Unpacking Wage Inequality: Minimum Wage Effects on Within- and Between-Firm Disparities

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Abstract

This paper examines how minimum wage policy affects wage inequality within and between firms. Using rich linked employer-employee administrative data from Germany, I exploit the introduction of the national minimum wage in 2015 to study changes in the overall variance of log daily wages and to decompose these changes into within-firm and between-firm components. Difference-in-Differences estimates show that the minimum wage reduces the variance of log daily wages by 8% to 12.6%. Most of this decline is explained by reductions in between-firm inequality, driven by lower worker-firm sorting, weaker worker segregation across firms, and a compression of the dispersion in firm-specific pay premiums. The results further show that spillover effects beyond directly exposed firms account for a meaningful share of the decline in wage inequality. Overall, the findings suggest that minimum wage policy reduces wage inequality primarily through changes in between-firm wage differentials, rather than through compression within firms.

JEL Classification: J31, J38, J21

Keywords: minimum wage, inequality, firm, wage- setting

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1. Introduction

Income inequality is a key topic in labor economics, raising important questions about its causes and solutions. Two critical areas of focus are: how labor market policies can reduce inequality, and the role of firms in shaping wage disparities. Among various policy tools, the minimum wage is widely regarded as an effective instrument for reducing wage inequality by boosting the earnings of low-wage workers and compressing the wage distribution. However, the minimum wage is not solely a worker-focused policy; it also directly influences firms' wage-setting power, potentially altering wage differentials across firms. While the minimum wage's effects on the overall wage distribution of workers are well-documented, its influence on the components of inequality within and between firms remains less explored. This raises a crucial question: can the minimum wage also function as an effective firm-centered policy to address wage disparities originating from firms?

This paper addresses these questions by examining the German minimum wage policy introduced in 2015, leveraging administrative employer-employee linked data. Previous literature highlights the increasing influence of firms on income inequality, particularly through firm pay heterogeneity and worker-firm sorting. In the United States, Song et al. (2019) demonstrate that two-thirds of the rise in the variance of log wages between 1978 and 2013 can be attributed to growing differences in wages between firms. This increase is largely driven by worker-firm sorting and segregation, reflecting changes in the composition of workers across firms. Similarly, in Germany, Card et al. (2013) reveal that rising dispersion in firm-specific pay premiums and increased worker-firm sorting accounted for more than half of the increase in wage inequality between 1985 and 2009. In this study, I decompose wage variance into within-firm and between-firm components using AKM regressions with cluster fixed effects. My findings show that the largest share of wage dispersion stems from between-firm inequality in Germany from 2012 to 2018, with the dispersion of firm-specific pay premiums, worker-firm sorting, and segregation accounting for about 50% of total wage inequality.

The significant role of firms in driving wage inequality underscores the importance of labor market policies that target not only worker-level factors, such as training and education, but also firm-level disparities and wage-setting practices (OECD, 2021). Previous research demonstrates that the introduction of minimum wages often has minimal to no adverse effects on employment (Card, 1993), while effectively mitigating wage dispersion and raising wages for workers in the lower tail of the wage distribution (Machin et al., 2003; Butcher et al., 2012; Autor et al., 2016; Fortin et al., 2021; Engbom and Moser, 2022).

In this study, I assess the effects of the minimum wage on wage inequality and its components using Difference-in-Differences estimations. The findings show that the minimum wage reduces the overall variance of log daily wages by approximately 8% to 12.6%. This decline is primarily driven by reductions in between-firm inequality, as the policy reduces differences in worker composition across firms and compresses the dispersion of firm-specific pay premiums.

Among the individual components, the largest contribution comes from the reduction in the covariance between firm and worker fixed effects, which accounts for 15% to 48% of the total decline in wage variance. This indicates that the minimum wage reduces worker-firm sorting. The second major channel is the reduction in worker segregation, which accounts for 15% to 34% of the total decline, suggesting that the policy reduces the concentration of low- and high-productivity workers in separate firms. In addition, the dispersion of firm-specific pay premiums declines and contributes around 12% to 23% of the overall reduction. By contrast, within-firm variance decreases only slightly, accounting for a modest 4% to 7% of the total reduction. Overall, these findings suggest that the minimum wage reduces wage dispersion mainly through its impact on between-firm differences.

My analysis also indicates that the reduction in worker-firm sorting and segregation is not merely a mechanical consequence of reduced within-firm inequality. Instead, the minimum wage has a substantive effect in reducing worker composition differences between firms. This finding aligns with existing research on the relationship between minimum wage policies and job mobility. For example, Dustmann et al. (2021) demonstrate that minimum wages facilitate the reallocation of low-wage workers to higher-paying firms, leading to a reduction in the covariance between worker and firm fixed effects. Similarly, Butschek (2022) show that firms affected by minimum wage policies tend to raise their hiring standards, prioritizing more productive workers. This shift likely reduces worker-firm sorting and segregation, particularly in treated firms that previously offered lower firm-specific pay premiums.

Additionally, the reduction in the variance of firm-specific pay premiums may be connected to research on the relationship between minimum wage policies and productivity. Haelbig et al. (2023) find that the German minimum wage increases productivity in treated firms. This narrowing of productivity gaps could explain the reduced dispersion in firm-specific pay premiums. Alternatively, the minimum wage might directly weaken the pass-through of productivity to firm-specific pay premiums, thereby limiting firms' wage-setting power (OECD, 2021).

Previous studies highlight the role of spillover effects in narrowing overall wage disparities, particularly in the middle part of the wage distribution (Machin et al., 2003; Butcher et al., 2012; Autor et al., 2016; Fortin et al., 2021; Engbom and Moser, 2022). Bossler and Schank (2023) reports that nearly half of the recent decline in wage inequality in Germany can be attributed to the introduction of the national minimum wage in 2015, with spillover effects accounting for about half of this reduction. These effects benefit workers who were earning above the minimum wage threshold.

Despite these findings, few studies examine the types of firms where such spillover effects occur. For example, Engbom and Moser (2022) show that minimum wage policies in Brazil accounted for 45% of the reduction in wage inequality between 1996 and 2018. In this context, firms play a crucial role, as those paying above the minimum wage also increase wages to maintain their relative rank compared to other firms. Similarly, Gopalan et al. (2021) find that spillover effects contribute approximately 20% of the total increase in labor costs for incumbent workers, though these effects are observed primarily in firms with a substantial share of low-wage employees.

Building on this literature, I investigate the spillover effects of the minimum wage by separately estimating its impact on firms that hired sub-minimum wage workers before the policy (exposed firms) and those that did not (non-exposed firms). My findings reveal that the minimum wage impacts not only firms directly affected by the policy but also reduces wage dispersion among firms that already pay higher wages. Spillover effects to non-exposed firms account for approximately 12% to 37% of the overall reduction in wage variance due to the minimum wage.

In summary, this study makes two key contributions to the literature. First, it quantifies the impact of minimum wages on both within-firm and between-firm wage inequality, demonstrating that this policy serves as a powerful tool for shaping firms' pay structures and practices while promoting job mobility. Second, it quantifies the contribution of spillover effects to the reduction in overall wage dispersion, showing that even firms not directly exposed to the minimum wage experience a decrease in wage dispersion. These spillover effects account for a significant portion of the overall reduction in wage variance.

The paper is organized as follows. Section 2 provides an overview of the German minimum wage policy and describes the dataset. Section 3 presents the measures of within- and between-firm wage inequality. Section 4 outlines the identification strategy, reports the main Difference-in-Differences results using Recentered Influence Functions, and discusses the estimated effects of the minimum wage on wage variance and its components. Section 6 explores potential explanations for the findings. Finally, Section 7 concludes the paper.

2. Institutional background and Data

2.1. German minimum wage

Germany implemented its first national minimum wage in January 2015, setting the minimum hourly wage at €8.50. Prior to this, only sector-specific minimum wages existed in Germany, covering industries such as construction, roofing, and hairdressing. These sector-specific wages applied to only a small fraction of the workforce. The 2015 nationwide minimum wage, however, applied to almost all employees, with a few exceptions, including apprentices, interns, volunteers, young workers under 18, and long-term unemployed individuals during their first six months of employment. The statutory minimum wage directly affected over 10% of the total workforce (Mindestlohnkommission, 2016).

The German Minimum Wage Commission reviews the wage threshold every two years. Since its introduction, the minimum wage has been gradually increased, reaching €8.84 in January 2017 and continuing to rise over time. By January 1, 2026, the threshold had reached €13.90. However, within my sample period (2012–2018), the 2017 increase is not particularly significant, as it was mainly an adjustment for inflation and did not substantially alter the real minimum wage.

Overall, the 2015 introduction of the national minimum wage represents the most significant policy shift in terms of both its scope, covering almost all employees, and its level, moving from no general minimum wage to €8.50. Accordingly, I treat the 2015 policy as a quasi-natural experiment and leverage regional-level treatment variations (see Section 4 for detail) of the policy.

2.2. Data

This study uses the Sample of Integrated Employer-Employee Data (SIEED) provided by the Institute for Employment Research (IAB) (vom Berge et al., 2020). The SIEED is constructed from the Integrated Employment Biographies (IEB) and is based on the Employee History (BeH). The sampling procedure starts with a 1.5% random sample of establishments from this population. I refer to these initially sampled establishments as panel-case establishments.[1] The dataset then includes all individuals who worked for at least one day in one of these panel-case establishments between 1975 and 2018, together with their complete employment histories recorded in the BeH. As a result, the data contain both employment spells in the sampled establishments and spells in other establishments linked through workers' employment trajectories. These linked establishments are only partially observed, because the data include only workers connected to the initially sampled establishments.

Sample construction.—The SIEED dataset provides comprehensive information on both establishments and workers. Establishment characteristics include location, industry classification, and size. Worker characteristics encompass demographic details such as age, gender, and education, alongside work-related attributes including wages, employment type, and employment duration. As wages in the SIEED dataset are top-censored at social security contribution ceilings, I impute these values based on the approach in Dauth and Eppelsheimer (2020). The imputation procedure groups observations by year, region (East/West Germany), and education level. Tobit regressions are then performed within each group to estimate log wages for censored observations. To account for individual and firm fixed effects, the regressions are repeated, incorporating leave-one-out means of workers' log wages over time, along with leave-one-out means of log wages for workers within each establishment for a given year.

The dataset, originally organized in spell format with each row representing an individual employment spell, is converted into an annual worker-year panel by assigning individuals to their employment status and establishment on June 30 (the annual reference date) of each year. For individuals holding multiple jobs in the same year, only the job with the highest earnings is retained.

[1]Throughout this study, the terms establishment" and firm" are used interchangeably.

Table 1: Summary statistics table

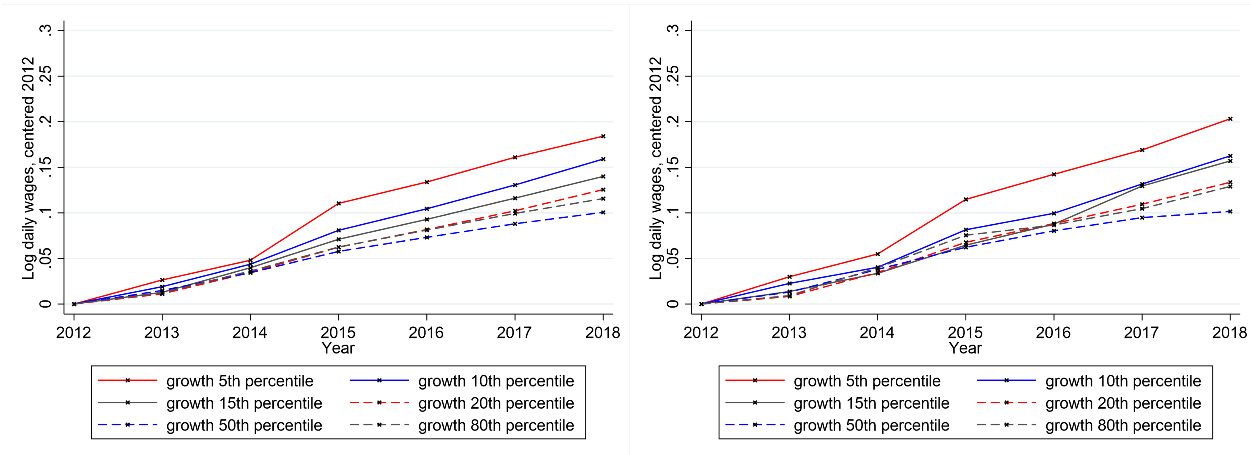
Variable	
Share of Female	0.305
Workplace in Eastern Germany	0.176
Mean age	42.663
Mean tenure	9.043
Daily wage	132.309
SD of daily wage	(98.408)
Log daily real wage	4.717
SD of log daily wage	(0.549)
Mean firm size (full time)	881.124
Firm size$<$10	0.168
Firm size: 10-99	0.350
Firm size:$>=$100	0.482
Observations	
Number of worker-year	1,861,046
Number of workers	508,663
Number of establishments	22,369

Notes: The table shows worker-year weighted summary statistics.
Data: SIEED, 2012-2018.

Sample restrictions.—Following Card et al. (2013), I analyze the distribution of daily wages, restricting the sample to full-time workers to minimize the influence of working hours on wage dispersion. Although hourly wages would be preferable for this analysis, the dataset lacks information on working hours. The sample is further restricted to workers aged 18 to 60 earning daily wages exceeding 10 Euros. Moreover, the baseline sample used for the main Difference-in-Differences analysis focuses on panel-case firms observed between 2012 and 2018.[2] This restriction maintains the representativeness of the sample while ensuring the inclusion of all workers meeting the sample criteria within each establishment. This approach also enables a clear distinction between firms directly exposed to the minimum wage and those that are not. Table 1 presents the summary statistics of the sample, which consists of approximately 1.86 million worker-year observations, 508,663 unique workers, and 22,369 unique firms. The sample includes firms of all sizes, including a significant share of very small firms with fewer than 10 employees.

[2]This restriction applies to the baseline Difference-in-Differences analysis, which constitutes the main empirical framework of the paper. The AKM analysis relies on a broader linked sample construction, as discussed in detail below.

Figure 1: Wage growth at various percentiles



(a) Growth of log daily wages of workers

(b) Growth of mean log daily wages of firms

Notes: The left panel illustrates the evolution of log differences between daily wage percentiles of workers, normalized to zero in 2012. The right panel presents the evolution of log differences between mean daily wage percentiles of firms, also normalized to zero in 2012.
Data: SIEED, panel-case firms, 2012-2018.

Figure 1a illustrates the wage growth of daily wages from 2012 to 2018, calculated as the difference between log daily wages in year t and log daily wages in 2012. From 2012 to 2014, wages at lower percentiles, such as the 5th and 10th, exhibit faster growth compared to higher percentiles. In 2015, the 5th percentile shows even more pronounced growth, as evidenced by the steeper slope in the figure.[3] Figure 1b depicts the growth of mean wages among firms, weighted by firm size. Similar to the wage growth observed among individual workers, wages at the 5th and 10th percentiles grow faster than those at higher percentiles, with an accelerated growth rate in 2015, suggesting the impact of the minimum wage. Both figures indicate that the introduction of the minimum wage may have contributed to a reduction in wage dispersion among individuals as well as a reduction in the dispersion of mean wages across firms. However, the change in firm-level average wages does not distinguish whether increases in mean wages at certain firms result from changes in worker composition, such as the entry of more skilled employees, or from firms raising pay for

[3]This figure also suggests that the share of minimum-wage-affected workers in the sample is likely below 10%, as only the 5th percentile shows a pronounced increase after 2015. To further assess this, I calculate the share of workers with daily wages below 47.4 euros, obtained by multiplying the hourly minimum wage of 8.5 euros by average weekly working hours of 39 and dividing by seven. This share is about 6% in the sample, which is consistent with Figure 1a. This is also plausible because the sample includes only full-time workers; the affected share is therefore expected to be lower than share based on all employment types, which are around 10%.

their workforce. To address this, the next section provides a more detailed decomposition of wages and their variance.

3. Decomposing within- and between-firm wage inequality

3.1. Worker and firm fixed effects

To quantify within- and between-firm wage inequality, I employ the AKM model (Abowd et al., 1999) and follow the estimation approach outlined in CHK (Card et al., 2013). The AKM model is specified as follows:

$$y_{i,t} = \boldsymbol{X_{i,t}\beta} + \theta_i + \phi_j + r_{i,t} \tag{1}$$

where $y_{i,t}$ denotes log daily wages. The term θ_i captures individual fixed effects, reflecting returns to ability or other time-invariant personal characteristics, while ϕ_j represents the firm-specific pay premium of firm j. The vector $\boldsymbol{X_{i,t}}$ comprises the full set of time-varying worker characteristics, including five education dummies fully interacted with year dummies, as well as a cubic polynomial in age normalized to 40.[4]

Equation 1 is estimated using the largest connected set of firms, defined as the largest group of establishments connected by worker mobility. Firm fixed effects are identified through these movers. An issue with AKM estimation is the limited mobility bias (Andrews et al., 2008), which arises when the number of workers moving between firms is small. While this does not bias the estimators of firm fixed effects directly, it leads to biased variance estimates. Specifically, the variance of firm fixed effects tends to be overestimated, and the covariance between firm and individual fixed effects is underestimated, even becoming negative. To address the limited mobility bias, I adopt the firm clustering method from BLM (Bonhomme et al., 2019). Firms are grouped into clusters based on their wage distributions.[5] The clustering process solves a weighted k-means problem,

[4]To avoid multicollinearity between the linear age and year terms, the linear age term is omitted, and the age variable is normalized so that its profile is flat at 40. For a more comprehensive explanation, please see Card et al. (2018).

[5]The clustering is implemented using the R package rblm provided by Bonhomme et al. (2019). I use only the clustering method from the BLM framework, no worker types are involved.

$$\min_{k(1),\ldots,k(J),H_1,\ldots,H_K} \sum_{j=1}^{J} n_j \int \left(\hat{F}_j(w) - H_{K_j}(w)\right)^2 d\mu(w),$$

where $k(1),\ldots,k(J)$ define a partition of firms into K clusters, $\hat{F}_j(w)$ represents the empirical cumulative distribution function (CDF) of log-wages for firm j, n_j is the average number of workers in firm j, and $H_1,\ldots,H_K$ are generic CDFs. I set the number of clusters to 1,000 and use firms' wage distributions, evaluated on 20 grid points of the wage distribution. After dividing firms into 1,000 clusters, cluster fixed effects are estimated instead of firm fixed effects:

$$y_{i,t} = \boldsymbol{X_{i,t}\beta} + \theta_i + \sum_{k=1}^{1000} \phi_k \mathbf{1}(j(i,t=k) + r_{i,t} \tag{2}$$

Since I am still interested in firm wage dynamics, I assign the corresponding cluster fixed effect back to each firm, denoted as ϕ_j.

