Heterogeneous Productivity, Monopsony Power, and Spillovers: Unpacking the Local Effects of Industry Shocks

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Abstract

We develop a unified theoretical framework to quantify how firms in local labor markets respond to industry-level productivity shocks. By extending the standard monopsony model of Card et al. (2018) to a general equilibrium setting, we incorporate cross-employer spillovers that allow firms to respond endogenously to changes in workers' outside options, which arise from productivity shifts in other local industries. Using German administrative data, we estimate the model using national industry wage premiums and their employment-weighted local averages as proxies for industry-specific and aggregate local productivity shocks. Our analysis reveals strong outside option effects and limited variation in local monopsony power. Our parameter estimates indicate that a 1% increase in an industry's productivity raises wages in that industry by approximately 0.47% while a 1% increase in average local labor market productivity raises all local wages by about 0.53% while 1% increase in productivity above the local labor market average increases employment share by 1.04%. A simulation of a 10% subsidy to the machinery sector demonstrates substantial wage spillovers varying from 0.01% to 1.2% and significant labor reallocation.

1 Introduction

Spatial income inequalities have been rising across most developed economies (OECD, 2023). Although part of these disparities reflects differences in workers' human capital, a substantial share originates from firm-level factors—particularly the uneven geographical distribution of rapidly expanding industries. Consequently, policymakers increasingly advocate place-based industrial policies that aim to attract high-growth, high-paying industries to economically distressed regions.

The literature identifies several channels through which geographically uneven industry expansions can amplify spatial wage inequalities. First, an industry-specific boom typically raises wages for workers employed in that industry, mechanically lifting average wages in locations where the industry's employment share is highest. Second, wage growth in one sector affects other local firms: higher wages in the booming sector can draw workers away from other employers or, in a search framework, improve the *outside options* of all local workers. This pressure wages to increase more broadly (Beaudry et al., 2012; Caldwell and Danieli, 2024). The strength of direct and indirect wage effects depends on *local monopsony power*. Empirical evidence shows that firms in larger cities face steeper labor-supply curves and set larger wage markdowns (Manning, 2009; Bamford, 2021; Hirsch et al., 2022), forcing them to respond weakly to their own productivity shocks and strongly to changes in workers' outside options. Higher markdowns, reflecting greater worker mobility, allow expanding industries to capture a larger share of local employment.

In this paper, we develop a unified, theory-driven framework that quantifies how three elements—direct productivity shocks, firms' monopsony power, and inter-firm competition for workers—shape firms' wage and employment responses to industry-level shocks within the whole local labor market. Existing studies typically neglect cross-employer spillovers or examine outside-option effects while treating sectoral employment shares as fixed. By contrast, our model endogenizes wages and employment in response to changes in both own-industry and other-industries productivity. We show theoretically that outside-option effects grow with the steepness of the local firms' labor-supply curve, a sufficient statistic for the level of local monopsony power. Empirically, we find sizable effects of inter-firm competition on industry wages and employment, and document substantial monopsony power among West German employers. Nevertheless, we see only modest variation in these responses across labor markets, suggesting limited heterogeneity in the degree of employers' monopsony power.

We begin our analysis by constructing a static logit model of local labor markets, where firms produce tradable goods with productivity determined jointly by industry-specific and local factors. Unlike the canonical partial equilibrium model of Card et al. (2018), our model explicitly incorporates cross-employer spillovers. In the limiting scenario of many firms per industry, individual firm wages depend not only on their own productivity but also indirectly, through co-dependent labor supply curves, on the productivity of other sectors. Conversely, firm-level employment primarily responds to productivity shocks relative to average productivity changes across the entire labor market. Importantly, reduced monopsony power amplifies the effect of average productivity shocks relative to direct industry productivity shock.

We estimate the model using the administrative German establishment-employee dataset provided by the Research Data Center of the German Institute for Employment Research (IAB). The detailed industry and geographic identifiers, combined with extensive longitudinal coverage, allow us to measure medium-term adjustments in industry-specific wage-setting policies across commuting zones. To isolate industry effects from worker sorting, we estimate the AKM (Abowd et al., 1999) model with time-varying industry-location fixed effects[1]. After controlling for worker sorting, we document sizable and increasing urban wage premiums explicitly driven by industry-location level wage policies. In particular, we show that due to the Hartz reforms, the impact of local industries on urban wage premiums became significantly stronger in the 2010s compared to the early 2000s.

We then implement our main empirical strategy, estimating industry-level wage and

[1]We follow the AKM modification by Lachowska et al. (2023); however, in our context, we estimate time-varying industry-location, rather than firm, fixed effects.

employment responses to aggregate local labor market productivity shocks. We proxy industry-specific productivity shocks by national changes in industry wage premiums, while employment-weighted averages of national industry premium changes approximate aggregate local labor market productivity shocks. This strategy closely parallels instruments employed by Beaudry et al. (2012) and Tschopp (2017) in the German context.

Our findings reveal a substantial impact of the average labor market industry wage premium in Western Germany, with estimated wage effects close to 0.91—slightly higher than previous findings by Tschopp (2017). Additionally, we document significant employment effects: a 1% increase in the average local labor market wage premium decreases individual industry employment by approximately 1.98%. Together, these results underscore robust inter-employer competition effects on wages and employment at the industry level. Despite Germany's relatively low overall labor supply elasticity faced by firms, we find limited variation in local monopsony power across commuting zones, implying negligible differences in markdowns.

Based on the regression results, we estimate the model's key parameters: firms' labor supply elasticity and labor demand elasticity. In our preferred specification, our estimate of firms' labor supply elasticity – 1.98 – is close to estimates from Western Germany based on separation elasticities Hirsch et al. (2022). These estimates suggest that a 1% increase in an industry's productivity raises wages in that industry by approximately 0.52%, while a 1% increase in average local labor market productivity raises all local wages by about 0.48%. Moreover, a 1% increase in productivity above the local labor market average increases the industry's employment share by approximately 1%.

Our framework is particularly suited for analyzing industry-specific policy interventions. We illustrate this potential by simulating the impact of subsidies targeting the machinery sector, one of Germany's flagship industries. A simulation of a 10% subsidy to the machinery sector demonstrates substantial spillovers: wages rise by around 5.7% within the targeted sector and between 0.01% and 0.9% in other local industries. At the same time, the employment share of machinery increases by 8 to 10%.

This paper contributes to the literature in three main ways. First, we develop a theoretical framework enabling reduced-form estimation of effects of inter-employers competition for workers (or outside option effects) on wages and employment, explicitly incorporating monopsony power at the firm level. Our approach extends the partial equilibrium framework of Card et al. (2018) by integrating cross-firm spillovers. We show theoretically that, in the limiting scenario with many firms, oligopsony effects vanish, while aggregate industry shocks still create spillovers across firms. Our empirical application estimates the effect of industry-level shocks on commuting-zone-defined labor markets, though the framework can also address other shocks, such as tax changes or immigration effects, and narrower labor market definitions. Thus, our model occupies an intermediate position between fully structural oligopsony models (Berger et al., 2022; Jarosch et al., 2019) and simpler partial equilibrium models that assume outside options are constant (Card et al., 2018) or exogenous (Lamadon et al., 2022). It provides a practical tool for contexts where strategic interactions among firms are negligible, yet aggregate shocks remain important.

Second, we contribute to the literature quantifying how workers' outside options affect firms' wage-setting behavior. Unlike most prior studies (Beaudry et al., 2012; Tschopp, 2017; Caldwell and Danieli, 2024), our framework allows other industries' productivity to influence firms' employment decisions and wage-setting. In this sense, our work is closest to Beaudry et al. (2018), who estimate wage and labor demand systems for U.S. commuting zones, and Rosa (2024), who analyze spillovers from national employer expansions. Distinct from these papers, we ground our empirical analysis in a novel monopsony-based model rather than a bargaining framework, employing administrative data that directly control for worker sorting via AKM fixed effects.

Lastly, we extend the small but growing literature examining the link between local monopsony power and urban wage premiums. Differing from previous studies (Manning, 2009; Hirsch et al., 2013; Bamford, 2021; Hirsch et al., 2022), we formally analyze how heterogeneity in firms' labor supply elasticity shapes the intensity of employers' competition for workers. Our empirical results for Germany suggest that the observed variation in local monopsony power cannot generate significant differences in these magnitudes.

2 Theoretical Framework

In this section, we derive an estimable specification for firms' wage and employment responses to both own industry-level productivity shocks and shocks of other industries. Unlike the standard model in the rent-sharing literature (e.g., Card et al. (2018)), our framework formalizes the wage spillovers so that wage increases in one sector may influence wage-setting behavior in other sectors. We also account for heterogeneity in labor supply elasticities across commuting zones, as discussed in Section 2.9.

2.1 Set-up

Consider a labor market in commuting zone c where firms from a set of sectors S_c operate. In each sector $s \in S_c$, there are $K_{s,c}$ identical firms indexed by (s, c, j). We assume that each firm produces the same tradeable good in the national market. Workers are immobile across commuting zones, and the total labor supply in zone c is denoted by L_c. Following Card et al. (2018), workers derive utility both from the wage and from idiosyncratic firm-specific preferences, where the latter are drawn from a Gumbel distribution. Specifically, worker i chooses to work for firm (s, c, j) by maximizing:

$$V_{i,s,c,j} = \beta^c \ln W_{s,c,j} + v_{i,s,c,j}.$$

Where β^c is a location-specific parameter assumed to be greater than 0. This specification implies that the probability a worker selects firm (s, c, j) is given by:

$$\gamma_{s,c,j} \;=\; \frac{\exp\Big(W_{s,c,j}^{\beta^c}\Big)}{\displaystyle\sum_{s' \in S_c} \sum_{k=1}^{K_{s',c}} \exp\Big(W_{s',c,k}^{\beta^c}\Big)},$$

so that $\gamma_{s,c,j}$ also represents the firm's share of total employment.

The cross-employment wage elasticities follow directly:

$$\epsilon_{s,c,j,s',c,k} = \frac{\partial \ln \gamma_{s,c,j}}{\partial \ln W_{s',c,k}} \;=\; -\beta^c \, \gamma_{s',c,k}, \tag{1}$$

$$\epsilon_{s,c,j} = \frac{\partial \ln \gamma_{s,c,j}}{\partial \ln W_{s,c,j}} \;=\; \beta^c \Big(1 - \gamma_{s,c,j}\Big). \tag{2}$$

Each firm produces a tradable good and chooses its wage to maximize profits:

$$\pi_{s,c,j} \;=\; \max_{W_{s,c,j}} \left\{ \frac{A_s \, \tilde{A}_{s,c} \, l_{s,c,j}^{1-\eta}}{1-\eta} \;-\; W_{s,c,j} \, l_{s,c,j} \right\},$$

where: A_s is the industry-wide productivity component, $\tilde{A}_{s,c}$ is a local, industry-specific productivity shock, and $l_{s,c,j}$ is the labor demand for firm (s, c, j).

