Youth Employment Effect of the New German Minimum Wage

by

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ABSTRACT

This study evaluates the short-term youth employment effect of statutory minimum wage introduced in Germany in 2014. We demonstrate that, following the minimum wage reform, youth employment faced a small decline in relation to a comparable synthetic control region. We estimate that by the second quarter of 2017 youth employment in the synthetic Germany was about 4.7% higher than in the actual Germany. Applying the inferential methods discussed in this thesis, we reveal the significance and the robustness of our estimates. In our analysis a combination of comparison units does a better job of reproducing the German youth employment trend than any single comparison country taken alone. On the one hand, we contribute to the existing scarce literature by providing evidence of youth employment change after the introduction of minimum wages in Germany. On the other hand, we contribute to the minimum wage literature by applying an increasingly popular data-driven method and by exploring the potential of synthetic control methods to comparative case studies in this area of research.

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INTRODUCTION

In April 2014 German government coalition made an announcement to propose a minimum wage reform in parliament. Consecutively on 1 January 2015 an hourly statutory minimum wage of € 8.50 was implemented. After the announcement but before the enforcement of the new minimum wage, the possible employment effects were strongly debated among economists and policy makers. As major benefits of minimum wage introduction proponents were highlighting decrease of inequality and aversion of poverty (Bosch (2007); Kalina (2014)). Meanwhile the opponents of the reform were estimating a significant rise in unemployment (Knabe et al. (2014); SZB (2013)). Finding out employment effects was a question of empirical analysis, thus there was a need of independent methodical ex-post assessments (Zimmermann (2014)). Accordingly, in this study we aimed to evaluate how state-level minimum wage introduction changed employment of young people in Germany in the short time span.

Recent ex-ante and ex-post German minimum wage literature applies difference-in-differences (DiD) assessments to establishment level or administrative data to assess the employment effects. This method is widely used due to its straightforward application and capacity to handle endogeneity issues that usually arise when heterogeneous units are compared with one another. Yet, the choice of the comparison units is often arbitrary and based on unquantifiable criteria of relationship between exposed and unexposed units in pre-minimum wage introduction period. On the contrary, the use of another method, the Synthetic Control Method (SCM), helps avoid the above-mentioned limitation. This method is based on the idea that a combination of unaffected units often constitutes a better comparison for the affected unit than any single unit taken alone (Abadie et al. (2012)).

Our objective was to apply synthetic control methods for estimating short term youth employment effects in Germany in post minimum wage reform period by applying a panel of country-level quarterly data.

The study contributes to the existing literature by providing first evidence on short-run youth employment effect of the new statutory minimum wage and by applying the Synthetic Control Method in the context of minimum wage reform in Germany. In the recent literature, famous studies of Sabia et al. (2012) and Allegretto et al. (2013) have measured the effects of state-level minimum wages in the U.S. on labor market outcomes using the SCM, similar to our undertaking.

All in all, with this study we contribute to the minimum wage literature by employing the data-driven Synthetic Control Method and by understanding closely its application in this novel context.

The structure of our study proceeds as follows: Chapter 1. Institutional Background presents the minimum wage law; Chapter 2. Literature Review covers both the international (mainly US) and German evidence on minimum wage studies and research methods applied in those studies; Chapter 3. Synthetic Control Method provides introduction to the methodology applied in for our analysis and discusses its advantages and limitations; Chapter 4. Data and Sample discusses the publicly available data source and the choice of predictors; Chapter 5. Construction of Synthetic Germany illustrates the estimation results including placebo studies and robustness tests; the last two sections address the conclusion of the study and its limitations.

CHAPTER 1. INSTITUTIONAL BACKGROUND IN GERMANY

Reduced collective bargaining coverage and increasing wage inequality brought into force the first statutory minimum wage (SMW) on 1 January 2015 in Germany. Backed by union support but contrary to business critique, an hourly SMW of € 8.50 was introduced. SMW in Germany was much lower than in France (highest SMW in European Union - € 9.61), but sufficiently high to have an effect.

The discussions of minimum wage triggered policy debates, which started with the federal election campaign in 2013. After this election the political situation shifted in support of the statutory minimum wage[1].The debates led to an important point in the coalition agreement of the grand coalition, where the introduction of SMW was announced. The coalition agreement was publicly announced end of 2013 and signed end of 2014[2]. It presented the time of introduction, also the amount of the SMW - € 8.50. This timeframe shows that the SMW legislation could have changed expectations even before it come in force.

Note that this is the first minimum wage in Germany that covered all sectors with few exceptions. Bossler (2017) mentions that sectorial minimum wages (MW) that were below the new minimum could delay their compliance for two-years. Likewise, sector specific collective bargaining agreements also were allowed for an adjustment period of two years until 31 December 2016. Additionally, long term unemployed people can have a compensation below € 8.50 MW for the first 6 month of employment. However, vom Berge et al. (2016) confirm that this exception is hardly used.

[1] In political scene the Social Democrats were the main driving force and proponents of the introduction of the minimum wage. They were arguing that the minimum wage would create a fiscal surplus. After the federal election in 2014 Social Democrats took the place of the Liberals as the coalition partner.
[2] The German Parliament voted for the SMW on July 2014, the second chamber Bundesrat confirmed the law on July 2014. The law came into force on August 2014

After introducing the Minimum Wage Law, the German Minimum Wage Commission also made recommendations for upcoming changes of the MW level. Considering the small employment changes in the first year after the introduction of the reform, the MW was raised up by € 0.34 per hour since beginning of January[3]. The German Customs Administration (GCA) is in charge of making checkups of employer companies and imposing compliance with social security laws and the MW Law. If GCA finds any dissent, the company may be fined up to € 500.000.

Before the introduction of federal minimum wage only certain industry specific minimum wages (MW) have been in force. Dating back in 1997 Germany introduced its first industry specific MW on some parts of the construction industry. According to Rattenhuber (2011) the MW referred to workers doing physically laborious job ("gewerbliche Arbeitnehmer") in the main construction trade with different rates in East and West Germany. Recently, few other sectors also bargained MW; a fixed MW was introduced in hair dressing (2013) or security services (2011). Before the minimum wage reform, Germany was one of seven EU countries without a federal minimum wage.

[3] More details can be found at Mindestlohnkommission, 2016b

CHAPTER 2. LITERATURE REVIEW

2.1. International Evidence

2.1.1. General employment effect

For a long time, minimum wage and its potential employment effects have been some of the most studied topics in economics. Despite this nowadays they continue to be debated in empirical literature and political discourse. In a naïve setting, proponents claim that a higher MW will automatically bring a better standard of living and will lift people's consumption. Opponents reason that it will give less incentive to employers to hire and would destroy job creation. The results of early time-series studies usually present small disemployment effects (Solon (1985); Wellington (1991)).

The debate over MW employment effects has taken a new twist after the publication of the well-known minimum wage experiment of Card and Krueger (1994), where relative MW increase in New Jersey was compared with that in Pennsylvania. Contrary to previous studies, the authors found that the MW increase in New Jersey did not decrease employment compared to Pennsylvania. Moreover, they found a positive effect on employment.

This controversial finding was challenged by Neumark and Wascher (2000), who argued that they have found negative employment effect applying an identical institutional set. These disagreements lasted several years resulting in publication of several famous studies such as Card and Krueger (2000), Neumark and Wascher (1992, 2000), etc.

In more recent literature, such as Adison et al. (2015) or Neumark et al. (2014), authors show only minor employment elasticities. Also, in scopes of the recent discussions new methods have been tested to study MW in US; synthetic control method (Abadie et al. (2010); Sabia et al.

