.70	-1.47
	Uncond.	0.40	-1.05	-0.91	-1.29	-0.78	-0.95	-1.69
Large Establishments	Cond.	N/A	-1.10	-1.01	-0.96	-0.62	-0.76	0.34
	Uncond.	0.42	-1.41	-1.14	-1.64	-0.65	-1.02	0.23
Without Wage Agreement	Cond.	N/A	-0.72	-0.73	-0.64	-0.71	-1.05	-1.08
	Uncond.	0.34	-1.03	-0.96	-1.06	-0.75	-1.25	-1.24
With Wage Agreement	Cond.	N/A	-1.03	-0.89	-0.81	-0.83	-0.51	0.01
	Uncond.	0.42	-1.37	-1.02	-1.48	-0.86	-0.76	-0.12
2010-2016	Cond.	N/A	-0.91	-0.69	-0.97	-0.63	-0.59	-1.28
	Uncond.	0.33	-1.17	-0.85	-1.46	-0.68	-1.00	-1.37
Medium or High Competition	Cond.	N/A	-0.96	-0.73	-0.99	-0.64	-0.68	-1.38
	Uncond.	0.33	-1.22	-0.88	-1.48	-0.69	-1.08	-1.46

Note. — The table illustrates robustness checks for the task-based approach. For reasons of parsimony, we focus on own-wage elasticities of labor demand. The alternative capital stock measure uses full-sample instead of three-year averages of approximated capital as starting values for the law of motion. Instead of twelve-month rates, our alternative measure for user cost of capital refers to three-month FIBOR (1993-1998) and EURIBOR (1999-2016) interest rates from German Bundesbank. Stratification variables include industry, size class, and federal state. The sample of establishments from East Germany refers to 1996-2016. Establishments from the consumption goods, production goods, and capital goods industry belong to 2-digit WZ 2008 classifications 10-18, 19-24, and 25-33. We use the threshold of 200 full-time employees to divide establishments into small and large ones. Establishments with a wage agreement abide by a collective agreement either at the firm or industry level. The sample of establishments with medium or high competitive pressure refers to 2010-2016. An. = Analytical. Cap. = Capital. Cogn. = Cognitive. Cond. = Conditional. FE = Fixed Effects. Inter. = Interactive. Man. = Manual. N.-R. = Non-Routine. R. = Routine. Uncond. = Unconditional. WZ = German Classification of Economic Activities. Sources: LIAB + Destatis, 1993-2016.

E Appendix: Job Polarization

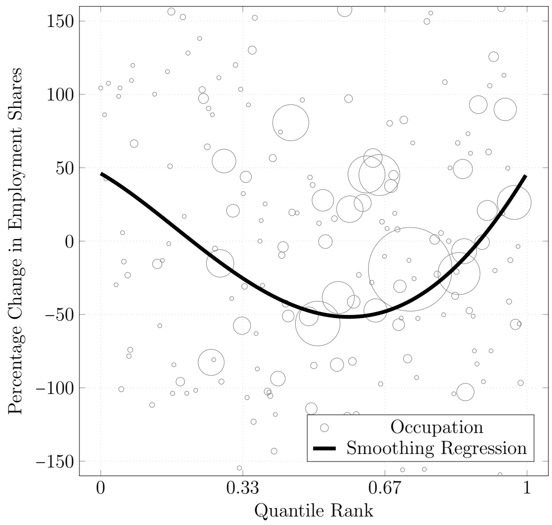
Figure E1: Change in Employment Shares by Occupational Quintile



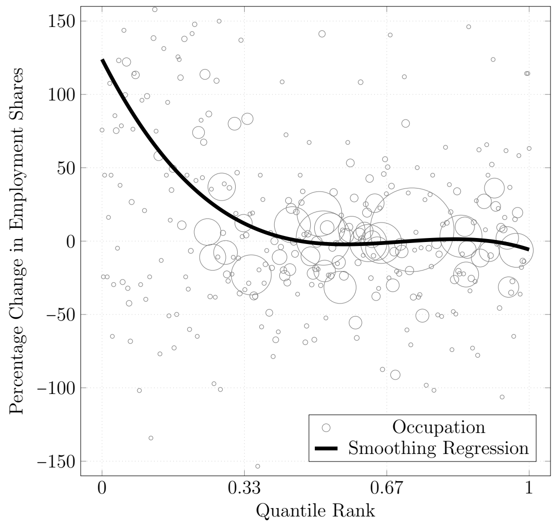
Note. — The figure depicts changes in log employment shares for occupational quintiles in German manufacturing. The bars refer to five equally-sized groups of KldB 1988 occupations given their quantile rank for mean daily labor cost in the year 2000. KldB = German Classification of Occupations. Source: LIAB, 1993-2016.