Given that workers choose firms according to the probability $\gamma_{s,c,j}$, the firm's labor demand is:

$$l_{s,c,j} \;=\; \gamma_{s,c,j} \, L_c \;=\; \frac{\exp\Big(W_{s,c,j}^{\beta^c}\Big)}{\displaystyle\sum_{s' \in S_c} \sum_{k=1}^{K_{s',c}} \exp\Big(W_{s',c,k}^{\beta^c}\Big)} \, L_c.$$

The first-order condition (FOC) for profit maximization then yields:

$$\ln W_{s,c,j} \;=\; \ln A_s + \ln \tilde{A}_{s,c} \;-\; \eta \, \ln\!\big(\gamma_{s,c,j} \, L_c\big) \;+\; \ln\!\Big(\frac{\epsilon_{s,c,j}}{1+\epsilon_{s,c,j}}\Big). \tag{3}$$

Therefore, in equilibrium, the wage is equal to sum of of the sectoral marginal product of labor: $A_s\,\tilde{A}_{s,c}\,l_{s,c,j}^{-\eta}$ multiplied by markdown $\frac{\epsilon_{s,c,j}}{1+\epsilon_{s,c,j}}$ (which by itself is determined by firm's supply elasticity $\epsilon_{s,c,j}$).

2.2 Wage spillovers formula

We start our analysis by considering the effect of the productivity shock A_s in a specific sector σ. Then, we generalize the observed formulas to shocks on different industries' productivity.

Let $x^*_{s,c,j}$ denote the equilibrium value of log x for firm (s,c,j) (i.e., $w^*_{s,c,j} = \ln W_{s,c,j}$). Then equation (3) becomes:

$$w^*_{s,c,j} \;=\; a_{s,c} \;-\; \eta\,\ln\gamma^*_{s,c,j} \;-\; \eta\,\ln L_c \;+\; \ln\!\Big(\frac{\epsilon_{s,c,j}}{1+\epsilon_{s,c,j}}\Big),$$

where we define

$$a_{s,c} = \ln A_s + \ln \tilde{A}_{s,c}.$$

Suppose that for a specific sector σ both A_σ and $\tilde{A}_{\sigma,c}$ experience small shocks denoted by $\Delta\ln A_\sigma$ and $\Delta\ln\tilde{A}_{\sigma,c}$, respectively, so that is $s=\sigma$, $\Delta a_{s,c} = \Delta\ln A_s + \Delta\ln\tilde{A}_{s,c}$ and $\Delta a_{s,c} = 0$ otherwise. Linearizing around the equilibrium (with Δx representing the change in $\frac{\partial\ln X}{\partial\ln A_\sigma} + \frac{\partial\ln X}{\partial\ln\tilde{A}_{\sigma,c}}$) yields to the following recursive equation:

$$\begin{aligned}\Delta w_{s,c,j} \;=\; & \underbrace{\Delta a_{s,c}}_{\text{Own Shock}} \; \underbrace{-\,\eta\sum_{s'\in S_c}\sum_{k=1}^{K_{s',c}}\frac{\partial\ln\gamma_{s,c,j}}{\partial\ln W_{s',c,k}}\,\Delta w_{s',c,k}}_{\text{Spillover on Employment Share }\gamma_{s,c,j}} \\ & - \underbrace{\frac{\gamma_{s,c,j}}{\Big(1-\gamma_{s,c,j}\Big)\Big(1+\beta^c\big(1-\gamma_{s,c,j}\big)\Big)}\left[\sum_{s'\in S_c}\sum_{k=1}^{K_{s',c}}\frac{\partial\ln\gamma_{s,c,j}}{\partial\ln W_{s',c,k}}\,\Delta w_{s',c,k}\right]}_{\text{Spillover on Markdown}}.\end{aligned} \tag{4}$$

This equation illustrates the recursive relationship between firms' wages. When a firm in sector σ changes its wage, the adjustment shifts both the employment share of sector σ firms and the shares of firms in other sectors. Consequently, both markdowns and employment of other-sector employers change, pressuring them to adjust their wages. These subsequent adjustments, in turn, feed back into the wages of both sector σ and other sectors, perpetuating the spillover dynamic.

Unlike wage-bargaining or matching-market models (Beaudry et al., 2012; Caldwell and Danieli, 2024), the spillovers here do not arise directly from workers' outside options (through wage negotiations); rather, a wage change by one employer reshapes the labor-supply curves faced by all others, so outside options matter only indirectly, a mechanism we nevertheless, for simplicity, label the *outside-option effect*.

The second distinction between our model and wage-bargaining or search-theoretic frameworks concerns timing. In logit choice (random utility) models—whether for product or labor markets—adjustments occur instantaneously, whereas in search models they unfold gradually. Consequently, estimating wage spillovers directly from the recursive equation 4, though appealing, would misrepresent the total effect of a productivity shock by capturing only the "first-round" response and thus biasing subsequent parameter estimates.[2]

2.3 Sectoral Productivity Shocks and Wage Determination in the Limiting Case

Spillovers to markdowns represent an intriguing channel that could potentially influence wages, particularly in highly concentrated labor markets. However, given the coarse labor market definitions (entire commuting zones) used in our empirical application, and for the sake of analytical clarity, we focus on the scenario in which each industry-commuting zone cell comprises many small firms. In this section, we demonstrate that under these conditions, the spillover effect on firms' markdowns (the third component in Equation 4) diminishes to zero, while the outside option effect on employment shares (the second component in Equation 4) remains significant.

[2] Ignoring these feedback effects is reasonable when spillovers stem from clearly exogenous wage changes—for example, union contracts, as in **?**.

Assume that in each sector s the number of firms is $K_{s,c} = N$ and consider the limit as $N \to \infty$. Denote the aggregate employment share and total employment of sector s in city c by:

$$\gamma_{s,c} \; = \; \sum_{j=1}^{N} \gamma_{s,c,j}, \;\; l_{s,c} = \gamma_{s,c} L_c$$

so that each firm in sector s has an employment share of approximately $\gamma_{s,c}/NL_c$. Under these conditions, the cross-derivatives aggregate to simplify the expression. In the limit,

$$\sum_{s' \in S_c} \sum_{k=1}^{N} \frac{\partial \ln \gamma_{s,c,j}}{\partial \ln W_{s',c,k}} \, \Delta w_{s',c,k} = \beta^c \left[(1 - \frac{\gamma_{s,c}}{N}) \, \Delta w_{s,c,j} \right] + \beta^c \left[\sum_{s' \in S_c} \left(\frac{N-1}{N} \gamma_{s',c} \mathbf{1}_{s'=s} + \gamma_{s',c} \mathbf{1}_{s' \neq s} \right) \Delta w_{s',c} \right]$$

Moreover, the term involving

$$\frac{\gamma_{s,c}/N}{\Big(1 - \gamma_{s,c}/N\Big)\Big(1 + \beta^c \Big(1 - \gamma_{s,c}/N\Big)\Big)}$$

vanishes as $N \to \infty$. Thus at the limit, given all the firms in the sector s change the wage in the same way, we can skip the firm's indicator, the system of linear equations simplifies to:

$$\Delta w_{s,c} \; = \; \Delta a_{s,c} \; - \; \eta \, \beta^c \left[- \sum_{s' \in S_c} \gamma_{s',c} \, \Delta w_{s',c} \; + \; \Delta w_{s,c} \right].$$

Therefore in the limiting case, general equilibrium effects—such as changes in total labor market productivity—still influence firms' decisions. Nevertheless, firms are too small to exert oligopsonistic power: their individual employment shares are too small to account for markdown changes when setting wages.

2.4 General Wage Effects Formula

Now, we derive the more general formula, allowing for all industries to have their own productivity shocks. Nevertheless, of the different sources of shocks, the main spillover mechanism is the same: firms experiencing shocks affect the employment share of other firms through wage changes, generating a spillover effect. Importantly, while we ignore here another possible source of wage changes (total local population change or taxes), they can be accommodated in this framework.

In matrix notation, if we define the vector of wage changes $\Delta\mathbf{w}_c$ and productivity shocks $\Delta\mathbf{a}_c$ across sectors, the equation can be written as:

$$\Delta\mathbf{w}_c \;=\; \Delta\mathbf{a}_c \;+\; \mathbf{D}_c\,\Delta\mathbf{w}_c,$$

where the elements of the matrix $\mathbf{D}_c$ are given by:

$$\mathbf{D}_{c,s,s} = \eta\beta^c(1-\gamma_{s,c}), \quad \mathbf{D}_{c,s,s'} = -\eta\beta^c\gamma_{s',c} \quad \text{for } s' \neq s.$$

Using the Sherman–Morrison formula,[3] we obtain the inverse:

$$(\mathbf{I} - \mathbf{D}_c)^{-1} \;=\; \mathbf{M}_c,$$

With entries:

$$\mathbf{M}_{c,s,s} \;=\; \frac{1}{1+\eta\beta^c} \;+\; \frac{\eta\beta^c\,\gamma_{s,c}}{1+\eta\beta^c}, \quad \mathbf{M}_{c,s,s'} \;=\; \frac{\eta\beta^c\,\gamma_{s',c}}{1+\eta\beta^c} \quad (s' \neq s).$$

Hence, the wage changes can be expressed as:

$$\Delta\mathbf{w}_c \;=\; \mathbf{M}_c\,\Delta\mathbf{a}_c.$$

[3] We rewrite $(\mathbf{I}-\eta\beta\mathbf{D}_c) = \mathbf{A}+vu^T$ where $\mathbf{A} = (1+\eta\beta^c)\,\mathbf{I}$, $u = -\eta\beta^c\,(1,\ldots,1)^T$, and $v = (\gamma_{1,c},\ldots,\gamma_{S_c,c})^T$, and apply the formula. Sherman–Morrison formula: $(\mathbf{A}+uv^T)^{-1} = \mathbf{A}^{-1} - \frac{\mathbf{A}^{-1}uv^T\mathbf{A}^{-1}}{1+v^T\mathbf{A}^{-1}u}$

In particular, for each sector s the approximate change in the log wage is:

$$\Delta \ln W_{s,c} \;=\; \underbrace{\frac{1}{1+\eta\beta^c}\,\Delta \ln A_s}_{\text{Own-industry Effect}} \;+\; \underbrace{\frac{\eta\beta^c}{1+\eta\beta^c}\Big(\sum_{s'\in S_c}\gamma_{s',c}\,\Delta\ln A_{s'}\Big)}_{\text{Spillover Effect}} \qquad (5)$$

$$+\; \underbrace{\frac{1}{1+\eta\beta^c}\,\Delta \ln \tilde{A}_{s,c} \;+\; \frac{\eta\beta^c}{1+\eta\beta^c}\Big(\sum_{s'\in S_c}\gamma_{s',c}\,\Delta\ln \tilde{A}_{s',c}\Big)}_{\text{Unobserved Local Shocks}}.$$

Thus, a higher labor-supply elasticity (β^c) lowers the pass-through of own-industry productivity shocks to wages and increases the weight placed on total labor market productivity shocks. Intuitively, when workers are highly mobile across firms—i.e. when β^c is large—they react more strongly to wage changes in other sectors. Such high mobility shifts firms' employment shares more sharply and therefore magnifies spillovers. At the same time, because markdowns are already high, the labor-supply curve each firm faces is effectively steeper, so even small wage adjustments trigger large changes in employment shares. Under decreasing returns to scale, firms operating in highly mobile labor markets therefore exhibit a smaller pass-through of their own productivity shocks than firms in less mobile environments.

Due to data limitations, we abstract from potential time variation in the elasticity parameter $\Delta\beta^c$. Nevertheless, in Appendix A, we extend the analysis to account for this possibility, formally demonstrating the compression effect of changing elasticity, as noted in the partial equilibrium framework by Autor et al. (2023).

