The Minimum Wage in the German Roofing Sector
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An Evaluation with the Synthetic Control Method

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Abstract: This paper estimates employment effects of the industry-specific minimum wage in the German roofing sector for West and East Germany. Rather than conducting a difference-in-difference estimation which is predominantly applied in such contexts, the synthetic control method is used. I give an introduction to the synthetic control method, guidance for implementation and discuss its advantages and limitations. The method increases both the likelihood of satisfying common trends and the objectivity in the choice of the control group. The analysis shows that estimates are sensitive with respect to the set of donor units. Applying a set including subconstruction and upstream sectors, I find that the introduction of the minimum wage has a negative effect on total employment in the roofing sector in West and East Germany, although significance can only be inferred for the West German estimate. The share of workers covered by the minimum wage appears to be unaffected.

JEL Classification: J38, J23
Keywords: synthetic control method; minimum wage; treatment effects

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1. Introduction

Estimating causal effects of minimum wage legislations on labor market outcomes has been the subject of many studies. While early time-series research finds generally significant, albeit small, disemployment effects, among others Brown et al. (1982), Solon (1985) and Wellington (1991), the introduction of comparative case studies in the 1990s gave rise to disagreement on the sign and the size of the effect (Card, 1990; Katz and Krueger, 1992). These early papers investigated predominately employment effects on low-skilled workers such as teenagers and immigrants. Today's empirical evidence on the effects of a statutory minimum wage on employment is still ambiguous. Applying different empirical methodology to the same data, Dube et al. (2010) and Allegretto et al. (2011) report small negative or even neutral employment effects from U.S. state minimum wage increases during the 1990s and 2000s, whereas Neumark et al.'s (2013) results reveal sizable disemployment effects.

Literature findings are mainly explained by two theoretical frameworks, the neoclassical model and the monopsonistic model. They fundamentally differ in their view on the competitiveness of the labor market. The former assumes that the labor market is perfectly competitive or at least close to a competitive equilibrium. Hence, an introduction or increase of a minimum wage will have either neutral employment effects, in the case of a non-binding minimum, or an adverse impact on employment when the minimum wage is binding. The latter rests on the idea that employers exhibit market power, implying that the labor market is subject to monopsonistic competition. Market imperfections arise due to asymmetric information, specific circumstances of individual workers such as preferences and individual restrictions or because employers are imperfect substitutes for each other (Manning, 2003). The monopsonistic model is able to explain neutral, negative and even positive employment effects. It is important to understand that both models lead to the same predictions under two specific circumstances. First, in the trivial case where the minimum wage is not binding neutral employment effects are expected. Second, in the case where the minimum wage is not only beyond the monopsonistic equilibrium level, but also beyond the competitive equilibrium wage level. Both approaches would then predict equivalent negative employment responses. The crucial disagreement between the models is, whether or not a level of a binding minimum wage exists that has no negative employment effects and simultaneously socially desirable consequences such as the rise of wages and the reduction in the number inefficient of job vacancies.

Other theoretical explanations for no disemployment effects caused by a change in minimum wage policy are the adjustment of working hours and increases in productivity (Metcalf, 2008). Furthermore, sectoral statutory minimum wages can lead to positive employment effects. In a dual labor market, the minimum wage is altered in one sector but not in another. The model predicts that job movement between the two sectors will take place until the expected earnings are equalized in both sectors (Borjas, 2013). So far, no theoretical model has been proven to be generally valid.

In 2011, the German Ministry of Labor and Social Affairs mandated the evaluation of eight of the twelve existing sectoral minimum wages in Germany, which led to numerous publications. In general, the studies did not find robust negative employment effects, despite the positive wage effects, especially high for East Germany, of the minimum wage. However, Aretz et al. (2013) show that the impact of the introduction of a minimum wage in the roofing sector on employment was negative on average. The results hold for East as well as for West Germany. The authors argue that negative employment effects in the roofing sector were caused by the relatively hard bite of the minimum wage.

Most of the recent German minimum wage research employs Difference-in-Differences (DiD) estimations to micro-data in order to identify employment effects. The method has become increasingly popular for estimating effects of an intervention on outcomes of interest. It belongs to the group of comparative case studies where the difference in outcomes after and before the intervention between affected and unaffected groups are compared. The control group typically consists of a single unit or an equally weighted average of units. Underlying assumptions are the common trend (CTA) and the stable unit value assumption (SUTVA). If these conditions are satisfied, the so called treatment effect can be identified. The great appeal of DiD estimation roots in its relative simplicity as well as its nature to handle endogeneity problems that typically occur when heterogeneous individuals are compared with each other. On the other hand, the selection of the control group is not formalized and often relies on statements of affinity based on certain indicators between the affected and unaffected units in the pre-intervention period. Hence, there is no clear objective criterion on which the choice of the control group rests.

A promising way to circumvent this problem is to use the Synthetic Control Method (SCM) designed by Abadie and Gardeazabal (2003) and Abadie et al. (2010). This method is based on the idea that a combination of comparison units often does a better job in reproducing the characteristics of a unit than any single comparison unit alone (Abadie et al., 2012). A synthetic control group is the weighted average of untreated units that optimally predicts the outcome of interest of the treated group in the pre-treatment period. It is a convex combination of potential control groups that mirrors most closely the outcome of interest before treatment. This increases, firstly, the likelihood of satisfying CTA and, secondly, promotes research honesty since it is a data driven procedure. The more similar a potential comparison group is to the treated group, the higher the weight assigned to this group by the procedure. The weights are used in the post-treatment period to construct the counterfactual outcome. The treatment effect is simply equal to the difference in the outcome of interest between the treated group and its corresponding synthetic control group in the post-treatment period.

The core object of this study is to examine whether synthetic control methods are useful for estimating employment effects of sectoral minimum wages in Germany. The article at hand exploits the method in the context of the minimum wage in the German roofing sector introduced in 1997. It offers an introduction to the synthetic control method, guidance for implementation and discusses its advantages and limitations. Since the synthetic control approach has hardly been applied up to date, it appears to be worthwhile to test the sensitivity of the approach by varying different parameters. Among others, the choice of predictors, the time frame and the choice of feasible donors will be addressed.

Furthermore, it is intended to conduct a robustness check on Aretz et al. (2013) findings. They apply intra- and intersectoral DiD estimations to evaluate the sign and the size of the employment effects for East and West Germany. The outcome of interest is the probability of staying employed in the roofing sector. As mentioned before, in contrast to other German minimum wage research, the authors find negative employment effects. For the intersectoral comparison they chose the plumbing as the control group, based on similarities in the market structure as well as in demand conditions. Using industry level data, this study tests whether the specific choice of the control group in the context is supported by the synthetic control method.

To my knowledge, this is the first paper to employ this method on the sectoral level in the context of minimum wage legislation. Sabia et al. (2012) and Allegretto et al. (2013) have estimated the effects of statewide minimum wages in the U.S. on labor market outcomes using the synthetic control group as robustness check to the results obtained by DiD estimators. The first paper to implement the synthetic control method on the sectoral level was conducted by Chung et al. (2013). They evaluate the impact of the China-specific safeguard between 2001 and 2013 on employment and wages in the U.S. tire industry.

All in all, this study aims to deepen the understanding of the implementation and feasibility of the synthetic control method and to contribute to the minimum wage literature.

The paper is structure as follows: Section 2 provides information on the German roofing sector and the introduction of the minimum wage. Furthermore, Aretz et al.'s (2013) estimation results are summarized and discussed. Section 3 introduces SCM. Section 4 presents the data used for the estimation and describes the empirical strategy. Estimation results are discussed in section 5 and robustness tests follow in section 6. Section 7 concludes.

2. Contextual Setting

2.1. Minimum Wage Regulations

Article 9, paragraph 3 of the German Constitution states that the sovereignty of wage bargaining belongs to the two sides of an industry, i.e. the representatives of employees and employers. Hence, unlike the US or England, Germany does not have federal or regionally fixed minimum wages. Minimum wages have been determined through separate negotiations in each industry, resulting in the coexistence of sectors with a legally binding minimum wage and sectors without. In 1997, the first sectors introduced a minimum wage. Today, fifteen selected German industries have wage floor agreements. Minimum wage agreements differ in the level of the minimum floor and the workers covered. In 2015 this will change, as the German Parliament on July 3$^{\text{rd}}$ 2014 passed a law that will introduce a countrywide statutory minimum wage. Germany will be the 27th out of the 36 OECD countries to introduce a nationwide wage floor. Nevertheless, the sectoral minimum wages will apply at least until 2017.

The first legally binding minimum wage was imposed on the German roofing sector in October 1997 in order to protect German workers from the feared wage and employment cuts which might have been caused by the establishment of the EU-Schengen area. The minimum wage level was negotiated between the responsible trade union (IG Bau) and the association of employers in the roofing sector (Zentralverband des Deutschen Dachdeckerhandwerks). This collective bargaining lead to a minimum wage of 15.14 DM (7.74 Euro) in East and at 16 DM (8.18 Euro) per working hour in West Germany, which applied henceforth to all blue-collar workers on German constructions sites not younger than 18 years and not apprentices or custodial workers. The level was successively raised over time and equalized within Germany to 9 Euro in 2003. During renegotiation of the agreements, short periods without any minimum wage legislation existed. Currently, the minimum wage is 11.55 Euro for the roofers working in Germany. Figure 1 shows the development of the level of the minimum wage in the roofing sector over time.

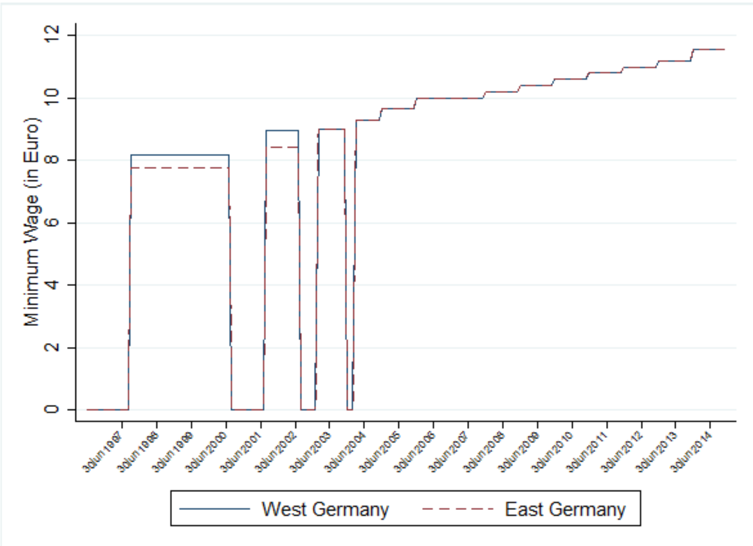


Figure 1: Minimum wage level in the German roofing sector by region, 1996-2014

2.2. Demand and Supply Structure in the Roofing Sector

Roofing is one of Germany's traditional crafts. Roofing firms mainly offer are the roofing of new buildings and the mending of old roofs. Recently, the installation of photovoltaic cells and insulation of old roofs also belong to the service range of roofing firms. A German roofing firm usually employs less than 15 workers and predominately supplies regional services for private home owners. A typical employee is male, has a comparable high level of qualification and works full-time (Table 1). According to Aretz et al. (2013) labor costs account for around 40 percent of total costs and technical advances constantly bring alterations to the roofing sector.

Table 1: Labor force characteristics and firm structure of the German roofing sector in 1995, 2005 and 2010

	1995	2000	2005
Labor Force			
Full-time (in %)	81	72	71
Male (in %)	92	99	99
Medium Skilled (in %)	52	48	48
High skilled (in %)	3	3	3
Minimum Wage Covered Workers (in %)	81	72	71
Firm Structure			
Number of companies (in SIAB)	1714	1659	1263
Less than 10 employees (in %)	44	39	66
11 to 15 employees (in %)	52	58	29
Number of Observations	2081	1923	1406

Source: SIAB data. Author's calculations.
Medium skilled: workers with training qualification; High skilled: workers with master certification.

The demand for roofing services can be described as rather inelastic, due to few existing substitutes. Furthermore, demand has been volatile in the past years. In the course of the German reunification, the entire construction sector experienced a boom in the early 1990s. This boom ended in the middle of the 1990s when total revenues of the roofing sector started to decline. During economic recession the minimum wage was introduced. The recession lasted until 2004. After that, the sector began to recover slowly again.

Given this structure of demand and supply, the effects of the minimum wage on employment are theoretically difficult to evaluate. In the neoclassical framework, arguments for strong negative employment effects are as follows: First, the level of the minimum wage was fixed at a relatively high level and the percentage of workers covered by the regulation was high, too (Table 1). Because of the wage increase, the relative price of labor rose so that firms had strong incentives to substitute labor with capital. Second, the wage floor was implemented in a period of economic recession when firms had difficulties to absorb increases in labor costs. Third, the roofing sector consists of many small firms, having less capital available than bigger firms to compensate such cost increases. On the other hand, as stated before, the demand for roofing services is rather inelastic. Thus, if the price of the services increased following the introduction of the minimum wage, the equilibrium quantity is not expected to change much and, the impact on employment will be therefore rather small. Furthermore, the rise in labor costs could be downsized by increases in productivity or using complementary and cheaper technologies. A tool to preserve demand, finally, is to expand the range of roofing services.

