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DISCUSSION PAPER SERIES

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ABSTRACT

Long-Term Employment Effects of the Minimum Wage in Germany: New Data and Estimators*

We investigate the long-term effects of the introduction of the German minimum wage in 2015 and its subsequent increases on regional employment. Using comprehensive survey data, we are able to measure the regional bite of the minimum wage in 2014, just before its introduction, as well as in 2018, before it was raised substantially in several steps. The introduction mainly affected the labour market in East Germany, while the minimum wage increases increasingly affected low-wage regions in West Germany, with about one third of regions changing their (binary) treatment status between 2014 and 2018. We use different specifications and extensions of the canonical difference-in-differences approach, as well as a set of new estimators that allow unbiased effect estimation with a staggered treatment adoption and heterogeneous treatment effects. Our results show a small negative effect on total dependent employment of 0.5%, driven by a significant reduction in marginal employment of 2.4%. The extended specifications suggest additional effects of the minimum wage increases, as well as stronger negative effects for those regions that were strongly affected by the minimum wage in both periods.

JEL Classification: J23, J31, J38

Keywords: minimum wage, employment, regional bite

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1 Introduction

The debate over the impact of minimum wages on employment has gained significant attention in the literature, particularly since the early 1990s (Card and Krueger, 1994, 2000; Neumark and Wascher, 2000). This ongoing controversy, especially regarding the direction of employment effects, has remained a central focus in more recent studies as well (Neumark *et al.*, 2014; Allegretto *et al.*, 2017; Cengiz *et al.*, 2019). While the existing literature focuses mainly on how minimum wages affect employment in the short run, little is known about the longer-term effects and whether the effects of newly introduced minimum wages differ from those of minimum wage increases.

We contribute to the minimum wage literature by estimating the medium- to long-term regional employment effects of the introduction of a nationwide statutory minimum wage in Germany and its subsequent increases. We are able to measure the regional minimum wage bite not only prior to the introduction, but also a few years later to account for potential changes in the treatment over time. We investigate the additional effects of minimum wage increases and the heterogeneity of the effects based on the treatment path. Furthermore, we add to the literature by applying newly developed difference-in-differences estimators that are robust to heterogeneous treatment effects in a setting with a staggered treatment adoption.

The introduction of a statutory minimum wage in Germany in 2015 was one of the country's biggest labour market policy reforms for many years, and it had been controversially debated in both academia and politics whether the German minimum wage of initially €8.50 per hour would cause substantial employment losses. Upon introduction, the minimum wage equalled about 49.8% (57.6%) of the mean (median) wage in Germany and about 11.4% of workers were affected by it (Structure of Earnings Survey, 2014).

In the meantime, the short- to medium-term employment effects of the German minimum wage introduction have been extensively studied in the literature (for summaries see Caliendo *et al.*, 2018, 2019; Bruttel, 2019; Bossler and Gerner, 2020; Mindestlohnkommission, 2020).[1] Overall, most studies find no or only small negative effects of the minimum wage introduction on total employment (Mindestlohnkommission, 2018; Bonin *et al.*, 2018; Caliendo *et al.*, 2019; Bruttel *et al.*, 2019; Pestel *et al.*, 2020). Hereby, the effect is predominantly

[1] There also exist older studies about the previously introduced sector-specific minimum wages, mostly not finding significant employment effects (see Bosch and Weinkopf, 2012 and Möller, 2012 for a detailed overview and Fitzenberger and Doerr, 2016 for a critical assessment of the applied methods). Nonetheless, there were some signs of a tendency towards negative labour market effects in East Germany, where the impact intensity of the minimum wage is substantially higher than in West Germany due to the overall lower wage level.

due to marginal employment, while employment subject to social security contributions remained stable (Caliendo *et al.*, 2018; Bonin *et al.*, 2018; Ahlfeldt *et al.*, 2018; Garloff, 2019; Holtemöller and Pohle, 2020; Schmitz, 2019; Pestel *et al.*, 2020).[2]

The existing literature on the German minimum wage focuses mainly on the short-term effects two to three years after the introduction of the minimum wage, while much less is known about the medium- and especially the long-term effects. This is important for several reasons. First, employment adjustments may take place over a longer period than just a few years, especially in the German labour market context where dismissals are rather difficult. Second, the minimum wage has been raised several times and may have caused additional employment effects after the initial adjustment phase of the introduction. In 2017 and 2019, the minimum wage was raised to €8.84 and €9.19, respectively, and since then it has been increased several more times to a current level of €12.[3] Moreover, previous studies have mainly relied on data from the 2014 (pre-introduction) Structure of Earnings Survey (SES) to determine the treatment status across labour market regions in Germany. However, the composition of the regions mainly affected by the introduction may differ from the composition of the regions affected by subsequent large minimum wage increases. Studying the longer-term effects of the German statutory minimum wage can also be informative about the potential effects of minimum wages elsewhere, as several other countries have nationwide minimum wages and have increased them over time (e.g. the UK, France, the Netherlands, Poland, Hungary).

Our analysis of the longer-term employment effects of the introduction of the minimum wage in Germany is based on aggregate administrative data on employment at the level of regional labour markets over the period from 2013-2022. Regions were affected differently by the minimum wage introduction due to regional differences in wage levels and the distribution

[2]Friedrich (2020) even identifies positive effects of the minimum wage on employment subject to social security contributions until the first increase in 2017. Pestel *et al.* (2020) find that the effects can be mainly attributed to the introduction of the minimum wage, while the first increase had no considerable additional effect, and regions/sectors with a below-average growth dynamic experienced stronger negative employment effects. Bossler (2016, 2017) and Bossler and Gerner (2020) show that the minimum wage had an impact on the employment dynamic by reducing the number of new hires. While focusing mainly on effects on wage inequality induced by the minimum wage, Bossler and Schank (2023) show that their finding of a significantly reduced inequality in monthly earnings is not driven by employment effects as they find no significant effects on employment. Biewen *et al.* (2023) also identify a significant increase in wages and a reduction in wage inequality due to the minimum wage introduction, but no significant effect on the distribution of weekly working hours. Dustmann *et al.* (2022) find that instead of the feared employment effects, a reallocation of the employees subject to the minimum wage into more productive firms took place. Hereby, they identify substantial wage gains in the lower part of the wage distribution, of which one quarter can be explained by changes from smaller (relatively low paying) to larger (relatively high paying) firms. This "upgrade" only occurs for low-wage workers and not for higher-earning workers.

[3]See Table A.1 in the Appendix for an overview of the development of the minimum wage level over time.

of wages. Thus, there is a strong variation in the regional bite of the minimum wage. We exploit this variation to apply a difference-in-differences (DiD) approach to estimate the causal effects of the minimum wage on employment. We operationalise the regional minimum wage bite using the regional wage gap based on the SES 2014. As the SES is carried out every four years, we can measure the regional wage gap again in 2018 with respect to the minimum wage level after it had been substantially raised. We thus have a measure of the degree of regional exposure to the minimum wage at two different points in time. Overall, the wage gap substantially declined between 2014 and 2018, while the fraction of affected workers declined to a much lesser extent. We find that a significant proportion of German labour market regions changed between treatment and control status between 2014 and 2018. To the best of our knowledge, we are the first to use two waves of the SES to investigate the employment effects of the minimum wage in Germany.

In our main specification, we estimate the effects of the minimum wage introduction alone using a treatment indicator based on the SES 2014. In a second step, we account for the minimum wage increases and the substantial change in strongly affected regions over time in multiple ways. First, we add interaction terms for the minimum wage increases to the baseline specification to test for additional effects of the increases. Second, we apply a specification with three treatment groups that are defined by having a relatively high minimum wage bite in 2014, 2018 or both years. Regions with a relatively low minimum wage bite in both years form the control group. Finally, we treat the introduction of the minimum wage and the increase in 2019 as one treatment that was introduced in a staggered manner, with some regions starting the treatment in 2014 and others in 2019. In this setting, the classical TWFE estimator may be biased if the treatment effects are heterogeneous across groups/units or over time. This bias may be caused by "forbidden comparisons" (Borusyak and Jaravel, 2017) between the outcomes of later and earlier treated units.

Recently, several new estimators have been developed to obtain unbiased DiD estimates despite a setting that differs from the canonical one with two groups and two periods. We compare the estimates of the classical TWFE with those of the new estimators for the longer-term effects of the German minimum wage on employment when treatment adoption is considered to be staggered. We use the estimators developed by Sun and Abraham (2021), Callaway and Sant'Anna (2021), Borusyak *et al.* (2021), and De Chaisemartin and d'Haultfoeuille (2022a).

To our knowledge, the studies by Dolton *et al.* (2012, 2015) are the most closely related to ours in terms of the methodological approach of including not only the minimum wage introduction but also the increases and the updating of the treatment over time. Dolton *et al.* (2012, 2015) apply an incremental difference-in-differences approach with interactions of each year with the annually updated continuous regional minimum wage bite (accounting for the annual increases in the minimum wage). Thus, their specification resembles a kind of yearly event study with a changing continuous treatment. By contrast, our approach of including the increases allows us to separate the longer-term effects of the introduction from those of subsequent increases. In addition, by using different specifications, as explained above, we take into account that the increases may have different effects depending on how much a region was affected by the introduction.

Our main findings confirm the negative but moderate short-term employment effects of the minimum wage introduction also in the longer term, mainly due to a significant reduction in marginal employment. While the effect on total dependent employment has diminished over time, the effect on marginal employment has increased over time. The negative employment effect on marginal employment is also substantially stronger for regions with a relatively low GDP growth rate prior to the introduction of the minimum wage. We find that the regional bite of the minimum wage declined in all regions, although not at the same rate, with the rankings of the regional bites changing substantially between 2014 and 2018. One consequence is that while the initial minimum wage introduction mainly affected the labour market in East Germany, the most recent minimum wage hikes are increasingly affecting lower-wage regions in West Germany as well. This leads to the conclusion that the minimum wage increases – especially the one in 2019 – have led to additional employment effects on top of the longer-term effects of the minimum wage introduction of 2015. Regions with a relatively high wage gap in 2014 and 2018 experience substantially stronger negative employment effects than those with a high wage gap in only one of the two years. Finally, we document that the alternative DiD estimators overall support our main findings.

The remainder of the paper is structured as follows. Section 2 describes the data and provides descriptive results. In Sections 3 and 4, we explain the empirical approach and present our regression results. Section 5 concludes.

2 Data and Descriptive Results

2.1 Data Sources

We use the SES of 2014 and 2018 to measure the regional minimum wage bite.[4] The SES is conducted every four years and the data is provided by the Federal Statistical Office of Germany. It includes information on earnings of employees in Germany as well as other detailed information about employment, such as the hours worked, industry, and personal characteristics of the employees. The data covers the month of April of the respective year and thus stems from a point in time directly prior to the introduction of the minimum wage, which was announced in July 2014. Firms are obligated to provide information and for a high level of representativeness, firms are chosen stratified for states, industry and firm size category (FDZ, 2019). The SES 2014 (2018) contains information about approximately one million employment relationships from about 71,000 (60,000) companies with at least one employee subject to social security contributions. The SES 2014 has previously been used for evaluating the minimum wage's employment effects (Bruttel *et al.*, 2018; Bonin *et al.*, 2018; Caliendo *et al.*, 2018; Pestel *et al.*, 2020) although – to our knowledge – we are the first to use the SES 2018.

The SES has two major advantages compared to other data sources that are firm-based: first, it allows a precise estimation of hourly wages on the individual level, which in turn allows determining the bite on different dimensions; and second, the large number of observations enables an analysis at the level of the 257 labour market regions, as in our analysis. However, results below the regional level of the federal state are not representative per se (FDZ, 2019). Another caveat is that the SES does not include regional information for civil servants below the level of the federal states, and thus we have to exclude them from our analysis. Since the SES 2014 and 2018 share the same characteristics, the SES 2018 allows smoothly continuing with the minimum wage evaluation and showing developments between the year prior to the minimum wage introduction and the year prior to the second increase in 2019. The 257 labour market regions are divided into a control and treatment group based on the wage gap calculated using the SES 2014. We also divide the labour market regions into a treatment and control group based on the SES 2018, which documents the development of the degree of exposure over time and which we will use in additional analyses.

[4]Source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, Structure of Earnings Survey, 2014 (DOI:10.21242/62111.2014.00.00.1.1.1) and 2018 (DOI:10.21242/62111.2018.00.00.1.1.0).

The data for our outcome measures of dependent employment up to the age of 64 years come from the statistical department of the Federal Employment Agency, which publishes the number of employed persons at the regional level on a quarterly basis.[5] The statistics are based on process data from the Federal Employment Agency as well as the statutory pension insurance and can be considered as very reliable. In our analysis we use data from the first quarter of 2013 to the first quarter of 2022.