Figure E2: Change in Occupational Employment Shares

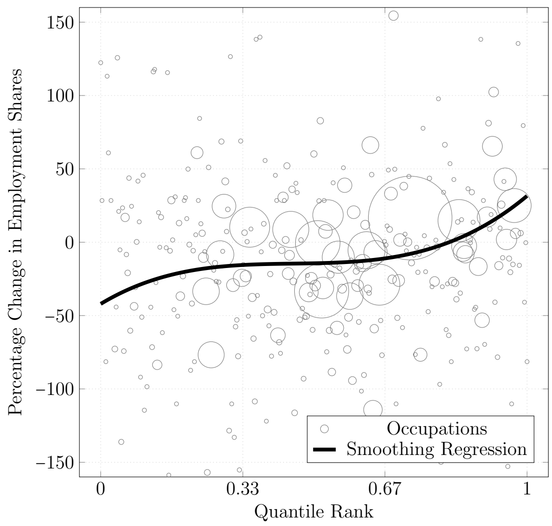
(a) 1993-2016



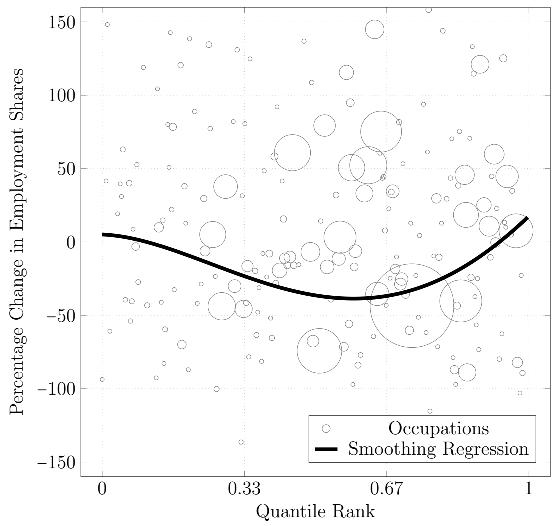
(b) 1993-2000



(c) 2000-2010

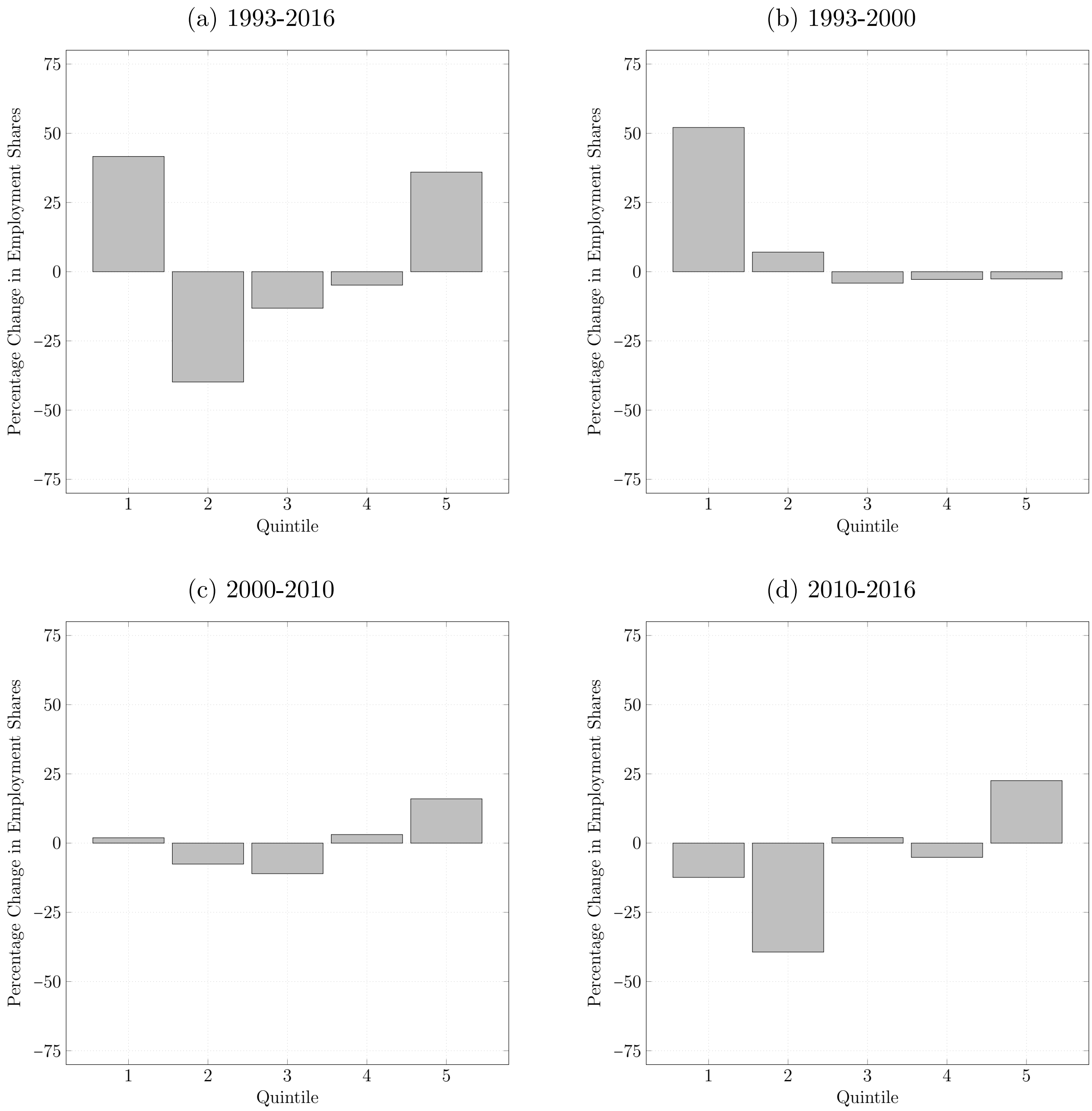


(d) 2010-2016



Note. — The figures depict changes in log employment shares (multiplied by 100) for 3-digit KldB 1988 occupations in German manufacturing. Each occupation holds a quantile rank given its mean daily labor cost in the year 2000. The size of each marker is proportional to occupational employment in the year 2000. Building on this pattern, we a employ kernel-weighted local polynomial smoothing regression with degree 3, a bandwidth of 0.8, and employment in 2000 as regression weight. The graphs are truncated at ±150 % for better illustration. KldB = German Classification of Occupations. Source: LIAB, 1993-2016.