2.3. Previous Research on Employment Effects

Employment effects of the introduction of the minimum wage in the German roofing sector are studied by Aretz et al. (2013). The authors examine the bite of the minimum wage and the effects on the chances of remaining employed in the sector using two administrative linked employer-employee micro-data sets. The first contains information, collected by the central pay office of the roofing sector (Lohnausgleichskasse, short LAK), which makes it possible to calculate hourly gross wages from information on monthly gross wages and monthly working hours of blue-collar worker. Furthermore, it includes the age and the sex of workers as well as firm characteristics such as firm size and workforce composition. Because of missing information on the occupational status, apprentice and custodial worker cannot be identified. Hence, they cannot separate all workers covered by the minimum wage. The second data set is a 75 percent subsample of companies in the roofing, painting, plumbing and glazing sector that are collected by the Federal Labor Agency (Bundesagentur für Arbeit, short BA) for all employees subject to social insurance contributions. It includes information on workers' sex, age, skill level, occupation and occupational status so that workers entitled to the minimum wages from workers that are not can be distinguished. Additionally, it contains daily gross wages, but due to a lack of information on working hours, it is not possible to infer hourly gross wages. The authors, thus, impute the computed hourly gross wage of the LAK data by a function of explanatory variables that are available in both data sets on the BA. It enables them to determine wages of covered workers and corresponding indicators for the bite of minimum wage introduction in the roofing sector.

The findings on the bite are presented in Table 2. The first measure is the share of workers in the roofing sector for whom the minimum wage is binding. These workers are expected to receive wage increases up to the level of the minimum wage if they remain employed. In West Germany, the share corresponded to 2.4 percent only, compared to 11.5 percent in East Germany. The latter is high relative to shares calculated for other minimum wage regulations, indicating that the bite was hard in East Germany. This is supported by two additional indicators that refer to the relative level of the minimum

Table 2: The bite of the minimum wage German roofing sector by region, measured in June prior to the introduction in 1997

	Share of workers with binding minimum wage (in %)	Wage gap[a] (in %)	Kaitz-Index
West Germany	2.4	11.0	64.7
East Germany	11.5	9.7	82.0

Source: Aretz et al. (2013), p. 290

[a] wage $\text{gap}_{it} = \frac{MW_{i,t+1} - w_{it}}{w_{it}}$ where $MW_{i,t+1}$ corresponds to the upcoming minimum wage and w_{it} to a worker's hourly wage.

wage to wages received before the introduction. First, the average wage gap for workers with a binding wage floor measures the ratio of the individual difference of the preceding minimum wage level and the individual hourly wage to individual hourly wage. Aretz et al. (2013) findings imply that the wages of employees with a binding minimum wage would experience a wage rise of 11 percent in East Germany, whereas West German workers would yield a rise of 9.7 percent if employed in both periods. Second, the Kaitz-Index, that is the ratio between the wage floor level and the median wage in the sector, is high for both regions of Germany. According to Dolton and Bondibene's (2012) classification, the Kaitz-Indices in the German roofing sector are high or even extremely high in international comparison.

Applying the imputation method described before allows the authors to determine the characteristics of workers with and without a binding minimum wage. Generally, it is assumed that low wage employees are most likely to suffer from disemployment effects. For West Germany, this expectation seems to hold. The average worker with a binding minimum wage corresponds to a marginal worker with below average human capital, short-tenure and part-time employment. But in East Germany, the average worker with and without a binding minimum wage do not differ substantially in their characteristics.

If employment in the roofing sector is influenced by the sectoral minimum wage, wages are the driving channel. The proportion of workers earning less than the minimum wage should decrease, while the proportion of workers earning exactly the minimum wage should increase. This leads to a compression of the wage distribution from below. Aretz et al. (2013) find evidence for this. Surprisingly, the comparison also reveals compression from above in East Germany, suggesting the existence of wage cuts and presumably employment effects also for top earners. The phenomenon might hint that, besides direct employment effects for low-wage workers, indirect employment effects via spillovers at the upper end of earners occur. Thus, the whole sector could be interpreted as being affected by the minimum wage introduction.

Aretz et al. (2013) apply inter- and intrasectoral DiD estimations to identify the causal effect on the changes of remaining employed. The choice of the outcome of interest allows them to include individual fixed effects in the estimation model to capture unobserved heterogeneity among employees. On the one hand, this is an advantage compared to using aggregated employment outcomes such as total employment where one has to assume that on average the heterogeneity is equally distributed in all sectors. On the other hand, the chance of remaining employed is likely to be very volatile, depending on the yearly stock of employed. Furthermore, only periodical outflows are measured but not the inflows of workers. Hence, not the total effects on employment are accounted for.

Aretz et al.'s (2013) basic estimation is a simple linear probability model (LPM) with fixed effects of the following form:

$$P(e_{it+1} = 1) = \alpha_g + \delta D_{it} + \beta X_{it} + v_t + c_i + \epsilon_{it} \tag{1}$$

where e_{it} denotes the employment status in period t for an individual i and $e_{it+1} = 1$ is defined as being employed in the same sector as in the previous period and $e_{it+1} = 0$ otherwise. Furthermore, α_g captures the time constant difference between control and treated group, v_t reflects yearly specific effects and c_i corresponds to the individual fixed effects. X is a set of control variables including individual occupational status and educational level dummies, age and qualification of the corresponding firm's workforce, company size and a second order polynomial of the mean daily gross wage. D_{it} is the treatment indicator which is equal to one for individuals belonging to the treatment group in the post minimum wage period and zero otherwise. The pre-treatment period covers three years (1994 to 1996) and the post-treatment window extends from 1997 to 2007.

A feasible control group needs to capture the counterfactual change in employment outcomes of the treated group in the absence of a minimum wage. To isolate the treatment effect, the control group must satisfy the common trend assumption (CTA) and the stable unit value assumption (SUTVA). The former requires that the treated and control group share the same development of the outcome variable in the absence of the treatment; here in absence of the introduction of the minimum wage in the roofing sector. The latter implies that the control group is unaffected by the treatment. The definition of the group can be on different levels, depending on the specific treatment and its implications. Because the German minimum wage legislation in the roofing sector applies to the entire sector, the identification of the impact of the wage floor on employment in the roofing sector cannot rest on regional variation as has been done by most minimum wage studies in the US, among others Allegretto et al. (2013), Dube et al. (2010) and Neumark et al. (2013). Given the minimum wage regulation, mainly two possible ways to isolate the causal effect of interest exist. Either one applies an intersectoral approach where the variation in treatment intensity within the sector is exploited. In this framework, workers in the roofing sector with and without a binding minimum wage are compared. It is somewhat plausible that CTA holds since both groups belong to the same sector, but

SUTVA could be violated if wages and/or employment of workers with a non-binding minimum wage are indirectly affected by the treatment. The other approach is based on an intersectoral DiD examination. That is, comparing a specific fraction or the entire roofing sector to the respective fraction of a sector without minimum wage legislation in the observation period that is also similar to the roofing sector. Defining the control group in a different sector of the economy most probably violates CTA, whereas defining the control group in the same supersector most probably violates SUTVA. Both violations lead to biased estimates of the treatment effect.

The study of Aretz et al. (2013) conducts the intersectoral DiD approach with a control group of a subsector of the construction sector. Minimum wage regulations are widely spread in the construction sector. Out of 14 potential control groups, only four subsectors did not have any binding minimum wage in place during the observation period of the sample (1994 to 2007). The BA sample enables researchers to choose only between the glazing and the plumbing sector because the third available sector in the data, the painting sector, has a wage floor since 2003. Generally, the selection of suitable control group relies on statements of affinity based on certain indicators between the affected unit and potential control units in the pre-treatment period. Due to the highest similarity of the business cycle behavior and market indicators between the plumbing and the roofing sector, the plumbing sector is chosen as control group instead of the glazing sector. The market indicators for the comparison are taken from 1996 for the number of firms, number of employees and average number of employees per company. Additionally, the revenue structure of the sectors and the average gross daily wage for full-time employees in 1996 are examined, as well as investment, productivity and labor costs measures (taken from Cost Structure Survey of the Federal Statistical Office) in 2001. The authors conclude that CTA is most plausible satisfied and treatment effect may be identified in absence of spillovers. Although this procedure to find a proper control group is reasonable – except that certain post-treatment values are compared –, there is no objective cause not to choose different pre-treatment years or indicators for the evaluation of the similarity of the sectors. Alternatively, one could also include pre-treatment values of the outcome of interest in the comparison, the share of female, part-time or marginal workers and so on. Alternative strategies might lead to a different selection of the control group.

The results of the intersectoral DiD, where the treatment group corresponds to all workers in the roofing sector covered by the minimum wage, while workers in the plumbing sector that would have been covered if they worked in the roofing sector are considered as control group, suggest that the chances of remaining employed decreased for East and West Germany workers by 2.9 and 1.2 percentage points, respectively. The same analysis with pooled LPM instead of LPM with fixed effects yields lower disemployment effects in East Germany and even a positive effect on employment of 1.2 percentage points in West Germany. All results are significantly different from zero at the 0.1 percent level. The difference in the estimations can be explained by layoffs which increased mainly among workers with poor observable characteristics. Hence, pooled estimations are upward biased, implying that it is crucial to control for individual fixed effects.

Aretz et al. (2013) conduct a set of robustness tests concerning the suitability of the plumbing sector as control group. In order to check whether the SUTVA holds, they perform an analysis of the demand structure and transition of workers between the two sectors. If roofing services were substituted by plumbing services after the minimum wage regulations, employment in the plumbing sector would have experienced a boost. This would lead to an overestimation of the causal effect. Nonetheless, the evidence does not show such a substitution because no substantial improvement in the revenues realized by the plumbing sector is observed. Moreover, Aretz et al. (2013) find negligible worker movement between the roofing and plumbing sector, implying the non-existence of spillovers.

Furthermore, applying an intersectoral comparison along the entire wage distribution of covered workers, the authors find that in East Germany the prospects of continued employment have deteriorated due to the minimum wage along the entire wage distribution. Thus, the minimum wage introduction might be the causing factor for the observed wage compression from above. In West Germany, upper wage deciles appear to be less affected by a binding minimum wage. Spillovers from the minimum wage introduction within the roofing sector cause these indirect effects. They can be explained, first, by substitution of workers with capital and that the degree of substitutability varies for different skill types and, second, by negative scale effects that dominate the positive substitution between different types of workers. The existence of spillover effects imply that intersectoral comparisons are biased. SUTVA, requiring exogeneity of a treatment to the individual level treatment status, is violated if the control group within the roofing sector itself experiences employment effects.

To summarize the paper's findings: Firstly, the minimum wage affected a large share of the workers in the plumbing sector, as indicated by a strong bite. Secondly, on average, the minimum wage in the roofing sector decreases the chances of remaining employed. This is especially true for East Germany. Thirdly, spillover effects are observed within the roofing sector, which leads to a rejection of intrasectoral comparisons in favor of intersectoral DiD approaches. However, the selection of the control group which should satisfy CTA in the intersectoral model rests on an ambiguous comparison which can be tested by using the synthetic control group methods.

3. Identification with Synthetic Control Methods

3.1. Introduction to Synthetic Control Methods

A major challenge in evaluating the impact of the minimum wage legislation in 1997 in the roofing sector is the separation of the actual policy impact from other factors such as macroeconomic trends. A typical identification strategy is the DiD approach which requires a proper selection of the control group to satisfy SUTVA and CTA (see section 2.3. for a discussion). Depending on the researchers, choice of indicators that should give insights about the similarity of the treated and the control group, different selections may arise leading to a variation in the estimated treatment effect. The Synthetic Control Method (SCM) presents a data driven and, hence, more objective alternative for the selection of the control group based on a quantifiable procedure. The approach rests on the idea that a combination of comparison units often does a better job in reproducing the characteristics of a unit than any single comparison unit alone. Moreover, a weighting scheme of potential control groups that best predict pre-treatment values of the treated group is the optimal comparison group because it increases the likelihood of fulfilling the common trend assumption. Card (1992) was the first to implement this for the evaluation of a minimum wage legislation. He compared the state California with an aggregate control formed by four southern states and one metro area that failed to raise their minimum wages during the 1987 to 1989 period. However, Card's selection of the comparison states is heuristic and not based on an optimization procedure. Abadie and Gardeazabal (2003) and Abadie et al. (2010) designed a method that searches for a optimally weighted average of untreated units over the outcomes of potential groups such that the average provides the best fit with the treatment group's outcome in the pre-treatment period. The obtained weighting scheme is used to produce the missing counterfactual in the post-treatment period. The more similar a potential comparison group is to the treated group, the higher is the assigned weight.

A specific feature of the model is that it allows the researcher to evaluate treatment effects only on aggregated levels which lowers the sensitiveness of the estimation to confounding factors. Furthermore, the basic version includes one treated unit only, implying that only one policy for a specific unit can be evaluated. If micro data are used in estimations, aggregation is based on common feature, for instance, geographical location or industrial affiliation. In the context at hand, the aggregated level corresponds to an employee's industry membership.

3.2. Synthetic Control Estimators

To motivate the model, suppose that $J+1$ industries, indexed by j, are observed at time periods, t=1,..., T. Without loss of generality, assume that only the first unit is exposed to a policy at period T_0, with $1 < T_0 < T$. In the case of the minimum wage introduction, this translates to: $j = 1$ corresponds to the roofing sector and T_0 to 1997. All J remaining industries serve as potential comparison groups and, hence, belong to the so called donor pool. T_0 is the number of available pre-intervention periods. The post-treatment period starts at $T_0 + 1$ and ends in T. The number of pre- and post-treatment periods depends on the amount of years available in the data set.

