University of Warwick

An Analysis of Post-Brexit U.K. Services Trade using Synthetic Control

Author
J.R. Knecht†
1615860

Supervisor
Dr. Christian Soegaard

Abstract

This paper asses the impact of the Brexit announcement on U.K. services trade, using the Synthetic Control Method (SCM). This methodology allows for a structural and data-lead approach to generate a synthetic UK counterfactual. Our analysis suggests that total services trade is 4.96% below what it would have been if Britain had not voted to leave the European Union. Further analysis breaks down the timing of this effect, suggesting that the sharpest decline in UK trade relative to its synthetic counterfactual occurred in the first quarters after the referendum. In addition, this analysis outlines an anticipatory effect, in that a slight deviation of actual from synthetic trade is observed up to two quarters prior to the referendum announcement. These results are robust to a series of placebo tests in time and space.

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1 Introduction

On the 23^{rd} of June 2016, Britain voted to leave the European Union in a narrowly won referendum. This decision has the potential to drastically alter the U.K.-EU relationship, with wide-ranging implication for large sectors of the economy. In particular, although dependent on the negotiations currently underway, the referendum may lead to profound changes in Britain's ability to obtain frictionless access to its largest trading partner. It must be noted that, at the time of writing, there have been no legal changes to the U.K.'s trade relation with the EU. As such, the effects isolated in this paper are driven by expectations about future policy characteristics. Though speculations are wide ranging, the central question remains; exactly how damaging, or possibly profitable, has and will Brexit be for the U.K.? Notably, one can observe wildly different answers depending on the source, making it exceedingly challenging to form a robust picture of the future.

In direct response to this jungle of opinions and results, this analysis proposes a completely different, and data-driven, approach to answering this question. Rather than constructing possible forecasts for the U.K.'s economic costs, we focus on a direct numeric estimation of the effect Brexit has already had on U.K. trade in services.

The methodology employed in this paper allows for levels of exogeniety otherwise unobtainable in forecasting, eliminating the need for a possibly weak set of assumptions. Notably, this analysis will build on recent work[1] done by Born et al. [2017] and extend the realm of Brexit analysis into services trade. As these form approximately 40%[2] of the U.K.'s economic ties with the EU, this is certainly a crucial analysis to conduct. To isolate and numerically evaluate the impact of Brexit on U.K. services trade, this paper employs the Synthetic Control Model (SCM). This is a fairly recent addition to the field of econometric policy analysis, first developed by Abadie [2012]. The SCM is uniquely promising in the field of econometric research, allowing for an entirely data driven approach to counterfactual analysis. We provide a detailed outline of the SCM optimization in section 2.

Turning to the literature surrounding Brexit effects on trade, we are unable to directly compare the results obtained in this analysis. Perhaps most

[1] We expand on this research in section 2.1
[2] Rhodes [2018]

closely related in the context of this analysis is recent work done by Crowley et al. [2018], outlining a clear reduction in international trade participation by British firms following the Brexit referendum. The SCM will allow for the evaluation of timing effects to support these findings. Moreover, Handley and Limão [2017] illustrate the structural importance of expectations about policy stability in fostering healthy trade in goods and services. As such, research by Swati Dhingra and Reenen [2016], suggesting a significant reduction in trade stability following the referendum, outlines the potentially detrimental trade effects of Brexit. This analysis will add to the existing literature by presenting a methodology which allows not just for the isolation of a policy shock, but also for an evaluation of the timing of these effect[3].

As seen in section 3, the SCM specification indicates a -4.94% reduction in U.K. services trade volume following the Brexit announcement. Intriguingly, this analysis suggests anticipatory deviations starting from the period in which the referendum was announced. As more recent data becomes available, we believe that a substantial negative effect on U.K. services trade will be observed.

2 Methodology

This section provides a detailed outline of the methodology employed in this analysis.

2.1 Methodology Overview

The synthetic control model presents a relatively recent addition to the field of econometric analysis. It was first implemented by Abadie and Gardeazabal [2001] in their analysis of the impact terrorism had on economic growth in the Basque country. This methodology has since been applied to study the economic impact of various large-scale isolated policy shocks, such as changing Tobacco legislation in California by Abadie [2012], or more recent efforts to quantify the economic benefits of membership in the EU, in Campos et al. [2014]. Almost paradoxically, in studying the relative gains from EU membership, Campos et al. [2014] outline the strikingly large positive impact on the U.K.'s economy after joining in 1973.

[3] These aspects of the SCM will become clear in the discussion seen in section 3

For purposes of this analysis, the methodology employed by Born et al. [2017] is most closely related. They present an application of the SCM to Brexit, establishing a real-time *Brexit-cost-tracker*. Their analysis estimates the economic cost of Brexit at 1.3% of U.K. GDP, projecting a 60 billion pound growth cutback by the end of 2018. This paper extends the field of analysis by focusing on a detailed description of the referendums impact on services trade. As the ONS outline, these form up to 40% of the total value of trade between the U.K. and European Union.

One promising aspect of utilizing the synthetic control model for purposes of counterfactual macroeconomic analysis is the data driven and largely exogenous selection process. But how exactly does the SCM work to generate a synthetic U.K. estimate?

The central idea behind the SCM is to use a matching algorithm to recreate a variable of interest, before treatment, as a weighted-linear-combination of non-treated controls. The weights obtained for each non-treated control unit are then used to generate the counterfactual. Under an adoption of the parallel trends assumption to the SCM[4], given that the pre-intervention fit is close enough, the synthetic counterfactual illustrates the variable of interest *'as if treatment had not occurred'*. Possible treatment effects will manifest themselves as a divergence between the SCM and the real time-series.

In this analysis, the treated unit is U.K. services trade, with Brexit specified as the treatment. Utilizing a set of 26 OECD countries to recreate this time-series, the divergence of the SCM and U.K. series post-Brexit clearly indicates the negative policy effects on U.K. services trade. Before discussing these results in detail, this analysis first develop the SCM methodology with more rigour.