Employees in Germany, with the exception of the self-employed and civil servants, and their respective employers are obliged to pay social security contributions. Employees earning up to a certain amount per month (in our observation period this threshold was €450) are exempt from paying social security contributions, but their employers are not. This type of employment is called marginal employment (or "minijobs"). The segment of employment with earnings above this threshold is called employment subject to social security contributions. The statistics of the Federal Employment Agency distinguish between employment subject to social security contributions and marginal employment, and further between exclusive marginal employment and marginal employment as a secondary job. Our main outcome of interest is the total number of persons in dependent employment, which we calculate as the sum of employment subject to social security contributions and exclusive marginal employment.[6]

Further, we use data for regional economic and demographic indicators such as GDP and population from the regional statistics of the Federal Statistical Office. Moreover, we include regional information about the settlement structure (classification in urban and rural areas) from the Federal Institute for Research on Building, Urban Affairs and Spatial Development.

[5] Our aim is to examine the employment effects for working-age individuals subject to the minimum wage. It is common in the minimum wage literature to define an upper bound for the (prime) working age population. While this limit varies somewhat across studies, our choice of 64 is within a typical range found in the literature (see, for example, Dustmann *et al.* (2022), Dolton *et al.* (2015) and Caliendo *et al.* (2018)). As the minimum wage only applies to employees aged 18 and over (unless they have completed an apprenticeship), we would prefer to include only employment for those aged 18 and over. However, the Federal Employment Agency only provides the broad age categories "15-24" or "under 25" (depending on the year). Therefore, we also have to include employees younger than 18.

[6] It is possible to be only marginally employed ("exclusive marginal employment") or to have a main job subject to social security contributions and also be marginally employed ("marginal employment as a secondary job"). Since we are interested in the number of persons in employment and do not want to double count persons who have a main job and a secondary job, we only add exclusive marginal employment to our measure of total dependent employment and not marginal employment as a secondary job.

2.2 Treatment Indicator

In order to identify a causal effect of the minimum wage on employment outcomes in Germany, we use a DiD approach (see Section 3). However, due to the universal nature of the minimum wage in Germany, there is no suitable control group that is not subject to the minimum wage.[7] Therefore, we divide regions into a control and a treatment group based on the degree to which they are affected by the minimum wage. To measure the degree to which a region is affected, we use the wage gap, describing the average absolute difference between the hourly wage and the minimum wage of €8.50 for the SES 2014 (€9.19 for the SES 2018) for hourly wages below the minimum wage, while the difference is equal to zero for wages of at least €8.50 (€9.19):

$$WageGap_{it} = \frac{\sum_{w=1}^{N_{it}} max[MW_t - Wage_{wit}, 0]}{N_{it}},$$

with i representing the region, t the year (2014 or 2018), w the individual worker, and N the number of workers. The concept of the wage gap that we use is based on the population of all employees not exempt from the minimum wage and quantifies the minimum wage exposure in respect to the number of employees as well as considering the level of the minimum wage relative to the base level of wages. We focus on the wage gap, because – in contrast to other measures (i.e. Kaitz- or Fraction-Bite) – it quantifies the size of the adaption of wages that is necessary to raise the hourly wage from April 2014 (April 2018) to the level of the minimum wage of €8.50 (€9.19). The final division between the treatment and control group is contingent on the median of the regional wage gaps (weighted by the regional population in 2013). Regions with a minimum wage gap above (below) the weighted median are part of the treatment (control) group.

2.3 Descriptive Statistics

Minimum Wage Bite Over Time The map on the left-hand side of Figure 1 shows the wage gap for all labour market regions in 2014. The wage gap is especially large in East Germany and lowest in the south, especially in the federal state of Bavaria. The size of the wage gap varies between 0.021 and 0.652. The right-hand side panel of Figure 1 shows

[7] There were a few exceptions from the minimum wage upon its implementation in 2015, yet the number of excepted employees is quite low, and these groups cannot be adequately compared to regular employees as they are mostly apprentices, interns, and teenagers below the age of 18. Further, sectors with their own minimum wages above the general minimum wage are also not an appropriate control group, because they represent a very selective sample of the labour market.

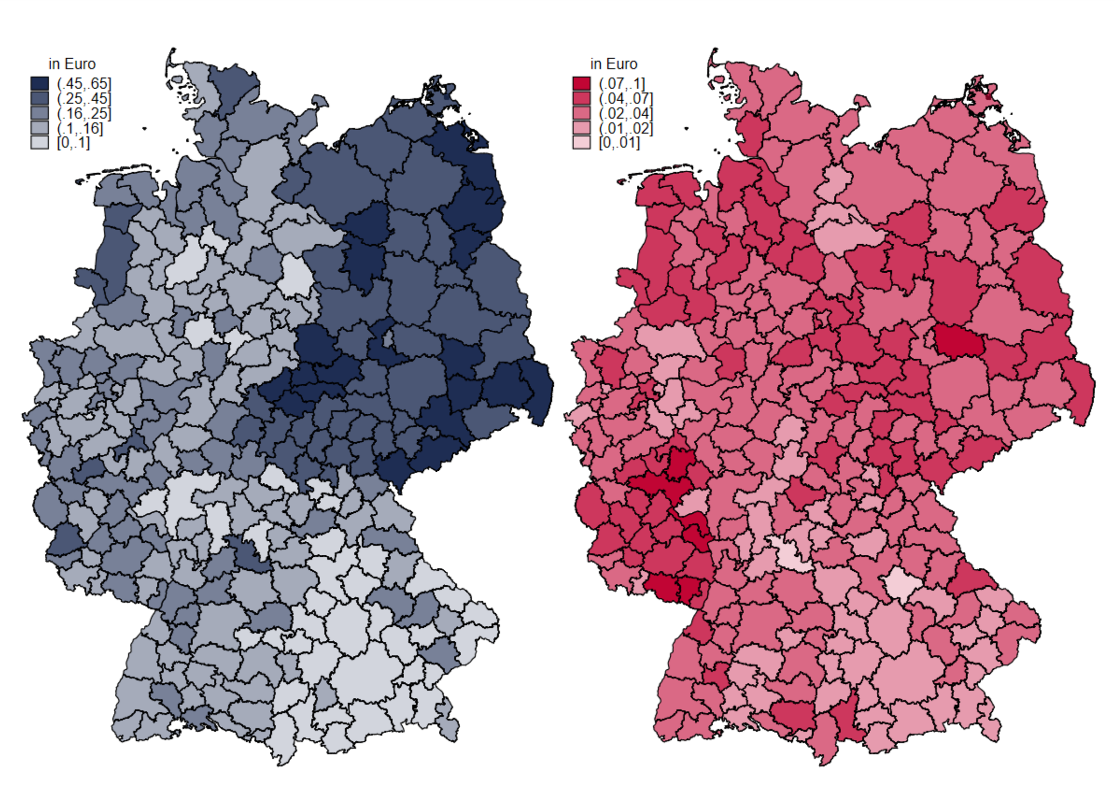
the wage gap for all labour market regions in 2018. While the wage gap has declined in all regions, the geographical distribution is no longer as clear. Especially, East Germany does not stand out any longer and there are substantially more regions in West Germany with an above-median wage gap. This change also becomes clear when looking at the correlations of the wage gaps in 2014 and 2018. The Pearson's correlation coefficient with 0.295 and the Spearman rank correlation coefficient of 0.4082 show that the two wage gaps are only weakly correlated.[8]

Table A.2 in the Appendix takes a closer look at characteristics of the labour market regions in 2014 and 2018 for the whole group as well as those with a relatively low and high wage gap separately. In 2014, 144 labour market regions belonged to the treatment group and 113 regions to the control group. The average overall wage gap was 0.203, while it was 0.281 in the treatment group and 0.104 in the control group. In 2018, the number of regions in the treatment group increased to 153, while the number in the control group decreased to 104. With 0.034, the average wage gap was substantially lower in 2018 than in 2014. Hereby, the average was 0.043 in the treatment and 0.019 in the control group. The settlement structure of regions in the two groups only slightly varied between 2014 and 2018. In both years, there are more urban regions in the control group and more rural areas in the treatment group. Further, there are no large differences between the treatment and control group or across years regarding the employment structure by sectors and in terms of the population share between the ages of 18 and 64 in 2013. In both years, the labour market regions in the treatment group experience a lower GDP growth between 2010 and 2013 and between 2015 and 2018. The share of regions with a GDP growth rate between 2010 and 2013 in the bottom quartile is higher in the control group than the treatment group in 2014. However, in 2018, the share is almost equal. The share of regions with a GDP growth rate between 2015 and 2018 in the bottom quartile is substantially higher in the treatment groups in 2014 and 2018.

Switching Treatment Status The majority of labour market regions do not change their binary treatment status between 2014 and 2018. Sixty-eight regions have a relatively low wage gap in both years and 108 regions a relatively high wage gap. However, a substantial

[8]For illustrative purposes, Figure A.1 in the Appendix shows scatter plots for the wage gap ranks 2014 (€8.50) / 2018 (€9.19), 2014 (€8.50) / 2014 (€9.19), and 2014 (€9.19) / 2018 (€9.19). The wage gap ranks of 2014 and 2018 show no strong relationship (irrespective of whether the wage gap in 2014 is relative to €8.50 or €9.19) while the two wage gaps in 2014 are very closely and positively related. This suggests that the change in wage gap ranks between 2014 and 2018 is not due to differences in the wage distribution in an interval between €8.50 and €9.19 that already existed in 2014.

Figure 1: Regional wage gap to €8.50 in 2014 (left) and to €9.19 in 2018 (right)

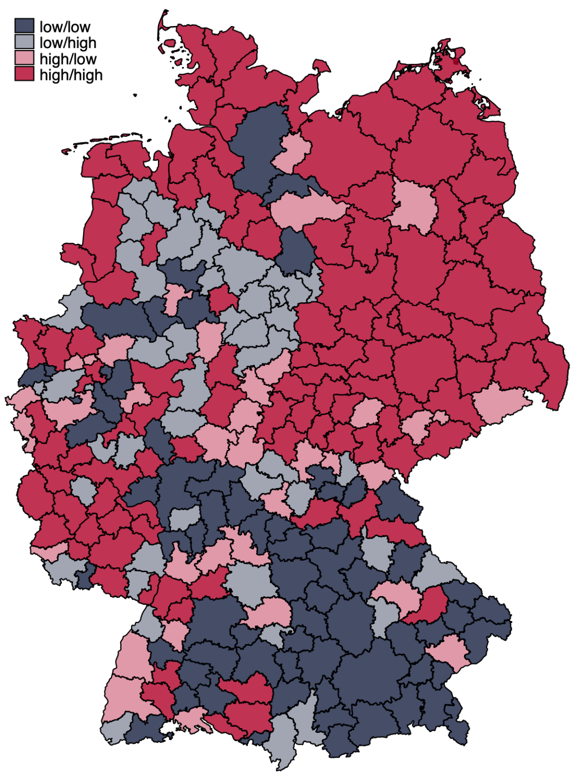


Source: SES 2014, 2018; own calculations. Note: The map on the left shows the regional wage gap to €8.50 in 2014. The map on the right shows the regional wage gap to €9.19 in 2018. The respective wage gaps are grouped into five categories (separately for 2014 and 2018) with a different shade of blue (2014) or red (2018) for each of them. For the definition of the wage gap, see Section 2.2.

share of about 31.5% of the regions change between a low and high wage gap in that period. Forty-five regions switched from a relatively low to a relatively high wage gap and 36 regions did the opposite. Based on this observation, we categorise the labour market regions into four different groups: "low/low group" (relatively low wage gap both in 2014 and 2018), "low/high group" (a low wage gap in 2014 and a high wage gap in 2018), "high/low group" (a high wage gap in 2014 and a low wage gap in 2018), and "high/high group" (a high wage gap in both years). We will use these four groups in one of our DiD specifications described in Section 3, where we estimate separate treatment effects for each group.

Figure 2 is a map showing the regional distribution of these four groups. While most East German regions are in the high/high group and many southern regions belong to the low/low group, there are especially (but not exclusively) many regions in the state of Lower Saxony in north-western Germany that switched between a relatively high and low wage gap. Table A.3 in the Appendix shows descriptive statistics similar to Table A.2 for the four groups. By definition, the average wage gap in 2014 (2018) is larger in the high/low and high/high (low/high and high/high) groups. Of special interest are the switchers. The regions in the low/high group decrease their minimum wage exposure in 2018 on average by almost 63% compared to 2014. At the same time, the regions in the high/low group reduced their exposure between 2014 and 2018 by about 91%. All groups reduced the fraction of employees directly affected by the minimum wage, but again there is large variation between the groups. The fraction in the low/high group only decreased by about 6%, while the high/low group experienced a large decrease in affected employees of approximately 62%. The average hourly wage was significantly lower for the high/low group than for the low/high group in 2014, although in 2018 the averages are virtually the same across both groups. Accordingly, the hourly wages increased at more than twice the rate in the high/low group compared with the low/high group (17.8% to 8.0%). These numbers suggest that the development of wages

Figure 2: Treatment groups based on the wage gaps in 2014 and 2018



Source: SES 2014, 2018; own calculations. Note: The map shows the labour market regions sorted into four groups based on their wage gaps in 2014 and 2018. "low" describes a wage gap below the weighted median of all regions in 2014 or 2018 and "high" describes a wage gap at or above that median. For the definition of the wage gap, see Section 2.2.

following the introduction of the minimum wage varied between groups and different regional developments between 2014 and 2018 led to changes in the exposure to the minimum wage increase relative to its introduction.