The sample used to estimate Equation 2 differs from that used in the main analysis. The worker-level restrictions remain the same, including full-time workers aged 18 to 60 with daily wages of at least 10 euros. However, to expand the set of establishments linked through worker mobility, the estimation includes both panel-case and non-panel-case firms from 2008 to 2018. The clustering procedure and the estimation of Equation 2 are carried out separately for seven rolling time windows covering $t-4$ to t (2008–2012, 2009–2013, ..., 2014–2018). In each window, the estimation is performed on the largest connected set of workers and clusters.[6]

Appendix A provides additional diagnostics for the AKM specification. First, the AKM model requires that, conditional on worker and firm effects, mobility is not systematically related to transitory wage shocks or match-specific earnings components. I therefore conduct an event-study analysis of wage dynamics around job transitions to assess the plausibility of the Conditional Random Mobility (CRM) assumption. Second, Appendix A.2 provides a complementary check of the additive structure of the AKM model by examining whether residuals display systematic patterns across worker effects and firm-specific pay premium deciles. The mean residuals are generally close to zero, although some positive deviations appear for high worker-effect observations assigned to low firm-specific pay premium deciles.

[6]The largest connected set is identified, and the estimation is conducted using the Stata command *reghdfe*.

To provide further background on the clustering approach, Appendix B.1 presents a simple illustration of the distribution of firms across clusters by firm size. The figure shows that, although the clustering procedure is data-driven, the resulting cluster assignment is not arbitrary but captures meaningful differences in firms' wage distributions that are related to observed characteristics such as firm size.

Appendix B.2 further reports information on the estimation sample used for Equation 2. Table B1 provides descriptive statistics for the mobility-extended sample used to estimate the AKM worker and firm wage components. Table B2 then reports the size of the largest connected set and the number of movers in each rolling time window. The largest connected set covers 100% of the estimation sample in all windows because connectedness is defined at the cluster level rather than at the establishment level. Grouping establishments into clusters substantially densifies worker mobility links, so that all observations satisfying the baseline sample restrictions are connected.

After estimating the worker and firm wage fixed effects[7], I refine the sample to match the main analysis by excluding non-panel-case firms. Within each rolling period, worker and firm fixed effects are constant over the five years of that period. Consequently, I retain only the final year of each rolling period. In other words, the worker and firm fixed effects for observations in year t are derived using data from the preceding five years, spanning $t-4$ to t.

3.2. Variance decomposition

Using the estimated parameters from Equation 2, the variance of log daily wages can be decomposed into components reflecting within-firm and between-firm wage variation:

$$\begin{aligned} var(y_{i,t}) &= var(\theta_i) + var(\phi_j) + var(\boldsymbol{X_{i,t}\beta}) + var(r_{i,t}) \\ &+2cov(\theta_i, \phi_j) + 2cov(\boldsymbol{X_{i,t}\beta}, \theta_i) + 2cov(\boldsymbol{X_{i,t}\beta}, \phi_j). \end{aligned} \tag{3}$$

If the time-variant term $\boldsymbol{X_{i,t}}$ is ignored, the within-firm variance simplifies to $var(\theta_i) + var(r_{i,t})$, while the between-firm variance becomes $var(\phi_j) + 2cov(\theta_i, \phi_j)$. Following Song et al. (2019), I

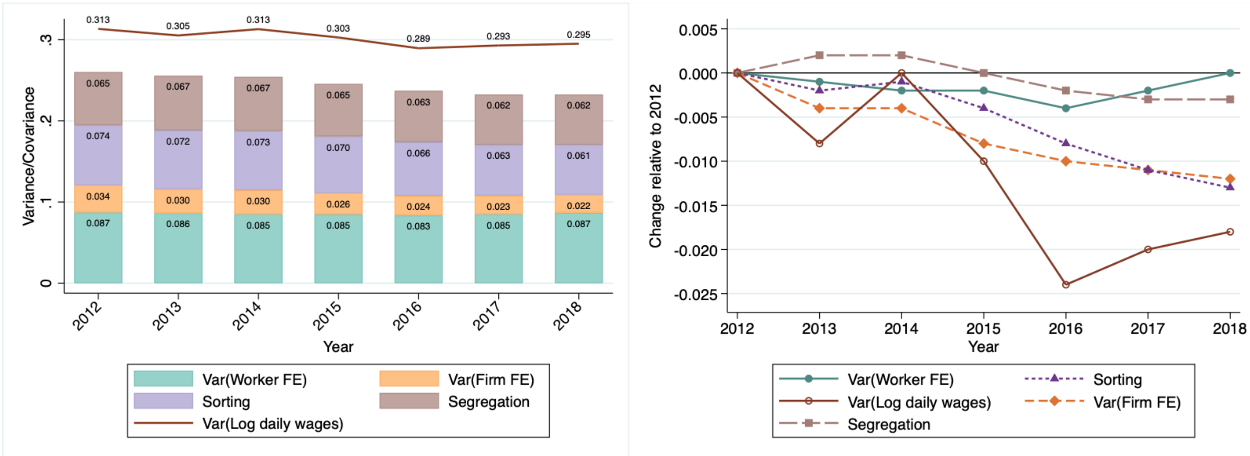
[7] For ease of presentation and for analyses that use the level of firm fixed effects, firm fixed effects are normalized in each period using the average firm effect in the hotel industry. For the variance decomposition, which relies on second moments of firm effects, this normalization does not affect the results. However, a common normalization is useful for analyses that compare or regress the level of firm fixed effects across periods, such as the spillover and heterogeneity analyses.

further decompose θ_i as $\theta_i = (\theta_i - \bar{\theta}_j) + \bar{\theta}_j$, where $\bar{\theta}_j$ represents the average θ_i within firm j. Using this decomposition, the variance of wages can be further expressed as

$$var(y_{i,t}) = \underbrace{var(\theta_i - \bar{\theta}_j) + var(r_{i,t})}_{\text{within-firm component}} + \underbrace{var(\phi_j) + var(\bar{\theta}_j) + 2cov(\bar{\theta}_j, \phi_j)}_{\text{between-firm component}},$$

where the between-firm components are weighted by the number of workers in firm j in year t. The within-firm component captures wage variations attributable to person-specific constant factors. The between-firm component represents variations across different firms and can be further decomposed into three parts. First, the variance of firm-specific pay premiums, $Var(\phi_j)$, captures differences in firms' wage-setting policies after accounting for worker composition, that is, the extent to which some firms systematically pay more or less than others for comparable workers. Second, worker segregation, $Var(\bar{\theta}_j)$, captures the dispersion of average worker person effects across firms, indicating the degree to which workers with relatively high or low person effects are concentrated in specific firms. Finally, the sorting term, $2Cov(\bar{\theta}_j, \phi_j)$, identifies the correlation between worker person effects and firm-specific pay premiums. It reflects, for instance, whether firms that employ workers with higher person effects also tend to pay systematically higher firm-specific pay premiums.

Figure 2: Variance decomposition



(a) Variance levels

(b) Change in variance relative to 2012

Notes: The left panel illustrates the variance of log daily wages over time, along with the contribution of each component to the total variance. Each component is depicted using a distinct color. The right panel presents the change of the variance of log daily wages and its components relative to 2012. The change is calculated as $(Var(y_{i,t}) - Var(y_{i,2012}))$.
Data: SIEED, 2012-2018.

3.3. Descriptive evidence on the evolution of wage inequality components

Figure 2 illustrates the evolution of the overall variance of log daily wages and the contributions of person fixed effects, firm-specific pay premiums, worker-firm sorting, and segregation to wage dispersion. Figure 2a reports the absolute value of each component, while Figure 2b shows the change in each component relative to its 2012 level.

According to Figure 2a, the variance of log daily wages declines from 0.313 in 2012 to 0.295 in 2018. In 2012, the largest component is the variance of person fixed effects, which equals about 0.088 and accounts for roughly 28% of total wage variance.[8] The second largest component is worker-firm sorting, with a value of around 0.075, corresponding to about 24% of the total variance. Segregation contributes approximately 0.066, or 21%, while the variance of firm fixed effects is the smallest component at about 0.034, corresponding to 11%. Taken together, the between-firm components, namely firm-specific pay premiums, worker-firm sorting, and segregation, sum to about 0.175 and account for 56% of total wage variance in 2012. In 2018, the between-firm components remain substantial, summing to about 0.145, or roughly 49% of total wage variance.

[8]Throughout the figure discussion, each component's share is calculated relative to the total variance of log daily wages in the same year, rather than relative to the sum of the four decomposition components.

Figure 2b shows the change in the variance of log daily wages and its components relative to 2012. The figure indicates that the most pronounced decline in overall wage dispersion occurs in 2015 and 2016. This decline is driven mainly by between-firm components, in particular by reductions in worker-firm sorting and the dispersion of firm-specific pay premiums. By contrast, the variance of worker fixed-effect remains comparatively stable over time.

These findings highlight that between-firm inequality accounts for about one half of total wage dispersion in Germany during this period. Furthermore, following the introduction of the minimum wage policy, the reduction in between-firm wage inequality is more substantial than the reduction in within-firm inequality.

4. Identification strategy

Given that the German minimum wage was implemented as a nationwide policy at the same time across the country, I use a continuous measure of minimum wage exposure: the gap variable from Dustmann et al. (2021):

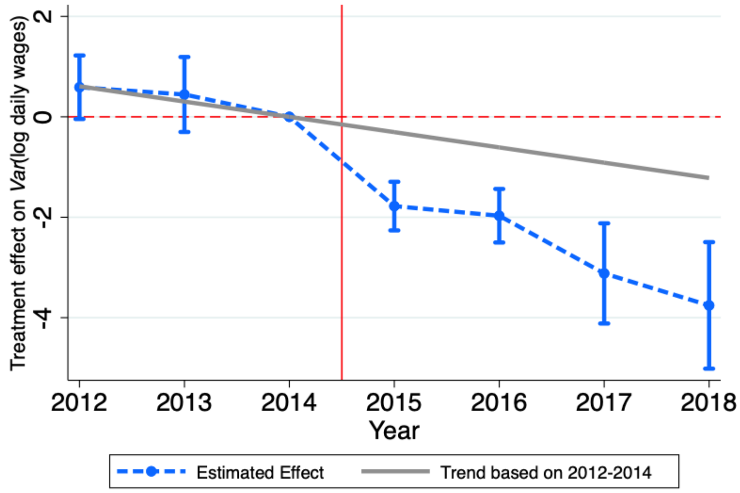
$$Gap_c = \frac{1}{4}\sum_{t=2011}^{2014} \frac{\sum_{i\in c} h_{i,t} Max\{0, 8.5 - wage_{i,t}\}}{\sum_{i\in c} h_{i,t} wage_{i,t}}$$

This variable represents the percentage increase required in the original total hourly wages (weighted by weekly working hours, $h_{i,t}$) within a region c to meet the minimum wage threshold of €8.50. Following Firpo et al. (2009), I use recentered influence functions (RIFs) to estimate the effect of minimum wage treatment on the unconditional distribution of wages. After calculating the RIFs for the relevant distributional statistics, these are incorporated into a DiD regression as dependent variables. The coefficient in a RIF regression is interpreted as the change in the unconditional distributional statistic of Y resulting from a one-unit increase in the unconditional mean of X (Rios-Avila, 2020). The distributional statistics used to measure inequality include variances and covariances, as described in Section 3.2. The RIFs are computed as follows

$$RIF(y, \sigma_Y^2) = (y - \mu_Y)^2$$

$$RIF((y_1, y_2), Cov(Y_1, Y_2)) = (y_1 - \mu_{Y1})(y_2 - \mu_{Y2}),$$

Figure 3: Non-detrended DiD results



Notes: The blue circles represent the non-detrended RIF-Difference-in-Differences (DiD) regression coefficients of $Gap_c * Year_{k,t}$, along with their 95% confidence intervals. The year 2014 is used as the reference year. The grey line indicates the estimated gap-specific trend, derived from data between 2012 and 2014. The vertical red line marks the introduction of the minimum wage policy.
Data: SIEED, 2012-2018.

where u_Y represents mean of variable Y. In this paper, the two variables used to calculate the RIF of covariance are the worker fixed effect and the firm fixed effect. Their covariance captures the sorting effect, which is measured as $2cov(\bar{\theta}_j, \phi_j)$. The corresponding RIF of the sorting effect is calculated using the expression $2(\bar{\theta}_j - \mu_{\bar{\theta}_j})(\phi_j - \mu_{\phi_j})$.

The Difference-in-Differences (DiD) estimation is specified as follows:

$$\begin{aligned} RIF(y_{i,t}, \sigma^2) = & \alpha_0 + \sum_{\tau \neq 2014} \beta_\tau \times Gap_c \times Year_{\tau,t} \\ & + \sum_{\tau \neq 2014} \delta_\tau \times Year_{\tau,t} + \gamma_c + \epsilon_{i,t}, \end{aligned} \tag{4}$$

where the years range from 2012 to 2018, with 2014 serving as the reference year. The term γ_c represents regional fixed effects, capturing county-specific time-invariant characteristics. The coefficient β_τ on the interaction term $Gap_c \times Year_{\tau,t}$ measures the treatment effects each year of the minimum wage on the unconditional variances or covariances of the components of log daily wages. Standard errors are clustered at the regional level to account for spatial correlations.

4.1. Treatment-specific trends

Figure 3 presents the DiD coefficients $\hat{\beta_\tau}$ for the interaction terms $Gap \times Year_\tau$ from Equation 4, along with their 95% confidence intervals. The dependent variable is the RIF of log daily wages. These coefficients capture the treatment effects of the minimum wage on the variance of log daily wages for each year. The vertical red line indicates the introduction of the minimum wage. The coefficients prior to the policy introduction suggest that the variance of log daily wages was already decreasing before the minimum wage policy, implying that regions more affected by the minimum wage experienced a relative reduction in wage dispersion compared to less-affected regions. This phenomenon may be attributed to mean reversion in wages. As illustrated in Figure 1a, lower wage percentiles, such as the 5th percentile, exhibited faster growth than higher percentiles during the period from 2012 to 2015. Moreover, regions with larger wage gaps tended to have a higher concentration of low-wage workers, contributing to a relative decrease in wage dispersion in these regions compared to high-wage regions.[9]

To account for the pre-policy treatment-specific trend, I use the grey line to represent the gap-specific trend, estimated using the following equation:

$$RIF(y_{i,t}, \sigma^2) = \alpha_0 + \lambda \times Gap_c \times T + \sum_{\tau \neq 2014} \delta_\tau \times Year_{\tau,t} + \gamma_c + \epsilon_{i,t}, \tag{5}$$

where only data from 2012 and 2014 are used to estimate the trend, which is then interpolated for the years 2015 to 2018. The grey line thereby illustrates the value of $\hat{\lambda} \times Gap_c \times T$.[10]

To address these pre-existing trends, I subtract the predetermined gap-specific trend from the dependent variable. The adjusted dependent variable is derived as $RIF(y_{i,t}, \sigma^2) - \hat{\lambda} \times Gap_c \times T$, which is then used as dependent variables in all DiD regressions specified in equation 4.

[9] A detailed analysis of the pre-policy gap-specific trends of other components is provided in Appendix C. .

[10] Since 2014 is the reference year, T is expressed as the relative period to 2014. Specifically, T takes the value -2 for 2012, -1 for 2013, 0 for 2014, 1 for 2015, and so on.

5. Results

5.1. Main results

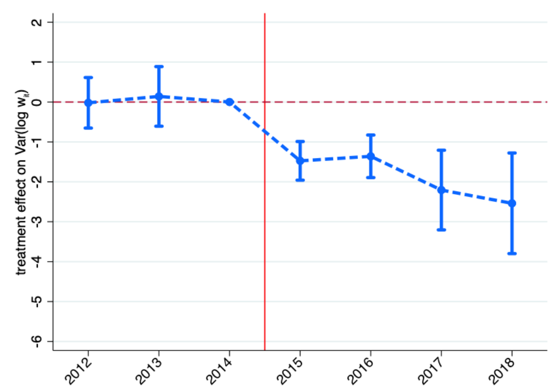
Figure 4a presents the baseline Difference-in-Differences estimates of the minimum wage's effect on the variance of log daily wages over time. The estimates indicate a clear and economically meaningful decline in wage dispersion following the 2015 introduction of the statutory minimum wage. Across the post-reform period, the estimates imply that, at the average regional minimum wage gap of 0.017, the policy reduced the variance of log daily wages by approximately 0.026 to 0.044 between 2015 and 2018. This corresponds to about 8%-14% of the 2014 pre-reform variance level of 0.313, indicating a substantial compression of overall wage inequality. This magnitude is broadly comparable to Bossler and Schank (2023), who document a reduction of 0.07 in the variance of log monthly wages, corresponding to about 7% of the unconditional variance in their sample.

Moreover, while the decline in wage dispersion is already visible in 2015, the magnitude of the estimated effect grows progressively larger through 2018, suggesting that the minimum wage generated not only direct wage-floor effects but also broader medium-run adjustments in wage-setting.

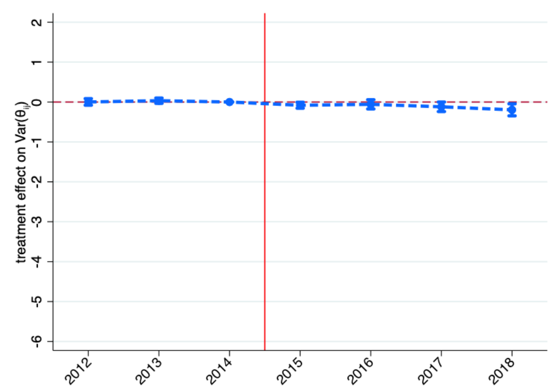
Figures 4b to 4e report the estimated effects of the minimum wage on the individual components of wage inequality. The results show that the policy has only a limited effect on within-firm inequality, measured by the dispersion of person-specific wage components. At the average regional minimum wage gap, the estimated reduction in this component is only about 0.003 in 2018. By contrast, the effects are substantially larger for between-firm components. In 2018, the estimated reductions in the dispersion of firm-specific pay premiums, worker-firm sorting, and segregation are approximately 0.009, 0.026, and 0.014, respectively.

