Using Synthetic Control to Study the Economic Impact of the Brexit Referendum

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Abstract

This research uses various synthetic control methods, including the augmented synthetic control and the synthetic difference-in-differences, to evaluate the impacts of the Brexit referendum which took place in 2016Q2 on the real GDP per capita and real gross disposable income per capita in the UK. I examine the short and medium term impacts till 2023Q3, and estimate that the Brexit referendum has caused a persistent drop in real GDP since 2016Q3, which accumulates to a 10% gap by 2023Q3. The same goes for real per capita gross disposable income, which amounts to a 16-22% gap by 2023Q3. By comparing the different methods, I find that the original synthetic control estimates are greater than those of the augmented synthetic control in magnitudes, although the assumptions for the original synthetic control are largely satisfied and there is no need to extrapolate beyond the convex hull of the control countries.

Link: Replication code on GitHub.

1 Introduction

On June 23, 2016, the UK held a referendum to determine its membership status in the European Union, and to the surprise of many, 51.89% of the people voted to leave the EU.

Prior to the referendum, most economists believed that leaving the European single market will do more harm than good to the UK economy and people rationally will not vote for "leave" As such, the referendum outcome came as a shock to the financial markets. The pound depreciated sharply after the referendum against the US dollar, dropping from 1.5 to 1.35. The global stock market fell around 5% on June 24, while government bond yields and safe haven assets such as gold surged in prices. UK's Economic growth has since remained sluggish, up till the COVID-19 pandemic, during which the economy took a big hit and is currently one of the worst performing among the developed countries. Real income growth has stagnated and standard of living barely rose for average Britons over the past 15 years.

This paper studies the impact of voting to leave the EU on real per capita gross domestic product (RGDP) and real gross disposable income per capita (RGDI) in the UK, by creating a synthetic UK using the other developed countries. I present three sets of results. The first set is obtained using the original synthetic control (SC) method proposed in Abadie and Gardeazabal (2003), Abadie, Diamond, and Hainmueller (2010), and Abadie, Diamond, and Hainmueller (2015). The second set implements the augmented synthetic control (ASC) method proposed by Ben-Michael, Feller, and Rothstein (2021). The last set uses the synthetic difference-in-differences (SDID) method proposed by Arkhangelsky, Athey, Hirshberg, Imbens, and Wager (2021). My conclusion is robust across all three methods, pointing to large negative economics impacts of the Brexit referendum.

To give a brief summary of the main results, per capita RGDP in the UK grew just 8% over the course of 16 years between 2007 to 2023. In the counterfactual world in which the UK did not vote to leave the EU, per capita RGDP would have grown 19% over the same period, which suggests a 9.2% shortfall in RGDP from leaving the EU. Per capita RGDI increased about 9% between 2007 to 2023. It would have been 30% in the counterfactual world, suggesting a massive negative impact on people's gross disposable income. The remaining sections are literature review, methodology, data, results, discussion, and conclusion.

2 Literature Review

To expound on the significance of this research and its contribution to previous work, I review two strands of literature. The first strand is related to the history of the synthetic control method and the second strand covers papers studying the economic impacts of Brexit.

For the first strand, Abadie and Gardeazabal pioneer the method of synthetic control and use it to investigate the economic effects of terrorism in the Basque Country (Abadie & Gardeazabal, 2003). Subsequently, Abadie, Diamond and Hainmueller further formalize SC, e.g. by suggesting procedures to choose the optimal covariate weighting matrix V, and apply SC to study the effect of California's tobacco control program and the economic cost of the 1990 German reunification respectively (Abadie et al., 2010) (Abadie et al., 2015). Abadie (2021) further discusses the settings where SC works well and those where it might fail, due to limitations such as the convex weights restriction.

To overcome these restrictions, more advance methods of SC are later proposed. In this paper, I focus on the augmented synthetic control (ASC) method proposed by Ben-Michael et al. (2021) and the synthetic difference-in-differences (SDID) method suggested by Ben-Michael et al. (2021). ASC improves on SC by adding a penalty term to estimate the counterfactual unobserved outcome and by allowing for negative weights (with regularization to prevent excessive extrapolation). On the other hand, SDID conflates the classical two-way fixed effect model and both synthetic control weights and time period weights to artificially create DID control groups to infer treatment effects. This paper contributes to this strand of literature by demonstrating the applications of SC, ASC and SDID to studying the effects of Brexit, and comparing their performances and estimates. As SC and ASC produce similar control country weights and results, I find that Brexit data is suitable for the original SC without additional bells and whistles. On the other hand, since the Arkhangelsky et al. (2021) version of SDID estimates a static effect, it fails to capture the dynamic nature of the economic effects of Brexit. In future studies, I seek to propose a new method of regularizing SC weights by optimizing low dimensional representations of high dimensional covariates. The advantage of using high dimensional data will be that the SC weights are entirely data-driven, eliminating the need for researcher's discretion in choosing covariates.

The next strand of literature is directly relevant to the Brexit application of this paper. Past work have found little positive effects of Brexit. Bloom et al. (2019) use the classical difference-in-differences regression and find that the UK's decision to leave the EU has gradually reduced business investment by 11% over the three years following June 2016, and productivity between 2-5%. Ahmad, Limão, Oliver, and Shikher (2023) apply an uncertainty-augmented gravity equation to the UK services trade with the EU and find that the threat of Brexit has lowered services exports by at least 20 log points. Broadbent, Di Pace, Drechsel, and Harrison (2023) estimates a small open economy model with tradable and non-tradable sectiosn and find that while tradable sector expands in the short run, while non-tradable sector contracts.

Regarding the spillover effects of Brexit on other EU countries, Sampson (2017) and McGrattan and Waddle (2020) find large negative effects on foreign direct investments and productivity for the UK, while other EU countries suffer much smaller losses. Previous work that employs SC include Opatrny (2021) which finds that the Brexit decision has no significant impact on the FTSE100 stock index but significant negative impact of 1.2 percentage points on the 10-year bond yield, and Venâncio and dos Santos (2024) which concludes that the Brexit referendum has reduced the number of UK-dependent workers in Portugal, particularly non-university educated male individuals. The most relevant work to my application is Born, Muller, Schularick, and Sedlacek (2019) which employs SC, as well as an expectation-augmented vector autoregression, and find that the Brexit vote has led to a 1.7-2.5% decrease in the UK output by the end of 2018.

These previous work apply the original SC, but without rigorously justifying the suitability of SC for Brexit. This paper contributes to previous work by focusing on RGDP and RGDI, and extends the sample period to the end of 2023 to evaluate both the short and medium term effects of Brexit. I provide inference both in the form of placebo studies, as well as conformal inference which gives a 95% confidence interval, to show that the Brexit effects are statistically significant. Moreover, this paper investigates the performance of the UK during the COVID-19 pandemic and provides evidence that the UK's poor economic performance during the pandemic relative to other developed countries can be attributed to the Brexit vote. Finally, by comparing across the three synthetic control methods, the paper finds that augmenting SC with regularization and negative weights leads to similar estimates as the original SC, hence justifying the suitability of the original SC for the Brexit data.

3 Methodology

Suppose there are n countries. WLOG, suppose there is a single treated country (which is the UK in our case) and let it be country 1. Further suppose treatment happens at time T (which is 2016Q3, the quarter right after the Brexit referendum). Then the observed outcome for the treated country for $t \geq T$ is:

$$Y_{1t} = Y_{1t}^N + \tau_{1t}$$

where Y_{1t}^N is the counterfactual untreated outcome of country 1 at time t and τ_{1t} is the treatment effect at time t.