2.2 The Synthetic Control Model

Adopting the notation of both Born et al. [2017] and Abadie [2012], consider a set of $J+1$ countries. Note that the first country will represent the treated unit, in this case the U.K.. Countries $\{2, ...J+1\}$ constitute the *donor pool*, denoted by J. This is the set of countries used to generate the synthetic counterfactual. Selection of these is non-trivial, as the aim should be to choose countries which could act as possible counterfactuals for the

[4]The technical aspects were developed in Abadie [2012]

U.K.. This analysis utilizes a set of 26 OECD economies. All variables are observed over a period T, in which T_0 denotes the treatment period. For purposes of this analysis T_0 is 2016 Q2. The period T is split such that $T < T_0$ denotes the matching-period and $T \geq T_0$ allows for inference of treatment effect between the SCM counterfactual and the real time-series.

Before discussing the method by which the SCM works to generate a counterfactual, it is important to develop this idea further. The necessary mathematical framework for the SCM counterfactual is outlined below. Let D_{it} be a dummy variable indicating treatment of unit i at time t, and Y_{1t}^N the treated series without treatment. Thus, the observed series Y_{it} is given by:

$$Y_{it} = Y_{it}^N + \alpha_{it} D_{it} \tag{1}$$

In the donors pool $i = 1$ at $t \geq T_0$ experiences treatment, such that D_{it} is as seen below.

$$D_{ij} = \begin{cases} 1 & \text{if i=1 \& } t \geq T_0 \\ 0 & otherwise \end{cases}$$

The SCM provides a data-driven approach to estimating $(\alpha_{1T_0}, \alpha_{1T_{0+1}}, \ldots, \alpha_{1T})$. Note that α_{1t} is the desired treatment effect on the treated at time t*: $\alpha_{1t} = Y_{1t^*} - Y_{1t^*}^N$. As Y_{1t}^N is not observed in the data the SCM provides means by which to estimate this as the *synthetic counterfactual*. Following Abadie [2012][5]. This analysis considers the following factor model for the process of Y_{1t}^N:

$$Y_{it}^N = \delta_t + \boldsymbol{\theta_t Z_i} + \boldsymbol{\lambda_t \mu_i} + \epsilon_{it} \tag{2}$$

Here $\boldsymbol{\theta_t}$ is a $(1 \times r)$ vector of parameters for the $(r \times 1)$ vector $\boldsymbol{Z_i}$ of observed covariates. Moreover, $\boldsymbol{\lambda_t}$ is a $(1 \times F)$ vector of unobserved common factors corresponding to the $(F \times 1)$ vector of factor loadings $\boldsymbol{\mu_i}$. δ_t and ϵ_{it} represent unobserved common factors and the error-process respectively.

Returning to the donor pool, consider a $(J \times 1)$ vector of weights $\boldsymbol{W} = (\omega_2, ..., \omega_{J+1})^\top$ for which the following conditions must hold: $\sum_{j=2}^{J+1} \omega_j = 1$ and $\omega_j \geq 0 \; \forall j \in J$. Each element ω_j in $\boldsymbol{W}$ represents the weight attached to the series from donor country j. Working with the factor model this yields:

$$\sum_{j=2}^{J+1} \omega_j Y_{jt} = \delta_t + \boldsymbol{\theta_t} \sum_{j=2}^{J+1} \omega_j \boldsymbol{Z_j} + \boldsymbol{\lambda_t} \sum_{j=2}^{J+1} \boldsymbol{\mu_i} + \sum_{j=2}^{J+1} \omega_j \epsilon_{it} \tag{3}$$

[5]It is crucial to note that in most of the literature this is treated as a linear model with a zero-intercept. The same minimization hold and results derived are identical

Given that there exists an ideal vector of weights $(\omega_2^*, ..., \omega_{J+1}^*)^\top$, these satisfy;

$$\sum_{j=2}^{J+1} \omega_j^* Y_{j1} = Y_{11}, \ldots, \sum_{j=2}^{J+1} \omega_j^* Y_{jT_0} = Y_{1T_0}, \sum_{j=2}^{J+1} \omega_j^* \boldsymbol{Z_j} = \boldsymbol{Z_1} \tag{4}$$

These weights, under the outlined conditions, provide a consistent and accurate counterfactual allowing us to isolate the treatment effect as;

$$\widehat{\alpha_{1t}} = Y_{1t} - \sum_{j=2}^{J+1} \omega_j^* Y_{jt} \tag{5}$$

This gets to the core of what the SCM is able to achieve, as it provides a data-driven route to obtaining credible estimates for Y_{1t}^N. Below the implementation of this optimization is outlined in more detail.

As previously mentioned, the data obtained for the SCM is split into two periods, used for matching and inference. This analysis will now develop the methodology by which the SCM generates a vector of donor weights using the data in $T < T_0$. Again, adopting the notation of Abadie and Gardeazabal [2001] as well as Abadie [2012], consider $\boldsymbol{X_1}$ as a $(k \times 1)$ vector of pre-treatment outcomes for the treated unit, indicated by the subscript. Now also consider $\boldsymbol{X_0}$, a $(k \times J)$ matrix of outcomes for the J country donor-pool defined on $T < T_0$. These are the pre-treatment control outcomes, and the SCM will generate a $(J \times 1)$ vector $\boldsymbol{W}$ of weights such that $\boldsymbol{X_0}$ most closely matches $\boldsymbol{X_1}$ over the pre-treatment period. As a measure of distance, i.e. $||\boldsymbol{X_1} - \boldsymbol{X_0}\boldsymbol{W}||$, we follow Abadie [2012] and choose:

$$||\boldsymbol{X_1} - \boldsymbol{X_0}\boldsymbol{W}||^6 = \sqrt{(\boldsymbol{X_1} - \boldsymbol{X_0}\boldsymbol{W})^\top \boldsymbol{V} (\boldsymbol{X_1} - \boldsymbol{X_0}\boldsymbol{W})} \tag{6}$$

Thus, in its implementation the SCM estimates $\widehat{\boldsymbol{W}}$ such that:

$$\widehat{\boldsymbol{W}} \longrightarrow \arg\min_{\omega_j \in \boldsymbol{W}} ||\boldsymbol{X_1} - \boldsymbol{X_0}\widehat{\boldsymbol{W}}|| \tag{7}$$

There are multiple elements in this minimization which are important to consider. First, Abadie and Gardeazabal [2001] outline the necessary restrictions on ω_j for consistent solutions. These imply that $\omega_j \geq 0 \ \forall j \in$