(2012); Allegretto et al. (2015)), border discontinuities (Dube et al. (2010)), and interactive fixed effects (Gobillon (2016)). Interestingly, newly applied methods also mostly failed to find non-positive employment effects.

Recent empirical minimum wage research targets the issue of constructing counterfactuals for treated units. The prospect of the Synthetic Control Method to produce suitable control units has been increasingly recognized during recent years. The SCM has become a commonly used technique that proposes a factor-based method to control for time-dependent covariates. The synthetic control is the weighted average of control states that best predict the treated country in the pre-intervention period.

Below, I shortly present studies where the SCM is applied in minimum wage reform evaluation literature.

An early paper by Card (1992) studied California's 1998 minimum wage increase. Card produced an aggregated control pool that involved other states and one metro area that did not increase minimum wages during the given time span. To some extent the control state reproduced the values of employment predictors in California before minimum wage came into force. Even though Card's choice of the donor pool states is experimental, his approach is considered as the ancestor of the modern SCM, where the selection of donor states is data-driven. Card(1992) found positive wage and employment point estimates for teens.

In recent literature Sabia et al. (2012) and Allegretto et al. (2013) have assessed the effects of the US state-level MW on employment applying the synthetic control group as robustness check to the findings attained with difference-in-difference method. Sabia et al. (2012) evaluated the employment effects of 2004-2006 New York minimum wage increase. In the Synthetic New York, geographically close states got higher weights. As a result, they found that increasing MW from \$5.15 to \$6.75 per hour significantly reduces the employment chances of less-skilled New Yorkers.

Dube and Zipperer (2015) criticized this study for failing to construct a synthetic New York that best reproduced the pre-treatment characteristics of the actual New York during the entire 2000-2004 pre-treatment period.

More recently, Dube and Zipperer (2015) implemented pooled synthetic control approach to estimate the minimum wage employment effects for 29 treatment states. Countries that did not face a minimum wage increase two years before and one year after the treatment constituted the pool of control states. Authors created synthetic controls for each treated state based on pre-intervention characteristics. As a result, pooled estimates of this study suggested modest teen employment effects.

The findings of Dube and Zipperer (2016) are similar to those of Allegretto et al. (2015). The latter applies parametric trends and geographic area controls, and estimates small-scale employment effects for youngsters after the MW increase.

2.1.2. Youth employment effect

Young people who are in the phase of entering the labor market are usually referred to as an at-risk group. Quintini et al. (2007) provides that vis-à-vis older people, they are less likely to be employed, more likely to shift between states of unemployment, training and working, and are more likely to end up working with a temporary or part time work contract. The high occurrence of minimum wage workers among youth makes them regularly an observed group in the MW literature (Neumark et al. (2014)).

There are various ex-post studies on the effects of introduction of minimum wages on young individuals. The results of such studies usually suggest that young people are comparatively highly affected by the enforcement of minimum wages, at the same time by increasing their income level and unemployment. This has been supported by Clemens and Wither (2016), Kalenkoski (2016), Neumark and Shupe (2018), Marimpi and Koning (2018), etc.

MW may decrease job specific training chances and delay the entrance to labor market of young individuals (Clemens and Wither (2016)). Even though economic research on the youth employment effects of minimum wages is quite extensive, usually external validity of those studies are in a sense limited; the study settings strongly depend on the specific context and on the underlying assumptions.

2.2. German Evidence

Below I cite ex-ante and ex-post studies that try to measure the employment effects of new minimum wage in Germany. As the statutory minimum wage introduction is quite a recent event, most of the existing literature is focused on industry specific minimum wage evaluations or constitutes of simulation studies.

2.2.1. Ex ante studies

There are many ex-ante studies evaluating the employment effects of the German SMW. Among them are Knabe et al. (2009), Müller and Steiner (2011), Knabe et al. (2014), Arni et al. (2014), Henzel et al. (2014). These studies find disemployment effects, but the magnitudes of the estimated effects are different.

Bossler (2017) measured the announcement effects of the new minimum wage on employer expectations in 2014. Based on the establishment of pre-MW introduction microdata Bossler (2017) finds a small negative effect on the treated employer’s employment expectations. Based on the main finding of this study the minimum wage announcement affected negatively on employers’ employment expectations. Similarly, in our analysis we decided to take 2014 as the treatment year (when the MW law was announced, but before it was in force).

2.2.2. Ex post studies

Those studies that present a descriptive or an ex-post analysis of employment effects of the SMW enforcement are scarce, because post minimum wage reform data for Germany is still rather limited and post MW reform period is quite short.

Bossler and Gerner (2016) pioneer in presenting ex-post effects of the SMW on employment. By using establishment level affectedness by MW[4] authors find that employment faced a slower growth due to the introduction of SMW. As a result, this study shows that employment progress was 60.000 individuals below that what would have been achieved in absence of treatment (introduction of SMW).

While Bossler and Gerner (2016) detect a small yet negative relationship between MW bite and total employment, Garloff (2016) does not find a reduction of employment growth. Part of the reason might be that Bossler and Gerner (2016) use survey data and Garloff (2016) applies regional data. Garloff (2016) argues that the expectation is that low wage establishments respond to surveys less regularly than others. Consequently, the MW bite is noticeably lower in the establishment panel than in the administrative data. Applying difference-in-differences type of specifications Garloff (2016) finds that SMW had a negative effect on marginal employment and positive effected on regular employment. The results provide an evidence of a shift from marginal to regular employment.

Based on a similar method and data applied by Garloff (2016), Stechert (2016) supports Garloff's findings for the prime age unit yet finds that young individuals (15–24 years) are negatively affected by the minimum wage. Applying regional SOEP[5] data, Caliendo et al. (2017)

[4] Survey data from the IAB establishment panel
[5] German Socio-Economic Panel, version 32, 2015

identify no effect on regular employment while marginal employment faced a negative effect because of the minimum wage reform.

2.2.3. Summary

Given the current literature no evidence of substantial employment losses due to the new minimum wage in Germany exists. Using administrative data on regional employment, Garloff (2016), Bossler and Gerner (2016), and Caliendo et al. (2017) find zero or a minor negative short-run employment effects. Similarly, in our study we find short term minor negative effect on youth employment by using aggregate employment. Instead of applying difference-in-difference estimation (used in most of the studies cited above), we conducted a synthetic control method (SCM) study. In the following chapter the SCM is introduced, its implementation, advantages and constraints are discussed. Later, applying new inferential approaches suggested in this study, we present the significance of our results. Our analysis depicts the sensitivity of our estimates with regards to the set of donor units.

CHAPTER 3. SYNTHETIC CONTROL METHOD

3.1. Introduction to Synthetic Control Methods

A significant body of social science research focuses on studying the effects of political or economic events or policy interventions on aggregate outcomes, such as cities, regions and countries. To evaluate the impact of these interventions or events, many studies apply comparative case study models. Due to prevalent access to wide range of economic and social aggregate data, application of comparative case study research is becoming extensive.

The idea behind comparative case studies is to use the untreated group's outcome to estimate the outcome that would have been obtained for the treated group without the intervention. Yet, comparative case study research in social sciences poses two main restrictions. One, in traditional comparative case study methods the fact that analyst chooses the comparison units raises questions about the arbitrariness of choice of untreated groups; for example, selection of comparison groups based on unquantifiable criteria of relationship between treatment and control units. Two, there is uncertainty weather the untreated group can reproduce the counterfactual outcome trend that the treated units would have experienced without the given intervention. Thus, the choice of control units is vital in comparative case studies, because using incompatible control groups may lead to fallacious inferences. If the control units are not similar enough to the unit of interest in pre-intervention phase, then the variances of outcomes of these two units may reflect the differences in their characteristics (King et al. 1994; Geddes, 2003; George and Bennett 2005).