Abadie and Gardeazabal (2003) propose using the weighted average outcomes of untreated countries to estimate Y_{1t}^N:

$$\hat{Y}_{1t}^N = \sum_{i=2}^{n} \hat{w}_i Y_{it}$$

where $\hat{w}_i$ is calculated as:

$$\hat{W} = argmin_W (X_1 - X_0 W)' V (X_1 - X_0 W)$$

where $W = [w_2, ...w_n]$ is a n x 1 vector of nonnegative weights that sum to 1, $X_1 = [Z_{11}, Z_{12}, ..Z_{1k}]$ is a k x 1 vector of k predictors of country 1, and $X_0 = [Z_2, Z_3, ...Z_n]$ is a k x (n-1) matrix of predictors of countries 2 to n, and $Z_i = [Z_{i1}, Z_{i2}...Z_{ik}]$ is a vector of k predictors of unit i, and V is a weighting matrix representing the relative importance of each predictor in computing the weights. One example of the k predictors could be the pre-treatment period outcomes.

The treatment effect estimator $\hat{\tau}_{1t}$ can be computed as:

$$\hat{\tau}_{1t} = Y_{1t} - \hat{Y}_{1t}^{N} = Y_{1t} - \sum_{i=2}^{n} \hat{w}_i Y_{it}$$

For the original SC, inference is done by permutation, i.e. running SC on the untreated countries as a placebo study and check if there are evident treatment effects in the absence of treatment. Note that this might not be the best way to do inference because permutation inference assumes random assignment, but Brexit is obviously not random for the UK.

However, there can be the case that using convex weights might not approximate the counterfactual untreated outcome well. Also, there can be overfitting to pre-treatment period training data when estimating $\hat{W}$. Moreover, the weights of the original SC method tend to be sparse, i.e. concentrated on a few countries while most countries have zero weights.

One way to improve on the original SC is the ASC method proposed by Ben-Michael, Feller and Rothstein. The counterfactual Y_{1t}^{N} is estimated by:

$$\hat{Y}_{1t}^{N} = \sum_{i=2}^{n} \hat{w}_i Y_{it} + \hat{\eta}' \left(X_1 - X_0 \hat{W} \right)$$

where $\hat{W}$ is the original SC estimated weights and $\hat{\eta}$ is a k x 1 vector of coefficients obtained from a ridge regression of Y_{it} onto demeaned X_0 using only untreated countries. Under certain conditions, it can be shown that the counterfactual outcome can be expressed as:

$$\hat{Y}_{1t}^{N} = \sum_{i=2}^{n} \hat{w}_i^{ASC} Y_{it} \quad \sum_{i=2}^{n} \hat{w}_i^{ASC} = 1$$

which is to say that the counterfactual outcome is a weighted average of observed untreated outcomes using ASC weights, and the weights sum to 1. Note that there is no nonnegativity constraint on the weights, meaning that ASC allows for extrapolation outside the convex hull of the untreated outcomes. Such extrapolation cannot be achieved in the original SC. Also note that such extrapolation is regularized by the term involving ridge regression coefficients. This enables ASC to estimate the counterfactual outcome more closely without introducing excessive bias.

Inference for ASC is done by conformal inference proposed by Chernozhukov et al (2021). The idea is to include post-treatment periods in computing the SC weights. Under the null hypothesis that there is no significant treatment effect, the distribution of the change in weights over time (by including the post-treatment periods) should be stationary. Then, we can test whether the weights computed using the extended periods conform to the weights computed using only the pre-treatment period.

Another way to improve on the original SC is SDID proposed by Arkhangelsky et al. (2021). SDID assumes homogeneous treatment effect and estimates it by:

$$(\hat{\tau}^{SDID}, \hat{\mu}, \hat{\alpha}, \hat{\beta}) = argmin_{\tau,\mu,\alpha,\beta} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} (Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau)^2 \hat{\omega}_i^{SDID} \hat{\lambda}_t^{SDID} \right\}$$

where τ is the treatment effect, ω_i^{SDID} is the synthetic control weight that is estimated using the original SC method with a regularization term, and λ_t^{SDID} is estimated by balancing pre-exposure time periods with post-exposure ones i.e. the average post-treatment outcome for each control country differs by a constant from the weighted average of the pre-treatment outcomes of the same country. The original SC method is basically SDID without the time weights λ_t^{SDID}.

Inference for SDID, in the case of a single treated country, can be done via placebo variance estimation. This is done by repeatedly drawing samples out of control units without replacement, calculate one SDID estimator for each sample, and compute the variance of the SDID estimators.

4 Data

I collect my data from the OECD database. I use a panel data of 20 countries, from 2007Q1 to 2023Q3. I pick the start date at 2007Q1 because that's the earliest time available for quarterly data of my dependent variable and predictors. I prefer to use quarterly rather than annual data as it paints a more granular picture of the variations across time.

I look at two outcome (dependent) variables: real GDP per capita and real gross household disposable income per capita. The former is representative of the level of economic activities on a per capita basis, while the latter is informative of the actual amount of income received by individuals. Both variables have levels in 2007Q1 normalized to 100. My predictors are the pre-treatment averages of:

- Unemployment rate
- Labor under-utilization rate
- Consumer price index

- Short term interes rate
- Stock market index
- Consumer confidence
- Real household final consumption expenditure per capita
- Household indebtedness level
- Household savings level
- Household networth

In addition, I include the pre-treatment average of the outcome variable, as well as the outcome variable in $1/4$ of the pre-treatment periods, evenly spaced out, in the list of predictors. The reason for picking these predictors is that they indicate various facets of a country's macroeconomic conditions. Countries that are very similar in these predictors should be highly identical economically.

Since the referendum result was announced at the end of June in 2016, I define the treatment time to be 2016Q3, so pre-treatment period is 2007Q1 to 2016Q2, and post-treatment period is 2016Q3 to 2023Q3.

5 Results

In this section, I first present the results obtained from the original SC method, followed by the ASC, and lastly SDID.

5.1 Synthetic control results

Figures 1 to 6 are related to the original SC method. Figure 1 shows that before the Brexit referendum in 2016Q2, the UK and the synthetic UK trajectories are very similar. RGDP dropped below the 2007Q1 level during the Great Financial Crisis and did not fully recover till 2014. The paths begin to diverge in 2016Q2, with the synthetic UK growing more quickly than the UK. In 2020Q2, both paths suffer a massive drop in RGDP, reflecting the COVID-19 pandemic. However, the UK's decline is more than twice the size of the synthetic UK's decline, implying that in the absence of Brexit, the UK might have suffer a smaller economic impact from COVID-19.