[6]This is an adaptation of the standard root mean squared predictive error. Born et al. [2017] use the MSPE though this does not change the optimization procedure

$\{2, J+1\}$ and crucially $\sum_{j=2}^{J+1} \omega_j = 1$. These conditions ensure that the estimates obtained for the counterfactual Y_{1t}^N are contained within the convex-hull of the donor-pool, i.e. the SCM generates a convex-linear-combination of donor-pool variables to generate Y_{1t}^N. This is crucial for consistency, as results will be interpolated and not extrapolated from the data obtained in the pre-treatment period. The second consideration in (6) is $\boldsymbol{V}$. This is a symmetric $(k \times k)$ positive-semidefinite matrix. As it appears in the solution to $\widehat{\boldsymbol{W}}$, its choice is not trivial. In (6), $\boldsymbol{V}$ represents the relative importance given to information obtained in $\boldsymbol{X_0}$ and $\boldsymbol{X_1}$. Following both Born et al. [2017] and Abadie [2012], this analysis will implement $\boldsymbol{V}$ as a diagonal matrix with non-negative elements in which weights are higher for donors with the largest predictive power, i.e. proportionally higher matching variance for the variable of interest Y_{1t} . These elements are obtained via the methodology developed in Abadie [2012], utilizing a data-driven cross-validation approach. Having obtained the set of optimal weights $\widehat{\boldsymbol{W}}$, section 2.3 will now focus on their implementation for inference of treatment effects.

2.3 Synthetic Control Inference and Assumptions

The minimization set out in (7) can also be interpreted as a data-driven matching algorithm which generate a time-series from a linear combination of donor-pool characteristics, such that the difference between this series and Y_{1t} is minimized. In other words, over the pre-intervention period the SCM tries to generate a curve which fits as close as possible to the U.K. trade in services from characteristics of the set of donor countries.

Once these weights have been obtained, the next step is to consider the actual method of inference which the SCM allows for. It follows from the derivation set out in 2.2 that one generates the counterfactual as:

$$\widehat{Y_{1t}^N} = \sum_{j=2}^{J+1} \omega_j Y_{jt} \forall t \in \{T_0, T\} \tag{8}$$

This constructed counterfactual then allows for the identification of the *treatment effect on the treated* as: $\widehat{\alpha_{1t}} = Y_{1t} - \widehat{Y_{1t}^N}\ \forall t \in \{T_0, T\}$. This effect manifests itself quite nicely in data representations as a possible divergence of the SCM and treated-unit. This will become apparent when one looks at the results outlined in section 3.

Before discussing the possibility of robustness analysis in the SCM, it is crucial to consider the identification assumptions underlying this ability to infer counterfactual effects. The main assumption is that there are no immediate spillover effects from the treated unit to the donor-pool. This is what makes the SCM so applicable to policy analysis, as these are usually localized and country-specific effects. This assumption is necessary for the isolation of the treatment effect $\widehat{\alpha_{1t}}$ as one assumes that the SCM can generate a counterfactual from units which are unaffected by the treatment. Robustness analysis using dominant-donor exclusion will aid in testing whether this assumption holds. The second implicit assumption, outlined in Cavallo et al. [2013], is that there are no secondary shocks which impact the entire donor-pool during the post-treatment period $T > T_0$. Given that these assumptions are met, the SCM will produce consistent results for a counterfactual.

2.4 Synthetic Control Robustness

Multiple methods for testing the significance of results obtained through the SCM have been developed over the past few years. The SCM is implemented outside the standard regression based framework. Thus, all forms of distribution based testing for significance are not applicable. To circumvent this problem, Abadie [2012] proposes conducting a number of placebo tests. These are analogous to permutation-tests, often performed in medical-statistics, and entail the variation of either treatment period or assignment dummy. This analysis also adopts methodology proposed in Abadie [2012] and Born et al. [2017] and presents a distribution of RMSPE ratios. These placebo tests can be seen in section 4.

2.5 Data

This section will briefly outline the structure of the data used for this estimation. This SCM implementation utilize data from the OECD, specifying trade in services results for 26 countries[7]. The set of covariates includes GDP per capita, goods and services exports and imports, CPI over all items, USD exchange rate with respect to the partner country, and FDI. These are all observed quarterly from 2009 Q1 to 2018 Q2. The series is truncated to start in 2009 Q1 as this increases pre-treatment fit, leaving out

[7] A full summary table can be found in Appendix A

changing growth paths stemming from the 2008 financial crisis. Eliminating these spillover effects appears crucial for maximizing pre-treatment fit. Total services trade is constructed as the quarterly sum of services imports and exports. This reduces the intrinsic volatility of the series and optimizes pre-treatment fit further.

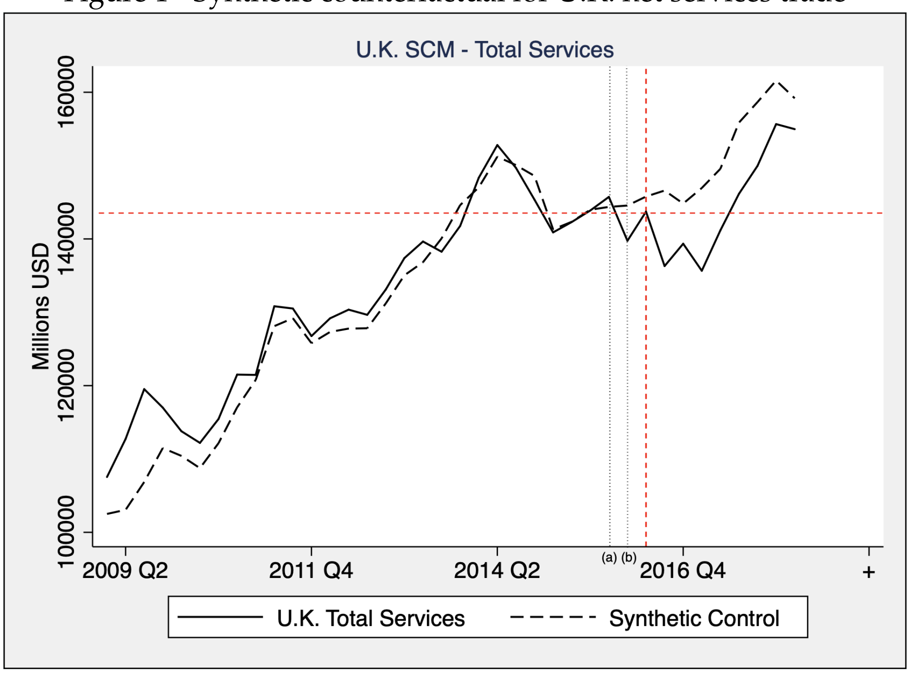
3 Results and Discussion

Having constructed the series of total U.K. services trade-volume, running from 2009 Q1 to 2018 Q2, we now turn to an analysis of the SCM results.

