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The Regional Effects of a National Minimum Wage

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The Regional Effects of a National Minimum Wage

Abstract

We estimate the spatially differential effects of a nationally uniform minimum wage that was introduced in Germany in 2015. To this end, we use a micro data set covering the universe of employed and unemployed individuals in Germany from 2011 to 2016 and a difference-in-differences based identification strategy that controls for heterogeneity in pre-treatment outcome trends. We find that the policy led to spatial wage convergence, in particular in the left tail of the distribution, without reducing relative employment in low-wage regions within the first two years.

JEL-Codes: J310, J580, R120.

Keywords: difference-in-differences, employment, Germany, minimum wage, wage inequality.

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1 Introduction

While there is a vast and controversial literature about the implications of minimum wages for employment and the distribution of wages, little is known about the spatial implications of such a policy. With productivity and, hence, wage differences across locations, the introduction of a national minimum wage affects regions to different extents. While the policy bites hard in poor places, there is only a small fraction of workers earning less than the minimum in rich places.

We follow this idea when exploring the wage, employment, and migration effects of the federal minimum wage that was introduced in Germany in 2015. Since then, German employers have to pay at least 8.50 euros per hour corresponding to 48 percent of the median salary of full-time workers. This level is high compared to the US (36 percent) and because no similar regulation preceded the statutory wage floor, it represented a potentially significant shock to regions in the left tail of the regional wage distribution. [1]

To identify the differential effects across locations, we exploit the variation in the fraction of workers who earned less than the minimum in 2014 across German counties. We compare counties subject to different intensities of treatment in a difference-in-differences (DD) strategy that accounts for heterogeneity in pre-treatment outcome trends. In doing so, we exploit a micro data set covering the universe of employment and unemployment in Germany from 2011 to 2016.

We show that the minimum wage policy raised the wages of low-wage workers without affecting employment. Unemployment even shrinks in regions with a high minimum-wage bite in 2015 relative to low-bite locations owed to a temporary reduction in in-migration, but these effects already vanish in 2016. The policy's primary effect thus far has been to transfer producer surplus to workers in low-wage regions, indicating that low-wage employees were paid below their marginal value product (Machin, Manning, and Woodland, 1993, Machin and Manning, 2004). Hence, the competitive labour market model has to be rejected.

This paper contributes to the literature on the labour market implications of minimum wages that largely builds on experience in the US. Our evidence is novel in that it based on the largest European economy, focuses on the *regional* implications of a national minimum wage, and covers the effects on regional migration.[2]

[1] The level is comparable to many other developed economies, see https://stats.oecd.org.

[2] See Brown (1999) and Neumark and Wascher (2008) for reviews and Dube, Lester, Reich (2010) and Baek and Park (2016) for more recent evidence.

2 Data

The empirical analysis is based on the Employment Histories (BeH) and the Integrated Employment Biographies (IEB) provided by the Institute of Employment Research (IAB) which contain individual-level data on the universe of labour market participants in Germany. Despite their comprehensiveness, the data do not include information about the number of hours worked. We therefore impute average working hours separately for full-time and part-time workers from an auxiliary regression that accounts for sector of employment, federal state of employment, and various socio-demographic attributes and uses a 1% sample from the 2012 census. We find that full-time employees work approximately 40 hours per week while the number is lower for regularly employed (21 hours) and for marginally employed part-time workers (10 hours).[3] Combining working hours with average daily earnings delivers hourly wages from which we compute the 2014 (the year prior to the policy change) share of workers (at the workplace) below the minimum wage for each of the 401 German counties (NUTS3 regions). Since labour markets are integrated across county borders, we define the minimum-wage bite as the average of the shares of below-minimum-wage workers at all counties, weighted by the bilateral commuting flows from the year 2010. Table 1 provides an overview of the key variables.