The difference in the impacts of COVID-19 is more evident in Figure 2, where we see a sharp broadening of the gaps in 2020Q2, as indicated by the abrupt dip in

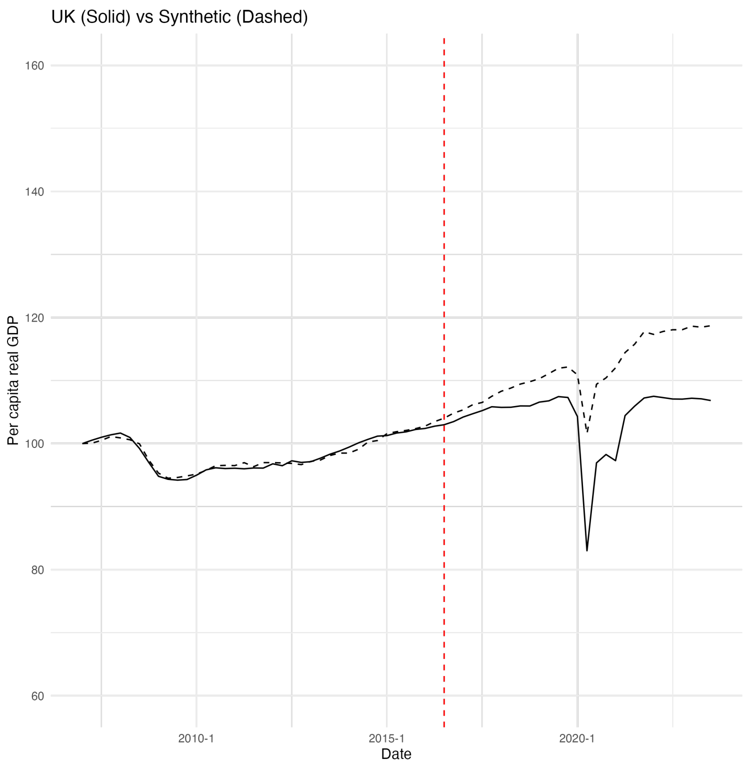

Figure 1: UK vs Synthetic real GDP per capita paths

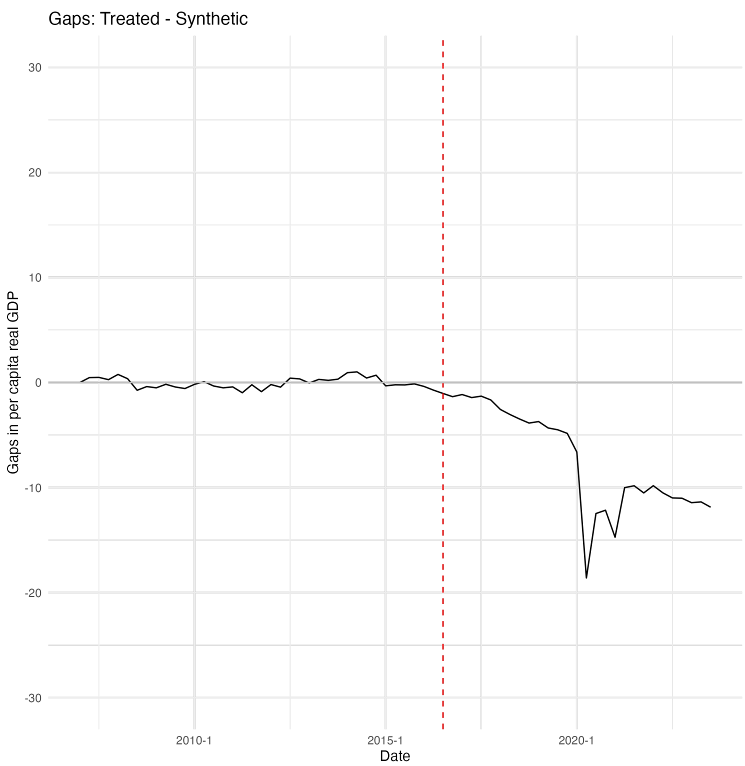

Figure 2: UK vs Synthetic real GDP per capita gaps

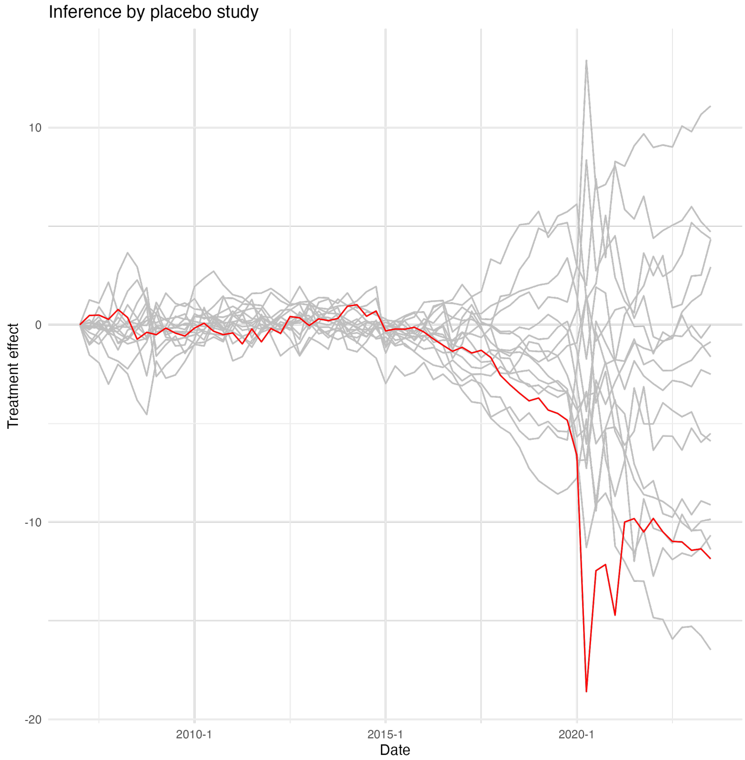

Figure 3: Real GDP per capita placebo study

the linear downward trend. The first dip is due to the pandemic while the second dip can be attributed to rate hikes in response to rising inflation. This suggestion is corroborated by numerous reports showing that the UK suffered more than other developed economies due to the adverse impact of Brexit on trade, labor mobility, financial capital flow and future expectations. Post COVID-19, the UK recovered more slowly than the synthetic UK. The overall impact is that RGDP per capita rose just 8% for the UK, but would have been 18% had the UK voted to remain in the EU.

Figure 3 displays the placebo study paths. SC is applied to countries in the control group. We see that the position of the UK's gap plot is one of the lowest among all gap plots, and the only gap plot displaying a massive downward dip during the pandemic. However, there are other gap plots that display some upward spikes around the time of the pandemic. It might be worthwhile to look more closely into those countries in further research. Hence, the permutation plot only provides weak support for the validity of the UK's result.

Figures 4 and 5 show the paths and gaps of the UK versus the synthetic UK for per capita RGDI which is the actual amount of money received as income by an individual on average in the UK. In the pre-treatment period, RGDI is affected to a smaller extent than RGDP by the Great Financial Crisis. RGDI recovered to the

