— ONLINE APPENDIX —

Comparative Politics and Causal Evaluation of Structural Reforms: The Case of the UK National Minimum Wage Introduction

Thomas König, Guido Ropers, & Anika Buchmann

Appendix A: Generalized Synthetic Control Method

The generalized synthetic control method tackles the problem of the missing counterfactual by imputing treated counterfactuals from a donor pool of untreated control countries based on a semiparametrical linear interactive fixed effects model which includes time-varying coefficients interacted with unit-specific intercepts (Xu 2017) .[10] Following Xu (2017), the functional form of the data generating process can be written as

$$Y_{it} = \delta_{it} D_{it} + x'_{it}\beta + \lambda'_i f_t + \epsilon_{it}$$

where Y_{it} is the outcome of interest of unit i at time t. D_{it} is the treatment indicator which equals 1 if unit i was exposed to the treatment prior time t and 0 otherwise; δ_{it} is the (heterogeneous) treatment effect on unit i at time t; x_{it} is a vector of covariates, β are the (unknown) constant coefficient parameters, f_t is a vector of unobserved time-varying common factors for which λ_i denotes the unit specific factor loadings; ϵ_{it} captures unobserved idiosyncratic shocks for unit i at time t assumed to have zero mean.

Based on the potential outcome framework of causal inference (Neyman 1923; Rubin 1974; Holland 1986), the causal effect δ_{it} at time t is defined as the difference between (1) the observed outcome, $Y_{it}(1)$, of unit i after a treatment, D, and (2) the observed outcome, $Y_{it}(0)$, of the same unit i without treatment (known as the counterfactual). Since the counterfactual outcome without treatment of unit i is always going to be missing, the main goal is to best estimate and/or impute the missing counterfactual, $\hat{Y}_{it}(0)$. Unlike DID and the original synthetic control approach, the GSC-estimator for $\hat{Y}_{it}$ in the post-treatment periods is not based on a weighted linear combination of control units[11] but on the (constant) effects of covariates and weighted latent factors as indicated in the following equation (Xu 2017, 63):

$$\hat{Y}_{it}(0) = x'_{it}\hat{\beta} + \hat{\lambda}'_i \hat{f}_t$$

[10]The explanation of the method and its intuition closely follows Xu (2017).

[11]Formally written as $\hat{Y}_{0,T}(0) = \mu + \sum_{i=1}^{N} w_i * Y_{i,T}^{Obs}$ where $\mu = 0$ for the original synthetic control approach (Abadie, Diamond, and Hainmueller 2015; Doudchenko and Imbens 2016).

where x_{it} is a $(k \times 1)$ vector of covariates, $\hat{\beta}$ are the estimated constant covariate parameters, $\hat{\lambda}_i$ denotes unit-specific estimated factor loadings, and $\hat{f}_t$ denotes the estimated time-varying common latent factors.

The treatment effect itself is estimated (imputed) based on a three-step procedure. First, an interactive fixed effects model is estimated to obtain $\hat{\beta}, \hat{F}, \hat{\lambda}_{co}$ using the data from the control group during the whole study period. Second, unit-specific factor loadings for the treated unit, $\hat{\lambda}_i$, are acquired by minimizing the mean squared error of the predicted treated outcome in pre-treatment periods. Third, the treated counterfactuals are calculated based on $\hat{\beta}, \hat{F}, \hat{\lambda}_i$. In order to avoid overfitting, Xu (2017) also incorporates a cross-validation procedure to select the number of factors. The algorithm takes the model that makes the most accurate predictions on average before estimating the causal effect. Finally, the GSC method provides uncertainty estimates from a parametric bootstrap procedure.[12]

[12]Note that in order to interpret the estimates as causal, the GSC method assumes *strict exogeneity* implying that the error term of any unit at any time is independent of treatment assignment, observed control variables, as well as unobserved cross-sectional and temporal heterogeneities. This can be formally written as $\epsilon_{it} \perp D_{js}, x_{js}, \lambda_j, f_s \quad \forall i, j, t, s$. In addition, we have to assume weak serial dependence of the error terms, regularity conditions, as well as cross-sectional independence and homoscedasticity of the error terms. See Xu (2017) for details.