These results indicate that the minimum wage reduced wage inequality mainly by compressing wage differences across firms rather than by reducing wage dispersion within firms. The largest contribution comes from the reduction in worker-firm sorting, measured by the covariance between person and firm fixed effects. This suggests that the minimum wage weakens the degree to which high-wage workers are concentrated in firms with high firm-specific pay premiums and low-wage workers in firms with low firm-specific pay premiums. The decline in segregation fur-

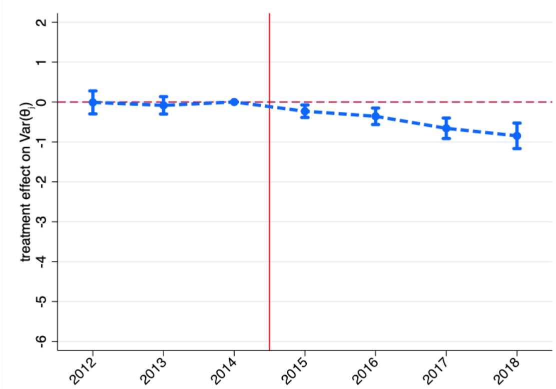
Figure 4: Minimum wage effect on Var(log real daily wages) and other variance components



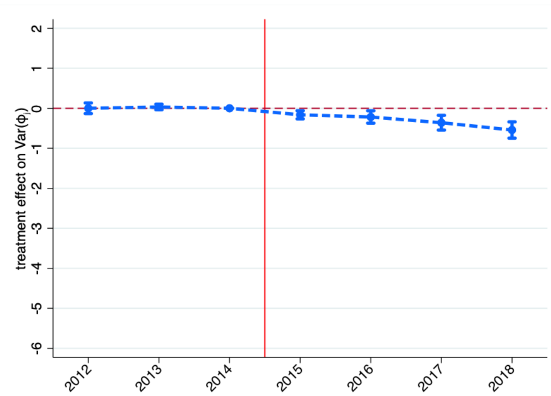
(a) $Var(log\ daily\ wages)$



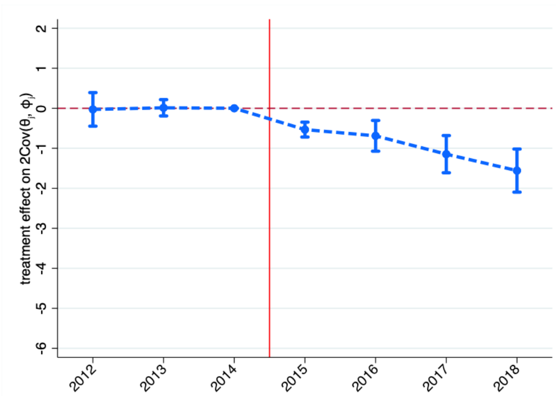
(b) $Var(\theta_i - \bar{\theta}_j)$



(c) $Var(\bar{\theta}_j)$



(d) $Var(\phi_j)$



(e) $2 * Cov(\bar{\theta}_j, \phi_j)$

Notes: The figure displays the detrended RIF-Difference-in-Differences (DiD) regression coefficients of $Gap_c * Year_{k,t}$, along with their 95% confidence intervals. The year 2014 is used as the reference year. The vertical red line denotes the introduction of the minimum wage policy. The dependent variables are indicated below each subfigure.
Data: SIEED, 2012-2018.

ther suggests that workers with similar person-specific wage components become less unevenly distributed across firms. In the Section 5.3, I quantify these effect sizes more explicitly and assess the relative contribution of each component to the overall decline in wage inequality.

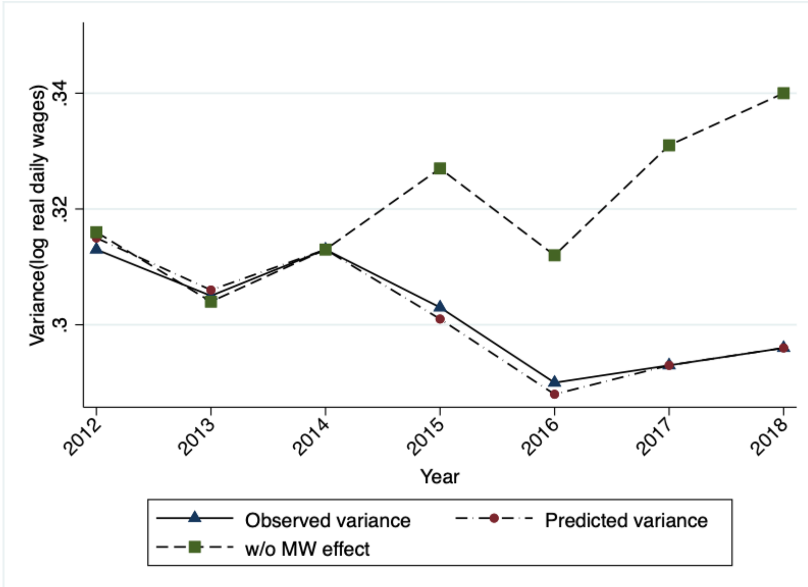
5.2. Robustness checks and heterogeneity checks

First, to assess the robustness of the DiD results, I use alternative measures of regional-level treatment intensity based on the 2014 German Structure of Earnings Survey (SES). The SES provides precise working-hour data collected directly from establishments' payroll records, enabling accurate calculation of hourly wages. Using this data, I construct both a gap variable and a bite variable, where the bite variable measures the proportion of sub-minimum-wage workers. Appendix E.1 presents results using the gap variable derived from all workers and only full-time workers, as well as the bite variable calculated for both groups. Across all specifications, the minimum wage effects on wage inequality follow a similar dynamic pattern over time, consistent with the main results. In all cases, the largest effects are observed for worker-firm sorting, reinforcing the central role of between-firm adjustments.

Second, I decrease the number of firm clusters from 1,000 to 100. The resulting DiD estimates (Appendix E.2) remain highly similar to the baseline results. Third, instead of using the hotel industry as the reference group for normalizing firm fixed effects, I use the restaurant industry, which is characterized by particularly low value added. The corresponding estimates (Appendix E.3) are likewise highly consistent with the baseline findings.

Finally, I explore regional heterogeneity by estimating the DiD models separately for Eastern and Western Germany. The estimated effects on the variance of log daily wages are not statistically significant in either region, although the point estimates are larger in Western Germany. This pattern differs from Bossler and Schank (2023), possibly because my sample excludes part-time and marginal workers, who may contribute substantially to the reduction in wage dispersion in Eastern Germany. Moreover, the overall decline in wage variance may partly reflect a reduction in between-region inequality, as mean wages increase in Eastern Germany (Appendix Figure E7b) but not significantly in Western Germany (Appendix Figure E8b). Importantly, the estimates for Western Germany still show significant reductions in segregation and worker-firm sorting, supporting

Figure 5: Estimated minimum wage effect on the variance of log real daily wages



Notes: The figure displays the variance of log daily wages over time. The blue triangles indicate the observed variance, while the red circles represent the predicted variance calculated using equation 6. The green squares depict the counterfactual variance of log daily wages in the absence of the minimum wage, as derived from equation 7.
Data: SIEED, 2012-2018.

the main finding that the minimum wage reduces wage inequality primarily through between-firm components.

5.3. Effect size

Using the Difference-in-Differences (DiD) estimation results, we can predict the magnitude of the minimum wage's effects by comparing the predicted values of wage dispersion under the policy to a counterfactual scenario in which no minimum wage implementation is assumed. Following the methodologies outlined in Bossler and Schank (2023) and Puhani (2012), the predicted variance of log daily wages (or other wage components) from the detrended DiD estimation is calculated as:

$$\begin{aligned}\hat{\sigma_{\tau 1}}^2 &= \overline{RIF(y_{ij\tau}, \sigma^2)} \text{ (with MW)} \\ &= \frac{1}{N_\tau}\sum_i^N \left(\hat{\alpha_0} + \hat{\beta_\tau} \times Gap_c + \hat{\gamma} \times Gap_c + \hat{\sigma_\tau} + \hat{\delta} \times Gap_c \times Trend_\tau\right),\end{aligned} \tag{6}$$

where $\hat{\sigma_{\tau}}_1^2$ denotes the predicted variance for each year τ under the introduction of the minimum wage. This value is computed as the average of the predicted recentered influence functions across all observations. The number of observations in year τ is N_τ. For each observation, the predicted RIF is derived by multiplying the estimated coefficients with the corresponding explanatory variables, incorporating Gap_c and its associated coefficients, with a gap-specific trend added to account for differential predetermined trends related to the wage gap.

The counterfactual variance of log daily wages in the absence of the minimum wage is defined as:

$$\begin{aligned}\hat{\sigma_{\tau}}_0^2 &= \overline{RIF(y_{ij\tau}, \sigma^2)} \text{ (without MW)} \\ &= \frac{1}{N_\tau}\sum_{i}^{N}\left(\hat{\alpha_0} + \hat{\gamma} \times Gap_c + \hat{\sigma_\tau} + \hat{\delta} \times Gap_c \times Trend_\tau\right),\end{aligned} \tag{7}$$

where $\hat{\sigma_{\tau}}_0^2$ represents the predicted variance for each year τ in the absence of the minimum wage. This is calculated similarly to $\hat{\sigma_{\tau}}_1^2$, except that the interaction term $\hat{\beta_\tau} \times Gap_c$ is set to zero to indicate that no treatment effects of the minimum wage occurred in the corresponding year. The gap-specific trend, however, remains included to account for predetermined trends associated with the wage gap, which are not influenced by the presence or absence of a minimum wage policy.

Figure 5 presents the observed variance of log daily wages (denoted by a blue triangle), the predicted variance of log daily wages$\left(\hat{\sigma_{\tau}}_1^2\right)$ (denoted by a red circle), and the counterfactual variance of log daily wages without a minimum wage $\left(\hat{\sigma_{\tau}}_0^2\right)$ (denoted by a green square). The observed and predicted variances are nearly identical each year; the slight differences arise because they coincide exactly only when using the full sample (all years) to compute their averages.

The observed variances decrease between 2015 and 2016, but a slight increase emerges from 2017 to 2018. In contrast, the counterfactual variance without any minimum wage effects increases in 2015, suggesting that the minimum wage reverses the trajectory of variance changes. Following a decline in 2016, the counterfactual variance rises significantly in 2017 and 2018, further widening the gap between the counterfactual and predicted variances.

Table 2 summarizes directly the effect sizes, where the total minimum wage effect in each year is given by the difference between the scenario with a minimum wage and the scenario without a minimum wage: $\hat{\sigma_{\tau}}_1^2 \; - \; \hat{\sigma_{\tau}}_0^2$.

Table 2: Estimated minimum wage effects on the variance of log daily wages

	2015 (1)	2016 (2)	2017 (3)	2018 (4)
Predicted variance	0.301	0.288	0.293	0.296
Counterfactual variance w/o MW	0.327	0.312	0.331	0.340
Total MW effects	-0.026	-0.024	-0.038	-0.044
- Rel. to counterfactual variance w/o MW	-0.080	-0.077	-0.115	-0.129

Notes: The first row presents the predicted values calculated using equation 6, while the second row displays the predicted values from equation 7. The third row shows the difference between these two predictions, and the fourth row presents the relative difference to the counterfactual variance in the absence of the minimum wage.
Data: SIEED, 2012-2018.

Table 3: Size of explained decrease in within- and between-firm wage inequality by year

		2015	2016	2017	2018
MW effects					
Within firm	$Var(\theta_i - \bar{\theta}_j)$	-0.001	-0.001	-0.002	-0.003
Segregation	$Var(\bar{\theta}_j)$	-0.004	-0.006	-0.011	-0.015
Firm FE	$Var(\phi_j)$	-0.003	-0.003	-0.006	-0.010
Sorting	$2Cov(\bar{\theta}_j, \phi_j)$	-0.007	-0.009	-0.014	-0.021
Share of total reduction					
Within firm	$Var(\theta_i - \bar{\theta}_j)$	3.8%	4.2%	5.3%	6.8%
Segregation	$Var(\bar{\theta}_j)$	15.4%	25.0%	28.9%	34.1%
Firm FE	$Var(\phi_j)$	11.5%	12.5%	15.8%	22.7%
Sorting	$2Cov(\bar{\theta}_j, \phi_j)$	26.9%	37.5%	36.8%	47.7%

Notes: MW effects are computed as the difference between the predicted and counterfactual variances. The shares are expressed relative to the total reduction in the variance of log daily wages in each year, as reported in row 4 of Table 2. Because the four reported components do not exhaust the full decomposition of total wage variance, the shares do not necessarily sum to 100 percent.
Data: SIEED, 2012–2018.

In 2015, the minimum wage reduces wage variance by 0.026, corresponding to an 8% reduction relative to the counterfactual scenario without the minimum wage. The effect size increases in 2017 and intensifies in 2018. In 2018, the total minimum wage effect on wage inequality is -0.044, corresponding to a 12.9% reduction in variance relative to the no-minimum-wage scenario.

Table 3 reports the reduction in four components of wage dispersion by year. The results show that the decline in wage inequality is primarily driven by between-firm margins. Among the reported components, worker-firm sorting contributes the most, followed by worker segregation and the dispersion of firm-specific pay premiums. Taken together, these three between-firm components account for a much larger share of the total reduction than the within-firm component in every post-reform year. Their combined share increases from 53.8% in 2015 to more than 100% in 2018.[11] By contrast, the within-firm component plays only a limited role, accounting for 3.8–6.8% of the total reduction. Appendix Figure D1 illustrates the evolution of the observed and predicted values for each of the four components of the variance of log daily wages.

5.4. Spillover effects

The baseline results show that the minimum wage reduces overall wage inequality. I next examine whether this effect operates only through directly exposed firms or also extends to firms that were initially not bound by the wage floor.

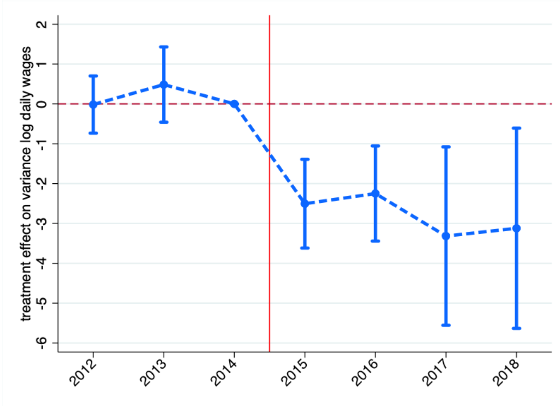
Previous studies show that minimum wage effects can extend to workers earning above the statutory threshold, although their size varies across settings. Evidence from the United States and Canada suggests that spillovers can contribute meaningfully to wage growth above the minimum and to reductions in lower-tail inequality (Gopalan et al., 2021; Fortin et al., 2021). For Germany, Bossler and Schank (2023) show that spillovers to workers paid above the minimum wage explain about half of the inequality reduction caused by the 2015 reform. However, worker-level spillovers do not necessarily identify whether the effects also operate through initially non-exposed firms, since workers earning above the minimum wage may be employed either in exposed firms or in firms that did not employ sub-minimum-wage workers before the reform.

To address this gap, this section distinguishes between exposed and non-exposed firms and quantifies the extent to which spillover effects among initially non-exposed firms contribute to the overall reduction in wage inequality.

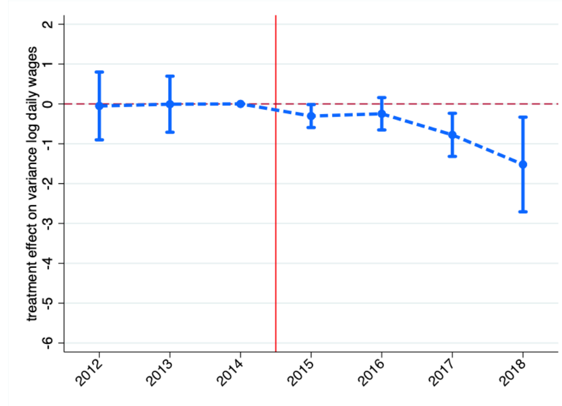
Exposed firms are those that employed at least one sub-minimum wage full-time worker prior to the policy, while non-exposed firms did not. Specifically, exposed firms are defined as those employing at least one worker whose daily wage fell below the minimum wage threshold of 47.4

[11] Since the table reports selected components rather than an exhaustive variance decomposition, these shares should be interpreted as indicating the relative importance of the main channels, not as additive shares that mechanically sum to 100%.

Figure 6: Minimum wage effect on the variance of log wages for exposed and non-exposed firms



(a) Exposed firms



(b) Non-exposed firms

Notes: The figure displays the detrended RIF-Difference-in-Differences (DiD) regression coefficients of $Gap_c * Year_{k,t}$, along with their 95% confidence intervals. The year 2014 is used as the reference year. The vertical red line denotes the introduction of the minimum wage policy. The dependent variables are indicated below each subfigure.
Data: SIEED, 2012-2018.

Euros in 2014.[12] Table D1 displays the descriptive characteristics of the exposed and non-exposed firms separately.

Figure 6a shows the estimated effect of the minimum wage on the variance of log wages among exposed firms. Over the post-reform period from 2015 to 2018, the DiD coefficients range from -2.200 to -3.266. Evaluated at the average regional minimum wage gap of 0.017, these estimates correspond to a reduction in the variance of log wages among exposed firms of approximately 0.037 to 0.056. Figure 6b reports the corresponding estimates for non-exposed firms. The coefficients are smaller in magnitude, ranging from -0.305 to -1.482 over the same period. At the average regional minimum wage gap, this implies a reduction in the variance of log wages among non-exposed firms of about 0.005 to 0.025.

