International Economics and Economic Policy (2021) 18:267–307
https://doi.org/10.1007/s10368-021-00493-7

ORIGINAL PAPER

# Quo Vadis, Britain? – Implications of the Brexit process on the UK's real economy

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Accepted: 6 January 2021 / Published online: 31 March 2021


## Summary

Using the Panel Data Approach (PDA) of Hsiao et al. *Journal of Applied Econometrics, 7*(5), 705-740 (2012) in combination with the LASSO method, this article aims to measure the effect of the Brexit process on the United Kingdom's real economy up to 2019Q2. The results are twofold: Firstly, compared to the existing literature, the PDA improves the measurement of the impact of Brexit on the real economy regarding computation intensity, the feasibility of statistical inference and a wider application area. Secondly, the estimated counterfactuals for the UK show that the Brexit process has played a crucial role in the UK's economy, leading to lower GDP (growth rates), lower private consumption, lower gross fixed capital formation (GFCF) and higher exports. On average, GDP growth has declined between 1.3 and 1.4 percentage points, whereby the cumulative loss ranges between 48 and 54 billion British pounds. Moreover, private consumption in the UK has declined 4.7 billion British pounds quarterly on average. The predicted counterfactuals show that the impact of the Brexit process on GFCF has begun in 2018Q1, whereby the average treatment effect amounts to −2.9 billion British pounds. The UK's exports increased since the referendum, most likely due to the depreciation of the British pound post-Brexit. The average quarterly effect of the Brexit process on exports is estimated here at 4.8 billion British pounds.

**Keywords** Brexit · Economic policy uncertainty · Counterfactual · Panel data approach · LASSO

**JEL classification** C23 · C54 · E65 · F42 · O47

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## 1 Introduction

On 23 June 2016, the United Kingdom (UK) voted to leave the European Union (EU). Several years after the referendum, the official British exit, commonly referred to using the portmanteau "Brexit", took place on 31 January 2020. As of late 2020, the Brexit negotiations between the UK and EU were continuing. The range of possible negotiation results spanned from a hard to a soft Brexit. Both sides are playing the so-called game of chicken (or hawk–dove game) where both maintain a collision course with the other in order to move the negotiating partner toward offering some concessions. Since neither of them is about to swerve and lose the game, the likelihood of a 'no deal' Brexit, where both parties lose, has increased during the Brexit process.. Uncertainty about the outcome of the negotiations has resulted in major planning problems in the real sector, since households and companies in the UK are faced with the loss of access to the European Single Market. That is why it is not surprising that the Brexit process itself led to major changes in the economic environment and trade flows of the UK due to the anticipation of the soft or hard Brexit.

Several studies focus on the impact of Brexit on economic factors such as income, welfare, exports, and foreign direct investment (FDI) in the UK, where many contributions employ the gravity model approach. Using a quantitative trade model covering 40 countries and 30 sectors, Dhingra et al. (2017) predict that a soft and a hard Brexit would lead to a fall of the UK's consumption per capita of about 1.3% and 2.7%, respectively. Furthermore, using a gravity model, they show that the UK's income per capita declines by between 6.3% and 9.4% due to Brexit. Brakman et al. (2017) use the gravity equation with counterfactual scenarios to analyze the impact of Brexit on exports. By taking 43 countries into account, they show negative trade consequences for both the UK and the EU. Baier and Welfens (2018) examine, using the gravity model, the impact of Brexit on FDI flows and estimate a decline of FDI inflows to the UK by about 42%. Using a panel data structural gravity approach, and assuming different counterfactual post-Brexit scenarios, Oberhofer and Pfaffermayr (2018) find that six years after Brexit occurs, the UK's (EU's) exports of goods to the EU (UK) are likely to decline by between 7.2% and 45.7% (or 5.9% and 38.2%). They also find that the UK's real income is likely to decline by between 1.4% and 5.7% under a hard Brexit scenario and that welfare effects for the EU are insignificant. Henkel and Seidel (2019) run a gravity-spatial model with labour mobility in two counterfactual exercises to study the impact of European integration on welfare and migration flows across 1280 European regions. They estimate welfare losses for the UK of 1.05% and for the EU of 0.41% in the most pessimistic Brexit scenario. Graziano et al. (2018) analyze the uncertainty effects of trade disagreements via a constant elasticity of substitution demand function and find that increasing probabilities of Brexit reduce bilateral export values.

Apart from the gravity model, some studies use program evaluation methodologies, which measure the impact of political or economic interventions by constructing counterfactuals. Usually, a counterfactual without treatment is estimated and compared with the observed series with treatment. In this way the significance and the impact of Brexit can also be measured. Based on Abadie and Gardeazabal (2003), the Synthetic Control Method (SCM) is one of these methodologies. Using the SCM, Douch et al. (2018) estimate the effects on bilateral trade between the UK, on one hand, and 14 EU and 14 non-EU trading partners, on the other hand, and find that compared with the synthetic UK, exports have declined to both EU and non-EU countries. Serwicka and Tamberi (2018) apply the SCM to examine FDI flows and show that the Brexit referendum reduced the UK's FDI inflows by around 16%–20%. Further recent research about the impact of Brexit on the real economic growth of the United Kingdom is published by Born et al. (2019). Using the SCM, the authors find that by the end of 2018 the gap between the counterfactual and actual GDP ranges between 1.7% and 2.4% of UK GDP and estimate the cumulative loss of the Brexit vote in terms of 2016 GDP at 55 billion British pounds. Moreover, by decomposing real GDP into its components, they find that primarily investments and consumption have been negatively impacted by the Brexit vote.

The main motivation of this paper is to measure the impact of the Brexit process on the real economy. Its primary contribution to the existing literature is in the use of a novel alternative method to the SCM, namely the Panel Data Approach (PDA) of Hsiao et al. (2012). Looking from a different methodological angle, results are obtained which will be compared with previous findings in the literature using SCM. The research mostly relates topically to the study of Born et al. (2019) and analyses the impact of Brexit on real GDP growth, gross fixed capital formation (GFCF), consumption and the export performance of the UK. As proposed by Li and Bell (2017), the PDA is combined with the least absolute shrinkage and selection operator (LASSO) method, which helps to select control units to make adequate out-of-sample predictions.

The results of this research article are twofold. Firstly, from a technically point of view, the PDA appears to be a more appropriate approach in order to measure the impact of Brexit. In contrast to the SCM, the use of the PDA allows to conduct classical inference. Moreover, the PDA approach is able to estimate quantitatively the impact of the Brexit process on consumption and investment, whereas the SCM approach of Born et al. (2019) can only point out the direction of the impact of these variables. This is due to the flexibility of the PDA. In addition to that, the flexibility and the simplicity of the computation of the PDA allow predicting counterfactuals for the UK using a donor pool of countries, whereby member countries of the European Single Market are excluded; indeed excluding major trading partners is adequate in order to avoid having an inadequate donor pool including countries which due to strong trade links partly automatically would lead to a pool of countries with quasi-similarities to the UK simply on the basis of trade links. Since the SCM application of Born et al. (2019) also includes EU countries, which themselves could be significantly affected by the Brexit process, the predicted counterfactuals could be biased due to endogeneity.

Secondly, most of the estimated figures are highly significant and show that, with the exception of UK exports, the Brexit process has been negatively impacting GDP, consumption and GFCF. By 2019Q2, the cumulative loss in terms of UK GDP amounts to between 48 and 54 billion British pounds, whereas the gap between actual output and the counterfactual prediction is approximately 2.5 to 2.7%. The estimated impact on UK exports is positive, most likely because of the depreciation of the British pound following the referendum and during the Brexit process.

The remainder of the paper is organized as follows. Section 2 presents the econometric methodology used, namely the PDA of Hsiao et al. (2012) in combination with the LASSO model selection method. Section 3 describes the data used and the modelling strategy. In Section 4, the empirical results for UK GDP, consumption, GFCF and exports are presented. Finally, Section 5 provides a summary including policy conclusions. To the best knowledge of the author, studies about the impact of Brexit using this econometric technique and time period do not exist.

## 2 Econometric method

Measuring treatment effects of policy interventions using non-experimental data is a difficult task, since the counterfactual scenario, where no intervention has occurred, is unobservable. In the literature, using the Difference-in-Differences (DID) methodology is one popular way to solve this problem. Nevertheless, the DID method has some urgent limitations regarding the sample selection and statistical behaviour of control and treatment units (Li and Bell 2017, p. 65). To obtain the treatment effect, the SCM compares the treated outcome with randomly matched untreated controls and thus, in contrast to the DID method, is more flexible. In particular, the SCM constructs a counterfactual by calculating a weighted combination of control groups. The objective here is to detect the vector of weights which minimizes the difference between calculated and observed data in the pre-treatment period using covariates between treated and control groups (Gardeazabal and Vega-Bayo 2017, p. 985). The PDA by Hsiao et al. (2012) pursues a similar but more straightforward strategy to calculate counterfactuals. However, the PDA varies from the SCM regarding both the technical focus and the approach (Gardeazabal and Vega-Bayo 2017, p. 987): In the SCM, the counterfactual outcome is predicted using covariates of a panel, whereas the PDA uses only the outcome variable of a panel to construct the prediction. The main idea of the PDA is that a set of common factors, which are the main forces that drive all outcomes of a panel, exists – for example, real GDP. Hence, a factor approach would be able to model the outcome of a unit. Since these factors are not observable, Hsiao et al. propose to use outcomes of the remaining units of a panel in lieu of the common factors in order to model the outcome of the treated unit in the pre-intervention period. Finally, estimated coefficients of the model can be used to construct a counterfactual outcome for the post-intervention period. Besides the simplicity of the computation, the advantage of this approach is the feasibility of significance tests, which is not provided by the SCM.[1]

Let $\mathbf{y}_t = (y_{1t}, y_{2t}, \ldots, y_{Nt})$ represent a vector of panel data across $N$ countries at time $t$. Following Hsiao et al. (2012), the treatment effect for the $i$th country at time $t$ is

$$\Delta_{it} = y_{it}^1 - y_{it}^0 \tag{1}$$

where $y_{it}^1$ and $y_{it}^0$ denote the outcome of the $i$th country at time $t$ under treatment and in the absence of treatment, respectively. As mentioned previously, $y_{1t}^1$ and $y_{1t}^0$ cannot be observed simultaneously. This can be formulated as follows:

$$y_{it} = d_{it}\, y_{it}^1 + (1 - d_{it})\, y_{it}^0 \tag{2}$$

[1] In case of the SCM, the probability distribution of the predicted pre-treatment outcome is not easily derivable, so that statistical tests cannot be performed (Hsiao et al. 2012, p. 711).

with

$$d_{it} = \begin{cases} 1, & \text{if the ith country is under treatment at time t} \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

Suppose the treatment, i.e. the Brexit vote, occurs at time $T_1$. Then, the vector of observed outcomes $\mathbf{y}_t$ before the policy change at $T_1$ can be noted as

$$\mathbf{y}_t = \mathbf{y}_t^0, \text{ for } t = 1, ..., T_1 \tag{4}$$

Moreover, suppose that the treatment has an impact only on the first country, i.e. the UK, and thus the outcomes of other units (countries) of the panel are not affected by the treatment:

$$y_{1t} = y_{1t}^1, for \ \ t = T_1 + 1, \dots, T \tag{5}$$

$$y_{it} = y_{it,}^0 \ \text{ for } i = 2, \dots, N, \text{for } t = 1, \dots, T \tag{6}$$

Under the assumption that $K$ common factors drive the outcomes of the panel, $y_{it}^0$ can be modelled as follows:

$$y_{it}^0 = \alpha_i + \mathbf{b}_i^{'}\mathbf{f}_t + \varepsilon_{it} \text{ with } i = 1, \dots, N, \text{for } t = 1, \dots, T \tag{7}$$

where $\mathbf{f}_t$ is the $K \times 1$ vector of (unobservable) common factors that vary over time, $\mathbf{b}_i^{'}$ is the $1 \times K$ vector of constants, which can vary across units $i$, $\alpha_i$ is the fixed unit-specific intercept and $\varepsilon_{it}$ is the idiosyncratic error term with $E(\varepsilon_{it}) = 0$. This factor model can be stacked together in terms of the $N$ units:

$$\mathbf{y}_t^0 = \boldsymbol{\alpha} + \mathbf{B}\,\mathbf{f}_t + \boldsymbol{\varepsilon}_t \ \text{ for } t = 1, \dots, T \tag{8}$$

where $\boldsymbol{\alpha}$ contains the $N \times 1$ vector of individual intercepts, $\mathbf{B} = (\mathbf{b}_1, \dots, \mathbf{b}_N)'$ denotes the $N \times K$ factor loading matrix and $\boldsymbol{\varepsilon}_t$ is the $N \times 1$ vector of error terms. As is usual in the literature, $\boldsymbol{\varepsilon}_t$ is assumed to be stationary and with $E(\boldsymbol{\varepsilon}_t) = 0$. Furthermore, it is assumed that $\boldsymbol{\varepsilon}_t$ is homoscedastic and that $E(\boldsymbol{\varepsilon}_t\mathbf{f}'_t) = 0$. Hsiao et al. (2012, p. 707) assume, that Rank $(\mathbf{B}) = K$ should hold, which implies that $N$ is greater than the number of common factors ($K$), which is easily satisfied in practice (Li and Bell 2017, p. 67).

Equations (1) and (7) show that for the post-treatment period of the first country, which is the unit affected by the policy change, the outcome can be written as follows:

$$y_{1t} = y_{1t}^1 = y_{1t}^0 + \Delta_{1t} = \alpha_1 + \mathbf{b}_1^{'}\mathbf{f}_t + \varepsilon_{1t} + \Delta_{1t} \ \text{ for } t = T_1 + 1, \dots, T \tag{9}$$

The number of common factors $K$ could be identified using the procedure of Bai and Ng (2002) in order to estimate $\mathbf{f}_t$. This holds only for large $N$ and $T$, which are often in practice not given. Hsiao et al. (2012, p. 709) show that the counterfactual prediction of $y^0_{1t}$ in the pre-treatment period can be realized by using $\tilde{\mathbf{y}}_t = (y_{2t}, \ldots, y_{Nt})'$, which are not affected by the policy change but which are affected by the common factors, in lieu of $\mathbf{f}_t$:

$$y^0_{1t} = \overline{\alpha} + \tilde{\mathbf{a}}' \tilde{\mathbf{y}}_t + \varepsilon^*_{1t} \tag{10}$$

where $\overline{\alpha}$ and $\tilde{\mathbf{a}}$ denotes the constant and the vector of coefficients, respectively, and $\varepsilon^*_{1t}$ is the error term. To construct the counterfactual, the following procedure is used by Hsiao et al. (2012):

Step 1: $y^0_{1t}$ has to be regressed on $\tilde{\mathbf{y}}_t$ for the pre-treatment period ($t = 1, \ldots, T_1$) using eq. (10).
Step 2: The obtained estimates for $\overline{\alpha}$ and $\tilde{\mathbf{a}}$ are used to calculate $\widehat{y}^0_{1t}$ for the post-treatment period ($t = T_1 + 1, \ldots, T$).