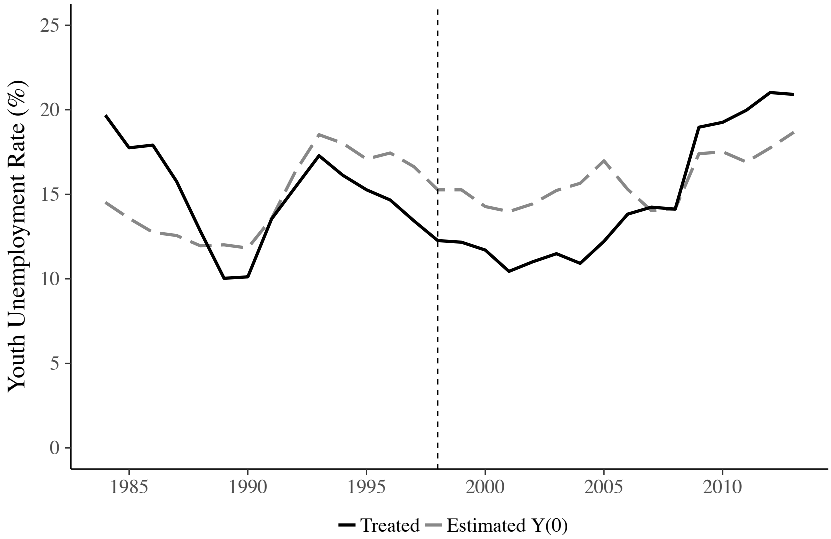


Figure A1. Difference-in-differences

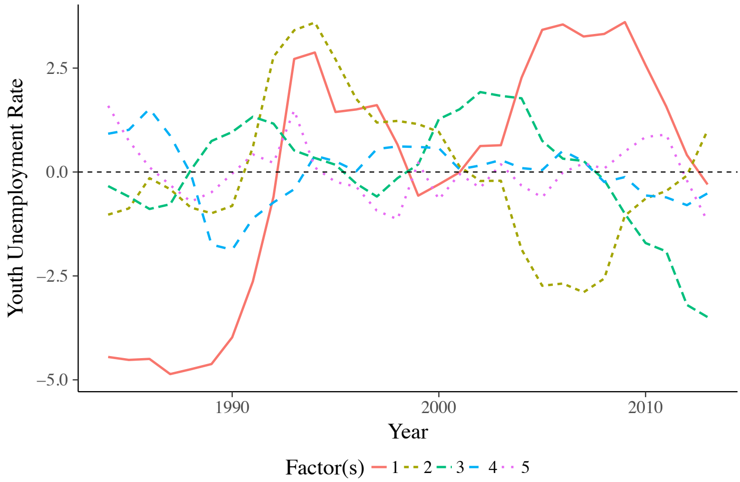


Figure A2. Estimated Factor sizes over time (main model).

Appendix B: Robustness Checks and Diagnostics

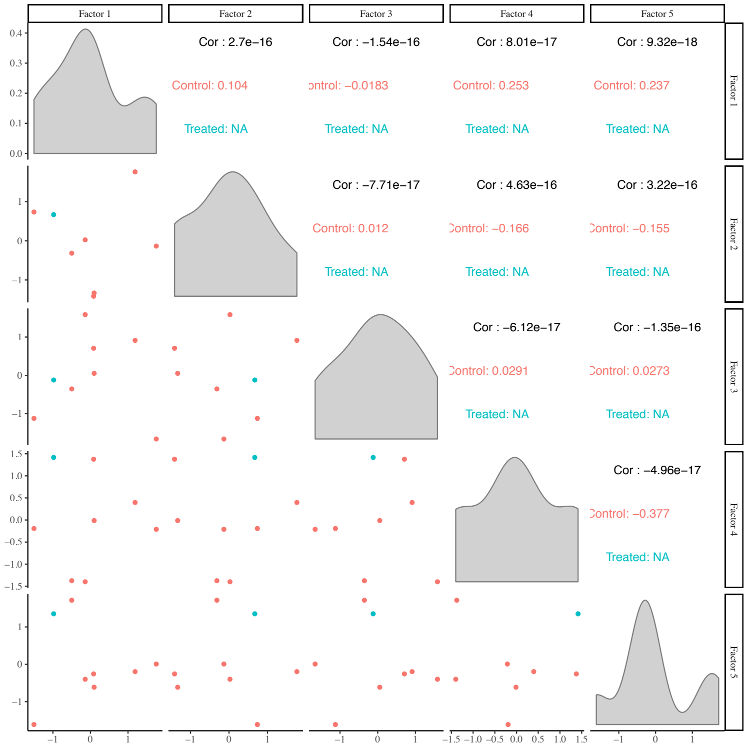
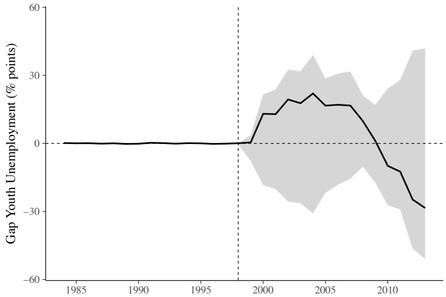
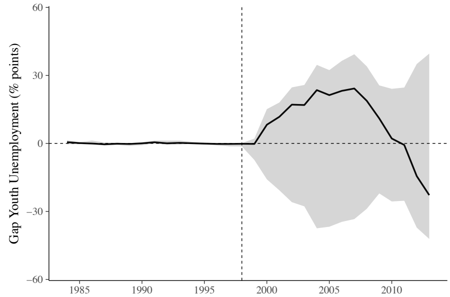