Tab. 1. Summary statistics

VARIABLES	(1) mean	(2) sd	(3) min	(4) p10	(5) p25	(6) p75	(7) p90	(8) max
2014 minimum wage bite	14.84	3.06	7.10	11.26	12.46	16.75	19.33	25.43
Ln hourly wage at the 10th percentile	1.94	0.12	1.50	1.77	1.86	2.03	2.09	2.24
Ln hourly wage at the 25th percentile	2.31	0.10	2.00	2.17	2.24	2.38	2.44	2.62
Ln hourly wage at the 50th percentile	2.72	0.12	2.34	2.54	2.65	2.80	2.86	3.11
Ln labour force	11.07	0.66	9.49	10.29	10.66	11.48	11.86	14.18
Ln employment	10.96	0.66	9.38	10.19	10.56	11.36	11.74	14.00
Unemployment rate (percentage points)	9.85	4.32	2.19	4.90	6.51	12.38	16.17	26.59

Notes: Unit of observation is county-year. 401 counties are repeatedly observed over 2011-2016.

3 Empirical strategy

To guide our empirical analysis, it is useful to adopt the potential outcomes framework that dates back to Rubin (1974) and Heckman (1990). Let's assume treatment is only in effect at time $t \geq z$, the post-period, but not during the pre-period $t < z$. Further, let superscripts one and zero denote potential outcomes in the presence and absence of a treatment. The change in the potential outcome in

[3] See online appendix for details.

county c at time t, dy_{ct}^1, conditional on treatment that is associated with a change in the continuous treatment measure dT_c in the post-period is given by:

$$E(dy_{ct}^1|t \geq z) = E(\beta_t dT_c|t \geq z), \tag{1}$$

where β_t is a year-specific parameter. While $E(dy_{ct}^1|t \geq z)$ can be inferred from our data, the standard identification problem is that the counterfactual effect $E(dy_{ct}^0|t \geq z)$ cannot. To define the treatment effect, we assume that the marginal effect of the treatment measure on the outcome interacts linearly with time and that the functional form observable during the pre-period extends to the post-period,

$$E(dy_{ct}^0|t \geq z) = E(\gamma_0|(t < z) + \gamma_1|(t < z) \times t)dT_c. \tag{2}$$

Thus, the treatment effect is defined as:

$$E(dy_{ct}^1|t \geq z) - E(dy_{ct}^0|t \geq z) = E\big(\beta_t - (\gamma_0 + \gamma_1 \times t)\big)dT_c, \tag{3}$$

with $E\big(\beta_t - (\gamma_0 + \gamma_1 \times t)\big)$ being the marginal treatment effect, which we aim at estimating. To this end, we use the following empirical specification:

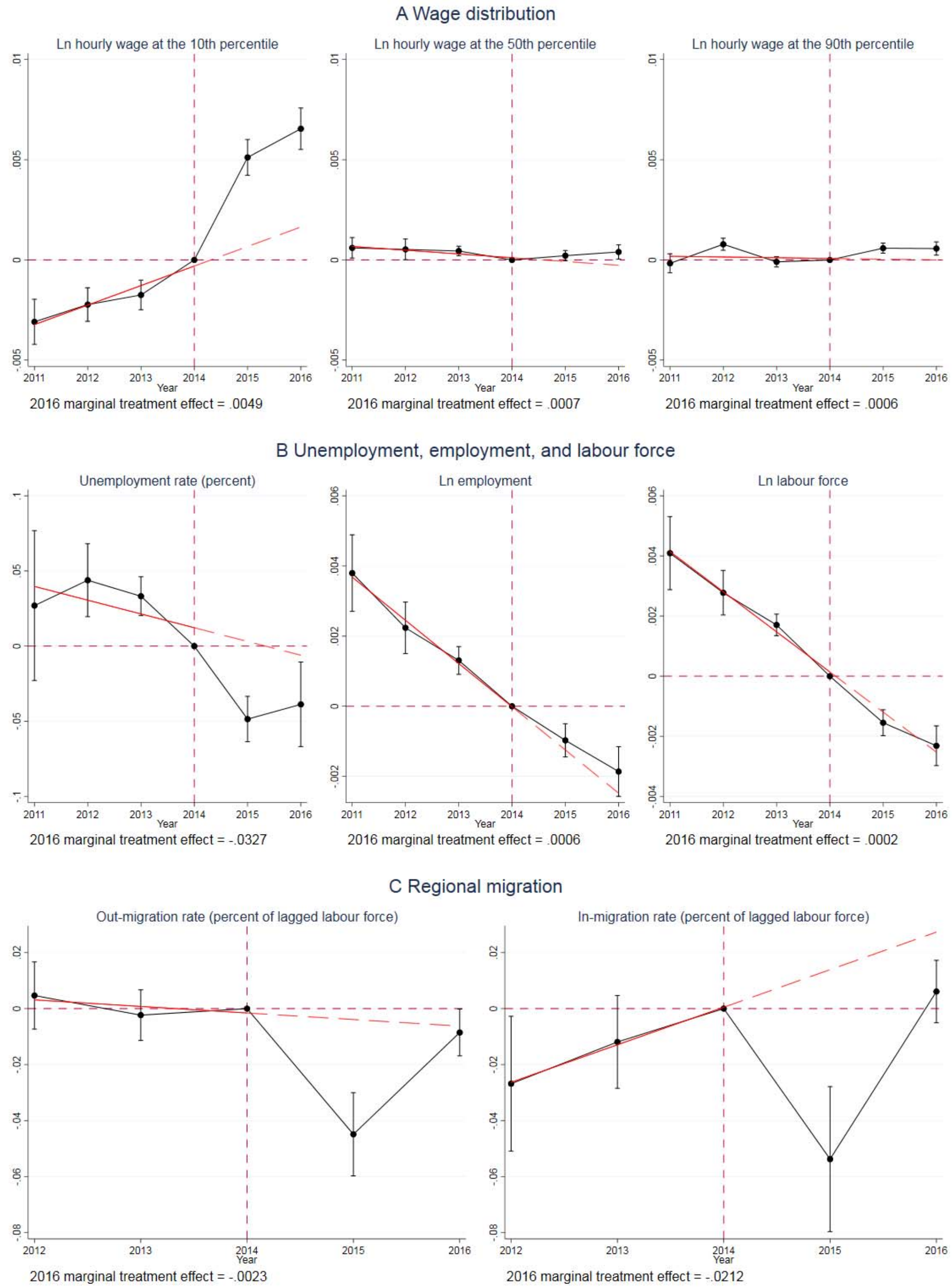
$$y_{c,g,t} = \textstyle\sum_{Z \neq 2014} \beta_Z T_c \times I(t = Z) + \mu_c + \vartheta_{g,t} + \epsilon_{c,g,t}, \tag{4}$$

where $y_{c,g,t}$ is an outcome for county c, in region g at year t. T_c is a treatment variable (the minimum wage bite) that interacts with time through a set of indicator variables $I(t = Z)$ that take the value of one if the condition is true, and zero otherwise. μ_c are county effects, $\vartheta_{g,t}$ are region (East Germany, West Germany) effects interacted with year effects and $\epsilon_{c,g,t}$ is a random error. Each of the estimated $\hat{\beta}_Z$ parameters represents a DD estimate of the marginal effect of the treatment on the outcome in year Z relative to 2014, the year before the policy intervention. To infer the marginal treatment effect, we take $\hat{\beta}_Z$ as an empirical approximation of β_t and approximate γ_0 and γ_1 in an auxiliary regression of $\hat{\beta}_Z$ against a time trend during the pre-period (up until 2014). We cluster standard errors at the county level. We acknowledge that T_c incorporates hours worked, which are measured with error at the individual level. Within each county, however, we aggregate over a large number of workers (≈150k on average), thus the county-level mean and variance of the error is likely near zero. With this empirical design, we not only control for arbitrary time-invariant regional heterogeneity and region-specific time trends, but also address unobserved heterogeneity in counterfactual trends to the extent that these are linear, an assumption whose validity can be evaluated within the pre-treatment period.

4 Results

In line with the spatial distribution of the minimum wage bite (see Figure A1), the minimum wage appears to have had a stronger bite in the economically still weaker eastern states. At the 10th percentile of the distribution within counties, hourly wages increased from 2014 to 2016 by about €1.25 in the eastern states, compared to less than €1 in the western states. We note that we hold the (imputed) hours worked constant, so hourly wages in our data cannot increase due to reductions in working hours.

Fig. 1. Effects of the minimum wage



Notes: Each panel illustrates the results of separate county-year-level DD regressions of an outcome against treatment-year interactions (excluding the 2014 base year), county effects and Year x East Germany effects. Treatment variable is the 2014 minimum wage bite (commuting-flow weighted average of shares of below-minimum-wage workers of surrounding counties). Dots are the estimated treatment-year effects and vertical error bars are the corresponding 95% confidence intervals. The red solid line is the linear fit into treatment-year effects up until 2014 and the dashed line is the linear extrapolation. The marginal treatment effect is the 2016 difference between the point estimate and the dashed line.