Because of arbitrary selection of indicators that should provide insights about the similarity of the affected and unaffected groups, selection biases may arise leading to different estimated treatment effects. For this reason, in this study, we apply data-generating approach introduced by Abadie and Gardeazabal (2003) and Abadie et al. (2010) that provides systematic way to choose comparison units and eliminates the subjectivity in the selection of control groups. The method, Synthetic Control Method (SCM), suggests that a combination of comparison units (also referred as “synthetic control’’) provides a better counterfactual for the treated unit than any single unit taken alone. For instance, Abadie, Diamond, and Hainmueller (2010) use a weighted combination of American states in the donor pool that most closely resembled California to estimate cigarette sales that California would have had without the introduction of Proposition 99, a major anti-smoking law enforced in California in 1988. Abadie and Gardeazabal (2003) use a combination of two Spanish regions to estimate the evolution of the Basque Country in the absence of terrorism. Additionally, taking the weighted averages of all potential control groups helps to construct a similar pre-intervention trend for the treated group.

The main challenge in evaluating the impact of national minimum wage introduction on youth employment in Germany is the separation of the policy impact from other macroeconomic trends. Usually DiD method[6] is applied in empirical studies in social sciences. The traditional DiD (fixed-effects) model permits the presence of unobserved variables but limits the effect of those variables to be nonvariant over time, thus they can be removed by taking time differences. On the contrary, our model allows the effects of unobserved confounders on the outcome to vary over time. The SCM is ideally applied when evaluating a policy specific to a geographical unit (city, state, country). While conventional regression designs give equal weight to all units (conditional on covariates), in the synthetic control study design comparison units obtain different weights. Reproducing the pre-intervention outcome of the unit of interest allows the SCM to deliver unbiased estimates for case studies even when there are several unobserved time factors. Typically, DiD models enforce a single factor assumption. Standard outcome involves a bundle of states and

[6] See Abadie, Diamond, and Hainmueller (2010) for a comprehensive coverage on the relationship between the synthetic control and the difference-in-differences estimator

their input to the synthetic control state. This allows the researcher to make well thought decisions about the comparison of control countries with the treated state.

To apply the Synthetic Control Method, I define model specifications presented in the next section. I follow the R (programming language) package for Synthetic Control Methods in Comparative Case Studies[7] (or just Synth method in R language) as defined by Abadie et al. (2011). My detailed application of this method and of model specifications is presented in Chapter 5; my code in R language is available in snippets in the Appendix.

3.2. Model Specification

To motivate the model, let's assume we have $J + 1$ countries that have an index j and are observed at time periods, $t = 1, \dots, T$. Without loss of generality, we assume that only the first country was exposed to policy intervention at period T_0 with $1 < T_0 < T$ ($j = 1$, treated unit) and other remaining J countries were not ($j = 2$, …, J, untreated units). In our case of statutory minimum wage introduction, this means: $j = 1$ corresponds Germany and T_0 to 2014Q1 (this is when the introduction of the minimum wage was announced, which had an effect of employer's expectations (Bossler 2017) before the actual roll-out of the policy in 2015). The rest of J countries constitute a comparison group and belong to the donor pool. T_0 shows the number of available pre-treatment periods and post treatment period starts at $T_0 + 1$ and ends in T. The latter in our case is 2017Q2, the point in time for which the latest data was available when gathering the data for this research. I present and explain my choice of J countries in the Chapter 4.

The treatment effect is presented as:

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

[7] R (programming language) package for Synthetic Control Methods in Comparative Case Studies - https://cran.r-project.org/web/packages/Synth/Synth.pdf

for post intervention period. Y_{1t}^{I} represents the outcome variable of the treated country that is observed for unit one at time $t \geq T_0 + 1$ and Y_{1t}^{N} corresponding unobserved counterfactual outcome variable. SCM adopts a data driven approach in a way that the summation of the intervention effect, $\tau_{1t}D_{1t}$, when D is the policy, and the counterfactual outcome equals to observed outcome:

$$Y_{1t}^{I} = \tau_{1t}D_{1t} + Y_{1t}^{N} = \tau_{1t}D_{1t} + \theta_t Z_j + \lambda_t \mu_j + \delta_t + \varepsilon_{jt} \tag{2}$$

here δ_t represents an unknown common factor with constant factor loadings across countries, Z_j is a $(1 \times r)$ vector of observed covariates (not affected by the treatment), θ_t corresponds to a $(1 \times r)$ vector of unknown parameters, λ_t is a $(1 \times F)$ vector of unobserved common factors, μ_j is a $(F \times 1)$ vector of unknown factor loadings, and ε_{jt} are error terms. This generalization of DiD model lets interactive fixed effects $\lambda_t \mu_j$ and country level unobserved characteristics to vary over time. Thus, the affected and unaffected countries do not have to follow common trends. If the true factor loadings μ_j of the affected country are known, we could create an unbiased control by taking the donor countries that have factor loadings averaging to μ_j. Since we do not have this value, the synthetic control produces a vector of weights W over the J donor countries in a way that weighted linear combination in the donor countries closely fit the treated country in pre-intervention outcomes. The weighted average of donors is the synthetic control.

As discussed before, a group of comparison units can better approximate the pre-treatment characteristics of the treated unit then a single untreated unit alone. By definition, synthetic control is weighted average of units, which means it can be presented by a $(J \times 1)$ vector of weights $W = (w_2, \ldots, w_{j+1})'$ subject to $0 \leq w_j \leq 1$ for $j = 2, \ldots, J$ and $w_1 + \ldots + w_{j+1} = 1$. It is apparent that each different value for W will result in having a different synthetic Germany. Hence choosing a valid subgroup of control countries is highly dependent on the choice of the weights W.

As Abadie, Diamond, and Hainmueller (2014) follow Mill's Method of Difference, for this study we also chose the value of Win a way that the characteristics of the treated unit are best presented by features of the control unit. Let X_1be a $(k \times 1)$ vector of pre-minimum wage introduction characteristics for treated country. Likewise, let X_0 be a $(k \times J)$ matrix that involves the values of the same features for the unaffected countries in J donor pool. The difference between the pre-treatment characteristics of the affected unit and its synthetic control is the following vector: $X_1 - X_0 W$. The distance between X_1 and $X_0 W$ is minimized due to the choice of an appropriate synthetic control, W^*, subject to $0 \leq w_j \leq 1$ for $j = 2, \ldots, J$ and $w_1 + \ldots + w_{j+1} = 1$. Let's further develop the model in the following mode. For $m = 1, \ldots, k$ let X_{1m} be the value of m-th variable for the affected unit and let X_{0m} be a $(1 \times J)$ vector comprising of the values of the m-th variable for the unaffected units. We choose a W^* as the value of W that minimizes:

$$\sum_{m=1}^{k} v_m (X_{1m} - X_{0m} W)^2 \tag{3}$$

where v_m is a weight that presents the comparative importance of the m-th variable. Classically, v_m shows the predictive power of a variable on outcome as presented in seminal studies of Abadie and Gardeazabal (2003); Abadie et al., (2010). An optimal choice of v_m means assignment of weights to linear combinations of the variables X_0 and X_1 to minimize the mean square prediction error (MSPE). Arguably, the choice of v_m can be subjective containing our prior knowledge of comparative importance of each predictor. Thus, in this study the choice of v_m is data driven, which implies we picked v_m in a way that the resulting synthetic Germany approximates the trajectory of the youth employment trend of Germany before the minimum wage reform introduction. Based on empirical approach of Abadie and Gardeazabal (2003), I choose v_m in a way that MSPE of the outcome variable is minimized for the pre- minimum wage introduction quarters. Additionally, in our case as the number of existing pre-treatment quarters is large enough, we computed the values of v_m and W^* by dividing the pre-intervention quarters into two periods, an initial training set and succeeding validation set. Abadie et al. (2010) argue that under certain circumstances, the bias of the treatment estimator of synthetic control method is constrained by a function that converges to zero as the number of pre-treatment periods increases. This means that the estimator is unbiased if the pre-intervention window is sufficiently large.