The treatment effect of interest is defined as:

$$\tau_{1t} = Y_{1t}^I - Y_{1t}^N \tag{2}$$

for any post-treatment period. Y_{1t}^I corresponds to the outcome variable of the treated industry that is observed for unit one at time $t \geq T_0 + 1$ and Y_{1t}^N the respective unobserved counterfactual outcome variable. Defining the policy as D, the minimum wage introduction, SCM assumes a data generating process such that the observed outcome is the sum of the treatment effect, $\tau_{1t}D_{1t}$, and the counterfactual outcome:

$$Y_{1t}^I = \tau_{1t}D_{1t} + Y_{1t}^N = \tau_{1t}D_{1t} + \beta_t Z_j + \lambda_t \mu_j + \delta_t + \epsilon_{jt} \tag{3}$$

where δ_t denotes an unknown common factor with constant factor loadings across industries, Z_j is a $(1 \times r)$ vector of time-invariant observed covariates unaffected by the treatment, and β_t the corresponding unknown vector of parameters. D_{1t} is equal to one in the post-treatment period, and zero otherwise. Additionally, ϵ_{jt} represents the standard error term.

Equation (3) provides a basis for estimating time-varying treatment effects. Furthermore, the model generalizes the conventional DiD model by allowing interactive fixed effects $(\lambda_t \mu_j)$ so that industry-level unobserved characteristics may vary over time. That is, treatment and control industries need not to follow common trends, conditional on observables. If the true factor loadings μ_1 of the treated industry are known, it would be possible to construct an unbiased control by taking donor industries whose factor loadings average to μ_1. Since we do not observe this value, the synthetic control procedure constructs a vector of weights W over the J donor industries such that the weighted linear combination of the donor industries closely matches the treated industry in pre-intervention outcomes. This weighted average of donors is called synthetic control. That is, a synthetic control is represented by a $(J \times 1)$ vector of weights $W = (w_2, \ldots, w_{j+1})'$ subject to $w_j \geq 0$ for $j = 2, ..., J+1$ and $\sum_{j=2}^{J+1} w_j = 1$. These restrictions are imposed to avoid extrapolation and to ensure uniqueness of W.

The counterfactual outcomes are obtained by a constrained quadratic optimization. Define a $(k \times 1)$ vector of pre-treatment characteristics of the treated industry, the roofing sector, as $X_1 = (Z_1', Y_i^{K_1}, \ldots, Y_i^{K_L})$, where $K = r + L$ and $Y_i^{K_l}$ are L linear combinations of pre-treatment outcomes. Similarly, X_0 is a $(k \times J)$ matrix containing the same characteristics for the unaffected industries in the donor pool. The j-column of X_0 represents the corresponding values of the j-industry. They are called predictor set. The difference between the pre-treatment characteristics of the treated unit and a synthetic control is given by the vector $X_1 - X_0 W$. The synthetic control, W^*, is chosen to minimize the size of the distance measured in terms of the mean square prediction error (MSPE).

$$\sum_{m=1}^{k} v_m (X_{1m} - X_{0m} W)^2 \tag{4}$$

over k pre-treatment characteristics and v_m measures the relative importance of the m-th variable. Typically, v_m is selected to weight covariates in accordance to their predictive power on the outcome (see Abadie and Gardeazabal, 2003; Abadie et al., 2010). Other possibilities are: v_m may reflect subjective measure of relative importance of the predictors. Or, the values are chosen such that the synthetic control has the lowest overall MSPE. Alternatively, if the number of pre-treatment periods is large enough, v_m and W^* can be obtained by a two-step minimization procedure. The pre-treatment period is divided into two periods, an initial training and a subsequent validation period. Given $v_1, \ldots, v_m$ from the validation period, W^* can be imputed by using data from the training period. Hence, the in-sample fit is maximized. Note that if $v_1, \ldots, v_m$ have equal size, all predictors are assigned the same weights, but $w_2, \ldots, w_{j+1}$ vary.

Using the optimal weights $w_2^*, \ldots, w_{j+1}^*$ for each of the donors, the synthetic control group at any time t is the weighted combination $\sum_{j=2}^{J+1} w_j^* Y_{jt}$, representing the counterfactual outcome in post-treatment periods. Thus, the estimated treatment effects at any $t \geq T_0 + 1$ on the outcome of interest become:

$$\hat{\tau}_{1t} = Y_{1t}^I - \hat{Y}_{1t}^N = Y_{1t}^I - \sum_{j=2}^{J+1} w_j^* Y_{jt} \tag{5}$$

Abadie et al. (2010) show that under certain conditions, the bias of the treatment estimator of SCM is bounded by a function that converges to zero as the number of pre-treatment periods increases. This implies that the estimator is unbiased if the pre-treatment window is sufficiently large.

To sum up the features of the SCM estimation model: Firstly, it generalizes the DiD approach by allowing unobserved characteristics to vary over time and, secondly, it provides a semi-parametric version of the lagged dependent variables model since the predictor set includes past information of outcome variables.

3.3. Specifications

Although SCM is a data driven method, there are certain specifications and restrictions which need discussion and consideration when applying the method. They concern the set of donor units, the predictor set and the choice of the time frame.

Firstly, units of the donor pool must meet CTA. This might sound surprising since the previous subsection highlighted the fact that, due to the optimization procedure, SCM is most likely to satisfy CTA. It is important to understand that SCM's weighting process is based on a set of outcome and exogenous variables that refer to the pre-treatment period. Hence, it ensures that CTA holds in the pre-treatment period. However different trends in the post-treatment period might occur, because units have experienced similar interventions or other forms of treatments. Furthermore, units that suffered a large idiosyncratic shock in the outcome of interest do not satisfy CTA. All these units have to be excluded from donor set. Moreover, without the knowledge of all proper exogenous characteristics and outcome variables, it is important to restrict the donor pool to units with characteristics similar to the affected unit. The reason is that SCM does not allow for extrapolation by imposing restrictions on the weights, while interpolation biases are present. This becomes a severe problem if the synthetic control matches characteristics of the affected unit by averaging away large discrepancies between certain characteristics of the affected unit and those of the units in the synthetic control group. A sophisticated solution of this issue is to include penalty terms in the objective function that depend on discrepancies. In some instances, a treatment effect may have indirect, so called spillover effects on untreated units. This corresponds to a violation of SUTVA. Indirectly affected units should not be included in the donor pool since they induce over- or underestimation of the treatment effect. Spillover effects are most probably to occur in units that are proximate to one another. Of course, this depends on the context of the estimation. Proximity can derive, for example, from geographical or industrial closeness between units. Note that there is a tradeoff between CTA and SUTVA requirements within the donor pool. On the one hand, one should restrict the donor pool to units that share common features with the affected unit. On the other hand, exactly these units may provide biased estimates due to spillovers. Abadie (2013) suggests that if units affected by spillovers are included in the synthetic control group, one can assess the potential direction of the bias in the resulting estimation. Furthermore, the synthetic control group must be able to approximate all relevant pre-treatment characteristics in the treated unit. This might not be the case if a value of a particular variable of the treated unit is extreme, meaning that it is the highest or lowest value compared to the donor units. Such a value may not be closely mirrored by a synthetic control. The convex hull condition, however, is not of much concern as long as the approximation is good enough so that the synthetic control group closely tracks the trajectory of the outcome variable for the unit affected during pre-treatment years.

Secondly, the researcher has to decide which characteristics to include for matching pre-treatment years of the treated unit with the synthetic control group. For each comparison set, one might obtain a different synthetic control groups because the method selects the synthetic control group that minimizes MSPE over all variables in the predictor set. On the one hand, it enables one to find specific synthetic controls for different outcomes of interest and to test for the sensibility of the estimator by varying the set. However, the scope of selection is wide and may lead to arbitrary choices. One can argue that the optimization will yield a good pre-treatment fit in any case. Still, there exists no overall measure or guidance, indicating which relevant time-invariant variables and pre-treatment outcomes should be included in the comparison. From previous studies applying SCM, certain basic rules can be derived. Abadie et al. (2010) argue that if the number of pre-treatment periods in the data is large, matching on pre-treatment outcomes helps controlling for the unobserved factors, affecting the outcome of interest as well as for heterogeneity of the effect of the observed and unobserved factors on the outcome of interest. Hence, it is advisable to include a set of pre-treatment values of the outcome of interest in the predictor set. The underlying rules of the choice of time-invariant characteristics differ substantially in the existing studies. Neumark et al. (2013), for example, do not include any time-invariant variables in the predictor set, whereas the studies of Abadie and co-authors choose predictor sets with averages of the exogenous variables over ten years prior to the treatments (Abadie and Gardeazabal, 2003; Abadie et al., 2010; Abadie et al., 2012). Other studies use only the value of the exogenous variables in the period prior to the treatment (Sabia et al., 2012; Chung et al., 2013). All papers except one do not discuss the reasons for their explicit choices. Not only the time reference for exogenous characteristics is not motivated, they also fail to explain the choice of relevant characteristics. In general, the exogenous variables correspond to shares of certain characteristics within a unit and measures of economic activity, depending strongly on the contextual setting. Dube and Zipperer (2013) introduce a method to obtain the ”best” predictor set for the estimation. They conduct a test on a range of possible predictor sets which selects the one that has overall the smallest root-mean-squared prediction error in cross-validation estimations of the pre-treatment period.

Thirdly, one needs to decide on the time window of the evaluation of the treatment effect and the time of the treatment. Since Abadie et al. (2010) prove that the bias of the SCM treatment effects decreases as the number of pre-treatment periods increases, it is advisable to include as many pre-treatment periods as possible. However, if there are diverging trends for the treated and the donor units for specific years, these periods should be excluded because the credibility of estimator depends on its ability to track the trajectory of the outcome variable previous to the treatment. The longer the post-treatment window is, the less probable it is that the observed treatment effect is exclusively driven by the actual treatment. Macroeconomic shocks that affect the units differently can also cause biases in the estimated treatment effects. At the same time, the time window has to be sufficiently long to capture the whole effect of an intervention. Lastly, an anticipation of the treatment by rational economic agents may also lead to biases in the estimators. One can check for anticipation in the data and if necessary backdate the treatment to a period before any such impact is visible.

3.4. Inference

The well-known tools for inference are not applicable in the SCM setting. Unlike traditional estimation techniques, the method only provides point estimates of the treatment effect. Hence, it is not possible to infer the standard error of the estimator. Furthermore, asymptotic statements do not hold since the number of observed aggregated units in the sample is generally low.

Abadie et al. (2010) propose to use placebo tests to judge the significance of an estimated effect. The alternative method of inference is based on the comparison of a synthetic control estimate with estimated effects in cases where the particular treatment did not take place. If the actual treatment effects is balanced or even outweighed by placebo estimates, it is assessed to be non-essential. This method is a version of a permutation test. Under the null hypothesis of no effect, the resulting placebo estimates are assumed to be a representation of the distribution of the estimate for the treated. Using the distribution one can derive a p-value, comparable to the t-tests, by calculating the proportion of estimated effects that are greater or equal to the treatment effect of interest.

The test can be applied in two dimensions, referred to as “in-time” and “in-donor-pool” placebos. In “in-time” placebo tests, the date of the treatment in the application of SCM is altered to a time prior to the real treatment. If the obtained synthetic control estimates reveal large effects, the confidence that the real effect is attributable to the actual treatment would greatly diminish. The tests are feasible if the available data contains a sufficiently large number of time periods when no structural shock to the outcome variable occurred. Another way to conduct the placebo analysis is to reassign the treatment to control units of the donor pool, where they each in turn are considered to be the treated unit. Hence, one estimates treatment effects when there is no treatment. In order to produce unbiased counterfactuals, the actual treated unit should not be included in the placebo donor pool.

The application of “in-donor-pool” placebo test has become standard in SCM studies, whereas “in-time” have been applied only by Abadie et al. (2012) so far. Placebo tests lead to valid inference under the assumption that the estimated effects are independent and identically distributed (i.i.d.). Only if this is fulfilled, the placebo estimates can be used as a representation of the distribution of the actual treatment effect. Ando and

Sävje (2013) remark that the latter assumption is strong and show that it does not hold if the treatment and the bias of the actual estimator are dependent. Reasons for the dependency are: correlation between treatment and the covariates and factor loadings, the particular construction of the placebos and the selective choice of comparison units in the application. The study also shows that the estimator might not be independent of the treatment even if the bias of the estimator is zero. They conclude that placebo tests are valid when the number of observed units is large and when the confounding factors have negligible influence. This, however, opposes the promoted strength of SCM: the insensitiveness to confounding factors and its applicability in small samples. Ando and Sävje (2013) suggest an alternative method of inference by using a procedure that is similar to the bootstrapping method. The sample size is artificially increased by multiple estimations from drawing smaller samples of control units from the donor pool. For each draw, a different synthetic control unit is obtained. Note, that the unit-period specific effect is constant for a treated unit over all draws. This allows one to estimate the corresponding value and infer the significance of the causal effect of the policy on the outcome of interest.

4. Sample and Empirical Specification

4.1. Data

The data for the evaluation of employment effects of the minimum wage introduction in the Germany roofing sector with SCM must meet three criteria. First, it should enable one to identify the number of employees in the roofing sector and sectors of a similar classification level at a given time period. This is difficult in so far as the roofing sector is a subsector of the construction sector. Most available data sets allow one to identify only employees working in the construction sector as a whole, but do not provide further information for subsectors. Second, in order to capture the total unbiased effect, the data set should cover sufficiently large time periods before and after the minimum wage introduction in 1997. Third, industry specific information has to be available in the data set such as employee characteristics, demand and business cycle measures to be included in the predictor set to find a well-suited synthetic control group.