In Figure 1, we use our baseline empirical specification (4) to more formally evaluate the effects of the minimum wage. Panel A shows that the minimum wage policy helped low-wage workers (10th percentile) to increase their wage relatively more in counties with a higher bite. The marginal treatment effect (gap between the 2016 dot and the dashed line) implies that an increase in the minimum wage bite by one percentage point is associated with a 0.5% larger increase in the low wage. The lower-bound of the 95% confidence interval (indicated by the error bar) of the 2016 treatment clearly exceeds the counterfactual trend (dashed line), so the effect can be considered statistically significant. The low wage in a county at the 90th percentile of the minimum wage bite distribution (henceforth high-bite county) compared to one at the 10th percentile (henceforth low-bite county) increased by some additional $4.0\%(= \exp(0.0049 \times (19.33 - 11.26)) - 1)$. The respective effects at the 50th and 90th percentiles of the wage distribution are economically small as expected.

These results imply a spatial wage convergence that was intended by the policy, but the results could be mechanically driven by reduced employment rates of low-wage workers. In Panel B we therefore replicate the analysis using the unemployment rate, employment, and labour force as outcome variables. We observe that a one-percentage point increase in the minimum-wage bite significantly reduces the unemployment rate by approximately 0.05 percentage points in 2015 and 2016. These changes appear initially to be driven by a combination of a higher employment level and a lower labour force in high-bite counties, while for the year 2016 the primary explanation is an increase in employment. To further assess the significance of these channels we obtain ancillary standard error estimates from a parametric regression equivalent to specification (4) in which we allow for a before-after comparison conditional on separate linear pre- and post-trend-treatment interactions to save degrees of freedom.[4] The results show that the marginal treatment effect on employment is 0.06% in 2016 which is significant at the 5 percent level, while the corresponding effect on the labour force in 2015 is -0.04% which just fails to be significant at the 5 percent level (see Table A3 in the appendix for details). A possible explanation for the decrease in the local labour force in high-bite counties in 2015 are changes in migration. Panel C shows that in-migration as well as out-migration rates drop sharply in 2015, but the former effect is considerably larger in magnitude. While the effect on the in-migration rate continues to be negative in 2016, there is no significant effect on the out-migration rate. While this combination may have led to a further reduction in the labour force, it appears that the increase in employment levels is sufficiently high to outweigh this effect.

[4] Formally, the model is described as $y_{c,g,t} = \beta_1 T_c \times I(t \geq 2015) + \beta_2 T_c \times I(t \geq 2015) \times (t - 2015) + \delta T_c \times (t - 2015) + \mu_c + \vartheta_{g,t} + \epsilon_{c,g,t}$,, where β_1 and β_2 are the parameters of interest. See the appendix for details.

5 Conclusion

Our analysis reveals that the introduction of the federal minimum wage in Germany in 2015 led to spatial wage convergence. As expected, wages in low-wage counties increased more rapidly than in high-wage counties, especially so for workers in the left tail of the wage distribution. This shift in the spatial distribution of wages did not come at the expense of significant job loss in low-wage regions (relative to high wage regions). In contrast, we find that locations with a higher share of low-wage workers experienced lower unemployment rates in 2015 and 2016. While these changes appear to be initially driven by a reduction in the size of the labour force in high-bite counties, increases in employment levels are the primary driver in the year 2016.

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The regional effects of a national minimum wage: Appendix

Version: February 2018

1 Introduction

This appendix adds to the main paper by providing complementary information, results and analyses. It is not designed to stand alone or replace the reading of the main paper.