The estimated treatment effect at any $t \geq T_0 + 1$ on the outcome of interest is:

$$Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt} \tag{4}$$

Y_{jt} is the outcome of the unit j at time t. Y_1 is a $(T_1 \times 1)$ vector containing the post treatment values of outcome for the affected unit. Correspondingly, Y_0 is a $(T_1 \times J)$ matrix, where column j collects the post treatment values of the outcome for unit $(j + 1)$. The synthetic control estimator is the difference between post treatment outcomes between the affected and unaffected units, $Y_1 - Y_0 W^*$. Equation (4) provides that for post treatment period $t,$ when $(t \geq T_0)$, the synthetic control estimator of the effect of intervention is the difference between the outcome of the treated unit and the outcome of synthetic control at that period.

3.3. Inference

As discussed in Abadie et al. (2010), large sample inferential tools are not well suited to comparative case studies when the number of units in control group is small. Thus, most common tools for inference are not applicable for SCM approach. In a way, Inference in SCM is an area under construction.

Abadie et. Al (2010) propose to use Permutation Methods of inference; firstly, by estimating a “placebo” intervention effect for each unit in the donor pool and secondly, by computing an empirical p-value for the effect estimated on the affected unit.

The idea behind “placebo study” is to measure weather the gap observed for Germany may have been created by factors other than national minimum wage introduction. In case of having no random assignment, Abadie et al. (2010) and Abandie et al. (2015) present the p-value from their placebo tests as “probability of obtaining an estimate at least as large as the one obtained for the unit representing the case of interest when the intervention is reassigned at random in the data set”. The explanation and implementation of the above-mentioned topic is presented in Placebo Studies section.

CHAPTER 4. DATA AND SAMPLE

We created dataset derived from OECD employment databases. We used quarterly country-level panel data for the period 2005Q1 to 2017Q2. The national minimum wage announcement was made in late 2013 and was implemented in beginning of 2015. Bossler (2017) studied the announcement effect of SMW on employer expectations and found that German SMW legislation changed expectations before it come in force. Thus, treatment year is considered 2014, giving us a pre-intervention period of 37 quarters and post-intervention period of 13 quarters. Sample period ends in 2017Q2, because more recent data is not available for all the variables used in the dataset.

Remember that the synthetic Germany is designed as a weighted average of potential control countries in the donor pool. My donor pool includes a sample of 8 OECD member countries that are commonly used in the economic literature as advanced industrialized economies and currently have no national minimum wage[8]. The sample includes the following economies: Austria, Denmark, Finland, Iceland, Italy, Norway, Sweden and Switzerland.

Given the limited discussion on the choice of predictors in the existing literature, we apply cross-validation to minimize MSPE errors for donor units and to choose the optimal sets of predictors. Several sets of predictors, such as economic, employment, educational and demographic, have been collected.

Educational _the labor market shift of youth is usually highly associated with the level of educational attainment (Quintini et al. 2007). That is why we account for secondary vocational and general education graduation rates.

[8] From World Bank economy classification list (2017 June) high income countries with no minimum wage have been selected. http://iccmoot.com/wp-content/uploads/2017/07/World-Bank-List-of-Economies.pdf

Employment _ youth-adult joblessness risk can be described by the higher job mobility and the higher probability of young individuals becoming inactive. An indicator depicting the magnitude of this risk is the share of youth neither in education nor in employment (NEET). In this set of predictors, we also include employment protection, labor force participation rates, weekly hours worked and hourly wages.

Economic _ we also include standard set of economic growth predictors and business cycle measures in the predictor set to form a well-suited synthetic control group.

Demographic _ population weighted averages for countries in donor pool are considered.

More details for the pre-intervention characteristics of Xjt, the list of all variables used in the analysis along with data sources, are provided in Data Appendix section.

The outcome variable, Yjt, is the youth employment rate, aged 15-24: number of employed people of a given age as a percentage of the total number of people in the same age group in country j at time t.

Using the techniques described in Model Specification section, we construct a synthetic Germany with weights (see Table 1) chosen so that the resulting synthetic Germany best reproduces the values of the predictors of youth employment rate in Germany in the pre-intervention period. All the above-mentioned predictors are weighted according to their predictive power for the youth employment rate prior to minimum wage introduction using a data-driven procedure. This ensures that the Synthetic Germany approximates Germany most closely on the most important predictors. We estimate the effect of the German national minimum wage introduction on youth employment in Germany as the difference in youth employment levels between Germany and its synthetic counterpart in the quarters following the statutory minimum wage announcement. Finally, we perform a series of placebo studies and robustness checks.

CHAPTER 5. CONSTRUCTION OF SYNTHETIC GERMANY

Applying the techniques explained in methodological part in Chapter 3, we created a synthetic Germany without SMW using our sample of countries. The weights are calculated with a data driven process in a way that synthetic Germany best imitates the values of the predictors of youth employment in Germany in pre SMW period. We applied a cross-validation method to obtain the weights v_m of (3) equation.

Firstly, we split the pre-intervention period into a training set including 1 to 20 quarters (2005Q1 – 2009Q4) and validation set of 21 to 37 quarters (2010Q1 – 2014Q1). Our motivation for such a split is getting balanced training and validation sets, which is common in the implementation of the *Synth* method in R language. The code snippet for the training and validation of my data is in Snippet 1 in the Appendix.

Secondly, taking predictors measured in the training set, we chose the weights v_m in a way that the synthetic control minimizes the root mean square prediction error (RMSPE) during the validation phase. The RMSPE calculates the lack of fit between the outcome variable of the treated country (in our case Germany) and its synthetic version. The pre-2014Q1 RMSP error for Germany is defined in formula (5).

$$RMSPE = \left(\frac{1}{T_0}\sum_{t=1}^{T_0}\left(Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}\right)^2\right)^{1/2} \tag{5}$$

RMSPE can be similarly calculated for other countries and time periods. In our research we run placebo studies and compare the synthetic Germany to synthetic version of each control country in order to confirm our confidence in the results. While in traditional statistical inference, a qualitative comparison between a study's findings and those of placebo effects can be operationalized using p-values, in synthetic control method the same can be achieved by estimating and comparing the proportional effects (ratios between pre-intervention and post-intervention variables of interest) of the actual findings and those of placebo effects (Abadie et al. 2015). We implement this approach in the later section of the thesis on placebo studies.

The cross-validation approach enables us to choose weights v_m to minimize out-of-sample prediction errors, thus making our weights choice robust. Previous studies by Abadie and Gardeazabal (2003) and Abadie et al. (2010) confirm that the above-mentioned approach results in optimal weights v_m that in turn result in best approximates of the synthetic control.

Using the *Synth* method in R language the above mentioned cross-validation and the calculation of optimal weights is automated using the *synth()* function that uses the output of the *dataprep()* function employed in the first step. This second step is illustrated in Snippet 2 in the Appendix. The result is data on the synthetic Germany adjusted using the automatically calculated optimal weights for all the predictor variables.