Development of Outcomes Over Time Figure A.2 in the Appendix shows the development of total employment over time separately for labour market regions with a high and a low wage gap upon its introduction. During the observation period, the dependent employment generally increases (with small seasonal cycles). It increased slightly more strongly in regions with a low wage gap and has been at the same level in both groups since the end of 2018. The employment subject to social security contributions makes up the large majority of the dependent employment and hence moves very similarly over time.

Marginal employment remained stable until the end of 2019 in regions with a low wage gap, while it decreased in regions in the treatment group after the introduction of the minimum wage. This already hints towards a reduction in marginal employment in the treatment group through the introduction of the minimum wage. The difference between the two groups increased over time and has remained constant from 2019 onwards. Throughout the Covid-19 pandemic, marginal employment strongly decreased in both groups, but the difference between them remained almost unchanged.

3 Empirical Approach

Our baseline DiD regression equation for estimating the cumulative effect of the German minimum wage on employment outcomes over the observation period reads as follows:

$$Log(Y_{it}) = \beta(WageGap^{high}_{i,2014} \times I_{t>Q2/2014}) + X_{it}\gamma + \theta_i + \theta_t + \epsilon_{it}, \tag{1}$$

where $Log(Y_{it})$ is the log of the dependent variable in labour market region i in quarter t. θ_i represents regional fixed effects that control for all time-invariant characteristics such as geographic location. θ_t adds quarter fixed effects that capture time-specific effects such as the overall economic development. The treatment variable in our DiD analysis $WageGap^{high}_{i,2014} \times I_{t>Q2/2014}$ is the interaction between a binary indicator for regions with a wage gap at or above the median and a binary indicator for post-treatment quarters. The treatment period in our specification starts after the second quarter of 2014 to account for potential anticipation effects since the law introducing the minimum wage was passed in July 2014. Consequently,

β is the coefficient of interest that measures the average treatment effect of a relatively high minimum wage bite on the respective outcome. X_{it} is a vector of control variables that can vary between labour market regions and over time such as differing trends for urban and rural regions.[9] We cluster the standard errors at the level of the labour market regions to allow for correlation of unobservable characteristics of a labour market region over time. Further, observations are weighted with the number of employees in April 2014, such that the results are not driven by relatively small labour market regions.

To analyse the dynamic development of the minimum wage effects over time, we apply an event-study approach. The corresponding estimation equation reads as follows:

$$Log(Y_{it}) = \sum_{\tau=Q1/2013,\tau\neq Q2/2014}^{Q1/2022} \beta_\tau (WageGap_{i,2014}^{high} \times I_{t=\tau}) + X_{it}\gamma + \theta_i + \theta_t + \epsilon_{it}, \qquad (2)$$

where $WageGap_{i,2014}^{high}$ is interacted with indicators for all quarters except for the baseline period (the second quarter of 2014). Thus, the coefficient vector β_τ contains the estimated treatment effect for every quarter before and after the minimum wage was announced relative to the baseline quarter. Insignificant estimates for pre-treatment periods support the identifying assumption of parallel trends between treated and control regions.

We also estimate Equations (1) and (2) with an additional interaction of the treatment indicator with a binary indicator for a relatively low GDP growth between 2010 and 2013 to test whether the treatment effect varies with the regional growth dynamic prior to the introduction of the minimum wage. Hereby, "low" is defined as a regional GDP growth rate in the bottom quartile of all regions.

We also extend Equation (1) to study additional effects of the minimum wage raises on January 1 of the years 2017 and 2019 to 2022:

$$\begin{aligned} Log(Y_{it}) = \beta(WageGap_{i,2014}^{high} \times I_{t>Q2/2014}) + \sum_{\tau=2016,\tau\neq 2017}^{2021} \delta_\tau (WageGap_{i,2014}^{high} \times I_{t>Q4/\tau}) \\ + X_{it}\gamma + \theta_i + \theta_t + \epsilon_{it}, \end{aligned} \qquad (3)$$

where the coefficients δ_τ indicate the additional effects of minimum wage raises beyond the initial introduction in 2015. Additionally, we also apply a shortened version only including the first two increases.

[9] The control variables included are interactions of: time, east, and population share between 18 and 64 years in 2013; time, east, and type of labour market region; time, east, and employment share in different sectors; and time and GDP per capita in 2013.

We exploit variation in the minimum wage bite between 2014 and 2018 by estimating an additional regression model using the four groups of regions that we introduced in Section 2.3. These groups are based on the regional wage gaps relative to the respective population-weighted median in 2014 and 2018: low/low, low/high, high/low, and high/high. We include treatment indicators for the last three groups, which makes the first group the control group. The corresponding estimation equation is:

$$\begin{aligned} Log(Y_{it}) = {} & \beta(WageGap_{i,2014,2018}^{low,high} \times I_{t>Q2/2014}) + \gamma(WageGap_{i,2014,2018}^{high,low} \times I_{t>Q2/2014}) \\ & + \delta(WageGap_{i,2014,2018}^{high,high} \times I_{t>Q2/2014}) + X_{it}\lambda + \theta_i + \theta_t + \epsilon_{it}. \end{aligned} \tag{4}$$

We also add a placebo term in the form of $\alpha(WageGap_{i,2014}^{high} \times I_{t<Q2/2014})$ to Equations (1) and (3). Equation (4) contains one placebo term of this kind for each of the three treatment groups. These placebo terms show whether the trends of the treatment and control group prior to the treatment were significantly different from each other. If this is not the case, it supports the common trend assumption necessary to identify a causal effect.

Finally, we also use an alternative estimation based on a staggered treatment adoption. Here, treatment starts in the third quarter of 2014 for those regions with a relatively high wage gap in 2014 (as is the case in the baseline setting) and in 2019 for regions that had a relatively low wage gap in 2014 and a high wage gap in 2018. Regions with a relatively low wage gap in both periods are never treated in this setting. The estimation equation reads as follows:

$$Log(Y_{it}) = \beta(WageGap_{i,year}^{high} \times I_{t \geq F}) + X_{it}\gamma + \theta_i + \theta_t + \epsilon_{it}, \tag{5}$$

with F referring to the time when a region starts treatment for the first time (Q3 2014 or Q1 2019). The corresponding year of the binary minimum wage bite is either 2014 or 2018. Once a region is treated, it remains treated for the whole observation period. Recent advances in the econometrics literature have shown that in settings with a staggered treatment adoption, TWFE estimates can be biased if treatment effects are heterogeneous across groups/units or time (see, for example, Sun and Abraham, 2021). If units are treated at different points in time, estimates of a classic TWFE model can include "forbidden comparisons" (Borusyak and Jaravel, 2017) between two treated groups or units (one earlier treated and one later treated). In case of heterogeneous treatment effects, this can cause the TWFE estimates to be biased. We see potential sources for such a treatment heterogeneity; for example, the treatment effect could differ between regions starting treatment in 2014 and 2019 or because the treatment intensity (the continuous wage gap) even differs within the treatment groups. Another possible reason is varying economic growth across regions that could affect the size of the treatment effect.

Several different new estimators have recently been developed to obtain unbiased DiD estimates despite a treatment that is adopted in a staggered manner. Usually, the idea behind the newly developed estimators is to only include "clean" comparisons between observations that are treated and those that have not (yet) been treated. These comparisons are then aggregated using different weights (that are to be chosen).[10] We compare the estimates of the classic TWFE with those of some of the newly developed estimators. The estimator developed by Sun and Abraham (2021) generalises the event-study approach to settings with a staggered treatment adoption and is based on cohort- and period- specific effect estimates. Treatment start is defined as the time when a unit's treatment status changes for the first time and the control group is either the never-treated or the last-treated group(s). By contrast, the estimator by Callaway and Sant'Anna (2021) can use the not-yet-treated or never-treated groups as controls. The basis of their approach is the estimation of group-time-average treatment effects. For example, these can be aggregated over groups (a group is defined by a common time of treatment start), by time relative to treatment start, or over all groups and periods to obtain an overall average treatment effect on the treated. The estimator proposed by De Chaisemartin and d'Haultfoeuille (2022a) generalises "the event-study approach to such designs, by defining the event as the period where a group's treatment changes for the first time" (De Chaisemartin and d'Haultfoeuille, 2022b, p.20). Borusyak *et al.* (2021) apply a different approach than the previously described estimators, developing an imputation estimator (others like Gardner (2022) use similar approaches). First, the counterfactual outcome for the treated observations is predicted by regressing the outcome on group and time fixed effects for the sample of not-treated observations. In a second step, the counterfactual outcome is subtracted from the observed outcome for the treated observations to obtain the treatment effect (Borusyak *et al.*, 2021; De Chaisemartin and d'Haultfoeuille, 2022b).

[10] See De Chaisemartin and d'Haultfoeuille (2022b) and Roth *et al.* (2023) for comprehensive overviews of the recent advances in the DiD literature.

4 Results

In this section, we present the results of our regressions. We start in Section 4.1 with the estimates of the employment effects of the minimum wage introduction based on Equations (1) and (2). In addition, we also estimate the treatment effects when the binary treatment is interacted with regional economic growth prior to the introduction of the minimum wage. In Sections 4.2 to 4.4, we present results for the incremental changes in the minimum wage, for estimations with three different treatment groups, and for a staggered treatment adoption. This is followed by a series of robustness analyses in Section 4.5 and a discussion of our results in the context of related studies in Section 4.6.

4.1 Long-Term Effects of the Minimum Wage Introduction

Baseline results We present our baseline findings for the long-term effects of the minimum wage introduction on employment outcomes in Table 1. Panel A shows the treatment estimates according to Equation (1) for dependent employment, employment subject to social security contributions, and marginal employment including all of the covariates described in Section 3.

Column (1) of Panel A of Table 1 shows that the introduction of the minimum wage had a significant negative impact on total dependent employment. The effect size is about -0.5% and is statistically significant at the 10% level. The coefficient on employment subject to social security contributions in column (2) is positive but very small and not statistically significant. Column (3) of Table 1 shows the results for marginal employment. The introduction of the minimum wage had a negative and statistically significant effect (at the 1% level) on the marginal employment of about –2.4%. The placebo terms are insignificant for all three outcomes, supporting the assumption of common pre-trends.

Figure 3 depicts the results of the extended DiD approach of Equation (2). In addition to the point estimate for each quarter, it also shows the 95% confidence intervals and vertical lines marking the announcement of the minimum wage and its introduction. Again, the specifications include all of the time-varying control variables. The assumption of parallel pre-trends seems to hold for all three outcomes, as the point estimates prior to the second quarter of 2014 are not significantly different from zero. Similar to the simple DiD model, the results show a persistently negative effect on total dependent employment. The coefficients alternate between significance at the 5% and 10% levels throughout the observation period.

This negative effect is hereby fully attributable to marginal employment, for which the effect has grown strongly in absolute terms over time. There is no statistically significant effect on the employment subject to social security contributions, although there seems to be a positive (though insignificant) trend in the last few quarters of the observation period.

Table 1: Effects of the minimum wage introduction on regional employment

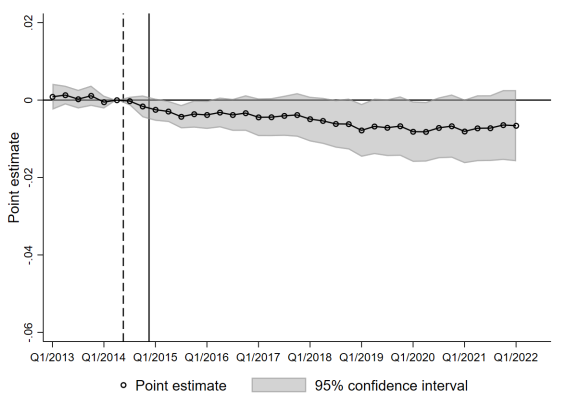
VARIABLES	Dependent employment	Employment subject to SSC	Marginal employment
Panel A: Binary treatment (wage gap)			
Treatment	-0.00511*	0.000456	-0.0239***
	(0.00260)	(0.00286)	(0.00763)
Placebo	0.000569	0.00142	-0.00140
	(0.00111)	(0.00107)	(0.00246)
R^2	0.597	0.584	0.472
Panel B: Binary treatment (wage gap) interacted with growth			
Treatment	-0.00434	0.000229	-0.0192**
	(0.00332)	(0.00357)	(0.00888)
Placebo (Treatment)	0.000593	0.00172	-0.00222
	(0.00124)	(0.00119)	(0.00281)
Treatment x Low growth 2010-2013	-0.00571	-0.00159	-0.0232*
	(0.00549)	(0.00661)	(0.0121)
Placebo (Treatment x Low growth 2010-2013)	0.00152	0.000757	0.00417
	(0.00228)	(0.00223)	(0.00473)
R^2	0.605	0.590	0.484
Observations	9,509	9,509	9,509
Labour market region FE	X	X	X
Quarter FE	X	X	X
Controls	X	X	X

Source: Regional Statistic of the Federal Employment Agency; SES 2014; Federal Statistical Office; Federal Institute for Research on Building, Urban Affairs and Spatial Development; own calculations. Note: The treatment effect refers to the coefficient β in Equation (1), estimated with TWFE. The binary treatment equals 1 if the regional wage gap is equal to or above the population-weighted median. The control variables included are interactions of: time, east, and population share between 18 and 64 years in 2013; time, east, and type of labour market region; time, east, and employment share in different sectors; time and GDP per capita in 2013. The specification in Panel B additionally includes the interactions of time and the indicator for a low GDP between 2010 and 2013. Standard errors (in parentheses) are clustered at the level of the labour market regions. Confidence level: ***p<0.01, **p<0.05, *p<0.1.