2.5 Employment effects

Using the relationships 1 and 2, we found that the industry's total employment changes, that is $\Delta \ln \gamma_{s,c} = \Delta \ln l_{s,c}$, is given by expression presented in equation 6.

$$\Delta \ln l_{s,c} = \frac{\beta^c}{1+\eta\beta^c}\left[\underbrace{\left(\Delta \ln A_s - \sum_{s'\in S_c}\gamma_{s',c}\Delta \ln A_{s'}\right)}_{\text{Relative Industry Shock}} + \underbrace{\left(\Delta \ln \tilde{A}_{s,c} - \sum_{s'\in S_c}\gamma_{s',c}\Delta \ln \tilde{A}_{s',c}\right)}_{\text{Unobserved Local Shocks}}\right] \quad (6)$$

Thus, labor always reallocates toward industries experiencing stronger productivity growth, but the strength of this adjustment depends on β^c. This has important implications for industrial policy: subsidies that mimic productivity shocks will be less effective—in terms of labor reallocation—in markets with higher monopsony power.

2.6 Total labor market wage effect

Summing up the average wage effects and reallocation effects and assuming that unobserved shocks are zero-mean:

$$\mathbf{E}\left[\sum_{s\in S_c}\left(\gamma_{s,c}\Delta \ln W_{s,c} + \Delta \ln \gamma_{s,c} \ln W_{s,c}\right)\right] =$$
$$= \sum_{s\in S_c}\gamma_{s,c}\Delta \ln A_{s,c} + \frac{\beta^c}{1+\eta\beta^c}\sum_{s\in S_c}\left(\Delta \ln A_s - \sum_{s'\in S_c}\gamma_{s',c}\Delta \ln A_{s'}\right)\ln W_{s,c}$$

Thus the β^c affects the average wage change through the reallocation effect.

2.7 Identification of Industry Shocks

Equation (5) expresses wage changes as a function of industry productivity shocks. Because these shocks cannot be observed directly, we employ the national wage premium method outlined in Beaudry et al. (2012). We select industry $s = 1$ as the reference category because establishments in this industry are present in every labor market (e.g., wholesale trade or similar service sectors). Define the industry premium v_s for industry s (operating in a set of cities C_s) as:

$$v_s \; = \; \frac{1}{|C_s|} \sum_{c \in C_s} \Big(\ln W_{s,c} - \ln W_{1,c} \Big).$$

According to equation (5), it follows that:

$$\Delta v_s \; = \; \frac{1}{|C_s|} \sum_{c \in C_s} \frac{1}{1+\eta\beta^c} \, \Big[(\Delta \ln A_s - \Delta \ln A_1) + \Big(\Delta \ln \tilde{A}_{s,c} - \Delta \ln \tilde{A}_{1,c} \Big) \Big] \, .$$

Assuming that $\tilde{A}_{s,c}$ is mean zero and uncorrelated with local characteristics, similar as in Beaudry et al. (2012), we have:

$$\text{plim}_{|C_s| \to \infty} \Delta v_s \; = \; \frac{1}{1+\eta\beta^c} \left(\Delta \ln A_s - \Delta \ln A_1 \right) .$$

If labor supply elasticities differ across cities, the above convergence does not hold if the industry location is correlated with β^c. In that case, assume we observe a variable $Z(c)$ that captures this heterogeneity in β^c. For tractability, we assume that β^c has a discrete type distribution, defined by the quartiles of Z_c distribution, denoted by $\{Z_1, Z_2, Z_3, Z_4\}$. In this case, we use the v_s^4 defined only for the highest quintile Z_4: this allows us to capture $(\Delta \ln A_s - \Delta \ln A_1)$ as multiplied by the same constant.

2.8 Estimating Equations

Firstly, we assume that β^c is constant across the cities. In this case, our estimating equation for wages is given by equation 7 while for employment is given by equation 8.

$$\Delta \ln W_{s,c} = \underbrace{\alpha^w_{s,t}}_{\text{Own-Industry Effect}} + \underbrace{\theta_w \Big(\sum_{s' \in S_c} \gamma_{s',c} \, \Delta v_{s'} \Big)}_{\text{Spillover Effect}} + \underbrace{u^w_{s,c}}_{\text{Unobserved Local Shocks}} \tag{7}$$

$$\Delta \ln l_{s,c} = \underbrace{\alpha^l_{s,t}}_{\text{Own-Industry Effect}} + \underbrace{\theta_l \Big(\sum_{s' \in S_c} \gamma_{s',c} \, \Delta v_{s'} \Big)}_{\text{Spillover Effect}} + \underbrace{u^l_{s,c}}_{\text{Unobserved Local Shocks}} . \tag{8}$$

The identifying assumption is that the unobserved local shocks are uncorrelated with the industry-specific productivity shocks. Under this assumption, the productivity shocks are exogenous. Based on Borusyak et al. (2021) result, under this assumption and endogenous industries' employment shares, the $\text{plim}_{|C_s| \to \infty} \theta_w = \eta \beta^c$, $\text{plim}_{|C_s| \to \infty} \theta_l = \beta^c$ and $\text{plim}_{|C_s| \to \infty} \alpha^w_{s,t} = \frac{1}{1+\eta\beta^c} \Delta \ln A_{s,t} - \Delta \ln A_{1,t}$.

Another important assumption is that all industry wage premiums are the result of only the productivity shocks. This assumption allow for local effects that change local wages, but not allow for for example national union-bargaining effects. Nevertheless, we believe that industry productivity is crucial for wage changes in the long period, such as 5 or 10 years. Moreover, in the empirical application, we added a group of controls for local labor market conditions (local population change and the workforce composition).

Labor Supply Heterogeneity To test the possible importance of regional elasticity, we also estimate the specification described in subsection 2.7. That is we assume that β^c is defined by the quintile of $Z(c) \in \{Z_1, Z_2.., Z_m\}$. The estimating equation is defined as:

$$\Delta \ln W_{s,c} = \underbrace{\alpha^w_{t,Z(c)}}_{\text{Own-Industry Effect}} + \underbrace{\sum_{Z_i} \mathbf{1}_{Z(c)=Z_i} \theta^w_{Z_i} \Big(\sum_{s' \in S_c} \gamma_{s',c} \, \Delta v^4_{s'} \Big)}_{\text{Spillover Effect}} + \underbrace{u_{s,c}}_{\text{Unobserved Local Shocks}} \tag{9}$$

$$\Delta \ln l_{s,c} = \underbrace{\alpha^w_{t,Z(c)}}_{\text{Own-Industry Effect}} + \underbrace{\sum_{Z_i} \mathbf{1}_{Z(c)=Z_i} \theta^l_{Z_i} \Big(\sum_{s' \in S_c} \gamma_{s',c} \, \Delta v^4_{s'} \Big)}_{\text{Spillover Effect}} + \underbrace{u_{s,c}}_{\text{Unobserved Local Shocks}} \quad . \tag{10}$$

Where θ_{w,Z_i} and θ_{l,Z_i} are collinear top $\frac{1}{1+\eta\beta^c}$. Given the analysis from subsection 2.4, we expect that if the regional monopsony power significantly influences the firm wage-setting behavior, then $\theta^w_{Z_i}$ should decrease with Z level, while $\theta^w_{Z_i}$ and $\theta^l_{Z_i}$should increase with Z_i value.

2.9 Why Firm-Level Labor Supply Elasticity Depends on Location

In our static framework, labor supply elasticity is governed by an exogenously specified parameter, β^c. However, previous research has shown that labor supply elasticity varies over the business cycle (Autor et al., 2023), across industries (Bassier et al., 2022), and—most relevant to our analysis—across locations (Manning, 2009; Hirsch et al., 2022). In this subsection, we connect these insights, typically derived from richer search-theoretic models, to our static setting.

Variation in labor supply elasticity across regions is shaped by several factors, particularly labor market tightness and the efficiency of job matching. Among these, labor market tightness appears most influential. In regions with tight labor markets—characterized by low unemployment and high job-to-job transition rates—workers have stronger outside options and can more readily respond to wage differentials by switching employers. In the standard Burdett and Mortensen (1998) model, this translates into higher labor supply elasticity, as firms must offer more competitive wages to retain their workforce. Conversely, in slack labor markets with limited job opportunities, firms enjoy greater monopsony power, reducing worker bargaining power and lowering labor supply responsiveness. Empirical evidence from Autor et al. (2023), Bassier et al. (2022), and Hirsch et al. (2022) supports this link between labor market tightness and firm-level labor supply elasticity.

Another important factor emphasized in the literature is labor market thickness—that is, the density of firms and workers in a given market. Martellini (2022) develops a theoretical framework showing that in larger, denser labor markets, search frictions are lower due to increasing returns to scale in job search. This improves matching efficiency and raises labor supply elasticity, as also noted by Moretti and Yi (2024).

Taken together, these findings suggest that labor supply elasticity might have a substantial local component, shaped by both the structure and performance of regional labor markets. In such case, accounting for geographic heterogeneity in β^c would be important for understanding local effects of industry shocks and firm wage-setting behavior in general. That is the reason we test this heterogeneity in the empirical section.

3 Data

Our analysis draws on a comprehensive dataset that integrates several sources to examine labour-market dynamics and wage structures. The primary sources are the Sample of Integrated Labour Market Biographies (SIAB; Graf et al. (2025)) and the Establishment History Panel (BHP; Eberle et al. (2018)), both provided by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB). SIAB is a 2 % representative sample of German workers and contains anonymised individual-level information—worker and firm identifiers, earnings, occupation, industry, education (see **?** for details)—and workplace location at the district (Kreis) level. We use the years 2000–2019, dividing them into sub-periods for different parts of the analysis. Although SIAB begins in 1975, we focus on post-2000 data to avoid disturbances from German reunification and to cover the phase of increased labour-market flexibility associated with the Hartz reforms. We restrict the sample to individuals aged 18–55 to study prime-age workers and to sidestep retirement-related selection.

Employer information comes from a quarterly version of the BHP, which compiles social-insurance records at the plant level as of each quarter-end (see Schmucker et al. (2018) for details). The BHP provides rich information on plant characteristics—workforce composition, industry classification, establishment size, and geographic identifiers at the NUTS-3 level.

Using these geographic identifiers, we allocate workers and jobs to 101 local labour markets (hereafter commuting zones or locations) in West Germany, as defined by Kosfeld and Werner (2012). We exclude commuting zones in East Germany and any West-German zone where more than 10 % of workers commute from the East. Industries are classified according to the 1993 edition of the German Classification of Economic Activities (WZ 93), which covers 222 detailed industries. District-level population and population-density data from the German Federal Statistical Office[4] supplement our analysis of population distribution across commuting zones.

To study spatial heterogeneity of labour supply elasticity, we construct employer–employee transition rates. A new job may arise from (i) an inter-firm move within employment (identified by a change in plant ID), (ii) a transition from registered unemployment, or (iii) an absence of prior employment records, implying non-employment or self-employment. Following Hirsch et al. (2022), we treat most such hires as originating from unemployment.

While the data reliably measure job duration and daily gross earnings, they lack information on hours worked, and wages are top-capped at the social-security contribution ceiling. We therefore (i) restrict the analysis to full-time workers and (ii) impute wages above the ceiling using the method of Dauth and Eppelsheimer (2020), retaining roughly 4.3 % of observations that would otherwise be lost. Education, reported by employers, contains missing

[4] Federal Statistics of Germany.

or inconsistent values; we impute these using the procedure in Fitzenberger et al. (2006).