To estimate the overall effect size of the minimum wage while accounting for heterogeneous impacts on exposed and non-exposed firms, I decompose the total variance of log daily wages for a given year τ into within-group and between-group components. For notational simplicity, the time subscript τ is omitted throughout this subsection. The predicted overall variance is expressed as:

[12]The minimum wage threshold for daily wages is calculated as €8.50 multiplied by the average weekly working hours of 39, then divided by 7.

$$\hat{\sigma}^2_{\text{overall}} = \underbrace{\sum_g p_g \hat{\sigma}^2_g}_{\text{within-group variance}} + \underbrace{\sum_g p_g (\hat{\mu}_g - \hat{\mu})^2}_{\text{between-group variance}}, \tag{8}$$

where $g \in \{E, N\}$ indexes exposed and non-exposed firms, respectively.[13] For each group g, p_g denotes the worker share, $\hat{\mu}_g$ is the group-specific predicted mean of log daily wages, and $\hat{\sigma}^2_g$ is the group-specific predicted variance. The overall mean is given by

$$\hat{\mu} = \sum_g p_g \hat{\mu}_g.$$

The predicted overall variance with the minimum wage effect is obtained by setting $s = 1$:

$$\hat{\sigma}^2_{1,\text{overall}} = \underbrace{\sum_g p_g \hat{\sigma}^2_{1,g}}_{\text{within-group variance}} + \underbrace{\sum_g p_g (\hat{\mu}_{1,g} - \hat{\mu}_1)^2}_{\text{between-group variance}}, \tag{9}$$

The counterfactual overall variance without any minimum wage effect is obtained by setting $s = 0$:

$$\hat{\sigma}^2_{0,\text{overall}} = \sum_g p_g \hat{\sigma}^2_{0,g} + \sum_g p_g (\hat{\mu}_{0,g} - \hat{\mu}_0)^2, \tag{10}$$

Calculating $\hat{\sigma}^2_{1,\text{overall}}$ and $\hat{\sigma}^2_{0,\text{overall}}$ requires the predicted and counterfactual group-specific variances and mean log wages for exposed and non-exposed firms. I obtain the group-specific mean

[13] For covariance components, I use the corresponding law of total covariance. For two variables X and Y, the overall covariance can be decomposed as

$$\widehat{\text{Cov}}(X, Y) = \sum_g p_g \widehat{\text{Cov}}(X, Y \mid g) + \sum_g p_g (\hat{\mu}_{X,g} - \hat{\mu}_X)(\hat{\mu}_{Y,g} - \hat{\mu}_Y),$$

where $g \in \{E, N\}$ indexes exposed and non-exposed firms, respectively. The first term captures the weighted within-group covariance, while the second term captures the between-group covariance arising from differences in group-specific means.

log wages from additional DiD regressions with log daily wages as the dependent variable. The total minimum wage effect on wage variance is calculated as

$$\hat{\sigma}^2_{1,\text{overall}} - \hat{\sigma}^2_{0,\text{overall}}.$$

To isolate spillover effects on non-exposed firms, I construct an additional counterfactual scenario in which exposed firms are allowed to respond to the minimum wage, while non-exposed firms are held at their no-minimum-wage counterfactual values. The overall mean in this no-spillover scenario is

$$\hat{\mu}_{NS} = p_E \hat{\mu}_{1,E} + p_N \hat{\mu}_{0,N}.$$

The corresponding overall variance is

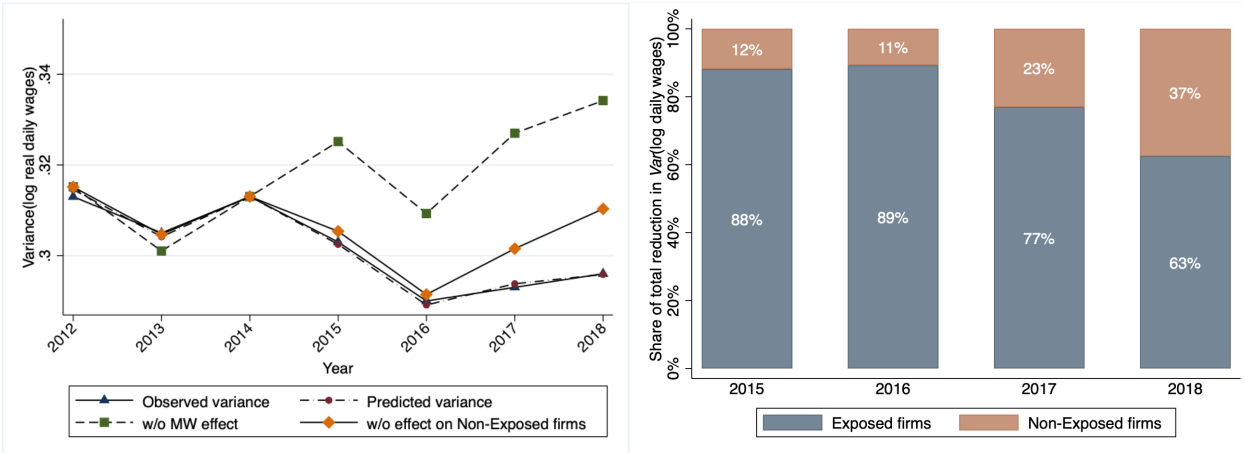
$$\hat{\sigma}^2_{NS} = \underbrace{p_E \hat{\sigma}^2_{1,E} + p_N \hat{\sigma}^2_{0,N}}_{\text{within-group variance}} + \underbrace{p_E (\hat{\mu}_{1,E} - \hat{\mu}_{NS})^2 + p_N (\hat{\mu}_{0,N} - \hat{\mu}_{NS})^2}_{\text{between-group variance}}. \tag{11}$$

The spillover effect is measured as the additional reduction in overall wage variance attributable to changes among non-exposed firms:

$$\hat{\sigma}^2_{1,\text{overall}} - \hat{\sigma}^2_{NS}.$$

Figure 7a compares the observed variance of log daily wages with three predicted series: the variance under the minimum wage, the counterfactual variance in the absence of the minimum wage, and the counterfactual variance excluding spillover effects on non-exposed firms. The observed and predicted variances closely align with those in Figure 5. In the immediate post-reform years, the no-spillover counterfactual remains close to the full minimum-wage prediction, indicating that the reduction in wage inequality is initially driven mainly by directly exposed firms. From 2017 onward, however, the gap between these two series widens, suggesting that spillover effects among non-exposed firms become increasingly important over time. This dynamic pattern indicates that the minimum wage's inequality-reducing effect gradually extends beyond directly exposed firms and increasingly affects broader between-firm wage dispersion.

Figure 7: Estimated minimum wage effects on the variance of log wages: spillovers



(a) Observed and counterfactual variance of log daily wages

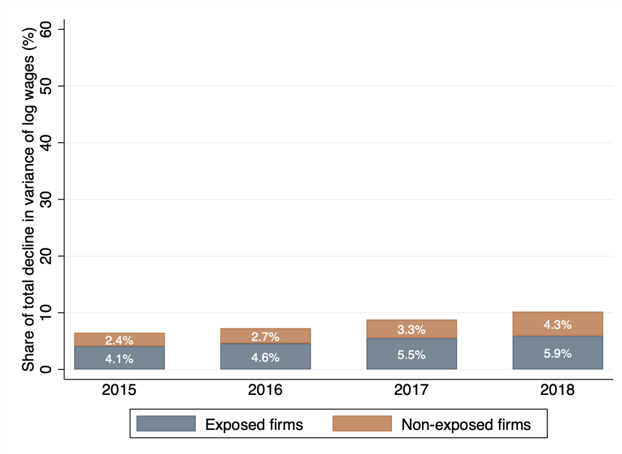
(b) Contribution of exposed and non-exposed firms to the reduction in wage inequality

Notes: Figure 7a shows the variance of log daily wages over time, including the observed variance, the predicted variance, the counterfactual variance in the absence of the minimum wage, and the counterfactual variance without spillover effects on non-exposed firms. Figure 7b reports the contributions of exposed and non-exposed firms to the total reduction in the variance of log daily wages. The share attributed to non-exposed firms is calculated as the spillover effect divided by the total reduction, while the remaining share is attributed to exposed firms.
Data: SIEED, 2012-2018.

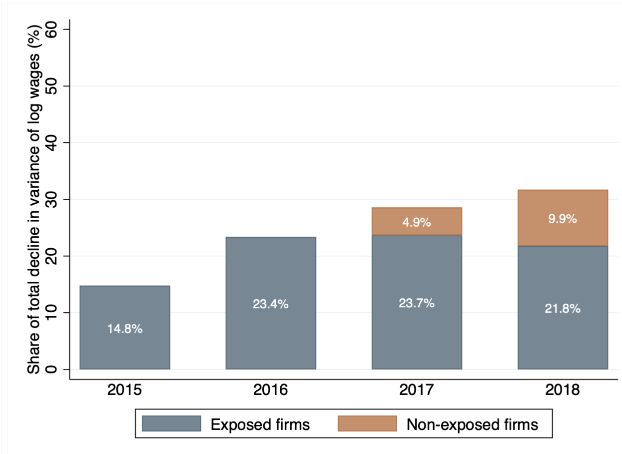
Figure 7b further demonstrates that the contribution of non-exposed firms to the total reduction in wage inequality increases markedly over time. In the immediate post-reform period, spillover effects account for only about 12–13% of the total decline in wage variance, indicating that inequality compression is initially concentrated among directly exposed firms. By 2018, however, spillover effects account for 37.7% of the total reduction, implying that a growing share of the minimum wage's inequality-reducing effect operates through firms not directly bound by the policy.

Figure 8 decomposes the reduction in the variance of log daily wages into contributions from different variance components and further separates each component into shares attributable to exposed firms and non-exposed firms (spillover effects). Consistent with Section 5.3, the overall decline in wage inequality is driven primarily by reductions in between-firm inequality, while within-firm inequality contributes only modestly. Across components, spillover effects are also more pronounced for between-firm components. Spillover effects on the dispersion of firm-specific pay premiums emerge relatively early, beginning in 2015, whereas spillover effects on worker segregation become more pronounced only after 2017. One possible interpretation is that changes

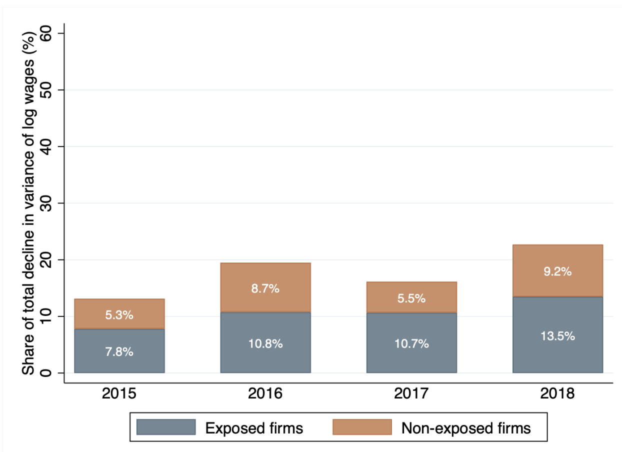
Figure 8: Contributions of exposed firms and spillover effects to the total decline in the variance of log wages



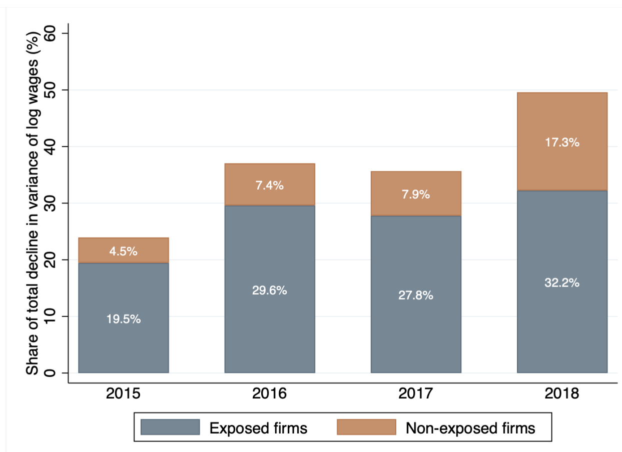
(a) $Var(\theta_i - \bar{\theta}_j)$



(b) $Var(\bar{\theta}_j)$



(c) $Var(\phi_j)$



(d) $2 * Cov(\bar{\theta}_j, \phi_j)$

Notes: The figure decomposes changes in selected wage-variance components into contributions from exposed firms and non-exposed firms. The contribution of non-exposed firms captures spillover effects. Each panel corresponds to one component of the wage-variance decomposition. Shares are expressed relative to the total reduction in the variance of log daily wages in the corresponding year, as displayed in Figure 7a.
Data: SIEED, 2012-2018.

in worker composition across firms adjust more gradually than firm pay structures. However, this interpretation should be viewed as suggestive, as the analysis does not directly identify the underlying adjustment mechanism.

6. Discussion

The results indicate that the minimum wage reduces wage inequality mainly through between-firm channels. While within-firm dispersion also declines, its contribution is small compared with the reductions in worker segregation, worker-firm sorting, and the dispersion of firm-specific pay premiums. This section discusses plausible explanations for these findings. However, the analysis does not directly observe the underlying mobility decisions, changes in skill composition, or hiring margins. The mechanisms discussed below should therefore be interpreted as suggestive explanations rather than directly identified causal channels.

Firm-specific pay premiums.—One possible explanation for the decline in the variance of firm-specific pay premiums is that the minimum wage narrows productivity differences across firms. More productive firms typically pay higher firm-specific pay premiums, and previous research suggests that minimum wages may increase productivity among treated firms while accelerating the exit of the least productive firms (Bossler et al., 2020; Dustmann et al., 2021; Haelbig et al., 2023). A second, not mutually exclusive, explanation is that the policy constrains firms' wage-setting power and thereby weakens the pass-through from productivity to wages. Under this interpretation, firms may remain heterogeneous in productivity, but their ability to translate that heterogeneity into wage differences becomes more limited after the reform. More broadly, these findings suggest caution when interpreting AKM firm fixed effects purely as measures of firm productivity, since labor market policies may alter not only firm productivity itself but also the extent to which productivity differences are reflected in firm-specific pay premiums.

Worker-firm sorting and segregation.—The reductions in worker segregation and worker-firm sorting suggest that the minimum wage also affects how workers are allocated across firms. This interpretation is consistent with Dustmann et al. (2021), who show that minimum wages can reallocate low-wage workers toward better-paying firms, and with Butschek (2022), who finds that affected firms may respond by upgrading their hiring standards. In the context of this study, these mechanisms imply that lower-wage workers may gain greater access to higher-paying firms and broader job opportunities, while previously low-paying firms may also have incentive to improve the composition of their workforce. Both mechanisms tend to weaken assortative matching.

Compared with worker-firm sorting, segregation captures the extent to which similar worker types are clustered in separate firms. A decline in segregation therefore suggests that workers with different fixed effects become more evenly distributed across firms, weakening labor market stratification. The reallocation mechanisms discussed above could also contribute to this decline in segregation. Moreover, lower segregation may improve learning and knowledge diffusion within firms. When workers with different skill levels are more evenly mixed, lower-productivity workers may learn from more productive peers and be exposed to better workplace practices. In this sense, reduced segregation may contribute to a more integrated and dynamic labor market.

Mechanical reduction.—A key caveat is that part of the decline in segregation and worker-firm sorting may arise mechanically from the compression of worker effects. As emphasized by Song et al. (2019), a reduction in the dispersion of θ_i[14] can lower both $Var(\bar{\theta}_j)$ and $2 \cdot Cov(\bar{\theta}_j, \phi_j)$ even if the assignment of workers to firms does not change. Let s_i denote individual i's skill level, and let r_0 and r_1 denote the returns to skill without and with the minimum wage. Using the 2018 effect size, suppose that the policy changes the returns to skill while leaving the underlying skill distribution unchanged. Then:

$$\left(\frac{r_1}{r_0}\right)^2 = \frac{Var_{\text{with MW}}(\theta_i)}{Var_{\text{w/o MW}}(\theta_i)} = 0.89$$

Since $\bar{\theta}_j = \frac{1}{N_j} \sum_{i|i \in j} \theta_i = r \times \frac{1}{N_j} \sum_{i|i \in j} s_i$, this mechanical channel also implies:

$$\left(\frac{r_1}{r_0}\right)^2 = \frac{Var_{\text{with MW}}(\bar{\theta}_j)}{Var_{\text{w/o MW}}(\bar{\theta}_j)} = 0.89$$

$$\frac{r_1}{r_0} = \frac{2 \cdot Cov_{\text{with MW}}(\bar{\theta}_j, \phi_j)}{2 \cdot Cov_{\text{w/o MW}}(\bar{\theta}_j, \phi_j)} = 0.94$$

The results in Section 5.3 imply a 19% decrease in $Var(\bar{\theta}_j)$ (calculated as $1 - \frac{0.062}{0.077}$) and a 25% decrease in $2 \cdot Cov(\bar{\theta}_j, \phi_j)$ (calculated as $1 - \frac{0.062}{0.083}$). After accounting for the mechanical component,

[14]The regression results and the corresponding predicted effect sizes for θ_i are presented in Appendix Figure D3.

about 42.1% of the reduction in segregation and 76% of the reduction in worker-firm sorting remain unexplained by pure wage compression alone. This calculation does not prove that worker mobility is the only remaining force, but it does suggest that the decline in between-firm worker composition differences is unlikely to be entirely mechanical.

Spillover effects.—The presence of spillover effects among initially non-exposed firms suggests that the minimum wage influences wage-setting beyond firms directly bound by the statutory threshold. One plausible mechanism is the adjustment of external wage ladders and outside options. As wages rise in directly affected low-wage firms, workers' reservation wages may increase, strengthening labor market competition. Firms that already paid above the minimum wage may therefore adjust wages to preserve relative pay differentials, retain workers, or remain competitive in hiring.

Spillover effects may also reflect broader competitive adjustments if minimum wages improve productivity among directly exposed firms. To the extent that treated low-wage firms respond through greater efficiency, lower turnover, or upgraded hiring standards, they may become more competitive than before despite higher labor costs. This could alter competitive pressures faced by non-exposed firms, indirectly influencing their wage-setting or employment strategies.

Limitations.—A key limitation is that the paper does not fully disentangle the mechanisms behind the decline in between-firm inequality. The reductions in worker-firm sorting, segregation, and the dispersion of firm-specific pay premiums may reflect several overlapping channels, including worker reallocation, changes in hiring standards, productivity adjustments, and shifts in firms' wage-setting behavior. Because each mechanism could constitute a separate research question, this paper focuses on documenting the overall structure and magnitude of inequality reduction. The findings should therefore be interpreted as reduced-form evidence, while the relative importance of specific mechanisms remains a promising avenue for future research.

A second limitation is the focus on full-time workers. This restriction improves comparability in wage measurement and reduces concerns related to heterogeneous working hours, but it limits the external validity of the results. Part-time and marginal workers were likely more directly affected by the minimum wage, especially in low-wage sectors and Eastern Germany. The estimates may therefore understate the broader distributional effects of the reform on the full labor market.

7. Conclusion

This paper studies how the introduction of the German minimum wage in 2015 affected wage inequality within and between firms. Using linked employer-employee administrative data and a Difference-in-Differences framework applied to recentered influence functions of wage-variance components, I show that the minimum wage reduced the overall variance of log daily wages among full-time workers by about 8% to 12.6%.