Figure A3. Factor loadings for all countries in the study group as provided by the `gsynth` *package.*

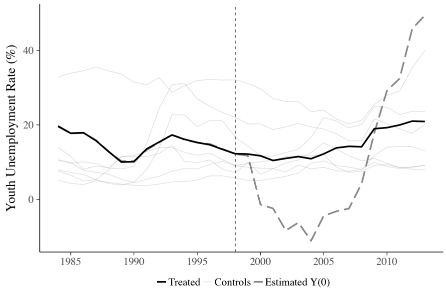
As our cross-country findings are based on a relatively small number of comparison units we conduct a number of diagnostic checks to ensure that the (imputed) results are not excessively extrapolated and robust to other specifications. First, we graphically examine the overlap of the estimated factor loadings of both the UK and the comparison units in the main model (see Figure A3). As proposed by Xu (2017), the factor loadings seem to reasonably overlap which suggests the validity of the estimated model.



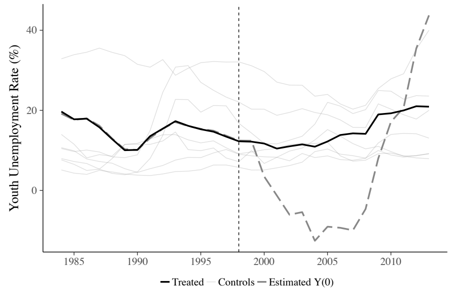
(a) Gap Plot: Four factors.



(b) Gap Plot: Three factors.



(c) Counterfactual Plot: Four factors.



(d) Counterfactual Plot: Three factors.

Figure A4. Robustness check: Manually reducing the number of estimated factors in the main analysis (without controls).

To reduce the risk of overfitting, Xu (2017, 59) incorporated a cross-validation scheme to automatically select the model with the correct number of factors with the highest probability, in our case five factors. When we reduce the number of estimated factors manually to four or three factors, respectively, our analysis runs into problems of excessive extrapolation (Figure A4). It leads to an imprecise estimation of the factors and an erroneous counterfactual estimate with high statistical uncertainty. Since we, therefore, cannot exclude the possibility of overfitting in our main analysis, we re-run our analysis using the original SCM.

With regard to the variables chosen to construct the counterfactual, we rely on the economic and political science literature on youth unemployment and labor market policymaking. Therefore, the variables themselves are not of direct interest in contrast to standard regression analysis. Instead, they are mainly included to improve the estimation of the pre-treatment fit. As a consequence, no claims are made regarding individual effects or causality.

Table A1 provides a list of the variables used as well as their data sources. Our original data set consisted of a much larger number of variables, however, their inclusion in the

Variable	Source	Minimum	Maximum	Mean
Unit Labor Cost (ULC)	OECD	0.28	0.83	0.58
Years left in current term	DPI	0.00	4.00	1.71
Legislative election in year t	DPI	0.00	1.00	0.26
Checks and Balances	DPI	3.00	7.00	4.45
Majority	DPI	0.25	0.86	0.55
Tax Revenue (total)	OECD	30.61	49.54	40.89
Employment Protection Index	OECD	1.03	2.87	2.35
Trade Union Density	OECD	17.87	83.86	51.99
Youth Cohort (20-24)	OECD	0.05	0.09	0.07
Inflation	OECD	-0.49	10.79	2.84
FDI	World Bank	-6.49	25.84	2.26
Openness	PWT	0.36	1.13	0.68
GDP per capita	OECD	19741.32	49134.69	30281.63

TABLE A1 *Variables used to construct the counterfactual and their sources.*

analysis did not substantially improve our results.

The economic variables, taken from the OECD and the World Bank, include standard measures of demand and supply factors that could reasonably affect youth unemployment. Most importantly, our unit labor cost (ULC) variable is the ratio of total labor costs and real output (productivity). It should matter because, if a country's ULCs increase compared to its competitors, its growth rate and, as a consequence, labor demand should be negatively affected (Taylor and Bradley 1997). A second measure is GDP per capita, which is included to trigger changes in macroeconomic cyclical conditions. Moreover, openness, which is taken from the Penn World Table (For details, see Feenstra, Inklaar, and Timmer 2015), is added to the analysis to investigate whether exposure to international trade creates or destroys jobs (Felbermayr, Prat, and Schmerer 2011). As Gozgor (2014) shows, openness, and globalization have a strong positive effect on employment in developed economies, we also take FDIs, that is foreign direct investments measured as the net inflow as a percentage of GDP into account. FDIs are supposed to serve as a channel of knowledge transfer across international borders and are, thus, assumed to encourage the creation of new jobs (Balcerzak and Zurek 2011).