Using $\widehat{y}^0_{1t}$ in eq. 1, the average treatment effect (ATE) can be estimated as follows:

$$\text{ATE} = \frac{1}{T-T_1} \sum_{i=T_1}^{T} y^1_{1t} - \widehat{y}^0_{1t} = \frac{1}{T-T_1} \sum_{i=T_1}^{T} \widehat{\Delta}_{1t} \tag{11}$$

In the case of stationary $\widehat{\Delta}_{1t}$, the significance of the treatment effect can be tested by a t-test. If the predicted treatment effect is serially correlated, the inference of ATE can be performed by applying an OLS model with only a constant as independent variable and a heteroskedastic-autocorrelation consistent variance-covariance estimator proposed by Newey and West (1987):

$$\widehat{\Delta}_{1t} = \alpha_0 + \widehat{\varepsilon}_t \tag{12}$$

where the constant $\alpha_0$ equates to the ATE. To evaluate the significance of the ATE, a t-test using HAC standard errors can be applied. Moreover, an AR($p$) model can be fit for the estimated treatment effects $\widehat{\Delta}_{1t}$:

$$\widehat{\Delta}_{1t} = \beta_0 + \sum_{i=1}^{p} \beta_i \widehat{\Delta}_{1(t-i)} + \widehat{\varepsilon}_t \tag{13}$$

The constant $\beta_0$ of the AR($p$) fit represents the short-run treatment effect (STE) and can be tested for significance by applying a t-test. Additionally, in the case that AR($p$) is stationary $\left(\left|\sum_{i=1}^{p} \beta_i\right| < 1\right)$ and thus converges towards a steady state, the implied long-run effect (LTE) can be measured as follows:

$$\text{LTE} = \frac{\beta_0}{1-\sum_{i=1}^{p} \beta_i} \tag{14}$$

By applying a Wald-test, the significance of the LTE can be evaluated.

To perform step 1, a model selection criterion is needed. Hsiao et al. (2012) suggest using the (corrected) Akaike Information Criterion (AIC and AICC) or the Bayesian Information Criterion (BIC) to select the most relevant predictors. The problem of these model selection methods is that in the case of a larger number of countries $N$ than the pre-treatment sample size $T_1$, ordinary least squares (OLS) cannot be applied, which means that the researcher is forced to make preliminary decisions (Li and Bell 2017, p. 66). However, the LASSO method, which shrinks less significant coefficients to zero, provides a model selection method which allows $N$ to be higher than the sample size (Meinshausen and Yu 2009). Moreover, as shown in Li and Bell (2017, p. 71), the PDA using the LASSO method leads to smaller out-of-sample predictive mean squared errors, smaller computational times and lower numbers of selected regressors compared to the use of AIC, AICC and BIC. It is also shown that, in the case of an increasing $N$, AICC tends to select more regressors, whereas the LASSO method provides rather robust numbers of regressors.[2]

Considering the factor model in eq. (10) for the pre-treatment period, the LASSO method solves the following problem to obtain the estimates for $\overline{\alpha}$ and $\tilde{\mathbf{a}}$ (Tibshirani 2011, p. 273):

$$\min_{\overline{\alpha},\tilde{\mathbf{a}}} \quad \left\{ \sum_{t=1}^{T_1} \left( y_{1t}^{0} - \left( \overline{\alpha} + \tilde{\mathbf{a}}' \tilde{\mathbf{y}}_t \right) \right)^2 + \lambda \sum_{j=1}^{N} \left| \widetilde{a}_j \right| \right\}, \tag{15}$$

where $\widetilde{a}_j$ is the $j$th element of the coefficient vector $\tilde{\mathbf{a}}$ and $\lambda$ is a tuning parameter. In eq. (15) one can see that the first term is the OLS loss function, whereas the second term penalizes the coefficients' size in order to decrease the variance of the estimation. A higher parameter $\lambda$ increases the penalty on coefficients $\widetilde{a}_j$, which means that the LASSO procedure shrinks more non-zero and high coefficients $\widetilde{a}_j$ towards zero. This is because higher coefficients lead to an increasing estimation variance and, by extension, to increasing errors, whereby the bias increases (Li and Bell 2017, p. 70). As a result, the LASSO method provides a technique where both the variance of the estimated coefficients $\left[ Var\left( \widehat{\tilde{\mathbf{a}}} \right) \right]$ and the bias of the estimated coefficients $\left[ E\left( \widehat{\tilde{\mathbf{a}}} \right) - \tilde{\mathbf{a}} \right]$ are regarded as trade-offs.

In practice, the tuning parameter calibration is solved by using cross-validation (CV) methods (Tibshirani 2011, p. 278). CV is a model validation technique which tests the out-of-sample accuracy of the model. Here, the parameter $\lambda$ is searched over a discrete

[2] This behaviour of the model selection methods explains the smaller predictive mean squared errors of the LASSO method, since a large number of regressors increases the variance of the estimation leading to poorer predictive accuracy (Li and Bell 2017, p. 69).

set $\Lambda_L = \{\lambda_1, \ldots, \lambda_L\}$. A popular CV method, which Li and Bell (2017, p. 70) propose for the LASSO method, is the leave-one-out (LOO) CV. For each pre-treatment period $t = 1, \ldots, T_1$ and for each element $\lambda_k (k = 1, \ldots, L)$ of $\Lambda_L$ the coefficients $\overline{\alpha}$ and $\tilde{\mathbf{a}}$ are estimated by solving the following problem:

$$\min_{\overline{\alpha}, \tilde{\mathbf{a}}} \left\{ \sum_{s=1, s \neq t}^{T_1} \left( y_{1s}^0 - \left( \overline{\alpha} + \tilde{\mathbf{a}}' \tilde{\mathbf{y}}_s \right) \right)^2 + \lambda_k \sum_{j=1}^{N} \left| \widetilde{a}_j \right| \right\}. \tag{16}$$

As a result of the minimizations, a $T_1 \times L$ set of coefficients $\widehat{\overline{\alpha}}_{-t,k}, \widehat{\tilde{\mathbf{a}}}_{-t,k}$ is estimated, whereby these coefficients are the LOO (leave the $t$-th observation out) estimates of $\overline{\alpha}$ and $\tilde{\mathbf{a}}$:

| | $\lambda_1$ | $\lambda_2$ | $\cdots$ | $\lambda_L$ |
|---|---|---|---|---|
| $t=1$ | $\widehat{\overline{\alpha}}_{-t=1,k=1}, \widehat{\tilde{\mathbf{a}}}_{-t=1,k=1}$ | $\widehat{\overline{\alpha}}_{-t=1,k=2}, \widehat{\tilde{\mathbf{a}}}_{-t=1,k=2}$ | $\cdots$ | $\widehat{\overline{\alpha}}_{-t=1,k=L}, \widehat{\tilde{\mathbf{a}}}_{-t=1,k=L}$ |
| $t=2$ | $\widehat{\overline{\alpha}}_{-t=2,k=1}, \widehat{\tilde{\mathbf{a}}}_{-t=2,k=1}$ | $\ddots$ | $\vdots$ | $\vdots$ |
| $\vdots$ | $\vdots$ | $\cdots$ | $\ddots$ | $\vdots$ |
| $t=T_1$ | $\widehat{\overline{\alpha}}_{-t=T_1,k=1}, \widehat{\tilde{\mathbf{a}}}_{-t=T_1,k=1}$ | $\cdots$ | $\cdots$ | $\widehat{\overline{\alpha}}_{-t=T_1,k=L}, \widehat{\tilde{\mathbf{a}}}_{-t=T_1,k=L}$ |

In order to obtain $\lambda$, for each tuning parameter $\lambda_k$ $(k = 1, \ldots, L)$ the average squared error over all $T_1$ observations is calculated by using the estimated coefficients $\widehat{\overline{\alpha}}_{-t,k}$, $\widehat{\tilde{\mathbf{a}}}_{-t,k}$ of eq. (16):

$$CV(\lambda_k) = \frac{1}{T_1} \sum_{t=1}^{T_1} \left( y_{1t}^0 - \left( \widehat{\overline{\alpha}}_{-t,k} + \widehat{\tilde{\mathbf{a}}}'_{-t,k} \widetilde{\mathbf{y}}_t \right) \right)^2 \quad \text{for}\, k = 1, \ldots, L. \tag{17}$$

The tuning parameter $\lambda_k$, which minimizes $CV(\lambda_k)$, is used in eq. (15). Finally, the coefficients of regressors, which the LASSO procedure shrinks to zero, are redundant for the factor model, whereas regressors, whose coefficients are non-zero, are selected as adequate predictors for the PDA.

## 3 Data and Modelling strategy

As mentioned previously, donor countries, which are serving as controls, should not be affected by Brexit. Therefore, several member countries of the European Single Market are excluded. The economic characteristics of donor countries should, as far as is reasonably possible, be similar to those of the UK. For this reason, countries which are covered in the database of the Organisation for Economic Co-operation and Development (OECD), namely all OECD member countries and some selected non-member countries, are considered as controls. As a last step, countries which do not belong to the UK's top 25 export partners of 2015, 2016 and 2017 and which do not have quarterly data available for a period of about ten years are also excluded.[3] Following these steps, the control countries remaining in the donor pool are: Australia, Brazil, Canada, China, India, Israel, Japan, Korea, Mexico, New Zealand, Russia, Turkey and the United States.

First of all, the LASSO-LOO procedure is used to obtain controls which result in the best (out-of-sample) fit for the pre-treatment period.[4] At this point, the econometric aim is not to deliver an explanatory model but to mimic the pre-treatment period in order to predict the post-treatment counterfactual output. Since economic characteristics, interdependencies and behaviours change over time, the use of recent data should be preferred to predict the current edge adequately. Therefore, for all donor countries and the UK, the following data in national currencies are extracted from the OECD database for the period 2008Q1 to 2019Q2: real GDP growth, GDP, private consumption, GFCF and exports. Table 1 gives a overview of the data used.[5] Since the Brexit referendum took place on 23 June, 2016, 2016Q2 is set as the cut-off point $T_1$. As a result, the pre-treatment and post-treatment period covers 34 or 12 observations for each control, respectively.

The prediction of the year-on-year growth rates of consumption, GFCF and exports using control group growth rates is rather difficult. That is why local currency levels of donor countries are used to predict the level for the UK.[6] In these cases, to avoid spurious regressions, the Engle and Granger (1987) single-equation cointegration test is performed, whereby the time series of the UK is used as the dependent variable of the regression. In the event that the LASSO-LOO procedure delivers (non-stationary) controls as predictors, whose linear combinations are not cointegrated, the procedure including the single-equation Engle-Granger test is iteratively repeated. In each iteration, donor countries are removed from the donor pool one-by-one in order to identify those countries which lead to a test statistic failing to reject the null hypothesis of no cointegration. The iteration stops when the LASSO-LOO procedure picks controls which lead to a rejection of the null hypothesis of no cointegration at least at the 10% significance level.[7]

[3] The export ranking of the UK is calculated using the World Integrated Trade Solution (WITS) database of the Worldbank. The exclusion of the member countries of the European Single Market and the consideration of the countries with high foreign trade activity with the British economy serves to prevent endogeneity problems and to estimate the post-treatment period using countries with strong affiliation to the UK economy in order to better reflect relevant shocks stemming from these countries. Nevertheless, as an anonymous referee has pointed out, it is important to be aware that an affiliated country could theoretically be affected from policy changes emanating from the UK. However, the exclusion of any possible endogeneity problems is practically impossible and lies in the "nature" of impact evaluation methods, which is also well-known in the literature (Wan et al. 2018, p.123): "For PDA and SCM to yield reasonable estimates of counterfactuals, the control units must not be affected by the intervention. It could be hard to find a control group that is invariant to such disruptions. For instance, it is not that easy to find control groups to measure the impact of the Iranian revolution on the Iranian economy".

[4] For the empirical study, the „*lasso*"function of MATLAB R2013b is used. The calibration set $\Lambda_L = \{\lambda_1, \ldots, \lambda_L\}$ comprises a geometric sequence with 100 $\lambda$-variations. The largest number $\lambda_L$ is set to result the first non-null model, where all coefficients are shrunk to zero.

[5] Desciptive statistics and unit root test result can be found in the Appendix in Tables 13 and 14.

[6] In this article, all figures given in British pound sterling are in terms of 2016.

[7] Cointegration relationships have apparently not been considered in previous empirical applications of the PDA in use of non-stationary variables (see e.g. Ke et al. 2017). In the opinion of the author, this could lead to spurious post-treatment projections. The present modeling strategy tries to avoid such problems and is therefore a more conservative and precautious implementation of the PDA. As a result, the LASSO is used to enhance the prediction accuracy, whereas the cointegration is checked for non-stationary variables to provide predictors with common stochastic trend.

**Table 1** Donor pool overview

| Dependent variable for UK | Real GDP growth* | GDP** | Priv. consumption** | GFCF** | Exports** |
|---|---|---|---|---|---|
| Australia | ✓* | ✓** | ✓** | ✓** | ✓** |
| Brazil | ✓* | ✓** | ✓** | ✓** | ✓** |
| Canada | ✓* | ✓** | ✓** | ✓** | ✓** |
| China | ✓* | – | – | – | – |
| India | ✓* | ✓** | ✓*** | ✓*** | ✓*** |
| Israel | ✓* | ✓** | ✓** | ✓** | ✓** |
| Japan | ✓* | ✓** | ✓** | ✓** | ✓** |
| Korea | ✓* | ✓** | ✓** | ✓** | ✓** |
| Mexico | ✓* | ✓*** | ✓*** | ✓*** | ✓*** |
| New Zealand | ✓* | ✓** | ✓** | ✓** | ✓** |
| Russia | ✓* | ✓** | ✓** | ✓** | ✓** |
| Turkey | ✓* | ✓** | ✓** | ✓** | ✓** |
| United States | ✓* | ✓** | ✓** | ✓** | ✓** |

*y-o-y, SA

**CVM, SA, LC

***Constant prices, SA, LC

CVM: chained volume measures; SA: seasonally adjusted; LC: local currency; y-o-y: year-on-year

Data source: OECD database, Quarterly National Accounts

To assess the precision of the estimators, 95% confidence bands for the counterfactual prediction are calculated using the Newey-West HAC variance-covariance estimator.[8]

Since country-specific shocks, particularly in the post-Brexit period, could lead to a bias of the counterfactual prediction, the whole econometric procedure will be repeated by dropping these countries from the donor pool. Possible candidates here are developing countries such as Turkey and Brazil, whose GDP growths were relatively volatile in the last three years.[9]

As mentioned previously, serially correlated treatment effects have to be fitted by an AR($p$) model. To identify the adequate number of lags $p$, the Schwarz information

[8] For all HAC estimations the Bartlett kernel density and the lag selection parameter of Andrews and Monohan (1992) are used.