The main finding is that this decline was driven primarily by between-firm rather than within-firm compression. Most of the reduction in wage inequality is accounted for by declines in worker-firm sorting, worker segregation, and the dispersion of firm-specific pay premiums, while the contribution of within-firm inequality is comparatively small. In addition, the results show that the effects of the policy were not confined to directly exposed firms. Spillover effects among non-exposed firms account for an economically meaningful share of the total decline in wage inequality, and their importance increases over time.

These findings contribute to the literature by showing that minimum wage policy can reshape firm-driven wage inequality, not merely raise pay at the bottom of the individual wage distribution. More broadly, the results suggest that labor market institutions can influence inequality through changes in the structure of pay differences across firms. This implies that the distributive consequences of minimum wages should be evaluated not only in terms of worker-level wage gains, but also in terms of how the policy compresses wage differentials between firms and affects the broader organization of the labor market.

At the same time, the paper leaves several questions open. In particular, the present analysis cannot fully disentangle whether the decline in between-firm inequality operates mainly through changes in productivity, wage-setting power, hiring standards, or worker mobility. Distinguishing more sharply between these channels would be a useful direction for future research. More generally, the results suggest that understanding the interaction between labor market institutions and firm heterogeneity is central to explaining how policy shapes the evolution of wage inequality.

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Online Appendix for

Unpacking Wage Inequality: Minimum Wage Effects on Within- and Between-Firm Disparities

by

Ying Liang

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A. AKM model diagnostics

A.1. Conditional random mobility assumption

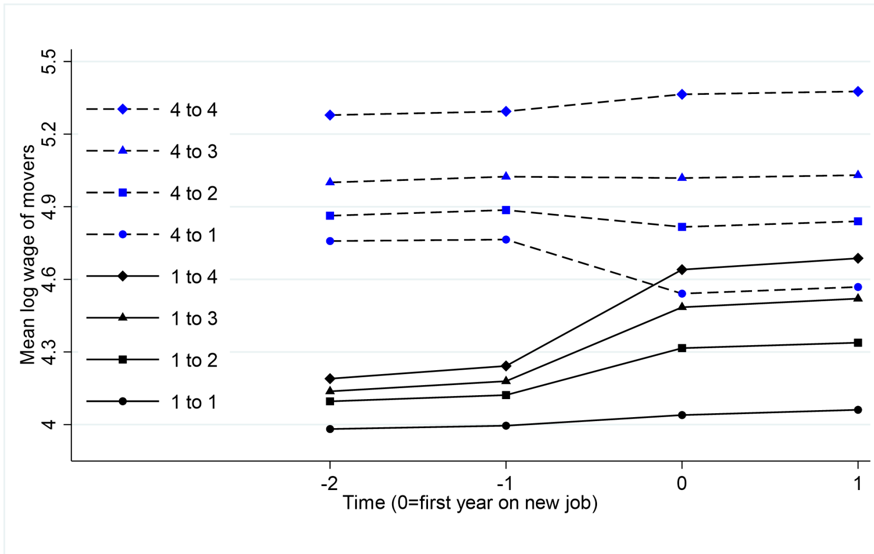
An underlying assumption of the AKM model is conditional random mobility, meaning that, conditional on worker and firm fixed effects, job moves occur randomly and are not systematically correlated with factors such as firm-worker-specific match effects. Workers who change jobs should experience wage changes that reflect the difference in firm-specific pay premiums between their origin and destination firms.

Following Card et al. (2013), I conduct an event study analysis to examine the effect of job changes on wages. Firms are categorized into quartiles based on the average pay of coworkers, and switchers are classified according to their mobility patterns. For instance, one pattern includes workers moving from a firm in the first quartile to another firm also in the first quartile, while other patterns represent different combinations of origin and destination firms across quartiles.

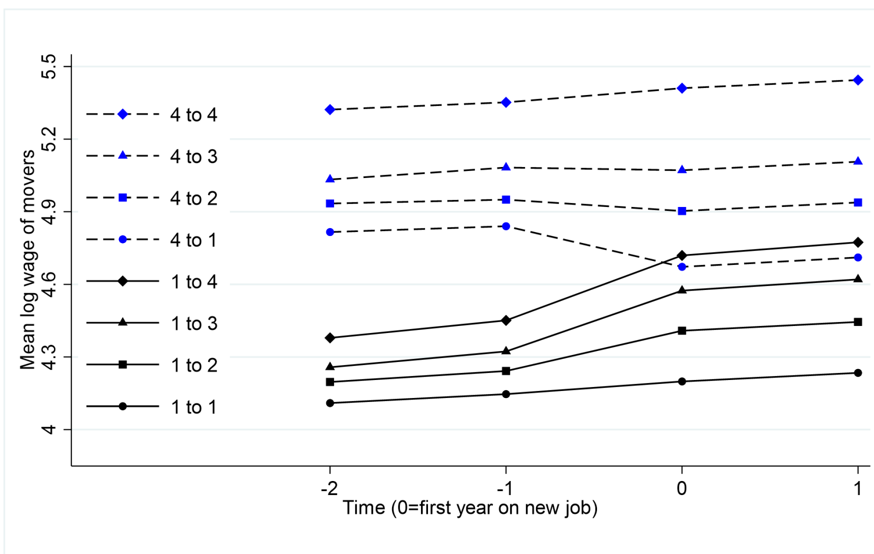
Figures A1a and A1b illustrate the mean log wages of movers across different mobility patterns, focusing on transitions between the first and fourth quartile firms. The sample includes only movers observed for at least two consecutive years before and after job changes, with the first year at the new job defined as time $t = 0$.

In both figures, the mean wages of movers remain largely unchanged when transitioning between firms within the same quartile, such as from the first to the first or from the fourth to the fourth quartile. Moreover, symmetric wage changes are observed: wages increase when moving from the first to the fourth quartile and decrease when moving from the fourth to the first. These findings suggest that wage changes associated with job transitions are not systematically correlated with firm-worker-specific matching factors and that firm-specific pay premiums closely approximate the wage differences experienced by job switchers. Overall, the evidence indicates that the CRM assumption is not substantially violated.

Appendix Figure A1: Event study of mean wages of job switchers



(a) Period: 2008-2012

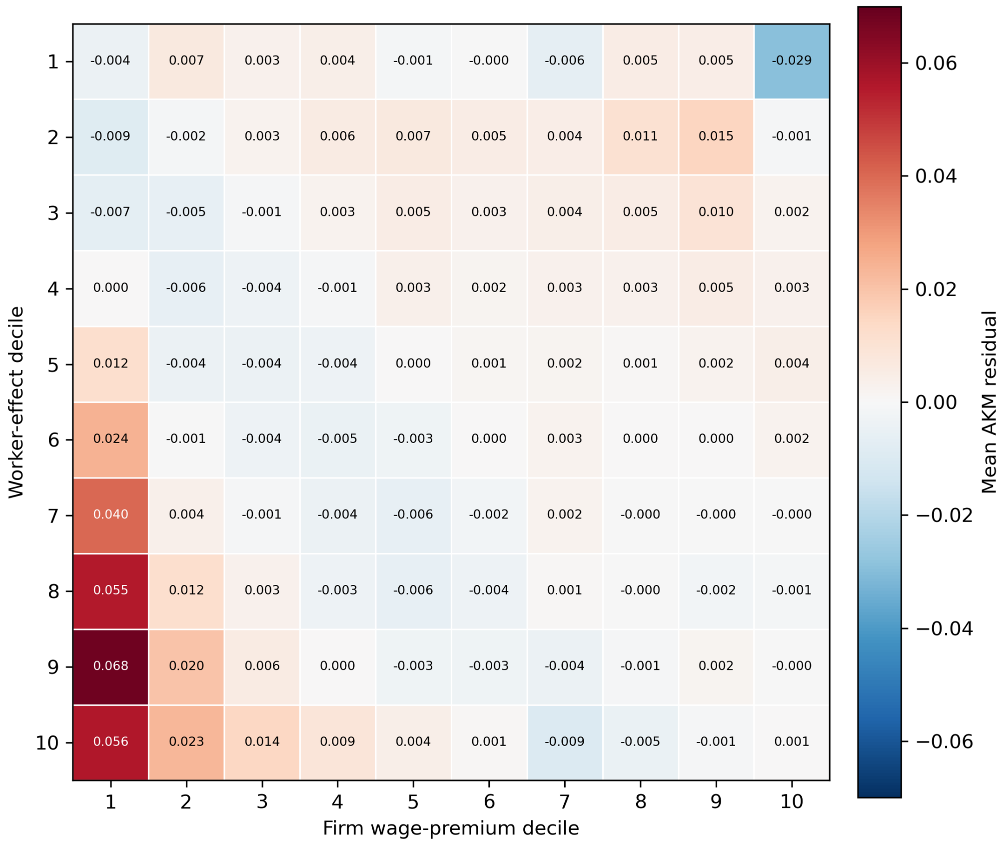


(b) Period: 2014-2018

Notes: The figures illustrate the mean log daily wages of workers who change jobs at time $t = 0$. Workers are classified based on their mobility patterns, defined by transitions between firms in different coworker wage quartiles. These quartiles are calculated separately for $t - 1$ and $t = 0$, weighted by the number of workers. The number of workers in each mobility category ranges from 607 to 26,480.
Data: SIEED, 2012-2018.

A.2. Residual patterns by worker effects and firm-specific pay premium deciles

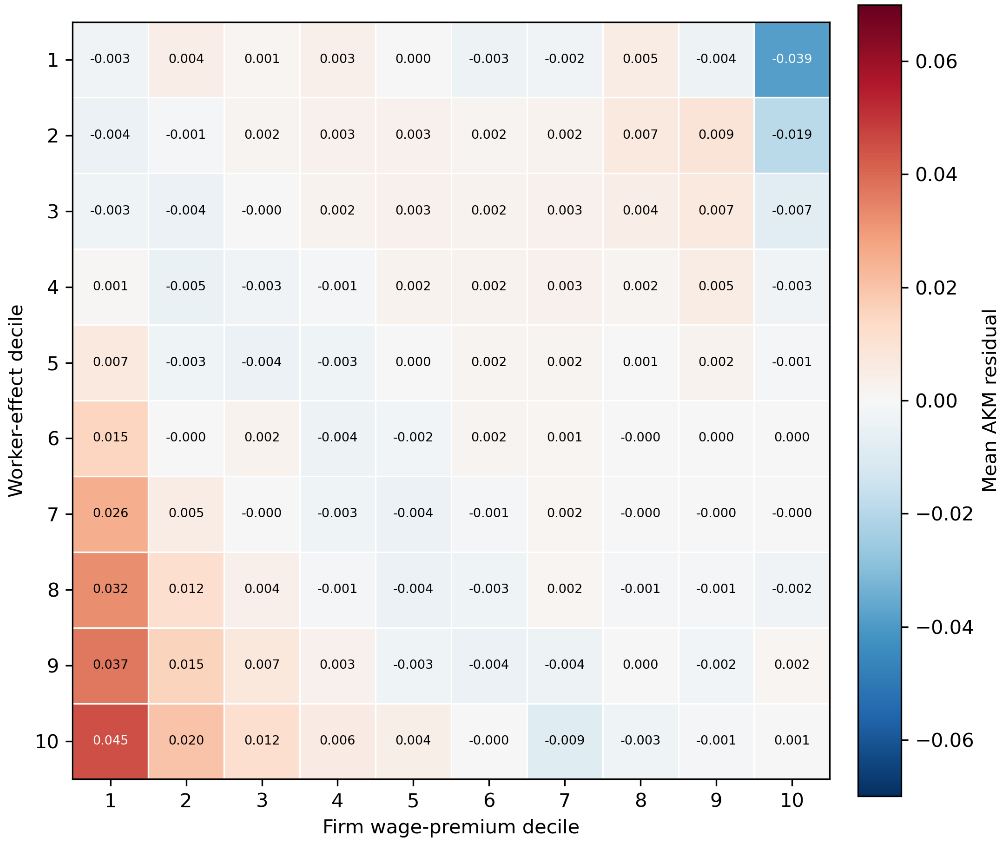
Appendix Figure A2: Mean AKM residuals by worker effects and firm-specific pay premium deciles, 2008–2012



Notes: The figure reports mean AKM residuals within cells defined by worker-effect deciles and firm-specific pay premium deciles. Deciles are constructed using the worker-year observation-level distribution. Decile 1 denotes the lowest estimated effect and decile 10 denotes the highest estimated effect.
Data: SIEED, 2008–2012.

As an additional diagnostic for the additive AKM specification, I examine whether the estimated residuals display systematic patterns across different combinations of worker and firm-specific pay premium groups. Following the diagnostic exercise in Card et al. (2013), I divide estimated worker fixed effects and firm-specific pay premiums into deciles within each rolling estimation window. I then compute the mean AKM residual in each of the 100 worker-effect-decile $\times$ firm-specific-pay-premium-decile cells.

Appendix Figure A3: Mean AKM residuals by worker effects and firm-specific pay premium deciles, 2014–2018



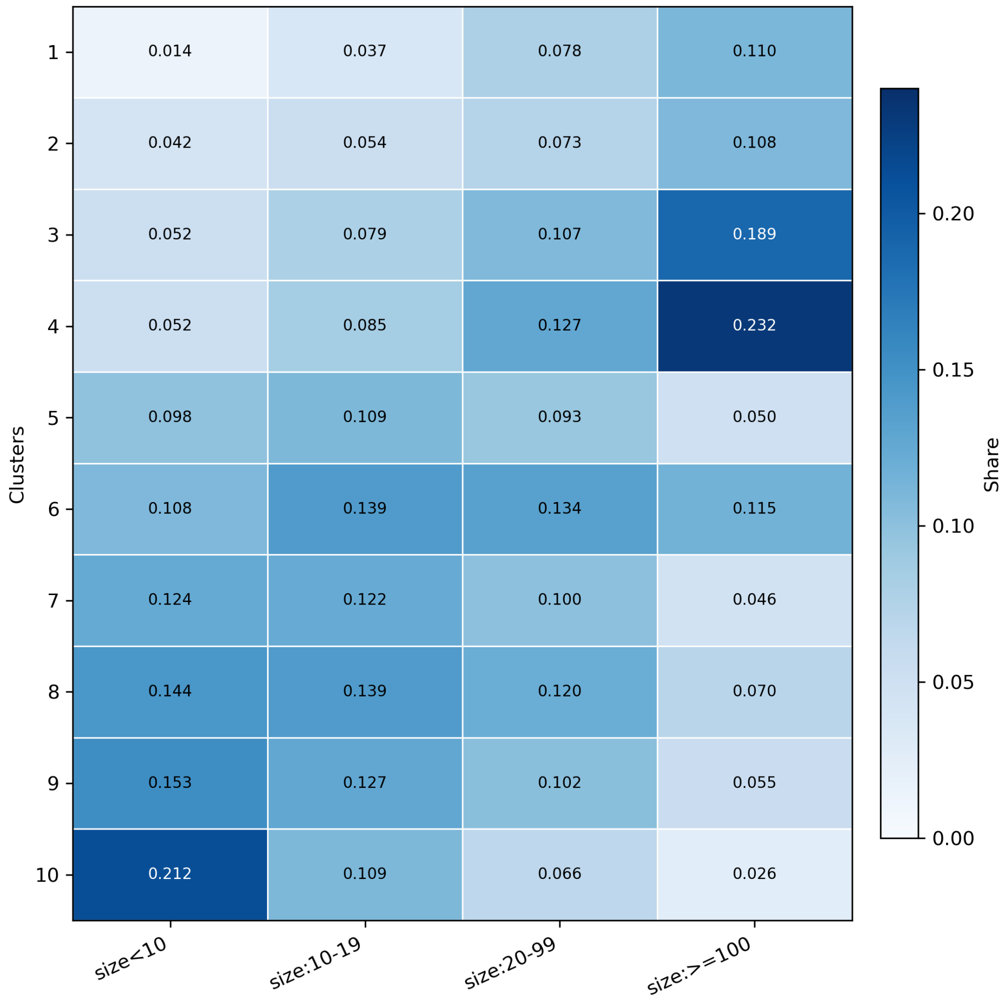
Notes: The figure reports mean AKM residuals within cells defined by worker-effect deciles and firm-specific pay premium deciles. Deciles are constructed using the worker-year observation-level distribution. Decile 1 denotes the lowest estimated effect and decile 10 denotes the highest estimated effect.
Data: SIEED, 2014–2018.

Appendix Figures A2 and A3 report the results for the 2008–2012 and 2014–2018 windows. Most cell-level mean residuals are close to zero, suggesting that the additive worker and firm-specific pay premium specification captures the main systematic structure of wages. However, the figure also reveals positive residuals among observations with high worker effects and low firm-specific pay premiums. This pattern indicates that high worker-effect individuals employed in firms with low firm-specific pay premiums earn somewhat more than predicted by a purely additive specification. Overall, the residual heatmaps suggest that the additive AKM specification provides a reasonable approximation to the wage structure, although it underpredicts wages for some high worker-effect observations in firms with low firm-specific pay premiums.

B. Firm clustering and mobility

B.1. Clusters and firm size

Appendix Figure B1: Distribution of firms across ten clusters by size group, 2009–2013



Notes: The figure illustrates the distribution of firms across ten clusters within each firm size category. For ease of illustration, the number of clusters is set to ten.
Data: SIEED, 2009-2013.

Appendix Figure B1 provides an intuitive characterization of the firm clusters. For ease of illustration, the figure uses 10 clusters rather than the 1,000 clusters used in the main analysis. It shows how firms in each size category are distributed across the 10 clusters, providing a simplified visual summary of the relationship between firm size and cluster assignment.

Although the weighted k-means procedure is data-driven and the resulting cluster assignment is not directly interpretable from observable firm characteristics, Figure B1 shows that the pattern is clearly not arbitrary. Firms of different sizes are distributed unevenly across clusters: smaller firms are more likely to be assigned to clusters 5 to 10, whereas larger firms are disproportionately concentrated in clusters 1 to 4. Since firm size is closely related to wage-setting and the wage distribution, this systematic relationship suggests that the clustering captures economically meaningful firm heterogeneity.

B.2. AKM estimation sample and connectedness

Appendix Table B1 reports summary statistics for the AKM estimation sample. Unlike the main analysis sample, which is restricted to panel-case establishments, this sample also includes non-panel-case establishments observed through workers' employment histories. This expansion substantially increases the number of workers and establishments used to estimate the worker and firm wage components. It is consistent with the structure of the SIEED, which is based on a 1.5% random sample of establishments and then extended to the full employment histories of workers linked to these establishments. The underlying SIEED is very large, covering 5,567,883 individuals and 5,248,850 establishments (Schmidtlein et al., 2020). Against this background, the numbers of unique workers and establishments reported in Appendix Table B1 are within a plausible range.