Figure E3: Change in Employment Shares by Occupational Quintile



Note. — The figures depict changes in log employment shares for occupational quintiles in German manufacturing. The bars refer to five equally-sized groups of KldB 1988 occupations given their quantile rank for mean daily labor cost in the year 2000. KldB = German Classification of Occupations. Source: LIAB, 1993-2016.

Table E1: Regressions with Alternative Threshold Years

	Low-Paid Occupations	Medium-Paid Occupations	High-Paid Occupations	All Occupations
1993-1998	-2.045***	-1.043***	-1.215***	-1.489***
	(0.150)	(0.138)	(0.125)	(0.080)
1998-2008	0.100	0.444***	0.300***	0.228***
	(0.077)	(0.093)	(0.089)	(0.049)
2008-2016	-0.068	0.878***	0.707***	0.478***
	(0.135)	(0.157)	(0.113)	(0.076)
1993-1999	-1.705***	-1.035***	-0.950***	-1.268***
	(0.141)	(0.133)	(0.114)	(0.074)
1999-2009	0.034	0.556***	0.473***	0.267***
	(0.077)	(0.090)	(0.086)	(0.048)
2009-2016	0.002	0.920***	0.796***	0.551***
	(0.146)	(0.171)	(0.121)	(0.082)
1993-2001	-0.452***	-0.784***	-0.276**	-0.455***
	(0.110)	(0.123)	(0.116)	(0.066)
2001-2011	0.197**	0.821***	0.625***	0.471***
	(0.082)	(0.109)	(0.090)	(0.052)
2011-2016	0.313	0.905***	1.008***	0.777***
	(0.202)	(0.211)	(0.159)	(0.108)
1993-2002	-0.350***	-0.399***	-0.126	-0.292***
	(0.092)	(0.111)	(0.108)	(0.058)
2002-2012	0.033	0.865***	0.543***	0.413***
	(0.092)	(0.123)	(0.093)	(0.058)
2012-2016	-0.181	0.696***	0.865***	0.474***
	(0.181)	(0.196)	(0.138)	(0.098)

Note. — The table shows slope estimates from regressions of yearly occupational changes in log employment share on yearly occupational changes in log average daily wages and a constant. Standard errors are in parentheses. We divide 3-digit KldB 1988 occupations into three equally-sized occupational groups based on their mean daily labor cost in the year 2000: low-paid occupations (quantile rank: 0-0.33), medium-paid occupations (quantile rank: 0.33-0.67), and high-paid occupations (quantile rank: 0.67-1). KldB = German Classification of Occupations. * = p<0.10. ** = p<0.05. *** = p<0.01. Source: LIAB, 1993-2016.

Table E2: Alternative Regressions with Rolling Sample

	Low-Paid Occupations	Medium-Paid Occupations	High-Paid Occupations	All Occupations
1993-1998	-2.045*** (0.150)	-1.043*** (0.138)	-1.215*** (0.125)	-1.489*** (0.080)
1994-1999	-1.705*** (0.141)	-1.035*** (0.133)	-0.950*** (0.114)	-1.268*** (0.074)
1995-2000	-1.136*** (0.143)	-1.076*** (0.140)	-0.720*** (0.139)	-0.986*** (0.081)
1996-2001	-0.312** (0.123)	-0.851*** (0.137)	-0.222* (0.135)	-0.375*** (0.074)
1997-2002	-0.015 (0.101)	0.234 (0.142)	0.144 (0.134)	0.062 (0.067)
1998-2003	0.210** (0.096)	0.374*** (0.134)	0.176 (0.135)	0.218*** (0.066)
1999-2004	0.255*** (0.096)	0.528*** (0.120)	0.622*** (0.127)	0.409*** (0.064)
2000-2005	0.307*** (0.094)	0.637*** (0.110)	0.731*** (0.126)	0.495*** (0.063)
2001-2006	0.316*** (0.084)	0.402*** (0.100)	0.750*** (0.107)	0.480*** (0.055)
2002-2007	-0.013 (0.091)	0.640*** (0.101)	0.593*** (0.102)	0.346*** (0.057)
2003-2008	-0.209* (0.126)	0.457*** (0.113)	0.347*** (0.102)	0.205*** (0.065)
2004-2009	-0.477*** (0.120)	0.541*** (0.118)	0.433*** (0.094)	0.136** (0.064)
2005-2010	-0.511*** (0.115)	0.653*** (0.128)	0.218** (0.091)	0.016 (0.063)
2006-2011	-0.215 (0.145)	0.942*** (0.175)	0.510*** (0.133)	0.335*** (0.085)
2007-2012	0.005 (0.157)	1.289*** (0.209)	0.399*** (0.142)	0.451*** (0.095)
2008-2013	0.114 (0.165)	1.023*** (0.214)	0.520*** (0.144)	0.485*** (0.098)
2009-2014	0.065 (0.165)	1.040*** (0.210)	0.760*** (0.144)	0.586*** (0.097)
2010-2015	0.246 (0.184)	1.020*** (0.212)	0.802*** (0.148)	0.687*** (0.102)
2011-2016	0.313 (0.202)	0.905*** (0.211)	1.008*** (0.159)	0.777*** (0.108)

NOTE. — The table shows slope estimates from regressions of yearly occupational changes in log employment share on yearly occupational changes in log average daily wages and a constant. Standard errors are in parentheses. We divide 3-digit KldB 1988 occupations into three equally-sized occupational groups based on their mean daily labor cost in the year 2000: low-paid occupations (quantile rank: 0-0.33), medium-paid occupations (quantile rank: 0.33-0.67) and high-paid occupations (quantile rank: 0.67-1). KldB = German Classification of Occupations. * = p<0.10. ** = p<0.05. *** = p<0.01. Source: LIAB, 1993-2016.