Table 1 compares the pre-intervention youth employment predictors of Germany with that of the synthetic Germany and population-weighted average of the entire sample. Table 1 shows that Synthetic Germany mirrors actual Germany better than the average of our sample countries. The Synthetic Germany is very comparable to the Germany in scopes of pre SMW introduction period GDP per capita, graduation rate of general and vocational education, inflation rate, investment rate, etc.

Table 1: Youth employment predictor means before German SMW introduction

	Germany	Synthetic Germany	Sample Mean
Inflation rate	1.554	1.679	2.135
Industry rate	30.051	30.799	28.5
Investment rate	19.677	19.03	22.762
Import	4.341	4.463	3.238
Export	4.83	4.762	3.089
Wage_private	100.332	100.466	98.628
Wage_manufacturing	100.078	100.985	98.814
GDP per capita	41233.529	41468.996	44096.346
Working hours_youth	33.98	32.662	30.017
Working hours_all	34.54	34.956	35.505
Labor force_youth	51.192	51.781	53.979
Labor force_all	60.088	62.203	66.218
Graduation rate_vocation educ	32.633	31.277	42.762
Graduation rate_general educ	34.125	32.813	44.926
NEET_ 15-19 years old	3.188	4.293	5.774
NEET_ 20-24 years old	11.574	12.068	14.568

Table 2 presents the weights of every country of donor pool in Synthetic Germany taking 2011Q3 as the time point for cross-validation (pre-2011Q3 data used for training the model, post-2011Q3 data used to fit the model). The weights illustrated in Table 2 are calculated using the algorithms of the R package Synth, namely the function *synth()*. The weights presented in Table 2 show that youth employment trend in Germany prior to SMW introduction is best approximated by a combination of Sweden, Austria, Norway, Denmark, Italy. The sum of all weights equals 1, in line with the research method by Abadie et al. (2011) we follow.

Table 2: Country weights in the synthetic Germany (2011Q3 as point of cross-validation)

Coutnry ID	w.weights	Country Name
1	0.226	Austria
2	0.19	Denmark
3	0	Finland
5	0	Iceland
6	0.094	Italy
7	0.165	Norway
8	0.324	Sweden
9	0	Switzerland

Synthetic control method offers a quantitative approach to weight and select comparison countries from donor pool. We also calculate these weights automatically using the algorithm defined by Abadie et. al (2011), namely the *synth()* function of the R package *Synth*. As a result, in their order of importance (weights) Sweden, Austria, Denmark, Norway and Italy constitute the synthetic Germany.

Similar to control country weights, to ensure the optimal distribution of predictor weights we used the algorithm by Abadie et. al (2011) and the *synth()* function of the R package *Synth.* We found that the following predictors have the highest weights and thus most influence over the model: Labor force (all), Investment rate, Graduation rate (upper secondary vocational education) and NEET_ 15-19 years old (share of young people who are not in education, employment or training). Other predictors, like Inflation rate, Industry rate, Imports, Exports, GDP per capita and so on, have very small weights and thus influence over the model. For more details on the data behind the predictors, see Data Appendix.

5.1. Short-run Effect on Youth Employment

Figure 1 presents the trends of youth employment rate in Germany and in the rest of sample countries. We notice that the rest of the sample countries taken together may not constitute a matching comparative bundle for Germany to observe the effect of SMW introduction. During pre-intervention period (1-15 quarters) the time series of youth employment rate in Germany and average youth employment rate in rest of donor pool countries don't fit well.

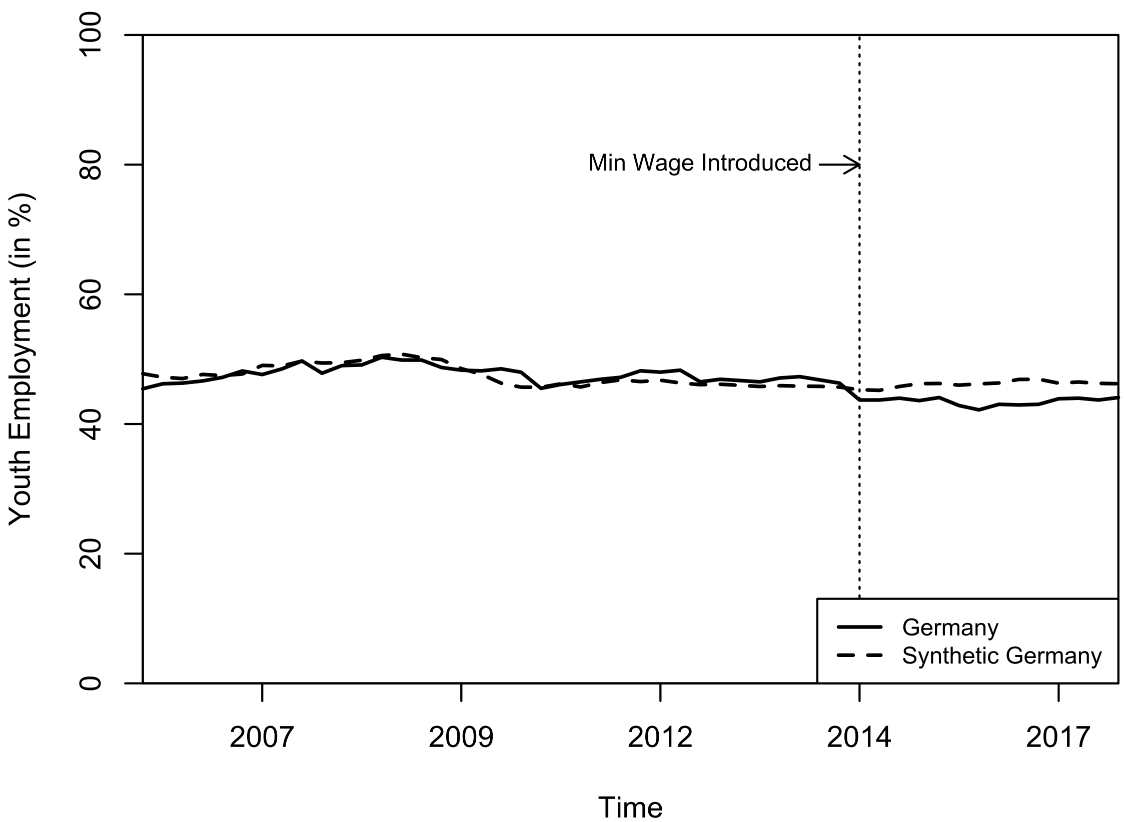
Figure 1: Trends in youth employment: Germany vs. the rest of the sample countries

Figure 2 presents the trends of youth employment rate in Germany and in synthetic Germany. We notice, contrary to the picture in Figure 1, in Figure 2 synthetic Germany closely reproduces youth employment rate in Germany for entire pretreatment period from 1 to 37 quarter

(2005Q1 to 2014Q1). Along with the high degree of balance on all youth employment rate predictors (Table 1), we derive that synthetic Germany presents a similar trajectory of youth employment that would have occurred in Germany in the absence of SMW announcement after 2014Q1.

The estimate of the effect of the SMW introduction on youth employment rate in Germany equals to the difference between Germany and its synthetic equivalent (see Figure 3). Overall, Figure 3 shows that Minimum Wage Law announcement had an effect on youth employment rate and that this effect increased in time once SMW was put in force.