The weakly anonymous version of the Sample of Integrated Labor Market Studies[2] (short SIAB) provided by the Research Data Center of the German Federal Employment Agency at the Institute for Employment Research (vom Berge et al., 2013) fulfills most these requirements. The administrative data set contains information on employees covered by social security, benefit recipients, job-seekers and participants in active labor

[2]Data access was provided via on-site use at the Research Data Centre of the German Federal Employment Agency and subsequently remote data access.

market programs. The employment subsample (Beschäftigtenhistorik, short BeH) is available for the time period 1975 to 2010. It is based on a representative two percent sample of all employees in Germany and combines individual with firm specific information. The individual section contains spell data of continued employment in a company within a full calendar year. A spell ends whenever an individual employment status alters or the year concludes. Several personal characteristics, such as age, educational background, type of employment, occupational status and gross daily wages are included for each individual. Establishment level information at the yearly cut-off date 30$^{\text{th}}$ of June is added, for example, the industry affiliation, number of employees and firm's location. The industry classifications unfortunately change over the observation period. However, due to overlaps of the classification in several reported years the 3-digit classification of 1973 is imputed for all years enabling to differentiate in total between 302 economic sectors. The roofers form a group and hence can be observed over the whole time period.

As a reminder, Aretz et al.'s (2013) BA sample is based on the same source. It is also generated from the BeH. Instead of a two percent sample of all employed individuals, the researchers requested a random sample for 75 percent of all companies in four subsectors of the construction sector, the roofing, painting, plumbing and glazing services sectors.

It is necessary to employ restrictions and transformation to the SIAB data in order to apply SCM to investigate the employment effects of the minimum wage. In this study, an employee is employed in a given year if his employment spell overlaps the 30$^{\text{th}}$ of June. The sample is restricted to employees aged between 16 and 65 that are actually occupied. Hence, dormant employment is excluded. Based on a firm's location, the sample is divided into East and West Germany. The study time period is from 1993 to 2010, because East German data is only representatively available from 1993 onwards. The main outcome variable of interest, the total number of employees of each industry classifications, is obtained by a yearly and quarterly headcount of all individuals working in respective sectors. Furthermore, alternative outcome variables such as the number of regular employed and of employees covered by the minimum wage are calculated. Multiplying these values with a weighting factor of 50 yields representative case numbers of the German population. Potential exogenous variables such as the industry's share of prime aged workers, of male workers, of medium skilled workers, middle sized firms and average tenure are available for each year.

4.2. Synthetic Control Method Specifications

The treatment year is 1997 when the minimum wage was introduced in the roofing sector. This treatment definition is most likely to fulfill the criteria of the identification strategy and guarantees to use a large set of appropriate donor pool units. It is imaginable to modify SCM to evaluate employment effects for each successive increase of the minimum wages after the introduction. The framework of incremental DiD (Dolton et al., 2012) for estimating the effects of multiple treatments to the same unit could be used as guidance. However, the set of eligible donor pool units will decrease since units need to experience a similar treatment history in order to apply SCM.

In the DiD framework one has to determine the group of individuals that are viewed as treated by an policy. In the context of the minimum wage legislation in the German roofing sector there are mainly three possible definitions of treated individuals. Either employees with a binding minimum wage, or who are entitled by the minimum wage legislation to receive the wage floor, or all workers of the sector. Aretz et al. (2013) study the employment effects for the first two groups by applying intra- and intersectoral comparisons. One of the main advantages of SCM is that the degree of heterogeneity is lowered by using aggregated outcomes. In hitherto SCM studies treatment effects on aggregated units such as geographical areas like states or three digit industries are considered. One could separate these units in terms of a common characteristics of individuals, such as all employees in the roofing sector subject to the minimum wage. This implies evaluating employment effects by comparing outcomes of workers that are covered by the wage floor in the roofing sector with employers in other sectors who would be covered if the same legislation were in place. Problematic with this approach is that the effect might be confounded by characteristics that are common in the whole industries environment. For example the capability to substitute labor with capital. These factors can be better controlled for if the whole industry is treated as affected. Another argument to regard the whole sector as treated becomes clear if one observes the development of the average gross wage over the years by wage deciles in the roofing sector. If employment effects are present, wages are the driving channel. Figure 2 shows that wage compression from above and below is existent for all full-time workers in East Germany, whereas there is little effect on average wages in West Germany. These findings are conform with Aretz et al. (2013) respective results for covered employees which amount to 70 to 80 percent of all workers during the observation period (see Table 1). Even though the wage compression from both sides in East Germany starts already before the treatment in 1997, the further narrowing afterwards might be linked to the minimum wage introduction because the latter increased total labor costs. Which in turn could lead to wage cuts due to the complementary of high and low skilled workers or the substitution of high skilled by technology. This evidence supports the choice to treat all employees in the roofing sector as exposed to the treatment.

In order to determine employment effects of the minimum wage introduction one should address the development of various outcome variables over time. The use of SIAB data restricts the choice set strongly since only variables with entries of more than 19 individuals per year and per industry are available for the estimation. The rule is implemented to secure the anonymity of individuals in the records. Especially the number of employees

Figure 2: Average gross daily wage of full-time employees for each wage decile in the roofing sector by region, 1993-2010. Price adjusted to prices in 2010

working full-time and marginal workers are uncommon in the subsectors of the construction sector. Hence, these outcome variables are not addressed here. However, information on total employment, number of workers covered by the minimum wage and of full-time workers can be obtained from the data. Note, that the term covered refers to workers that, given their characteristics, would receive the wage floor. It excludes white-collar employees, custodial workers, apprentices and individuals younger than 18 years. An analysis of the covered workers reveals that they almost correspond one to one to the number of full-time employed workers in the roofing sector. Hence, beside the total number of employees, the study focuses on estimating the effects only for covered workers. Figure 3 present the development of total employment which includes all workers in all types of employments and the share of covered workers in the roofing sector over the observation period for West and East Germany. Employment stayed fairly stable (about 60'000 on average) in West Germany despite the boom in the early 1990s and the recession in the construction sector from the mid 1990s until 2004. Even after the new wage policy in 1997 employment experienced an increase. In contrast, the eastern German employment in the roofing sector moves along the business cycle. Employment starts to decline in 1996 before the policy was implemented. Until 2004 the employment is more than halved from initially 42'300 to less than 20'000 workers. The driving force between the decline is most certainly the recession in the construction sector. The question is whether it can also be partly explained by the minimum wage floor and if so how big its size is. Interestingly the share of covered workers falls in Western Germany. Admittedly, already before the policy came into effect. The variable experienced a drop from 83 percent in 1993 to 70 percent in 2001. After this period, the value fluctuates until 2010 between 70 to 75 percent. Again, it is possible that the minimum wage introduction in 1997 caused a further decrease than what would have been expected in the absence of the treatment. Possible strategies to circumvent paying a minimum wage while keeping the total employment in a firm and thus the labor input constant are to declare a worker as clerks or to employ

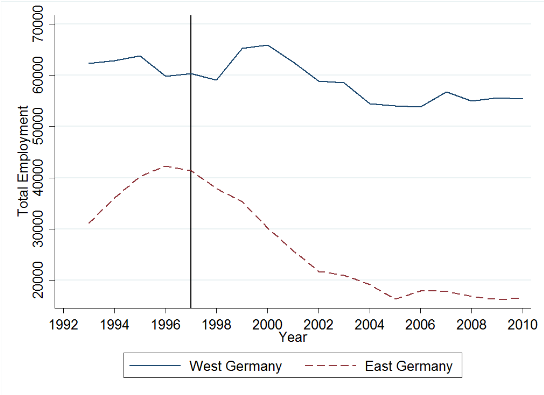


Figure 3: Employment in the roofing sector by region, 1993-2010

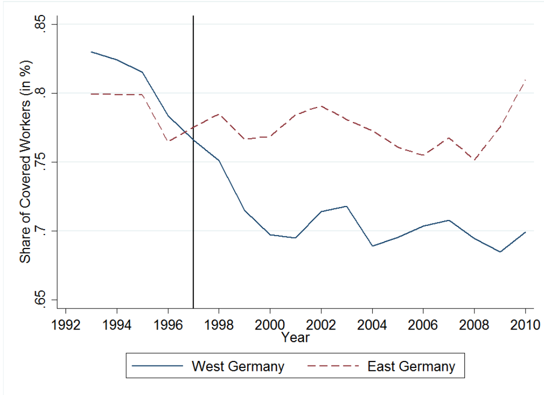


Figure 4: Share of covered workers (in %) in the roofing sector by region, 1993-2010

more apprentices while dismissing regular workers. Hence, parts of the change in workers' composition after the minimum wage introduction might be attributable to the policy. The corresponding values in East Germany do not perform a similar trend. The share of covered workers remains comparably constant over time between 80 and 75 percent. The difference in the development can be either explained by East German employers that did not make use of outlined strategies or the decrease of the Western value is caused by other factors.

However, also the stability of employment in West Germany and of the share of covered workers could be influenced by the minimum wage introduction. If the sectors in the donor pool, which are by assumption not affected by the policy and did not experience a similar policy or any idiosyncratic shock themselves, have experienced common down- or upturns after 1997, this might imply that the minimum wage had an opposite or constant impact on the outcomes of interest.

To evaluate the effect of the minimum wage on employment outcomes in the roofing sector, the central question is how the respective outcomes would have evolved in the roofing sector after 1997 in the absence of the legislation. The SCM constructs a synthetic roofing sector as the convex combination of sectors in the donor pool that most closely mirrors the roofing sector in terms of pre-treatment values of employment outcomes and exogenous predictors. If all assumptions are satisfied, the difference in the outcomes between the roofing sector and the synthetic control group after the minimum wage introduction can be interpreted as treatment effect. As stated in section 3.3., due to interpolation biases in SCM, it is advisable to select donor units that share common characteristics with the roofing sector. Thus, other subsectors of the construction sector which in total amount to 13 potential comparison units seem to be a good choice. Donor units that were exposed to a similar policy during the observation period should be excluded from the pool in order to yield an unbiased estimator of the treatment effect. Only three sectors, namely the plumbing, the glazing and the stove maker, are prospective donor pool units that satisfy the requirement. In 1997 the main construction and the electrician, in 2003 the painters, in 2007 the staging sector introduced a collectively bargained wage floor. The risk of severe spillover biases from the minimum wage legislation is high when using this donor pool with the three subsectors of construction. One concern is that the legislation triggered worker movement. Either workers from not affected sectors search and find jobs in the roofing sector or in the case of negative employment effects that laid off roofers move to unaffected sectors. Both seems plausible since the required skills are quite similar within the construction sector. The dual labor market theory predicts that job movements between sectors with and without wage floors will take place until expected earnings are the same in both sectors (Borjas, 2013). Furthermore firms in unaffected sectors could offer certain services of the roofing sector at a lower price to consumers since they can pay their workers lower wages. Irrespective of the sign of the employment effect, these spillovers induce an overestimation in absolute terms. That is the reason why this study performs additionally a synthetic control estimation with a second, bigger donor pool. Besides the units of the first donor pool, it consists of component suppliers of the construction sector. Corresponding sectors are identified via input-output tables of the years 2000 and 2005 provided by Federal Bureau of Statistics[3]. On the one hand, the supplier sectors have similar characteristics as the roofing sector and are subject to a comparable economic environment due to intensive intersectoral trade and other interdependencies. These are reasons to assume that CTA holds after the treatment period. At the same time, spillover bias will probably be small, because worker and service mobility is more restricted. Note, that this reasoning is also used in DiD approaches in order to justify choice of a control group from an upstream sector. After excluding the mining sector, because it is exposed in most parts since 2009 to a minimum wage, this strategy increase the size of the donor pool by 14 units. That is, the second donor pool consists of 17 sectors in total.

The chosen specification yields in total eight separate estimations of employment effects. Four for West and East Germany each, where one version corresponds to each combination of the two donor pool definitions and two outcomes of interest. This framework allows one to examine the sensitivity of the SCM to alterations in parameters and to assess which result components remain constant over all versions of SCM. By varying the set of donors it is analyzed how the prediction fit of the synthetic control group in terms the pre-treatment outcomes with the respective values of the roofing sector alters prior to the minimum wage introduction and how potential spillovers affect the treatment effect estimations. Furthermore, the two different outcome variables enable one to emblaze two separate types of employment effects. Since total employment and the share of covered workers do not exhibit the same time trend for West and East Germany, one can

[3]Industries are selected that supplied the construction sector with at least 1000 million Euros worth of products in the years 2000 and 2005 each.

expect that the optimal weights assigned by the method differ. However, if an industry is dominantly represented in all synthetic control groups with high weights, this would give confidence that the respective industry would be an suitable control industry in conventional DiD. Last but not least, the full potential of SCM and arising problems or drawbacks such as the restrictive convex hull condition are addressed.

In order to have comparable results, the time-invariant part of the predictor set remains constant over all versions. Besides the yearly pre-treatment outcomes of interests, the set contains industry's labor force characteristics such as the share of men, medium skilled and prime aged workers among all workers. Furthermore, as a measure of competition within sectors, the share of firms with more than 11 and less than 15 employees across all firms are added. The exogenous variables are averaged over the whole pre-treatment period. The selection of these particular variables was in a first step dictated by the data provided in SIAB and second restricted due to the mentioned anonymity rules when working with the data set.