Table E3: Composition of Occupational Groups

(a) Shares of Skill Types

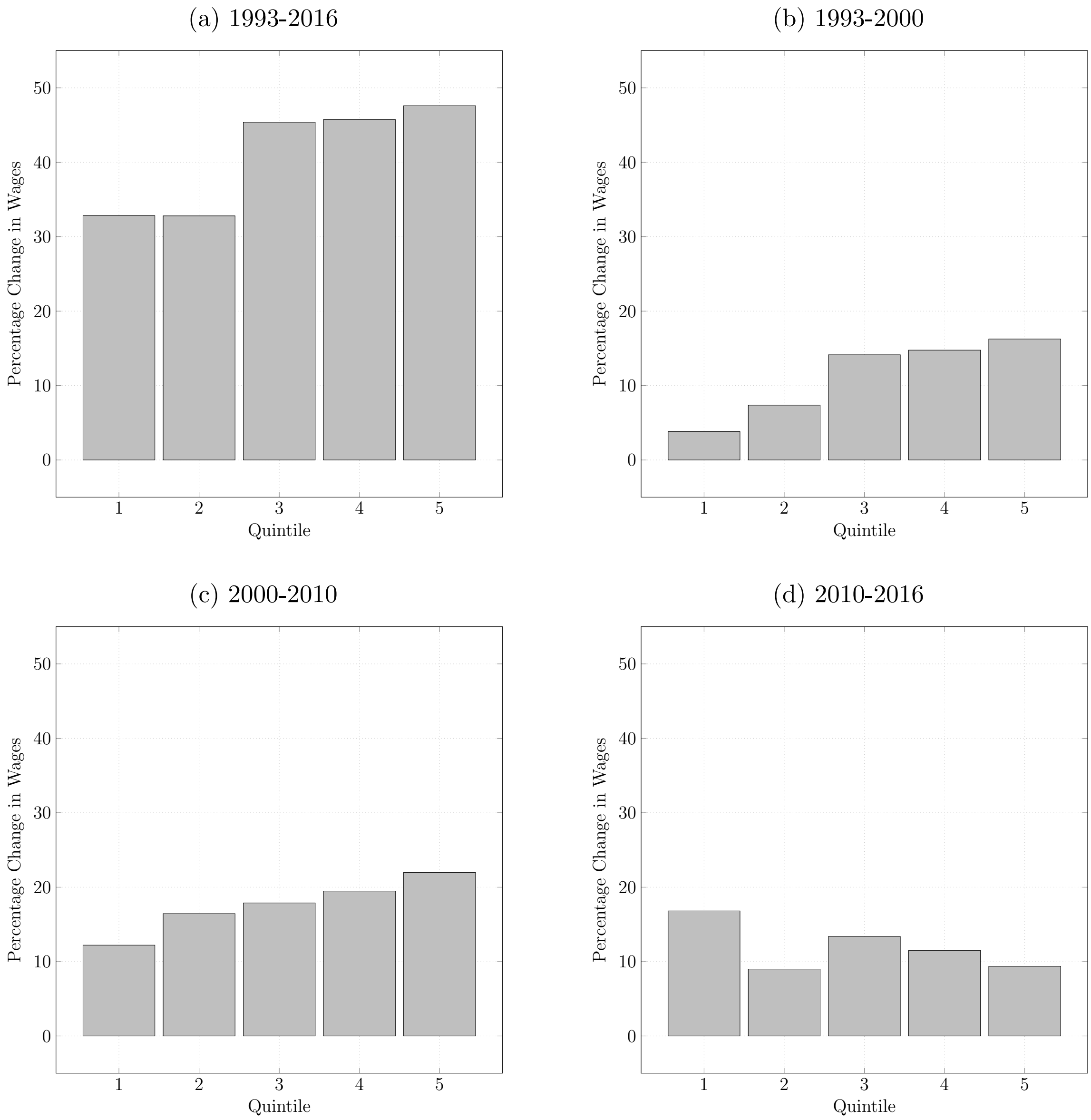
Group \ Skill	Low-Skilled Workers	Medium-Skilled Workers	High-Skilled Workers	All Workers
Low-Paid Occupations	24.7	73.1	1.05	100
Medium-Paid Occupations	13.7	83.9	1.40	100
High-Paid Occupations	2.61	60.9	36.3	100
All Occupations	11.0	73.7	14.6	100

(b) Shares of Main Task Types

Group \ Main Task	Man. R. Tasks	Man. N.-R. Tasks	Cogn. R. Tasks	Inter. N.-R. Tasks	An. N.-R. Tasks	All Tasks
Low-Paid Occupations	69.8	26.8	1.83	0.38	0.74	100
Medium-Paid Occupations	46.4	4.98	38.6	0.96	4.57	100
High-Paid Occupations	3.79	1.04	44.4	2.43	48.3	100
All Occupations	33.4	6.45	35.8	1.44	20.7	100

NOTE. — The table reports relative frequencies of skill and main task types within occupational groups for the years 1993-2016. Values are expressed in percentage points. We divide 3-digit KldB 1988 occupations into three equally-sized occupational groups according to their mean daily labor cost in the year 2000: low-paid occupations (quantile rank: 0-0.33), medium-paid occupations (quantile rank: 0.33-0.67) and high-paid occupations (quantile rank: 0.67-1). Row and/or column sums may not add up to 100 percent due to rounding errors. An. = Analytical. Cogn. = Cognitive. Inter. = Interactive. Man. = Manual. N.-R. = Non-Routine. R. = Routine. Source: LIAB, 1993-2016.