After all sample restrictions, the dataset comprises 52 271 industry–location cells, covering about 0.91 million individuals and 0.9 million firms. The mean log wage is 4.25. We aggregate the data to quarterly frequency; employment-transition rates are computed from roughly 45 million person-quarter observations. For 2000–2014 (pre-minimum-wage), we form five-year intervals. AKM fixed effects and wage premiums are estimated at the commuting-zone–three-digit-industry–interval level. Table 1 and Table 2 provide descriptive statistics.

3.1 Institutional framework

Since the early 1990s, Germany's labor market has undergone significant changes, driven by economic integration, labor market reforms, and global trends. Germany's labor market has shifted from centralized collective agreements toward decentralization, particularly following reunification. The Hartz reforms (2003-2005) were central to this shift, significantly impacting wage-setting and employment patterns.

3.1.1 Labor market reforms and shift to Decentralization

Before reunification in 1990, West Germany followed a centralized system of sectoral bargaining where unions and employer associations set wages and working conditions across entire industries. However, reunification triggered major economic upheaval—many East German industries were shut down, and unemployment soared. To adapt, Germany began shifting toward a more flexible and decentralized labor market.

By the mid-1990s, rising unemployment and global competition pushed policymakers to move away from centralized wage-setting. Firms gained more freedom to negotiate wages and conditions based on their own needs. As a result, sectoral agreement coverage dropped by 2007, 44% of West German workers had wages set outside of these agreements, up from 27% in 1995 (Card et al., 2013). Opt-out or "opening" clauses also became common, letting companies deviate from central agreements. By 2000, nearly half of Germany's top firms had adopted them (Hassel and Rehder, 2001), affecting 43% of their workers by the early 2000s (Eichhorst and Tobsch, 2015). This shift was driven by a mix of domestic pressures and the need to stay competitive in a global economy (Fund, 2021).

3.1.2 The Hartz Reforms and Their Impact

The Hartz reforms of 2003–2005 pushed Germany's labor market further toward flexibility, aiming to cut unemployment by making it easier for firms to hire under less rigid terms. A key move was loosening wage-setting for temporary and part-time roles, which opened the door to more mini-jobs—low-paid, part-time positions with minimal social protections. Combined with earlier decentralization, the Hartz reforms deepened labor market segmentation. Job security, wages, and benefits became more tied to contract type, fueling a rise in precarious employment and increasing labor market flexibility.

4 Empirical Implementation

Our research aims to estimate the effects of outside options on firms' (aggregated at the 3-digit industry - local labor market cell) wage and employment policies. First, to disentangle local firms' policies from worker sorting, we estimate an AKM regression with time-varying fixed effects. Unlike the original approach by Lachowska et al. (2023), which uses firm-specific fixed effects, we incorporate location $\times$ 3-digit industry $\times$ time-period fixed effects. With industry wage premiums estimated, we then calculate national industry productivity shocks based on the industry's national wage premium, following the methodology described in Section 2.7.

Next, we proceed with our main analysis, estimating the effects of industry-specific productivity shocks and average local labor market productivity shocks on changes in local industries' wage premiums and employment, as derived in Equations 7–8.

Lastly, we address cases where firms' labor supply elasticities differ across commuting zones. In this scenario, we implement a correction when estimating industry shocks, as detailed in Section 2.7, and estimate Equations 9–10.

4.1 Estimating Local Industry Wage Policies and National Industry Wage Premiums

To estimate the responsiveness of industry-level wages and employment to both industry-specific and aggregate labor market productivity shocks (Equations 7–8), we first construct proxies for local industry wage policies. We obtain these proxies by estimating an AKM model with commuting zone × 3-digit industry × time-period fixed effects:

$$\ln W_{i,t} = \alpha_i + \alpha_t + \varphi_{SC(i,t),\tau} + X'_{i,t}\nu + \varepsilon_{i,t} \tag{11}$$

Where, $\ln W_{i,t}$ denotes the log quarterly wage of worker i in year-quarter t within five-year period τ[5]. The terms α_i and α_t represent individual and year-quarter fixed effects, respectively. The function $SC(i,t)$ identifies worker i's commuting zone and industry in year-quarter t. Lastly, $X_{i,t}$ comprises standard worker-specific covariates, including a third-order polynomial in (age-40) and fixed effects for worker apprenticeship status. To estimate industry-commuting zone effects, we dropped the cells with less than 30 quarterly observations. Those restrictions on average kept 95% of local labor market employment; in the worst case, it is 80%.

Using the estimated industry-location-time fixed effects, we define the national industry wage premium for industry s, observed in period τ across locations C_s, as:

$$\hat{\upsilon}_{s,\tau} = \frac{1}{|C_s|} \sum_{c \in C_s} \left(\hat{\varphi}_{s,c,\tau} - \hat{\varphi}_{1,c,\tau} \right) \tag{12}$$

[5] τ is defined as 1 for 2000–2004, 2 for 2005–2009, and 3 for 2010–2014.

where $\hat{\varphi}_{1,c,\tau}$ is the fixed effect for the retail sale in non-specialized stores industry in location c. This formulation aligns with Section 2.7. To further avoid potential endogeneity issues, we use a leave-one-out version of Equation 12:

$$\hat{v}_{s,\tau,-c} = \frac{1}{|C_s| - 1} \sum_{c' \in C_s, c' \neq c} (\hat{\varphi}_{s,c',\tau} - \hat{\varphi}_{1,c',\tau}) \tag{13}$$

As outlined in Equations 7–8, we approximate the average local labor market productivity changes with a weighted average of changes in national industry wage premiums that shift labor supply of all industries, denoted as $\Delta\text{LSS}c, \tau$ for simplicity. Empirically, we define this measure as:

$$\Delta\text{LSS}_{c,\tau} = \sum_{s \in S_c} \gamma_{s,c,\tau-1} \Delta\hat{v}_{s,\tau,-c} \tag{14}$$

Here, $\gamma_{s,c,\tau-1}$ represents the employment share, measured by a total number of full-time workers, of industry s in location c during period $\tau - 1$[6].

Descriptive Statistics for Industries and Local Labor Markets. Table 3 presents descriptive statistics for industry–local labor market cells, while Table 4 reports statistics at the level of local labor markets. We observe the constructed measure $\Delta\text{LSS}_{c,\tau}$ and find that most industries are present in many local labor markets: on average, an industry is represented in 88 different commuting zones. Nevertheless, there is substantial variation—2% of industry–location cells belong to industries with fewer than 10 locations.

Industry–location effects were estimated using an average of 550 worker–quarter observations, though in some cases, as few as 30 observations were used. While the vast majority of industry–local labor market cells have employment shares below 2%, a non-negligible number exceed 5%, which may induce collinearity between the industry effect and the outside option measure LSS_c. Therefore, in our preferred specification, we restrict attention to cells with smaller employment shares.

[6] We compute shares only for industries with estimated $\hat{\varphi}_{s,c',\tau-1}$. In cases where an industry exits in period τ, we use $\hat{v}_{s,\tau}$.

In periods 1 and 2 (2000–2004 and 2005–2009), we excluded two and one local labor markets, respectively, due to insufficient observations for the anchor industry. Among the remaining markets, we find that the average local labor market contains about 155 industries, each with a relatively small employment share. The average industrial Herfindahl–Hirschman Index (HHI) across industries within a labor market is low—approximately 260—indicating low concentration. However, as discussed in the policy simulation section, some local labor markets are highly specialized.

4.2 Regression Equations

We estimate the impact of the local labor market's average industry wage premium on wages in location-industry cells, as described in theoretical Equation 7. Our initial empirical specification for industry s in commuting zone c during period τ is given by:

$$\Delta \hat{\varphi}_{s,c,\tau} = \alpha_{s,\tau} + \theta_w \Delta \mathrm{LSS}_{c,\tau} + \varepsilon^{w}_{s,c,\tau}. \tag{15}$$

We also estimate the employment effects at the industry-commuting zone level, measured by changes in the total number of full-time workers during period τ. Following theoretical Equation 8, our baseline specification is:

$$\Delta \ln l_{s,c,\tau} = \alpha_{s,\tau} + \theta_l \Delta \mathrm{LSS}_{c,\tau} + \varepsilon^{l}_{s,c,\tau}. \tag{16}$$

For simplicity, our theoretical framework assumes a constant commuting-zone population. In reality—even though the German labor market exhibits relatively low mobility (Heise and Porzio, 2021)—we observe non-trivial fluctuations in local population levels. To address this, we include the change in commuting-zone population as a covariate in both regressions, since it may directly affect non-tradable industry outcomes or influence productivity through agglomeration spillovers. Following Stock and Watson (2003), we treat population change as a control variable that accounts for its own impact as well as that of any correlated, omitted factors. Consequently, despite its potential correlation with unobservables, we do not instrument for population change.

4.2.1 Regression Equations with Labor Supply Heterogeneity

In our final set of analyses, we explore scenarios where firms' labor supply elasticities vary across commuting zones. As highlighted by Hirsch et al. (2022), accurately measuring local labor supply elasticity remains challenging. Following their methodology, we proxy local labor supply elasticity using the ratio of job-to-job (EE) to total transitions. This measure intuitively captures the degree of labor market competition, as firms that heavily rely on worker poaching face more responsive worker transitions in reaction to their wage policies' changes.

To simplify the analysis, we discretize local labor supply elasticity into quartiles based on the EE transitions to total transitions ratio, resulting in four distinct elasticity values. Because heterogeneity in labor supply elasticity may bias estimates of national industry shocks, as previously discussed in Section 2.7 we recalculate changes in national wage premiums using only data from the highest elasticity quartile (quartile 4), denoted by $\hat{v}^4_{s,\tau,-c}$. Using these revised national wage premium changes, we then compute the local labor market average of industry wage premium changes, $\Delta\mathrm{LSS}^4_{c,\tau}$. Consequently, our empirical equations, analogous to the theoretical Equations (9)–(10), become:

$$\Delta\hat{\varphi}_{s,c,\tau} = \alpha_{s,\tau,q(c)} + \sum_{q=1}^{4} \mathbf{1}_{q(c)=q}\theta_{w,q}\Delta\mathrm{LSS}^4_{c,\tau} + \varepsilon^w_{s,c,\tau}, \tag{17}$$

$$\Delta\hat{\varphi}_{s,c,\tau} = \alpha_{s,\tau,q(c)} + \sum_{q=1}^{4} \mathbf{1}_{q(c)=q}\theta_{l,q}\Delta\mathrm{LSS}^4_{c,\tau} + \varepsilon^l_{s,c,\tau}. \tag{18}$$

Here, $q(c)$ identifies the quartile of commuting zone c in terms of the ratio of EE transitions to total transitions.

5 Results

In this section, we analyze spatial wage inequalities in Germany, their evolution between 1995 and 2014, and the role of heterogeneous local industry policies. We then estimate how changes in the local labor market average industry wage premium affect local firms at the aggregate industry level, both under uniform labor supply elasticity and in cases where elasticity varies across commuting zones.

5.1 Worker Sorting and Industry Wage Policies Across Local Labor Markets

In Germany, as in other developed economies, there is a substantial urban wage premium. As illustrated in the upper panel of Figure 1, average log wages increase with local labor market population density, exhibiting an elasticity of approximately 0.05 during both the 2000–2004 and 2010–2014 periods.