The matrix V, which measures the relative importance of predictors, is chosen among all positive definite and diagonal matrices to minimize the MSPE of the outcomes of interest during the pre-treatment period. In some cases, this method is not applicable because the optimization does not reach a minimum. Then, the elements of V are obtained via a regression of the outcome on the predictors. Thus, the predictors are weighted according to their predictive power in explaining the outcomes of interest before the minimum wage floor was introduced in the roofing sector. The two step procedure where the pre-treatment period is split in a training and validation period to gain insights on the V matrix is not adoptable in this study. The observation window prior to the treatment is too small.

The time of observation is set from 1993 to 2010. This gives a pre-treatment window of four years in which the roofing sector experienced the end of economic boom and the beginning of the recession. The size of the window is constrained, because East German data are only representatively available from 1993 onwards. In order to yield an unbiased estimate of the treatment effect (Abadie et al., 2010) the window is chosen as large as possible. To capture the full extent of the treatment effect the post-treatment period window is 13 years. This corresponds to the largest available time span in the data.

5. Results

5.1. Effects on Total Employment

First, the impact of the minimum wage on total employment are examined for West Germany, applying SCM with two donor pools. The performances of the two synthetic control groups are displayed in Table 3. Donor pool two, including construction and supplier sectors, mirrors the roofing sector characteristics on average much better than the construction donor pool. RMSPE decreases substantially when the donor pool two instead of one is used, as its value declines from 1009.61 to 304.81. Also, the trajectory of the outcome of the roofing sector prior to the treatment is reproduced more accurately by the donor pool two (Figure 5, right graph).

Table 3: Total employment predictors for West Germany by donor pool

		Roofing Sector	
Variables	Real	Synthetic I	Synthetic II
Percent male	91.13	82.11	83.65
Percent medium skilled	49.69	51.47	37.75
Percent prime aged	73.36	68.20	76.27
Percent of small sized firms	55.63	42.98	42.26
Total employment 1993	62300	61856	62508
Total employment 1994	62850	62275	62728
Total employment 1995	63800	62966	63589
Total employment 1996	59850	61819	60429
Total employment 1997	60300	60312	60098
RMSPE		1009.61	304.81

Note: Synthetic I: Subsectors of the construction sector; Synthetic II: Subsectors of the construction sector and suppliers.
All variables except for lagged employment are averaged over 1993 to 1997. RMSPE is the root mean squared prediction error over all variables in the predictor set during the pre-treatment period.

Figure 5 (left graph) displays total employment for the roofing sector and its two synthetic control groups during the entire study period. The employment effect equals the difference between total employment in the roofing sector and its synthetic versions during the post-treatment period, given an acceptable prediction fit. Immediately after the introduction of the minimum wage in 1997, both synthetic control groups and the actual outcome are fairly alike. The counterfactual outcome of the synthetic control group, consisting of construction donor units, begins to diverge considerably from the roofing sector in 1999. The line stays below the roofing sector's development until the end of the study period, suggesting positive employment effects from the minimum wage policy. At first sight (Figure 5, right graph), the magnitude of the gap indicates that the policy has a large positive effect on total employment and that this effect increased over time. It seems as if the wage floor triggered job creation. Employment increased by approximately 12'500 which is equivalent to a rise of 22 percent compared to the synthetic control group. However, when supplier sectors are included in the donor pool, the size and the sign of the effect change. Right after the minimum wage introduction, the counterfactual line of donor pool two suggests no substantial employment effect. Then, the lines diverge. From 2004 to 2010 the effect is about -9'000. This corresponds to a decline in employment of approximately 17 percent.

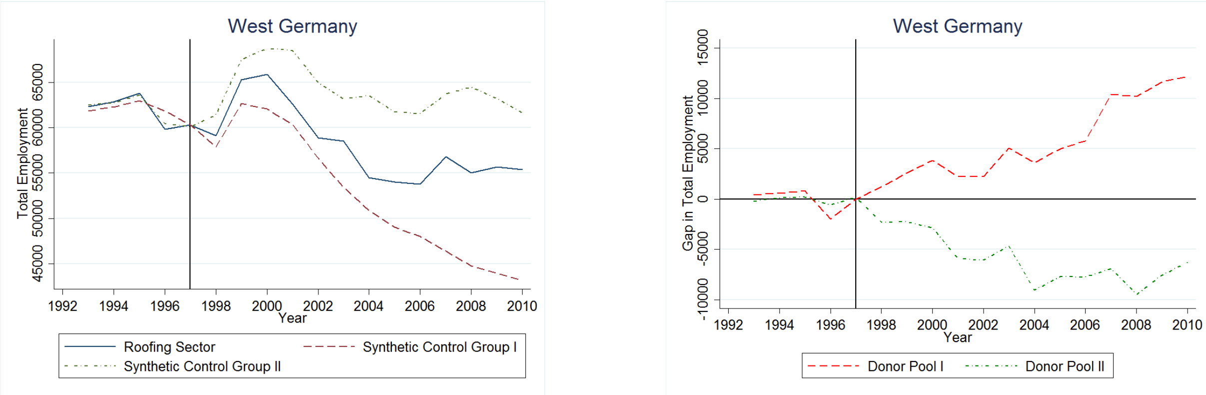


Figure 5: Total employment in the roofing sector and the synthetic control groups in West Germany and corresponding gaps by donor pool, 1993-2010

Table 5 reports the weights assigned by the quadratic constraint optimization to each donor unit for both donor pool specifications. The plumbing sector (weight equals 0.563) is most affine to the roofing sector in donor pool one. Together with the glazing sector (0.437), the synthetic control group is formed. Adding supplier sectors, former sectors are not represented anymore. The manufacturer of plastics sector inherits the position (0.404) as the sector with the highest similarity to the roofing sector. Now, the counterfactual roofing sector is a convex combination of the sectors manufacturer of plastics, of builders' carpentry, of metal small-wares and locksmithery. All other sectors in the donor pool receive zero weights. Hence, no construction subsector is represented in the second synthetic control group.

The estimations for East Germany yield comparable results. Firstly, donor pool two produces a better counterfactual for the roofing sector in terms of the prediction fit than donor pool one. RMSPE falls from 4616.09 to 2465.98 (see Table 4). Note, checked against the SCM in West Germany estimations, the East Germany RMSPEs outweigh the respective values by far.

Figure 6 (left graph) also reflects this mismatch. In the pre-treatment period, the lines of the actual roofing sector and both synthetic controls differ substantially. The gap (Figure 6, right graph) is not stable over time. Both synthetic control groups underperform during the economic boom and overperform during the recession in the construction sector.

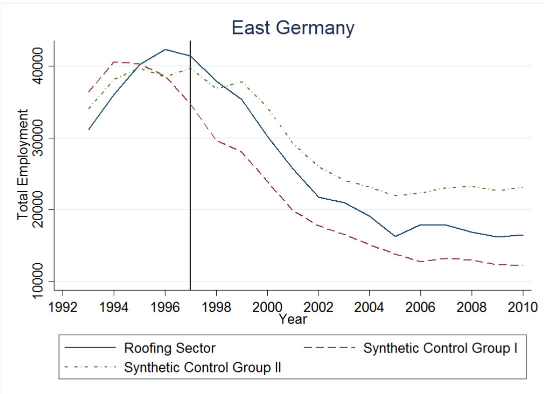
Secondly, the estimates for the employment effects alter in the same directions for both donor pools. The obtained effects in East Germany should be interpreted carefully, due to the bad pre-treatment fit of the synthetic control groups. Much of the gap between the real and synthetic roofing sectors after 1997 is likely to be created by the lack of fit, rather than by the impact of the minimum wage introduction. If one is willing to accept that the second donor pool produces a proper control group, the result suggest that employment decreased by approximately 40 percent in 2010.

As in West Germany, the plumbing sector is assigned the highest weight (0.618) in the

Table 4: Total employment predictors for East Germany by donor pool

		Roofing Sector	
Variables	Real	Synthetic I	Synthetic II
Percent male	91.84	85.78	86.61
Percent medium skilled	58.03	60.34	59.91
Percent prime aged	69.69	67.83	73.53
Percent of small sized firms	69.89	44.84	47.42
Total employment 1993	31150	36394	34082
Total employment 1994	36050	40592	38156
Total employment 1995	40250	40343	39752
Total employment 1996	42300	38631	38526
Total employment 1997	41400	34696	39701
RMSPE		4616.09	2465.98

Note: Synthetic I: Subsectors of the construction sector; Synthetic II: Subsectors of the construction sector and suppliers.
All variables except for lagged employment are averaged over 1993 to 1997. RMSPE is the root mean squared prediction error over all variables in the predictor set during the pre-treatment period.



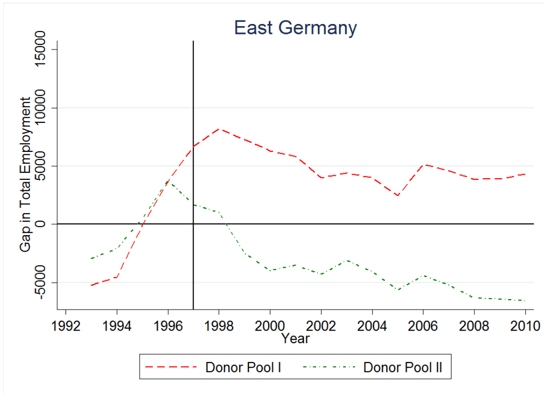


Figure 6: Total employment in the roofing sector and the synthetic control groups in East Germany and corresponding gaps by donor pool, 1993-2010

construction donor pool, implying that the plumbing sector is most similar to the roofing sector. Including supplier sectors, the plumbing sector still is important in explaining the trajectory of the roofing sector (0.309). Now, the roofing sector is best reproduced by a convex combination manufacture of builders' carpentry (0.691) and the former.

In order to evaluate the significance of the estimates, the question arises as to whether the findings could be driven merely by chance. To assess this issue, placebo studies are run by iteratively applying SCM to sectors in the respective donor pools. In each iteration, the treatment is reassigned to another sector while the roofing sector is dropped from the placebo donor pool. Figure 7 displays the actual gap and the placebo gaps of the first donor pool for West and East Germany. The gray lines represent the gaps associated with each of the three test runs. The superimposed black line denotes the gap estimated for the roofing sector. If all pre-treatment fits are good and the actual treatment outweighs the placebo treatments, the treatment effect estimates is statistically significant at the 25 percent (corresponds to 1/4) level. For West Germany SCM produces bad prediction fits among all donor units. Especially, the pre-treatment employment outcome of the plumbing cannot be reproduced. This, however, does not come at a surprise. The plumbing sector is the sector with the highest employment for every year before the policy change. Hence, its values do not lie within the convex hull of the donor units. The same issue occurs in East Germany. Furthermore, the trajectory of two other sectors in terms of pre-treatment outcome cannot be mirrored by SCM in West Germany. Due to this problem, the placebo method applied in donor pool one does not allow an inference on the significance of the minimum wage's impact on total employment in the roofing sector. The significance of the employment effect estimate in East Germany can also not be assessed, as the roofing sector's synthetic control group performs too bad in the pre-treatment period.

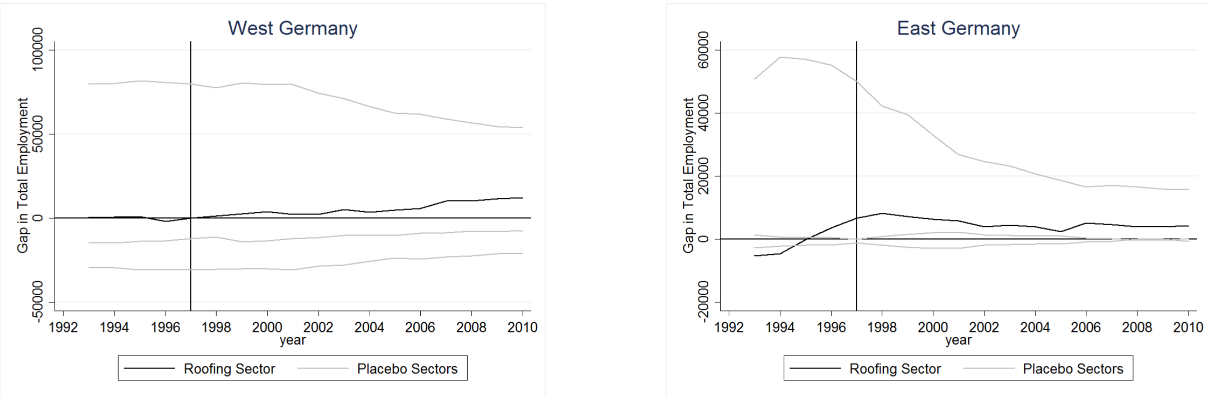


Figure 7: Total employment gap in the roofing sector and placebo gaps in donor pool one by region, 1993-2010

The same placebo strategy is applied within the second donor pool. The median RMSPE of all placebo studies and the actual SCM corresponds to 618.45 and 203.50 for West and East Germany, respectively. The median is used as cutoff for West Germany placebo studies. Sectors with higher values are discarded. This restriction is chosen because placebo runs with poor fits prior to 1997 do not provide information to measure the relative rarity of estimating a large post-treatment gap for a sector that was well fitted prior to the policy. The median cannot be used as a cutoff point in East Germany since the roofing sector's RMSPE is higher than the median. Here, placebo gaps are dropped which are higher than the roofing sector's RMSPE. The procedure discards in West Germany (East Germany) nine (two) sectors with extreme RMSPEs, leaving eight (15) gaps to infer the significance of the finding. Figure 8 displays the results. In West Germany, the actual treatment effect outweighs all placebo treatment effects except for one. This indicates that the minimum introduction has a disemployment effect in West Germany which is significant at 22 percent (2/9). As stated before, RMSPE for the roofing sector for East Germany is too high. Thus, again, the placebo method does not allow one to judge the significance of the effect in this case. Appendix A displays the gaps for all 17 donor sectors.