[9] Regarding the post-Brexit referendum period, the standard deviation of the GDP growth of Turkey and Brazil are 4.6 and 1.5 times higher, respectively, than the mean of the standard deviation of the growth rates of the donor pool. Turkey's economy suffered from US sanctions and tariffs in 2018 and also from the offensive into north-eastern Syria in 2019. The recent country-specific political, legal and economic turmoil in Turkey are discussed in Grübler (2017, pp. 11–12). Between 2014 and 2017, Brazil's economy slumped into a recession due to a political crisis, high fiscal deficits and a collapse in commodity and oil prices.

Since remarkable country-specific developments should be excluded as far as possible from the counterfactual prediction, results after these exclusions have been considered more reliable in the subsequent section. It would be not quite surprising, that these exclusions from the donor pool lead to differing results, in particular when crucial country-specific economic developments have taken place in the post-Brexit period. Also for this reason numerical results should be viewed with a certain degree of caution.

criterion (BIC) is used. Since the residuals of the AR($p$) estimation could still be serially correlated, Newey-West HAC variance-covariance estimators are used for inference.[10]

## 4 Results of the PDA LASSO-LOO approach

### 4.1 Results for GDP growth and GDP level

To quantify the impact of the Brexit-process on real GDP growth, the described econometric approach is applied for three different donor pool compositions. The estimation results are reported in Appendix Tables 2, 3 and 4, whereas Figs. 1, 2 and 3 illustrate the actual and predicted values of the growth rate.[11] In the first estimate, real GDP growth rates of all available donor countries are used in the LASSO-LOO procedure, which picks all controls as regressors in order to construct the counterfactual growth path. Apparently, the actual and the counterfactual growth path diverge in the post-Brexit referendum period. The ATE is −1.00 percentage points and is, according to the t-test with HAC standard errors, significant at the 1 % level. Since the estimated treatment effects are serially correlated, an AR(4) model is fitted:

$$\hat{\Delta}_{1t} = -\underbrace{1.8292}_{(0.0026)} + \underbrace{0.0110}_{(0.9593)}\hat{\Delta}_{1(t-1)} + \underbrace{0.3170}_{(0.3369)}\hat{\Delta}_{1(t-2)} - \underbrace{0.0789}_{(0.8848)}\hat{\Delta}_{1(t-3)} - \underbrace{0.7453}_{(0.0405)}\hat{\Delta}_{1(t-4)} + \hat{\varepsilon}_t \tag{18}$$

where estimated HAC $p$ values are in parentheses. The STE and the LTE are −1.83 and − 1.22 percentage points, respectively, and are significant at the 1 % level. Nevertheless, it is remarkable that at the end of the post-Brexit referendum period actual and predicted growth rates converge.

Considering the discussed country-specific shocks, Turkey is excluded from the donor pool in the second estimate, whereas in the third estimate developing countries like Turkey, Brazil, India and Mexico are excluded. The second and third estimates show similar predictions. A comparison of the first with the second and third estimates implies that the convergence of the actual and predicted path in the first estimate is mainly caused by a country-specific shock in Turkey. The ATEs of the second and third estimate are 1.39 and 1.31 percentage points, respectively, and are both statistically significant at any significance level. The treatment effects of the second estimate are fitted by an AR(1) model:

$$\hat{\Delta}_{1t} = -\underbrace{0.5970}_{(0.1139)} + \underbrace{0.5912}_{(0.0232)}\hat{\Delta}_{1(t-1)} + \hat{\varepsilon}_t \tag{19}$$

[10] As the BIC is known to be very strict in selecting the number of variables to be included, it might also be possible to overcome the problem of the autocorrelation of residuals by including further time lags instead of correcting the variance-covariance matrix. However, due to the closeness of the Brexit vote, the limited number of observations for the post-treatment period may make it difficult to estimate the autoregressive model.

[11] The following Tables of results (Tables 2-12) can be found in the Appendix.

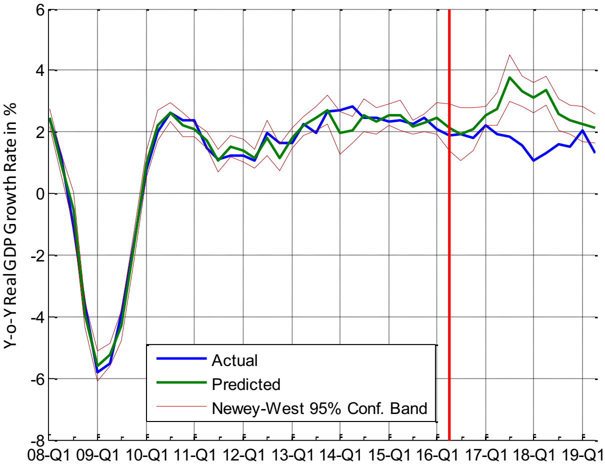


**Fig. 1** The UK's actual and predicted real GDP growth rates. Prediction computed by using all available donors (first estimate)

The LTE is −1.46 percentage points and, according to the Wald-test, significant at the 1 % level. The treatment effects of the third estimate are also fitted by an AR(1) model:

$$\hat{\Delta}_{1t} = -\underbrace{0.5993}_{(0.1239)} + \underbrace{0.5679}_{(0.0154)}\hat{\Delta}_{1(t-1)} + \hat{\varepsilon}_t \tag{20}$$

The LTE is −1.39 percentage points and also significant at the 1 % level.

As described previously, the econometric approach is also applied for GDP in local currency levels. The estimation results are reported in Appendix Tables 5 and 6, whereas Figs. 4 and 5 illustrate the actual and predicted GDP. In the first estimate, where all available controls are used, the LASSO-LOO procedure picks Japan, Korea and the United States as predicators. The

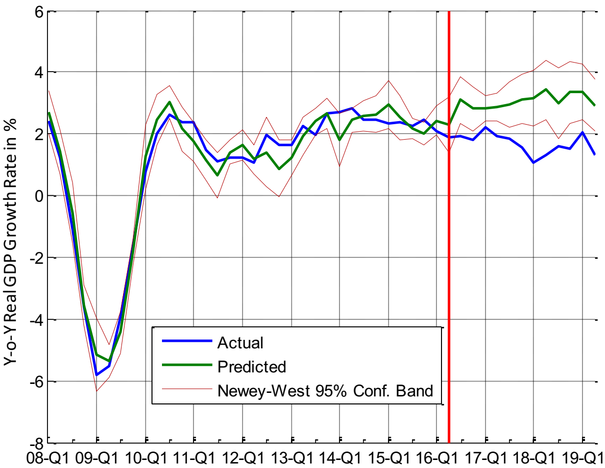


**Fig. 2** The UK's actual and predicted real GDP growth rates. Prediction computed after removing Turkey from the donor pool (second estimate)

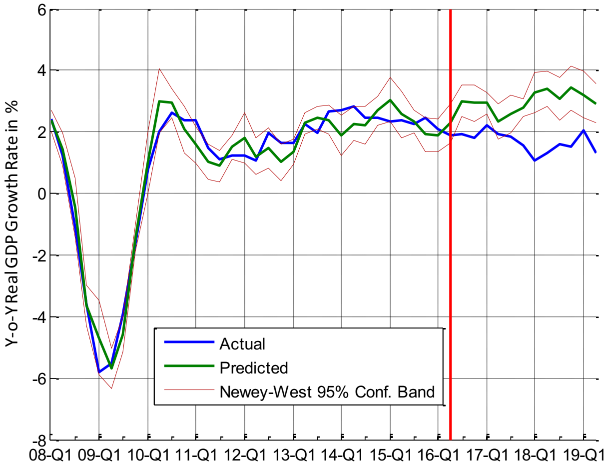


**Fig. 3** The UK's actual and predicted real GDP growth rates. Prediction computed after removing Turkey, Brazil, Mexico and India from the donor pool (third estimate)

Engle-Granger test shows that the null hypothesis of no cointegration can be rejected with a $p$ value of 0.0682. The ATE of the first estimate is −3.99 billion British pounds but narrowly misses the 10 % significance level (p value = 0.12). Due to serial correlation, an AR(2) model is fitted for the treatment effect:

$$\hat{\Delta}_{1t} = -\underbrace{1.3574}_{(0.0091)} + \underbrace{1.2957}_{(0.0004)}\hat{\Delta}_{1(t-1)} - \underbrace{0.3305}_{(0.1618)}\hat{\Delta}_{1(t-2)} + \hat{\varepsilon}_t \tag{21}$$

The STE and the LTE are −1.36 and − 39.04 billion British pounds, respectively, and are both significant at the 1 % level. By summing up the differences of actual and

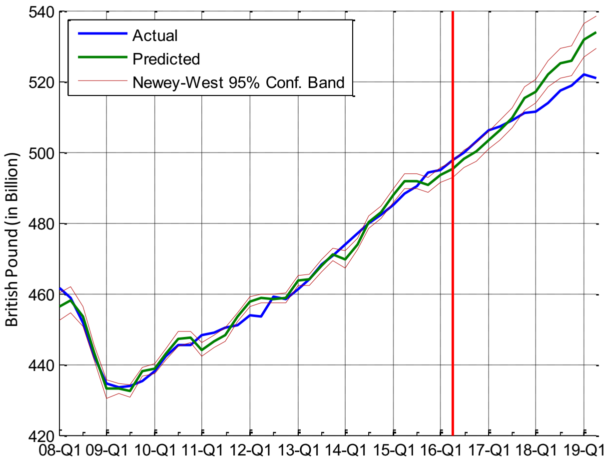


**Fig. 4** The UK's actual and predicted GDP (in billion British pounds, CVM). Prediction computed by using all available donors (first estimate)

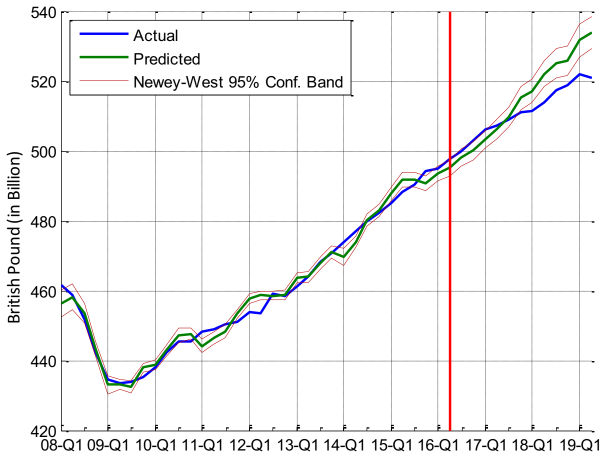


**Fig. 5** The UK's actual and predicted GDP (in billion British pounds, CVM). Prediction computed after removing Japan from the donor pool (second estimate)

predicted GDP, the cumulative treatment effect of the Brexit-process is approximately −48 billion British pounds.

In the second estimate for GDP, Japan is removed from the donor pool in order to increase the cointegration relationship. Here, the LASSO-LOO procedure picks Australia, Canada, Korea and the United States as predictors. Nevertheless, the Engle-Granger test shows a higher $p$ value than in the first estimation, namely 0.09. Apart from the weak cointegration, there are fairly stable links between the UK and the predictors of the second estimate, since the LASSO-LOO selects, besides the United States, two Commonwealth countries. The ATE of the second estimate is −4.49 but with a p value of 0.12 is also not

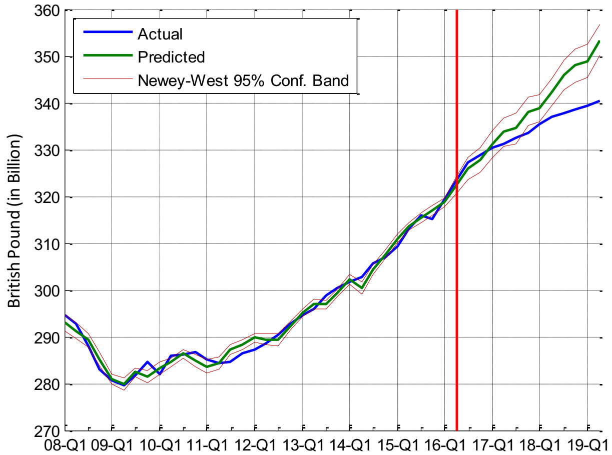


**Fig. 6** The UK's actual and predicted private consumption (in billion British pounds, CVM). Prediction computed by using all available donors

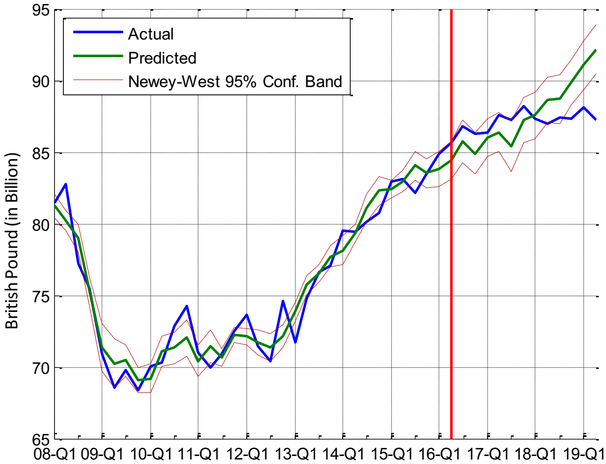


**Fig. 7** The UK's actual and predicted GFCF (in billion British pounds, CVM). Prediction computed by using all available donors (first estimate)

significant at the 10 % level. The treatment effects of the second estimate are also fit to an AR(2) model:

$$\hat{\Delta}_{1t} = -\underbrace{1.3544}_{(0.0041)} + \underbrace{1.3377}_{(0.0000)}\hat{\Delta}_{1(t-1)} - \underbrace{0.3493}_{(0.0286)}\hat{\Delta}_{1(t-2)} + \hat{\varepsilon}_t \tag{22}$$

The STE of the second estimate is also −1.36 billion British pounds and significant at the 1 % level. The LTE in the second estimate is −117.1 billion British pounds and is also significant at the 1 % level. However, it differs strongly from the result in the first estimate, which is due to higher dynamics in the autoregressive representation.