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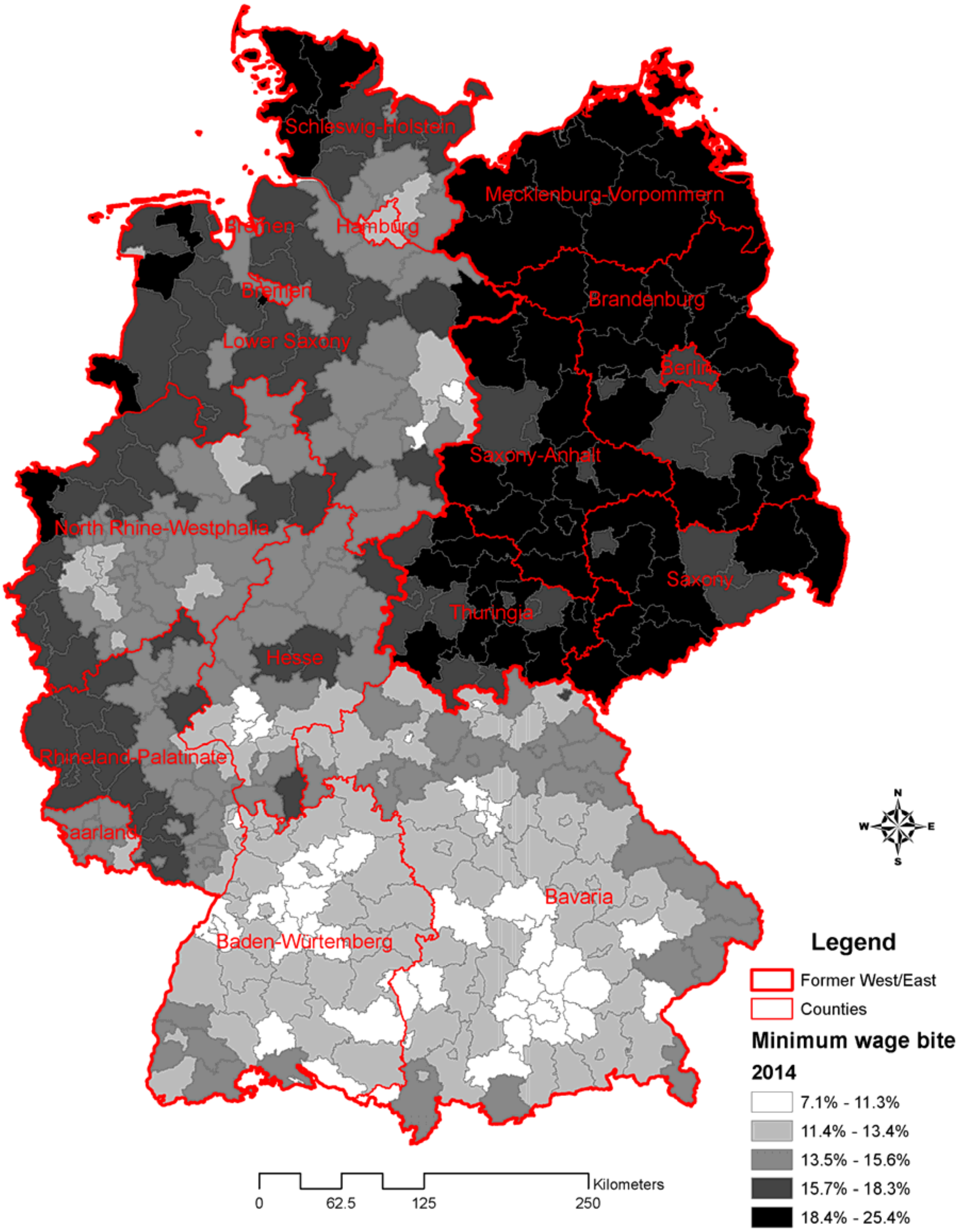