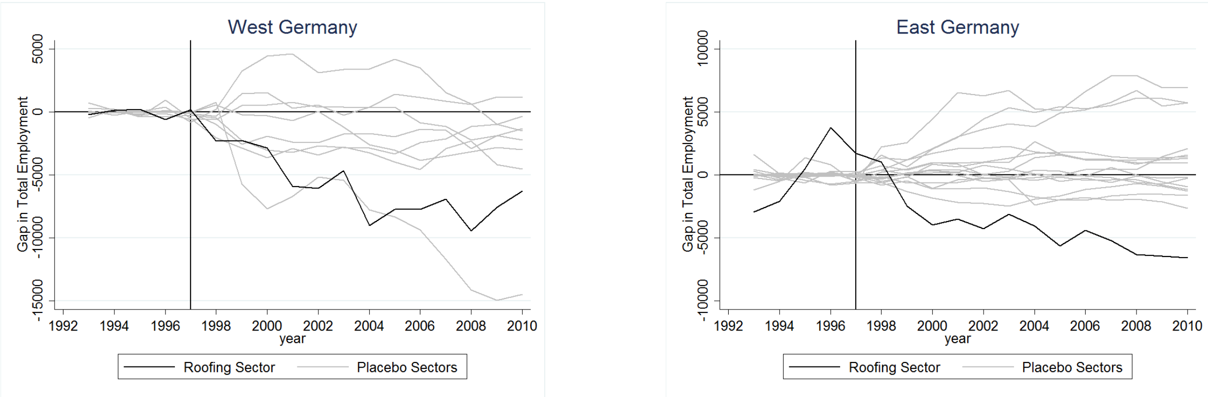


Figure 8: Total employment gap in the roofing sector and placebo gaps in donor pool two by region, 1993-2010

Table 5: Weights assigned to each sector by region and donor pool, outcome variable total employment

Region	West Germany		East Germany	
Donor Pool	I	II	I	II
Plumbing	0.563	0	0.618	0.309
Glazing	0.437	0	0	0
Stove maker	0	0	0.382	0
Manufacture of builders' carpentry, joinery		0.194		0.691
Manufacture of plastics		0.404		0
Locksmithery, welding, grinding		0.344		0
Sawmilling, planing of wood		0		0
Manufacture of sheet metal products		0		0
Manufacture of ceramics, tiles, and tiled stoves		0		0
Manufacture of steel tube furniture		0		0
Manufacture of metal small-wares		0.058		0
Manufacture of stoneware, pottery		0		0
Manufacture of plywood, particle board		0		0
Custom steel forming		0		0
Manufacture of heating, cooking equipments		0		0
Manufacture of general hardware		0		0
Manufacture of woodturned products and basketry		0		0

Note: Donor Pool I: Subsectors of the construction sector; Donor Pool II: Subsectors of the construction sector and suppliers.

5.2. Effects on the Share of Covered Workers

As pointed out in section 4.2., even though, employment stayed roughly constant in West Germany, the share of covered workers declined remarkably right after the treatment. A possible explanation for this observation is that employers try to circumvent paying the minimum wage floor by declaring a worker as clerks or to employ more apprentices while dismissing regular workers. Applying SCM to the share of covered workers helps to evaluate whether this type of employment effect occurred or not.

The results for the performance of the two synthetic control groups in West Germany are displayed in Table 6. Again, the supplier donor pool has a lower RMSPE than the first. The value drops from 12.43 to 2.35. Also, the former mirrors the pre-treatment outcomes in the roofing sector better (Figure 9). The bad fit prior to 1997 for the construction donor pool is caused by the extreme value of the share of covered workers in the roofing sector. No other unit in the construction sector has a similarly comparable high share.

Table 8 displays the weights received by SCM for each donor sector. In the donor pool, consisting of construction subsectors, the glaziers are assigned the weight 1 which mismatches the actual outcome by 8 to 15 percentage points in each pre-treatment year. The glazing sector experiences the second highest outcomes among all subconstruction sectors. Thus, the convex hull condition is not fulfilled and SCM does not produce any eligible predictions of the treatment effects. The second, bigger donor pool matches the roofing sector characteristics on average better than the construction donor pool. However, the synthetic counterpart of the roofing sector is also only represented by one sector, namely the sawmilling industry.

Table 6: Share of covered workers predictors for West Germany by donor pool

		Roofing Sector	
Variables	Real	Synthetic I	Synthetic II
Percent male	91.13	76.63	86.17
Percent medium skilled	49.70	46.67	27.58
Percent prime aged	73.36	71.29	75.86
Percent of small sized firms	55.63	45.13	58.83
Share of covered workers 1993 (in %)	82.99	68.64	79.77
Share of covered workers 1994 (in %)	82.42	68.51	79.90
Share of covered workers 1995 (in %)	81.50	67.26	79.69
Share of covered workers 1996 (in %)	78.36	67.79	79.70
Share of covered workers 1997 (in %)	76.62	68.95	79.03
RMSPE		12.43	2.35

Note: Synthetic I: Subsectors of the construction sector; Synthetic II: Subsectors of the construction sector and suppliers.
All variables except for lagged shares of covered workers are averaged over 1993 to 1997. RMSPE is the root mean squared prediction error over all variables in the predictor set during the pre-treatment period.

Figure 9 (right graph) displays the gap in the shares of covered workers and its synthetic control groups. Due to donor pool one's bad prediction fit, it makes no sense to infer employment effects. For donor pool two, the treatment gap evolves sharply along the zero line in a range between -5 to 0 percentage points over the post-treatment window. This contradicts the previously expressed notion that the minimum wage introduction causes the observed decline in the share in West Germany. The result implies that other factors might be responsible for this phenomena.

In East Germany, the outcome of interest remained stable after the introduction of the minimum wage. Hence, one expects to find a neutral employment effect. The estimations for East Germany yield very different results in terms of the pre-treatment fit. The reason being that the roofing sector's corresponding share can be mirrored by a convex

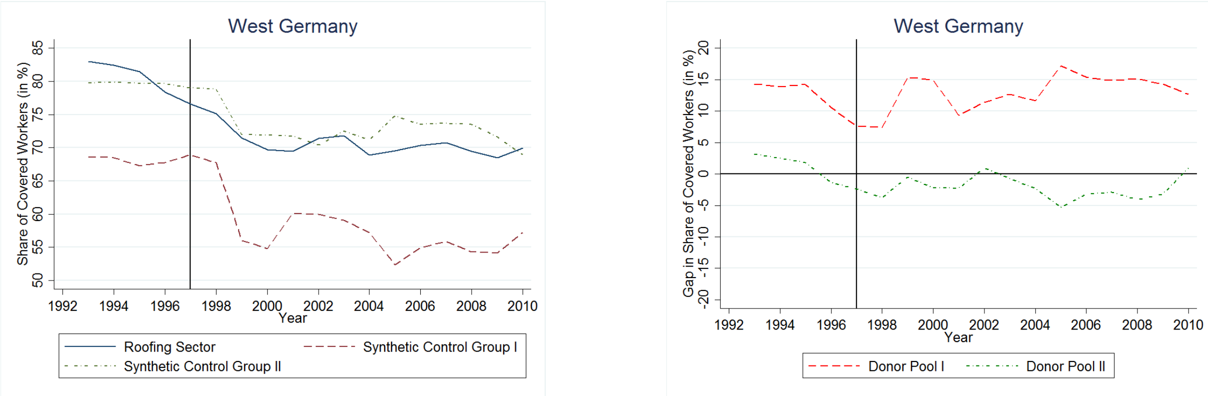


Figure 9: Share of covered workers in the roofing sector and the synthetic control groups in West Germany and corresponding gaps by donor pool, 1993-2010

combination of both donor pools. The second donor pool has again a lower RMSPE than the first, respectively 6.58 and 0.37. This gives confidence that the obtained treatment effects are not primarily driven by the difference in the outcomes previous to the treatment, but by the policy treatment. Figure 10 displays the trajectory of the outcome variable in the roofing sector and its two synthetic counterparts, as well as the corresponding gaps. The first synthetic version of the roofing sector overstates the actual outcomes during the whole pre-treatment period by 2 to 8 percentage points. Version two, on the other hand, reproduces the outcomes closely. Hence, one can infer treatment effects from the second. The gap indicates that the roofers experienced positive employment effects compared to the control unit. The gap ranges between 2.5 and 10 percentage point during the post-treatment period.

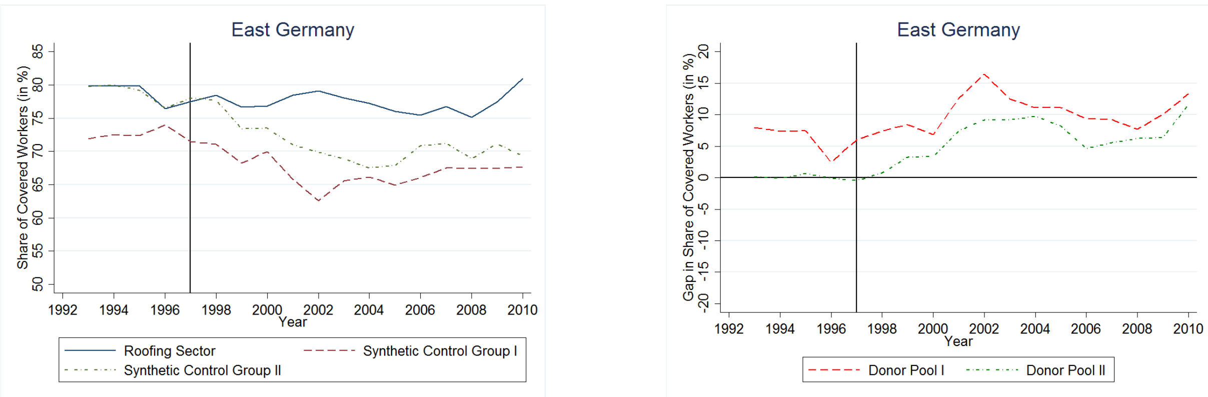


Figure 10: Share of covered workers in the roofing sector and the synthetic control groups in East Germany and corresponding gaps by donor pool, 1993-2010

Table 8 displays how SCM assigns the weights to the donor units in the two specifications. Compared to the estimations on total employment, also the plumbing sector is most affine to the roofing sector receiving a weight of 0.627. But instead of the stove making, now the glazing sector receives the second highest weight. It corresponds to 0.373. When the donor pool including the suppliers is applied, the weights alter substantially. The

Table 7: Share of covered workers predictors for East Germany by donor pool

		Roofing Sector	
Variables	Real	Synthetic I	Synthetic II
Percent male	91.84	84.75	66.56
Percent medium skilled	58.02	60.21	58.56
Percent prime aged	69.69	75.06	77.07
Percent of small sized firms	69.89	48.84	49.71
Share of covered workers 1993 (in %)	79.94	71.94	79.78
Share of covered workers 1994 (in %)	79.89	72.53	79.99
Share of covered workers 1995 (in %)	79.88	72.38	79.23
Share of covered workers 1996 (in %)	76.48	74.00	76.55
Share of covered workers 1997 (in %)	77.54	71.53	78.01
RMSPE		6.58	0.37

Note: Synthetic I: Subsectors of the construction sector; Synthetic II: Subsectors of the construction sector and suppliers.
All variables except for lagged shares of covered workers are averaged over 1993 to 1997. RMSPE is the root mean squared prediction error over all variables in the predictor set during the pre-treatment period.

synthetic control group consists of five donor units, namely the manufacturer of builders' carpentry (0.440), of stoneware (0.256), of woodturned products (0.155), of steel tube furniture (0.100) and of sheet metal products (0.049).

Placebo studies are performed in order to gain insights in the significance of the obtained effects. Since the RMSPEs within donor pool one are too high for both German regions, the discussion of the significance of those estimates is omitted. The estimations do not provide any information from which significance could be judged. Appendix B shows the obtained results. However, studying the SCM with donor pool two, may yield results that are interpretable. The median of the all RMSPEs is 0.21 and 1.33 for West and East German estimations, respectively. Unfortunately, taking the median cutoff is again not applicable for one of the regions. In West Germany it would discard the actual treated gap. Hence, another cutoff is chosen in this case. The rule for the West German specification is, as before: Placebos gaps are dropped which have a higher RMSPE than the roofing sector. This deletes two placebo estimations. Figure 11, shows that in West Germany, the treatment effect is well bounded by all placebo treatment effects during the post-treatment period. For East Germany the median cutoff applies. Thus, half of the placebo units are omitted. The remaining placebo gaps in East Germany also frame on average the actual treatment effect after 1997. These findings imply that the minimum wage introduction in the roofing sector had neutral employment impacts in terms of the share of covered workers in West and East Germany.