Compared with the main analysis sample in Table 1, the AKM estimation sample remains broadly similar along key observable dimensions. The female share, the share of workplaces in Eastern Germany, and mean age are very close across the two samples. The AKM estimation sample has lower average tenure and lower daily wages, consistent with the inclusion of additional employment spells outside panel-case establishments, such as jobs held before or after employment in a panel-case establishment. Since these spells are observed through workers' mobility links, they may include more short-tenure employment relationships than the main panel-case sample. Overall, the expanded sample provides more mobility information for AKM estimation while not differing sharply from the main analysis sample in observable composition.

Appendix Table B1 reports the distribution of clusters by the number of movers across rolling five-year windows in the sample used to estimate the AKM model with firm clustering. In each window, the largest connected set covers the entire estimation sample after the baseline sample restrictions are imposed. This is mainly because connectedness is defined at the cluster level rather than the establishment level. Once establishments are grouped into clusters, mobility links become much denser, making observations more likely to belong to the same connected set.

The table also shows that the clusters are large in terms of worker mobility. Most clusters contain between 101 and 2,000 movers, while the average number of movers per cluster ranges from about 1,113 to 1,750 across time windows. Taken together, these patterns indicate that the clustering approach delivers a broadly connected estimation sample with substantial mobility within clusters.

Appendix Table B1: Summary statistics for the AKM estimation sample, 2008–2018

Variable	Mean
Share of female workers	0.314
Workplace in Eastern Germany	0.177
Mean age	42.491
Mean tenure	6.464
Daily wage	116.409
SD of daily wage	(90.943)
Log real daily wage	4.582
SD of log real daily wage	(0.564)
Mean firm size, full-time workers	613.081
Firm size < 10	0.191
Firm size: 10–99	0.390
Firm size: ≥ 100	0.420
Observations	
Number of worker-year observations	17,290,616
Number of workers	2,604,362
Number of establishments	1,066,647

Notes: The table reports worker-year weighted summary statistics for the AKM estimation sample. The sample includes panel-case establishments and additional non-panel-case establishments observed through workers' employment histories.
Data: SIEED, 2008–2018.

Appendix Table B2: Distribution of clusters by number of movers across time windows

	2008–12	2009–13	2010–14	2011–15	2012–16	2013–17	2014–18
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
0–100 movers	0	0	0	0	0	0	0
101–500 movers	180	159	189	230	269	317	338
501–1,000 movers	325	331	337	338	349	349	361
1,001–2,000 movers	318	328	304	286	269	239	222
2,001–3,000 movers	100	103	93	79	56	46	40
More than 3,000 movers	77	79	77	67	57	49	39
Number of clusters	1,000	1,000	1,000	1,000	1,000	1,000	1,000
Average movers per cluster	1,687	1,750	1,659	1,507	1,337	1,196	1,113
Unique workers	2,348,030	2,348,585	2,304,740	2,219,835	2,167,993	2,125,620	2,049,890
Unique establishments	753,375	811,322	738,187	652,965	582,921	525,034	469,280
Share of largest connected set	100%	100%	100%	100%	100%	100%	100%

Notes: The table reports the distribution of clusters by the number of movers in each five-year time window, along with the corresponding sample size. A mover is defined as a worker observed in more than one distinct cluster within a given five-year window. The table is based on the largest connected set. Since the clusters are sufficiently large, no workers or establishments are excluded for lack of links to other clusters. The sample is not restricted to panel-case establishments.
Data: SIEED, 2008-2018.

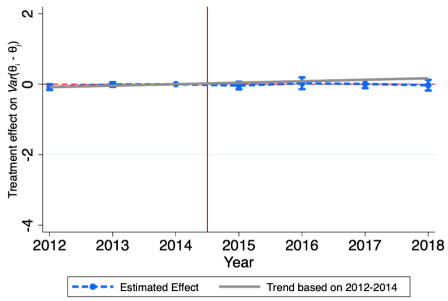
C. Trend analysis

Appendix C examines pre-policy gap-specific trends for the individual components of the variance decomposition. As shown in Figure C1, pre-existing trends are not uniform across components. While some components display positive trends, others exhibit negative trends or remain close to zero. For example, the pre-policy trends are relatively flat for within-firm dispersion in Figure C1a and for the variance of observed worker characteristics in Figure C1e, whereas several between-firm components, such as segregation in Figure C1b, the dispersion of firm-specific pay premiums in Figure C1c, and worker-firm sorting in Figure C1d, display more pronounced positive pre-trends. By contrast, some covariances involving observed worker characteristics, particularly Figures C1g and C1h, exhibit negative pre-policy trends. Overall, this pattern suggests that the negative pre-trend in the overall variance of log daily wages reflects the combined effect of several offsetting component-specific dynamics, rather than a uniform decline across all margins of wage dispersion.

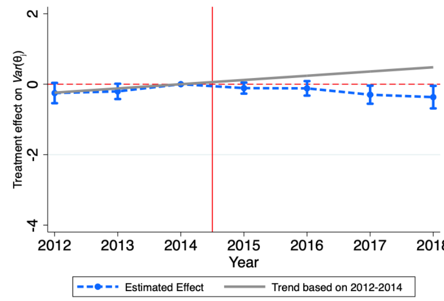
These heterogeneous patterns indicate that high- and low-exposure regions already differed in their pre-reform trends, but that these differences were not uniform across variance components. Since the direction and magnitude of pre-policy trends vary across outcomes, they cannot be attributed to a single mechanism. Instead, Figure C1 primarily serves to document the presence of differential pre-trends and to motivate the detrending strategy used in the baseline analysis.

The presence of component-specific pre-trends motivates the detrending procedure used in the baseline analysis. By removing the predetermined gap-specific trend from each outcome, the main specification focuses on deviations from pre-policy dynamics after the introduction of the minimum wage. The post-reform estimates should therefore be interpreted as effects relative to these component-specific pre-existing trends.

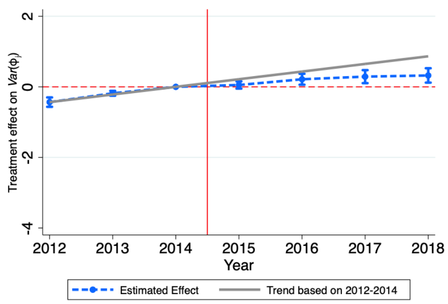
Appendix Figure C1: Minimum wage effect on components of Var(log real daily wages), non-detrended



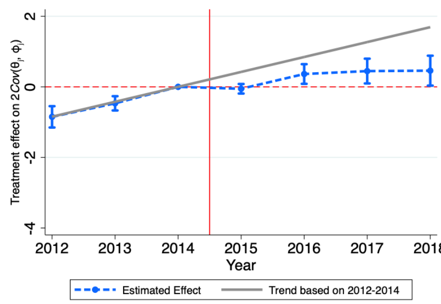
(a) $Var(\theta_i - \bar{\theta}_j)$



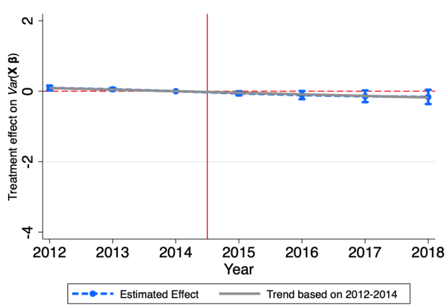
(b) $Var(\bar{\theta}_j)$



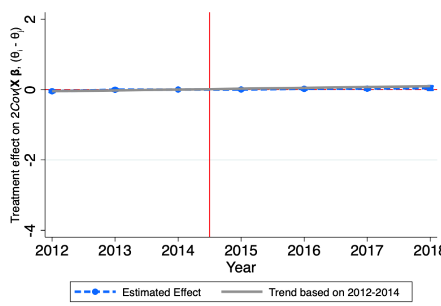
(c) $Var(\phi_j)$



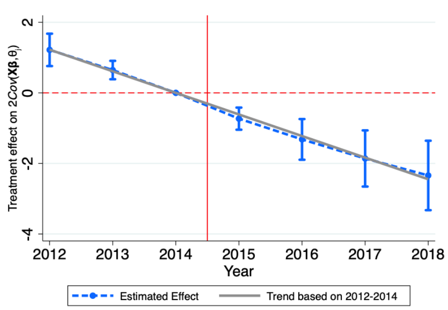
(d) $2 * Cov(\bar{\theta}_j, \phi_j)$



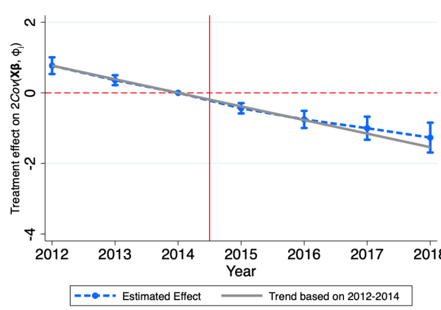
(e) $Var(\boldsymbol{X\beta})$



(f) $2 * Cov(\boldsymbol{X\beta}, \theta_i - \bar{\theta}_j)$



(g) $2 * Cov(\boldsymbol{X\beta}, \bar{\theta}_j)$

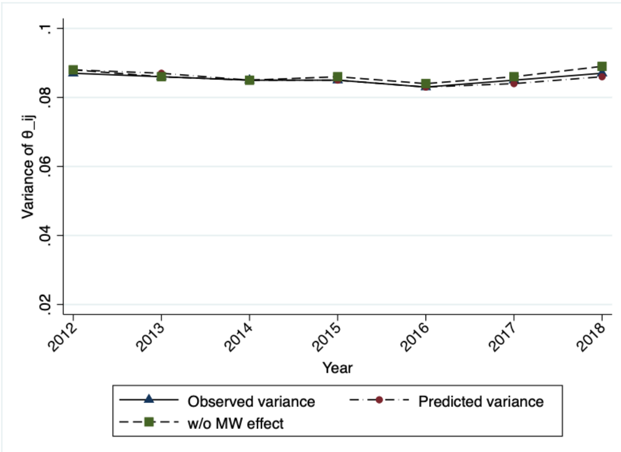


(h) $2 * Cov(\boldsymbol{X\beta}, \phi_j)$

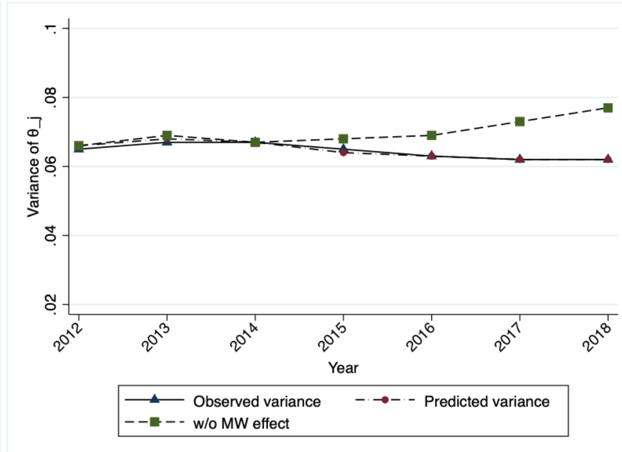
Notes: The blue circles represent the non-detrended RIF-Difference-in-Differences (DiD) regression coefficients of $Gap_c * Year_{k,t}$, along with their 95% confidence intervals. The year 2014 is used as the reference year. The grey line indicates the estimated gap-specific trend, derived from data between 2012 and 2014. The vertical red line marks the introduction of the minimum wage policy.
Data: SIEED, 2012-2018.

D. Additional results

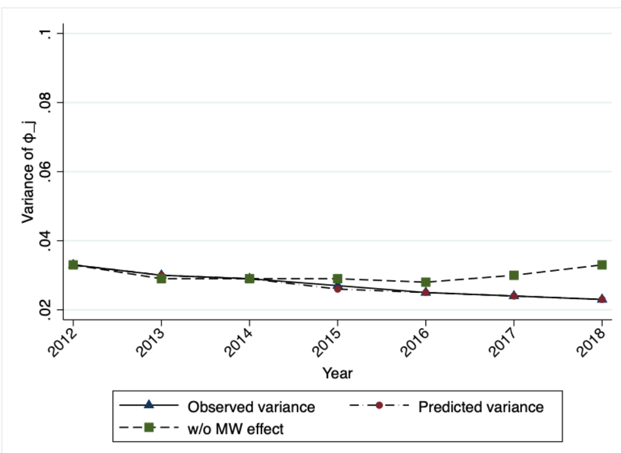
Appendix Figure D1: Development of the observed and the predicted variances and covariances



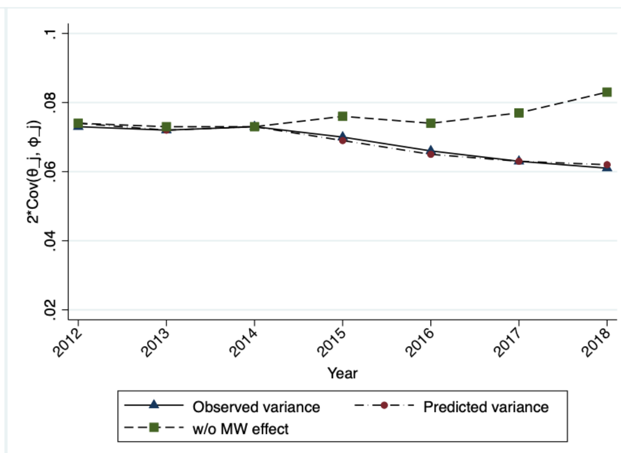
(a) $Var(\theta_i - \bar{\theta}_j)$



(b) $Var(\bar{\theta}_j)$



(c) $Var(\phi_j)$



(d) $2 * Cov(\bar{\theta}_j, \phi_j)$

Notes: The figure displays the observed values, the predicted values under the minimum wage, and the corresponding counterfactual values without the minimum wage for each variance component. The construction follows the same approach as in Figure 5, applied separately to the indicated components.
Data: SIEED, 2012-2018.

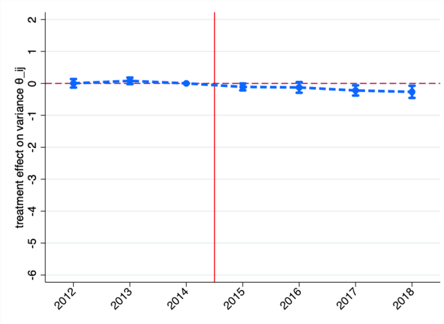
Appendix Table D1: Summary statistics for exposed and non-exposed firms

	Exposed firms	Non-exposed firms	Total
Share of Female	0.346	0.269	0.305
Workplace in Eastern Germany	0.188	0.166	0.176
Mean age	42.436	42.856	42.663
Mean tenure	9.292	8.830	9.043
Daily wage	135.324	129.738	132.309
SD of daily wage	(108.636)	(88.675)	(98.408)
Log daily real wage	4.697	4.735	4.717
SD of log daily wage	(0.629)	(0.470)	(0.549)
Mean firm size (full time)	1655.679	220.383	881.124
Firm size<10	0.095	0.230	0.168
Firm size: 10-99	0.257	0.429	0.350
Firm size:>=100	0.648	0.341	0.482
Observations			
Number of worker-year	856,735	1,004,311	1,861,046
Number of workes	235,388	273,275	508,663
Number of establishments	6,364	16,005	22,369

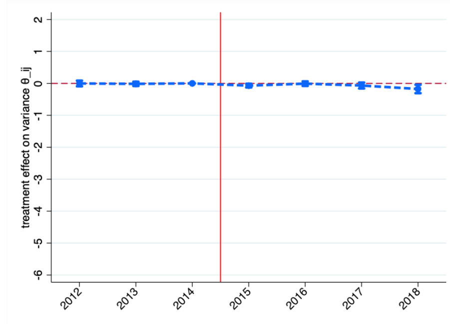
Notes: The table shows worker-year weighted summary statistics. Standard deviations are in parentheses.

Data: SIEED, 2012-2018.