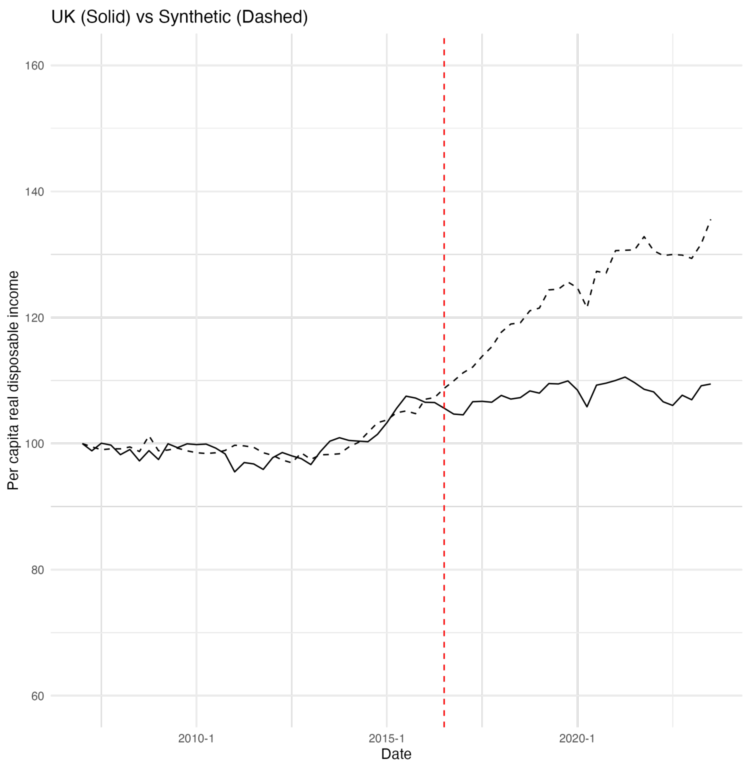

Figure 4: UK vs Synthetic real disposable income per capita paths

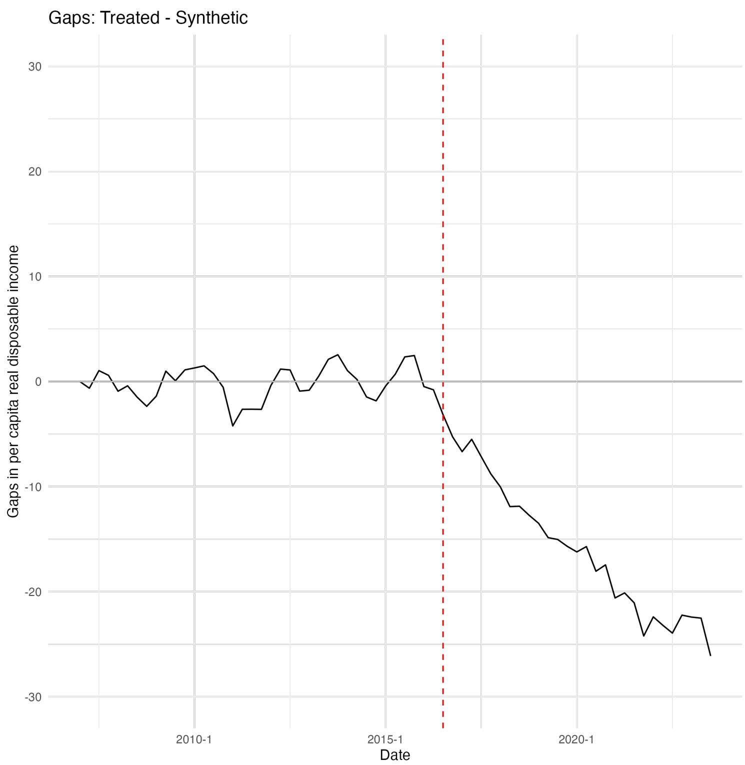

Figure 5: UK vs Synthetic real disposable income gaps

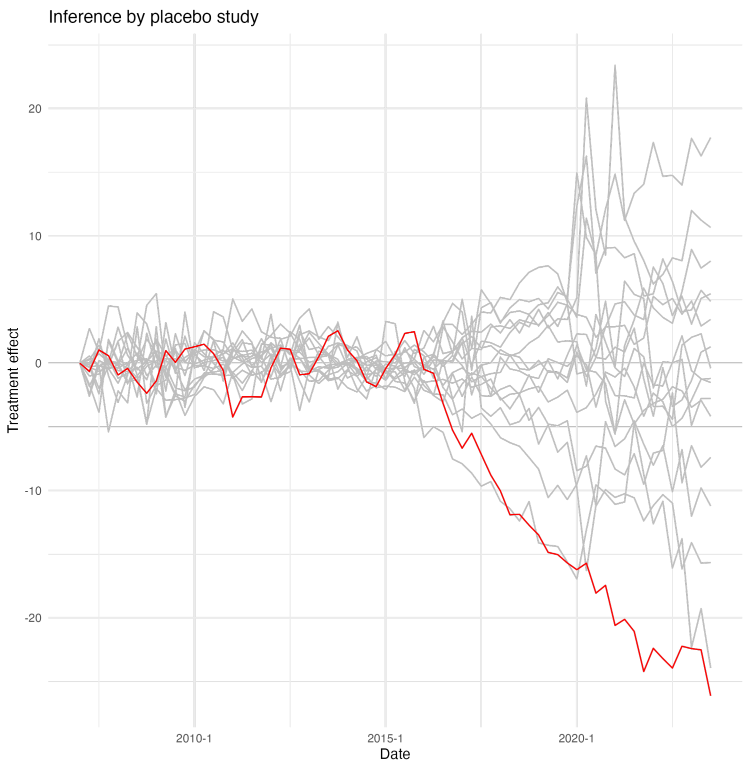

Figure 6: Real disposable income per capita placebo study

pre-crisis level in 2014 and embarked on an upward trend. However, for the UK, the growth is disrupted by the Brexit referendum, as we can see in Figure 4 that the synthetic UK continues on the upward trend while the UK's RGDI path flattens. The cumulative effect is that the UK's RGDI grew only 10% between 2007-2023, as compared to 35% for the synthetic UK, meaning that people in the UK are 18% poorer as a resulting to voting to leave the EU. The massive gap in RGDI might be explained by this narrative: after recovering from the Great Financial Crisis, RGDI began to take off in developed countries in Europe. The UK's take-off is disrupted half-way by the Brexit referendum, i.e. the UK misses the opportunity of per capita RGDI increase because of the Brexit shock, and ends up much poorer.

Figure 6 shows the placebo study of RGDI. This is similar to Figure 3 and only lends weak support to the UK's results.

5.2 Augmented synthetic control results

Next, we move onto the results of ASC as shown in Figures 7 and 8. Figure 7 displays the gaps in RGDP between the UK and the synthetic UK, as well as 95% confidence interval from conformal inference. The results of ASC largely agree with that of the original SC. Before 2016Q2, the gaps are small and close to 0. After the Brexit referendum, the gap widens gradually and dips drastically during the

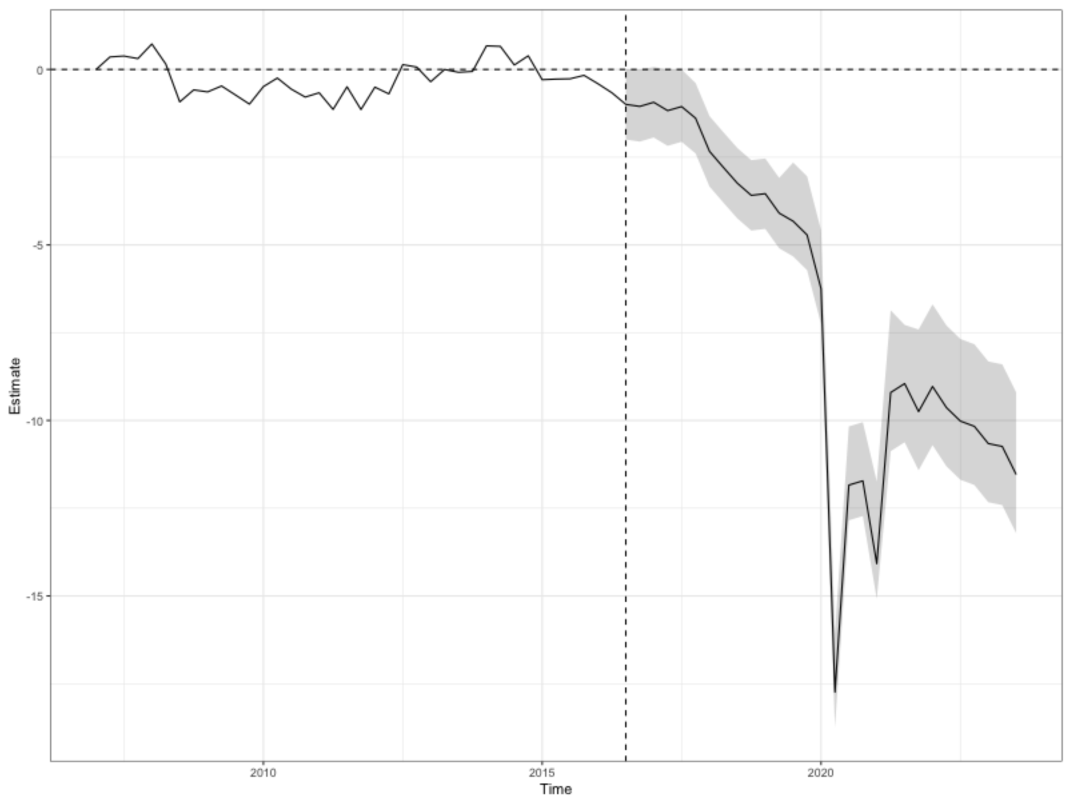

Figure 7: UK vs Synthetic gaps in real GDP per capita using augmented synthetic control

COVID-19 pandemic in 202Q2 and during the lockdowns and rate hikes in 2021. The confidence interval is very narrow during the COVID-19 dips because given the wild fluctuations in RGDP, it is very unlikely that the SC weight estimates involving treated periods will evolve stationarily over time, hence very strongly reject the null hypothesis in conformal inference.