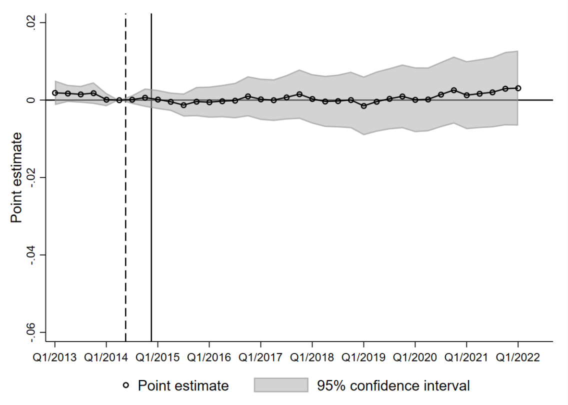
Interaction with Economic Growth In order to ascertain whether regions are affected differently by the treatment based on their economic growth prior to the introduction of the minimum wage, we interact the binary treatment with an indicator for low growth between

Figure 3: Effect of the minimum wage on employment

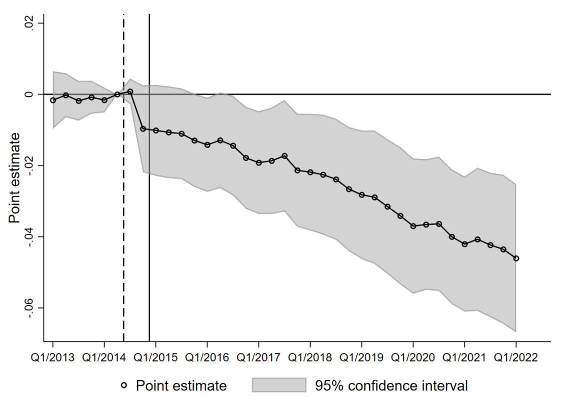
(a) Dependent employment



(b) Employment subject to SSC



(c) Marginal employment



Source: Regional Statistic of the Federal Employment Agency, SES 2014, Federal Statistical Office, Federal Institute for Research on Building, Urban Affairs and Spatial Development (FBUS); own calculations. Note: The vertical lines show the points of time when the minimum wage law was passed (August 2014) and introduced (January 1, 2015). The point estimates and confidence intervals refer to the vector β in equation 2. The control variables included are interactions of: time, east, and population share between 18 and 64 years in 2013; time, east, and type of labour market region; time, east, and employment share in different sectors; time and GDP per capita in 2013. Standard errors (in parentheses) are clustered at the level of the labour market regions.

2010 and 2013. Low growth is defined as a growth rate in the bottom quartile of all labour market regions.

The results for the total effect are presented in Panel B of Table 1. The main treatment coefficient for dependent employment remains negative but is no longer significant. The estimate for the interaction with a low growth rate is negative but also insignificant. For employment subject to social security contributions, the main treatment indicator is again positive and insignificant, while the interaction term with economic growth is also negative and insignificant. The main treatment effect for marginal employment is statistically significant at the 5% level and negative, but has decreased in magnitude to about -1.9%. The interaction with a low pre-treatment growth rate is significant at the 10% level at -2.3%. While the marginal employment falls on average in all treated regions, it falls more than twice as much in regions with low growth dynamics between 2010 and 2013.[11]

Figure 4 shows the event-study results separately for the treatment interacted with a relatively low growth rate and the main treatment indicator (which shows the treatment effect for regions with a relatively high growth rate). In Panels (a) and (b) it becomes clear that the treatment effects on dependent employment and employment subject to social security contributions are insignificant for regions with a relatively high growth rate throughout the observation period. In contrast, the effect on dependent employment is significantly negative (at the 5% level) in most periods for regions with a relatively low GDP growth. For marginal employment, the main treatment effects become significantly negative at the end of 2018, while they are negative and significant from the start for regions with a low economic dynamic.

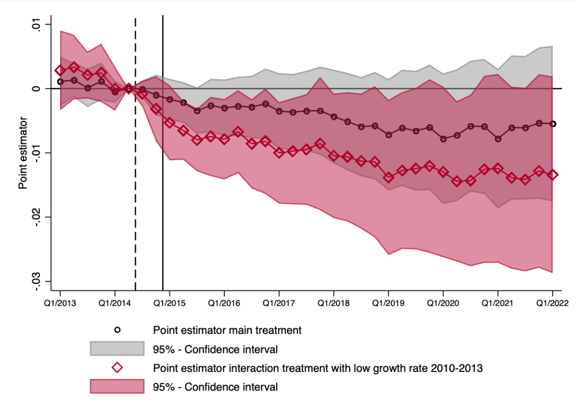
4.2 Effects of the Minimum Wage Increases

So far, we have presented estimates of the longer-term effects of the initial introduction of the German minimum wage in 2015. In the next step, we explicitly consider the subsequent increases in the level of the minimum wage after its introduction. To do this, we use Equation (3), which includes treatment interaction terms and indicators for the post-increase periods. We include the minimum wage increases from January 1 of each year between 2017 and 2022 (except 2018). We do not consider the increase from July 1, 2021, due to its small magnitude. We also consider a shorter version that only includes the increases in 2017 and 2019. The results are presented in Table 2, where Panel A shows the results for the short estimation with only two increases and Panel B shows the results for the full Equation (3).

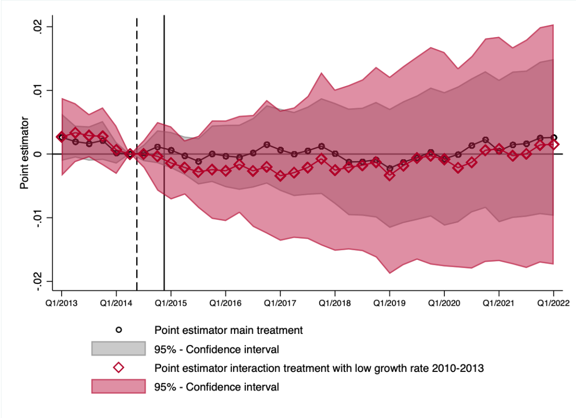
[11] To check that this difference in treatment effect is not simply due to regions with lower growth rates having a higher wage gap, we look at both (continuous) measures together. The Pearson correlation coefficient between the wage gap in 2014 and GDP growth between 2010 and 2013 is very low at -0.0799 (for regions with a wage gap above the median it is even lower at -0.0383). Furthermore, the unweighted (weighted) mean wage gaps for regions with a relatively high and low growth rates are not far apart at 0.2041 (0.1776) and 0.2000 (0.1779) respectively, and the difference is not statistically significant with a p-value of 0.829 (0.983). For regions with a wage gap above the median, the respective unweighted (weighted) means are 0.2765 (0.2496) and 0.2948 (0.2530). Again, this difference is not statistically significant with a p-value of 0.4815 (0.882). Thus, we can conclude that having a low growth rate prior to the introduction of the minimum wage is connected to experiencing a stronger negative employment effect and is not just another proxy for the treatment intensity.

Figure 4: Effect of the minimum wage on employment interacted with the regional economic growth

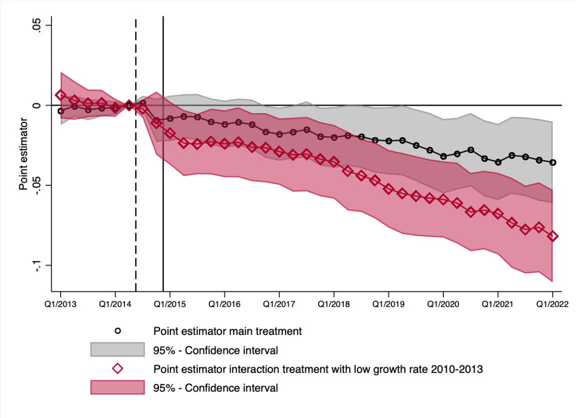
(a) Dependent employment



(b) Employment subject to SSC



(c) Marginal employment



Source: Regional Statistic of the Federal Employment Agency, SES 2014, Federal Statistical Office, Federal Institute for Research on Building, Urban Affairs and Spatial Development (FBUS); own calculations. Note: The vertical lines show the points of time when the minimum wage law was passed (August 2014) and introduced (January 1, 2015). The point estimates and confidence intervals refer to coefficients of Equation (2) augmented by an interaction of the binary treatment and a binary indicator for having a regional GDP growth in the lower 25% of all regions and an interaction of time and low growth between 2010 and 2013. The black markers show the point estimates for the main treatment indicator and the red markers those for the interaction of treatment and low growth between 2010 and 2013. The control variables included are interactions of: time, east, and population share between 18 and 64 years in 2013; time, east, and type of labour market region; time, east, and employment share in different sectors; time and GDP per capita in 2013. Standard errors (in parentheses) are clustered at the level at the labour market regions.

Table 2: Effects of the minimum wage introduction and its raises on regional employment

VARIABLES	(1) Dependent employment	(2) Employment subject to SSC	(3) Marginal employment
Panel A: Minimum Wage increases in 2017 and 2019			
Treatment 2014	-0.00294**	-0.000116	-0.0113*
	(0.00144)	(0.00151)	(0.00590)
Placebo	0.000595	0.00141	-0.00124
	(0.00112)	(0.00107)	(0.00246)
Treatment 2014 x (Time > 2016)	-0.00197	0.000380	-0.0101***
	(0.00188)	(0.00194)	(0.00357)
Treatment 2014 x (Time > 2018)	-0.00233	0.000845	-0.0160***
	(0.00188)	(0.00188)	(0.00395)
R^2 (within)	0.598	0.585	0.487
Panel B: Minimum Wage increases in 2017, 2019, 2020, 2021, and 2022			
Treatment 2014	-0.00294**	-0.000111	-0.0113*
	(0.00144)	(0.00151)	(0.00590)
Placebo	0.000595	0.00141	-0.00123
	(0.00112)	(0.00107)	(0.00246)
Treatment 2014 x (Time > 2016)	-0.00197	0.000388	-0.0101***
	(0.00188)	(0.00194)	(0.00357)
Treatment 2014 x (Time > 2018)	-0.00219	-0.000423	-0.00925***
	(0.00133)	(0.00130)	(0.00310)
Treatment 2014 x (Time > 2019)	-0.000443	0.00122	-0.00678***
	(0.00114)	(0.00119)	(0.00239)
Treatment 2014 x (Time > 2020)	0.000305	0.000907	-0.00466**
	(0.000976)	(0.00105)	(0.00230)
Treatment 2014 x (Time > 2021)	0.000650	0.00111	-0.00389**
	(0.000727)	(0.000747)	(0.00174)
R^2 (within)	0.598	0.585	0.488
Observations	9,509	9,509	9,509
Labour market region FE	X	X	X
Quarter FE	X	X	X
Controls	X	X	X

Source: Regional Statistic of the Federal Employment Agency; SES 2014; Federal Statistical Office; Federal Institute for Research on Building, Urban Affairs and Spatial Development; own calculations. Note: The treatment effects refer to the coefficients δ_τ in Equation (3), estimated with TWFE. The binary treatment equals 1 if the regional wage gap is equal to or above the population-weighted median. The control variables included are interactions of: time, east, and population share between 18 and 64 years in 2013; time, east, and type of labour market region; time, east, and employment share in different sectors; time and GDP per capita in 2013. Standard errors (in parentheses) are clustered at the level of the labour market regions. Confidence level: ***p<0.01, **p<0.05, *p<0.1.

The estimate for the treatment effect of the minimum wage introduction for dependent employment in column (1) shows a significant effect (at the 5% level) of −0.3% in both Panels A and B, while the placebo terms are insignificant. The effect size is smaller in magnitude compared to the results for the introduction alone in Table 1. The coefficients are negative for the increases between 2017 and 2020 and become positive for the subsequent increases. However, they are all very small and insignificant, suggesting that the minimum wage increases had no additional significant effects on total dependent employment. The main treatment effect on employment subject to social security contributions in column (2) is insignificant in both specifications, as was the case in the main results in Table 1. The coefficients for all increases are insignificant and, except for the estimate for the increase in 2019 in Panel B, they are all positive but very small. Finally, the main treatment coefficient for marginal employment is similar and significant at the 10% level in both panels at −1.1%. Thus, it is smaller in magnitude compared to Table 1. In addition to the introduction, all increases appear to have significant additional negative effects between 0.4 and 1.6%. Overall, these results suggest significant additional effects of the minimum wage increases, especially for the first two in 2017 and 2019, and on marginal employment.