While the overall urban wage premium remained stable across the three main analysis periods, its underlying components, estimated from Equation 11, changed significantly. As depicted in the lower panel of Figure 1, industry-location effects have markedly increased over time. This trend aligns with the implementation of the Hartz labor market reforms, which provided firms greater flexibility in wage-setting, enabling them to adjust wages more precisely to local labor market conditions. Concurrently, worker sorting has weakened, possibly due to increased immigration rates post-2007.

Therefore, unlike the US context examined by Card et al. (2023), in Germany, industry-level wage-setting policies (firms aggregated to industries) appear to be the primary drivers of spatial wage inequality, at least in the period following 2000. Understanding the key determinants influencing these industry-level wage adjustments thus becomes even more critical.

5.2 Estimation Results and Model Parameters

Table 5 presents estimates from Equations 15 and 16 under several specifications. Each specification includes time-period fixed -industry fixed effects. To address potential collinearity between the average local labor market industry wage premium change and the industry wage premium itself, particularly in cases where industries account for a large share of local employment, in our preferred specification, we restrict to industries-location cells to ones with employment shares below 2%.

Across all specifications, we observe a robust response of individual industry wages to changes in the average local labor market industry wage premium, which we interpret as a proxy for changes in average local labor market productivity. In our preferred specification, a 1% increase in the average local labor market wage premium results in a nearly 0.91% increase in wages at the industry–commuting zone cell level, significant at the 0.1% level. These effects are slightly smaller, but still economically meaningful, when restricting to manufacturing industries, where the estimated effect is approximately 0.66%. These findings support the theoretical relevance of the outside option channel derived in Equation 5.

We also find that changes in the average local labor market wage premium significantly affect employment in the industry–commuting zone cell. In our preferred specification, a 1% increase in the local labor market wage premium leads to a 2% decline in employment at the industry–commuting zone cell level, significant at the 1% level. For manufacturing industries, the estimated decline exceeds 4%, remaining statistically significant at the 5% level.

Taken together, these results highlight the importance of the inter-firm competition for workers or the outside option channel for both firm-level wage-setting and employment decisions, consistent with the theoretical predictions from Equations 5 and 6.

As described in Section 2.8, the estimates of $\hat{\theta}_w$ and $\hat{\theta}_l$ allow us to recover key model parameters: firm's labor supply elasticityβ^c and labor demand elasticity η, where $\hat{\beta} = -\hat{\theta}_l$ and $\hat{\eta} = -\frac{\hat{\theta}_w}{\hat{\theta}_l}$. Table 6 reports estimates for both parameters across specifications, with standard errors for $\hat{\eta}$ computed via the Delta method. Our preferred specification—restricted to relatively small industries—suggests a relatively low firm-level labor supply elasticity ($\hat{\beta} = 1.98$) and a standard labor demand elasticity ($\hat{\eta} = 0.46$). These values are close to the estimates for the German economy estimated from separation elasticities of Hirsch et al. (2022) and Bamford (2021).

Under this specification, the pass-through of own-industry productivity to wages is 0.52, while the pass-through of average labor market productivity changes is 0.48. To illustrate the magnitudes, consider an industry σ with a 5% employment share that experiences a large, 10% productivity shock, while other industries in the local labor market remain unaffected. In this case, wages in industry σ would increase by 5.3%, while wages in the rest of the labor market would rise by 0.24%. Additionally, the employment share of industry σ would increase by 10%, corresponding to a 0.5 percentage point increase.

5.3 Robustness Checks

We perform several robustness checks on our baseline specifications to verify that the main results are insensitive to additional controls and alternative variable definitions.

Additional Controls. First, we augment the baseline regressions with controls for employment composition, measured by the change in the share of university-educated workers, and for industry specialization, proxied by the Herfindahl–Hirschman index. As shown in the first column of Table 7, the estimated coefficients remain nearly identical to those in the main specification.

We also included the results with additional, post-minimum wage period 2015-2019, presented in the second Column of Table 7. The wage effects are slightly stronger, and the employment effects are slightly weaker, but in general, the minimum wage introduction hasn't drastically changed the main outside-option mechanism.

Alternative Shock Definition. Second, we redefine the industry shock using changes in employment share rather than wage changes. Specifically, we set

$$\hat{v}^l_{s,\tau,-c} = \frac{1}{|C_s|-1} \sum_{\substack{c' \in C_s \\ c' \neq c}} \big(\ln \gamma_{s,c',\tau} - \ln \gamma_{s,c',\tau-1}\big), \tag{19}$$

and the corresponding local-market industry premium by

$$\Delta \mathrm{LSS}^l_{c,\tau} = \sum_{s \in S_c} \gamma_{s,c,\tau-1}\, \Delta \hat{v}^l_{s,\tau,-c}. \tag{20}$$

Under this definition (cf. eq. (8)), $\hat{v}^l_{s,\tau,-c}$ equals $\beta^c/(1+\eta\beta^c)$ times the industry productivity shock, rather than $1/(1+\eta\beta^c)$ as in the wage-based case. Consequently, the coefficient on the average industry premium in the wage regression should converge to η, and the coefficient in the employment regression to unity. The third to fourth columns of table 7 report estimates of $\eta \approx 0.26$, somewhat lower than in the wage-based. The employment effect is below one but not significantly different from unity.

We found those findings supporting our baseline results as we estimted the outside option effects significant using different shock definitions, and we found the parameter estimates not drastically different from the estimated one. Nevertheless, we prefer the original estimates than those based on robustness results as employment share changes do not control for workers sorting, different from changes in industry premiums.

Alternative Anchor Industry. Finally, one might question the use of retail sale in non-specialized stores as the anchor sector for computing the industry wage premium, given its low tradability. We therefore recomputed the premium using the manufacture of plastic products as the anchor. As shown in Table 8, the results closely match those of the baseline.

5.4 Heterogeneity in Labor Supply Elasticity

Figure 2 presents estimates from Equation 17, where the share of EE transitions to total transitions is interacted with changes in the average local labor market wage premium (ΔLSS_c^4). As described in Subsection 4.2.1, all three variables are constructed using only observations from the fourth quartile.

Except for the first quartile—where outcome volatility is highest—the estimates for quartiles 2 through 4 are relatively stable. The coefficients on the average local labor market wage premium, which approximate overall productivity changes at the local labor market level, exhibit a modest upward trend but remain statistically insignificant. These estimates are also stable and even show a slight downward trend for the regressions for employment changes.

We interpret these findings as evidence that local labor supply elasticity does not differ substantially across West German commuting zones. This does not imply that these labor markets are highly competitive—our estimates indicate that the average firm-level labor supply elasticity is low. However, this elasticity appears relatively uniform across regions.

6 Policy Experiment: Subsidy to the Machinery and Equipment Industry

National industry productivity shocks can arise from innovations, shifts in global demand or trade, or targeted national policies. In this section, we illustrate how our framework can quantify the impact of the latter. Specifically, we simulate a 10% subsidy—equivalent to a 10% productivity boost from the firms' perspective—applied over the period 2010–2014 to Germany's machinery and equipment sector, one of its flagship industries featuring numerous hidden champions (Rammer and Spielkamp, 2015).[7]

[7] The 3-digit industries receiving the subsidy in our experiment are: (i) Manufacture of machinery for the production and use of mechanical power, except aircraft, vehicle, and cycle engines; (ii) Manufacture of other general-purpose machinery; (iii) Manufacture of agricultural and forestry machinery; (iv) Manufacture

We base our simulations on the four parameter sets reported in Table 6. Figure 4 displays the effects under our preferred specification, which uses estimates obtained from industries with employment shares below 2%. Under this calibration, wages in the machinery industry rise from 5.4% to 6.2%. The spillover to other industries varies with the local machinery employment share: southern commuting zones in western Bavaria and Baden-Württemberg—particularly the manufacturing hub of Schweinfurt—experience non-machinery wage gains between 0.6% and 0.9%, whereas less industrialized northern commuting zones see effects below 0.3%.

In contrast, employment responses are stronger in areas with lower initial machinery shares, since machinery firms face less competition for workers. Across all local labor markets, the increase in the machinery employment share ranges from 8% to 10%, with variation of at most 2%.

Figures 5–7 report policy outcomes under the three alternative parameter sets. The results using estimates from all industries closely mirror our preferred case. However, simulations based solely on manufacturing-industry estimates predict smaller wage spillovers (0.1%–0.75% in non-machinery sectors) and larger employment effects (21%–27% increases in the machinery employment share).

These findings underscore the importance of outside-option effects in evaluating industrial policy. A targeted subsidy to Germany's machinery sector can generate substantial wage and employment impacts throughout the local labor market. Moreover, our analysis offers insights into the potential consequences of recent tariff disputes, which effectively constitute negative productivity shocks for core export industries.

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of machine tools; (v) Manufacture of other special-purpose machinery; (vi) Manufacture of weapons and ammunition; (vii) Manufacture of domestic appliances n.e.c.; and (viii) Manufacture of office machinery and computers.

7 Conclusions

In this paper, we develop a unified framework to estimate the effects of industry shocks on spatial wage inequalities. Building on the partial-equilibrium framework of Card et al. (2018), we extend the model to incorporate general-equilibrium effects while preserving estimability via linear equations. We show that when an aggregate shock directly affects a non-negligible share of firms—e.g., within the same industry—cross-employer spillovers can induce widespread changes in wage and employment across the entire local labor market.

We estimate the model using German administrative employer–employee data, employing changes in AKM industry–location fixed effects as proxies for productivity shocks. We find robust evidence of outside option effects on both wages and employment, indicating that general-equilibrium forces influence firms' wage-setting processes over a medium (five-year) horizon. Moreover, we find no evidence of substantial variation in labor supply elasticities across West German local labor markets, at least not at a level that would generate large differences in outside-option effects. In a counterfactual simulation of a 10% subsidy to the machinery sector, we predict it would raise wages in that sector by about 5%, increase wages in other sectors by 0.01 –0.9%, and boost the machinery sector's employment share by roughly 8–10%.

Our findings suggest that place-based industrial policies may have amplified effects: they not only boost wages and employment in targeted sectors but also generate positive spillovers that raise wages throughout the local labor market. However, because targeted sectors compete for workers, policies that concurrently target multiple industries may be less effective at reallocating labor toward any single sector.

Finally, we believe that our framework might offers a valuable tool for future research analyzing the aggregate consequences of trade shocks that typically affect a limited number of spatially uneven industries. These insights can improve understanding of how such shocks impact the most affected local labor markets.