3.1 SCM on U.K. services trade

The computed SCM counterfactual can be seen in figure 1. One can clearly observe the desired pre-intervention fit and treatment-divergence structure. Before discussing the divergence in more detail, it is crucial to first turn to an analysis of the pre-intervention fit.

Figure 1 - Synthetic counterfactual for U.K. net services trade



Below, the distribution of country specific weights is provided, denoted by ω_j in section 2. Having driven most country weights to zero, as the

SCM conducts data-driven variable selection. This SCM indicates non-zero significance for the donors France, Luxembourg, Turkey, and the United States.

Table 1: SCM Weights

Donor country	Weight $\{\omega_j\}$
FRA	0.569
LUX	0.100
TUR	0.117
USA	0.215

Considering the results in figure 1, the SCM observe an initial deviation from the U.K. series in the period following 2009 Q1. This is the manifestation of spill-over effects from the financial crisis. Given the significant portion of U.K. services trade accounted for by the financial sector, the SCM struggles to match the severity of the 2007/8 financial crisis for the U.K. series. Financial services constitute one of the largest sectors of the U.K. economy, employing 1.1 million people[8], or 3.2% of the active labour force. However, one can observe very close fit of the SCM and U.K. series as these approach the treatment period. As outlined in Abadie [2012], for consistent results one requires the synthetic and real series to converge the closer these run to the treatment period. As seen in fig. 1, one can clearly observe this structure as the SCM is able to match the U.K. series increasingly closely towards 2016 Q2[9]. Notably this series observes remarkably close fit in the period following 2014, capturing the initial growth and following decline in services trade volume.

In analysing the post-Brexit deviation, the SCM suggests an average negative Brexit effect of up to -4.96% over the period from 2016 Q1 to 2018 Q2. Under the SCM assumption, outline in section 2, these results imply a significant increase in total services trade volume had Brexit not occurred. Deviations over individual post-treatment periods can be seen in table 2 below.

[8]Following Rhodes [2018]

[9]Following Abadie [2012] we specify an SCM which increases the relative importance of RMSPE weights as treatment approaches

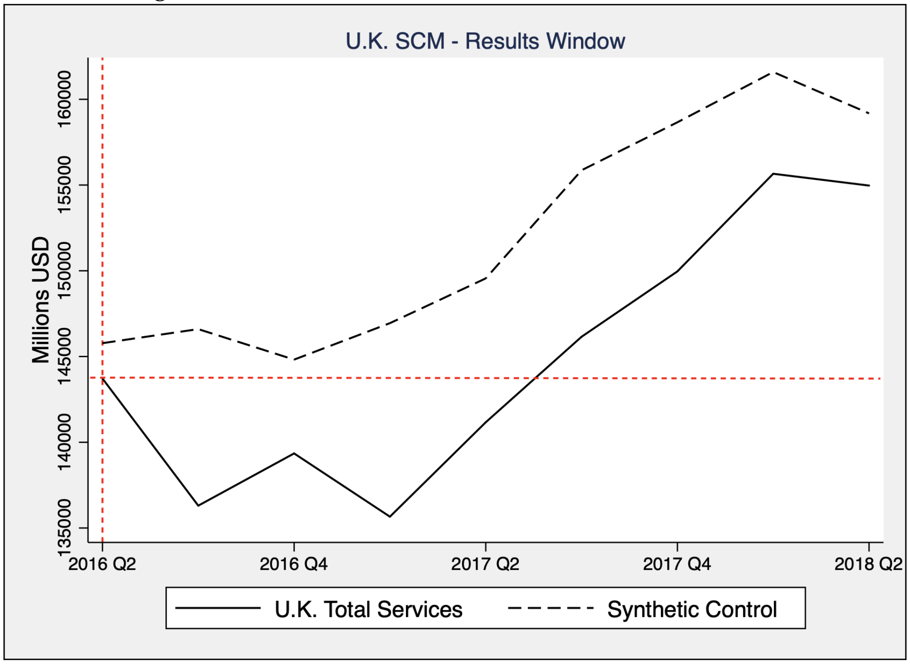
Table 2: Full Synthetic Control Results

Treatment Period	Treated Series Y_{1t}	SCM Estimate Y_{1t}^N	Deviation $\Delta(\%)$
2016 Q1	139750.56	144557.11	-3.44
2016 Q2	143717.19	145779.6	-1.44
2016 Q3	136303.59	146597.74	-7.55
2016 Q4	139349.67	144821	-3.93
2017 Q1	135660.73	146947.16	-8.32
2017 Q2	141165.7	149557.19	-5.94
2017 Q3	146152.53	155863.41	-6.64
2017 Q4	149966.23	158660.71	-5.80
2018 Q1	155659.72	161592.11	-3.81
2018 Q2	154969.44	159180.42	-2.72
Period Avr.	144269.536	151355.645	-4.96
Diff-in-Diff w. *Country-FE*			-1.06^{**}

$p < 0.1^{*} p < 0.05^{**} p < 0.01^{***}$

As seen in table 2, one can observe a significant deviation, i.e. Brexit effect, following 2016 Q1. This initial deviation, before the announcement of the referendum result, outlines the anticipatory nature of the Brexit effect. Seen in figure 1 as (b), the U.K.-SCM deviation originates from the announcement of the referendum and widens throughout the campaign process. It appears that the introduction of uncertainty about the U.K.'s future trade relations with the EU had immediate negative effects on total trade, amounting to a –3.44% and –1.44% deviation respectively. These results are clearly in-line with those outlined in cite Crowley et al. [2018] and Born et al. [2017]. Though the severity of these observed deviations varies over the treatment window, seen in figure 2 below, these do illustrate a significant and persistent negative level-difference.