4.3 Effects of the Minimum Wage for Switching Treatment Groups

In Section 2, we have documented that the regional wage gap changed substantially between 2014 and 2018, as did the regional ranking by size of the wage gap. We account for these changing wage gaps by estimating effects for three different treatment groups, defined on the basis of the relative size of the regional wage gap compared to the median in 2014 and 2018. As already described in Section 2, these groups are as follows: low wage gap in 2014, high wage gap in 2018 (low/high group); high wage gap in 2014, low wage gap in 2018 (high/low group); high wage gap in 2014 and 2018 (high/high group). The group of regions with a relatively low wage gap in both years forms the control group for this analysis (low/low group). This specification considers the entire treatment path combined, rather than single treatments at different points in time. In addition to the three treatment indicators, we also include a placebo term for each of them.

The results are presented in Table 3. The effect on dependent employment is negative for all three treatment groups and the placebo terms are all insignificant. The estimate is insignificant for both the low/high and high/low groups. The effect is largest and statistically significant at the 1% level for the high/high group at −1.1%. Thus, the effect for the group

Table 3: Effects of the minimum wage introduction on regional employment with multiple treatment groups

VARIABLES	(1) Dependent employment	(2) Employment subject to SSC	(3) Marginal employment
Group low/low: Reference group			
Group low/high	-0.00710	-0.00511	-0.0208***
	(0.00439)	(0.00448)	(0.00676)
Group high/low	-0.00372	0.00165	-0.0207*
	(0.00364)	(0.00411)	(0.0117)
Group high/high	-0.0108***	-0.00378	-0.0401***
	(0.00286)	(0.00335)	(0.00956)
Placebo Group low/high	0.00181	0.00259	-0.000553
	(0.00177)	(0.00166)	(0.00351)
Placebo Group high/low	0.00167	0.00288**	-0.000956
	(0.00128)	(0.00134)	(0.00340)
Placebo Group high/high	0.00108	0.00222	-0.00204
	(0.00144)	(0.00142)	(0.00290)
Observations	9,509	9,509	9,509
R^2 (within)	0.601	0.587	0.480
Labour market region FE	X	X	X
Quarter FE	X	X	X
Controls	X	X	X

Source: Regional Statistic of the Federal Employment Agency; SES 2014; Federal Statistical Office; Federal Institute for Research on Building, Urban Affairs and Spatial Development; own calculations. Note: The treatment effects refer to the coefficients β, γ, and δ in Equation (4), estimated with TWFE. Group low/low is the reference group and includes regions with a wage gap below the weighted median in 2014 and 2018. Group low/high includes regions with a wage gap below (at or above) the median in 2014 (2018). Group high/low includes regions with a wage gap at or above (below) the median in 2014 (2018). Group high/high includes regions with a wage gap at or above the median in 2014 and 2018. The control variables included are interactions of: time, east, and population share between 18 and 64 years in 2013; time, east, and type of labour market region; time, east, and employment share in different sectors; time and GDP per capita in 2013. Standard errors (in parentheses) are clustered at the level of the labour market regions. Confidence level: ***p<0.01, **p<0.05, *p<0.1.

that is strongly affected by the minimum wage in 2014 and 2018 is about twice as large as the overall effect in Panel A of Table 1. For the employment subject to social security contributions, all three coefficients are insignificant and the placebo term for the high/low group is significant. In contrast, all placebo terms are insignificant when estimating the effects on marginal employment. The coefficients for the low/high and high/low groups are about the same size at almost -2.1% each. The former is significant at the 1% level and the latter at the 10% level. The effect on marginal employment for the high/high group is almost twice as large at -4.0% and is significant at the 1% level.

4.4 Staggered Treatment Adoption

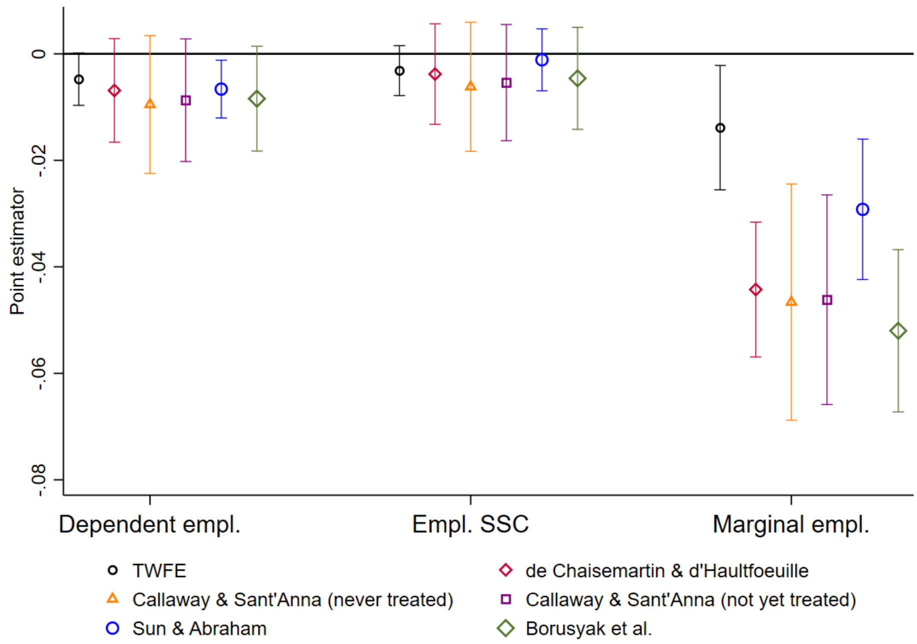
Another way to exploit both the 2014 and 2018 wage gaps for treatment estimation is to combine them into a treatment that is adopted in a staggered manner at two points in time, namely 2014 and 2019. In doing so, we assume that the treatment is absorbing, i.e. a region that is treated once remains treated until the end of the observation period. First, we estimate the effect of this staggered treatment using the TWFE model applied in the previous sections and apply the decomposition of the treatment coefficient introduced by Goodman-Bacon (2021). As described in Section 3, effect estimates of a staggered treatment may be biased if treatment effects are heterogeneous across time and/or regions. We therefore test the robustness of the TWFE estimates against using alternative new estimators by Callaway and Sant'Anna (2021), Sun and Abraham (2021), De Chaisemartin and d'Haultfoeuille (2022a), and Borusyak *et al.* (2021).

Table A.7 in the Appendix shows the estimates for the staggered treatment using the same TWFE model as before (see Equation (5)). The coefficient for the total dependent employment is identical in direction and significance level and very similar in magnitude to the one in Table 1. The estimate for employment subject to social security contributions changes its sign and is now negative, but it remains small and insignificant. While the estimate for the marginal employment is negative and significant – as was the case in Table 1 – its magnitude has decreased substantially from 2.4 to 1.4%.

We decompose our TWFE estimates according to Goodman-Bacon (2021) (using the user-written Stata command "bacondecomp" (Goodman-Bacon *et al.*, 2019)) to identify the different components of the total DiD estimates and their respective weights.[12] These components include 2x2 DiDs comparing the two treatment groups with the never-treated group. Other components are comparisons between the earlier and later treated groups and a within-group component driven by differences in covariates within groups. The overall DiD estimate is the weighted sum of these terms. The decomposition results show that the effect estimates for the 2x2 DiD between the later-treated and never-treated groups are smaller in absolute terms than the 2x2 DiD estimate for the earlier-treated and never-treated groups. The DiD estimates comparing the two treatment groups with each other are positive in all cases and they have a weight of about one third. The fact that these estimates have substantial weight and that they include "forbidden" comparisons between earlier and later treated units sup-

[12] The detailed decomposition results are provided by the authors upon request.

Figure 5: Effect of the minimum wage on employment with staggered treatment adoption and different estimators



Source: Regional Statistic of the Federal Employment Agency; SES 2014, 2018; Federal Statistical Office; Federal Institute for Research on Building, Urban Affairs and Spatial Development; own calculations. Note: The treatment effect refers to the coefficient β in Equation (5). The binary treatment equals 1 if the regional wage gap is equal to or above the population-weighted median. The exact choice of control variables varies between estimators due to their varying ability to accommodate covariates. TWFE and Sun and Abraham (2021): interactions of: time, east, and population share between 18 and 64 years in 2013; time, east, and type of labour market region; time, east, and employment share in different sectors; time and GDP per capita in 2013. Callaway and Sant'Anna (2021): type of labour market region, the GDP per capita in 2013, the population share between 18 and 64 years in 2013, and the employment shares of different sectors in 2013 as constant controls (it can only accommodate invariant controls). Borusyak *et al.* (2021): the same variables as for Callaway and Sant'Anna (2021), but interacted with time. De Chaisemartin and d'Haultfoeuille (2022a): reduced number of controls without "east/west" in the interactions.

ports the idea of testing the robustness of the results using the newly developed estimators mentioned above.

Figure 5 compares the estimates for the staggered treatment based on the TWFE model with those of the aforementioned estimators by De Chaisemartin and d'Haultfoeuille (2022a), Callaway and Sant'Anna (2021) (with the never -treated regions and the not-yet-treated regions as controls), Sun and Abraham (2021), and Borusyak *et al.* (2021).[13,14] All estimates

[13]The results were estimated using the Stata packages "did_multiplegt" (de Chaisemartin and d'Haultfoeuille, n.d.), "csdid" (Rios-Avila *et al.*, n.d.), "eventstudyinteract" (Sun, 2021), and "did_imputation" (Borusyak, n.d.).

[14]The exact choice of control variables varies between estimators due to their varying ability to accommodate covariates. The estimator by Sun and Abraham (2021) allows for the same set of time varying controls as the TWFE estimator described in Section 3. The estimator by Callaway and Sant'Anna (2021) can only accommodate invariant controls, so we add the type of labour market region, the GDP per capita in 2013, the population share between 18 and 64 years in 2013, and the employment shares of different sectors in 2013 as constant controls. For the estimator by Borusyak *et al.* (2021) we include the same variables, but interacted

for all three outcomes are negative, so the direction of the effects is the same whether a TWFE or one of the new estimators is used. The TWFE coefficient for dependent employment is smaller in absolute terms than any of the other estimators, although the difference is only moderate. With the exception of the Sun and Abraham (2021) estimator, all of the other coefficients have wider confidence intervals, so that their coefficients are not statistically significant. The TWFE estimate is significant at the 10% level and the Sun and Abraham (2021) estimate at the 5% level. For employment subject to social security contributions, the effect sizes are even closer together, so that no systematic difference exists. None of the coefficients reach conventional levels of significance. The difference between the TWFE and all other coefficients is largest for marginal employment. While all estimates are negative and statistically significant, the magnitude of the effect is stronger with each of the newly developed estimators compared to the TWFE model. While most of the new estimators yield similar results between -4.4% and -5.2%, the coefficient for Sun and Abraham (2021) of -2.9% is between them and the TWFE estimate of -1.4%.

There appear to be two main explanations for the apparent downward bias in the magnitude of the TWFE estimates. First, the treatment effect (compared to the never-treated group) appears to be different for regions starting treatment in 2014 and 2019. As the coefficient is a combination of the treatment effect of regions starting in 2014 and those starting in 2019, this affects the magnitude of the overall estimate. Second, the later treated group is compared to the early treated group and vice versa. As the early-treated regions are already experiencing a treatment effect before the late-treated regions start treatment, this biases the estimated effect for the late-treated regions.

4.5 Robustness Analysis

Continuous Treatment Our baseline results are based on a binary treatment definition, i.e. comparing employment trajectories in regions with a high vs. low wage gap. While there are clear advantages to defining a binary treatment indicator, it can be informative to additionally run the analysis with the underlying continuous wage gap as the treatment variable.[15]

with time. We cannot include "east/west" in the set of interactions because the estimator does not allow controls that perfectly predict treatment status. As all eastern regions start treatment in 2014, this would be the case here. Finally, the estimator by De Chaisemartin and d'Haultfoeuille (2022a) seems to have estimation problems when adding the large number of interactions included in the TWFE estimation. We therefor add a reduced number of controls, dropping "east/west" from the interactions.

[15] One advantage of a binary treatment is that it simplifies the interpretation of the estimated coefficients. Furthermore, unlike a continuous treatment indicator, a binary treatment indicator, does not require a linearity assumption with respect to the treatment effect. Moreover, a binary treatment indicator allows for flexible

The results using the continuous wage gap as the treatment variable are presented in Table A.4. The coefficients show the estimated effect of the continuous wage gap on each outcome. The point estimates are negative for all three employment outcomes. The effect on dependent employment is statistically significant at about −8.6%, while the effect on employment subject to social security contributions is rather small at −3.4% and not statistically significant. Fr both outcomes, however, the coefficient for the placebo is statistically significant at the 10% (dependent employment) or 5% (employment subject to social security contributions) level. We should therefore be more cautious about a causal interpretation of these results. The estimated treatment effect on marginal employment is statistically significant and the largest, in line with the results based on the binary treatment. The coefficient corresponds to a decrease in marginal employment of 32.9% for a region with a wage gap of one compared to a region with a wage gap of zero. To give an idea of what this result implies for the actual wage gaps observed in the data, we provide some examples, assuming linear treatment effects. The highest, median and lowest regional wage gaps in 2014 are 0.652, 0.143 and 0.021 respectively. Given the estimated treatment coefficient, these translate into reductions in marginal employment of about −21.5%, −4.7% and −0.7%, respectively. Furthermore, the total average effect on marginal employment (weighted average regional wage gap of 0.178 times the estimated treatment effect) is −5.8%.