Figure 8 shows the gaps in RGDI. The pre-treatment fit of RGDI is slightly worse than RGDP as seen from the larger deviations from 0 in the pre-treatment periods. After 2016Q2, RGDI gap gradually broadens between the UK and the synthetic UK. The treatment effects are statistically significant as shown by the 95% confidence interval. Again, the ASC results largely agrees with the original SC results.

Figure 9 illustrates the weights of the control countries. We see from the left panel of SC weights that the US and Denmark add up to 0.8, with the remaining 0.2 formed by Hungary, Finland, Ireland, Greece and Italy. More than half of the countries in the control group have weights near zero. The weights distribution is not surprising as both the US and Denmark are wealthier by the UK. This is counterbalanced by a bunch of countries that are poorer than the UK.

It is notable that the SC and ASC weights are surprisingly similar. The only ma-

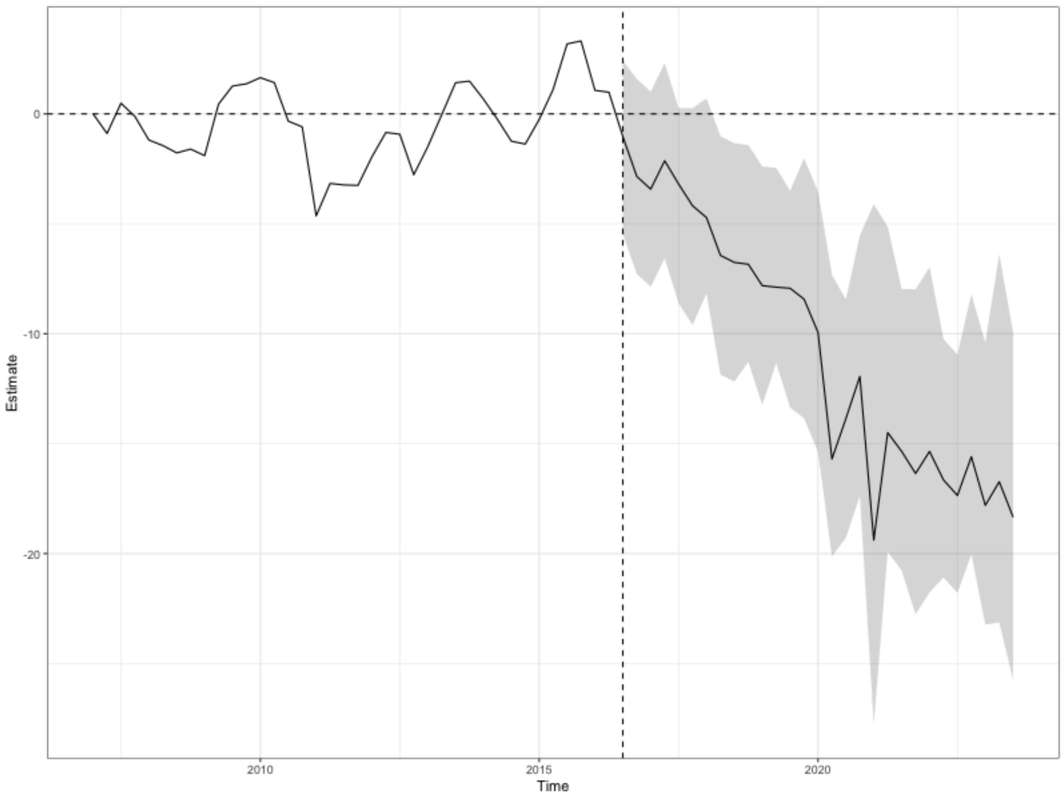

Figure 8: UK vs Synthetic gaps in real disposable income per capita using augmented synthetic control

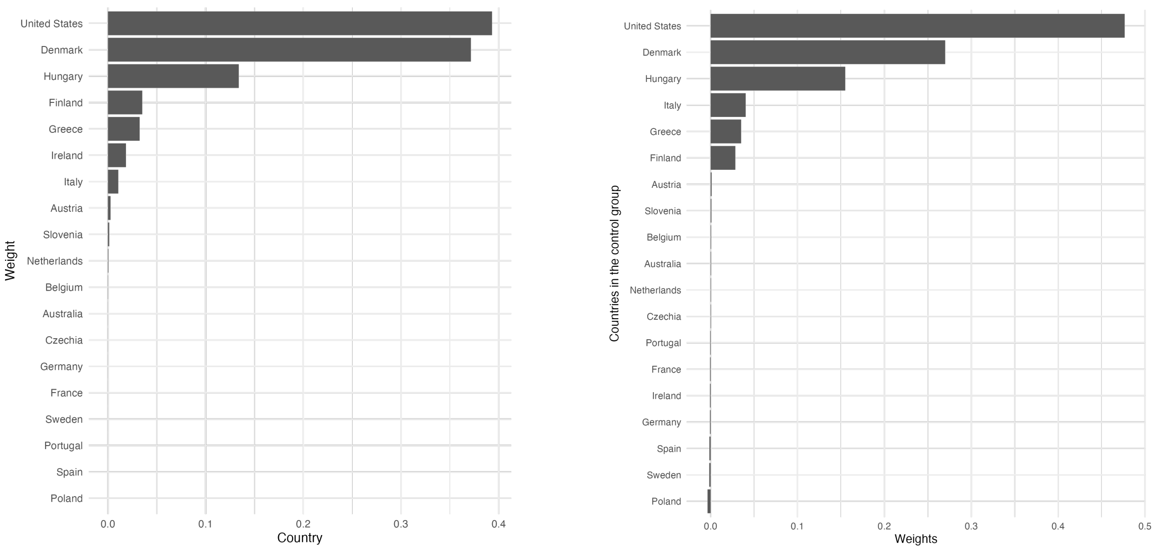

Figure 9: SC weights (left) vs ASC weights (right)