Figure 2 - U.K. Services-trade SCM results window



Over the entirety of this treatment window, i.e. the period over which treatment has occurred and the results of the Brexit referendum had entered the markets expectations, we observe a lack of convergence. This suggests the possibly long-lasting negative impacts Brexit has had on the U.K.'s services-trade.

Seen in table 2, a difference-in-difference estimation with country fixed-effects suggests a statistically significant negative Brexit-effect, amounting to a -1.06% deviation[10]. These results underline those observed in the SCM implementation as they mirror similar dynamics. It is important to note here, following recent technical work conducted by Doudchenko and Imbens [2016] as well as Kinn [2018], that a diff-in-diff estimation can be written as a restricted SCM. Furthermore, as Doudchenko and Imbens [2016] suggest, the pre-intervention weight optimization allows the SCM, under certain conditions, to capture more nuance in the estimated parameter space for α_{t1}. We thus believe this diff-in-diff implementation works as a good indication of the robustness of our SCM results. As is clearly visible in fig. 1 and fig. 2, the specified SCM isolated not just a Brexit-effect over all post-

[10]We provide a full specification and results table in Appendix A

treatment periods, but also illustrates timing dynamics. Thus, these results add another dimension of analysis, as these illustrate the severity and immediacy of the Brexit-shock effects on U.K. services trade. Though the negative impact Brexit has had on the U.K. economy is widely reported in literature such as Kierzenkowski et al. [2016] and Driffield [2016], this analysis highlights the short-run effects of such a significant structural shock. As U.K. services are constituted to large part of financial provisions, this may provide a possible channel for explaining the immediacy of observed deviations. Moreover, financial market volatility may well explain the severity of the observed shocks.

It is important to note that, though there is no direct comparison, the results outlined in this paper are fully in-line with SCM literature on Brexit, as Born et al. [2017] indicate a -1.3% GDP deviation. As services-trade forms a considerable constituent part of the GDP effect, we are very confident that the results outlined in this analysis follow similar dynamics to those observed in other research. Adding to the literature, this analysis is able to illustrate the immediacy of the Brexit effect. These results allow for an analysis of the timing of such policy shocks, and act as a clear message to policy makers. The uncertainty surrounding Brexit, driven by parliamentary gridlock and an apparent lack of common strategy, has had, and is having, a severe negative effect on one of the U.K.'s most crucial economic sectors.

We now consider a series of robustness checks to outline the confidence of the observed Brexit-effects discussed above.

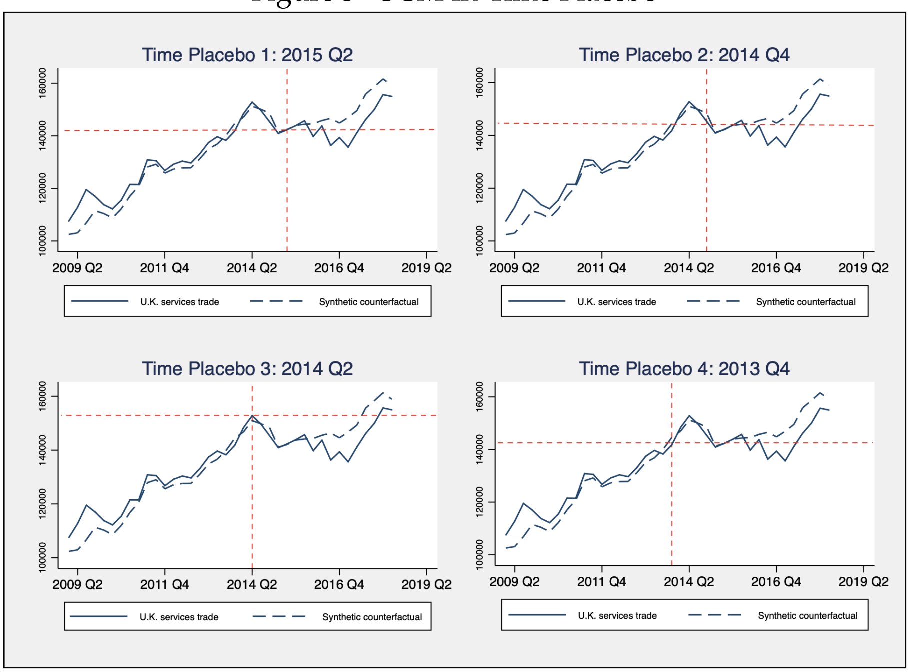
4 Robustness analysis of SCM results

As outlined in section 2, the SCM is implemented outside the standard regression based GLM framework. As such, one is unable to estimate a distribution of parameters, making distribution based testing impossible. Without the aid of $\mathcal{F}$ and t distributions, we turn to an application of permutation based testing developed in Abadie [2012]. This entails running SCM placebos in time and space, implying systematically varying either treatment period, T_0, or assignment dummy, D_{it}, respectively. Furthermore, expanding on methodology developed in Abadie et al. [2015], this analysis will present a form or exclusion based testing to inform the optimal in-space placebo. Lastly, section 4.4 considers the distribution of prior-to-posterior *RMSPE* of all in-space placebos. This will allow for an approximate likelihood estimate of the observed deviation structure in a random sample.

4.1 In-Time Placebo

Testing with a time-placebo implies re-running the matching algorithm with different inputs for the treatment period. One runs the SCM having specified the Brexit date as sometime prior to 2016. Under the assumptions necessary for robustness of the SCM results, one should not observe a difference in the divergence structure following the actual treatment. Running time-placebos by specifying Brexit in the second and fourth quarters of 2013,2014, and 2015, obtains remarkably robust results seen below:

Figure 3 - SCM In-Time Placebo



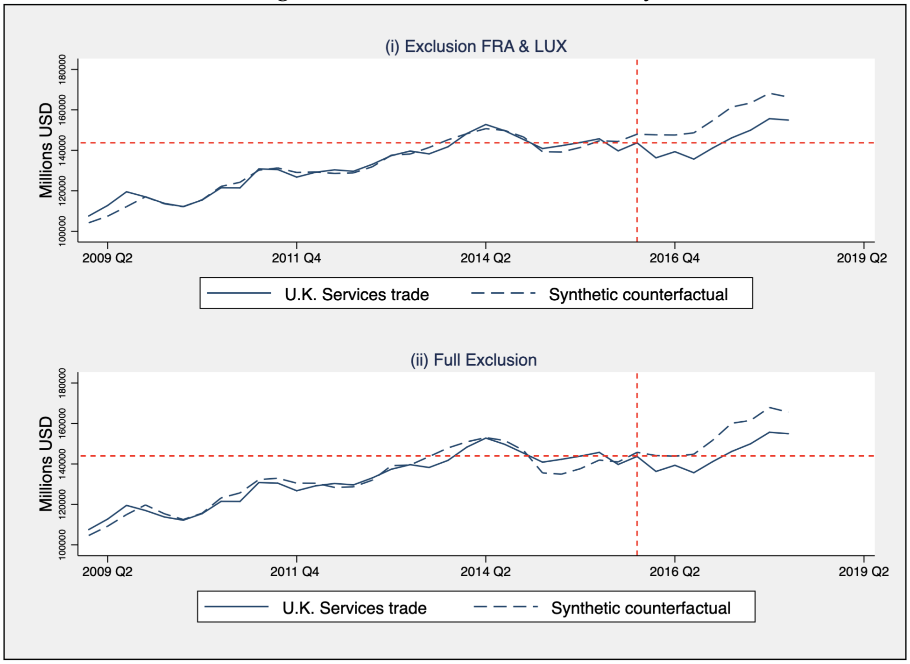
As can clearly be seen in *fig.3*, specifying the Brexit data prior to 2016 Q2 does not change the divergence observed in previous results. This indicates that this divergence is not driven by the selection of the period, but rather by structural effects isolated to 2016 Q1-Q2. By isolating the treatment period in this way, as was first outlined in Abadie [2012], we are able to confidently reject the hypothesis that the divergence observed was driven by anything other than effects localised to 2016 Q2. Furthermore, these results are especially robust given the accuracy with which the SCM is able to match the U.K.'s 2014 trend. Even after having specified a possible treatment prior to this growth-decay structure, we do not observe a significant deviation in placebo 3 or 4.

4.2 Dominant donor exclusion study

Having considered placebos in-time, this section presents an adaptation of methodology developed in Saia [2017] and Abadie et al. [2015], in their SCM study of German re-unification. Under the assumptions outlined in Abadie [2012] and expanded upon in Doudchenko and Imbens [2016], one requires the SCM results to be independent of the economic performance of individual donors. This limits the possibility for interpolation bias, i.e. results driven by donor-specific characteristics. Observing similar deviation structures with an SCM specified on the restricted sub-sample of the donor pool indicates a structural treatment effect not driven by possibly endogenous donor specific characteristics. It is also expected that the pre-intervention fit will be worsened by this restriction, as one is forcing the algorithm to use donors which were previously identified as non-optimal. These results can be observed in figure 4, having systematically excluded first France and Luxembourg[11], and then all donors with positive weight, i.e. $\omega_j > 0$.

[11]We exclude FRA as this donor received the highest weight, and LUX as this small economies significance in matching the U.K. is uncharacteristically large

Figure 4 - SCM Exclusion Study



As is clearly seen above, one can observe the same deviation structure as previously reported in fig. 1. As a comparison to the results presented in table 1, we summarize the average treatment-deviations over the period following 2016 Q2 below[12].

Table 3: Exclusion Deviations

SCM(1)	Exclusion 1	Full Exclusion
-4.96%	-7.45%	-5.72%

Notably, these are all within similar bounds and suggest that the observed SCM results are structural in nature and not driven by the underlying economic characteristics of individual donors. The problem of interpolation bias, i.e. donor specific characteristics changing the estimated effects, is thus limited in this analysis as the exclusion of dominant-donors does not change the observed deviation structure. Furthermore, the distribution of optimal weights in the restricted SCM is provided in table 4 below:

[12] A full exclusion table is provided in Appendix A

Table 4: Exclusion Weights (1)

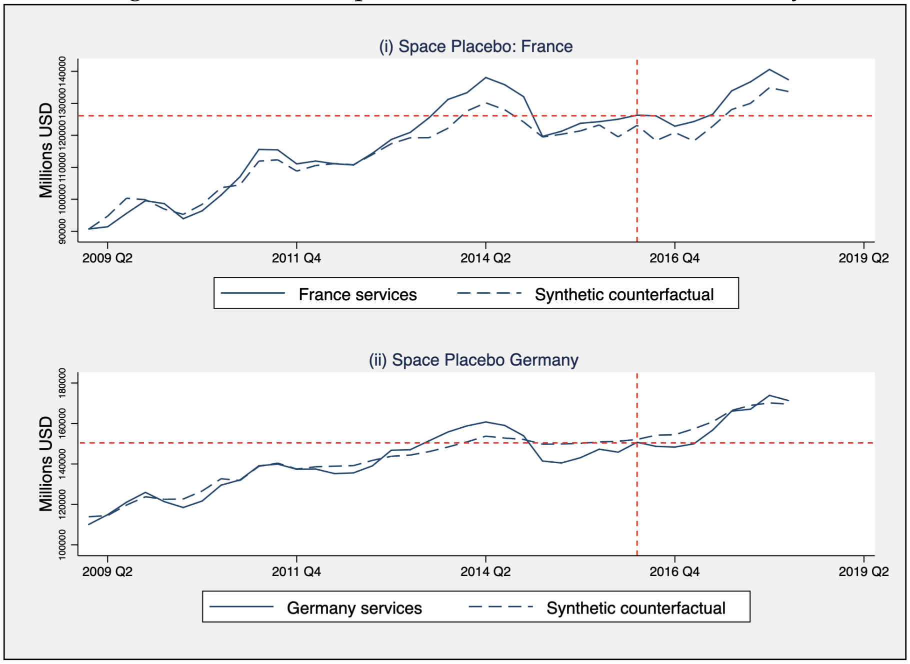
Donor country	Weight $\{\omega_j\}$ (i)	Weight $\{\omega_j\}$ (ii)
TUR	0.115	—
USA	0.125	—
GER	0.629	0.916
IRL	0.132	0.084

As can be seen above, the SCM algorithm identifies Germany (DEU) and Ireland (IRL) as optimal donors in the restricted pool. It is important to note that this is entirely exogenously chosen. These weight dynamics clearly follow economic intuition, as Germany and Ireland appear the closest economies to the U.K. in the restricted pool of donors.