As a supply-side control, we include the youth cohort, capturing the relative size of the people aged 20 to 24 years. Self-evidently, a rise in the size of the youth population increases competition for jobs and should negatively affect the youth employment rate (Korenman and Neumark 2000). The inflation rate variable is used as a control for a possible trade-off between inflation and unemployment of the Phillips-curve type (Baccaro and Rei 2005, 6). Finally, we include the total tax revenue of the general government as a percentage of GDP (Nickell 1997).

The political variables used in our analysis are mainly taken from the World Bank database of political institutions (DPI) (Beck et al. 2001). As electoral competition, partisan politics, and upcoming elections should matter (see, for example, Alesina 1989), we included the years left in the current term. In addition, we try to capture this effect using a dummy variable indicating whether it is an election year for the legislature. Moreover, the number of veto players should be considered. They affect the degree to which stakeholders can anticipate policies regarding the youth unemployment rate by impacting policy stability within a political system (Tsebelis 1995). In order to take the effect of political fragmentation into account, we include the number of government seats as a fraction of the total number of seats in parliament to measure the majority margin.

We also account for labor market policies and institutions which might have an influence on youth employment (for a detailed description, see Bassanini and Duval 2006). The first of these measures is trade union density. According to mainstream economics, high union density has the effect of driving wages above their market-clearing level and thus to strengthen disemployment effects. Properly designed employment protection laws should, in turn, help to offset these effects. This is why we also include the Employment Protection Index by the OECD, measuring the procedures and costs involved in hiring and firing workers, into our analysis.

Based on the data set described above, we use the synthetic control approach[13] to construct the synthetic UK by selecting the weights v_m such that the root mean square prediction error (RMSPE) in the period prior to the introduction of the minimum wage is minimized. Figure A5 displays the weights of each country from the donor pool. It shows that the youth unemployment rate in the UK in the pre-treatment period is best reproduced by a combination of Norway, Germany, and Austria of which Norway contributes the largest share. All other countries received a weight close or equal to zero.

With regard to the pre-treatment characteristics of the data, Table A2 compares the UK to its synthetic counterpart with weighted averages of the country values. With a few exceptions probably due to the large weight assigned to Norway for constructing the synthetic control unit, most values are more similar to the actual UK compared to the sample mean of the seven OECD countries in the donor pool.

The relative weights of each predictor variable for the synthetic control unit are shown in Table A3. The employment protection index as an economic variable has the highest weight (.26), followed by tax revenue (.19), foreign direct investment (.12), and and the relative size of the youth cohort (.11). In addition, the number of years left in the current legislative term also shows the significance of a political variable (.09).[14]

[13]All analyses are conducted using the R software. For the analysis, the synth package is used (Abadie, Diamond, and Hainmueller 2010).

[14]Despite the fact that some of the variables received a weight of almost zero they were still included as they improved the pre-treatment fit. Nonetheless, the results did not change substantially when excluding them. The concerning estimation results are available upon request.

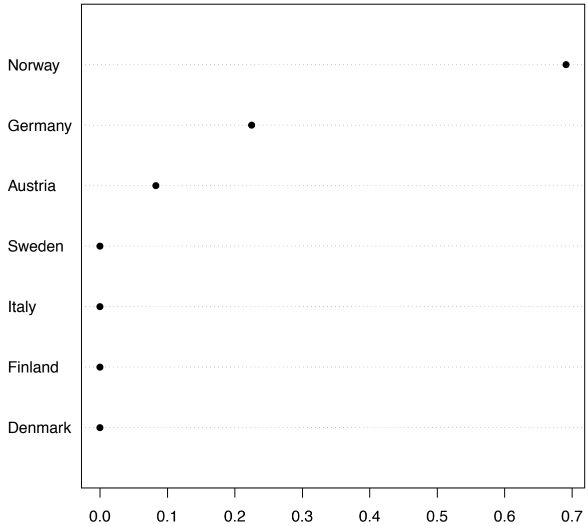


Figure A5. Country weights for synthetic control unit

Variable	UK	Synthetic UK	OECD Sample
ULC	0.54	0.45	0.55
Years left in current term	2.00	1.49	1.50
Legislative election in year t	0.20	0.28	0.29
Checks and Balances	3.90	4.21	4.67
Majority	0.55	0.47	0.54
Tax Revenue	32.45	41.19	42.13
Employment Protection Index	1.03	2.40	2.56
Trade Union Density	35.21	59.71	57.74
Youth Cohort	0.07	0.07	0.07
Inflation	3.70	2.69	3.09
FDI	2.34	1.32	1.27
Openness	0.53	0.67	0.62
GDP per capita	26068.43	32709.38	27780.16

TABLE A2 *Predictor Means before Introduction of Minimum Wage in 1999*

Generally speaking, however, economic variables have the highest weight for predicting the development of youth unemployment which is in line with findings from the vast research on minimum wage research discussed before.