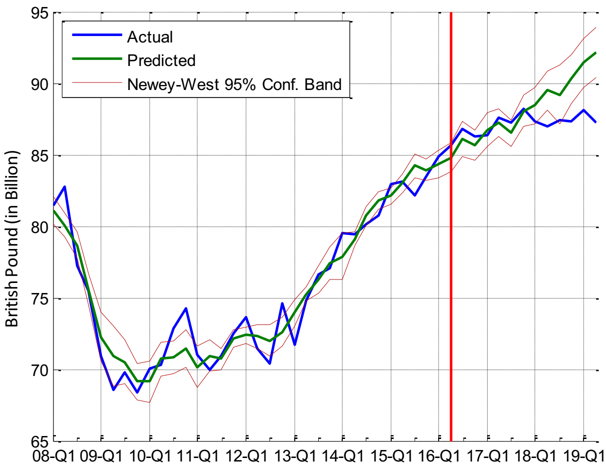


**Fig. 8** The UK's actual and predicted GFCF (in billion British pounds, CVM). Prediction computed after removing Brazil from the donor pool (second estimate)

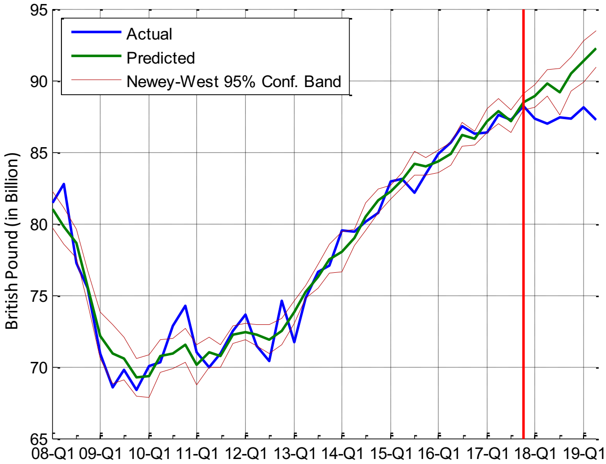


**Fig. 9** The UK's actual and predicted GFCF (in billion British pounds, CVM). Prediction computed after removing Brazil from the donor pool and with cut-off point 2018Q1 (third estimate)

The cumulative loss since the Brexit referendum is approximately 54 billion British pounds.

### 4.2 Results for private consumption

Using private consumption panel data, the LASSO-LOO procedure picks Australia, Japan, New Zealand and the United States as predictors of British private consumption. The *p* value of the Engle-Granger test (0.0346) is below the 5 % level and thus indicates the presence of a cointegration relationship. In addition to that, the chosen predictors are, like the UK, developed countries, whereas two of them belong to the group of Commonwealth countries. Regarding these stable links, further estimations

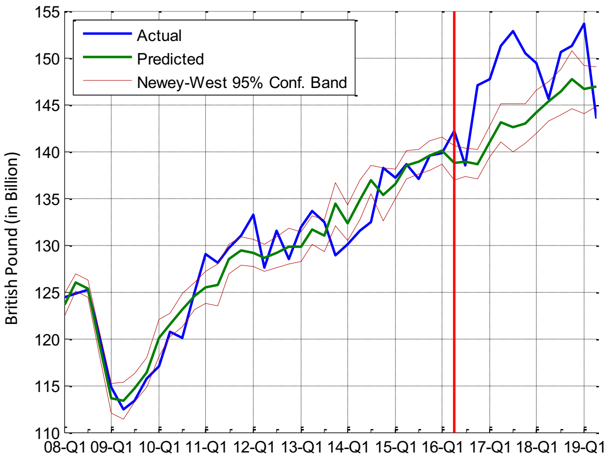


**Fig. 10** The UK's actual and predicted exports (in billion British pounds, CVM). Prediction computed by using all available donors (first estimate)

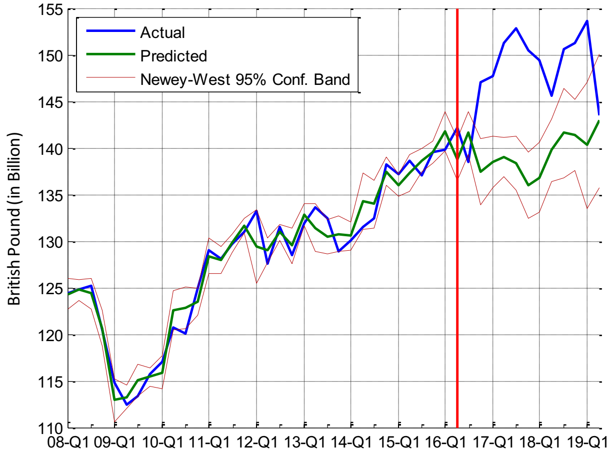


**Fig. 11** The UK's actual and predicted exports (in billion British pounds, CVM). Prediction computed after removing Brazil from the donor pool (second estimate)

have been found unnecessary. Appendix Table 7 summarizes the results for the UK's private consumption, whereas in Fig. 6 the actual and counterfactual paths are plotted.

At first glance, the changing trend of the actual path in the post-Brexit vote period stands out, whereas the predicted path of private consumption holds the trend of the previous period. As a result, the actual and the predicted consumption path diverge evidently. Regarding the t-statistic using Newey-West standard errors, the ATE on UK's private consumption, which is −4.67 billion British pounds, is significantly different from zero at the 5 % level. The treatment effects are serially correlated and are fitted using a (non-stationary) AR(2) model:

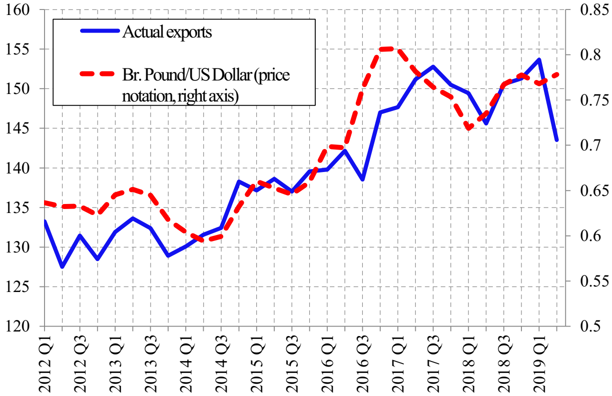


**Fig. 12** The UK's exports and the British pound/US dollar exchange rate (price notation). Source: OECD Monthly Monetary and Financial Statistics, own calculations.

$$\hat{\Delta}_{1t} = -\underbrace{1.7623}_{(0.0015)} + \underbrace{0.4428}_{(0.1969)}\hat{\Delta}_{1(t-1)} + \underbrace{0.6240}_{(0.0977)}\hat{\Delta}_{1(t-2)} + \hat{\varepsilon}_t \tag{23}$$

The STE is −1.76 billion British pounds and is statistically significant at the 1 % level. However, the LTE cannot be calculated since the sum of the AR-coefficients is greater than one and thus does not lead to a convergent result due to non-stationary dynamics in the AR-process. For the post-Brexit referendum period, the cumulative treatment effect for the UK's private consumption is approximately 56 billion British pounds.

### 4.3 Results for GFCF

According to the LASSO-LOO procedure using the whole GFCF panel data, the adequate predictors of the UK's GFCF are Australia, Japan, New Zealand, United States and Brazil. Appendix Table 8 outlines the estimation results, whereas Fig. 7 displays the actual and predicted values of the UK's GFCF. Regarding the $p$ value of the Engle-Granger test (0.0075), the linear combination of the variables used is cointegrated below the 1 % significance level. Apparently, fixed investments are not impacted by the Brexit process until the end of 2017. After 2017Q4, the UK's actual GFCF breaks the trend of the previous periods and proceeded to stagnate, whereas the predicted GFCF holds the trend. As a result, the actual and predicted GFCF begin to diverge starting from 2018Q1.

The ATE is 0.57 billion British pounds and is not significantly different from zero. The treatment effects are serially correlated and thus fit to a (non-stationary) AR(1) model:

$$\hat{\Delta}_{1t} = -\underbrace{0.5200}_{(0.0584)} + \underbrace{1.1536}_{(0.0000)}\hat{\Delta}_{1(t-1)} + \hat{\varepsilon}_t \tag{24}$$

The STE is −0.52 and is only significant at the 10 % level.

In the second estimation, Brazil is excluded from the donor pool. Appendix Table 9 and Fig. 8 show the result of this setting. Here again, the Engle-Granger test indicates the presence of a cointegration relationship at the 5 % significance level. Regarding the post-Brexit referendum period, the behaviours of the actual and predicted curves are similar to those of the first estimate including the break in 2017Q4. However, it is remarkable that between 2016Q3-2017Q4 the prediction fits very closely the actual path and its turning points. Again, the ATE, which is 2.00 billion British pounds, is not significantly different from zero. The treatment effects are again serially correlated and fitted by a (non-stationary) AR(1) model:

$$\hat{\Delta}_{1t} = -\underbrace{0.4448}_{(0.0936)} + \underbrace{1.0760}_{(0.0000)}\hat{\Delta}_{1(t-1)} + \hat{\varepsilon}_t \tag{25}$$

The STE in the second estimation is −0.44 but narrowly significant at the 10 % level. Since the impact of the Brexit process on the GFCF becomes apparent in 2018, the low ATE and STE significances in both estimates are not surprising results.[12]

Because of that, a third estimate is performed, where the cut-off point $T_1$ is set to 2017Q4. The summarized results can be seen in Appendix Table 10, whereas the actual and counterfactual predicted values are plotted in Fig. 9. Additionally to the predictors in the second estimate, the LASSO-LOO procedure also picked Korea as predictor. Again, the *p* value of the Engle-Granger test (0.0098) indicates a close cointegration relationship. Particularly between 2016Q1 and 2017Q4 the prediction closely matches the actual data including its turning points. The ATE in the third estimate is −2.92 billion British pounds and is significant at the 1 % level.[13] The sum of the treatment effects reveals that the cumulative treatment effect between 2018Q1 and 2019Q2 is approximately −17.5 billion British Pounds.

### 4.4 Results for exports

Appendix Tables 11 and 12 display the summarized results of the estimates for the export panel data, whereas Figs. 10 and 11 illustrate the actual and predicted values for exports. At first glance, the positive treatment effect stands out, where a strong drop of the actual data can be seen at the end in 2019Q2. All in all, the actual path appears to be more volatile after the Brexit vote than during the period before. In Fig. 12, the UK's exports and the British pound / US dollar exchange rate are plotted.[14] The (lagged) parallelism of both series is remarkable. Apparently, a reason for the increasing export activity in the post-Brexit vote period could be the depreciation of the British pound, as a consequence of the Brexit process, which made UK goods more competitive.[15] This positive impulse on exports appears to be a short-term phenomenon, since it loses momentum about 5 quarters after the Brexit referendum.

Using the complete export panel data, the LASSO-LOO procedure picks Canada, United States and Brazil as predictors of the counterfactual. The Engle-Granger test of this first estimate implies that the null hypothesis of no cointegration can be rejected with the p value of 0.060. Using the BIC, a

[12] The delayed impact of the Brexit process on investment could be explained by the changed expectations for soft and hard Brexit after the EU-UK negotiations started in the second half of 2017. Another reason could be the reorganisation of production, particularly in supply chains, where planning and implementation may show some delay.

[13] Since in these settings only six observations for the treatment effects are present, the use of an AR-model is limited. Hence, only the ATE using Newey-West standard errors is calculated in order to deal with the serial correlation.

[14] Monthly exchange rate data are extracted from the Monthly Monetary and Financial Statistics of the OECD database and recalculated to compile quarterly data by taking the mean of three months.

[15] The impact of Brexit on British pound exchange rates has been investigated by Korus and Celebi (2019). They find that particularly the Brexit vote and "bad"/"hard" Brexit news have led to a depreciation of the British pound exchange rate against both the US dollar and the euro.

constant model fits the treatment effects the best, so that an AR-model is not required. The ATE of the Brexit process on exports is 4.81 billion British pounds and, according to the HAC t-statistic, is statistically significant at the 1 % level. In the first estimate, the cumulative treatment effect is 57.7 billion British pounds.

In the second estimate, Brazil is excluded from the donor pool, so that the LASSO-LOO procedure picked Australia, Canada, Israel, Japan, Korea, New Zealand, Turkey and the United States as predictors. The Engle-Granger p value drops slightly to 0.058. In this broader predictor constellation, the ATE increases to 9.01 and is again statistically significant at the 1 % level. In this set-up, the BIC approach leads to an AR(1) fitting:

$$\hat{\Delta}_{1t} = \underbrace{9.8315}_{(0.0000)} + \underbrace{0.0285}_{(0.8929)} \hat{\Delta}_{1(t-1)} + \hat{\varepsilon}_t \tag{26}$$

The STE is 9.83 billion British pounds and is significantly different from zero at the 1 % level. Since the dynamics of the AR-model are rather low, LTE is close to STE but not significant, which supports also the short-term phenomenon conjecture. In the second estimate, the cumulative treatment effect is 108.1 billion British pounds.

## 5 Conclusion

In this paper, the impact of the Brexit process on the British real economy is investigated. In technical terms, this study shows the adequacy of the PDA of Hsiao et al. (2012) to quantify the treatment effects in the case of the Brexit. Comparing it with the topically related article of Born et al. (2019), where the SCM is adopted to analyse the impact of Brexit, the PDA stands out in two different ways. Firstly, in contrast to the SCM, the use of the PDA allows to conduct inference. Secondly, the PDA is on the whole more flexible and thus can be used for a wider range of macroeconomic variables due to the simplicity of the computation. In the case of Brexit, the method can still be performed even in the absence of European Single Market member countries.

Taken as a whole, the results indicate that although the Brexit was not yet officially a fait accompli, the whole process has already had an impact on the real economy of the UK. Apparently, the upcoming Brexit and thus changing economic framework conditions had – at least to some extent – already been anticipated before the UK withdrewed from the EU on 31 January 2020. Note that, despite the calculated LTE, the used technique cannot predict the future, since the executed Brexit could lead to a structural break.

All measures for the impact of the Brexit process on real GDP growth are negative and significantly different from zero at any significance level. Thus, there is very strong evidence that the Brexit process has already cost the UK in terms of economic growth. The results show that the ATE of the Brexit process on real GDP growth is between −1.0 and − 1.4 percentage points. Taking into account that the first estimate is likely affected by a country-specific shock in

Turkey, the ATE ranges most likely between −1.3 and − 1.4 percentage points approximately. Due to autoregressive dynamics, the LTE ranges between approximately −1.39 and − 1.46 percentage points and is again highly significant.

The ATE on British GDP, in terms of 2016 British pounds, ranges between −4.0 and − 4.5 billion but narrowly misses the 10 % significance level. The STE is −1.36 for both conducted estimates and again is highly significant. The calculated LTE in both estimates are quite dispersed, namely −39 and − 117 billion British pounds. Although the report of an accurate level for the LTE is therefore difficult, both estimated figures are again highly significant. However, the figures for the cumulative loss of the Brexit process since the vote in both estimates are relatively close, namely 48 and 54 billion British pounds. The gap between the actual and counterfactual GDP ranges between 2.5 and 2.7%.

To compare these results with the findings of Born et al. (2019), the estimated figures have to be adjusted, since the sample of Born et al. (2019) ends in 2018Q4. Additionally, since a number of countries revised their GDP calculations due to methodological improvements in 2019Q2, the comparison should be treated with caution.[16] By the end of 2018, the gap between the actual and counterfactual prediction estimated with the PDA ranges between 1.3 and 1.7%, whereas Born et al. (2019) predict, generally speaking, a higher gap, namely 1.7 to 2.4%. The cumulative loss of both estimates conducted with the PDA is approximately 25 and 29 billion British pounds by the end of 2018, whereas Born et al. (2019) estimate 55 billion British pounds regarding the counterfactual with a 2.4% gap.