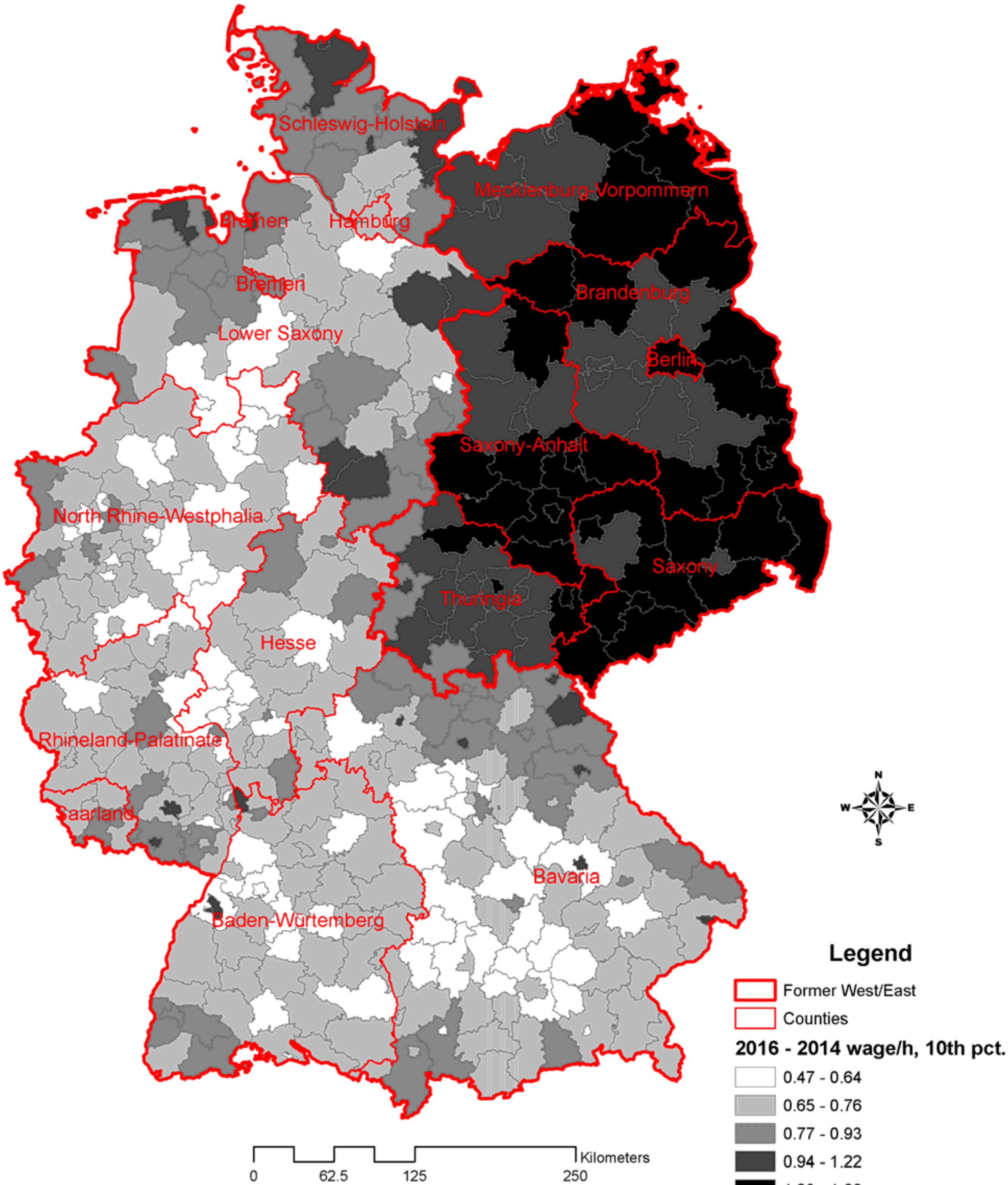
2 Spatial minimum wage bite and changes in low wages

