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Abstract

The United Kingdom (UK) reported record employment levels following its vote to Leave the European Union (EU), leading to many pundits discarding the dire pre-Brexit vote impact assessments as part of "project fear." This paper studies the cost of the Brexit-vote to date across UK regions finding significant evidence suggesting that the economic costs of the Brexit-vote are both sizable and far from evenly distributed. Among 382 districts, at least 168 districts appear to be Brexit-vote losers, having lost, on average 8.54 percentage points of output in 2018 compared to their respective synthetic controls. The Brexit-vote costs are increasing in a districts: a) support for Leave in 2016; b) the size of its manufacturing sector; c) the share of low skilled. The Brexit-vote induced economic divergence across regions is already exacerbating the regional economic inequalities that the 2016 EU referendum vote made apparent. Indirect evidence further suggests that firms may, amidst the significant (trade) policy uncertainty, have shifted away from capital to labor in the short-term given that Brexit has, to date, not led to changes in market access. The resulting short-term employment- and payroll growth post-2016 is not supported by productivity increases in most parts of the UK. This sets up the possibility for significant labor market adjustments once Brexit becomes a de-facto reality. Further, there is some evidence suggesting that COVID19 may exacerbate the regional economic impact of the Brexit-vote to date.

Keywords: Brexit, economic impact, evaluation, trade barriers
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1 Introduction

An overwhelming majority of economists would agree with the statement that the Brexit-vote has left the United Kingdom (UK) with worse growth prospects going forward. Evidence of the economic impact of the Brexit-vote to date suggests that since 2016, the UK has lost around 2.5% of annual output (see Born et al., 2019; Springford, 2019). Firms and households unwillingness to commit investment in the UK seems to be a primary driver of the cost of Brexit-vote to date, despite Brexit still not being a de-facto reality more than four years after the vote. This paper is a first attempt to shed light on the regional economic distribution of the costs of Brexit up to 2019Q3 – the most recent date for which subnational data on economic activity is broadly available.

We follow Born et al. (2019) in leveraging a synthetic control method approach to estimate the economic impact of the Brexit vote for each of the UK's 12 regions using quarterly data up to 2019 Q3 and, for each of the UK's 382 local authority districts using annual data available up to 2018. Bearing in mind the challenges that working with a relatively short panel of low frequency data (annual) data have for the validity of synthetic control estimates (Abadie, 2020), we construct a total of more than 100 different synthetic control estimates *for each district* and leverage ensemble methods as suggested by Athey et al. (2019). This allows us to arrive at a district-level estimate of the output losses attributable to Brexit to date. A simulation approach complements the analysis and aims to address specific concerns about potential overfitting due to a mechanically exploding donor pool when invoking subnational data produces very similar results.

Using quarterly data across the UK's regions, we find that nearly all regions have lost economic activity vis-a-vis their respective synthetic controls. In relative terms, by 2019, the West Midlands (-5.29 percent), Northern Ireland (-4.67 percent), the South West (-3.5 percent) and South East (-3.08 percent) appear to have lost most in relative terms, highlighting that economic divergence between the UK's regions may be exacerbated by Brexit. In absolute terms, the economic impact of the Brexit-vote so far appears largest in London and the South East. Aggregated up, our results match quite well the UK-wide estimates of the cost of Brexit-vote

to date by Born et al. (2019).

Turning to the analysis of annual district-level data available up to 2018, the results suggests that by 2018, among the 382 districts of the UK, 255 districts record a 2018 Gross value added that is smaller compared to their synthetic control – while half as many, 127 districts, report a higher value for 2018 compared to their synthetic control. Around 168 districts can be labelled as "Brexit-vote losers" – these are districts that very consistently exhibit lower levels of output relative to their respective synthetic controls across a host of estimates. Only a small number of 78 districts are classified as relatively clear "Brexit-vote winners" with the remaining districts exhibiting patterns that are are too ambiguous to assign a label. On average, districts classified as "Brexit-vote losers", by 2018, exhibit output that is, on average, 8.54 percentage points lower compared to their respective synthetic controls. The small subset of "Brexit winners" exhibit , on average, 6.54 percentage points higher output relative to their respective synthetic controls. The overall aggregated-up Brexit-vote losses again, compare very well with the estimates obtained from the region-level analysis as well as country-wide studies. This highlights that the estimates are not sensitive to the specific choice of the donor pool; the specific geographic aggregation of the data; or the specific data set we study.