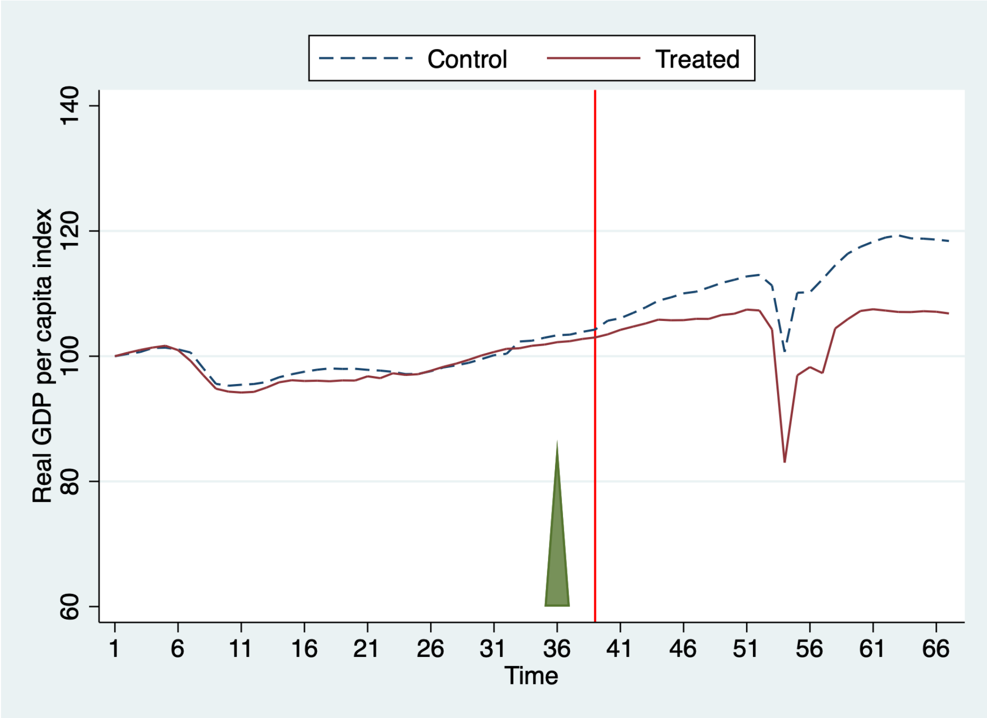

Figure 10: UK vs Synthetic gaps in real GDP per capita using SDID

jor difference is that in ASC, Ireland is assigned a zero weight and Italy is assigned a larger weight than Greece and Finland. Several countries at the bottom of the right panel have small negative weights that are close to 0, indicating almost no extrapolation outside the convex hull of control countries. This justifies the convex hull condition in using the original SC method. Additionally, since Ireland is likely to have been affected by the Brexit vote due to its close geographical proximity to the UK, the ASC estimates which do not include Ireland in the control might be a more accurate estimate of the treatment effects.

5.3 Synthetic difference-in-differences results

Lastly, we move onto the SDID results.

Figures 10 and 11 show the paths of the UK versus the synthetic UK for RGDP and RGDI respectively. The results are largely similar to the original SC and the ASC. However, the pre-treatment fit of SDID for RGDI is poor in comparison.

Figure 12 shows the SDID weights $\hat{\omega}_i^{SDID}$ for every country in the control group. Larger circles indicate larger weights. We see that the developed countries like the US, Denmark, Australia, France and Germany that have similar level of economic development as the UK have larger weights. Hungary also has a relatively large weight, similar to the original SC. The key difference between SC and SDID weights is that the SDID weights are more evenly distributed among all control

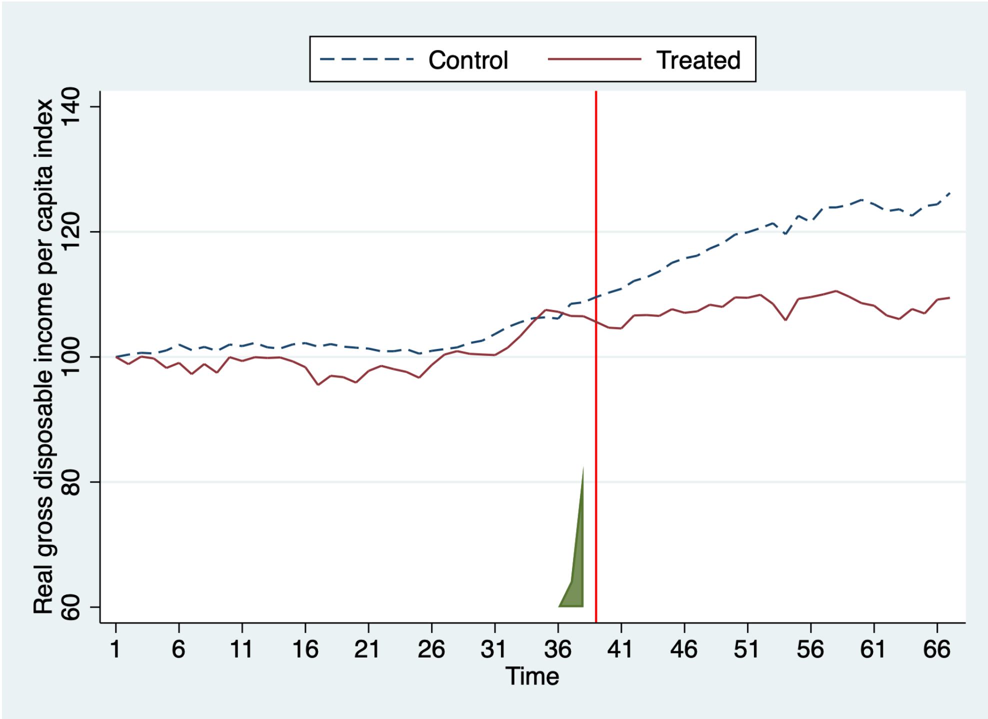

Figure 11: UK vs Synthetic gaps in real disposable income per capita using SDID

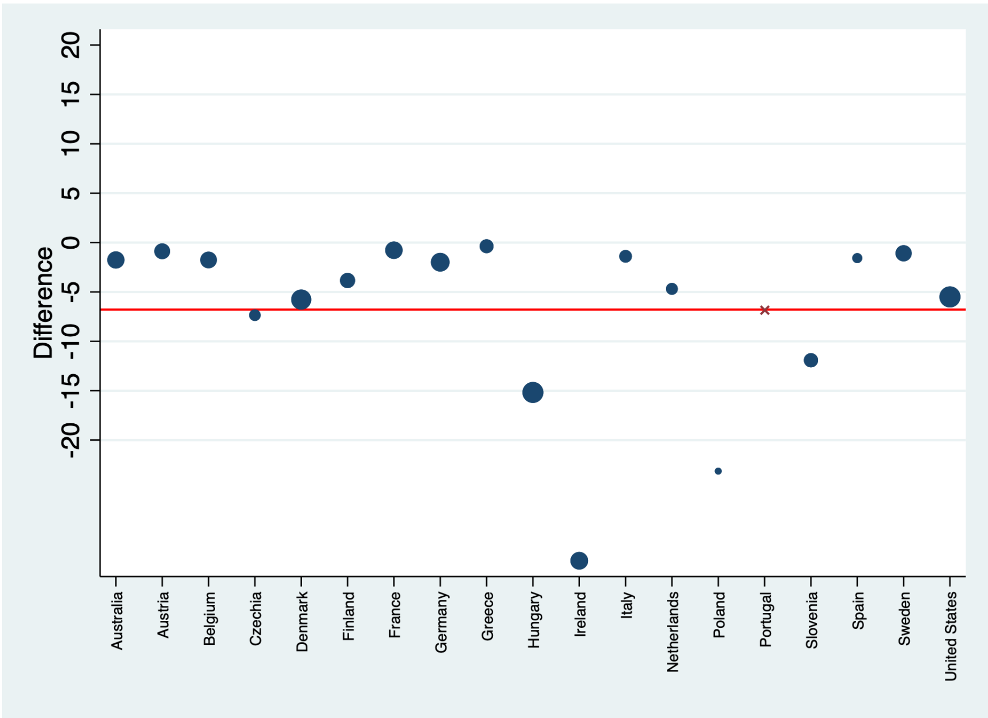

Figure 12: Weights using SDID for real GDP per capita

	(1)	(2)
	RGDP	RGDI
Treatment effect	-6.781	-9.366
	(5.892)	(6.581)
N	1340	1340

Standard errors in parentheses
* p¡0.10, ** p¡0.05, *** p¡0.01

Table 1: SDID estimated τ

countries and there are very few countries with very small weights e.g. Spain and Poland. This is a characteristics of the SDID method which includes something akin to L2-regularization in computing the unit weights and penalizes large weights.