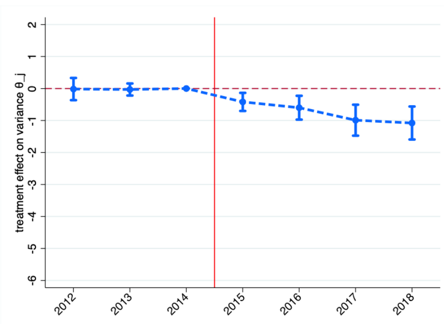
Appendix Figure D2: Minimum wage effect on components of Var(log real daily wages)



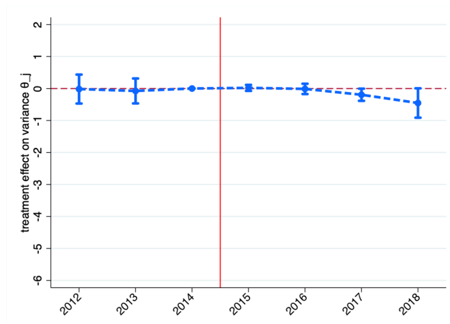
(a) $Var(\theta_i - \bar{\theta}_j)$, Exposed firms



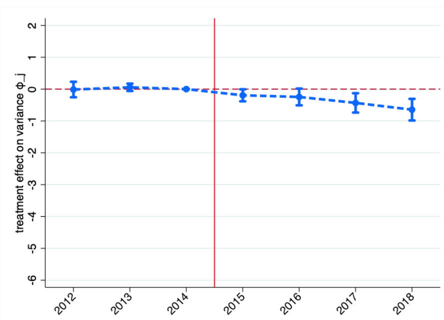
(b) $Var(\theta_i - \bar{\theta}_j)$, Non-Exposed firms



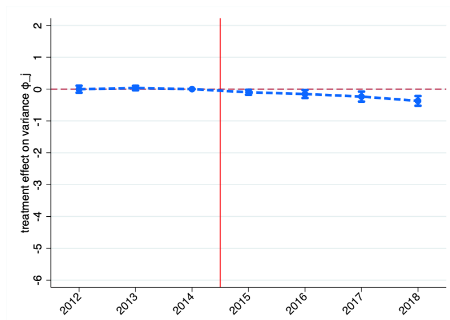
(c) $Var(\bar{\theta}_j)$, Exposed firms



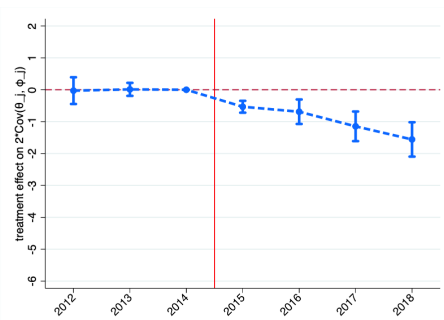
(d) $Var(\bar{\theta}_j)$, Non-Exposed firms



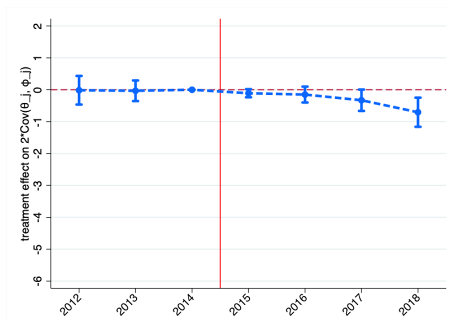
(e) $Var(\phi_j)$, Exposed firms



(f) $Var(\phi_j)$, Non-Exposed firms



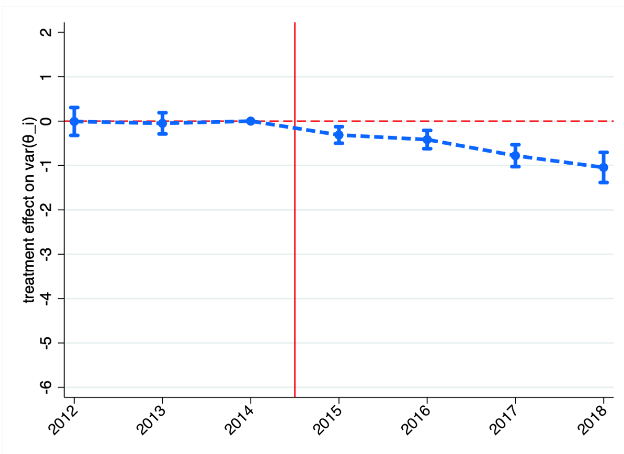
(g) $2 * Cov(\bar{\theta}_j, \phi_j)$, Exposed firms



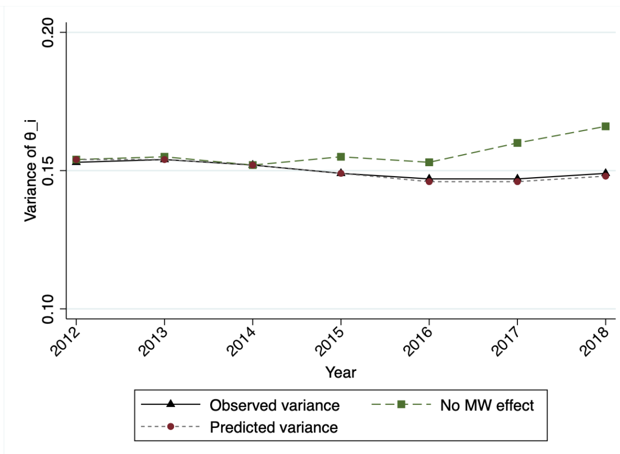
(h) $2 * Cov(\bar{\theta}_j, \phi_j)$,Non-Exposed firms

Notes: The figure displays the detrended RIF-Difference-in-Differences (DiD) regression coefficients of $Gap_c * Year_{k,t}$, along with their 95% confidence intervals. The year 2014 is used as the reference year. All left panels show the results for Exposed firms, while the right panels present those for Non-exposed firms. The vertical red line denotes the introduction of the minimum wage policy. The dependent variables are indicated below each subfigure.
Data: SIEED, 2012-2018.

Appendix Figure D3: Minimum wage effects on Var(θ_i)



(a) DiD estimates for the effect on Var(θ_i)



(b) Observed and counterfactual values of Var(θ_i)

Notes: Figure D3a displays the detrended RIF-Difference-in-Differences (DiD) regression coefficients of $Gap_c * Year_{k,t}$, along with their 95% confidence intervals. The year 2014 is used as the reference year. The vertical red line denotes the introduction of the minimum wage policy. The dependent variables are indicated below each subfigure. Figure D3b shows the observed variance of worker fixed effects, the predicted variance, and the counterfactual variance in the absence of the minimum wage.
Data: SIEED, 2012–2018.

E. Robustness Checks

In this appendix, I assess the robustness of the baseline treatment measure by using alternative county-level indicators of minimum-wage exposure constructed from the 2014 German Structure of Earnings Survey (SES). Let c index counties. The baseline specification in the main text uses the regional gap measure from Dustmann et al. (2021), denoted by Gap_c, which is constructed from IEB data using information from 2011 to 2014. As alternatives, I consider four SES-based treatment variables.

First, I use two bite measures, which capture the share of workers paid below the statutory minimum wage of 8.50 per hour: $Bite_c^{FT}$ for full-time workers only, and $Bite_c^{All}$ for all workers. Second, I use two gap measures based on wage-bill shares among sub-minimum-wage workers. The full-time version is defined as

$$Gap_c^{FT} = \frac{\sum_{i \in FT,\, w_i < 8.50} w_i h_i}{\sum_{i \in FT} w_i h_i},$$

where w_i denotes wages and h_i weekly hours. The corresponding measure for all workers is

$$Gap_c^{All} = \frac{\sum_{i:\, w_i < 8.50} w_i h_i}{\sum_i w_i h_i}.$$

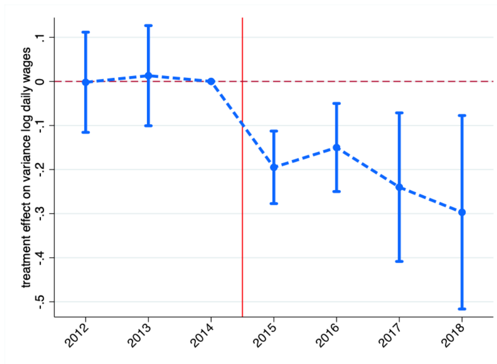
All four SES-based treatment variables are calculated at the county level.

Using the baseline gap measure, which has an average treatment intensity of approximately 0.017, the implied reduction in the variance of log daily wages is about 0.044 in 2018. The SES-based measures yield smaller, but still economically meaningful, implied effects. For the SES bite measure based on all workers, with a mean of 0.119, the implied reduction is about 0.035 in 2018. The full-time-only bite measure, with a mean of 0.074, implies a reduction of about 0.028 in 2018. The SES gap measures have much smaller average treatment values, around 0.005, so despite their larger estimated coefficients, they imply more modest reductions of about 0.017 in 2018. Overall, all alternative treatment definitions produce the same qualitative pattern as the baseline measure, with negligible pre-trends and consistently negative post-2015 effects. Moreover, the largest effects are found for segregation and worker-firm sorting, consistent with the main finding that the decline in wage inequality is primarily driven by between-firm components.

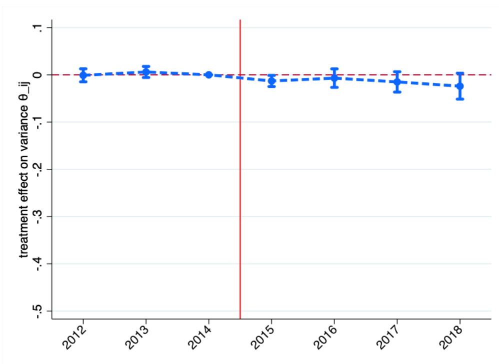
Overall, the SES-based treatment measures produce smaller effect sizes than the baseline gap measure. One possible explanation is that the baseline treatment is constructed from near-universe IEB data over 2011–2014 and therefore likely captures persistent regional pre-reform exposure to the minimum wage. By contrast, although the SES-based measures contain more accurate information on working hours, they are based on a single 2014 cross-section and may therefore be more sensitive to sampling variation or transitory shocks. In addition, because the SES-based measures are constructed from a different data source, exact equality in magnitudes should not be expected.

E.1. Using alternative treatment measure

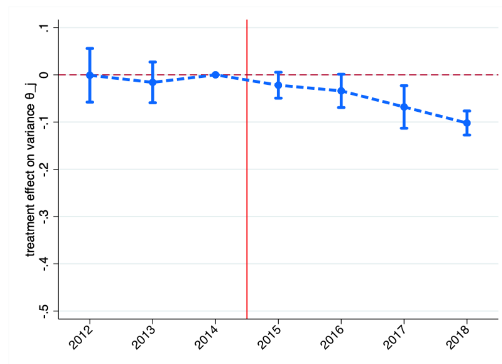
Appendix Figure E1: Minimum wage effect on Var(log real daily wages) and other variance components, using bite variable derived from all types of jobs



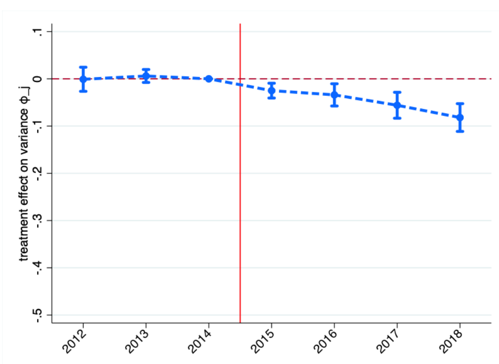
(a) $Var(log\ daily\ wages)$



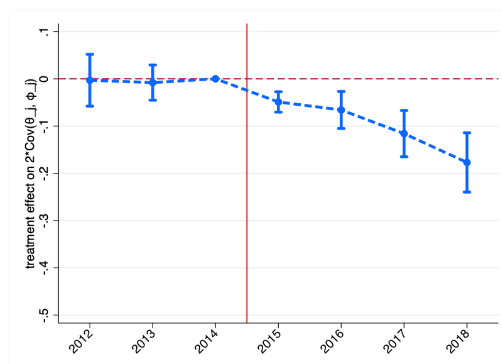
(b) $Var(\theta_i - \bar{\theta}_j)$



(c) $Var(\bar{\theta}_j)$



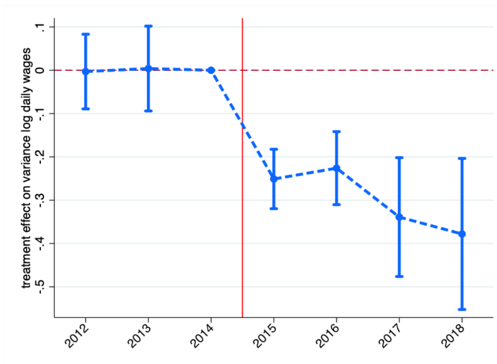
(d) $Var(\phi_j)$



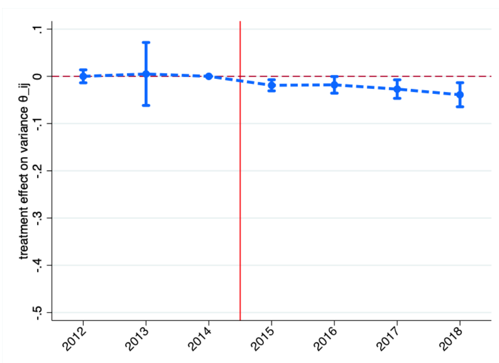
(e) $2 * Cov(\bar{\theta}_j, \phi_j)$

Notes: The figure displays the detrended RIF-Difference-in-Differences (DiD) regression coefficients of $Bite_c * Year_{k,t}$, along with their 95% confidence intervals. The year 2014 is used as the reference year. The vertical red line denotes the introduction of the minimum wage policy. The dependent variables are indicated below each subfigure.
Data: SIEED, 2012-2018.

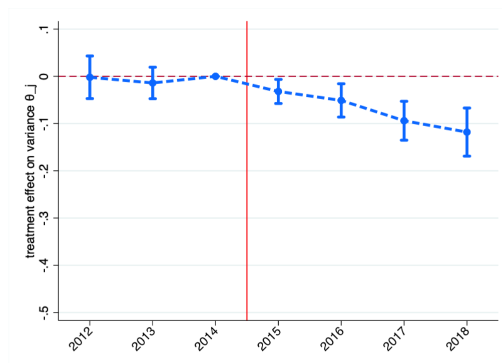
Appendix Figure E2: Minimum wage effect on Var(log real daily wages) and other variance components, using bite variable derived from full-time jobs



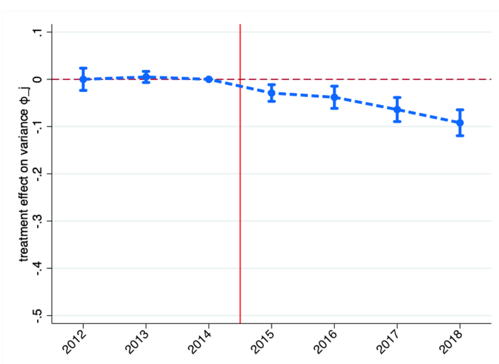
(a) $Var(log\ daily\ wages)$



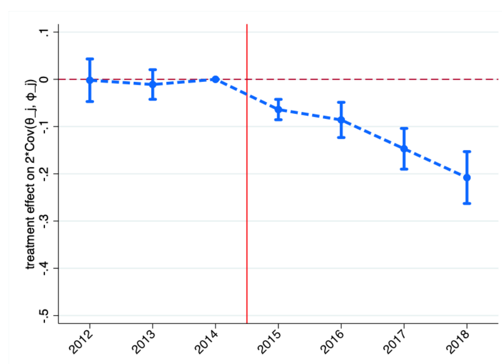
(b) $Var(\theta_i - \bar{\theta}_j)$



(c) $Var(\bar{\theta}_j)$



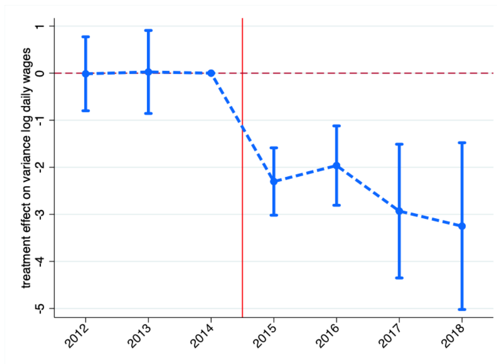
(d) $Var(\phi_j)$



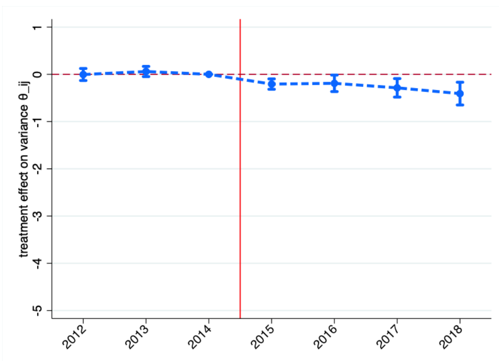
(e) $2 * Cov(\bar{\theta}_j, \phi_j)$

Notes: The figure displays the detrended RIF-Difference-in-Differences (DiD) regression coefficients of $Bite_c * Year_{k,t}$, along with their 95% confidence intervals. The year 2014 is used as the reference year. The vertical red line denotes the introduction of the minimum wage policy. The dependent variables are indicated below each subfigure.
Data: SIEED, 2012-2018.

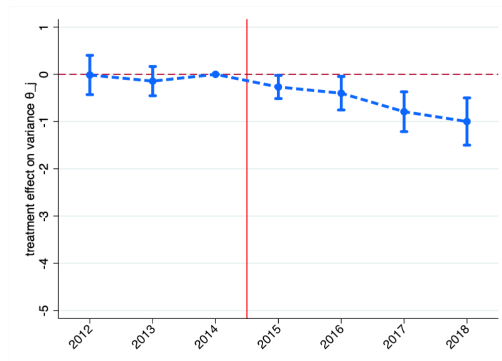
Appendix Figure E3: Minimum wage effect on Var(log real daily wages) and other variance components, using gap variable derived from all types of jobs



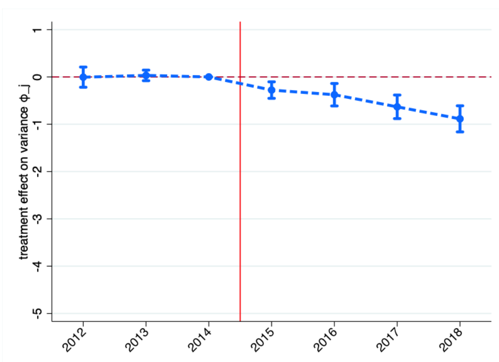
(a) $Var(log\ daily\ wages)$



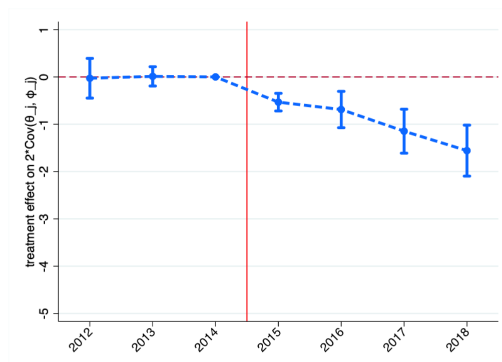
(b) $Var(\theta_i - \bar{\theta}_j)$



(c) $Var(\bar{\theta}_j)$



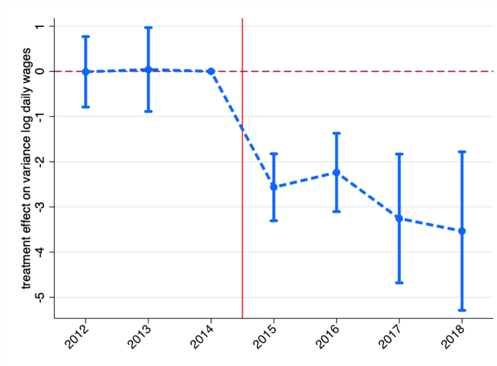
(d) $Var(\phi_j)$



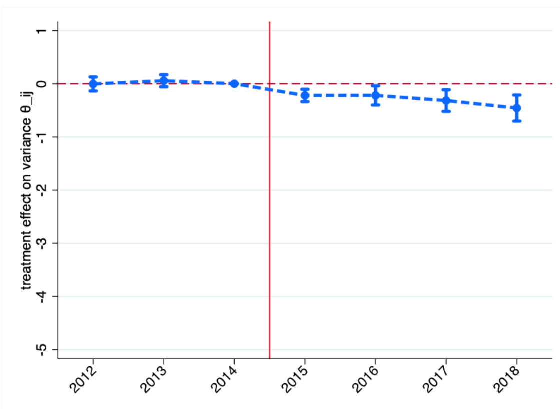
(e) $2 * Cov(\bar{\theta}_j, \phi_j)$

Notes: The figure displays the detrended RIF-Difference-in-Differences (DiD) regression coefficients of $Gap_c * Year_{k,t}$, along with their 95% confidence intervals. The year 2014 is used as the reference year. The vertical red line denotes the introduction of the minimum wage policy. The dependent variables are indicated below each subfigure.
Data: SIEED, 2012-2018.