The economic costs of the Brexit-vote are far from evenly distributed across the UK's regions. A regression analysis of the covariates of the Brexit-vote induced output losses suggests that the "Brexit-vote costs" are more concentrated in districts with sizable manufacturing sector employment and value added – a finding that is not surprising given that this sector is very reliant on frictionless trade with the EU's single market and is integrated in its just-in-time supply chains (Berlingieri et al., 2019; Pisch, 2020). The results further suggest that areas that had higher support for Leave have experienced significantly lower levels of economic growth relative to their respective synthetic control units. Further, Brexit-costs appear concentrated in regions with a higher share of residents with relatively low qualifications. Overall, the results suggest that the cost of the Brexit-vote up to 2018 may significantly exacerbate regional inequalities that became particularly apparent in the 2016 EU Referendum vote patterns (Becker et al., 2017).

Further, we present some evidence that may shed light on the underlying eco-

nomic mechanisms that may nevertheless help understand why the UK recorded record employment levels post 2016. Much of the focus of the literature studying the impacts of the Brexit-vote so far highlight the importance of uncertainty over the future trading relationship between the UK and Europe. This work anchors around models of economic behavior in which firms or consumers are forward looking agents that form expectations about the macroeconomy (see Coibion et al., 2019; Fuster et al., 2010, 2012; Coibion and Gorodnichenko, 2012, 2015a,b; Coibion et al., 2018; Malmendier and Nagel, 2011 for some related literature). This uncertainty is *still not resolved* as Brexit, while becoming a de-jure reality in January 2020, is not a de-facto economic reality with negotiations for the future trading relationship – under the threat of a No Deal exit from January 2021 – yet to be concluded. In this setting, unsurprisingly, firms may have been holding off long term capital investments, which may come with some fixed costs and be only partially irreversible, and rather substitute towards labor that can be more easily adjusted in case an unfavorable Brexit deal becomes an economic reality. Such substitution away from capital to labor may help explain the record levels of employment post 2016 in the UK.[1] One way to gauge whether this type of substitution did indeed occur is by studying productivity. Firms, by holding off on investing in capital, were not keeping optimal capital-to-labour ratios. This should result in lower labor productivity – which should be more concentrated in areas that saw the biggest drop in output vis-a-vis their synthetic controls. This is an observation we indeed can document: while almost consistently, employment levels increased across districts in the UK – irrespective of whether a district appears to be a Brexit-winner or a Brexit-loser – output per worker significantly declined, in particular in the regions with the largest gap vis-a-vis their respective synthetic controls. The temporary substitution away from capital to labor sets up the possibility for dramatic employment adjustments once a hard Brexit may become economic reality.

Lastly, we also document some tentative evidence that suggests that the economic impact from Brexit to date, may be exacerbated by significant output adjustments that may take place due to COVID19. Districts that saw the most notable

[1]See for a similar argument made in Faccini and Palombo (2019); Broadbent et al. (2019) highlight that the devaluation of the pound may have provided an additional temporary cushion.

drops in output relative to their synthetic control due to the Brexit-vote to date see significantly higher levels of workers being furloughed. For every one percentage point higher gap between a district and its synthetic control, capturing the Brexit cost to date, the share of employments furloughed are 0.15 percentage points higher, suggesting that these districts may be more severely hit if a sizable share of furloughed employments are being lost.

Our findings complement much of the economic literature that has highlighted that there are indeed, good reasons to believe that the economic impact of Brexit will not be evenly spread. Multiple studies conducted before and in the wake of the EU referendum vote suggest that cost of Brexit will be highly heterogenous across the UK's nations and even across regions. Los et al. (2017) suggest that regions that voted strongly for Brexit are expected to be among those that are more economically dependent on EU markets, and that are more likely to be negatively affected by Brexit. Borchert and Tamberi (2018) suggests that Brexit shocks may cause an adverse economic impact on the North East and the Midlands because these are the regions that export the most to EU markets. Focusing on manufacturing specifically, Gasiorek et al. (2018) conduct an ex-ante impact modelling finding that Brexit is more likely to negatively affect regions that depend on manufacturing the most. HM Government (2018) extensive modelling point to significant spatial heterogeneity of the impact of different new trade regimes coming into place that may exacerbate regional inequalities. The analysis considers sectoral specialisation and the fact that the economic impacts can flow between regions due to integrated supply chains. Analysis conducted by Cambridge Econometrics (2018) suggests that a change in trading regime with the EU will induce a slowing down of growth across the UK but to a lesser degree for London and the South East. Oliver Wyman (2018), focusing on consumption and income, suggest that Brexit has notably heterogenous impacts across household across regions. Dhingra et al. (2017) estimate economic consequences of leaving the European Union for living standards in the UK by estimating the welfare effects of changes in trade and fiscal transfers following Brexit. They find static losses range between 1.28% and 2.61% of welfare