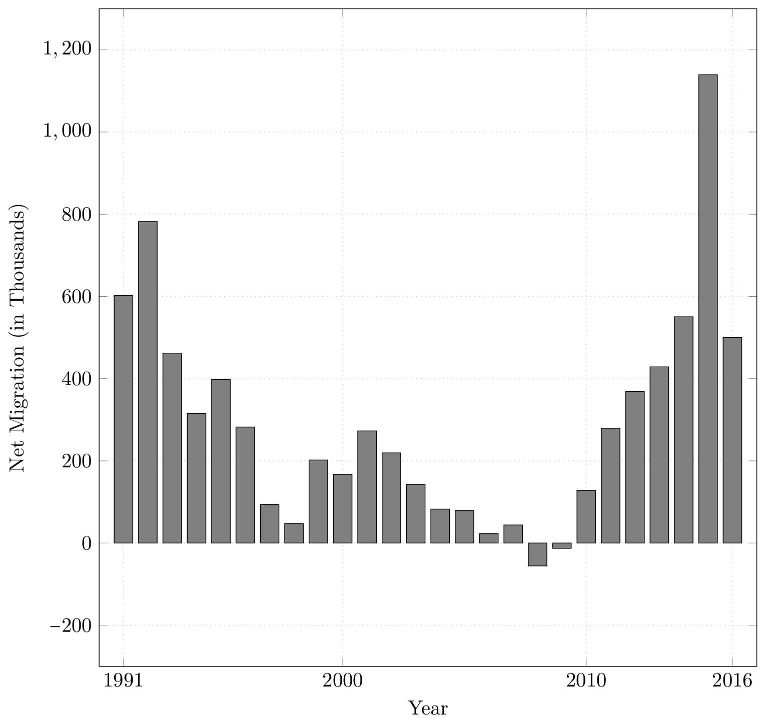
Figure E4: Change in Wages by Occupational Quintile



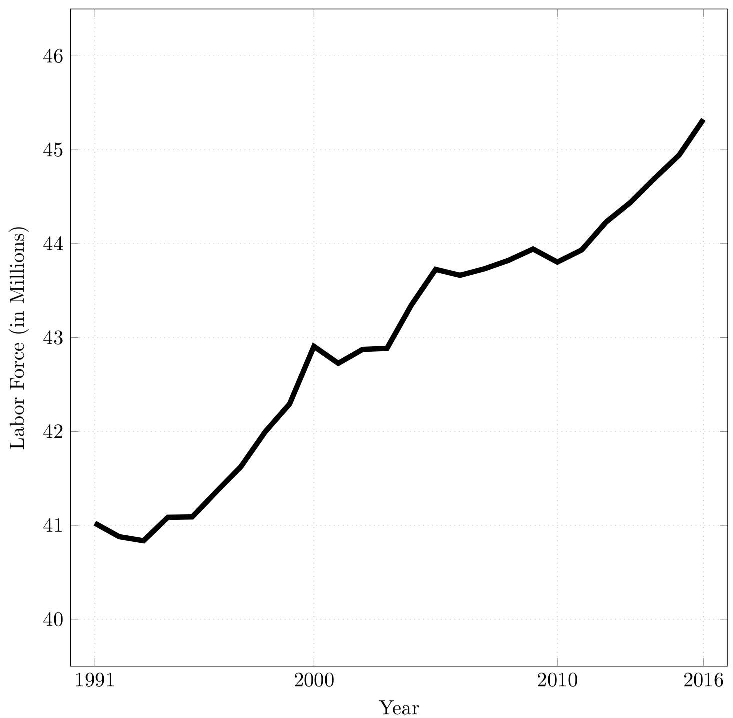
Note. — The figure depicts changes in log average labor costs for occupational quintiles in German manufacturing. The bars refer to five equally-sized groups of KldB 1988 occupations given their quantile rank for mean daily labor cost in the year 2000. KldB = German Classification of Occupations. Source: LIAB, 1993-2016.