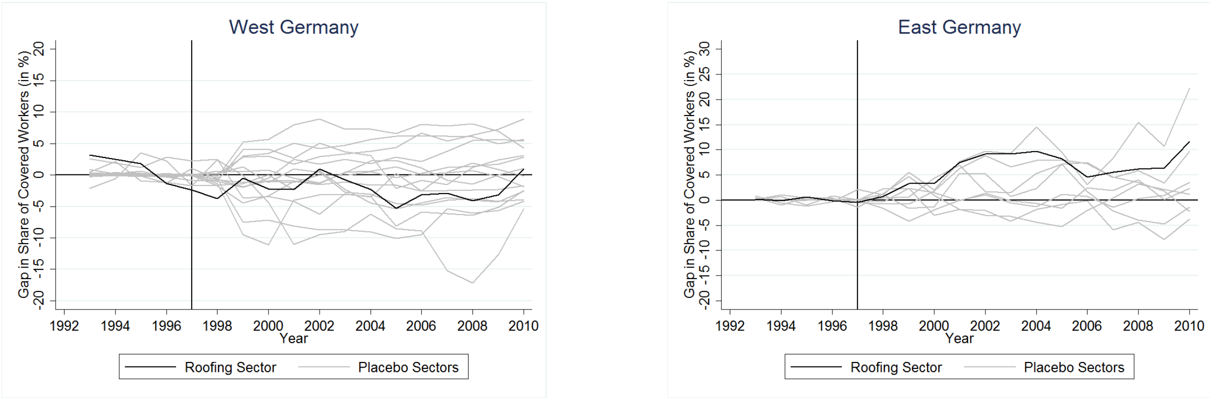


Figure 11: Share of covered workers gap in the roofing sector and placebo gaps in donor pool two by region, 1993-2010

Table 8: Weights assigned to each sector by region and donor pool, outcome variable share of covered workers

Region	West Germany		East Germany	
Donor Pool	I	II	I	II
Plumbing	0	0	0.627	0
Glazing	1	0	0.373	0
Stove maker	0	0	0	0
Manufacture of builders' carpentry, joinery		0		0.440
Manufacture of plastics		0		0
Locksmithery, welding, grinding		0		0
Sawmilling, planing of wood		1		0
Manufacture of sheet metal products		0		0.049
Manufacture of ceramics, tiles, and tiled stoves		0		0
Manufacture of steel tube furniture		0		0.100
Manufacture of metal small-wares		0		0
Manufacture of stoneware, pottery		0		0.256
Manufacture of plywood, particle board		0		0
Custom steel forming		0		0
Manufacture of heating, cooking equipments		0		0
Manufacture of general hardware		0		0
Manufacture of woodturned products and basketry		0		0.155

Note: Donor Pool I: Subsectors of the construction sector; Donor Pool II: Subsectors of the construction sector and suppliers.

5.3. Discussion

The findings on the impact of the introduction of the minimum wage in the roofing sector on employment outcomes estimated by SCM allow to make statements about employment effects and the empirical method.

Firstly, contrasting the effects on total employment for both donor pools suggests violations of the identifying assumptions when donor pool one, including only construction sectors, is applied. For both German regions, the former suggests unreasonable strong positive employment effects. However, the specification adding supplier sectors, yields neutral or disemployment impacts. This evidence indicates that SUTVA and/or CTA do not hold. A potential violation of SUTVA might be present when workers in unaffected subconstruction sectors seek and find jobs in the roofing sector. Hence, construction sectors in the donor pool might be indirectly affected by the minimum wage introduction. Aretz et al. (2013) perform a robustness test for potential spillovers in the plumbing sector which corresponds to the sector that is according to SCM on average most similar to the roofing sector. They find negligible worker movements between the roofing and plumbing sector, implying the non-existence of spillovers. If the plumbing or any other sector in the donor pool experiences an idiosyncratic shock at any point in the observation period, CTA will not hold. The assumption requires that the treated and the control group share the same development of the outcome variable in the absence of the treatment. Figure 12 plots the time series of total employment in the roofing sector and the plumbing sector in West and East Germany. Before the minimum wage introduction in 1997, the trends of the outcomes differs especially strong in East Germany. Employment in the East German plumbing sector declines from 1994 onwards, but the roofing sector's just shortly before the treatment. Furthermore, the plumbing sector experiences a massive decline in em-

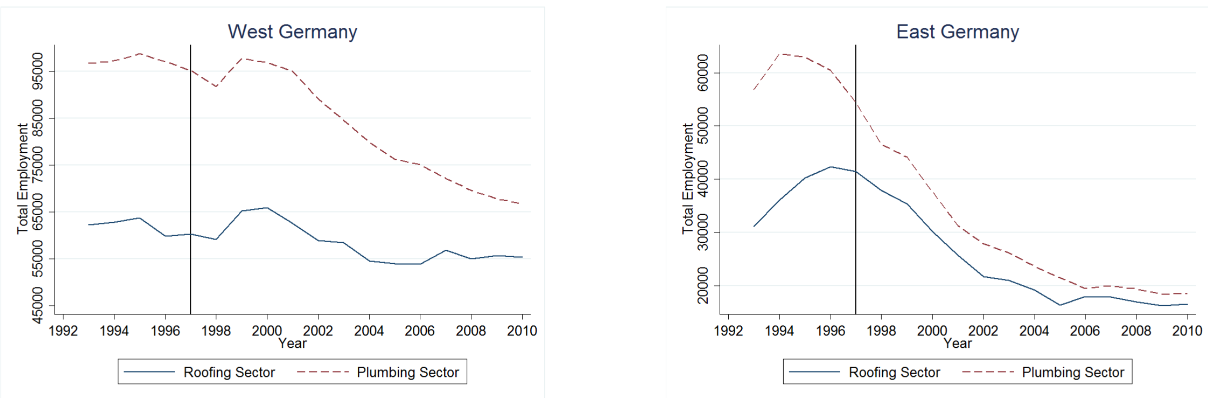


Figure 12: Total employment in the roofing and in the plumbing sector by region, 1993-2010

ployment in both regions during the entire study period. It corresponds to approximately 30 percent in West and to 65 percent in East Germany. This could imply that the sector was, besides being one of the only construction sector without a wage floor and exposed to a severe recession, subject to an idiosyncratic shock. The evidence suggests that CTA is violated and, thus, SCM estimates obtained from donor pool one are biased. Also, it challenges Aretz et al.'s (2013) selection of the plumbing sector as an appropriate control group in their DiD framework.

Secondly, Aretz et al.'s (2013) results from pooled LPM with fixed effects for West Germany are confirmed when using the larger donor pool. The minimum wage causes negative total employment effect. SCM suggests, also disemployment effects for the roofing sector in East Germany. In 2010 this effect amounts to a 40 percent decline compared to the synthetic control group. However, due to a bad prediction fit prior to 1997, one neither can rely on the size nor on the significance of the estimate. Hence, Aretz et al.'s (2013) results cannot be vindicated, which suggest significant negative employment effects. The authors find that chances of remaining employed in the roofing sector declines by -2.9 percentage points. It is rather surprising that Aretz et al. (2013) and this study find employment effects of equal sign. The former uses the plumbing sector as control group in the DiD estimation. However, SCM estimations assigning high weights to the plumbing sector yield positive employment effects. It could be the case, that the effects depend on the outcome of interest. Here, total employment is studied, whereas Aretz et al. (2013) consider the chances of remaining employed.

Thirdly, this study suggests that the wage floor had no effect, neither in West nor in East Germany, on the share of covered workers in the roofing sector. The SCM estimates show that the minimum wage introduction cannot explain the substantial shift in West Germany's workforce towards young workers and clerks.

Fourthly, the plumbing sector receives on average the highest weight in all synthetic control groups. At first sight, this suggests that plumbers form the most appropriate control group in the DiD framework to evaluate the effects of the wage floor in the roofing sector. But then, as discussed above, the plumbing sector might not meet CTA, making it impossible to identify the treatment effect.

In addition, the application of SCM in this study reveals weaknesses of the method. These arise if a synthetic control group is not able to mirror the pre-treatment outcomes of the roofing sector. One reason for this phenomenon is the violation of the convex hull condition. That is, the roofing sectors experiences extreme values in the outcome of interest that cannot be reproduced by a convex combination of the donor units. It poses a problem for the evaluation of the minimum wage's impact on the share of covered workers in West Germany. Even if the convex hull condition applies, it can occur that trajectory of the roofing sector's outcome cannot be resembled by any synthetic control if its trend is unique. In this study, this problem arises for the estimation of the impact on total employment in East Germany. Both cases induce that treatment effects cannot be measured and that significance is not inferable.

6. Robustness

In this section a set of robustness checks are run to test for the sensitivity of the main results to changes in specifications of SCM. It is assessed how the optimal weights and thus the results change when the predictor set varies, more comparison units are included in the donor pool, the pre-treatment window is narrowed and widen or when the time of treatment is reassigned to a period before 1997. The checks are exemplified using as benchmark model the estimations with donor pool two consisting of construction and supplier sectors.

In a first robustness test, additional predictors of employment are included among the variables used to construct the synthetic control. Namely, the sector-level share of workers without an university entrance qualifications and the proportion of clerks among all employed. All other parameters remain constant. The resulting weights for each comparisons groups in each of the four estimation do not alter. The same occurs when the predictor set only consists of lagged dependent yearly values. Since the weights are robust to the changes in the exogenous predictors, the resulting effects are identical to the benchmark models.

Next, the donor pool is enlarged. All available 3-digit level sectors in SIAB and which have values for all years of the observation period 1993 to 2010 are included in the donor pool. For West Germany, this yields in total 269, in East Germany 274 additional comparison sectors for the construction of the synthetic control. Remember that the selection of construction related units within the donor pool in the benchmark models rooted in the danger of interpolation biases. Large discrepancies between the characteristics of the affected unit and those of the units in the synthetic control group could be averaged away by SCM. Hence, control units that do not share defining similarities with the roofing sector might receive high weights. Moreover, one expects that the pre-treatment fits of the synthetic control group with the affected units increases. Note that there exists a potential bias. On the one hand, it is favorable to have a good prediction fit in order to have clear inference. On the other hand, CTA is likely not to hold after the treatment, because sectors are represented in the synthetic control that are distant to the economic setting of the construction sector. This would make it impossible to identify the treatment effect. The estimations are conducted to check whether this trade-off appears. The obtained results support the apprehension of interpolation biases. Distant sectors such as the hunting, labor leasing or processing asbestos receive substantial weights for three out of four estimations. Nevertheless, in the evaluation of the employment effect in West Germany, using total employment as outcome of interest, the highest weight is still assigned to the manufactures of plastic. For all estimations, RMSPE decreases substantially, as expected, while the signs of the employment effects remains constant. The described findings cannot be displayed in this study since they are only obtainable by on-site use of the SIAB data.

Furthermore, it is tested how the SCM results change, especially with regard to the optimal weights, when the pre-treatment window is shortened. For this purpose, the estimations of the change in total employment are conducted with a matching period restricted to the recession in the construction industry. Thus, the window before the policy is set from 1995 to 1997, leaving three instead of five yearly pre-treatment outcomes in the predictor set. Since, the recession was strongest experienced by the construction sectors itself and only indirectly by suppliers, one expects that the subconstruction sectors receive higher weights than before. If the sectors that are assigned substantial weights in the benchmark models, remain in the synthetic control, this would give confidence that they are overall important for the counterfactual construction of the roofing sector outcome. Furthermore RMSPE, the measure for the prediction fit, should decrease naturally due to less years over which the synthetic control group is constructed. Indeed, RMSPE declines substantially for all specifications compared to the benchmark cases. Appendix C.1 displays how the weights evolve for total employment with the modification of the pre-treatment period. The first three rows of the table correspond to the construction subsectors. In the West German specification, among these, only the plumbing sector receives a negligible weight. Furthermore, the relative allocation of the weights is altered. However, the manufacture of plastics (0.486) is still predominantly represented in the synthetic control group. In East Germany, on the other hand, the ranking remains constant when using the shorter pre-treatment window. Compared to the benchmark case, the plumbing sector receives a higher weight (0.376). Thus, the modification induced a small shift towards a subconstruction sector. The robustness check depicts that the assignment of the weights in SCM is relatively robust to changes in the matching period.

The findings for the benchmark model hold when total employment is measured in log transforms instead of levels. In two SCM estimations, East Germany with total employment and West Germany with the share of covered workers, the method was unable to find a counterfactual roofing sector that reproduced the actual roofings sector outcomes of interest good prior to the treatment. The latter was caused by extreme values in the outcomes in the roofing sector. A strategy to yield nevertheless eligible results, is to transform the variables into growth rates. The focus of this robustness study is on how this modification changes employment effects. For the specifications, where the fits were appropriate before the treatment, no substantial alterations occur in the sign of estimates over time. The figures in appendix C.2. display the gaps of the placebo studies and the actual gaps for the two other specifications. For West Germany, the findings are robust to the growth transformation of the covered workers. The estimates are bounded by placebo gaps indicating that the estimates are driven by chance and are not different form zero. The second specification, which studies the growth in employment in East Germany shows that the roofing sectors has experienced a remarkable decline in employment right after the introduction of the minimum wage until 2003. Evaluated against the distribution of the gaps of eight control sectors with good prediction fits (RMSPE less than the median), however, the gap of the roofing sector appears to be well bounded in absolute terms. This applies also for all other post-treatment years. Hence, this robustness test implies that the East German roofing sector experienced no substantial employment effect caused by the minimum wage introduction in terms of growth rates.