Figure 2: Trends in youth employment: Germany vs. Synthetic Germany



According to our estimate, during 4 quarters after SMW announcement youth employment faced a minor decline. After the enforcement of SMW (2015Q1) youth employment rate in Germany faced a bigger decline until 2016Q3 than its synthetic version. We find that over the entire period of quarters 37 – 50 (2014Q1 – 2017Q2) the youth employment was reduced by -2.68 percentage points per year on average, which amounts to approximately 5.79% of the quarter 36 (2013Q4) baseline level. For comparison, youth employment in Germany increased by 0.16 percentage points per year on average over the entire pre-intervention period of quarters 1-36 (2005Q1 – 2013Q4). This confirms the effect of the SMW reform on youth employment we identified in our study. In the quarter 50 (2017Q2) the youth employment in the synthetic Germany is estimated to be about 4.79% higher than in the actual Germany.

Figure 3: Youth employment rate gap between Germany and synthetic Germany

5.2. Placebo Studies

We followed a common tool of placebo studies for validating the reliability our results. We run several placebo studies, where we first assigned new hypothetical time points to the SMW introduction, and second, we run the same study setup on countries different than Germany. If the placebo effect were strong, we couldn't be confident that our results in Figure 2 were caused by the SMW intervention but rather by other or arbitrary factors, or by setup flaws.

To assess the placebo effect, we first chose a different (hypothetical) time point in our data and assume it to be the time for the introduction of minimum wage in Germany (instead of the actual time point). In the in-time placebo study (as opposed to the in-space placebo study), we chose the quarter 27 (2011Q3) as the assumed time of the minimum wage introduction, instead of the quarter 37 (2014Q1) that is the actual date of the announcement.

In the new setup of our study, we reassigned the pretreatment period to be from the quarter 1 to the quarter 27 (2005Q1 – 2011Q3), with the placebo intervention in the quarter 27 (2011Q3), 10 quarters before the actual minimum wage introduction announcement. We used the same out-of-sample cross-validation method for the computation of our synthetic control, using training and validation sets with different predicators.

Figure 4 illustrates the findings of our in-time placebo study. We observe that youth employment in synthetic Germany changes in line with the actual Germany in the post-treatment period of the quarters 27 – 37 (2011Q3 – 2014Q1). No significant deviation can be observed after the placebo time point of intervention, as the synthetic and actual trajectories are not divergent. Thus, the placebo effect is negligible, which in turn supports our baseline finding. As a result, we suggest that the gap analysis illustrated in Figure 2 shows the impact of the minimum wage introduction in Germany on the youth employment in Germany, and not another effect that could have happened in a different time point.

For further validation, we rerun similar in-time studies with other placebo dates of the hypothetical SMW introduction (namely 2009Q1 and 2012Q1), which resulted in similar figures further confirming our findings. To illustrate this, we compare the results of our baseline study with those of the placebo studies. In the baseline study we found that youth employment was reduced by -2.68 percentage points per year on average, compared to the youth employment increase by 0.16 percentage points per year on average over the entire pre-intervention period. On the contrary the in-time placebo study with 2011Q3 as time of SMW introduction, results in pre- and postintervention trends of youth employment of much smaller margin. In the placebo study, we observed a post-intervention decline of youth employment by -3.45 percentage points, however this was not caused by the intervention, because the pre-intervention trend for the entire period was -3.56, a comparable decline ensuring a more or less constant trend for youth employment over the entire pre- and postintervention period. The placebo studies using 2009Q1 and 2012Q1 as intervention time points produced equivalent results.

Second, we run another set of placebo studies changing the treated country from Germany to other countries in our sample as comparison units. We calculated the synthetic control estimates for these countries that had not experienced the policy intervention of interest (SMW introduction). We compared the effects of the hypothetical intervention to these countries with that in Germany. We would consider the effect of the minimum wage introduction on Germany significant if the effect was considerably larger than that of the placebo interventions in control countries. Following the common application of such placebo studies, here we did not focus on the exact changes in youth employment resulting in each placebo test (like we did previously). As mentioned in Chapter 5, this method enables testing the significance of our results. In particular, if the ratio for the treated country (Germany) in our case is much larger than that of the control countries, we can state that our findings are significant and that the chance of getting the same result by replacing the treatment country with a random one from the control pool is small.

Figure 4: Placebo SMW introduction in 2011Q3 – Effect on youth employment[9]

The findings of our second set of placebo studies are illustrated in Figure 5 including the ratios between the post-2014Q1 RMSPE and pre-2014Q1 RMSPE that are calculated using formula (5) from the previous section of the thesis "Construction of Synthetic Germany". To reiterate, RMSPE calculates the lack of fit between the outcome variable of the treated country

[9] Note the difference of the initial fit in Figure 4 and that in Figure 1 (our original study). This is due to technical reasons. First, due to a choice of an earlier time point for the placebo intervention, we had to also take an earlier time point for training and fitting our model, which caused minor deviations in the country weights and thus in the data for the constructed synthetic Germany. Second, there is no constant in the factor model.

(in this case Germany and each of the control countries in our placebo studies) and its synthetic version. It's important to note that a large pre-intervention RMSPE does not constitute a large effect of the event if the post-intervention RMSPE is also large. To address this consideration, we calculate the ratios of post-SMW-introduction RMSPE to pre-SMW-introduction RMSPE by dividing them for each country in our pool.

Figure 5: Ratio of post-SMW-introduction RMSPE to pre-SMW-introduction RMSPE: Germany and control countries

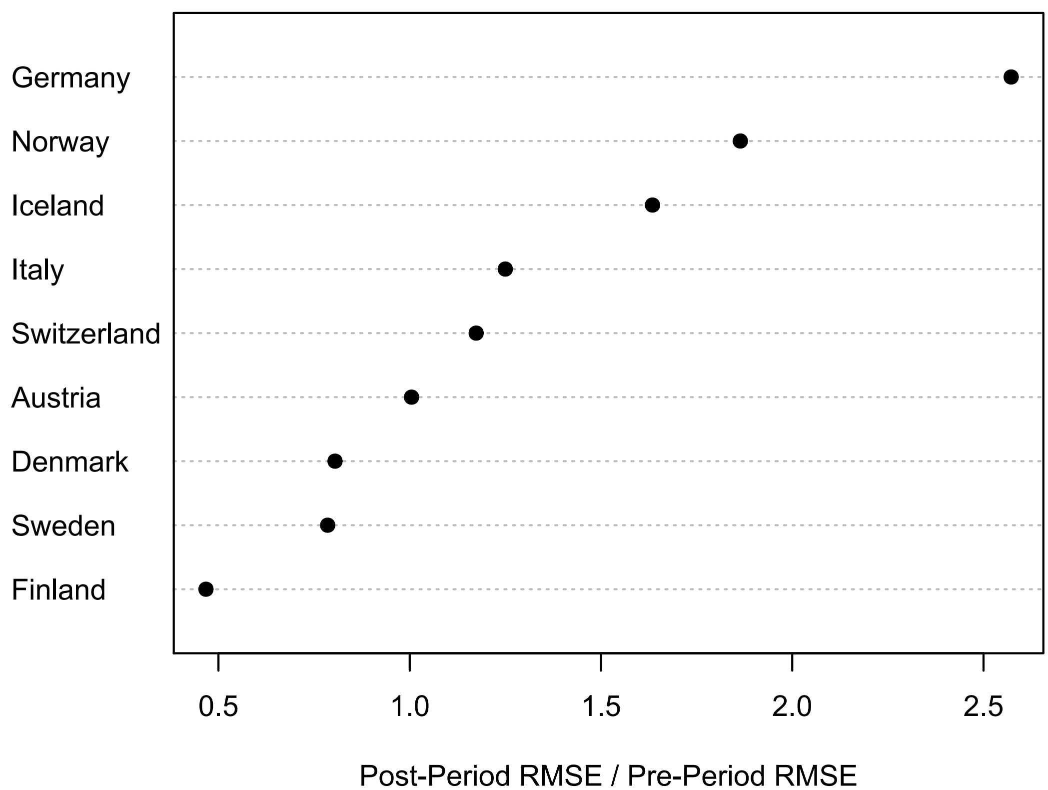


Figure 5 shows that Germany stands out as the country with the highest RMSPE ratio, which confirms that our findings are not a result of random factors and that Germany could not be arbitrarily replaced by any of the control countries from our placebo studies. As per Figure 5, in a randomly chosen country from the control pool the SMW introduction would only have about a 1/2.6 probability of having the same effect on youth employment as that in Germany.