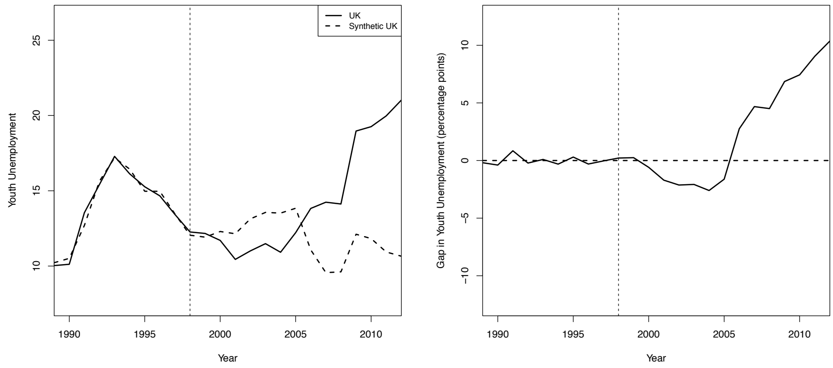
Variable	Weight
Employment Protection Index	0.26
Tax Revenue	0.19
FDI	0.12
Youth Cohort	0.11
Years left in current term	0.09
Legislative election in year t	0.07
Trade Union Density	0.05
Checks and Balances	0.04
Majority	0.02
Inflation	0.02
ULC	0.01
Openness	0.01
GDP per capita	0.01

TABLE A3 *Variable Weights for Synthetic Control Unit*

As we can see in Figure A6, the overall trajectory of youth unemployment rate of the estimated synthetic UK corresponds to the estimated treatment effect of the generalized synthetic control group. The solid line in Figure A6a shows the development of youth unemployment in the UK from 1989 to 2012.[15] The dashed line captures the synthetic approximation (prior to the introduction of the minimum wage in 1999) and its extrapolation afterwards.

The synthetic control group closely corresponds to the development of the actual youth unemployment rate in the UK prior to the reform treatment. As in the GSC model, we observe a non-linear effect trajectory. In the first years after the introduction, the youth unemployment rate in the counterfactual UK without a national minimum wage is higher than in the UK with a minimum wage. To this regard, the SCM results suggest that the unemployment reducing effect started only in 2000 while the GSC estimates suggest the effect to unfold already in 1999. Afterwards, the initially decreasing development turns into an increasing youth unemployment effect over time. The SCM does not come with easily interpretable uncertainty estimates, which make it difficult to pinpoint the exact time when the effect becomes differentiable from zero. Nevertheless, the overall similarity in the estimated counterfactual trajectory of the youth unemployment rate in the UK between the two approaches provides further support that the long-term effect of the NMW is due to inherent characteristics of the NWM.

[15]Note that we limit our pre-treatment period to the years 1989-1998 as it best matches the trajectory of the actual UK in pre-treatment period. It better allows us to extrapolate the post-treatment periods.



(a) Synthetic Control *(b) Gap Plot*

Figure A6. Robustness Check: Original Synthetic Control Estimates

Furthermore, we re-run our main analysis by including additional demand and supply variables of youth unemployment, which are taken from the OECD and the World Bank.[16] The graphical estimates can be found in Figures A7 to Figure A13. We observe some variation in the estimation of the long-term trajectory during the 2007/2008 financial and economic crisis which lies, however, within the uncertainty bounds of our main analysis. More importantly, all analyses show the same general trend of a short-term decreasing effect and a long-term increasing effect of NMW on youth unemployment.

To assess the presence of anticipation effects, we conduct placebo tests by setting the treatment years to 1997 and 1998, respectively. Figure A14 shows a similar development of the average effect size of the UK national minimum wage as in the main model when moving the pre-treatment period one or two years back. It points towards the presence of an anticipation effect coming either from the policy-makers or firms. As discussed before, this is not surprising and in line with our theoretical expectation: Labour first announced its plan to introduce a minimum wage in their party manifesto in 1992 (Pyper 2014). After winning the 1997 parliamentary elections, the introduction of a national minimum wage was prepared since July 1997 (Metcalf 1999). This test, therefore, supports our main

[16]We separately include foreign direct investment measured as the net inflow as percentage of GDP, inflation rate, the OECD employment protection index measuring the procedures and costs involved in firing individuals or groups of workers, unit labor costs measuring the ratio of total labor costs and real output, (total) government tax revenue, trade union density, and government debt as share of GDP.

conclusion of the importance to account for strategic timing in the analysis of reform implementation and is in line with a positive short-term anticipation effect of the UK NMW.