The triangles above the x-axis in Figures 10 and 11 show the time weights $\hat{\lambda}_t^{SDID}$. The time weights are concentrated on the periods right before the Brexit referendum. This is not too surprising because both RGDP and RGDI are on a long-run upward trend. To balance the post-treatment mean with the weighted average pre-treatment mean such that they differ by a constant, the SDID estimator places more weight on the pre-treatment periods with larger values of the outcome variables.

In SDID, the treatment effect is encapsulated in a single parameter τ and the estimates are displayed in Table 1. The average decline in RGDP is 6.8% while the that in RGDI is 9.4%. This agrees with the SC and ASC results that RGDI is impacted to a greater extent than RGDP, as shown by the magnitudes of the cumulative drops by 2023Q3 which is the end of the treated period. However, both estimates are not statistically significant at 10% level, due to the large standard error. This might be because the true treatment effect is dynamic and heterogeous in time, while the SDID estimator summarizes the dynamic treatment effect in a single estimator. The dynamic nature of the treatment effect on RGDP and RGDI could stem from the fact that Brexit puts the UK on a permanently lower growth trajectory, hence the gaps between the UK and the synthetic UK i.e. the treatment effect steadily grow wider over time. As such, SC and ASC might be more appropriate than SDID in the setting of this study.

6 Discussion

6.1 Plausibility of using SC

In order to obtain valid inference from the original SC methods, there are several necessary conditions. Firstly, the treatment effect has to be "large", else it might be indistinguishable from estimation noise. Based on previous literature, the effects of the Brexit vote are likely to be very large for the UK. Secondly, the control countries need to satisfy the stable unit treatment values (SUTVA) assumption. This point is more contentious than the other points because economic theories suggest Brexit affects both the UK and its trading partners. However, based on financial news reports and previous work, the EU countries most affected by the Brexit uncertainty are likely to be France, Germany, Ireland, Netherlands, Luxembourg, due to their close financial and trade ties to the UK. Looking at my SC weights, the highest weighted countries are the US, Denmark, Hungary, Finland, Greece, Ireland and Italy. The effects of Brexit on all these countries are likely to be extremely small except Ireland, which might have benefited from the diversion of international trade and capital flow from the UK. This might suggest that our negative estimates of the Brexit vote is an overestimate of the true negative effect. However, given that Ireland only has a weight of less than 0.05 in the control units, the bias is likely to be extremely small. Moreover, the effect of Brexit acts in both ways for EU countries. Some might benefit from financial capital leaving the UK, while others might suffer from the trade and labor movement frictions with the UK. Therefore, the combined effects of the Brexit vote on the RGDP and RGDI of countries like Hungary, Greece and Italy might be insignificant, as suggested by previous work. The violation of SUTVA is likely to be very mild.

Thirdly, SC requires no anticipation. This is satisfied as I define treatment to happen in 2016Q3 which is a week after the Brexit vote, and as aforementioned, the decision to leave the EU largely came as a surprise. Fourthly, SC imposes the convex hull condition, which is shown to be satisfied from our ASC results since negative weights are all extremely close to zero. Lastly, the length of the pre-intervention period has to be long enough. I use quarterly data starting from 2007Q1. As treatment is defined to be on 2016Q3, we can be reassured that the pre-intervention period offer us a reliable estimate of SC weights.

The reason why SC and ASC yield similar estimates could be explained by the fact that these conditions for using SC are likely to be satisfied. As the pre-treatment fit is good, the penalty term in ASC is close to zero and hence ASC is close to SC.

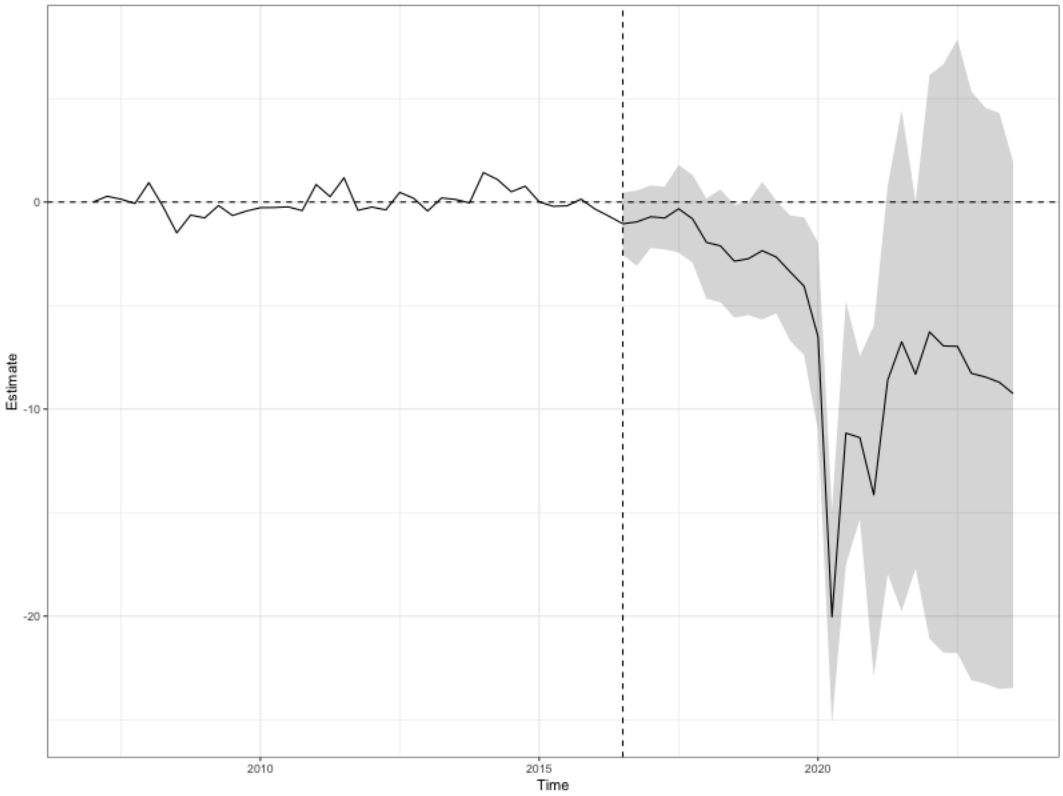

Figure 13: Gaps in RGDP per capita residuals using ASC

6.2 Robustness checks

I have presented three different forms of synthetic control methods that arrive at similar conclusions. As further robustness checks, I fit ASC on the residuals of the outcome variables after partialing out all the covariates, and the results are presented in Figures 13 and 14.

Using residuals of GDP and GDI, the estimated gaps look similar to using outcome variables and covariates directly, as in Figures 8 and 9. However, the 95% confidence interval is wider, perhaps owing to the estimation errors coming from the first stage residualization.

In addition, for robustness check, I remove one country from the set of control countries at a time and run ASC using the smaller dataset. Results change little from removing any one country from the control group, implying that the conclusions of this study do not depend heavily on any one country being in the control group.