A proper comparison of results stemming from the SCM and PDA could be made using the estimates of Springford (2019) who, broadly speaking, replicates the SCM approach of Born et al. (2019) using updated (revised) data.[17] The calculated gap between the actual and counterfactual GDP here is 2.9% and is, therefore, about 0.2 to 0.4 percentage points higher than the estimated figures using the PDA.

Both Born et al. (2019, p. 2735) and Springford (2019) generate counterfactual projections for the UK’s consumption, GFCF, imports and exports by simply decomposing the response of the UK’s GDP into its components. Thus, these projections are predictions of the GDP counterfactual prediction. That is why this technique can only point out the direction of the impact of the Brexit process. By contrast, the PDA approach is able to construct counterfactual predictions directly.

Using the PDA on the private consumption panel data, the results show that the estimated ATE on the UK’s private consumption is −4.7 billion British pounds and is significant at the 5 % level. The cumulative treatment effect since the Brexit vote is −56 billion British pounds.

[16] See, for example, the Office for National Statistics (2019), section 7 (“Revision to GDP”).

[17] Note that Springford (2019) also uses European Single Market member countries in the donor pool, which could bias the estimated figures as in Born et al. (2019).

The results for the GFCF panel show that there is no impact of the Brexit process on the UK's fixed investments until the end of 2017. From 2018Q1 on, the actual and predicted fixed investments diverge with an ATE of −2.9 billion British pounds, which is significant at the 1 % level. Starting from 2018Q1, the resulting cumulative treatment effect is −17.5 billion British pounds.

The PDA results for British exports illustrate a positive impact of the Brexit process. The ATE is 4.8 billion British pounds and significantly different from zero at the 1 % level, whereas the cumulative treatment effect is approximately 58 billion British pounds. These results are contrary to the projection of Springford (2019), who estimates lower actual exports than predicted. Regarding the UK's exports path and the British pound / US dollar exchange rate, the positive impact could be due to the depreciation of the British currency, which increased the competitiveness of the UK. Note that the positive impact on exports appears to be a short-term impulse.

### 5.1 Further perspectives and policy conclusions

Regarding these results, it is advisable for the EU and, more importantly, the UK to abandon the 'game of chicken' as soon as possible in order to finalise a Brexit deal by which the UK retains at least a certain degree of access to the European Single Market. Although households have anticipated the upcoming Brexit to a certain extent, it is uncertain whether a no deal Brexit in the end of 2020 will cause a further structural break and further negative impulses.

To redeem the losses incurred through Brexit, the British government has two key policy elements available. Firstly, the government can seek to boost growth via expansive fiscal policies. Especially in the current phase, where private consumption and investment in the UK are declining due to Brexit and interest rates are relatively low, the possibility of a crowding out effect is lower than usual. In addition to that, the UK's long-term government bond yields are at historically low rates, which favour the funding of fiscal expenditures.

Possible policies could be tax reductions - above all in relation to personal income taxes and corporate taxes - which could particularly stimulate the economic activity through higher work and production incentives (Devereux and Love 1994). In addition to that, a reform of capital income taxes could notably foster growth via two channels: firstly, this policy could increase private investments (Rebelo 1991). Combined with well-targeted tax incentives, in particular for research and development (R&D) investments, lower capital income taxation could increase the productivity of the UK (IMF 2015). Secondly, in line with Froot and Stein (1991), the devaluation of the British pound attracts foreign investment, which foster economic growth. Combined with reforms for easing business procedures and providing access for foreign investors to the domestic credit market, a declining tax rate on capital income would boost in particular foreign direct investment (FDI).

Related to this issue, an expansive monetary policy could also help to stimulate growth due to increasing consumption and investment incentives. Moreover, the expansive monetary policy could lead to a further depreciation of the pound sterling, which would increase exports and foreign investments.

Further possible policies could be public infrastructure and R&D investments. In particular, higher education and health investments could be helpful to attract human capital, which is known as a main driver of long-term growth (Lucas 1988) (Barro 2001). Since technological progress and intangible assets are also main drivers of growth, the enlargement of R&D investments, which include also positive externalities, should be prioritised (Demmou et al. 2019). At this point, the British government can realise this through tax breaks or subsidy incentives or by directly investing in R&D.

The second key element to redeem the losses of Brexit is the concluding of free trade agreements. Because of the strong economic ties between the UK and the US, an adapted version of the Transatlantic Trade and Investment Partnership (TTIP) agreement could foster the growth of the UK's economy the most. Estimated growth gains stemming from the TTIP do not yet exist for the UK. However, Jungmittag and Welfens (2016) estimated for Germany a real income gain of 2%. Assuming that this estimated figure would also be an appropriate prediction for the possible gain of the UK due to the adapted TTIP, a large proportion of the current estimated gap between the actual and counterfactual prediction could be compensated via such an agreement. However, it must be remembered that such trade agreements are not usually realised in the short-run. Therefore, the discussed fiscal policy measures stand out as the primary key element to offset the losses of the Brexit.

Based on the econometric method used here, future research dealing with the impact of the Brexit process on the UK's FDI inflows and the UK's domestic value-added in gross exports could reveal some further information about the external trade changes. A very interesting issue in future will be the effects of the Brexit day itself, now most likely to be January 31, 2020. Several quarters after the official completion of the Brexit process, the econometric method presented in this paper can be repeated in order to measure the treatment effects for the, by then, non-EU member UK. Additionally, further investigations dealing with the impact of Brexit could be interesting, in which causal implications among macroeconomic variables such as GDP, consumption and GFCF are explored.

## Appendix

**Table 2** Counterfactual prediction of the UK's real GDP growth rates in percent using all donors (first estimation)

| | | | |
|---|---|---|---|
| Panel A: Weights of LASSO-predictors for the pre-Brexit referendum period (2008Q1 – 2016Q2) | | | |
| | Coefficient | Std.dev. | *T* |
| Constant | 2.5623 | 0.9249 | 2.7705 |
| Australia | −0.5099 | 0.1731 | −2.9464 |
| Brazil | −0.0394 | 0.0616 | −0.6398 |
| Canada | 0.0176 | 0.1771 | 0.0993 |
| China | −0.3798 | 0.1532 | −2.4797 |
| India | 0.1449 | 0.0759 | 1.9077 |
| Israel | −0.1682 | 0.1794 | −0.9374 |
| Japan | −0.0602 | 0.0606 | −0.9936 |
| Korea | 0.1859 | 0.1305 | 1.4247 |
| Mexico | −0.2525 | 0.0938 | −2.6925 |
| New Zealand | 0.3948 | 0.1147 | 3.4429 |
| Russia | 0.2805 | 0.0419 | 6.6862 |
| Turkey | 0.1355 | 0.0320 | 4.2279 |
| United States | 0.5684 | 0.1142 | 4.9771 |
| $R^2$ =0.9830 | | | |
| Panel B: Treatment effects in the post-Brexit referendum period (2016Q3 – 2019Q2) | | | |
| | Actual | Predicted | Treatment |
| 2016 Q3 | 1.91 | 1.92 | −0.01 |
| 2016 Q4 | 1.81 | 2.09 | −0.28 |
| 2017 Q1 | 2.23 | 2.53 | −0.31 |
| 2017 Q2 | 1.94 | 2.75 | −0.81 |
| 2017 Q3 | 1.83 | 3.75 | −1.92 |
| 2017 Q4 | 1.58 | 3.31 | −1.73 |
| 2018 Q1 | 1.05 | 3.10 | −2.05 |
| 2018 Q2 | 1.33 | 3.34 | −2.01 |
| 2018 Q3 | 1.62 | 2.58 | −0.96 |
| 2018 Q4 | 1.54 | 2.39 | −0.86 |
| 2019 Q1 | 2.07 | 2.25 | −0.19 |
| 2019 Q2 | 1.31 | 2.12 | −0.82 |
| Mean | 1.68 | 2.68 | −0.99 |
| Std. dev. | 0.34 | 0.58 | 0.75 |
| *T* | 4.90 | 4.62 | −1.32 |
| Constant OLS model with HAC standard errors: | | | |
| ATE=−0.9950 | Std.dev. = 0.3081 | *T* =−3.2298 | p value=0.0080 |
| Treatment fits to a stationary AR(4)-model:<br>LTE=−1.2226 (Wald-stat. = 9.9648) | | | |

**Table 3** Counterfactual prediction of the UK's real GDP growth rates in percent after removing Turkey from the donor pool (second estimation)

| Panel A: Weights of LASSO-predictors for the pre-Brexit referendum period (2008Q1 – 2016Q2) | | | |
|---|---|---|---|
| | Coefficient | Std.dev. | $T$ |
| Constant | 2.0447 | 1.2311 | 1.6608 |
| Australia | −0.6017 | 0.2306 | −2.6095 |
| Brazil | −0.0870 | 0.0814 | −1.0696 |
| Canada | −0.0012 | 0.2377 | −0.0049 |
| China | −0.2912 | 0.2038 | −1.4291 |
| India | 0.1534 | 0.1020 | 1.5046 |
| Israel | 0.0842 | 0.2272 | 0.3706 |
| Japan | 0.0453 | 0.0742 | 0.6113 |
| Korea | 0.0825 | 0.1721 | 0.4790 |
| Mexico | −0.1897 | 0.1244 | −1.5254 |
| New Zealand | 0.3764 | 0.1539 | 2.4459 |
| Russia | 0.2872 | 0.0563 | 5.1017 |
| United States | 0.6292 | 0.1521 | 4.1353 |
| $R^2$ =0.9679 | | | |
| Panel B: Treatment effects in the post-Brexit referendum period (2016Q3 – 2019Q2) | | | |
| | Actual | Predicted | Treatment |
| 2016 Q3 | 1.91 | 3.10 | −1.20 |
| 2016 Q4 | 1.81 | 2.81 | −1.00 |
| 2017 Q1 | 2.23 | 2.82 | −0.59 |
| 2017 Q2 | 1.94 | 2.85 | −0.91 |
| 2017 Q3 | 1.83 | 2.94 | −1.11 |
| 2017 Q4 | 1.58 | 3.12 | −1.54 |
| 2018 Q1 | 1.05 | 3.15 | −2.10 |
| 2018 Q2 | 1.33 | 3.42 | −2.09 |
| 2018 Q3 | 1.62 | 2.99 | −1.37 |
| 2018 Q4 | 1.54 | 3.35 | −1.82 |
| 2019 Q1 | 2.07 | 3.36 | −1.29 |
| 2019 Q2 | 1.31 | 2.93 | −1.62 |
| Mean | 1.68 | 3.07 | −1.39 |
| Std. dev. | 0.34 | 0.22 | 0.47 |
| $T$ | 4.90 | 14.16 | −2.98 |
| Constant OLS model with HAC standard errors: | | | |
| ATE=−1.3874 | Std.dev. = 0.1895 | $T$ =−7.3196 | p value=0.0000 |
| Treatment fits to a stationary AR(1)-model:<br>LTE=−1.4604 (Wald-stat. = 7.4559) | | | |

**Table 4** Counterfactual prediction of the UK's real GDP growth rates in percent after removing Turkey, Brazil, India and Mexico from the donor pool (third estimation)

| | | | |
|---|---|---|---|
| Panel A: Weights of LASSO-predictors for the pre-Brexit referendum period (2008Q1 – 2016Q2) | | | |
| | Coefficient | Std.dev. | *T* |
| Constant | 3.4726 | 1.1396 | 3.0472 |
| Australia | −0.5050 | 0.2080 | −2.4276 |
| Canada | −0.3483 | 0.1517 | −2.2964 |
| China | −0.4919 | 0.1423 | −3.4561 |
| Israel | 0.3536 | 0.1610 | 2.1965 |
| Japan | 0.0047 | 0.0727 | 0.0641 |
| Korea | 0.1894 | 0.1324 | 1.4306 |
| New Zealand | 0.2710 | 0.1300 | 2.0837 |
| Russia | 0.2173 | 0.0510 | 4.2573 |
| United States | 0.7043 | 0.1593 | 4.4224 |
| $R^2$ =0.9577 | | | |
| Panel B: Treatment effects in the post-Brexit referendum period (2016Q3 – 2019Q2) | | | |
| | Actual | Predicted | Treatment |
| 2016 Q3 | 1.91 | 3.01 | −1.10 |
| 2016 Q4 | 1.81 | 2.94 | −1.13 |
| 2017 Q1 | 2.23 | 2.93 | −0.71 |
| 2017 Q2 | 1.94 | 2.32 | −0.38 |
| 2017 Q3 | 1.83 | 2.59 | −0.76 |
| 2017 Q4 | 1.58 | 2.78 | −1.21 |
| 2018 Q1 | 1.05 | 3.28 | −2.23 |
| 2018 Q2 | 1.33 | 3.40 | −2.06 |
| 2018 Q3 | 1.62 | 3.08 | −1.46 |
| 2018 Q4 | 1.54 | 3.43 | −1.90 |
| 2019 Q1 | 2.07 | 3.22 | −1.15 |
| 2019 Q2 | 1.31 | 2.92 | −1.61 |
| Mean | 1.68 | 2.99 | −1.31 |
| Std. dev. | 0.34 | 0.33 | 0.57 |
| *T* | 4.90 | 9.18 | −2.31 |
| Constant OLS model with HAC standard errors: | | | |
| ATE=−1.3078 | Std.dev. = 0.2248 | $T$=−5.8165 | p value=0.0001 |

Treatment fits to a stationary AR(1)-model:
LTE = −1.3871 (Wald-stat. = 8.8885)

**Table 5** Counterfactual prediction of the UK's GDP (in billion British pounds, CVM) (first estimate)

| | | | |
|---|---|---|---|
| Panel A: Weights of LASSO-predictors for the pre-Brexit referendum period (2008Q1 – 2016Q2) | | | |
| | Coefficient | Std.dev. | *T* |
| Constant | −51.7130 | 20.0640 | −2.5774 |
| Japan | 0.0008 | 0.0003 | 3.0466 |
| Korea | −0.0003 | 0.0001 | −5.5885 |
| United States | 0.1277 | 0.0097 | 13.1580 |
| $R^2$ =0.9838 | | | |
| Engle-Granger cointegration tau-statistic=−4.28 (p value=0.06824) | | | |
| Panel B: Treatment effects in the post-Brexit referendum period (2016Q3 – 2019Q2) | | | |
| | Actual | Predicted | Treatment |
| 2016 Q3 | 499.84 | 497.96 | 1.87 |
| 2016 Q4 | 503.08 | 500.06 | 3.02 |
| 2017 Q1 | 505.98 | 503.34 | 2.64 |
| 2017 Q2 | 507.26 | 506.17 | 1.08 |
| 2017 Q3 | 508.98 | 509.65 | −0.67 |
| 2017 Q4 | 511.01 | 515.16 | −4.14 |
| 2018 Q1 | 511.30 | 517.15 | −5.85 |
| 2018 Q2 | 514.02 | 522.07 | −8.05 |
| 2018 Q3 | 517.22 | 525.15 | −7.93 |
| 2018 Q4 | 518.87 | 525.87 | −7.00 |
| 2019 Q1 | 521.87 | 531.61 | −9.74 |
| 2019 Q2 | 520.74 | 533.85 | −13.11 |
| Mean | 511.68 | 515.67 | −3.99 |
| Std. dev. | 7.06 | 12.28 | 5.44 |
| *T* | 72.50 | 42.01 | −0.73 |
| Constant OLS model with HAC standard errors: | | | |
| ATE=−3.9898 | Std.dev. = 2.3928 | *T* =−1.6674 | p value=0.12362 |