Extended Pre-Treatment Period In our main analysis, we include a pre-treatment period of six quarters (Q1/2013 to Q2/2014). We decided not to include a longer pre-treatment period in our main analysis due to the lack of comparable regional and quarterly employment data for people of working age (up to 64 years). However, such data are available for total employment including all age groups, so we are able to conduct an additional analysis with a pre-treatment period starting in Q3/2011, where the first six quarters refer to employment regardless of age and the rest of the observation period refers to employment up to the age of 64, as in the main analysis. The corresponding results are shown in Table A.5. First of all, the three placebo coefficients remain insignificant, further supporting the validity of the common trends assumption. The negative effect on dependent employment remains marginally significant and is slightly stronger than in the main results. The coefficient on employment subject to social security contributions becomes negative, but remains very close to zero and still insignificant. Finally, the treatment effect on marginal employment remains highly significant

and relatively easy to interpret interactions with other relevant (binary) variables.

and is almost unchanged in magnitude. Overall, this additional analysis shows that our main results and conclusions are robust to the inclusion of a longer pre-treatment period. Figure A.3 shows event studies with the longer pre-period and they also confirm the robustness of our results.

Alternative Bite Measure in 2018. In this robustness analysis, we use a bite measure for 2018 that only considers employees who earn a wage that is at least equal to the April 2018 minimum wage level of €8.84 to be affected by the minimum wage. Therefore, this alternative wage gap will only be updated in 2018 for this group of employees. The idea is that employers who were not complying with the minimum wage in the past may continue to do so in the future as well. Overall, about 36.7% of the (unweighted) observations earning below the new minimum wage of 2019 in the SES 2018 have a reported wage below €8.84 (the level of the minimum wage at the time to which the SES 2018 refers). At first glance, this may seem like a large proportion. However, a large number of these employees have a reported wage just below this threshold. About 49.4% of those reporting a wage below €8.84 earn at least €8.79, and only 22.9% have a wage below the starting level of the minimum wage of €8.50. The large number of wages just below €8.84 suggests issues of measurement and reporting errors rather than "real" non-compliance. This observation reinforces our approach to include all wages below €9.19 in our main bite specification for 2018.

In Table A.6, we present the results for the multiple treatment group specification with the alternative definition of the wage gap in 2018. It can be seen that, despite some minor changes in significance levels and effect sizes, the main pattern of the coefficients is unchanged compared to Table 3. We perform the same robustness check for the staggered treatment adoption setup. The corresponding results are shown alongside the main results in Figure A.4. The new coefficients and their confidence intervals are very similar, and for some of the estimators even virtually unchanged, compared to the main estimates.

Exclusion of Regions Dropping out of Treatment In the staggered treatment adoption setting, we now exclude regions for which we document a relatively high wage gap in 2014 and a relatively low wage gap in 2018. It could be argued that these regions drop out of treatment and therefore do not fit into an absorbing treatment setting.[16] Figure A.5 shows that the point estimates still follow the same pattern, albeit with mostly larger confidence

[16] With the exception of the estimator of De Chaisemartin and d'Haultfoeuille (2022a), all of the new estimators are meant for absorbing treatments that stay on once started.

intervals, and the conclusions remain unchanged.

4.6 Comparison with the Literature

In order to make our results comparable with other estimates in the literature, we relate our employment effect estimates, which are based on the continuous wage as a treatment variable, to wage effects that can be interpreted as employment or labour demand elasticities (see, e.g., Cengiz *et al.*, 2019; Dube and Zipperer, 2024). As our data sources do not allow us to estimate wage effects ourselves, we rely on estimates by Bossler and Schank (2023), who studied the wage inequality effects of the German minimum wage introduction. However, it is important to note that the following back-of-the-envelope calculation should be interpreted with caution, as the estimation settings of our analysis and those of Bossler and Schank (2023) are not fully comparable due to differences in data sources, observation periods, the definition of the minimum wage bite and the regional level studied.

Bossler and Schank (2023) document that the wage effects vary across the wage distribution between a 21% increase at the 20th percentile and a mere 2% effect at the median, with no further effects in the top half of the wage distribution. Taking our estimate for total dependent employment in Table A.4 of -0.086 multiplied by the mean of the continuous wage gap of 0.178 and dividing this by the 21% wage effect found by Bossler and Schank (2023) gives us an employment elasticity of about -0.073, which seems reasonably within the range of estimates in the U.S. minimum wage literature (Cengiz *et al.*, 2019). In a recent meta analysis, Dube and Zipperer (2024) provide a comprehensive overview of own-wage elasticity estimates of national minimum wages and provide a categorization of the range of estimates by size. An elasticity of -0.073 falls into the range they label as "small negative" (Dube and Zipperer, 2024, p. 14). Applying the same back-of-the-envelope calculation to our estimate for marginal employment (-0.329), we find an elasticity of about -0.279. However, since Bossler and Schank (2023) report different wage effects along the wage distribution, it seems more appropriate to apply a wage effect at the bottom of the wage distribution in the context of marginal employment. To this end, we use Bossler and Schank (2023)'s estimate for the 5th wage percentile, as they state that the 10th percentile roughly coincides with the monthly earnings threshold for marginal employment. This gives a much stronger employment elasticity of around -0.49, which is just below the lower bound of the benchmark estimates documented by Cengiz *et al.* (2019) for the U.S., ruling out elasticities more negative than -0.45 at the 95% confidence level. According to the categorization of Dube and

Zipperer (2024), this corresponds to falling into the category labelled "medium negative". This seems reasonable, as a very robust finding of the empirical literature on the employment effects of the German minimum wage documents pronounced negative effects for the marginal employment segment.

5 Conclusion

Our analysis contributes to the literature by providing longer-term employment effects of minimum wages. We show that the introduction of the statutory minimum wage in Germany in 2015 had significant negative effects on dependent employment during the period until the first quarter of 2022. However, the effect is rather small with −0.5% less dependent employment in regions with a relatively high wage gap compared to those with a relatively low wage gap. Moreover, the magnitude of the effect decreased compared to previous studies (Pestel *et al.*, 2020), which analysed the period up to the first quarter of 2019. The results also show that the effect is entirely attributable to marginal employment, for which the trend of an increasingly negative effect over time has become even stronger. We cannot detect a significant effect on employment subject to social security contributions. Interestingly, the overall effect as well as the estimates in the last quarters of the observation period are positive, but very small and insignificant. These results are robust to the use of a continuous rather than a binary treatment definition. A back-of-the-envelope estimation based on the estimated employment effects using the continuous treatment and estimates for wage effects from Bossler and Schank (2023) suggests employment elasticities of about −0.073 for total dependent employment and −0.49 for marginal employment. Our results also suggest that increases in the minimum wage (especially the first two increases in 2017 and 2019) have had additional negative effects, particularly on the marginal employment.

We were able to extend the existing literature on the German minimum wage by using measures of regional exposure to the minimum wage at two points in time. Based on these data, we found variation in the minimum wage bite over time, with about 32% of regions changing their treatment status over time. Among these switching labour market regions, 18% (14%) were weakly (strongly) affected by the minimum wage in 2014 before its introduction, and then strongly (weakly) affected in 2018, before the second increase. When taking into account these treatment changes over time, we find that the employment effects are strongest for the group of regions that were strongly affected at both times. Even early on, these regions experienced a larger decline in marginal employment than the regions that were also strongly affected in 2014, but later changed their treatment status. These findings are relevant beyond the German context, as many countries have a uniform minimum wage that increases over time, while having sizeable differences in regional wage levels. Thus, our finding that the (relative) regional bite of a minimum wage can change substantially over time should be taken into account when studying the longer-term effects of minimum wages in other countries.

Overall, the results are in line with previous studies and they show that, even after up to seven years, the minimum wage does not appear to have the large negative employment effects that some had predicted prior to its introduction. However, the negative employment effects are stronger for regions with a relatively low GDP growth rate before the introduction of the minimum wage, especially for marginal employment. The analysis based on the multiple treatment groups suggests that regional labour markets evolved quite differently even within the treatment and control group of 2014. While all regions experienced a strong decrease in the average wage gap with respect to the current minimum wage between 2014 and 2018, the size of the decrease (in absolute and relative terms) was quite heterogeneous, with many regions switching between the treatment and control groups. Finally, defining the treatment as staggered and applying newly developed estimators alongside the classical TWFE approach shows that the latter seems to underestimate the effect of the minimum wage on the regional employment, especially on marginal employment. The coefficient of the TWFE estimator suggests an effect of -1.4%, while the new estimators mostly suggest a reduction of more than 4%.

There is a need for further research into the longer-term employment effects of the introduction of minimum wages, as well as the short- to medium-term effects of additional increases. The German minimum wage will continue to serve as a valuable example for further research. It has been substantially increased to €12 from October 1, 2022, onwards, which raises the question of non-linearities in the effects of minimum wages. Similar to the introduction of the minimum wage of €8.50 in 2015, the ad hoc increase to €12 represents a deep cut in the wage structure for many companies and employees. As it cannot be ruled out that the effects of the statutory minimum wage are characterised by non-linearities, there may be a tipping point beyond which a further increase has stronger negative effects on employment. Similarly, large increases in the minimum wage could have different effects than a series of moderate adjustments (see Ahlfeldt *et al.*, 2022). Such non-linearities have not yet been sufficiently studies. The experience with relatively high minimum wages at the local level in the US (e.g. $15 in Seattle) is not representative, as the wage levels in the concerned cities are higher and thus the depth of intervention of the minimum wage is lower compared to the national wage level (see Dube, 2019).

It is also of interest to investigate the mechanism(s) driving the differential development of the labour market regions after the introduction of the minimum wage. The open questions concern the causes of the substantial changes in the order of regional wage gaps between 2014 and 2018 and the reasons why some regions with a high wage gap experience a much larger negative employment effect than others.

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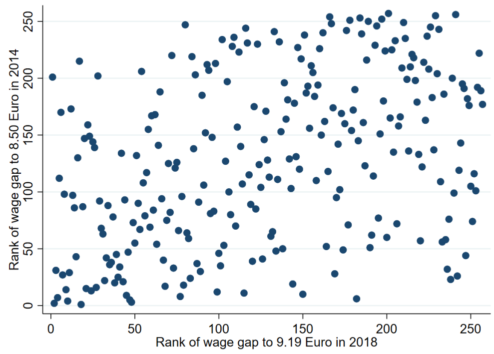
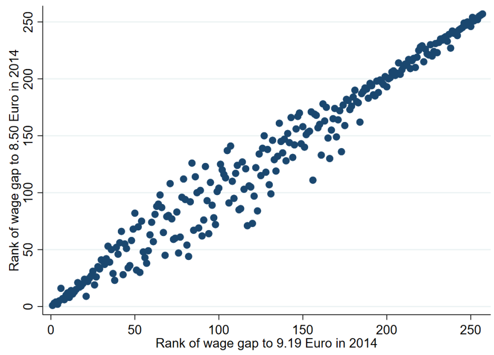
Appendix

Figure A.1: Wage gap ranks of labour market regions in 2014 and 2018

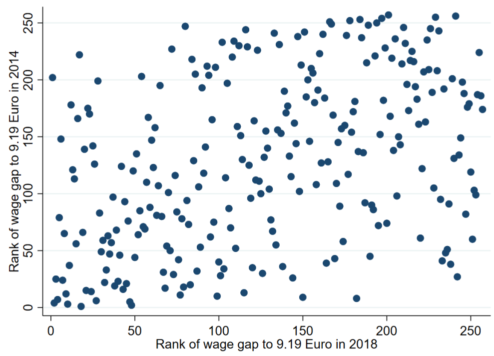
(a) Wage gap ranks 2014 (to €8.50) and 2018 (to €9.19)



(b) Wage gap ranks 2014 (to €8.50 and to €9.19)

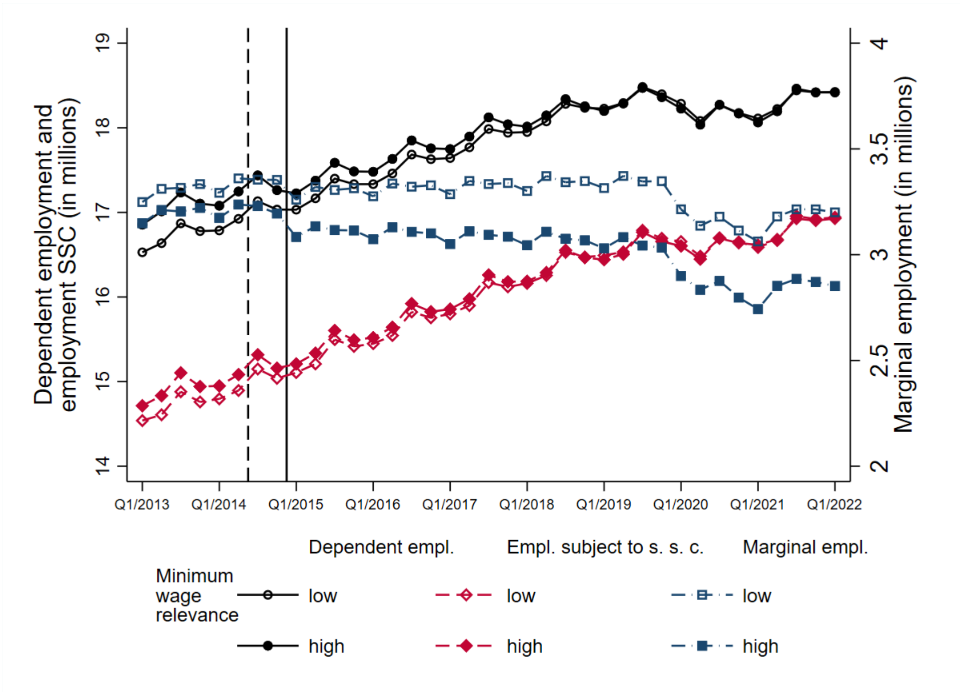


(c) Wage gap ranks 2014 (to €9.19) and 2018 (to €9.19)



Source: SES 2014, 2018; own calculations. Note: Scatter plots of labour market region ranks in terms of the wage gaps in 2014 and 2018. Scatter plot a) plots the ranks of the labour market regions in terms of their wage gap to €8.50 against the rank according to their wage gap to €9.19 in 2018. Scatter plot b) plots the ranks of the labour market regions in terms of their wage gap to €8.50 against the rank according to their wage gap to €9.19 in 2014. Scatter plot c) plots the ranks of the labour market regions in terms of their wage gap to €9.19 against the rank according to their wage gap to €9.19 in 2018.