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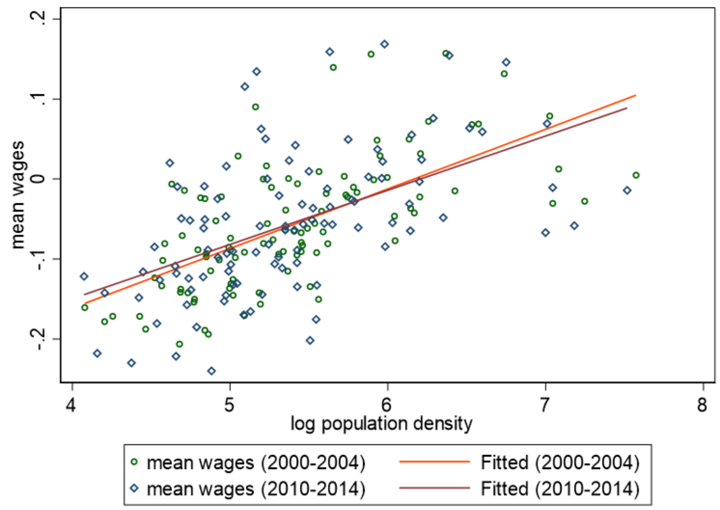
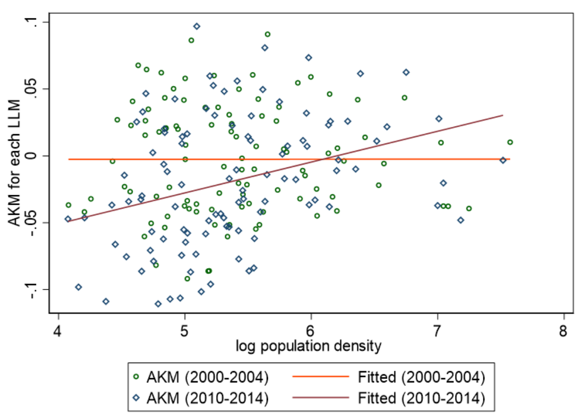
8 Figures

Figure 1: Urban Premium and Workers' and Industries' Sorting

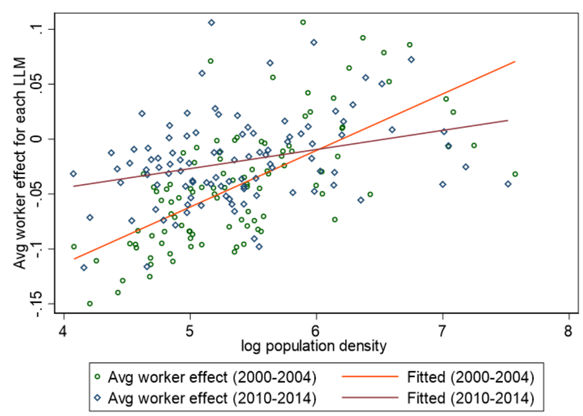
(a) Mean wages



(b) Mean Industry-Location AKM Effect

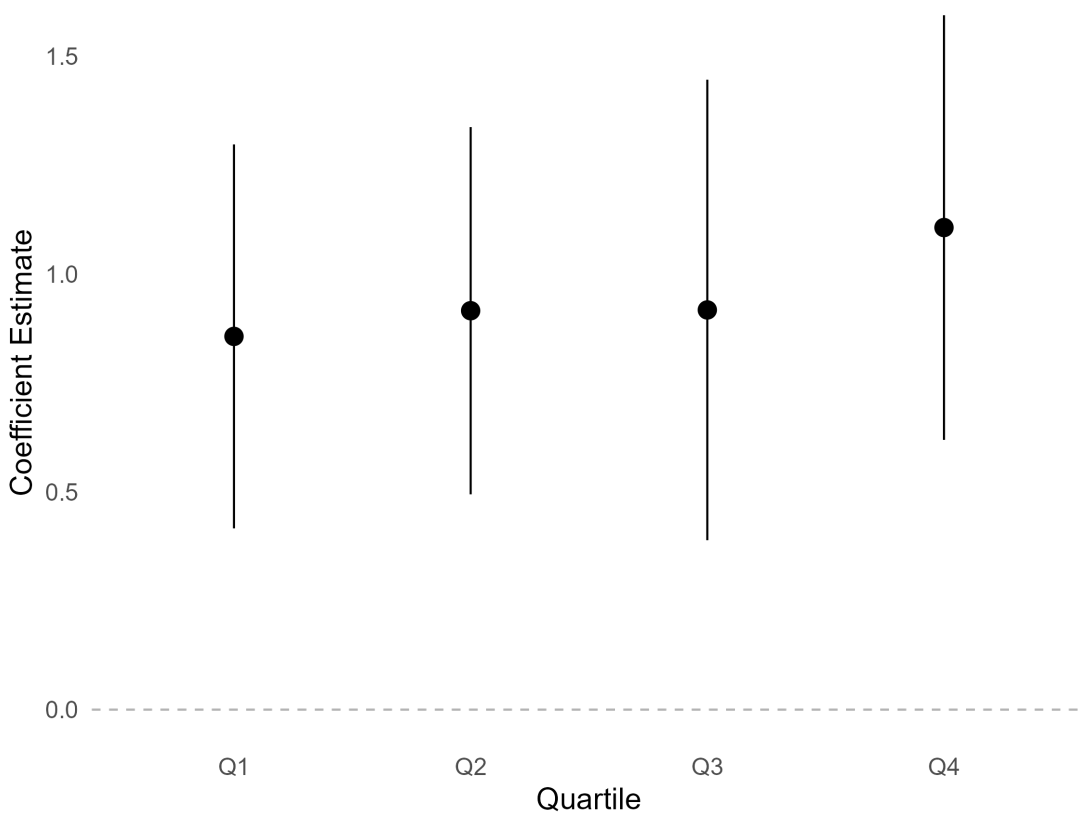


(c) Mean AKM worker fixed effects



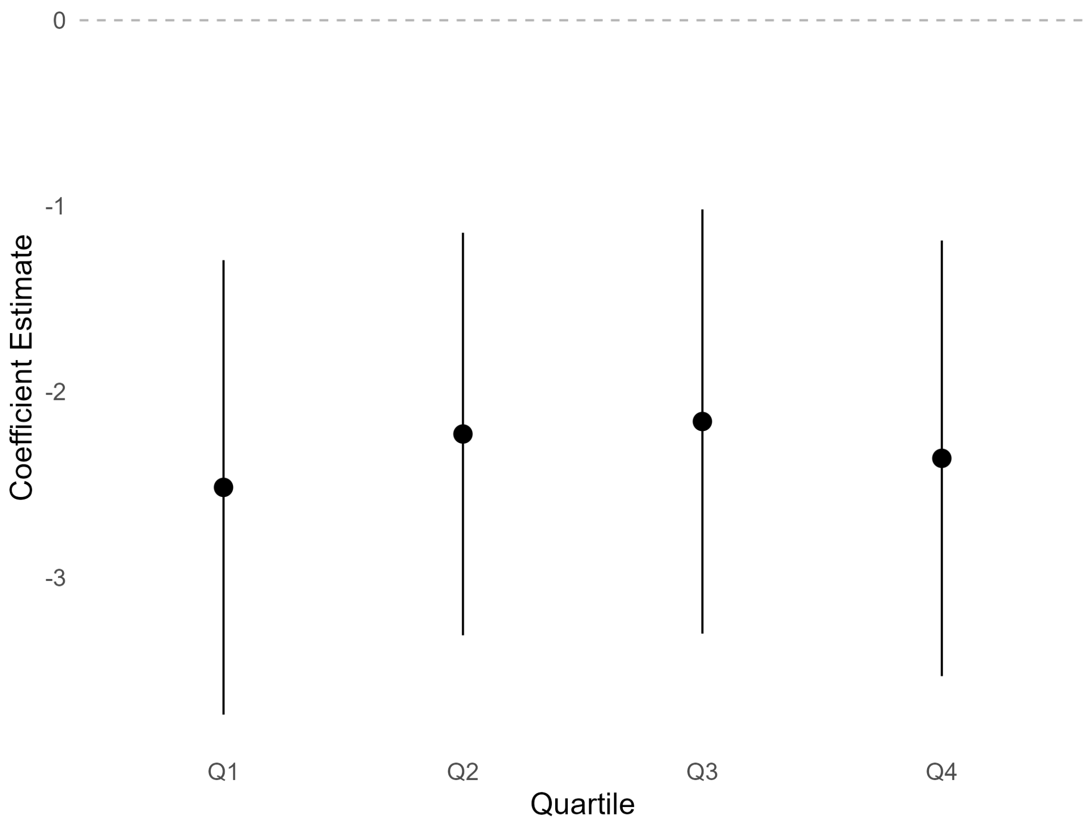
This figure plots the recentered average log wage and its main components against local labor market population density, computed for period 2000-2004 and 2010-2014. The upper panel shows a scatter plot of the recentered average wage among full-time workers. The lower left panel displays the recentered average industry-location fixed effects estimated from Equation 11, weighted by the number of full-time workers. The lower right panel shows the recentered average worker fixed effects from Equation 11.

Figure 2: Estimates Under Firms' Labor Supply Heterogeneity: Wage Effects



This figure displays coefficients from the regression in Equation 17, where the dependent variable is the five-year change in the industry–commuting zone wage premium, measured using changes in the AKM fixed effects from Equation 11. Black points show the estimated effects of changes in the average labor market wage premium (as defined in Equation 13), also interacted with quartiles of the unemployment transition share. Standard errors are two-way clustered by industry and local labor market.

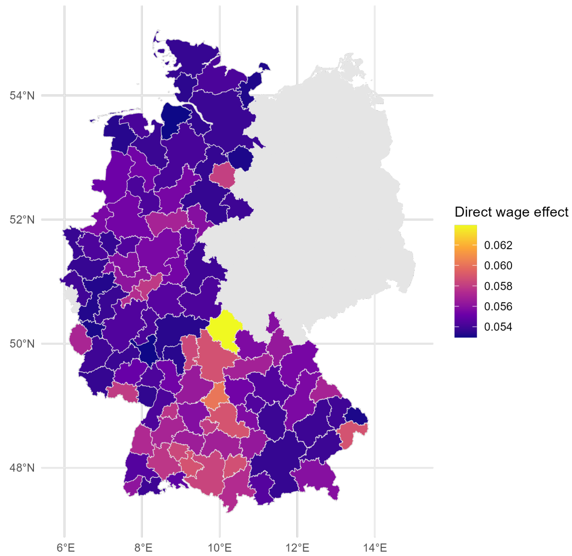
Figure 3: Estimates Under Firms' Labor Supply Heterogeneity: Employment Effects



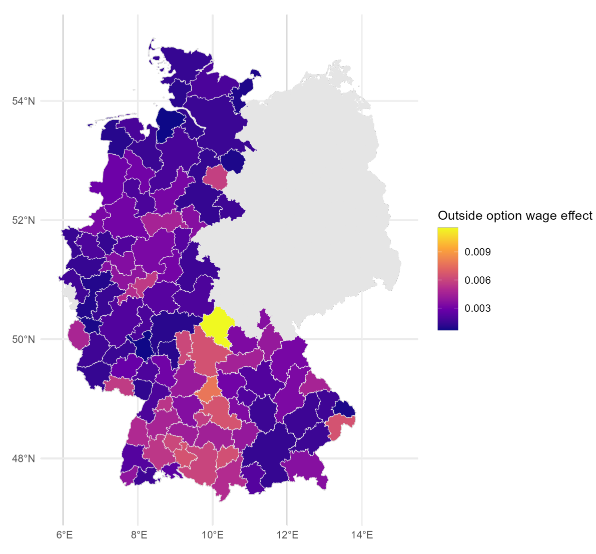
This figure displays coefficients from the regression in Equation 18, where the dependent variable is the five-year change in the industry–commuting zone employment. Black points show the estimated effects of changes in the difference between national industry wage premium (as defined in Equation 12) and changes in the average labor market wage premium (as defined in Equation 13), interacted with quartiles of the local labor market's share of transitions from unemployment to total transition rate. Standard errors are two-way clustered by industry and local labor market.