Figure E5: Indicators of Labor Supply

(a) Migration Balance

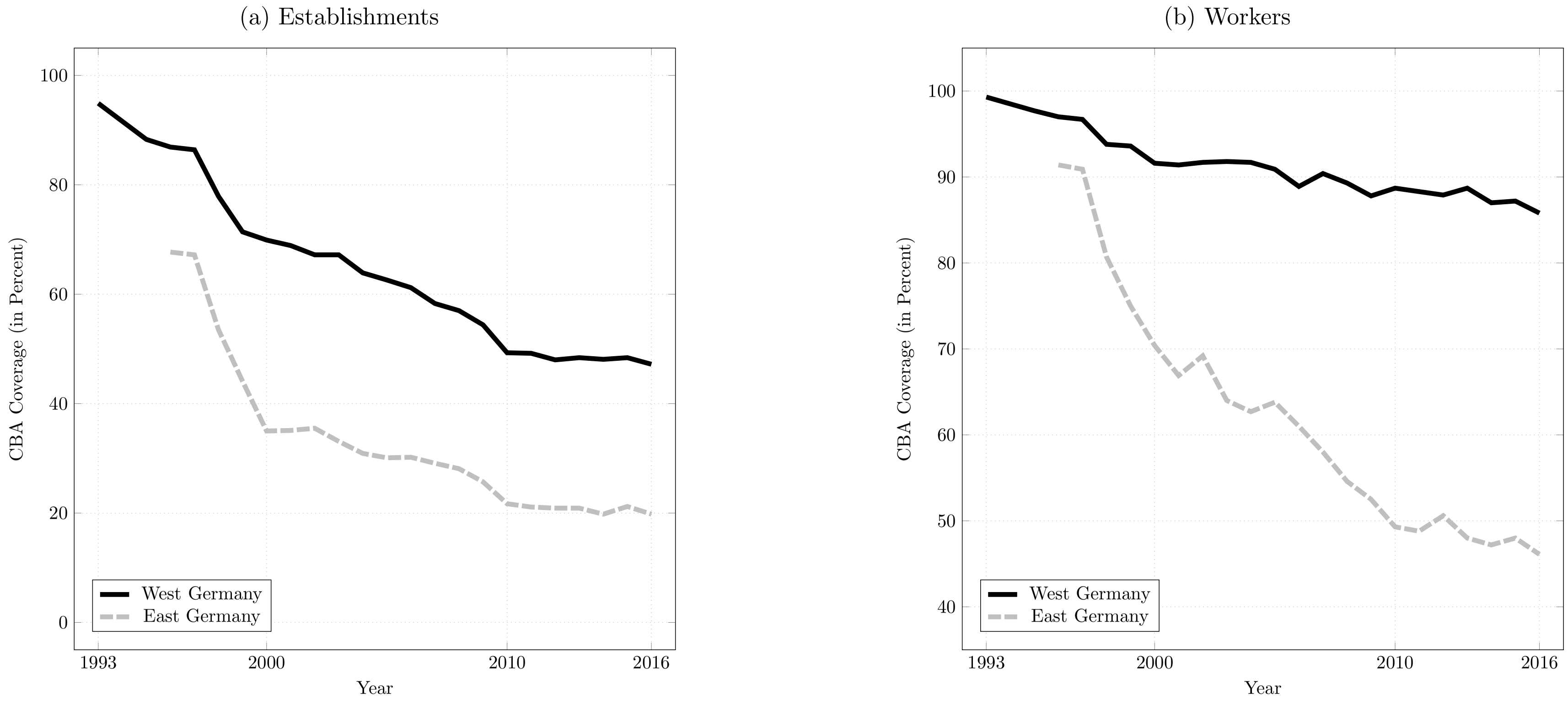


(b) Labor Force



NOTE. — The table illustrates the development of indicators for German labor supply between 1991 and 2016. In Panel a, the migration balance describes net migration into Germany (i.e., the number of immigrants minus the number of emigrants). In Panel b, the labor force is made up of all employed and unemployed persons. Following the definition of the International Labour Organization, employed persons are persons aged 15 or older who work for pay for at least one hour per week in any occupation or employment or who are self-employed. Unemployed persons are persons between the ages of 15 and 74 who are not employed, who have actively sought employment in the last four weeks, and who are available immediately (i.e., within two weeks) to take up employment. Source: Destatis, 1991-2016.

Figure E6: Coverage of Collective Bargaining Agreements



NOTE. — The figure shows the percentage share of establishments and workers that are subject to collective bargaining agreements in the German manufacturing sector. Workers refer to full-time workers in regular employment. In the year 1994, the LIAB does not contain information on collective bargaining agreements. Before 1996, East German establishments were not included in the IAB Establishment Panel. CBA = Collective Bargaining Agreement. Source: IAB Establishment Panel, 1993-2016.

Table E4: Simulation of Minimum Wage Introduction

(a) Skill-Based Approach

	West Germany	East Germany	Overall
Low-Skilled Labor	-2316	-772	-3088
Medium-Skilled Labor	-3271	-10486	-13757
High-Skilled Labor	429	684	1113
Overall	-5158	-10574	-15732

(b) Task-Based Approach

	West Germany	East Germany	Overall
Manual Routine Tasks	-1312	-4974	-6286
Manual Non-Routine Tasks	-188	-639	-827
Cognitive Routine Tasks	-2826	-3051	-5877
Interactive Non-Routine Tasks	-181	-910	-1091
Analytical Non-Routine Tasks	-1725	-1149	-2874
Overall	-6232	-10723	-16955

NOTE. — The table shows simulated labor demand effects from the introduction of a nation-wide minimum wage of 8.50 Euro per hour in Germany on January 1, 2015. The analysis refers to the manufacturing sector. Percentage changes in labor demand stem from interacting underlying percentage changes in mean wages per input factor with our matrix of unconditional wage elasticities of labor demand. In a next step, we multiply percentage changes per skill and task type by the respective number of full-time workers within the manufacturing sector. Row and/or column sums may not add up to 100 percent due to rounding errors. Sources: LIAB + Destatis, 1993-2016.

References for Online Appendix

Abowd, J. M. and Kramarz, F. (1999). The Analysis of Labor Markets Using Matched Employer-Employee Data. In: *Handbook of Labor Economics: Vol. 3B*, ed. by Ashenfelter, O. C. and Card, D., Amsterdam: North Holland, pp. 2629–2710.