Treatment fits to a stationary AR (2)-model:

LTE = −39.036 (Wald-stat. = 85.4672)

**Table 6** Counterfactual prediction of the UK's GDP (in billion British pounds, CVM) after removing Japan from the donor pool (second estimate)

| | | | |
|---|---|---|---|
| Panel A: Weights of LASSO-predictors for the pre-Brexit referendum period (2008Q1 – 2016Q2) | | | |
| | Coefficient | Std.dev. | *T* |
| Constant | −9.0572 | 18.5240 | −0.4889 |
| Australia | −0.2821 | 0.1319 | −2.1394 |
| Canada | 0.1017 | 0.1142 | 0.8900 |
| Korea | −0.0001 | 0.0001 | −1.3959 |
| United States | 0.1457 | 0.0119 | 12.2590 |
| $R^2$ =0.9820 | | | |
| Engle-Granger cointegration tau-statistic=−4.52 (p value=0.0898) | | | |
| Panel B: Treatment effects in the post-Brexit referendum period (2016Q3 – 2019Q2) | | | |
| | Actual | Predicted | Treatment |
| 2016 Q3 | 499.84 | 498.27 | 1.57 |
| 2016 Q4 | 503.08 | 500.06 | 3.02 |
| 2017 Q1 | 505.98 | 503.26 | 2.72 |
| 2017 Q2 | 507.26 | 506.21 | 1.05 |
| 2017 Q3 | 508.98 | 509.36 | −0.37 |
| 2017 Q4 | 511.01 | 514.83 | −3.82 |
| 2018 Q1 | 511.30 | 517.49 | −6.19 |
| 2018 Q2 | 514.02 | 522.18 | −8.17 |
| 2018 Q3 | 517.22 | 526.69 | −9.47 |
| 2018 Q4 | 518.87 | 527.84 | −8.97 |
| 2019 Q1 | 521.87 | 532.74 | −10.87 |
| 2019 Q2 | 520.74 | 535.12 | −14.39 |
| Mean | 511.68 | 516.17 | −4.49 |
| Std. dev. | 7.06 | 12.84 | 5.98 |
| *T* | 72.50 | 40.21 | −0.75 |
| Constant OLS model with HAC standard errors: | | | |
| ATE=−4.4897 | Std.dev. = 2.6641 | *T* =−1.6853 | p value=0.1200 |

Treatment fits to a stationary AR (2)-model:

LTE = −117.104 (Wald-stat. = 153.587)

**Table 7** Counterfactual prediction of the UK's private consumption (in billion British pounds, CVM)

| | | | |
|---|---|---|---|
| Panel A: Weights of LASSO-predictors for the pre-Brexit referendum period (2008Q1 – 2016Q2) | | | |
| | Coefficient | Std.dev. | *T* |
| Constant | −20.8660 | 27.9190 | −0.7474 |
| Australia | −0.9172 | 0.0955 | −9.6040 |
| Japan | 0.0014 | 0.0003 | 4.1043 |
| New Zealand | 3.6082 | 1.2760 | 2.8278 |
| United States | 0.1121 | 0.0153 | 7.3239 |
| $R^2$ =0.9848 | | | |
| Engle-Granger cointegration tau-statistic=−5.04 (p value=0.0346) | | | |
| Panel B: Treatment effects in the post-Brexit referendum period (2016Q3 – 2019Q2) | | | |
| | Actual | Predicted | Treatment |
| 2016 Q3 | 327,260 | 325,933.61 | 1326.39 |
| 2016 Q4 | 328,703 | 327,746.04 | 956.96 |
| 2017 Q1 | 330,363 | 331,143.53 | −780.53 |
| 2017 Q2 | 331,307 | 333,731.63 | −2424.63 |
| 2017 Q3 | 332,521 | 334,573.24 | −2052.24 |
| 2017 Q4 | 333,573 | 338,078.90 | −4505.90 |
| 2018 Q1 | 335,383 | 338,811.42 | −3428.42 |
| 2018 Q2 | 337,034 | 342,269.35 | −5235.35 |
| 2018 Q3 | 337,889 | 345,938.28 | −8049.28 |
| 2018 Q4 | 338,478 | 347,928.02 | −9450.02 |
| 2019 Q1 | 339,451 | 348,883.64 | −9432.64 |
| 2019 Q2 | 340,488 | 353,403.38 | −12,915.38 |
| Mean | 334,370.83 | 339,036.75 | −4665.92 |
| Std. dev. | 4398.22 | 8795.70 | 4487.02 |
| *T* | 76.02 | 38.55 | −1.04 |
| Constant OLS model with HAC standard errors: | | | |
| ATE=−4.6659 | Std.dev. = 1.9285 | *T* =−2.4194 | p value=0.0340 |

Treatment fits to a non-stationary AR (2)-model

**Table 8** Counterfactual prediction of the UK's GFCF (in billion British pounds, CVM) (first estimate)

| | | | |
|---|---|---|---|
| Panel A: Weights of LASSO-predictors for the pre-Brexit referendum period (2008Q1 – 2016Q2) | | | |
| | Coefficient | Std.dev. | *T* |
| Constant | 33.2430 | 7.3437 | 4.5267 |
| Australia | −0.3980 | 0.0811 | −4.9052 |
| Brazil | 0.1121 | 0.0666 | 1.6843 |
| Japan | 0.0005 | 0.0004 | 1.2599 |
| New Zealand | −0.1004 | 0.8921 | −0.1125 |
| United States | 0.0813 | 0.0233 | 3.4877 |
| $R^2$ = 0.9449 | | | |
| Engle-Granger cointegration tau-statistic = −6.23 (p value = 0.0076) | | | |
| Panel B: Treatment effects in the post-Brexit referendum period (2016Q3 – 2019Q2) | | | |
| | Actual | Predicted | Treatment |
| 2016 Q3 | 86.82 | 85.74 | 1.07 |
| 2016 Q4 | 86.30 | 84.90 | 1.41 |
| 2017 Q1 | 86.34 | 86.05 | 0.29 |
| 2017 Q2 | 87.55 | 86.38 | 1.17 |
| 2017 Q3 | 87.22 | 85.39 | 1.83 |
| 2017 Q4 | 88.20 | 87.25 | 0.95 |
| 2018 Q1 | 87.36 | 87.57 | −0.21 |
| 2018 Q2 | 86.98 | 88.63 | −1.65 |
| 2018 Q3 | 87.40 | 88.69 | −1.29 |
| 2018 Q4 | 87.31 | 89.85 | −2.54 |
| 2019 Q1 | 88.07 | 91.06 | −2.99 |
| 2019 Q2 | 87.24 | 92.18 | −4.94 |
| Mean | 87.23 | 87.81 | −0.57 |
| Std. dev. | 0.58 | 2.32 | 2.11 |
| *T* | 150.44 | 37.77 | −0.27 |
| Constant OLS model with HAC standard errors: | | | |
| ATE = −0.5748 | Std.dev. = 0.8953 | *T* = −0.6421 | p value = 0.5340 |

Treatment fits to a non-stationary AR (1)-model

**Table 9** Counterfactual prediction of the UK's GFCF (in billion British pounds, CVM) after removing Brazil from the donor pool (second estimate)

| | | | |
|---|---|---|---|
| Panel A: Weights of LASSO-predictors for the pre-Brexit referendum period (2008Q1 – 2016Q2) | | | |
| | Coefficient | Std.dev. | *T* |
| Constant | 32.7780 | 7.5674 | 4.3315 |
| Australia | −0.2867 | 0.0485 | −5.9072 |
| Japan | 0.0005 | 0.0004 | 1.3520 |
| New Zealand | 0.0296 | 0.9165 | 0.0323 |
| United States | 0.0720 | 0.0234 | 3.0830 |
| $R^2$ =0.9393 | | | |
| Engle-Granger cointegration tau-statistic=−5.39 (p value=0.0173) | | | |
| Panel B: Treatment effects in the post-Brexit referendum period (2016Q3 – 2019Q2) | | | |
| | Actual | Predicted | Treatment |
| 2016 Q3 | 86.82 | 86.10 | 0.72 |
| 2016 Q4 | 86.30 | 85.66 | 0.64 |
| 2017 Q1 | 86.34 | 86.72 | −0.38 |
| 2017 Q2 | 87.55 | 87.20 | 0.35 |
| 2017 Q3 | 87.22 | 86.53 | 0.69 |
| 2017 Q4 | 88.20 | 88.06 | 0.14 |
| 2018 Q1 | 87.36 | 88.43 | −1.06 |
| 2018 Q2 | 86.98 | 89.49 | −2.51 |
| 2018 Q3 | 87.40 | 89.17 | −1.78 |
| 2018 Q4 | 87.31 | 90.29 | −2.98 |
| 2019 Q1 | 88.07 | 91.41 | −3.34 |
| 2019 Q2 | 87.24 | 92.13 | −4.89 |
| Mean | 87.23 | 88.43 | −1.20 |
| Std. dev. | 0.58 | 2.11 | 1.88 |
| *T* | 150.44 | 41.88 | −0.64 |
| Constant OLS model with HAC standard errors: | | | |
| ATE=−1.1995 | Std.dev. = 0.7966 | *T*=−1.5059 | p value=0.1603 |
| Treatment fits to a non-stationary AR(1)-model | | | |

**Table 10** Counterfactual prediction of the UK's GFCF (in billion British pounds, CVM) after removing Brazil from the donor pool and with cut-off point 2018Q1 (third estimate)

| | | | |
|---|---|---|---|
| Panel A: Weights of LASSO-predictors for the period 2008Q1 – 2017Q4 | | | |
| | Coefficient | Std.dev. | *T* |
| Constant | 28.5660 | 8.9588 | 3.1886 |
| Australia | −0.2834 | 0.0419 | −6.7580 |
| Japan | 0.0007 | 0.0004 | 1.6845 |
| Korea | 3.68E-05 | 4.30E-05 | 0.8562 |
| New Zealand | −0.1624 | 0.9055 | −0.1794 |
| United States | 0.0689 | 0.0206 | 3.3429 |
| $R^2$ =0.9640 | | | |
| Engle-Granger cointegration tau-statistic=−5.93 (p value=0.0098) | | | |
| Panel B: Treatment effects in the period 2018Q4 – 2019Q2 | | | |
| | Actual | Predicted | Treatment |
| 2018 Q1 | 87.36 | 88.90 | −1.54 |
| 2018 Q2 | 86.98 | 89.82 | −2.83 |
| 2018 Q3 | 87.40 | 89.20 | −1.81 |
| 2018 Q4 | 87.31 | 90.45 | −3.14 |
| 2019 Q1 | 88.07 | 91.33 | −3.25 |
| 2019 Q2 | 87.24 | 92.20 | −4.96 |
| Mean | 87.23 | 88.73 | −2.92 |
| Std. dev. | 0.58 | 1.98 | 1.22 |
| *T* | 150.44 | 44.92 | −2.39 |
| Constant OLS model with HAC standard errors: | | | |
| ATE=−2.9226 | Std.dev. = 0.5628 | *T* =−5.1929 | p value=0.0035 |
| Treatment fits to a non-stationary AR(2)-model | | | |

**Table 11** Counterfactual prediction of the UK's exports (in billion British pounds, CVM) (first estimation)

| | | | |
|---|---|---|---|
| Panel A: Weights of LASSO-predictors for the pre-Brexit referendum period (2008Q1 – 2016Q2) | | | |
| | Coefficient | Std.dev. | *T* |
| Constant | 34.9180 | 6.2522 | 5.5850 |
| Brazil | 0.8180 | 0.3679 | 2.2238 |
| Canada | 0.2656 | 0.0818 | 3.2459 |
| United States | 0.0520 | 0.0215 | 2.4161 |
| $R^2$ =0.9177 | | | |
| Engle-Granger cointegration tau-statistic=−4.34 (p value=0.0604) | | | |
| Panel B: Treatment effects in the post-Brexit referendum period (2016Q3 – 2019Q2) | | | |
| | Actual | Predicted | Treatment |
| 2016 Q3 | 138.54 | 138.83 | −0.29 |
| 2016 Q4 | 147.01 | 138.63 | 8.38 |
| 2017 Q1 | 147.66 | 141.04 | 6.61 |
| 2017 Q2 | 151.19 | 143.05 | 8.14 |
| 2017 Q3 | 152.77 | 142.53 | 10.24 |
| 2017 Q4 | 150.51 | 142.99 | 7.52 |
| 2018 Q1 | 149.44 | 144.19 | 5.25 |
| 2018 Q2 | 145.60 | 145.33 | 0.27 |
| 2018 Q3 | 150.59 | 146.32 | 4.27 |
| 2018 Q4 | 151.30 | 147.66 | 3.64 |
| 2019 Q1 | 153.66 | 146.60 | 7.06 |
| 2019 Q2 | 143.54 | 146.94 | −3.40 |
| Mean | 148.48 | 143.68 | 4.81 |
| Std. dev. | 4.31 | 3.06 | 4.10 |
| *T* | 34.46 | 46.95 | 1.17 |
| Constant OLS model with HAC standard errors: | | | |
| ATE=4.80732 | Std.dev. = 1.2688 | *T* =3.78899 | p value=0.0030 |