A final concern is whether the effect of the NMW is limited to youth unemployment only. While teens are usually the core of minimum wage studies as this population group is strongly affected by minimum wage policies, it is possible that youth unemployment effects are, for example, compensated by higher employment rates of other groups (Allegretto et al. 2017, 562). However, when we replace youth unemployment with the overall unemployment rate (Figure A15), we see a similar trend for the overall effect of the NMW implementation although not as large. Moreover, the positive long-term effect does not become "statistically significant" as the bootstrapped confidence intervals include zero.

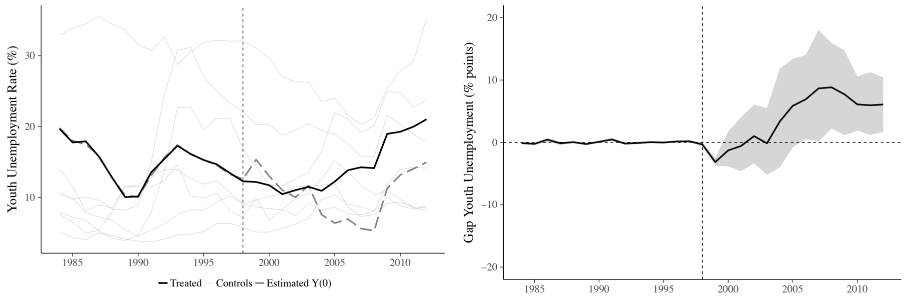


Figure A7. Robustness check: Main model conditioned on foreign direct investment (1984-2012).

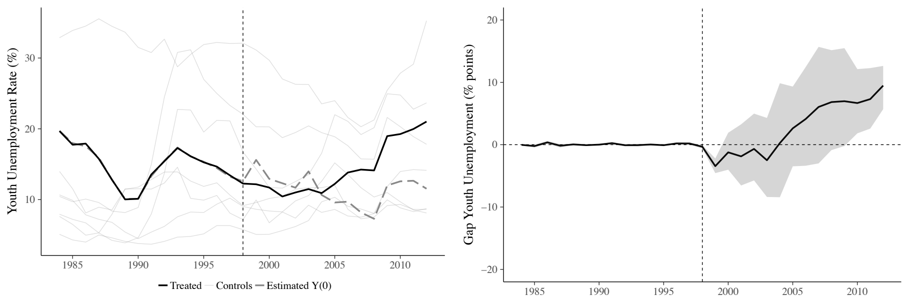


Figure A8. Robustness check: Main model conditioned on inflation rate (1984-2012).

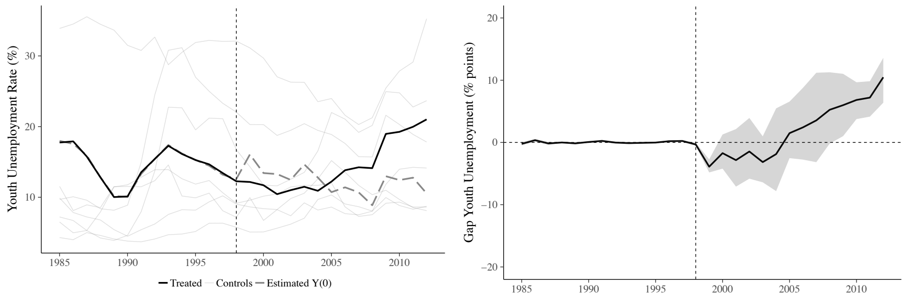


Figure A9. Robustness check: Main model conditioned on OECD employment protection index (1985-2012).

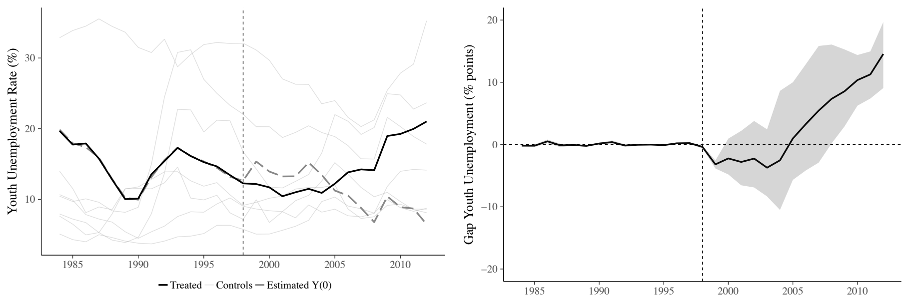


Figure A10. Robustness check: Main model conditioned on unit labor costs (1984-2012).