Fig A1. Minimum wage bite



Notes: The minimum wage bite is the commuting-flow weighted average of the shares of below-minimum-wage workers (at workplace) of surrounding counties.

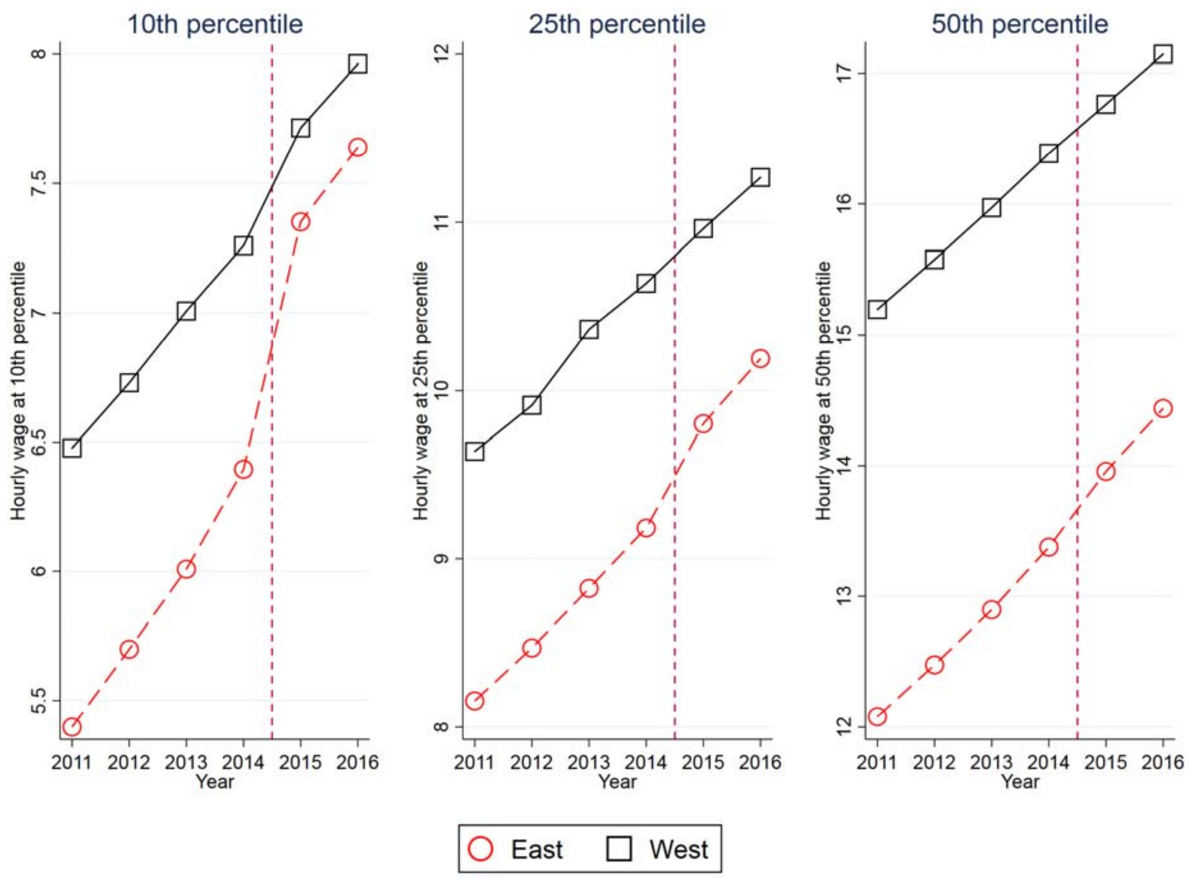
Fig A2. Change in low wages from 2014 to 2016



Notes: The low wage is defined as the 10th percentile in the distribution of hourly wages (in euros) in a county.

3 Descriptive evidence

Fig A3. Trends in wages by region and percentiles



Notes: East indicates six federal states within the territory of former East-Germany, including Berlin.

4 Estimating the number of hours worked per week

The Employment Histories (BeH) contain an employee's average daily earnings, but no information on the number of hours worked. In order to estimate an hourly wage variable and to determine whether an individual earns above or below the minimum-wage threshold, we utilize information from the 2012 version of the German census. This dataset is derived from a representative household survey that is conducted by the statistical offices of the federal states. It contains detailed individual- and household-level information on approximately 1% of households in Germany.

The main variable used in the analysis is the number of hours regularly worked per week. In order to control for differences in working hours between different groups in the population, we regress this variable on a set of indicators for gender, part-time status, place of employment at the level of the federal state and sector of employment. We use the 21 sectors based on the 2008 version of the

Klassifikation der Wirtschaftszweige. In addition, we control for mean adjusted individual- and household-level characteristics (age, German nationality, tertiary education, marital status, personal income, household size, number of children and household income) as shown in Equation S1:

$$\ln[h_i] = \alpha_0 + \alpha_1 fem_i + \alpha_2 pt_i + \alpha_3 fem_i pt_i + \sum_{j=2}^{16} \beta_j D_i(state_i = j) + \sum_{k=2}^{21} \gamma_k D_i(sector_i = k) + \boldsymbol{\delta_i}'\boldsymbol{x_i} + u_i \tag{A.1}$$

We estimate (A.1) separately for regular and marginal employees. Setting individual- and household-level characteristics to their sample means, we next compute the predicted number of hours worked for each cell defined by type of employment, gender, part-time status, place of employment and sector of employment. Since this set of variables is also part of the BeH data, we are able to assign the corresponding predicted number of hours to all individuals within the corresponding cells. Table A.1 provides an overview of the predicted average number of hours for different cells.