Acemoglu, D. and Autor, D. H. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In: *Handbook of Labor Economics: Vol. 4B*, ed. by Ashenfelter, O. C. and Card, D., Amsterdam: North Holland, pp. 1043–1171.

Addison, J. and Teixeira, P. (2005). Employment Adjustment in Two Countries with Poor Reputations: Analysis of Aggregate, Firm, and Flow Data for Portugal and Germany. *International Economics and Economic Policy* 1 (4), pp. 329–348.

Addison, J. T., Portugal, P., and Varejão, J. (2014). Labor Demand Research: Toward a Better Match between Better Theory and Better Data. *Labour Economics* 30, pp. 4–11.

Aguilar, G. and Rendon, S. (2008). Matching Bias in Labor Demand Estimation. *Economics Letters* 100 (2), pp. 297–299.

Aguilar, G. and Rendon, S. (2010). Employment and Deadweight Loss Effects of Observed Nonwage Labor Costs. *Economic Inquiry* 48 (3), pp. 793–809.

Alam, M. F., Omar, I. H., and Squires, D. (2002). Sustainable Fisheries Development in the Tropics: Trawlers and Licence Limitation in Malaysia. *Applied Economics* 34 (3), pp. 325–337.

Amiti, M. and Wei, S.-J. (2005). Fear of Service Outsourcing: Is It Justified? *Economic Policy* 20 (42), pp. 307–347.

Amiti, M. and Wei, S.-J. (2006). *Service Offshoring and Productivity: Evidence from the United States*. Centre for Economic Policy Research, CEPR Discussion Paper 5475.

Arellano, M. and Bond, S. (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *Review of Economic Studies* 58 (2), pp. 277–297.

Arnone, L., Dupont, C., Mahy, B., and Spataro, S. (2005). Human Resource Management and Labour Demand Dynamics in Belgium: A Microeconometric Analysis Using Employers' Matched Data. *International Journal of Manpower* 26 (7-8), pp. 724–743.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *Quarterly Journal of Economics* 118 (4), pp. 1279–1333.

Ayala, S. A. (2012). *Payroll Taxes and Labour Demand: Evidence from Colombian Manufacturing Industry*. University of Barcelona, Discussion Paper.

Beaudry, P., Green, D. A., and Sand, B. M. (2018). In Search of Labor Demand. *American Economic Review* 108 (9), pp. 2714–2757.

Begg, D., Lindbeck, A., Martin, C., and Snower, D. (1989). Symmetric and Asymmetric Persistence of Labor Market Shocks. *Journal of the Japanese and International Economies* 3 (4), pp. 554–577.

Blanchflower, D. J., Millward, N., and Oswald, A. J. (1991). Unionism and Employment Behaviour. *Economic Journal* 101 (407), pp. 815–834.

Blien, U., Kirchhof, K., and Ludewig, O. (2006). *Agglomeration Effects on Labour Demand.* Institute for Employment Research, IAB Discussion Paper 28/2006.

Burgess, S. M. (1988). Employment Adjustment in UK Manufacturing. *Economic Journal* 98 (389), pp. 81–103.

Cox, M., Peichl, A., Pestel, N., and Siegloch, S. (2014). Labor Demand Effects of Rising Electricity Prices: Evidence for Germany. *Energy Policy* 75, pp. 266–277.

Crihfield, J. B. and Panggabean, M. P. H. (1996). The Structure of Metropolitan Factor and Product Markets. *Journal of Regional Science* 36 (1), pp. 17–41.

Dengler, K., Matthes, B., and Paulus, W. (2014). *Occupational Tasks in the German Labour Market: An Alternative Measurement on the Basis of an Expert Database.* Institute for Employment Research, FDZ Method Report Series 12/2014.

Deno, K. T. (1988). The Effect of Public Capital on U.S. Manufacturing Activity: 1970 to 1978. *Southern Economic Journal* 55 (2), pp. 400–411.

Faini, R. and Schiantarelli, F. (1985). Oligopolistic Models of Investment and Employment Decisions in a Regional Context: Theory and Empirical Evidence from a Putty-Clay Model. *European Economic Review* 27 (2), pp. 221–242.

Fajnzylber, P. and Maloney, W. F. (2005). Labor Demand and Trade Reform in Latin America. *Journal of International Economics* 66 (2), pp. 423–446.

Haltiwanger, J., Lane, J., Spletzer, J., Theeuwes, J., and Troske, K. (1998). International Symposium on Linked Employer-Employee Data. *Monthly Labor Review* 121 (7), pp. 48–60.

Hamermesh, D. S. (1993). *Labor Demand.* Princeton: Princeton University Press.

Hamermesh, D. S. (1999). LEEping into the Future of Labor Economics: The Research Potential of Linking Employer and Employee Data. *Labour Economics* 6 (1), pp. 25–41.

Haouas, I. and Yagoubib, M. (2008). The Effect of International Trade on Labour-Demand Elasticities: Empirical Evidence from Tunisia. *Applied Economics Letters* 15 (4), pp. 277–286.

Harrison, A. E. and McMillan, M. S. (2006). *Outsourcing Jobs? Multinationals and U.S. Employment.* National Bureau of Economic Research, NBER Working Paper 12372.

Heise, M. (1987). *Arbeitsnachfrage und Beschäftigung.* Göttingen: Vandenhoeck & Ruprecht.