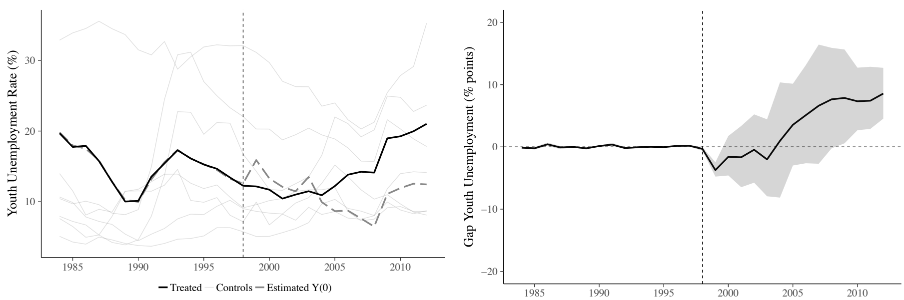


Figure A11. Robustness check: Main model conditioned on tax revenue (1984-2012).

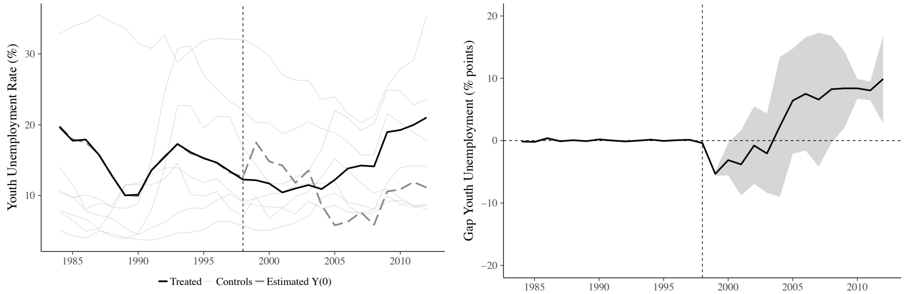


Figure A12. Robustness check: Main model conditioned on trade union density (1984-2012).

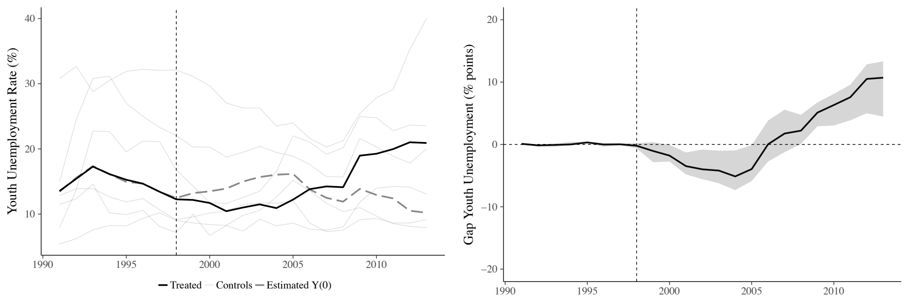
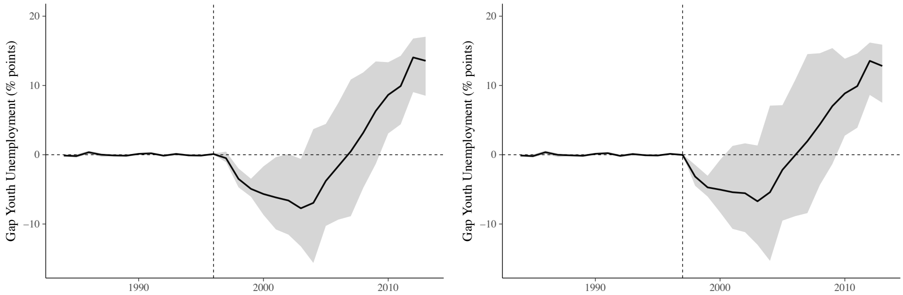


Figure A13. Robustness check: Main model conditioned on government debt as share of GDP (1991-2013).



(a) Setting treatment year to 1997 *(b) Setting treatment year to 1998*

Figure A14. Robustness check: Changing the intervention period to control for anticipation effects.

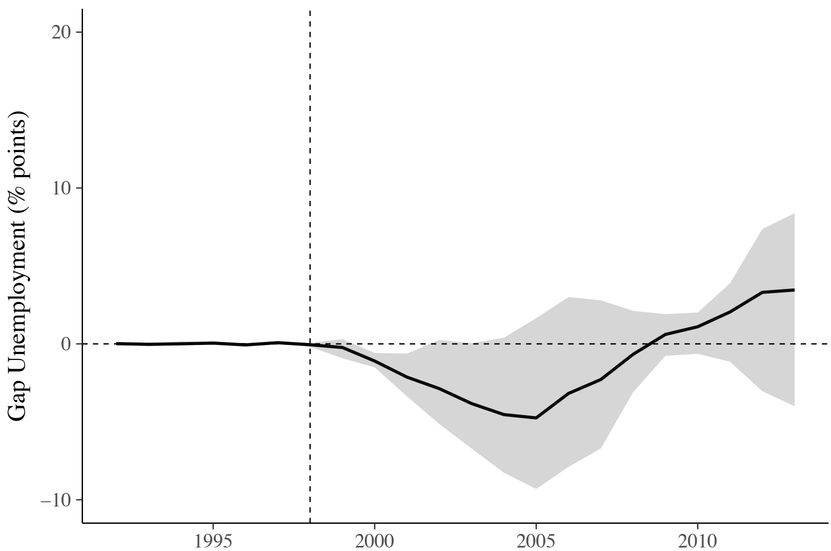


Figure A15. Robustness check: Unemployment rate as dependent variable (no controls)