Figure 4: Policy Simulation: Preferred Specification

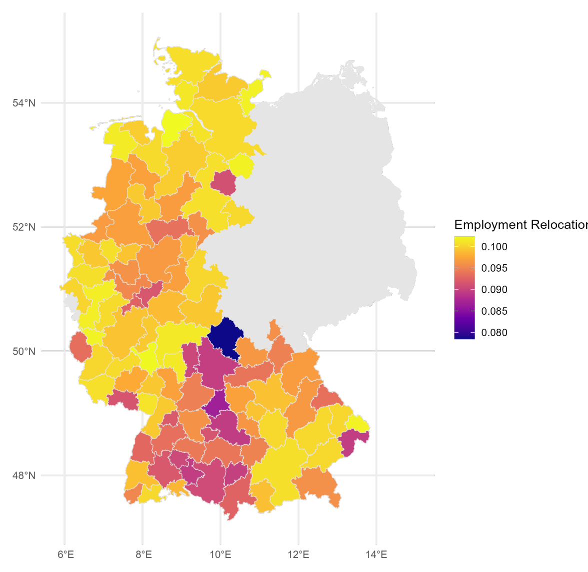
(a) Log Wage Change for Machinery Industries



(b) Log Wage Change for Non-Machinery Industries



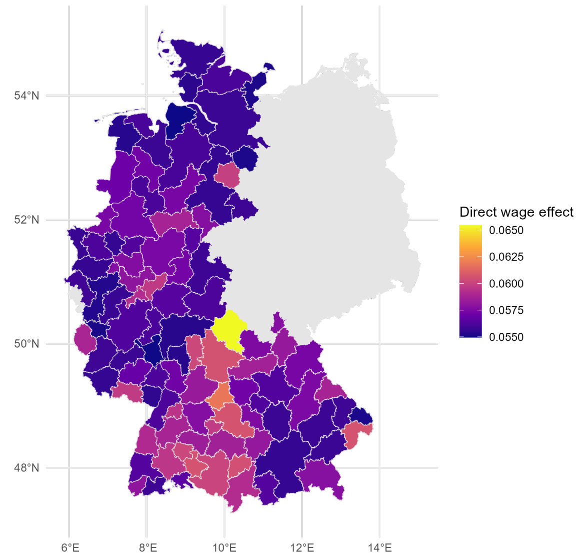
(c) Log Change in Employment Share of the Machinery Industry



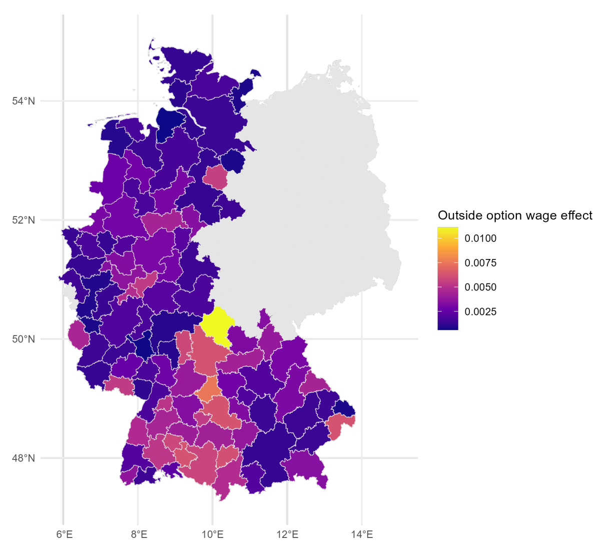
These figures show the counterfactual point estimates for 10% subsidy in machinery industries under $\hat{\beta} = 1.98$ and $\hat{\eta} = 0.46$.

Figure 5: Policy Simulation: Parametrization 2

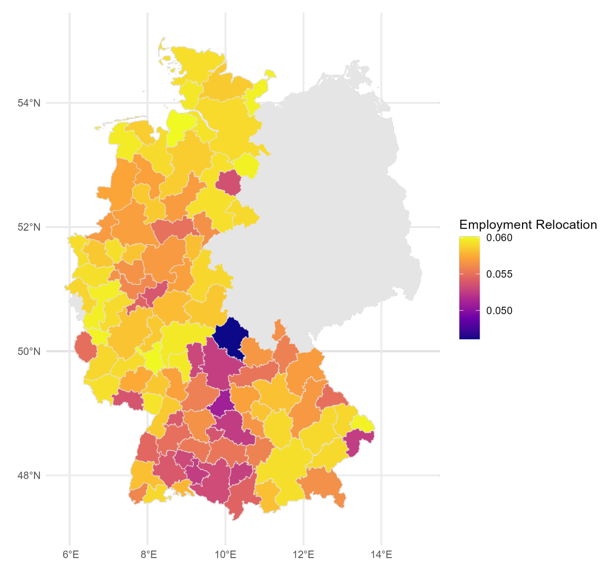
(a) Log Wage Change for Machinery Industries



(b) Log Wage Change for Non-Machinery Industries



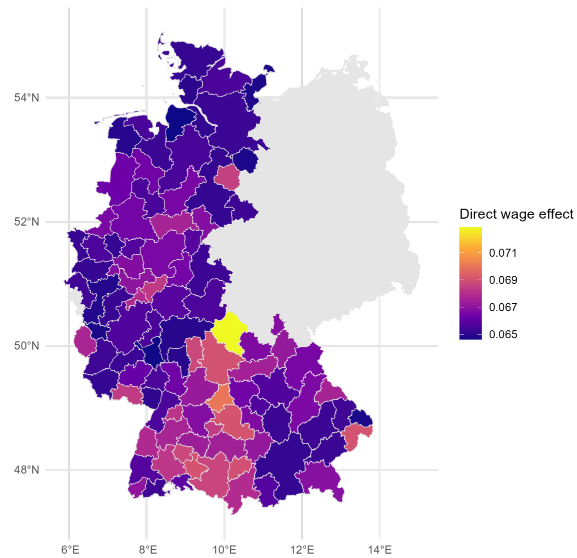
(c) Log Change in Employment Share of the Machinery Industry



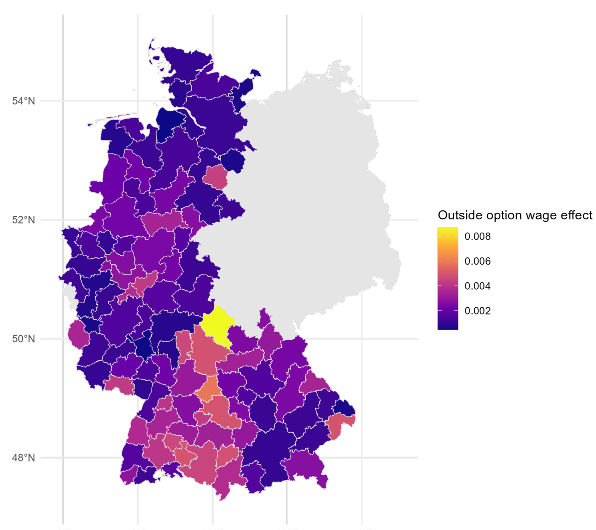
These figures show the counterfactual point estimates for 10% subsidy in machinery industries under $\hat{\beta} = 1.12$ and $\hat{\eta} = 0.75$.

Figure 6: Policy Simulation: Manufacturing Parameters 1

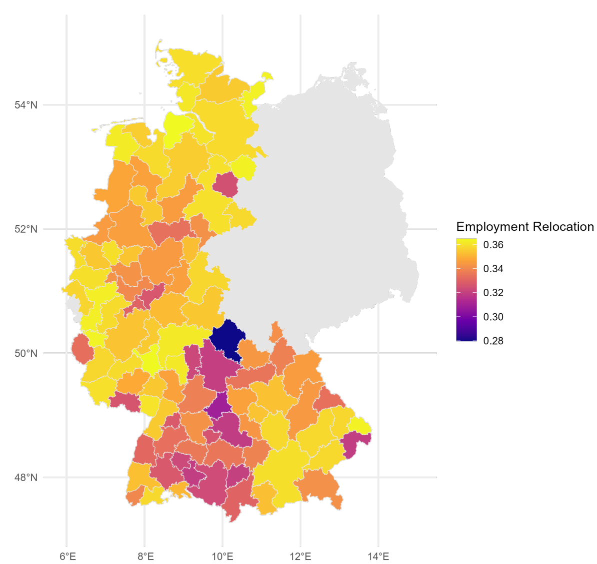
(a) Log Wage Change for Machinery Industries



(b) Log Wage Change for Non-Machinery Industries



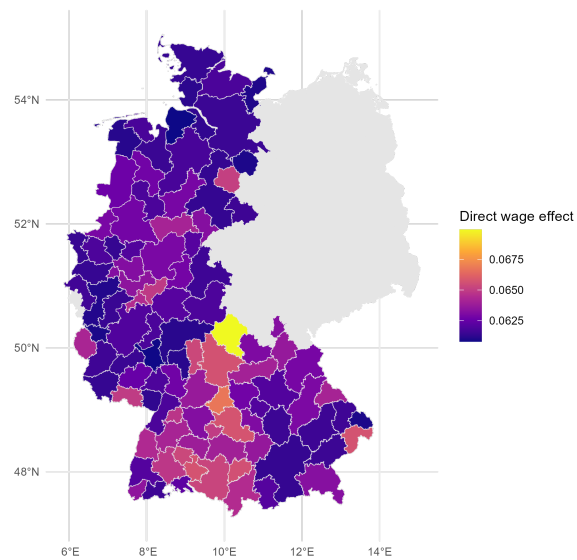
(c) Log Change in Employment Share of the Machinery Industry



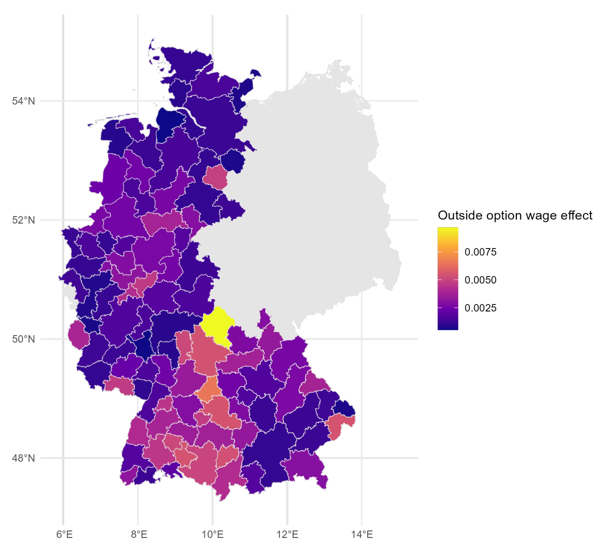
These figures show the counterfactual point estimates for 10% subsidy in machinery industries under $\hat{\beta} = 5.76$ and $\hat{\eta} = 0.1$.