5.3. Robustness Tests

We run a robustness test on the sensitivity of our results to the changes in the country weights, W*. As we saw in Table 2, synthetic Germany is estimated as a weighted average of Sweden, Austria, Denmark, Norway and Italy, in decreasing order of weights.

To review the robustness of our study we check to which extent our results are driven by any one country from the control pool. To achieve this, we iteratively re-run the baseline model to construct a synthetic Germany dropping one of the control countries in each iteration.

Figure 6: Leave-one-out distribution of the synthetic control for Germany

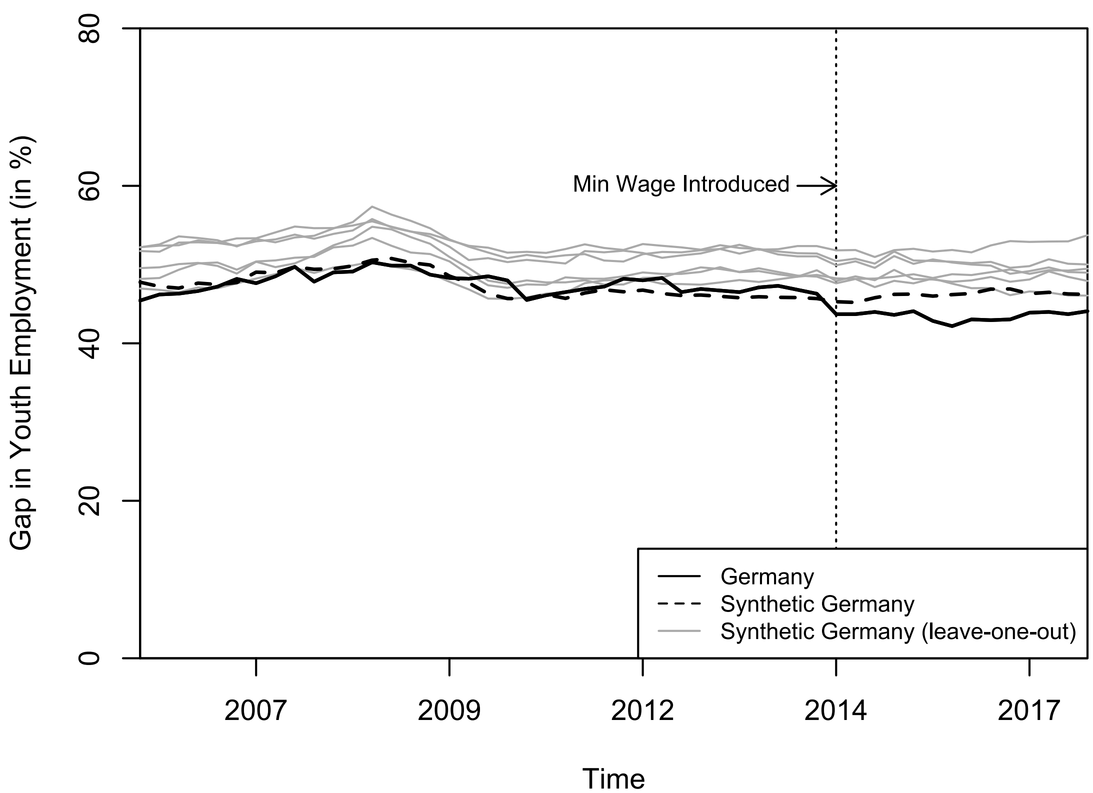


Figure 6 displays the results of our robustness studies. The figure is based on Figure 2 but adds to it the so-called leave-one-out estimates (grey lines) – each of the control countries with positive weights is left out and the synthetic Germany curves are reproduced in grey. As a result, we observe that our findings are robust to omitting any of the control countries.

Table 3: Country weights in the synthetic Germany (2008Q3 as point of cross-validation)

Coutnry ID	**w.weights**	**Country Name**
1	0.482	Austria
2	0.201	Denmark
3	0	Finland
5	0	Iceland
6	0.026	Italy
7	0.143	Norway
8	0.143	Sweden
9	0	Switzerland

We further demonstrate the robustness of our setup by rerunning our model using different times for cross-validation (training and validation sets) and comparing the resulting weights with the ones we get in our initial setup. We expected the weights for the control countries to differ somewhat, but not drastically. Otherwise, if we got drastically differing weights we could not be sure in the robustness of our setup. We rerun our study using pre-2008Q3 (quarter 15) data for training and post-2008Q3 data for fitting the model. This resulted in new country weights for the control countries, illustrated in Table 3. The resulting weights, though different from the initial values presented earlier in Table 2 (where the cross-validation time point is 2011Q3), are comparable. Namely the same countries have zero value weights: Finland, Iceland and Switzerland. Denmark and Norway have very similar weights to the initial snapshot: Denmark (0.201 vs. 0.19) and Norway (0.143 vs. 0.165). Some differences are that in the new model Austria has higher weight (0.482) than that in the initial study (0.226). On the contrary, Sweden lost some of its weight from 0.324 to 0.143. However, these differences would not significantly affect our results, as the model looks at the control countries as a pool balancing out the effects of different countries. We went on to rerun a similar robustness test taking 2012Q3 as the cross-validation time point, which resulting in comparable results to those in our initial setup. We conclude that control country weights are more or less constant over time, thus we can be confident that the synthetic Germany we constructed is a good approximation of the actual Germany.

CONCLUSION AND POLICY IMPLICATIONS

In this thesis we evaluated the effect of the statutory minimum wage introduction in Germany on its short-term youth employment. Our initial hypothesis was that the SMW announcement and introduction would indeed affect Germany's short-term youth employment. We set up this study to address this hypothesis and in case of its validity to measure this effect in time. To achieve this goal, we chose the relatively novel and data-driven method of synthetic control. As we highlighted, this method corresponds well to the type of our study and has been used by other researchers in the field. In the synthetic control pool, we included countries that are comparable to Germany but do not have minimum wage regulations. Using the data for these countries we constructed synthetic Germany (were no minimum wage policy was introduced) and put it next to the actual data from Germany.

We found that the SMW – announced in 2014 and introduced in 2015 – had an impact on Germany's short-term youth employment since 2014. Though minor, the effect is clear and forms a trend illustrated in Figures 1 and 2.

We found that after the minimum wage reform Germany's youth employment faced a small decline in relation to the comparable synthetic control region. We estimated that by 2017Q2 the youth employment in synthetic Germany was about 4.7% higher than that in actual Germany.

We demonstrated the rigor of our method and the significance of our results by running a series of placebo studies and robustness tests. We run in-time and in-space placebo studies looking for the potential placebo effects on our findings. We found that changing the time of the policy intervention would not result in similar findings, thus confirming that our findings do indeed result from the SMW announcement in 2014 and introduction in 2015, and could not be randomly achieved in a different time point. This is illustrated in Figure 4. We also found that changing the treatment country from Germany to others in the control pool would not yield the same results. After running series of placebo studies, we derived Figure 5 where we observe the ratios of post- and preintervention RMSP errors, as an indicator of how likely the treatment of other countries would result in the same findings as that of Germany. In Figure 5, we see that Germany is well ahead of the others confirming that our findings are not a result of random factors, but rather of the minimum wage reform in Germany. Finally, we run a set of robustness tests that further confirm the rigor of our method and the significance of our results. The leave-one-out estimates in Figure 6 demonstrate that our results are fairly robust to omitting any of the control countries.