Figure A.2: Outcome evolution over time by treatment status



Source: Regional Statistic of the Federal Employment Agency; SES 2014; own calculations. Note: The graph shows the development of dependent employment, employment subject to social security contributions, and marginal employment between 2013 and 2022 separate for labour market regions with a wage gap at or above and below the population-weighted median.

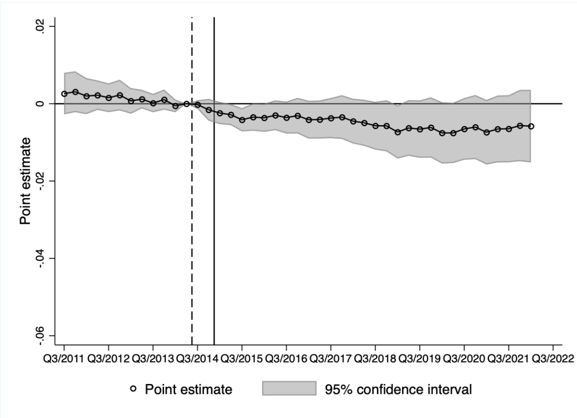
Table A.1: Development of the minimum wage level in Germany

Date	MW level (in €)	Δ (in %)
01.01.2015	8.50	
01.01.2017	8.84	4.00
01.01.2019	9.19	3.96
01.01.2020	9.35	1.74
01.01.2021	9.50	1.60
01.07.2021	9.60	1.05
01.01.2022	9.82	2.29
01.07.2022	10.45	6.42
01.10.2022	12.00	14.83

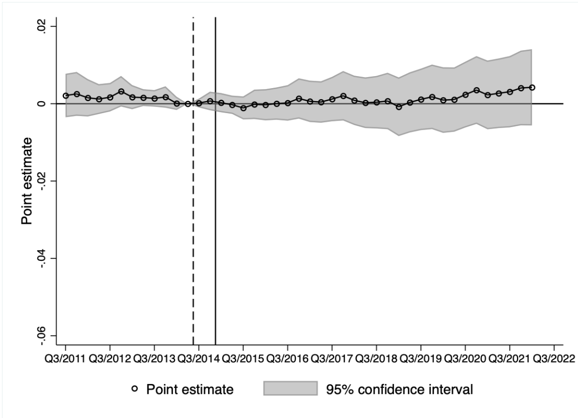
Source: Federal Statistical Office; own calculations. Note: The first column shows the date on which the respective increase of the minimum wage was implemented. The second column shows the new level of the minimum wage after it was increased. The third column displays the percentage change of the minimum wage due to the respective increase with respect to the previous level of the minimum wage.

Figure A.3: Effect of the minimum wage on employment with a longer pre-treatment period

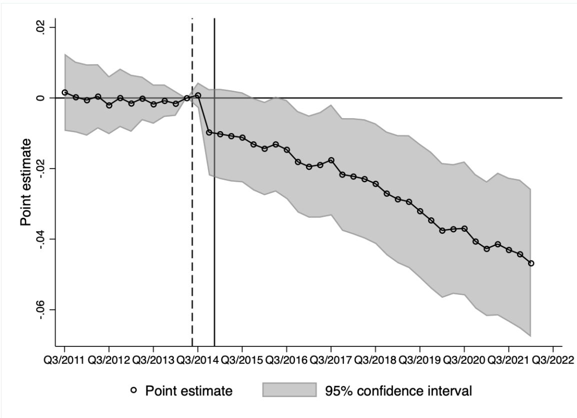
(a) Dependent employment



(b) Employment subject to SSC

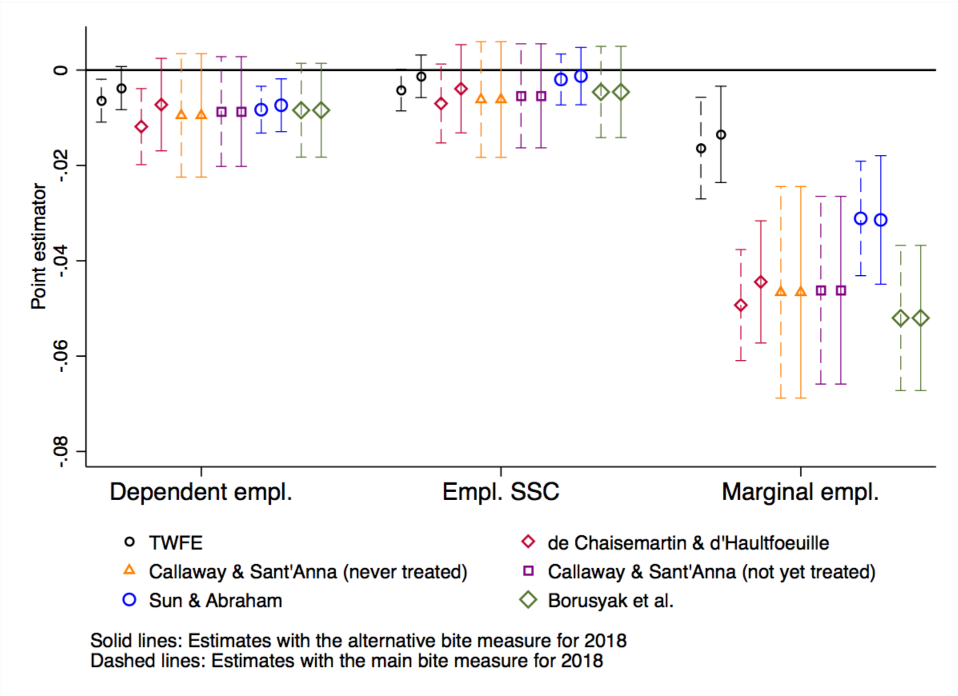


(c) Marginal employment



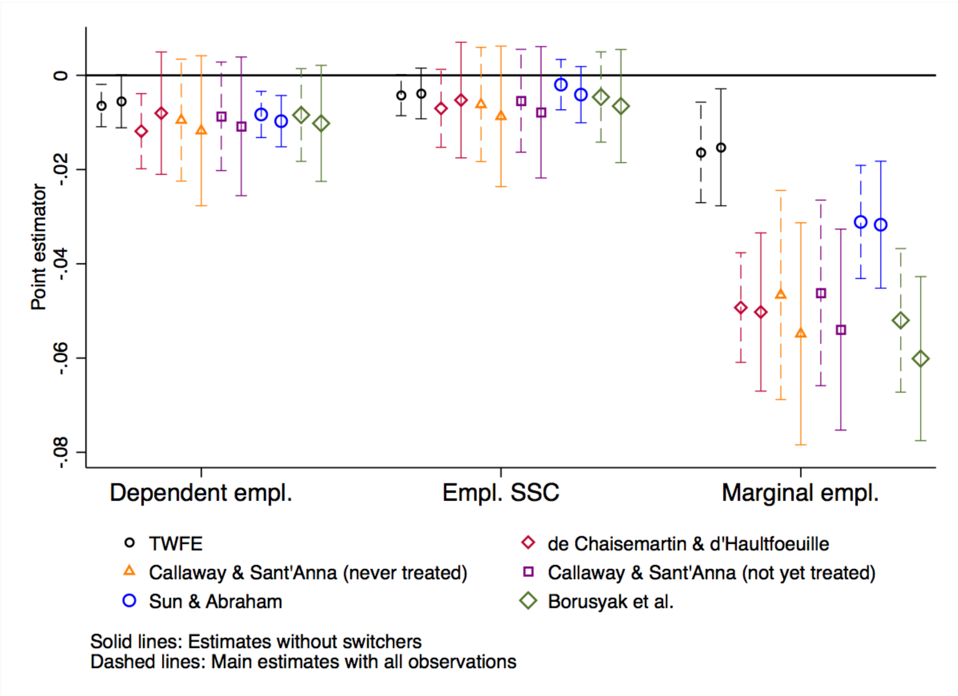
Source: Regional Statistic of the Federal Employment Agency, SES 2014, Federal Statistical Office, Federal Institute for Research on Building, Urban Affairs and Spatial Development (FBUS); own calculations. Note: The vertical lines show the points of time when the minimum wage law was passed (August 2014) and introduced (January 1, 2015). The point estimates and confidence intervals refer to the vector β in equation 2. The control variables included are interactions of: time, east, and population share between 18 and 64 years in 2013; time, east, and type of labour market region; time, east, and employment share in different sectors; time and GDP per capita in 2013. Standard errors (in parentheses) are clustered at the level of the labour market regions.

Figure A.4: Effect of the minimum wage on employment with staggered treatment adoption and different estimators using a bite measure for 2018 that is only updated for employees earning a wage of at least €8.84 (the level of the minimum wage in April 2018)



Source: Regional Statistic of the Federal Employment Agency; SES 2014, 2018; Federal Statistical Office; Federal Institute for Research on Building, Urban Affairs and Spatial Development; own calculations. Note: The treatment effect refers to the coefficient β in Equation (5). The binary treatment equals 1 if the regional wage gap is equal to or above the population-weighted median. The exact choice of control variables varies between estimators due to their varying ability to accommodate covariates. TWFE and Sun and Abraham (2021): interactions of: time, east, and population share between 18 and 64 years in 2013; time, east, and type of labour market region; time, east, and employment share in different sectors; time and GDP per capita in 2013. Callaway and Sant'Anna (2021): type of labour market region, the GDP per capita in 2013, the population share between 18 and 64 years in 2013, and the employment shares of different sectors in 2013 as constant controls (it can only accommodate invariant controls). Borusyak *et al.* (2021): the same variables as for Callaway and Sant'Anna (2021), but interacted with time. De Chaisemartin and d'Haultfoeuille (2022a): reduced number of controls without "east/west" in the interactions. In contrast to Figure 5, the treatment here is based on a bite in 2018 that is only updated for employees who earn at least the current minimum wage of €8.84 in April 2018 (the point in time to which the SES 2018 refers).

Figure A.5: Effect of the minimum wage on employment with staggered treatment adoption without observations that switch from treatment to control group in 2019



Source: Regional Statistic of the Federal Employment Agency; SES 2014, 2018; Federal Statistical Office; Federal Institute for Research on Building, Urban Affairs and Spatial Development; own calculations. Note: The treatment effect refers to the coefficient β in Equation (5). The binary treatment equals 1 if the regional wage gap is equal to or above the population-weighted median. The exact choice of control variables varies between estimators due to their varying ability to accommodate covariates. TWFE and Sun and Abraham (2021): interactions of: time, east, and population share between 18 and 64 years in 2013; time, east, and type of labour market region; time, east, and employment share in different sectors; time and GDP per capita in 2013. Callaway and Sant'Anna (2021): type of labour market region, the GDP per capita in 2013, the population share between 18 and 64 years in 2013, and the employment shares of different sectors in 2013 as constant controls (it can only accommodate invariant controls). Borusyak *et al.* (2021): the same variables as for Callaway and Sant'Anna (2021), but interacted with time. De Chaisemartin and d'Haultfoeuille (2022a): reduced number of controls without "east/west" in the interactions. In contrast to Figure 5, the estimation sample here does not include regions with a wage gap above the median in 2014 and below the median in 2018.