**Table 12** Counterfactual prediction of the UK's exports (in billion British pounds, CVM) after removing Brazil from the donor pool (second estimate)

| Panel A: Weights of LASSO-predictors for the pre-Brexit referendum period (2008Q1 – 2016Q2) | | | |
|---|---|---|---|
| | Coefficient | Std.dev. | *T* |
| Constant | 15.6880 | 12.7280 | 1.2325 |
| Australia | −0.4881 | 0.1786 | −2.7322 |
| Canada | 0.7291 | 0.1296 | 5.6260 |
| Israel | 0.1428 | 0.1693 | 0.8433 |
| Japan | −0.0001 | 0.0006 | −0.2385 |
| Korea | 0.0003 | 0.0001 | 3.3446 |
| New Zealand | 3.6418 | 1.1355 | 3.2071 |
| Turkey | −0.3170 | 0.1214 | −2.6117 |
| United States | −0.0877 | 0.0551 | −1.5925 |
| $R^2$ =0.9594 | | | |
| Engle-Granger cointegration tau-statistic=− 6.18 (p value=0.05820) | | | |
| Panel B: Treatment effects in the post-Brexit referendum period (2016Q3 – 2019Q2) | | | |
| | Actual | Predicted | Treatment |
| 2016 Q3 | 138.54 | 141.62 | −3.07 |
| 2016 Q4 | 147.01 | 137.45 | 9.56 |
| 2017 Q1 | 147.66 | 138.47 | 9.18 |
| 2017 Q2 | 151.19 | 139.04 | 12.15 |
| 2017 Q3 | 152.77 | 138.32 | 14.45 |
| 2017 Q4 | 150.51 | 136.02 | 14.48 |
| 2018 Q1 | 149.44 | 136.83 | 12.61 |
| 2018 Q2 | 145.60 | 139.75 | 5.85 |
| 2018 Q3 | 150.59 | 141.60 | 8.99 |
| 2018 Q4 | 151.30 | 141.38 | 9.91 |
| 2019 Q1 | 153.66 | 140.27 | 13.39 |
| 2019 Q2 | 143.54 | 142.92 | 0.62 |
| Mean | 148.48 | 139.47 | 9.01 |
| Std. dev. | 4.31 | 2.15 | 5.47 |
| *T* | 34.46 | 64.87 | 1.65 |
| Constant OLS model with HAC standard errors: | | | |
| ATE=9.0109 | Std.dev. = 1.6450 | *T* =5.4776 | p value=0.0002 |

**Table 13** Descriptive statistics for the whole sample and for the pre- and post-Brexit referendum period

Panel A: real GDP in % (year-on-year)

| Period | | AUSTRALIA | BRAZIL | CANADA | CHINA | INDIA | ISRAEL | JAPAN | KOREA | MEXICO | NEW ZEALAND | RUSSIA | TURKEY | UNITED KINGDOM | UNITED STATES |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **2008q1-2019q2** | Mean | 2.57 | 1.54 | 1.63 | 8.03 | 7.07 | 3.49 | 0.57 | 3.10 | 1.99 | 2.20 | 1.28 | 4.62 | 1.19 | 1.67 |
| | Median | 2.55 | 1.24 | 1.82 | 7.45 | 7.04 | 3.57 | 0.70 | 2.92 | 2.75 | 2.67 | 1.64 | 5.33 | 1.86 | 2.07 |
| | Maximum | 4.72 | 9.04 | 3.80 | 12.20 | 13.69 | 5.78 | 5.51 | 7.78 | 7.27 | 4.78 | 11.00 | 11.49 | 2.82 | 3.98 |
| | Minimum | 1.40 | −5.47 | −4.02 | 6.20 | 0.16 | −0.15 | −8.68 | −1.91 | −7.76 | −2.33 | −9.40 | −12.53 | −5.81 | −3.92 |
| | Std. Dev. | 0.68 | 3.49 | 1.77 | 1.67 | 2.20 | 1.44 | 2.57 | 1.87 | 2.66 | 1.66 | 3.81 | 5.02 | 2.04 | 1.74 |
| **2008q1-2016q2** | Mean | 2.63 | 1.93 | 1.45 | 8.53 | 7.07 | 3.40 | 0.34 | 3.25 | 2.01 | 1.91 | 1.18 | 5.02 | 1.01 | 1.38 |
| | Median | 2.60 | 2.57 | 1.78 | 7.90 | 6.98 | 3.56 | 0.31 | 3.24 | 2.86 | 2.25 | 1.69 | 5.84 | 1.98 | 1.72 |
| | Maximum | 4.72 | 9.04 | 3.65 | 12.20 | 13.69 | 5.78 | 5.51 | 7.78 | 7.27 | 4.78 | 11.00 | 11.49 | 2.82 | 3.98 |
| | Minimum | 1.40 | −5.47 | −4.02 | 6.40 | 0.16 | −0.15 | −8.68 | −1.91 | −7.76 | −2.33 | −9.40 | −12.53 | −5.81 | −3.92 |
| | Std. Dev. | 0.73 | 3.92 | 1.99 | 1.68 | 2.50 | 1.64 | 2.94 | 2.13 | 3.05 | 1.82 | 4.42 | 5.22 | 2.35 | 1.93 |
| **2016q3-2019q2** | Mean | 2.41 | 0.45 | 2.13 | 6.63 | 7.06 | 3.73 | 1.21 | 2.69 | 1.94 | 3.01 | 1.56 | 3.50 | 1.68 | 2.48 |
| | Median | 2.41 | 0.93 | 1.88 | 6.70 | 7.09 | 3.58 | 1.28 | 2.80 | 1.88 | 3.06 | 1.64 | 4.70 | 1.71 | 2.47 |
| | Maximum | 3.12 | 2.23 | 3.80 | 6.80 | 8.59 | 4.75 | 2.36 | 3.77 | 3.28 | 4.07 | 3.01 | 11.02 | 2.23 | 3.20 |
| | Minimum | 1.44 | −2.50 | 1.30 | 6.20 | 5.11 | 2.95 | 0.17 | 1.60 | 0.10 | 2.12 | 0.48 | −2.93 | 1.05 | 1.56 |
| | Std. Dev. | 0.53 | 1.43 | 0.75 | 0.20 | 0.98 | 0.63 | 0.70 | 0.59 | 1.04 | 0.53 | 0.77 | 4.43 | 0.34 | 0.48 |

Panel B: real GDP, chained volume measures; seasonally adjusted,all figures in million local currencies

| Period | | AUSTRALIA | BRAZIL | CANADA | INDIA | ISRAEL | JAPAN | KOREA | MEXICO | NEW ZEALAND | RUSSIA | TURKEY | UNITED KINGDOM | UNITED STATES |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **2008q1-2019q2** | Mean | 415,094 | 290,292 | 469,431 | 25,478 | 277,186 | 127,030,260 | 393,591,967 | 4,125,655 | 53,998 | 21,269,543 | 343,994 | 474,236 | 4,199,644 |
| | Median | 415,004 | 293,668 | 471,236 | 24,527 | 277,173 | 126,980,238 | 394,389,000 | 4,089,546 | 52,603 | 21,542,643 | 348,457 | 469,497 | 4,143,528 |
| | Maximum | 475,208 | 311,519 | 523,082 | 36,225 | 333,287 | 134,764,125 | 459,813,400 | 4,648,487 | 63,427 | 22,482,099 | 441,754 | 521,873 | 4,755,465 |
| | Minimum | 360,869 | 253,376 | 418,835 | 17,051 | 229,480 | 115,824,900 | 324,843,200 | 3,470,290 | 47,374 | 19,040,657 | 242,931 | 433,618 | 3,783,529 |
| | Std. Dev. | 35,945 | 15,366 | 30,696 | 5910 | 32,644 | 4,692,301 | 41,122,204 | 356,614 | 5114 | 951,423 | 64,545 | 28,183 | 294,165 |
| **2008q1-2016q2** | Mean | 398,850 | 289,147 | 455,694 | 22,654 | 262,251 | 125,009,390 | 375,364,218 | 3,964,669 | 51,511 | 20,988,128 | 315,618 | 461,021 | 4,060,596 |

**Table 13** (continued)

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Median | 401,001 | 293,668 | 455,882 | 22,372 | 261,651 | 125,184,013 | 376,676,800 | 3,976,907 | 50,884 | 21,389,780 | 310,984 | 458,676 | 4,041,028 |
| | Maximum | 443,841 | 311,519 | 487,481 | 30,030 | 301,407 | 129,720,100 | 425,793,300 | 4,406,333 | 58,498 | 22,274,887 | 395,713 | 497,593 | 4,409,854 |
| | Minimum | 360,869 | 253,376 | 418,835 | 17,051 | 229,480 | 115,824,900 | 324,843,200 | 3,470,290 | 47,374 | 19,040,657 | 242,931 | 433,618 | 3,783,529 |
| | Std. Dev. | 26,181 | 17,663 | 22,438 | 3852 | 23,239 | 3,637,374 | 30,952,929 | 263,736 | 3235 | 938,868 | 49,015 | 19,409 | 193,774 |
| **2016q3-2019q2** | Mean | 461,117 | 293,536 | 508,353 | 33,479 | 319,501 | 132,756,058 | 445,237,258 | 4,581,783 | 61,044 | 22,066,886 | 424,396 | 511,681 | 4,593,613 |
| | Median | 462,166 | 294,254 | 509,776 | 33,593 | 320,691 | 133,107,588 | 445,986,850 | 4,604,952 | 61,018 | 22,115,596 | 428,792 | 511,157 | 4,595,090 |
| | Maximum | 475,208 | 298,399 | 523,082 | 36,225 | 333,287 | 134,764,125 | 459,813,400 | 4,648,487 | 63,427 | 22,482,099 | 441,754 | 521,873 | 4,755,465 |
| | Minimum | 444,489 | 286,315 | 490,086 | 30,523 | 305,027 | 130,061,025 | 427,931,900 | 4,456,441 | 58,810 | 21,523,775 | 383,560 | 499,836 | 4,433,769 |
| | Std. Dev. | 10,144 | 3811 | 10,409 | 1970 | 9815 | 1,411,626 | 10,341,776 | 67,186 | 1522 | 346,937 | 17,159 | 7057 | 110,782 |

Panel C: real private consumption, all figures in million local currencies

| **Period** | | AUSTRALIA | BRAZIL | CANADA | INDIA | ISRAEL | JAPAN | KOREA | MEXICO | NEW ZEALAND | RUSSIA | TURKEY | UNITED KINGDOM | UNITED STATES |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **2008q1-2019q2** | Mean | 231,491 | 191,229 | 265,867 | 14,300 | 150,818 | 73,144,982 | 195,028,074 | 2,758,240 | 32,466 | 11,502,168 | 211,963 | 305,220 | 2,879,983 |
| | Median | 231,211 | 194,801 | 264,675 | 13,906 | 147,695 | 73,547,125 | 194,740,000 | 2,714,679 | 31,731 | 11,588,636 | 218,152 | 299,613 | 2,803,884 |
| | Maximum | 263,544 | 209,618 | 301,766 | 20,439 | 186,191 | 76,513,400 | 221,901,200 | 3,118,079 | 39,273 | 13,332,278 | 269,154 | 340,488 | 3,312,510 |
| | Minimum | 200,484 | 160,679 | 234,310 | 9339 | 122,972 | 69,200,450 | 167,793,600 | 2,375,293 | 27,463 | 9,742,847 | 151,584 | 279,557 | 2,604,334 |
| | Std. Dev. | 19,757 | 13,591 | 21,370 | 3419 | 19,982 | 1,802,476 | 15,216,652 | 221,146 | 3698 | 897,220 | 36,406 | 20,579 | 221,958 |
| **2008q1-2016q2** | Mean | 222,638 | 189,107 | 255,898 | 12,664 | 141,290 | 72,580,298 | 188,019,665 | 2,650,891 | 30,625 | 11,368,413 | 196,810 | 294,932 | 2,771,053 |
| | Median | 224,866 | 193,140 | 254,856 | 12,612 | 140,292 | 72,903,300 | 188,309,700 | 2,647,181 | 30,350 | 11,390,793 | 195,359 | 291,572 | 2,745,361 |
| | Maximum | 246,742 | 209,618 | 280,644 | 16,608 | 168,741 | 76,513,400 | 205,868,800 | 2,904,474 | 35,292 | 13,332,278 | 244,431 | 323,666 | 3,052,821 |
| | Minimum | 200,484 | 160,679 | 234,310 | 9339 | 122,972 | 69,200,450 | 167,793,600 | 2,375,293 | 27,463 | 9,742,847 | 151,584 | 279,557 | 2,604,334 |
| | Std. Dev. | 14,598 | 15,166 | 14,730 | 2216 | 13,227 | 1,757,780 | 10,639,067 | 141,873 | 2192 | 999,594 | 29,551 | 12,369 | 134,926 |
| **2016q3-2019q2** | Mean | 256,576 | 197,244 | 294,112 | 18,934 | 177,815 | 74,744,921 | 214,885,233 | 3,062,396 | 37,685 | 11,881,142 | 254,897 | 334,371 | 3,188,619 |
| | Median | 257,382 | 198,061 | 295,599 | 18,852 | 178,124 | 74,843,763 | 215,620,600 | 3,080,371 | 37,709 | 11,925,051 | 255,590 | 334,478 | 3,189,077 |
| | Maximum | 263,544 | 201,701 | 301,766 | 20,439 | 186,191 | 75,580,775 | 221,901,200 | 3,118,079 | 39,273 | 12,318,613 | 269,154 | 340,488 | 3,312,510 |
| | Minimum | 248,095 | 191,820 | 282,775 | 17,209 | 170,330 | 73,928,925 | 207,332,600 | 2,953,279 | 35,818 | 11,399,315 | 237,246 | 327,260 | 3,072,266 |