We demonstrate the potential of using a pool of countries rather than a single one as comparison cases in running counterfactual scenarios. Our work aims to contribute to the existing limited body of literature by providing evidence of youth employment effect after the introduction of minimum wages in Germany. We also contribute to the minimum wage research by applying a novel, data-driven and increasingly popular research method of synthetic control in this field.

Policy implications: It could be interesting for a policymaker to learn about the size and the sign of employment effect that young individuals face in case of statutory minimum wage introduction. In this context, for further policy considerations, our findings provide plausible evidence that state-level minimum wage can have a small yet significant adverse employment effect and will likely “hit” youth in short run. From a policy perspective this could imply developing education related policies that facilitate the transition process between education/training and the labor market.

Policy measures can be classified into two categories; active labor market policies (ALMPs) and educational policies aiming to combat unemployment. ALMPS could play an integral role in averting the rise of long-run unemployment following an economic downturn or introduction of SMW. Educational policies could help to reduce the mismatch between the requirements of employers and the skills learnt at educational institutions by new participants of the labor market. This will help to smoothen student-employee transition.

LIMITATIONS

We accept the limitations of our study. Firstly, our post treatment period (13 quarters) allows us only to evaluate the short-term effects of the minimum wage introduction with quite limited available predictors. Hereafter, long term effects might differ and should be assessed in future research. This aspect is important since the effects of the new SMW could be different in an economic decline. When average productivity shrinks during an economic decline, disemployment effects are likely to be bigger.

Secondly, our data does not cover undeclared youth employment. There is a likelihood that the decrease in youth employment may have paid off with a rise in undeclared employment.

Additionally, with our data we are not able to account the regional variation. In Germany states cannot fix their own wage floor higher than the SMW, not like in US. Yet, an hourly MW of 8.50 € has quite different effects across the country. In more industrialized cities, such as Hamburg or Frankfurt, usually employed people already have a wage above € 8.50. It would be interesting in the future with more regional data available to consider regional variations as well.

Lastly, we recognize our method related limitation. The application of the synthetic control approach is not straightforward in the minimum wage setting. In the Abadie et al. (2010) a single treatment (a tobacco control program) was implemented in one state (California), and there were long-term datasets on potential control states without such a policy. In contrast, the state minimum wages are enacted repeatedly and at high frequency, so we can match only on a short period before any minimum wage increase and must drop many potential control states that increased their minimum wage around the same time.

DATA APPENDIX

The data sources employed for the application are:

Youth employment rate: aged 15-24, number of employed people of a given age as a percentage of the total number of people in the same age group. Source OECD employment data

Standard set of economic predictors:

GDP per capita: fixed PPP constant prices, reference year 2010. Source: OECD

Inflation: annual percentage change in consumer prices,

Industry: Industry share of value added (% of GDP). Source: Source: World Bank WDI Database

Investment: ratio of investment as a percent of GDP: Source IMF data

Import: Volume of imports of goods and services, percent change: Source IMF data

Export: Volume of exports of goods and services, percent change: Source IMF data

Set of employment predictors: Source: OECD employment data

Weekly hours worked youth: average usual weekly hours worked in main job, total declared employment, aged 15-24

Weekly hours worked all: average usual weekly hours worked in main job, total declared employment, aged 15-64

Labor force: aged 15-24

Labor force: aged 15 and above

Employment protection: individual dismissals, strictness of regulation on dismissals and the use of temporary contracts

Employment protection: collective dismissals, strictness of regulation on dismissals and the use of temporary contracts

NEET: 15-19 years old, percent of same age group, share of young people who are not in education, employment or training

NEET: 20-24 years old, percent of same age group, share of young people who are not in education, employment or training

Wage hourly private: Hourly earnings in private sector

Wage hourly manufacturing: Hourly earnings in manufacturing sector

Set of education predictors: Source: OECD education data

Graduation rates: less than 25, upper secondary vocational education, total

Graduation rates: less than 25, upper secondary general education, total

Set of demographic predictors

Population: Total amount

Population 15-19: Total amount

Population 20-24: Total amount

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APPENDIX

Snippet 1: Data preparation for training and validation sets

Dataprep for the training data set

```
dataprep.out <- dataprep(
  foo = data,
  predictors    = c("infl", "wage.h.priv", "Ind", "Inv", "Imp", "Exp",
                    "wage.h.manuf"),
  predictors.op = "mean",
  dependent     = "emp.youth",
  unit.variable = "id",
  time.variable = "Time",
  special.predictors = list(
    list("gdp.pc",            1:20, "mean"),
    list("w.hrs.youth",       c(1,5,9,13,17), c("mean")),
    list("w.hrs.all",         c(1,5,9,13,17), c("mean")),
    list("Lf.youth", c(1,5,9,13,17), c("mean")),
    list("Lf.all",     c(1,5,9,13,17), c("mean")),
    list("grad.voc.youth", c(21,29,33),c("mean")),
    list("grad.gen.youth", c(21,29,33,37), c("mean")),
    list("neet.15.19",      c(1,5,9,13,17), c("mean")),
    list("neet.20.24",     c(1,5,9,13,17), c("mean"))),
  treatment.identifier = 4,
  controls.identifier = c(1,2,3,5,6,7,8,9),
  time.predictors.prior = c(21:30),
  time.optimize.ssr = c(31:37),
  unit.names.variable = "Country",
  time.plot = 1:50
)
```

Dataprep for the validation data set

```
dataprep.out <- dataprep(
  foo = data,
  predictors    = c("infl", "wage.h.priv", "Ind", "Inv", "Imp", "Exp",
                    "wage.h.manuf"),
  predictors.op = "mean",
  dependent     = "emp.youth",
  unit.variable = "id",
  time.variable = "Time",
```

```
  special.predictors = list(
    list("gdp.pc",              21:37, "mean"),
    list("w.hrs.youth",         c(21,25,29,33,37), c("mean")),
    list("w.hrs.all",          c(21, 25, 29,33,37), c("mean")),
    list("Lf.youth", c(21, 25, 29,33,37), c("mean")),
    list("Lf.all",     c(21,25,29,33,37), c("mean")),
    list("grad.voc.youth", c(21,29,33),c("mean")),
    list("grad.gen.youth", c(21,29,33,37), c("mean")),
    list("neet.15.19",      c(21,25,29,33,37), c("mean")),
    list("neet.20.24",     c(21,25,29,33,37), c("mean"))),
  treatment.identifier = 4,
  controls.identifier = c(1,2,3,5,6,7,8,9),
  time.predictors.prior = c(1:41),
  time.optimize.ssr = c(1:37),
  unit.names.variable = "Country",
  time.plot = 1:50
)
```

Snippet 2: Identification of the optimal weights

Dataprep for the training data set (see Snippet 1)

```
synth.out <-
  synth(
    data.prep.obj=dataprep.out,
    Margin.ipop=.005,Sigf.ipop=7,Bound.ipop=6
  )
```

Dataprep for the validation data set (see Snippet 1)

```
synth.out <- synth(
  data.prep.obj=dataprep.out,
  custom.v=as.numeric(synth.out$solution.v)
)
```

R script

You can access our full R script here:

https://drive.google.com/open?id=1qwyQ14K0po-6dxY-k1gGbfv-7GlH4J_M