Table A.2: Descriptive statistics for labour market regions prior to the introduction and the increase of the minimum wage

Minimum wage exposure (relative to the median wage gap)	SES 2014 All	SES 2014 Low	SES 2014 High	SES 2018 All	SES 2018 Low	SES 2018 High
Average wage gap 2014 (in €)	0.203	0.104	0.281			
Average wage gap 2018 (in €)				0.034	0.019	0.043
Regions in East Germany in %)	21	0	37.5	21	7.7	30.1
Settlement structure (in %)						
Urban	44.7	52.2	38.9	44.7	51.9	39.9
Rural with tendencies to densification	24.9	22.1	27.1	24.9	25	24.8
Sparsely populated, rural	30.4	25.7	34	30.4	23.1	35.3
Empl. structure by sector 2013 (in %)						
Empl. in agriculture, forestry and fishing	2.4	2.3	2.5	2.4	2.1	2.6
Empl. in services	13.7	13.7	13.7	13.7	13.9	13.5
Empl. in manufacturing	29.2	31	27.8	29.2	30.5	28.3
Empl. in the public sector	30.5	28.9	31.7	30.5	29.3	31.2
Empl. in trade, transport and hospitality	24.2	24.1	24.3	24.2	24.2	24.3
Popul. share 18-64 years (2013, in %)	62.4	62.6	62.2	62.4	62.6	62.2
Economic growth						
GDP growth rate 2010-2013 (in %)	9.8	10.2	9.5	9.8	10.4	9.4
Low GDP growth 2010-2013 (share in %)	25.7	30.1	22.2	25.7	25	26.1
GDP growth rate 2015-2018 (in %)	10.1	11.2	9.3	10.1	10.8	9.7
Low GDP growth 2015-2018 (share in %)	29.2	20.4	36.1	29.2	22.1	34
Number of labour market regions	257	113	144	257	104	153

Source: SES 2014, 2018; Federal Institute for Research on Building, Urban Affairs and Spatial Development (FBUS), Federal Statistical Office; own calculations. Note: The table presents mean values for all regions and separately by relative size of the regional wage gap for 2014 and 2018. A high (low) minimum wage gap means that the wage gap is above (below or equal to) the median. The division of the labour market regions in types of settlement structure is based on information from the FBUS. The employment by sector, the gross domestic product, and the population shares are taken from the regional statistic from the Federal Statistical Office. Services: Financial, insurance, and business services, real estate and housing. Public services: public and other services, education and health. Trade, transport and hospitality includes information and communication services.

Table A.3: Descriptive statistics for labour market regions grouped according to their treatment status in 2014 and 2018

Minimum wage exposure in 2014/2018 (relative to the median wage gap)	(1) Low/ Low	(2) Low/ High	(3) High/ Low	(4) High/ High
Minimum wage bite				
Average wage gap 2014 (in €)	0.098	0.113	0.234	0.296
Average wage gap 2018 (in €)	0.019	0.042	0.021	0.044
Absolute difference (in €)	-0.079	-0.071	-0.214	-0.252
Percentage difference	-80.6	-62.8	-91.5	-85.1
Fraction with hourly wage below 8.50€ 2014 (in %)	8.86	10.35	16.58	19.49
Fraction with hourly wage below 9.19€ 2018 (in %)	5.73	9.74	6.22	10.98
Difference in percentage points	-3.13	-0.61	-10.36	-8.51
Percentage difference	-35.3	-5.9	-62.5	-43.7
Regions in East Germany in %)	0	0	22.2	42.6
Settlement structure (in %)				
Urban	51.5	53.3	52.8	34.3
Rural with tendencies to densification	26.5	15.6	22.2	28.7
Sparsely populated, rural	22.1	31.1	25	37
Empl. structure by sector 2013 (in %)				
Empl. in agriculture, forestry and fishing	2.2	2.6	2	2.7
Empl. in services	13.9	13.4	14.1	13.6
Empl. in manufacturing	31.8	29.8	28	27.7
Empl. in the public sector	28.2	30	31.5	31.8
Empl. in trade, transport and hospitality	24	24.3	24.5	24.3
Popul. share 18-64 years (2013, in %)	62.7	62.3	62.4	62.2
Economic growth				
GDP growth rate 2010-2013 (in %)	10.7	9.4	9.8	9.5
Low GDP growth 2010-2013 (share in %)	26.5	35.6	22.2	22.2
GDP growth rate 2015-2018 (in %)	11.5	10.7	9.5	9.2
Low GDP growth 2015-2018 (share in %)	19.1	22.2	27.8	38.9
Hourly wage				
Average hourly wage 2014 (in €)	16.92	16.03	14.87	14.20
Average hourly wage 2018 (in €)	18.67	17.32	17.50	16.02
Absolute difference (in €)	1.75	1.29	2.64	1.81
Percentage difference 2014-2018	10.3	8.0	17.8	12.7
Number of labour market regions	68	45	36	108

Source: SES 2014, 2018; Federal Institute for Research on Building, Urban Affairs and Spatial Development (FBUS), Federal Statistical Office; own calculations. Note: The table presents mean values for four different groups of regions that are defined by the relative size of their wage gaps in 2014 and 2018. A high (low) minimum wage gap means that the wage gap is above (below or equal to) the median. The division of the labour market regions in types of settlement structure is based on information from the FBUS. The employment by sector, the gross domestic product, and the population shares are taken from the regional statistic from the Federal Statistical Office. Services: Financial, insurance, and business services, real estate and housing. Public services: public and other services, education and health. Trade, transport and hospitality includes information and communication services.

Table A.4: Effects of the minimum wage introduction on regional employment with a continuous treatment variable

VARIABLES	Dependent employment	Employment subject to SSC	Marginal employment
Treatment (continuous)	-0.0863***	-0.0339	-0.329***
	(0.0193)	(0.0229)	(0.0700)
Placebo	0.0141*	0.0197**	0.0105
	(0.00798)	(0.00836)	(0.0159)
R^2 (within)	0.603	0.587	0.491
Observations	9,509	9,509	9,509
Labour market region FE	X	X	X
Quarter FE	X	X	X
Controls	X	X	X

Source: Regional Statistic of the Federal Employment Agency; SES 2014; Federal Statistical Office; Federal Institute for Research on Building, Urban Affairs and Spatial Development; own calculations. Note: The control variables included are interactions of: time, east, and population share between 18 and 64 years in 2013; time, east, and type of labour market region; time, east, and employment share in different sectors; time and GDP per capita in 2013. The specification in Panel B additionally includes the interactions of time and the indicator for a low GDP between 2010 and 2013. Standard errors (in parentheses) are clustered at the level of the labour market regions. Confidence level: ***p<0.01, **p<0.05, *p<0.1.

Table A.5: Effects of the minimum wage introduction on regional employment with a longer pre-treatment period

VARIABLES	Dependent employment	Employment subject to SSC	Marginal employment
Treatment	-0.00667*	-0.000727	-0.0243***
	(0.00383)	(0.00393)	(0.00884)
Placebo	-0.00141	-0.000475	-0.000945
	(0.00121)	(0.00118)	(0.00278)
R^2 (within)	0.616	0.590	0.535
Observations	11,050	11,050	11,050
Labor market region FE	X	X	X
Quarter FE	X	X	X
Controls	X	X	X

Source: Regional Statistic of the Federal Employment Agency; SES 2014; Federal Statistical Office; Federal Institute for Research on Building, Urban Affairs and Spatial Development; own calculations. Note: The treatment effect refers to the coefficient β in Equation (1), estimated with TWFE for an observation period from Q3 2011 until Q1 2022. The binary treatment equals 1 if the regional wage gap is equal to or above the population-weighted median. The control variables included are interactions of: time, east, and population share between 18 and 64 years in 2013; time, east, and type of labour market region; time, east, and employment share in different sectors; time and GDP per capita in 2013. The specification in Panel B additionally includes the interactions of time and the indicator for a low GDP between 2010 and 2013. Standard errors (in parentheses) are clustered at the level of the labour market regions. Confidence level: ***p<0.01, **p<0.05, *p<0.1.

Table A.6: Effects of the minimum wage introduction on regional employment with multiple treatment groups and a bite measure for 2018 that is only updated for employees earning a wage of at least €8.84 (the level of the minimum wage in April 2018)

VARIABLES	(1) Dependent employment	(2) Employment subject to SSC	(3) Marginal employment
Group low/low: Reference group			
Group low/high	-0.00862*	-0.00517	-0.0205***
	(0.00450)	(0.00473)	(0.00751)
Group high/low	-0.00286	0.00275	-0.0224**
	(0.00331)	(0.00387)	(0.0109)
Group high/high	-0.0132***	-0.00511	-0.0402***
	(0.00280)	(0.00339)	(0.00985)
Placebo Group low/high	0.00118	0.00152	-0.000890
	(0.00148)	(0.00143)	(0.00335)
Placebo Group high/low	0.000184	0.00119	-0.00238
	(0.00151)	(0.00152)	(0.00381)
Placebo Group high/high	0.00174	0.00271*	-0.00129
	(0.00166)	(0.00161)	(0.00313)
Observations	9,509	9,509	9,509
R^2 (within)	0.604	0.588	0.478
Labour market region FE	X	X	X
Quarter FE	X	X	X
Controls	X	X	X

Source: Regional Statistic of the Federal Employment Agency; SES 2014; Federal Statistical Office; Federal Institute for Research on Building, Urban Affairs and Spatial Development; own calculations. Note: The treatment effects refer to the coefficients β, γ, and δ in Equation (4), estimated with TWFE. Group low/low is the reference group and includes regions with a wage gap below the weighted median in 2014 and 2018. Group low/high includes regions with a wage gap below (at or above) the median in 2014 (2018). Group high/low includes regions with a wage gap at or above (below) the median in 2014 (2018). Group high/high includes regions with a wage gap at or above the median in 2014 and 2018. The control variables included are interactions of: time, east, and population share between 18 and 64 years in 2013; time, east, and type of labour market region; time, east, and employment share in different sectors; time and GDP per capita in 2013. Standard errors (in parentheses) are clustered at the level of the labour market regions. In contrast to Table 3, the treatment here is based on a bite in 2018 that is only updated for employees who earn at least the current minimum wage of €8.84 in April 2018 (the point in time to which the SES 2018 refers). Confidence level: ***p<0.01, **p<0.05, *p<0.1.

Table A.7: Effects of the minimum wage introduction on regional employment with a staggered treatment

VARIABLES	(1) Dependent employment	(2) Employment subject to SSC	(3) Marginal employment
Treatment (staggered)	-0.00475*	-0.00315	-0.0139**
	(0.00251)	(0.00239)	(0.00596)
Observations	9,509	9,509	9,509
R^2 (within)	0.598	0.586	0.469
Labour market region FE	X	X	X
Quarter FE	X	X	X
Controls	X	X	X

Source: Regional Statistic of the Federal Employment Agency; SES 2014; Federal Statistical Office; Federal Institute for Research on Building, Urban Affairs and Spatial Development; own calculations. Note: The treatment effect refers to the coefficient β in Equation (5), estimated with TWFE. The treatment is binary, staggered, and absorbing. Regions with a wage gap equal to or above the population-weighted median in 2014 start treatment in Q3 2014 and regions with a wage gap below (equal to or above) the population-weighted median in 2014 (2018) start treatment in Q1 2019. The control variables included are interactions of: time, east, and population share between 18 and 64 years in 2013; time, east, and type of labour market region; time, east, and employment share in different sectors; time and GDP per capita in 2013. Standard errors (in parentheses) are clustered at the level of the labour market regions. Confidence level: ***p<0.01, **p<0.05, *p<0.1.

Supplementary Appendix

Table B.1: Results for the Goodman-Bacon decomposition of the TWFE results with a staggered treatment

VARIABLES	Dependent employment	Employment subject to SSC	Marginal employment
Overall DiD estimate	-0.004784	-0.003177	-0.013888
Overall DiD variance	0.000006	0.000006	0.000036
DiD estimate between treatment groups	0.001759	0.002070	0.009555
DiD estimate between early treated and never treated groups	-0.032767	-0.022127	-0.104456
DiD estimate between late treated and never treated groups	-0.012759	-0.007378	-0.031371
DiD estimate within	0.020987	0.011631	0.056897
Weight on DiD estimate between treatment groups	0.354919	0.354919	0.354919
Weight on DiD estimate between early treated and never treated groups	0.213239	0.213239	0.213239
Weight on DiD estimate between late treated and never treated groups	0.221776	0.221776	0.221776
Weight on DiD within estimate	0.210065	0.210065	0.210065

Source: Regional Statistic of the Federal Employment Agency; SES 2014, 2018; Federal Statistical Office; Federal Institute for Research on Building, Urban Affairs and Spatial Development; own calculations. Note: The table shows the results for a decomposition of the TWFE estimate with a staggered treatment (coefficient β of Equation (5)) according to Goodman-Bacon (2021). The coefficients for the overall DiD estimate are negligibly different from those in Table A.7 in the Appendix, because of slight differences in the underlying estimation between the commands "bacondecomp" and "reghdfe" (the former is used for the decomposition and the latter is used for the TWFE estimations throughout the paper). The regressions underlying the decomposition include all control variables that are also included in all the TWFE estimations throughout the paper. These control variables are interactions of: time, east, and population share between 18 and 64 years in 2013; time, east, and type of labour market region; time, east, and employment share in different sectors; time and GDP per capita in 2013. "Between treatment groups" refers to 2x2 DiDs between the later and the earlier treated groups. This includes valid estimates for the treatment effect on the earlier treated group with the later treated group as control group as well as "forbidden" comparisons with the earlier treated group as the control group for the later treated group. "Between early (late) treated and never treated groups" refers to 2x2 DiDs between the earlier (later) and the never treated groups. "within estimate" refers to the component of the overall DiD estimate that is caused by differences in covariates within groups.