Figure 7: Policy Simulation: Manufacturing Parameters 2

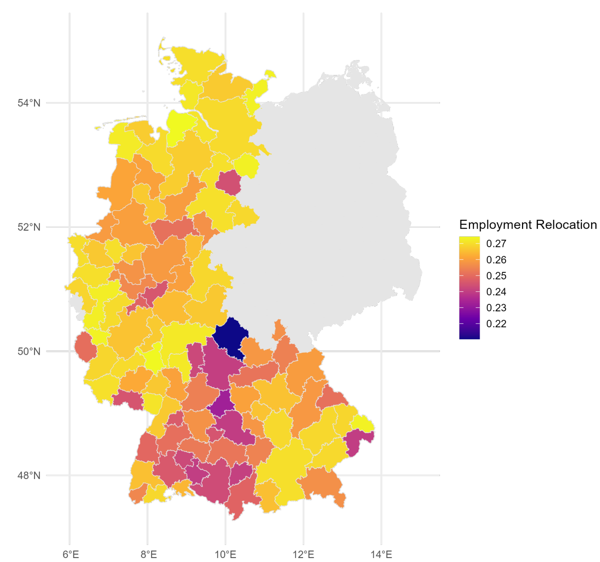
(a) Log Wage Change for Machinery Industries



(b) Log Wage Change for Non-Machinery Industries



(c) Log Change in Employment Share of the Machinery Industry



These figures show the counterfactual point estimates for 10% subsidy in machinery industries under $\hat{\beta} = 4.62$ and $\hat{\eta} = 0.143$.

9 Tables

Table 1: Descriptive Sample Statistics

	Mean
Log daily wage	4.25
	(0.707)
Males	55.7
age	36.85
	(10.48)
Education	
Above University	14.8
Below University	85.2
Employment Stats	
Transition rates (Full sample)	0.39
	(0.024)
Transition rates (Males)	0.41
	(0.029)
Observations	13,163,035

This table presents the sample statistics for (log) daily wages, worker education, age, and job transition rates (ratio of job-to-job transitions to total transitions) in the estimation sample. The figures in the brackets denote the standard deviation of the statistic. Log wages in terms of 2015 Euros. Source: SIAB.

Table 2: Industry Group's distribution

Industry	Frequency (%)
Agriculture, Forest & Fisheries	1.17
Mining	0.28
Construction	5.93
Manufacturing	22.19
Services	55.12
Wholesale & Retail Trade	15.30

This table presents a broad-industry frequency distribution of the sample statistics. Source: SIAB.

Table 3: Descriptive Industry-Location Cell Statistics

	Overall	2000-2004	2005-2009	2010-2014
$\hat{\varphi}_{s,c,\tau}$	-0.02	-0.01	-0.01	-0.02
	(0.16)	(0.15)	(0.16)	(0.16)
$\Delta\hat{\varphi}_{s,c,\tau}$	-0.01	-0.00	-0.01	-0.02
	(0.10)	(0.10)	(0.10)	(0.10)
$\Delta \text{LSS}_{c,\tau}$	0.01	0.03	0.01	0.01
	(0.003)	(0.004)	(0.003)	(0.03)
Workers-Quarter Observations	557	563	556	551
	(1070)	(1047)	(1073)	(1089)
Industry's Locations	88.06	86.81	87.86	89.48
	(17.81)	(17.26)	(18.03)	(18.02)
Employment share	0.01	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Observations	30,578	10,057	10,287	10,234

This table presents descriptive statistics for industry–commuting zone cells in our sample. $\hat{\varphi}s, c, \tau$ denotes the industry–commuting zone fixed effect estimate from Equation 11, while $\Delta\hat{\varphi}s, c, \tau$ represents the change in this estimate over a five-year period. $\Delta \text{LSS}_{c,\tau}$ denotes the average change in the commuting zone's industry wage premium, as defined in Equation 13. Source: SIAB.

Table 4: Descriptive Local Labor Market Statistics

	Overall	2000-2004	2005-2009	2010-2014
Av. Daily Wage	102.08	102.65	100.36	103.23
	(10.32)	(9.61)	(10.10)	(11.04)
Av. Worker FE	-0.01	-0.00	-0.01	-0.02
	(0.04)	(0.04)	(0.04)	(0.05)
Industries	153.64	155.18	152.33	153.48
	(25.99)	(25.58)	(26.56)	(26.00)
Industry HHI	260.39	258.48	262.61	260.02
	(77.05)	(76.12)	(82.20)	(73.31)
Workers-Quarter Observations	51480	52720	51400	50340
	(55740)	(55660)	(56280)	(55780)
Observations	298	97	100	101

This table presents descriptive statistics for local labor markets (commuting zones) in our sample. Mean Worker FE refers to the average worker fixed effect estimate from Equation 11. Daily wages are reported in 2015 Euros. Source: SIAB.

Table 5: Regression Results

	Location-Industry's Wage Policy Change				Location-Industry's Employment Change			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Avg. Labor Market Industry	0.84***	0.91***	0.56***	0.66***	−1.12**	−1.98**	- 5.76***	−4.61***
Wage Premium (ΔLSS_c)	(0.20)	(0.20)	(0.21)	(0.22)	(0.46)	(0.52)	(0.70)	(0.77)
Industry×Period FE	✓	✓	✓	✓	✓	✓	✓	✓
Only Employment share< 0.02	NO	YES	NO	YES	NO	YES	NO	YES
Only Manufacturing	NO	NO	YES	YES	NO	NO	YES	YES
R^2	0.24	0.22	0.21	0.19	0.17	0.16	0.10	0.11
Observations	20,620	17,993	8,351	7,591	20,620	17,993	8,351	7,591

*** p<0.01, ** p<0.05, * p<0.1

This table reports coefficients and corresponding standard errors from the regressions described in Equations 15 and 16. Columns 1–4 present results where the dependent variable is the five-year change in the industry–commuting zone wage premium, measured by changes in AKM fixed effects from Equation 11. Columns 5–8 report results where the dependent variable is the five-year change in employment at the industry–commuting zone level. ΔLSS_c denotes the change in the average local labor market wage premium, as defined in Equation 13. All regressions are weighted by the square root of the number of worker–quarter observations. All regressions control for local labor market population changes. Standard errors, clustered two-way by industry and local labor market, are reported in parentheses.

Table 6: Parameters' Estimates

	All	Emp. share< 0.02	Manuf.	Manuf. & Emp. share< 0.02
$\hat{\beta}$	1.12	1.98	5.76	4.61
	(0.46)	(0.52)	(0.70)	(0.77)
$\hat{\eta}$	0.75	0.46	0.097	0.143
	(0.35)	(0.16)	(0.044)	(0.053)

Estimates of firms' labor supply elasticity β and labor demand elasticity η, based on estimates of Equations 15 and 16. For η: Delta-Method Confidence Intervals.

A Elasticity shocks

We examine how changes in labor supply elasticity affect wages when productivity remains constant. From the same first-order conditions, one can show that in the limit:

$$\Delta \ln W_{s,c} \;=\; \frac{1}{\beta^c(1+\beta^c)}\,\Delta\beta^c \;-\; \frac{\eta}{1+\eta\beta^c}\left(\ln W_{s,c} - \sum_{s'\in S_c}\gamma_{s',c}\,\ln W_{s',c}\right)\Delta\beta^c.$$

Following Autor et al. (2023), this result implies that an increase in labor supply elasticity compresses wages within a city—lower-paying sectors tend to experience larger wage increases, while higher-paying sectors see a smaller impact.

A.1 Combining Both Effects

When both productivity shocks and elasticity changes are present, the combined equation is:

$$
\begin{aligned}
\Delta \ln W_{s,c} \;=\; & \underbrace{\frac{1}{1+\eta\beta^c}\,\Delta \ln A_s}_{\text{own-industry effect}} \;+\; \underbrace{\frac{\eta\beta^c}{1+\eta\beta^c}\Big(\sum_{s'\in S_c}\gamma_{s',c}\,\Delta \ln A_{s'}\Big)}_{\text{spillover effect}} \\
& +\; \underbrace{\left[\frac{1}{\beta^c(1+\beta^c)} - \frac{\eta}{1+\eta\beta^c}\left(\ln W_{s,c} - \sum_{s'\in S_c}\gamma_{s',c}\,\ln W_{s',c}\right)\right]\Delta\beta^c}_{\text{labor supply elasticity change}} \\
& +\; \underbrace{\frac{1}{1+\eta\beta^c}\,\Delta \ln \tilde{A}_{s,c} \;+\; \frac{\eta\beta^c}{1+\eta\beta^c}\Big(\sum_{s'\in S_c}\gamma_{s',c}\,\Delta \ln \tilde{A}_{s',c}\Big)}_{\text{unobserved local shocks}}\,.
\end{aligned}
\tag{21}
$$

B Tables

Table 7: Regression Results Robustness I

	Location-Industry's Wage Policy Change				Employment Change
	(1)	(2)	(3)	(4)	(5)
Δ Avg. Labor Market Industry	0.89^{***}	1.09^{***}			
Wage Premium ($\Delta \mathrm{LSS}_c$)	(0.20)	(0.20)			
Δ Avg. Labor Market Industry			0.23^{***}	0.25^{***}	-0.82^{***}
Employment Premium ($\Delta \mathrm{LSS}_c^l$)			(0.06)	(0.07)	(0.20)
Industry×Period FE	✓	✓	✓	✓	✓
Additional Controls	✓				
Only Employment Share < 0.02	YES	YES	NO	YES	YES
R^2	0.24	0.22	0.21	0.19	0.17
Observations	17,993	26,795	20,620	17,993	17,993

*** p<0.01, ** p<0.05, * p<0.1

This table reports coefficients and corresponding standard errors from the regressions described in Equations 15 and 16. Columns 1–4 present results where the dependent variable is the five-year change in the industry–commuting zone wage premium, measured by changes in AKM fixed effects from Equation 11. Column 5 reports results where the dependent variable is the five-year change in employment at the industry–commuting zone level. $\Delta \mathrm{LSS}_c$ denotes the change in the average local labor market wage premium, as defined in Equation 13. $\Delta \mathrm{LSS}_c^l$ denotes the change in the average local labor market industry employment premium, as defined in Equation 19. Additional controls include the log of university-educated workers and the industry HHI in the local labor market. All regressions control for local labor market population change. All regressions are weighted by the square root of the number of worker–quarter observations. Standard errors, clustered two-way by industry and local labor market, are reported in parentheses.

Table 8: Regression Results Robustness II

	Location-Industry's Wage Policy Change		Location-Industry's Employment Change	
	(1)	(2)	(3)	(4)
Δ Avg. Labor Market Industry	0.74^{***}	0.82^{***}	-1.22^{***}	-2.13^{**}
Wage Premium (ΔLSS_c)	(0.20)	(0.21)	(0.45)	(0.50)
Industry×Period FE	✓	✓	✓	✓
Only Employment share< 0.02	NO	YES	NO	YES
R^2	0.24	0.22	0.17	0.16
Observations	20,620	17,993	20,620	17,993

*** p<0.01, ** p<0.05, * p<0.1

This table reports coefficients and corresponding standard errors from the regressions described in Equations 15 and 16. Columns 1–4 present results where the dependent variable is the five-year change in the industry–commuting zone wage premium, measured by changes in AKM fixed effects from Equation 11. Columns 5–8 report results where the dependent variable is the five-year change in employment at the industry–commuting zone level. ΔLSS_c denotes the change in the average local labor market wage premium, as defined in Equation 13, that uses a plastics manufacturing as an anchor industry. All regressions control for local labor market population change. All regressions are weighted by the square root of the number of worker–quarter observations. Standard errors, clustered two-way by industry and local labor market, are reported in parentheses.