Appendix References

Abadie, Alberto, Alexis Diamond, and Jens Hainmueller. 2010. "Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program." *Journal of the American Statistical Association* 105 (490): 493–505.

———. 2015. "Comparative Politics and the Synthetic Control Method." *American Journal of Political Science* 59 (2): 495–510.

Alesina, Alberto. 1989. "Politics and Business Cycles in Industrial Democracies." *Economic Policy* 4 (8): 55–98.

Allegretto, Sylvia, Arindrajit Dube, Michael Reich, and Ben Zipperer. 2017. "Credible Research Designs for Minimum Wage Studies: A Response to Neumark, Salas, and Wascher." *ILR Review* 70 (3): 559–592.

Baccaro, Lucio, and Diego Rei. 2005. *Institutional Determinants of Unemployment in OECD Countries: A Time Series Cross-Section Analysis (1960-98).* International Institute for Labour Studies Geneva.

Balcerzak, Adam P., and Miroslawa Zurek. 2011. "Foreign Direct Investment and Unemployment: VAR Analysis for Poland in the Years 1995-2009." *European Research Studies; Anixis* 14 (1): 3–14.

Bassanini, Andrea, and Romain Duval. 2006. "The Determinants of Unemployment Across Oecd Countries: Reassessing the Role of Policies and Institutions." *OECD Economic Studies; Paris* 42 (1): 7–86, 5.

Beck, Thorsten, George Clarke, Alberto Groff, Philip Keefer, and Patrick Walsh. 2001. "New Tools in Comparative Political Economy: The Database of Political Institutions." *The World Bank Economic Review* 15 (1): 165–176.

Doudchenko, Nikolay, and Guido W. Imbens. 2016. *Balancing, Regression, Difference-In-Differences and Synthetic Control Methods: A Synthesis.* Working Paper 22791. National Bureau of Economic Research, October. Accessed December 12, 2017. `http://www.nber.org/papers/w22791`.

Feenstra, Robert C., Robert Inklaar, and Marcel P. Timmer. 2015. "The Next Generation of the Penn World Table." *American Economic Review* 105 (10): 3150–3182.

Felbermayr, Gabriel, Julien Prat, and Hans-Joerg Schmerer. 2011. "Trade and Unemployment: What Do the Data Say?" *European Economic Review* 55 (6): 741–758.

Gozgor, Giray. 2014. "The Impact of Trade Openness on the Unemployment Rate in G7 Countries." *The Journal of International Trade & Economic Development* 23 (7): 1018–1037.

Holland, Paul W. 1986. "Statistics and Causal Inference." *Journal of the American Statistical Association* 81 (396): 945–960.

Korenman, Sanders, and David Neumark. 2000. "Cohort Crowding and Youth Labor Markets (A Cross-National Analysis)." *NBER:* 57–106.

Metcalf, David. 1999. "The Low Pay Commission and the National Minimum Wage." *The Economic Journal* 109 (453): 46–66.

Neyman, Jerzy. 1923. "On the Application of Probability Theory to Agricultural Experiments. Essay on Principles." *Statistical Science* 5 (4): 465–480.

Nickell, Stephen. 1997. "Unemployment and Labor Market Rigidities: Europe versus North America." *The Journal of Economic Perspectives* 11 (3): 55–74.

Pyper, Douglas. 2014. "The National Minimum Wage: Historical Background." *Commons Briefing Papers,* no. SN06897.

Rubin, Donald B. 1974. "Estimating Causal Effects of Treatments in Randomized and Nonrandomized Studies." *Journal of Educational Psychology* 66 (5): 688–701.

Taylor, Jim, and Steve Bradley. 1997. "Unemployment in Europe: A Comparative Analysis of Regional Disparities in Germany, Italy and the UK." *Kyklos* 50 (2): 221–245.

Tsebelis, George. 1995. "Decision Making in Political Systems: Veto Players in Presidentialism, Parliamentarism, Multicameralism and Multipartyism." *British Journal of Political Science* 25 (3): 289–325.

Xu, Yiqing. 2017. "Generalized Synthetic Control Method: Causal Inference with Interactive Fixed Effects Models." *Political Analysis* 25 (1): 57–76.