Lastly, for future studies, I will experiment with using only developing countries that are geographically faraway from the UK as control units, because they are highly likely to be unaffected by the Brexit uncertainty. The point of doing this is to be assured that the SUTVA assumption is satisfied. However, there are two

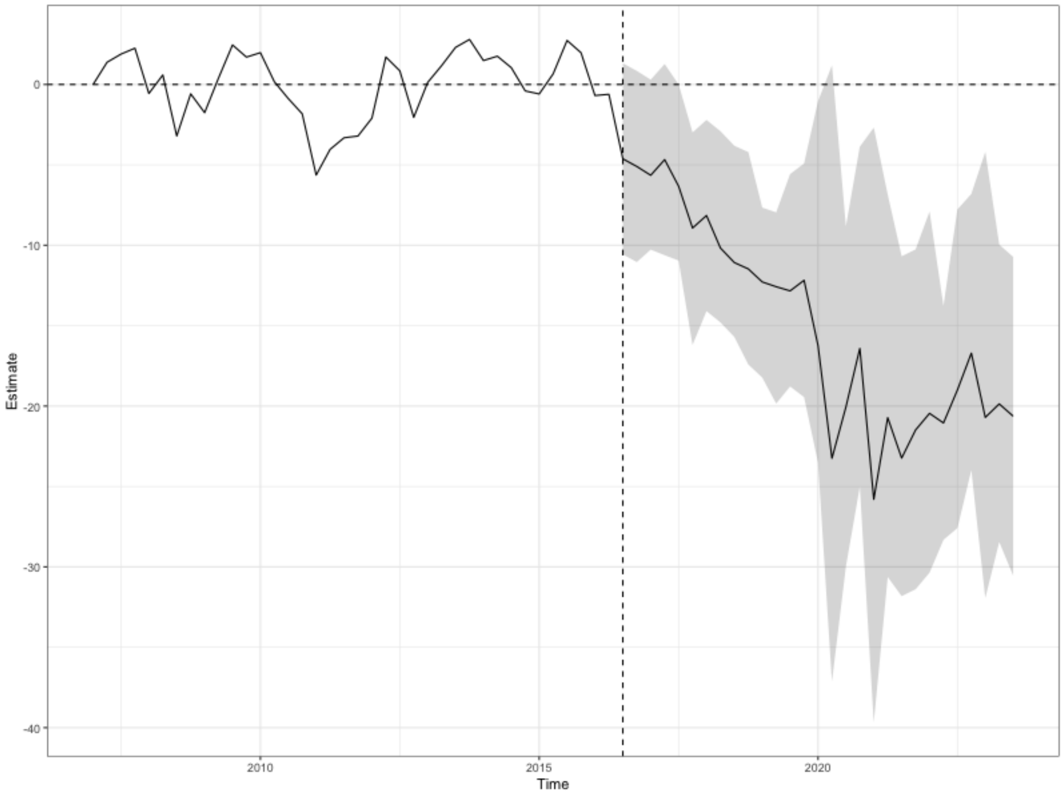

Figure 14: Gaps in RGDI per capita residuals using ASC

challenges to this future study. One is that economic data in developing countries might be missing or contain greater measurement error, undermining the feasibility of using those countries. Another is that the UK will surely lie outside the convex hull of the developing countries, rending extrapolation unavoidable and hence ASC must be employed and negative weights will surely be present. This might not form a direct comparison to my current design of using developed countries, but it is worth trying for robustness.

6.3 Comparison of estimators

The following table summarizes the results from SC, ASC and DID for both RGDP and RGDI. Note that the values in the bracket under the ASC columns are the 95% confidence intervals. The SC column has no standard error or confidence interval estimate because inference is done using placebo studies. SDID only has one estimate because it assumes a static treatment effect.

Estimate	(GDP) SC	(GDP) ASC	(GDP) SDID	(GDI) SC	(GDI) ASC	(GDI) SDID
τ			-6.781			-9.366
			(5.892)			(6.581)
2017Q2	-1.432	-1.174**		-5.497	-2.134	
		(-2.18, 0.00)			(-7.23, 0.61)	
2018Q2	-3.041	-2.793***		-11.903	-6.437***	
		(-3.80, -1.79)			(-11.86, -1.02)	
2019Q2	-4.323	-4.093***		-14.858	-7.883***	
		(-5.10, -3.09)			(-11.33, -2.46)	
2020Q2	-18.598	-17.739***		-15.707	-15.699***	
		(-18.74, -16.07)			(-22.11, -6.34)	
2021Q2	-10.001	-9.204***		-20.116	-14.501***	
		(-10.88, -6.87)			(-20.91, -7.11)	
2022Q2	-10.497	-9.635***		-23.199	-16.650***	
		(-11.31, -7.30)			(-21.09, -8.27)	
2023Q2	-11.360	-10.740***		-22.515	-16.735***	
		(-12.41, -8.40)			(-22.16, -6.39)	

Comparing the SC column to the ASC column, we see that SC estimates are larger than ASC estimates in magnitudes, although the control country weights are largely similar between them. This can be attributed to the additional penalty term in ASC which adjusts counterfactual estimates based on errors in pre-treatment fits. For RGDP, the difference between SC and ASC is less than 1 percentage point, while for RGDI, the difference is much larger at around 6 percentage points post pandemic. In my opinion, ASC might be slightly more reliable than SC since the former assigns a weight close to zero to Ireland, on which the Brexit vote has spillover effects. As such, the ASC is more likely to have satisfied SUTVA. The ASC estimate is close to Born et al. (2019) 's estimate of 1.7-2.5% decrease in GDP by the end of 2018. Moreover, ASC offers the highly interpretable and convincing confidence interval from conformal inference.

The SDID estimates appear to be some form of weighted average of the dynamic treatment effects. Estimates for both RGDP and RGDI are statistically insignificant, perhaps because static treatment effect is a mis-specification. Nevertheless, the sign of the treatment effect is correct. For future work, I will explore a dynamic version of SDID and compare it to SC results.

7 Conclusion

This paper examines the economic impact of the Brexit referendum on RGDP and RGDI using various methods of synthetic control. Results of these methods point to the same conclusion that both RGDP and RGDI in the UK are much lower than in the counterfactual world in which the UK voted to remain in the EU. This paper contributes to the literature by demonstrating the applications of various synthetic control methods to a highly relevant event study setting, and by comparing the performances of the original SC to the more advanced ASC and SDID. Additionally, it confirms the previous work's findings, which use economic modelling, that Brexit has a largely negative impact on the UK's economy through a data-driven approach, and extends the studies on short-term effects to look at a medium-term horizon given more recent data.

Note that the "leave" vote exceeded the 50% margin by a tiny 1.89%. According to news reports and later surveys, many Britons believed that people would not rationally vote the leave the EU, and hence did not cast their vote despite wanting to remain in the EU. Moreover, later surveys have estimated that more than 50% of Britons actually would have voted for "remain". Hence, the Brexit referendum might not have reflected the opinion of the majority of Britons, but rather was an unfortunate coincidence that have changed the fate of a nation and altered the lives of millions of people.

Nevertheless, the Brexit referendum kicked started a four year period of inexorable exit process. Although the actual Brexit would only take place in 2020 and many new regulations were postponed to 2021 due to the pandemic, the UK began to suffer from the adverse impact of Brexit way before that due to the expectations of investors and businesses that the UK will not do as well after Brexit. In some way, this is a self-fulfilling prophecy.

For future studies, it might be worthwhile to look into the impact of Brexit referendum on other more fundamental economic indicators such as foreign direct investment, domestic business investment, trade and financial flow to investigate the mechanisms through which Brexit affects the UK economy. RGDP and RGDI offer an aggregate and high level overview of the performance of the UK economy. It would be interesting to look into the breakdowns of these aggregate variables via synthetic control or other causal inference methods.

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