4.3 In-Space Placebo

Having outlined the robustness of the observed results to interpolation-bias, this analysis now turns to the possibility of spill-over effects. These are the possible secondary shocks that Brexit has had on donors, and can present a limiting factor to the accuracy of SCM results. Though it is hardly possible to eliminate all spill-over effects, i.e. one is unable to obtain the ideal estimates presented as ω^*_{1t} seen in section 2, it is important to consider their impact on observed deviations. As such, this section considers a series of in-space placebos. These imply a systematic re-definition of the treatment dummy D_{jt} to countries in the donor pool outside the treatment group. For robust results, not driven by possibly large spill-over effects, one requires donors to have no significant over performance with respect to their respective SCM in the post-treatment period. A lack of deviation suggests that the series was relatively unaffected by Brexit, limiting spill over. We inform initial space-placebo selection by the weight dynamics in the exclusion trial and choose France and Germany as space-placebos. These can be seen below.

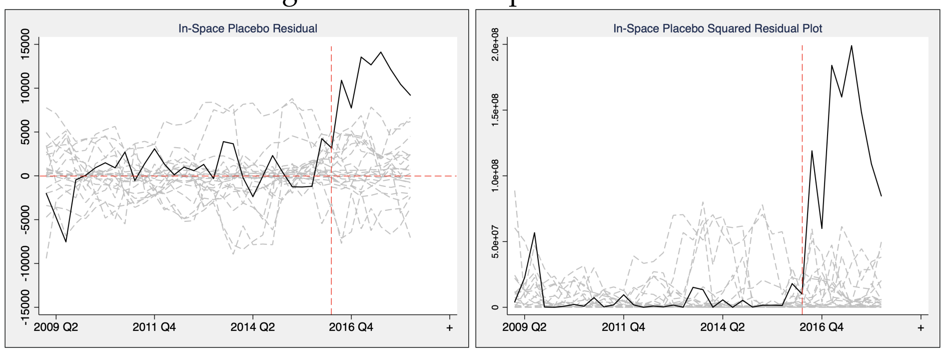
Figure 5 - SCM In-Space Placebo: France and Germany



Notably we do not observe a significant over-performance of the French series and almost none in the German placebo. These results suggest that, though there may be some spill-over, its magnitude is certainly limited. One does however want to consider all available in-space placebos to further investigate the magnitude of spill-over effects. Thus, we construct the series of SCM residuals and their square over the entire period for all in-space placebos.

Optimally, one requires the actual treated series to be in the bound of pre-intervention placebos and outside the bound of post-treatment placebos. This implies sufficient pre-intervention fit and a significant treatment effect. Below we provide these figures:

Figure 6 - SCM In-Space Residual



This summary of all in-space placebos very much highlights the significance of the observed results. The U.K. is well within the bound[13] of the placebos before the specified treatment. Following Brexit, the U.K. series shows the most significant deviation over the post-treatment period lending credibility to the limited magnitude of possible spill-over effects.

Having addressed treatment localisation in-time, the lack of significant interpolation bias through exclusion, and the limited scope of spill-over effects in-space, we now turn to an analysis of the distribution of RMSPE, first presented in Abadie [2012].

4.4 Root-Mean-Square-Predictive-Error Distribution

The analysis of prior-to-posterior RMSPE ratios for all in-space placebos provides a viable methodology to compute an approximate likelihood of the observed effect. In other words, by analysing the distribution of pre-treatment to post-treatment fit of in-space placebos, one can obtain an approximation of the likelihood of observing a similar SCM divergence structure in a fully random sample. As such, we compute the following value for all possible in-space placebos and present their distribution in fig.7.

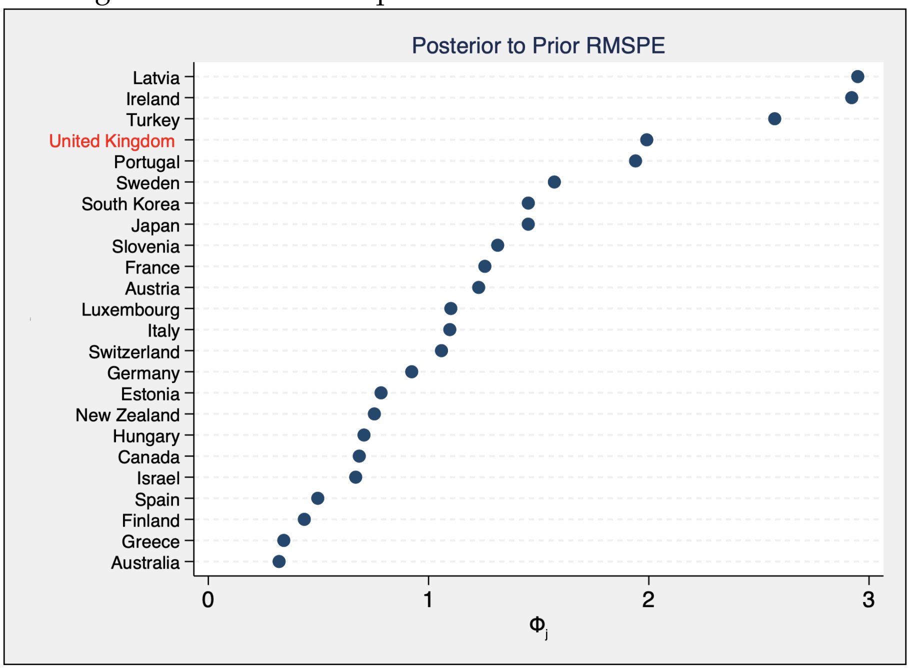
$$\phi_j = \sqrt{\frac{T_2^{-1}\sum_{T_0}^{T}[Y_{jt} - \sum_{j=2}^{J+1}\omega_{j1}Y_{jt}]^2}{T_1^{-1}\sum_{1}^{T_0-1}[Y_{jt} - \sum_{j=2}^{J+1}\omega_{j2}Y_{jt}]^2}} \tag{9}$$

As the RMSPE provides the measure of SCM fit, this ratio tends to increase for close pre-intervention matching followed by a significant post-treatment deviation. One desires the ratio $\phi_{U.K.}$ to appear towards the top

[13]Sometimes referred to as the support of the placebos

of the distribution. Note here that T_0 denotes the treatment period, T_2 and T_1 denote the number of post and pre-treatment periods respectively, where ω_{j2} and ω_{j1} denote the SCM weights for country j.