**Table 13** (continued)

| Period | | AUSTRALIA | BRAZIL | CANADA | INDIA | ISRAEL | JAPAN | KOREA | MEXICO | NEW ZEALAND | RUSSIA | TURKEY | UNITED KINGDOM | UNITED STATES |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Std. Dev. | 5365 | 3488 | 6307 | 1171 | 5735 | 493,518 | 5,069,021 | 56,078 | 1152 | 289,233 | 9034 | 4398 | 79,578 |
| Panel D: real gross fixed capital formation,all figures in million local currencies | | | | | | | | | | | | | | |
| **Period** | | AUSTRALIA | BRAZIL | CANADA | INDIA | ISRAEL | JAPAN | KOREA | MEXICO | NEW ZEALAND | RUSSIA | TURKEY | UNITED KINGDOM | UNITED STATES |
| **2008q1-2019q2** | Mean | 106,269 | 58,329 | 107,116 | 8247 | 55,208 | 29,374,886 | 116,530,515 | 878,797 | 12,523 | 4,684,755 | 96,043 | 78,812 | 837,957 |
| | Median | 108,068 | 57,235 | 107,581 | 8016 | 55,201 | 29,886,850 | 111,974,250 | 888,260 | 12,392 | 4,773,275 | 100,051 | 79,471 | 830,251 |
| | Maximum | 116,851 | 71,674 | 118,263 | 11,617 | 71,400 | 32,370,000 | 143,486,500 | 959,782 | 15,807 | 5,101,094 | 131,704 | 88,201 | 998,493 |
| | Minimum | 92,949 | 46,357 | 88,847 | 5303 | 41,319 | 26,249,125 | 96,860,000 | 750,688 | 9608 | 4,004,183 | 54,145 | 68,380 | 688,142 |
| | Std. Dev. | 6898 | 7682 | 6566 | 1707 | 9243 | 1,941,951 | 13,859,990 | 61,308 | 2004 | 318,287 | 23,162 | 6829 | 96,541 |
| **2008q1-2016q2** | Mean | 105,413 | 61,098 | 106,764 | 7428 | 50,881 | 28,606,025 | 109,446,174 | 859,991 | 11,630 | 4,629,840 | 87,249 | 75,840 | 795,157 |
| | Median | 106,199 | 63,177 | 107,370 | 7784 | 53,016 | 28,465,413 | 107,961,550 | 864,840 | 11,277 | 4,689,304 | 87,129 | 74,697 | 798,841 |
| | Maximum | 116,851 | 71,674 | 118,263 | 9437 | 62,840 | 30,828,500 | 126,793,800 | 959,782 | 14,309 | 5,101,094 | 116,805 | 85,674 | 904,602 |
| | Minimum | 92,949 | 46,357 | 88,847 | 5303 | 41,319 | 26,249,125 | 96,860,000 | 750,688 | 9608 | 4,004,183 | 54,145 | 68,380 | 688,142 |
| | Std. Dev. | 7706 | 7033 | 7514 | 1038 | 6323 | 1,642,640 | 7,498,031 | 60,335 | 1496 | 343,765 | 19,922 | 5348 | 71,711 |
| **2016q3-2019q2** | Mean | 108,692 | 50,484 | 108,112 | 10,568 | 67,469 | 31,553,327 | 136,602,817 | 932,081 | 15,055 | 4,840,344 | 120,957 | 87,233 | 959,223 |
| | Median | 109,518 | 50,355 | 107,822 | 10,684 | 67,928 | 31,601,550 | 136,396,650 | 933,147 | 15,217 | 4,833,053 | 121,003 | 87,275 | 963,451 |
| | Maximum | 111,761 | 52,913 | 111,535 | 11,617 | 71,400 | 32,370,000 | 143,486,500 | 956,392 | 15,807 | 5,064,842 | 131,704 | 88,201 | 998,493 |
| | Minimum | 102,662 | 48,719 | 104,115 | 9318 | 62,816 | 30,532,050 | 129,553,500 | 895,955 | 14,361 | 4,501,258 | 101,797 | 86,302 | 910,840 |
| | Std. Dev. | 2801 | 1477 | 2352 | 864 | 2775 | 573,171 | 4,748,571 | 16,280 | 514 | 155,509 | 9376 | 580 | 31,561 |
| Panel E: real exports, all figures in million local currencies | | | | | | | | | | | | | | |
| **Period** | | AUSTRALIA | BRAZIL | CANADA | INDIA | ISRAEL | JAPAN | KOREA | MEXICO | NEW ZEALAND | RUSSIA | TURKEY | UNITED KINGDOM | UNITED STATES |
| **2008q1-2019q2** | Mean | 79,107 | 36,604 | 145,090 | 5663 | 89,418 | 19,728,709 | 164,840,800 | 1,322,828 | 15,687 | 5,190,887 | 76,892 | 133,646 | 557,055 |
| | Median | 76,266 | 36,119 | 142,094 | 5952 | 91,252 | 19,773,225 | 175,408,250 | 1,289,917 | 15,196 | 5,119,064 | 77,290 | 132,148 | 572,932 |
| | Maximum | 102,453 | 43,876 | 169,349 | 7613 | 105,119 | 23,526,475 | 198,282,100 | 1,749,114 | 18,676 | 6,195,430 | 105,590 | 153,660 | 639,979 |
| | Minimum | 62,100 | 29,652 | 116,652 | 3688 | 67,006 | 12,862,175 | 117,732,100 | 838,697 | 13,237 | 4,281,682 | 52,718 | 112,494 | 425,683 |

**Table 13** (continued)

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Std. Dev. | 13,275 | 3552 | 14,218 | 1089 | 8736 | 2,442,964 | 24,977,141 | 254,653 | 1603 | 528,597 | 15,565 | 11,450 | 60,441 |
| **2008q1-2016q2** | Mean | 72,759 | 35,093 | 139,203 | 5260 | 86,283 | 18,680,360 | 156,293,226 | 1,210,634 | 14,954 | 4,931,521 | 70,221 | 128,410 | 534,323 |
| | Median | 70,671 | 35,434 | 139,000 | 5485 | 89,572 | 18,802,688 | 164,532,900 | 1,246,730 | 14,821 | 4,888,753 | 71,522 | 129,361 | 545,090 |
| | Maximum | 90,341 | 39,590 | 159,638 | 6586 | 95,234 | 21,093,200 | 183,340,400 | 1,503,511 | 17,346 | 5,497,113 | 85,687 | 142,154 | 600,073 |
| | Minimum | 62,100 | 29,652 | 116,652 | 3688 | 67,006 | 12,862,175 | 117,732,100 | 838,697 | 13,237 | 4,281,682 | 52,718 | 112,494 | 425,683 |
| | Std. Dev. | 8780 | 2637 | 11,556 | 941 | 7619 | 1,903,686 | 23,520,782 | 193,099 | 1134 | 319,392 | 11,534 | 8017 | 53,517 |
| **2016q3-2019q2** | Mean | 108,692 | 50,484 | 108,112 | 10,568 | 67,469 | 31,553,327 | 136,602,817 | 932,081 | 15,055 | 4,840,344 | 120,957 | 87,233 | 959,223 |
| | Median | 109,518 | 50,355 | 107,822 | 10,684 | 67,928 | 31,601,550 | 136,396,650 | 933,147 | 15,217 | 4,833,053 | 121,003 | 87,275 | 963,451 |
| | Maximum | 111,761 | 52,913 | 111,535 | 11,617 | 71,400 | 32,370,000 | 143,486,500 | 956,392 | 15,807 | 5,064,842 | 131,704 | 88,201 | 998,493 |
| | Minimum | 102,662 | 48,719 | 104,115 | 9318 | 62,816 | 30,532,050 | 129,553,500 | 895,955 | 14,361 | 4,501,258 | 101,797 | 86,302 | 910,840 |
| | Std. Dev. | 2801 | 1477 | 2352 | 864 | 2775 | 573,171 | 4,748,571 | 16,280 | 514 | 155,509 | 9376 | 580 | 31,561 |

Data source: OECD database, Quarterly National Accounts

**Table 14** *P* value of the Phillips-Perron unit root tests for levels and first differences

| Country | Real GDP growth rate in % | | Real GDP | | Real priv. Consumption | | Real GFCF | | Real exports | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Level | First difference | Level | First difference | Level | First difference | Level | First difference | Level | First difference |
| AUSTRALIA | 0.0259 | – | 0.8810 | 0.0000 | 0.5564 | 0.0000 | 0.6016 | 0.0060 | 0.8315 | 0.0000 |
| BRAZIL | 0.0363 | – | 0.9713 | 0.0014 | 0.9417 | 0.0023 | 0.3579 | 0.0010 | 0.6908 | 0.0000 |
| CANADA | 0.0839 | – | 0.0012 | 0.0050 | 0.0512 | 0.0101 | 0.5224 | 0.0043 | 0.6873 | 0.0000 |
| CHINA | 0.0993 | – | – | – | – | – | – | – | – | – |
| INDIA | 0.0457 | – | 0.7911 | 0.0002 | 0.5175 | 0.0000 | 0.8967 | 0.0346 | 0.8961 | 0.0000 |
| ISRAEL | 0.0329 | – | 0.3478 | 0.0026 | 0.9514 | 0.0000 | 0.6141 | 0.0097 | 0.9958 | 0.0000 |
| JAPAN | 0.0080 | – | 0.6395 | 0.0000 | 0.5754 | 0.0000 | 0.6123 | 0.0002 | 0.0401 | 0.0001 |
| KOREA | 0.0288 | – | 0.5061 | 0.0000 | 0.7796 | 0.0000 | 0.3091 | 0.0135 | 0.3141 | 0.0000 |
| MEXICO | 0.0315 | – | 0.0265 | 0.0031 | 0.0006 | 0.0022 | 0.8722 | 0.0019 | 0.7343 | 0.0024 |
| NEW ZEALAND | 0.2689 | – | 0.9996 | 0.0000 | 0.0056 | 0.0000 | 0.8674 | 0.0270 | 0.8859 | 0.0000 |
| RUSSIA | 0.0013 | – | 0.6678 | 0.0046 | 0.9255 | 0.0163 | 0.0993 | 0.0986 | 0.3034 | 0.0000 |
| TURKEY | 0.0500 | – | 0.5621 | 0.0000 | 0.4710 | 0.0000 | 0.7975 | 0.3240 | 0.8735 | 0.0000 |
| UNITED KINGDOM | 0.0353 | – | 0.4346 | 0.0764 | 0.4550 | 0.0039 | 0.9035 | 0.0003 | 0.2419 | 0.0000 |
| UNITED STATES | 0.1259 | – | 0.9642 | 0.0033 | 0.9982 | 0.0349 | 0.5206 | 0.0214 | 0.4003 | 0.0006 |

**Acknowledgements** I am grateful for the helpful comments, suggestions and criticism of Andre Jungmittag (Frankfurt University of Applied Sciences and DG Joint Research Centre of the European Commission), Paul J.J. Welfens (EIIW/University of Wuppertal), Ronald Schettkat (University of Wuppertal), Tian Xiong (EIIW/ University of Wuppertal), participants of the 22nd Annual INFER Conference, participants of the 13th FIW Research Conference in International Economics and seminar participants at the Chair for Macroeconomic Theory and Policy and at the Chair for Economic Policy, University of Wuppertal. I would like to express my sincere thanks to David Hanrahan (EIIW) and Kennet Stave (EIIW) for editorial assistance and also gratefully acknowledge comments and suggestions by two anonymous referees that have significantly helped to improve this paper. Remaining errors are my own.

**Data availability** No

## Declaration

**Conflict of interest** Not applicable.

**Code availability** No

## References

Abadie A, Gardeazabal J (2003) The economic costs of conflict: a case study of the Basque Country. Am Econ Rev 93(1):113–132

Andrews DWK, Monohan JC (1992) An improved Heteroskedasticity and autocorrelation consistent covariance matrix estimator. Econometrica 60:953–966

Bai J, Ng S (2002) Determining the number of factors in approximate factor models. Econometrica 70(1):191–221

Baier FJ, Welfens PJJ (2018) BREXIT and Foreign Direct Investment: Key Issues and New Empirical Findings. Int J Financ Stud 6(46)

Barro R (2001) Human capital and growth. Am Econ Rev 91(2):12–17

Born B, Müller GJ, Schularick M, Sedláček P (2019) The costs of economic nationalism: evidence from the Brexit experiment. Econ J 129(10):2722–2744

Brakman S, Garretsen H, Kohl T (2017) Consequences of Brexit and options for a "global Britain". CESifo Working Paper Series 6448, CESifo

Demmou L, Stefanescu I, Arquié A (2019) Productivity growth and finance: the role of intangible assets - a sector level analysis. OECD Economics Department Working Papers, No. 1547, Paris

Devereux M, Love D (1994) The effects of factor taxation in a two-sector model of endogenous growth. Can J Econ 27(3):509–536

Dhingra S, Huang H, Ottaviano G, Pessoa JP, Sampson T, Van Reenen J (2017) The costs and benefits of leaving the EU: trade effects. CEP Discussion Paper 1478, Centre for Economic Performance, LSE

Douch M, Edwards H, Soegaard C (2018) Estimating the trade effects of the Brexit announcement shock. The UK in a Changing Europe Available at: http://ukandeu.ac.uk/estimating-the-trade-effects-of-the-brexit-announcement-shock/. Accessed 05 Januar 2020

Engle RF, Granger CWJ (1987) Co-integration and error correction: representation, estimation, and testing. Econometrica 55(2):251–276

Froot KA, Stein JC (1991) Exchange rates and foreign direct investment: an imperfect capital markets approach. Q J Econ 106(4):1191–1217

Gardeazabal J, Vega-Bayo A (2017) An Empirical Comparison Between the Synthetic Control Method and HSIAO et al.'s Panel Data Approach to Program Evaluation. J Appl Econ 32(5):983–1002

Graziano A, Handley K, Limão N (2018) Brexit uncertainty and trade disintegration. NBER working paper no. 25334, National Bureau of Economic Research

Grübler J (2017) Wirtschaftliche Konvergenz trotz politischer Unsicherheit. The Vienna Institute for International Economic Studies, Forschungsbericht 7

Henkel M, Seidel T (2019) A spatial perspective on EUROPEAN integration: heterogeneous welfare and migration effects from the single market and the BREXIT. Econ Inq 57(1):333–352

Hsiao C, Ching HS, Wan SK (2012) A panel data approach for program evaluation: MEASURING the benefits of political and economic integration of Hong KONG with mainland China. J Appl Econ 27(5): 705–740

IMF (2015) Fiscal policy and long-term growth. IMF Policy Paper, USA: International Monetary Fund

Jungmittag A, Welfens PJJ (2016) Beyond EU-US trade dynamics: TTIP effects related to foreign direct investment and innovation. EIIW Discussion Paper No. 212, European Institute for International Economic Relations, University of Wuppertal

Ke X, Chen H, Hong Y, Hsiao C (2017) Do China's high-speed-rail projects promote local economy?—new evidence from a panel data approach. China Econ Rev 44:203–226

Korus A, Celebi K (2019) The impact of Brexit news on British pound exchange rates. Int Econ Econ Policy 16:161–192

Li KT, Bell DR (2017) Estimation of average treatment effects with panel data: asymptotic theory and implementation. J Econ 197(1):65–75

Lucas R (1988) On the mechanics of economic development. J Monet Econ 22:3–42

Meinshausen N, Yu B (2009) Lasso-type recovery of sparse representations for high-dimensional data. Ann Stat 37(1):246–270

Newey WK, West KD (1987) A simple, positive semi-definite, Heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55(3):703–708

Oberhofer H, Pfaffermayr M (2018) Estimating the trade and welfare effects of Brexit: a panel data structural gravity model. Department of Economics Working Paper Series, 259. WU Vienna University of Economics and Business

Office for Natinal Statistics (2019) GDP quarterly national accounts, UK: April to June 2019. [Online] Available at: https://www.ons.gov.uk/economy/grossdomesticproductgdp/bulletins/quarterlynationalaccounts/apriltojune2019. Accessed 23 December 2019

Rebelo S (1991) Long-run policy analysis and long-run growth. J Polit Econ 99(3):500–521

Serwicka I, Tamberi N (2018) Not backing Britain: FDI inflows since the Brexit referendum. Briefing Paper 23, UK Trade Policy Observatory, University of Sussex

Springford J (2019) CER INSIGHT: The cost of Brexit to June 2019. [online] Available at: https://www.cer.eu/sites/default/files/insight_JS_16.10.19.pdf. Accessed 23 December 2019

Tibshirani R (2011) Regression shrinkage and selection via the lasso: a retrospective. J R Stat Soc Ser B Methodol 73(3):273–282

Wan S, Xie Y, Hsiao C (2018) Panel data approach vs synthetic control method. Econ Lett 164:121–123