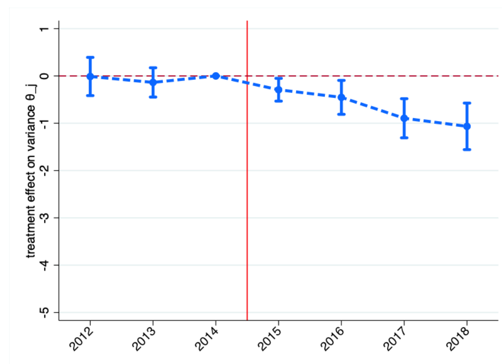
Appendix Figure E4: Minimum wage effect on Var(log real daily wages) and other variance components, using gap variable derived from full-time jobs



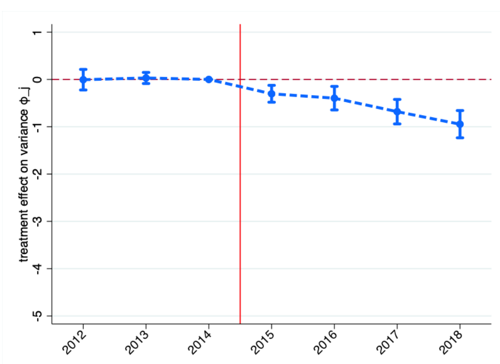
(a) $Var(log\ daily\ wages)$



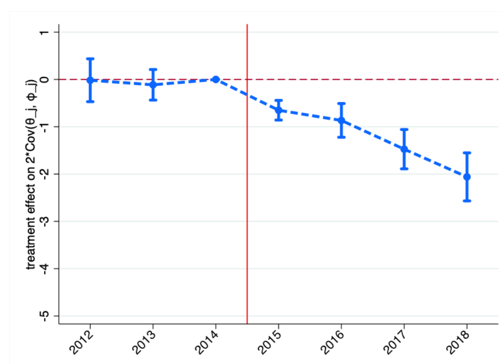
(b) $Var(\theta_i - \bar{\theta}_j)$



(c) $Var(\bar{\theta}_j)$



(d) $Var(\phi_j)$

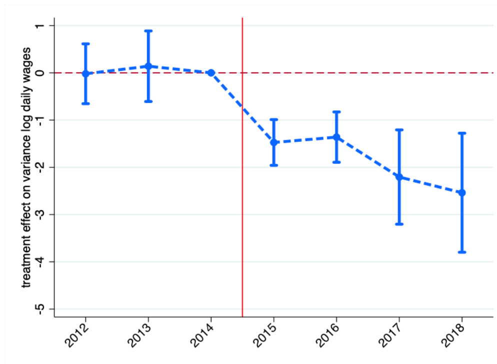


(e) $2 * Cov(\bar{\theta}_j, \phi_j)$

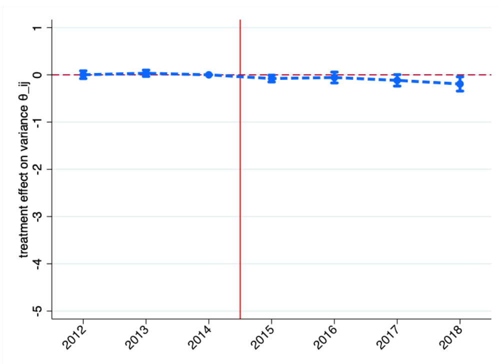
Notes: The figure displays the detrended RIF-Difference-in-Differences (DiD) regression coefficients of $Gap_c * Year_{k,t}$, along with their 95% confidence intervals. The year 2014 is used as the reference year. The vertical red line denotes the introduction of the minimum wage policy. The dependent variables are indicated below each subfigure.
Data: SIEED, 2012-2018.

E.2. Clustering firms into 100 groups

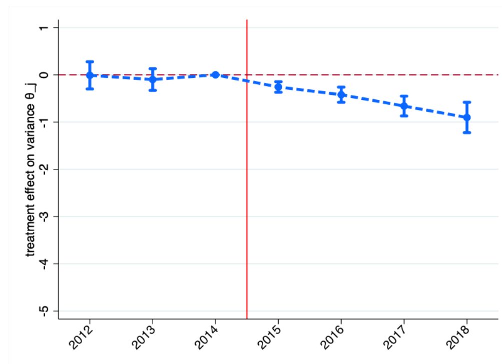
Appendix Figure E5: Minimum wage effect on Var(log real daily wages) and other variance components, firms are clustered into 100 groups



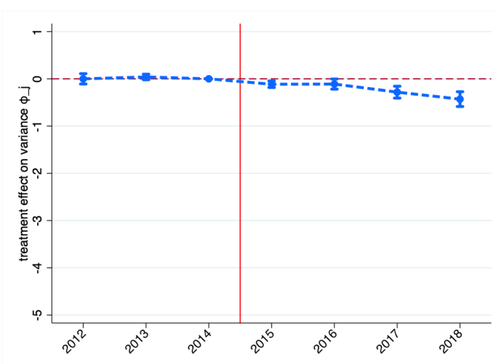
(a) $Var(log\ daily\ wages)$



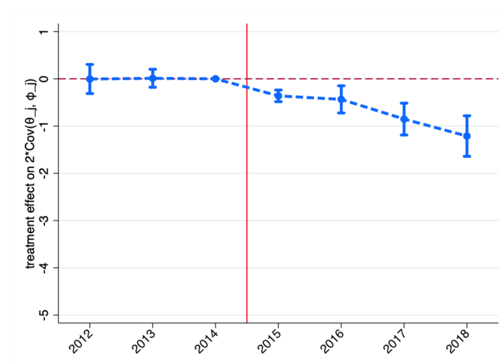
(b) $Var(\theta_i - \bar{\theta}_j)$



(c) $Var(\bar{\theta}_j)$



(d) $Var(\phi_j)$

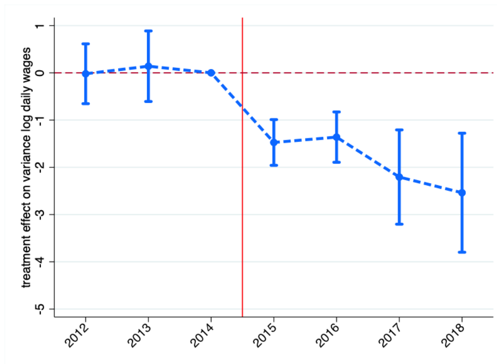


(e) $2 * Cov(\bar{\theta}_j, \phi_j)$

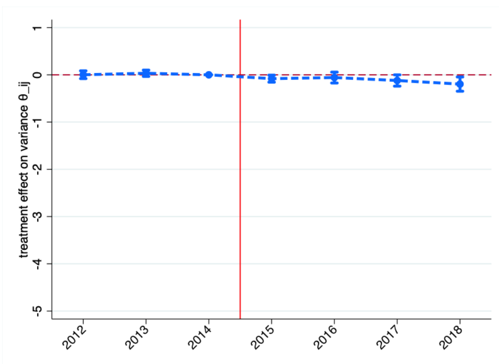
Notes: The figure displays the detrended RIF-Difference-in-Differences (DiD) regression coefficients of $Gap_c * Year_{k,t}$, along with their 95% confidence intervals. The year 2014 is used as the reference year. The vertical red line denotes the introduction of the minimum wage policy. The dependent variables are indicated below each subfigure.
Data: SIEED, 2012-2018.

E.3. Using alternative industry to normalize firm fixed effects

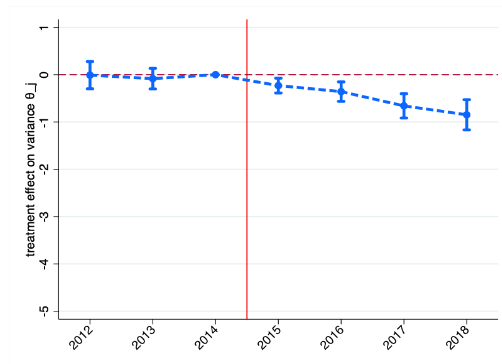
Appendix Figure E6: Minimum wage effect on Var(log real daily wages) and other variance components, firm fixed effects are normalized based on restaurant industry



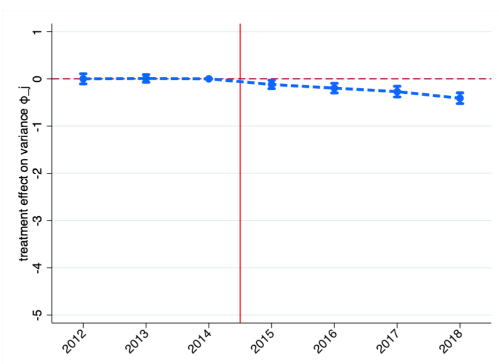
(a) $Var(log\ daily\ wages)$



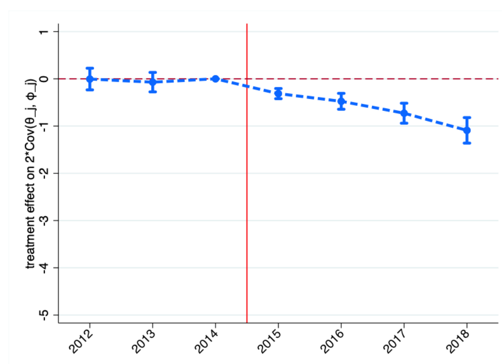
(b) $Var(\theta_i - \bar{\theta}_j)$



(c) $Var(\bar{\theta}_j)$



(d) $Var(\phi_j)$

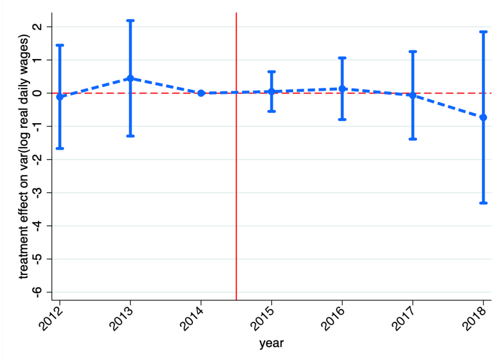


(e) $2 * Cov(\bar{\theta}_j, \phi_j)$

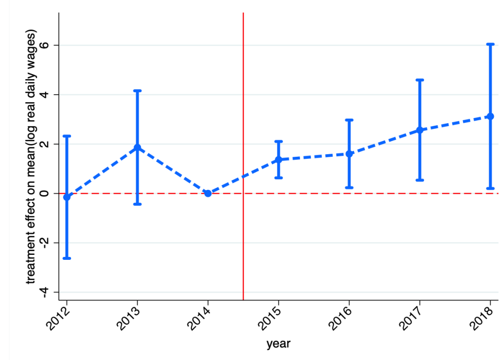
Notes: The figure displays the detrended RIF-Difference-in-Differences (DiD) regression coefficients of $Gap_c * Year_{k,t}$, along with their 95% confidence intervals. The year 2014 is used as the reference year. The vertical red line denotes the introduction of the minimum wage policy. The dependent variables are indicated below each subfigure.
Data: SIEED, 2012-2018.

E.4. Eastern and Western Germany

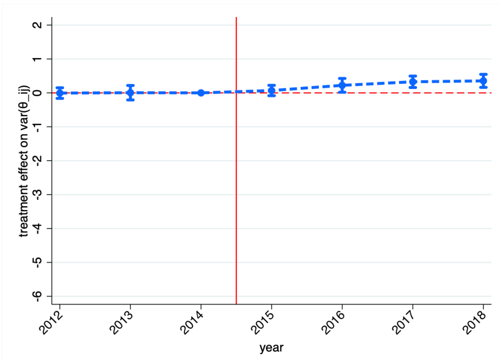
Appendix Figure E7: Minimum wage effect on Var(log real daily wages) and other variance components, eastern Germany



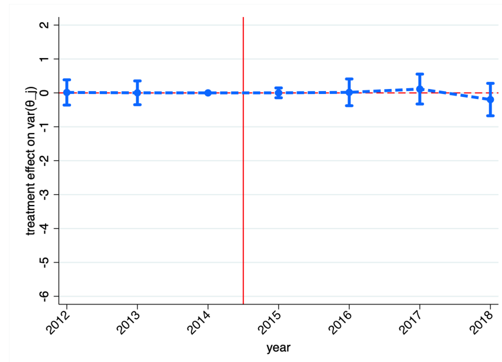
(a) $Var(log\ daily\ wages)$



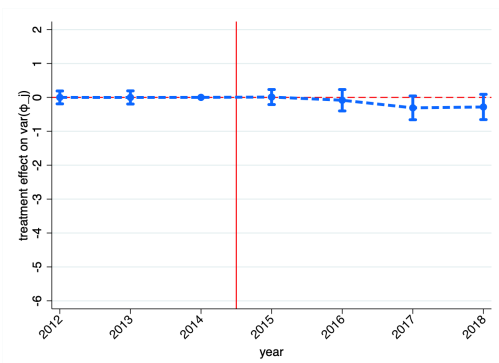
(b) $log\ daily\ wages$



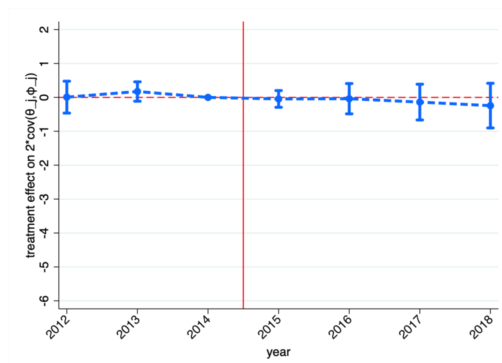
(c) $Var(\theta_i - \bar{\theta}_j)$



(d) $Var(\bar{\theta}_j)$



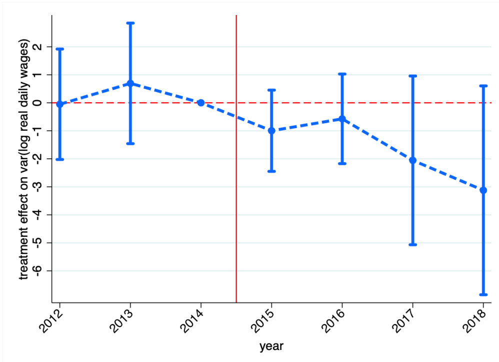
(e) $Var(\phi_j)$



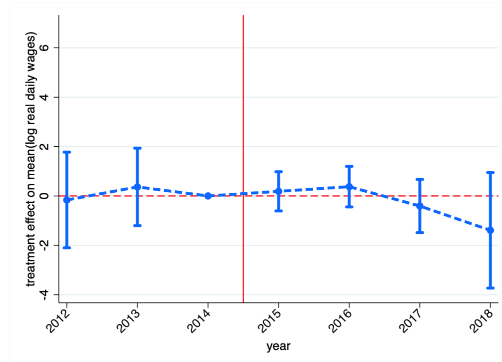
(f) $2 * Cov(\bar{\theta}_j, \phi_j)$

Notes: The figure displays the detrended RIF-Difference-in-Differences (DiD) regression coefficients of $Gap_c * Year_{k,t}$, along with their 95% confidence intervals. The year 2014 is used as the reference year. The vertical red line denotes the introduction of the minimum wage policy. The dependent variables are indicated below each subfigure.
Data: SIEED, 2012-2018.

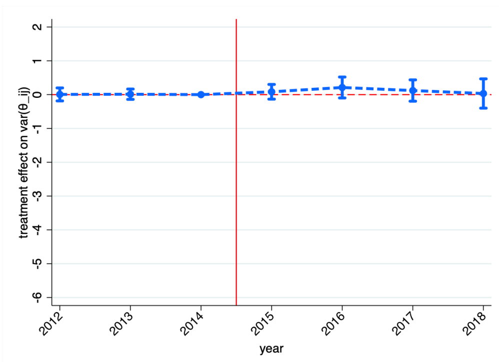
Appendix Figure E8: Minimum wage effect on Var(log real daily wages) and other variance components, western Germany



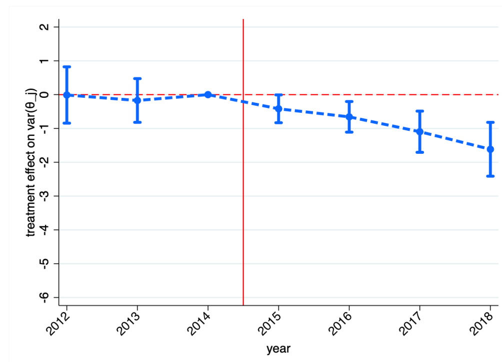
(a) $Var(log\ daily\ wages)$



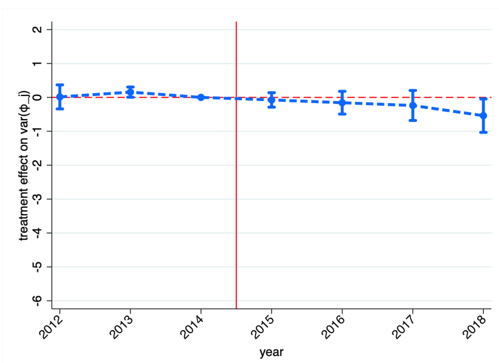
(b) $log\ daily\ wages$



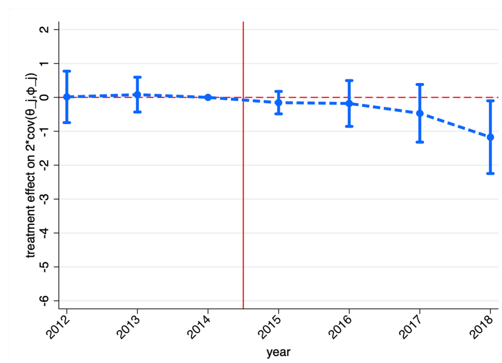
(c) $Var(\theta_i - \bar{\theta}_j)$



(d) $Var(\bar{\theta}_j)$



(e) $Var(\phi_j)$



(f) $2 * Cov(\bar{\theta}_j, \phi_j)$

Notes: The figure displays the detrended RIF-Difference-in-Differences (DiD) regression coefficients of $Gap_c * Year_{k,t}$, along with their 95% confidence intervals. The year 2014 is used as the reference year. The vertical red line denotes the introduction of the minimum wage policy. The dependent variables are indicated below each subfigure.
Data: SIEED, 2012-2018.