Figure 7 - Root-Mean-Squared-Predictive-Error Distribution



As seen above, $\phi_{U.K.}$ appears towards the top end of this distribution. Reducing the donor pool to those not previously indicated as optimal for th U.K. SCM in section 3, one arrives at an approximate random-sample likelihood of $Pr.(\phi_{j^*} > \phi_{U.K.}) = 2/19 \simeq 0.11$. The exclusion of donors previously selected for SCM estimation reduces the pool to a more 'random' sample of countries, as the SCM matching algorithm did not indicate similar structural components with respect to the U.K. series.

Considering the positive results from all possible in-space and in-time placebos, exclusion and RMSPE studies, this analysis suggests a very robust Brexit effect.

5 Concluding remarks

Throughout this analysis, the focus has been to present an implementation of the synthetic control model on post-Brexit U.K. services trade. Aided by a comprehensive robustness analysis, this paper presents a very significant Brexit effect on U.K. services trade, amounting to a -4.96% deviation. Utilizing the data-driven nature of the SCM procedure, this analysis is also able to add a timing dimension to the realm of Brexit-shock literature. We find that the observed deviation occurs much faster then previously thought, as contemporaneous policy impacts are felt immediately following the referendum. Moreover, the results outlined in section 3 indicate significant anticipatory effects emanating from the announcement of the referendum. All these indicate the significant role expectations about future trade stability and access to the EU market play in determining U.K. services trade. We suggest the volatility of the financial services market as a possible channel for these effects.

Lastly, as outlined in section 3.1, this analysis should act as a clear deterrent to policy makers. In times such as these, where polarising political rhetoric and partisan gridlock are running rampant in almost all developed western democracies, it is important to remember the real impacts such uncertainty can have on massive sectors of the economy. Though these might only manifest themselves as lines diverging on graphs, they present real challenges to real people.

Appendix A

2.5 Donor Pool

All donors are observed across all covariates and quarterly from 2009 Q1 to 2018 Q2. Data is taken from the OECD [1990-2018] comprehensive data-set of country specific economic indicators.

Table 5: SCM Donor-Pool Summary

Australia	AUS	Austria	AUT
Canada	CAN	Czech-Rep.	CHE
Germany	DEU	Spain	ESP
Estonia	EST	Finland	FIN
France	FRA	United-Kingdom	GBR
Greece	GRC	Hungary	HUN
Ireland	IRL	Iceland	ISL
Israel	ISR	Italy	ITA
Japan	JPN	South-Korea	KOR
Luxembourg	LUX	Latvia	LVA
New Zealand	NZL	Portugal	PRT
Slovenia	SVN	Sweden	SWE
Turkey	TUR	United-States	USA

3.1 Difference-in-Difference specification

As a form of preliminary robustness analysis, we include a diff-in-diff specification of the Brexit effect on the trade in services series. Below we report the full specification and the results table from which we calculate the percent deviation effect.

$$Y_{jt} = \alpha + \beta(T_j) + \delta(P_t) + \lambda(T_j \times P_t) + \phi_j + \eta_{jt} \tag{10}$$

In this specification T_j represents a dummy indicating treatment, i.e. Brexit occurring, P_t indicates the post-treatment period, i.e. $t \geq T_0$, and ϕ_j is a country-level fixed-effects parameter. Following this specification, λ indicates the diff-in-diff parameter and will be used to calculate the Brexit-effect.

On the next page we report the full results from this specification:

Table 6: Difference-in-Difference

	Net Services
GDP	-0.000
	(0.07)
Exports	0.127^{***}
	(11.40)
Imports	-0.091^{***}
	(9.44)
Service_Exp	1.578^{***}
	(99.63)
CPI	-30.43^{**}
	(2.38)
Exchange rate	-4.869
	(1.12)
P_t	891.864^{***}
	(4.99)
$T_j \times P_t$	$-1,540.833^{**}$
	(1.99)
_cons	$8,010.600^{**}$
	(6.45)
R^2	0.96
N	954

$p < 0.1^{*} p < 0.05^{**} p < 0.01^{***}$

We now utilize the implied Brexit-effect in $\lambda = -1,540.833^{**}$ to estimate a approx. average $\Delta(\%)$

Table 7: U.K. Treated Series 2016 Q2 - 2018 Q2

	Net Services
2016 Q2	135660.7
2016 Q3	136303.6
2016 Q4	139349.7
2017 Q1	141165.7
2017 Q2	143717.2
2017 Q3	146152.5
2017 Q4	149966.2
2018 Q1	154969.4
2018 Q2	155659.7
Avr. $\longrightarrow$ 144771.63	

From this we are able to calculate the implied $\Delta(\%)$ to compare to the SCM results.

$$\frac{144771.63 - (144771.63 - 1540.833)}{144771.63} \approx -0.0106 \tag{11}$$

This translates to the -1.06% deviation which we quote in section 3.1.

4.2 SCM Exclusion Tables

Below we report the full results table from the SCM exclusion study seen in section 4.2:

Table 8: Synthetic Control Exclusion Study

Treatment Period	SCM(1) $\Delta(\%)$	Exclusion (1) $\Delta(\%)$	Exclusion (2) $\Delta(\%)$
2016 Q1	-3.44	-3.32	-0.90
2016 Q2	-1.44	-2.97	-1.42
2016 Q3	-7.55	-8.34	-5.76
2016 Q4	-3.93	-5.91	-3.22
2017 Q1	-8.32	-9.58	-6.76
2017 Q2	-5.94	-9.61	-7.49
2017 Q3	-6.64	-10.43	-9.55
2017 Q4	-5.80	-8.96	-7.69
2018 Q1	-3.81	-8.08	-7.88
2018 Q2	-2.72	-7.34	-6.86
Period Avr.	-4.96	-7.45	-5.75

In section 4.2 we report the last row of table 8 for brevity.

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