Lastly, the robustness with respect to time is investigated. The checks are exemplified with the specification of total employment in West Germany. The choice is motivated by the availability of the data in SIAB. West German data are collected from 1975 onwards. In a first test, the optimal weights obtained from SCM, are applied to the years before 1993 in order to examine how the counterfactual is able to mirror the roofing sector over a longer time. The results are displayed in appendix C.3. The lines of the roofing sector and its counterfactual do not follow the same track before 1993. There are three different phases. In phase one from 1980 to 1982, the counterfactual is bigger than the actual outcome. The reverse hold for phase two from 1983 to 1987. Then again, the counterfactual outcome is higher until 1993 from which onwards the lines are fairly alike. This robustness check implies that the optimal weighting scheme from the benchmark is not able to track the counterfactual in the previous years when no policy took place. It is also checked which comparison units are selected to form the synthetic control group if the predictor set includes several years prior the treatment. The first specification includes four employment values from 1980 to 1995, every fifth year, the second yearly values for the period 1980 to 1985. For both, the exogenous variables are averaged over the years 1985 to 1990. The table in appendix D.4 displays the optimally assigned weights. There is a clear shift in both synthetic control groups in favor of subconstruction sectors. The plumbing sector receives around 60 percent and the stove maker sector in the first specification 37 and in the second 24 percent. Other sectors have negligible weights. One possible explanation for this finding is that over time construction and supplier sector only recently developed strong interdependencies [4].

7. Conclusion

This paper applies the synthetic control method to examine the impact of the minimum wage introduction in the German roofing sector on employment. The effects on total employment and the share of covered workers are separately examined for West and East Germany. Strong emphasis is placed on the implementation and discussion of the method. Based on a matching procedure in the pre-treatment period, the approach constructs a convex combination of unaffected units which is used as control group. Employment effects

[4]The robustness check's results are selectively reported in the appendix for specific cases to secure confirmability.

are estimated with two sets of donor units, the first consisting of construction subsectors and the second including additionally supplier sectors. The estimates from synthetic control methods imply that the approach is sensitive to changes in the donor pool. There appears to be a tradeoff between prediction fit and interpolation. Also, the results suggest that identification of the effects within the construction sector, where the plumbing sectors is highly represented in the synthetic control group, is not possible and leads to biased estimates. This is most likely caused by the violation of CTA. Applying the alternative donor pool including additionally supplier sectors, indicates that the introduction of the minimum wage has a negative effect on total employment in the roofing sector in West and East Germany, although significance can only be inferred for the West German estimate. Surprisingly, these results are in line with Aretz et al. (2013) even though they choose the plumbing sector as control group. However, the significance of the later cannot inferred from commonly applied SCM placebo studies. The share of covered workers in the roofing sector is unaffected by the minimum wage introduction for both regions. The SCM estimates show that the minimum wage introduction cannot explain the substantial shift in West Germany's workforce towards young workers and clerks.

One should be aware that the presented evidence should not be interpreted as the effects on the total roofing sector because SIAB data does not include self-employed workers.

An advantage of SCM compared to the DiD framework is that the choice of the control group is objectified. Nevertheless, the composition of the synthetic control group is sensitive to certain alterations in the parameters of SCM. Thus, like in DiD, one has to discuss and test the criteria on which the selection is rooted.

For each outcome of interest, a different synthetic control group is created, which extends the scope of application and exploitable information. A caveat of the basic SCM is that it can only be used on aggregate levels. Hence, empirical studies with individual data cannot be conducted. Moreover, restrictions exists in terms of the ability in reproducing suitable counterfactuals in the pre-treatment period caused by extreme values or unusual trends in the outcomes of the affected unit, making it impossible to identify treatment effects.

Given the information available in SIAB, this study matches synthetic control groups based on lagged outcomes of interest and labor market characteristics only. A promising extension would be an inclusion additional industry level attributes, such as demand and business cycle measures. Another possible extension of this work would be to test the significance of the employment effects using the technique introduced by Ando and Sävje (2013). Furthermore, the impact of the successive increases in the minimum wage level of the roofing sector on employment could be evaluated. Dube and Zipperer (2013) extend SCM such that it allows them to identify treatment effects for recurring treatments and multiple cases. Moreover, this method could be applied in order to evaluate an average employment effect of all sectoral minimum wages in Germany.

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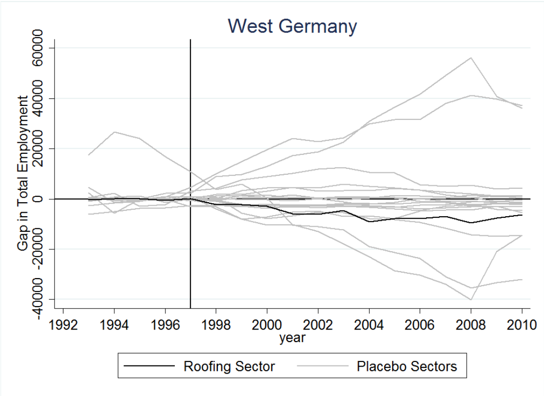
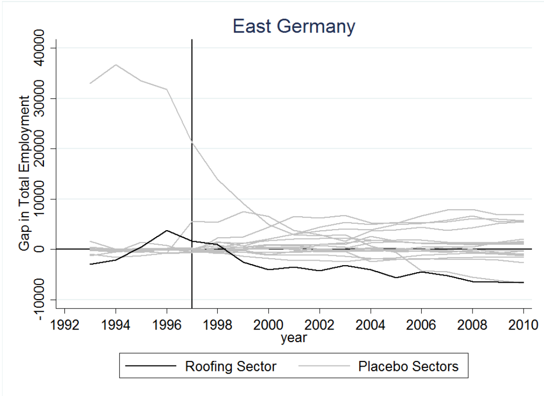
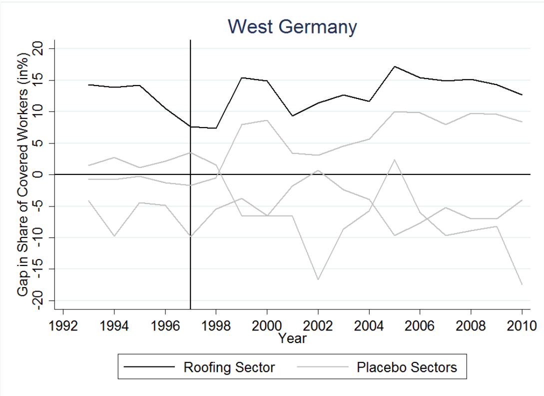
Appendix

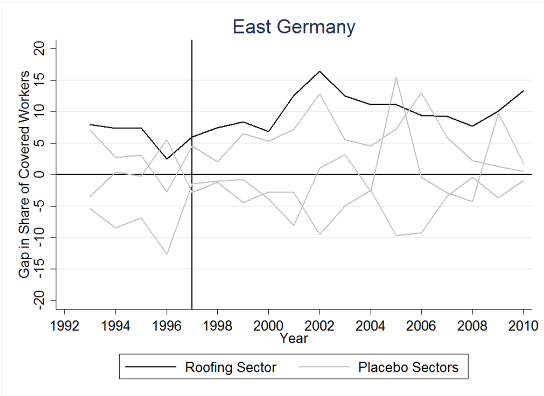
A - Total employment gap in the roofing sector and placebo gaps in all 17 construction and supplier donor sectors, 1993-2010



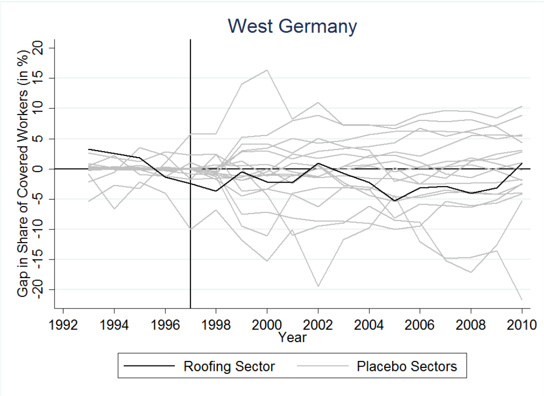


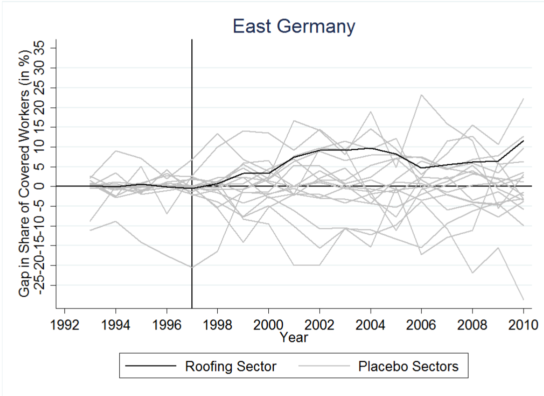
B.1 - Gap in the share of covered workers in the roofing sector and placebo gaps in all three construction donor sectors, 1993-2010





B.2 - Gap in the share of covered workers in the roofing sector and placebo gaps in all 17 construction and supplier donor sectors, 1993-2010



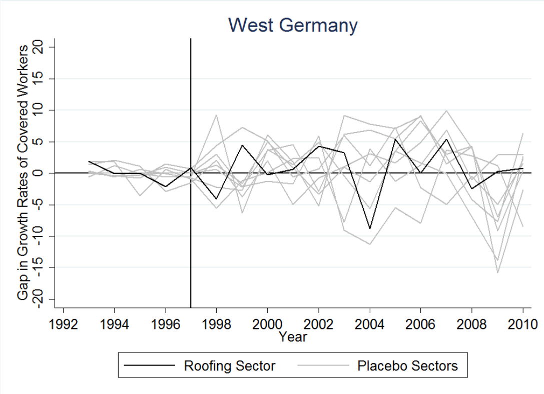


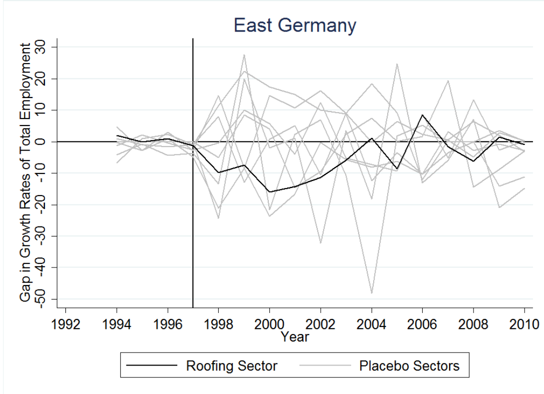
C.1 - Robustness test: Benchmark compared to pre-treatment window narrowed to recession period

Region	West Germany		East Germany	
Pre-treatment window	I	II	I	II
Plumbing	0	0.091	0.309	0.376
Glazing	0	0	0	0
Stove maker	0	0	0	0
Manufacture of builders' carpentry, joinery	0.194	0	0.691	0.624
Manufacture of plastics	0.404	0.486	0	0
Locksmithery, welding, grinding	0.344	0	0	0
Sawmilling, planing of wood	0	0	0	0
Manufacture of sheet metal products	0	0	0	0
Manufacture of ceramics, tiles, and tiled stoves	0	0	0	0
Manufacture of steel tube furniture	0	0	0	0
Manufacture of metal small-wares	0.058	0.423	0	0
Manufacture of stoneware, pottery	0	0	0	0
Manufacture of plywood, particle board	0	0	0	0
Custom steel forming	0	0	0	0
Manufacture of heating, cooking equipments	0	0	0	0
Manufacture of general hardware	0	0	0	0
Manufacture of woodturned products and basketry	0	0	0	0

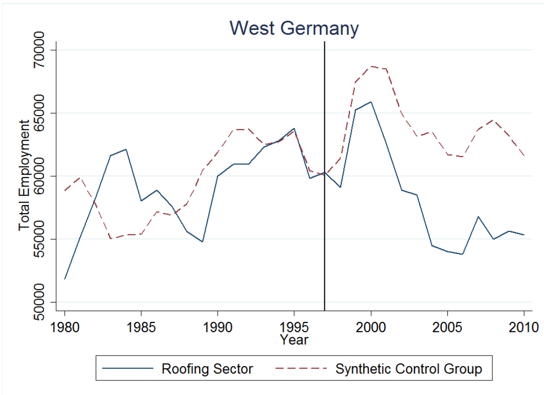
Note:
Pre-treatment window I: Benchmark, 1993-1997; Pre-treatment window II: Recession, 1995-1997.

C.2 - Gap in growth rates in the roofing sector and placebo gaps in eight construction and supplier donor sectors, 1993-2010





C.3 - Total employment in the roofing sector and its counterfactual in West Germany, 1980-2010



C.4 - "In-time" robustness tests with varying predictor sets

Region	West Germany		
Precictor Set	I	II	III
Plumbing	0	0.610	0.609
Glazing	0	0	0
Stove maker	0	0.367	0.241
Manufacture of builders' carpentry, joinery	0.194	0	0
Manufacture of plastics	0.404	0	0.151
Locksmithery, welding, grinding	0.344	0	0
Sawmilling, planing of wood	0	0	0
Manufacture of sheet metal products	0	0	0
Manufacture of ceramics, tiles, and tiled stoves	0	0	0
Manufacture of steel tube furniture	0	0	0
Manufacture of metal small-wares	0.058	0	0
Manufacture of stoneware, pottery	0	0	0
Manufacture of plywood, particle board	0	0	0
Custom steel forming	0	0.023	0
Manufacture of heating, cooking equipments	0	0	0
Manufacture of general hardware	0	0	0
Manufacture of woodturned products and basketry	0	0	0

Note: Predictor Set I: Benchmark, 1993-1997; Predictor Set II: 1980 to 1995 (5 year steps); Predictor Set III: 1981 to 1985 (1 year steps).