Tab. A1. Predicted weekly working hours

Gender	Part-time status	Hours (regular)	Hours(marginal)
Female	Full-time	39.43	-
Female	Part-time	21.24	9.98
Male	Full-time	41.22	-
Male	Part-time	20.71	10.43

Notes: Mean values across federal states and sectors.

5 Parametric treatment effects

In the main paper, we report intervention-study type time-varying treatment effects. To save degrees of freedom, we replicate all models using a more parsimonious DD specification that allows the treatment to have an effect on the outcome level and trend.

$$y_{c,g,t} = \beta_1 T_c \times I(t \geq 2015) + \beta_2 T_c \times I(t \geq 2015) \times (t - 2015) + \delta T_c \times (t - 2015) + \mu_c + \vartheta_{g,t} + \epsilon_{c,g,t}, \tag{A.2}$$

where β_1 and β_2 are the parameters of interest, and all the other variables are defined as in the baseline specification (4). The point estimate of the year t treatment effect is computed as $\hat{\beta}_1 + \hat{\beta}_2(t - 2015)$, where hats indicate estimated values. The standard errors are computed according to the delta method following Ahlfeldt, Feddersen (2017), who estimate a similar specification. Below, we present the results.

Tab. A2. Parametric treatment effect on wages

	(1) Ln hourly wage at the 10th percentile	(2) Ln hourly wage at the 50th percentile	(3) Ln hourly wage at the 90th percentile
T x (year >= 2015)	0.0044***	0.0003**	0.0005
	(0.0004)	(0.0001)	(0.0002)
T x (year >= 2015) x (year - 2015)	0.0005	0.0004***	0.0000
	(0.0003)	(0.0001)	(0.0001)
2016 treatment effect	0.0049***	0.0007***	0.0006**
	(0.0006)	(0.0002)	(0.0002)
County effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
T * trend	Yes	Yes	Yes
East * year effects	Yes	Yes	Yes
R^2	0.990	0.998	0.998
Obs.	2,406	2,406	2,406

Notes: Standard errors (in parentheses) clustered on counties. Berlin assigned to East-German states. Treatment (T) is the percentage of workers below the minimum wage in 2014 (the year before the policy was introduced). (year >= 2015) is a dummy variable taking the value of one if the condition is true. T x trend is an interaction of the treatment and a linear trend term with zero value in 2015). * p < 0.1, ** p < 0.05, *** p < 0.01.

Tab. A3. Parametric treatment effect on employment and migration rates

	(1) Unemployment rate (percent)	(2) Ln employment	(3) Ln labour force	(4) Out-migration rate (percent of lagged labour force)	(5) In-migration rate (percent of lagged labour force)
T x (year >= 2015)	-0.0517***	0.0003	-0.0004	-0.0410***	-0.0677***
	(0.0159)	(0.0002)	(0.0002)	(0.0083)	(0.0153)
T x (year >= 2015) x (year - 2015)	0.0190	-0.0003**	0.0006***	0.0387***	0.0464***
	(0.0137)	(0.0002)	(0.0002)	(0.0087)	(0.0145)
2016 treatment effect	-0.0327	0.0006**	0.0002	-0.0023	-0.0212
	(0.0269)	(0.0003)	(0.0004)	(0.0082)	(0.0160)
County effects	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes
T * trend	Yes	Yes	Yes	Yes	Yes
East * year effects	Yes	Yes	Yes	Yes	Yes
R^2	0.990	0.999	0.999	0.970	0.934
Obs.	2,406	2,406	2,406	2,005	2005

Notes: Standard errors (in parentheses) clustered on counties. Berlin assigned to East-German states. Treatment (T) is the share of workers below the minimum wage in 2014 (the year before the policy was introduced). (year >= 2015) is a dummy variable taking the value of one if the condition is true. T x trend is an interaction of the treatment and a linear trend term with zero value in 2015). * p < 0.1, ** p < 0.05, *** p < 0.01

6 Reference

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