Higgins, J. (1986). Input Demand and Output Supply on Irish Farms: A Micro-Economic Approach. *European Review of Agricultural Economics* 13 (4), pp. 477–493.

Hijzen, A. and Swaim, P. (2010). Offshoring, Labour Market Institutions and the Elasticity of Labour Demand. *European Economic Review* 54 (8), pp. 1016–1034.

Kim, Y. H. (1988). Analyzing the Indirect Production Function for U.S. Manufacturing. *Southern Economic Journal* 55 (2), pp. 494–504.

Kintis, A. A. and Panas, E. E. (1988). The Capital-Energy Controversy: Further Results. *Energy Economics* 11 (3), pp. 201–212.

Kirkpatrick, G. (1982). Real Factor Prices and German Manufacturing Employment: A Time Series Analysis, 1960:1 - 1979:4. *Review of World Economics* 118 (1), pp. 79–103.

Klein, C. C. and Kyle, R. (1997). Technological Change and the Production of Ocean Shipping Services. *Review of Industrial Organization* 12 (5-6), pp. 733–750.

Koebel, B. and Laisney, F. (2016). Aggregation with Cournot Competition: An Empirical Investigation. *Annals of Economics and Statistics* 121/122, pp. 91–119.

Kölling, A. (2018). Asymmetries in Labor Demand: Do Loss Aversion and Endowment Effects Affect Labor Demand Elasticities on the Establishment Level? *Journal of Economic Asymmetries* 18, No. e00098.

Krishna, P., Mitra, D., and Chinoy, S. (2001). Trade Liberalization and Labor Demand Elasticities: Evidence from Turkey. *Journal of International Economics* 55 (2), pp. 391–409.

Lee, M. and Ma, H.-O. (2001). Substitution Possibility between Unpriced Pulp and Wastepaper in the U.S. Paper and Paperboard Industry. *Environmental and Resource Economics* 18 (3), pp. 251–273.

Lewis, P. E. T. and MacDonald, G. (2002). The Elasticity of Demand for Labour in Australia. *Economic Record* 78 (1), pp. 18–30.

Lichter, A., Peichl, A., and Siegloch, S. (2015). The Own-Wage Elasticity of Labor Demand: A Meta-Regression Analysis. *European Economic Review* 80, pp. 94–119.

Lichter, A., Peichl, A., and Siegloch, S. (2017). Exporting and Labour Demand: Micro-Level Evidence from Germany. *Canadian Journal of Economics* 50 (4), pp. 1161–1189.

Lopez, R. E. (1984). Estimating Substitution and Expansion Effects Using a Profit Function Framework. *American Journal of Agricultural Economics* 66 (3), pp. 358–367.

Mairesse, J. and Dormont, B. (1985). Labor and Investment Demand at Firm Level: A Comparison of French, German and U.S. Manufacturing, 1970-1979. *European Economic Review* 28 (1-2), pp. 201–231.

Mitra, D. and Shin, J. (2012). Import Protection, Exports and Labor-Demand Elasticities: Evidence from Korea. *International Review of Economics and Finance* 23 (C), pp. 91–109.

Nickell, S. J. and Symons, J. (1990). The Real Wage-Employment Relationship in the United States. *Journal of Labor Economics* 8 (1), pp. 1–15.

Peichl, A. and Siegloch, S. (2012). Accounting for Labor Demand Effects in Structural Labor Supply Models. *Labour Economics* 19, pp. 129–138.

Pencavel, J. and Holmlund, B. (1988). The Determination of Wages, Employment, and Work Hours in an Economy with Centralised Wage-Setting. *Economic Journal* 98 (389), pp. 1105–1126.

Revenga, A. (1997). Employment and Wage Effects of Trade Liberalization: The Case of Mexican Manufacturing. *Journal of Labor Economics* 15 (S3), pp. 20–43.

Sala, H. and Trivin, P. (2013). *Structural Changes in the Spanish Labour Demand: Does Rodrik's Conjecture Hold?* University of Barcelona, Discussion Paper.

Segerson, K. and Mount, T. D. (1985). A Non-Homothetic Two-Stage Decision Model Using AIDS. *Review of Economics and Statistics* 67 (4), pp. 630–639.

Senses, M. Z. (2010). The Effects of Offshoring on the Elasticity of Labor Demand. *Journal of International Economics* 81 (1), pp. 89–98.

Slaughter, M. J. (2001). International Trade and Labor-Demand Elasticities. *Journal of International Economics* 54 (1), pp. 27–56.

Spitz-Oener, A. (2006). Technical Change, Job Tasks, and Rising Educational Demands. *Journal of Labor Economics* 24 (2), pp. 235–270.

Symons, J. and Layard, R. (1984). Neoclassical Demand for Labour Functions for Six Major Economies. *Economic Journal* 94 (376), pp. 788–799.

van Reenen, J. (1997). Employment and Technological Innovation: Evidence from U.K. Manufacturing Firms. *Journal of Labor Economics* 15 (2), pp. 255–284.

Wadhwani, S. B. (1987). The Effects of Inflation and Real Wages on Employment. *Economica* 54 (213), pp. 21–40.

Wadhwani, S. B. and Wall, M. (1990). The Effects of Profit-Sharing on Employment, Wages, Stock Returns and Productivity: Evidence from UK Micro-Data. *Economic Journal* 100, pp. 1–17.

Woodland, A. (1977). Estimation of a Variable Profit and of Planning Price Functions for Canadian Manufacturing, 1947-70. *Canadian Journal of Economics* 10 (3), pp. 355–377.