Levell and Keiller (2018) find that some industries (e.g. transport equipment)

are more likely to adversely affected by potential trade barriers. In regions that are largely dependent on these industries, low-educated workers may find it especially difficult to adapt to new conditions. Chen et al. (2018) compares the economic exposure to Brexit on regions in the UK and Europe finding that the UK regions will be most affected. Clarke et al. (2017) suggest that London and the South East may be least affected by negative consequences of new tariff and non-tariff barriers. Similar to Clarke et al. (2017), Morris (2018) suggest that London and the South East are least likely to be badly affected by Brexit. In terms of price impacts, areas outside London are more likely to be affected by a hard Brexit. The findings from this paper, with evidence up to 2018, suggest that in relative terms, the West Midlands, Northern Ireland, and the South West are most affected by Brexit to date. These findings are quite consistent with Dhingra et al. (2018), who found that areas in the South of England, and urban areas, are predicted to be harder hit by Brexit under both a hard- and a soft-Brexit scenario.

Much of the existing work has purely focused on ex-ante impact modelling as Brexit only became a legal reality in January 2020, more than three-and-a-half years after the EU referendum, with a change in the actual trading regime only becoming effective, potentially from January 2021 after the end of the transition period. Our work complements several strands studying the regional economic impact of the Brexit-vote to date. This is related to a larger strand of literature that has attempted to study the economic impact of Brexit to date through a host of mechanisms. Steinberg (2017) suggests, using a dynamic general equilibrium model, that the Brexit may have reduced welfare of UK households is 0.4-1.2 percent lower with a non-neglible share of this cost being attributable to Brexit-induced trade policy uncertainty. Broadbent et al. (2019) highlight that the depreciation of the pound in the wake of the Brexit vote in 2016 created a temporary positive windfall for exporters which may have had a positive temporary effect on local economies. Breinlich et al. (2020) study foreign direct investment (FDI), using a synthetic control approach, finding that the 2016 Brexit vote had a sizable impact decreasing FDI projects of EU27 member countries in the UK. At the same time, the UK saw a notable increase in outflowing FDI into the EU27. McGrattan and Waddle (2020) use simulations from a multi-country neoclassical growth model to analyze several

post-Brexit scenarios finding significant heterogeneity of the impacts depending on the policy response of multinational firms. Breinlich et al. (2017) highlight how the surge in consumer prices, driven by the devaluation of the pound in the wake of the Brexit vote, has significantly depressed real incomes and negatively affected consumer spending. This paper adds to and complements the existing literature which, to date, has not studied the regional economic implications of Brext-vote to date – apart from through ex-ante economic impact modelling.

The rest of the paper is organized as follows. Section 2 introduces the variations around the synthetic control method used along with the subnational data we leverage; Section 3 presents the results across UK regions; Section 4 presents the main district-level estimates, decomposes the variation and discusses the underlying mechanism. The last section concludes.

2 Method

In this paper we estimate the region-specific cost of Brexit to date. To do this, we leverage on the synthetic control method as introduced by Abadie and Gardeazabal (2003) (see also Abadie et al. (2015, 2010)). In the context of Brexit, Born et al. (2019) estimate a synthetic control at the country level and documents that Brexit until the end of 2018 has cost the UK economy between 1.7-2.5 percent of GDP. Their careful analysis is, however, silent on the regional distribution of this output loss across different parts of the UK – this paper fills this gap.

2.1 Data

UK subnational economic activity We leverage two data sources that capture the UK's subnational economic activity. First, we draw on experimental high frequency subnational real GDP measures. This data is available for England and Wales from the ONS[2], while Scotland[3] and Northern Ireland[4] produce their own

[2]This data can be accessed here https://www.ons.gov.uk/economy/grossdomesticproductgdp/datasets/quarterlycountryandregionalgdp, 24.06.2020.

[3]The Scottish Data is available here https://www.gov.scot/publications/gdp-quarterly-national-accounts-for-scotland-2019-q4/, accessed 25.06.2020.

[4]The Northern Irish data is available here https://www.nisra.gov.uk/statistics/economic-output-statistics/ni-composite-economic-index, accessed 25.06.2020.

estimates. These data are not classified as Official Statistics but have been produced as experimental statistics at quarterly cadence for each of the UK's fourteen regions capturing the UK's twelve NUTS1 regions. The data are available from 2012Q1 up to 2019Q3. The combined data set represents the UK as 12 spatial units over 31 time periods.

We further leverage annual subnational economic data from 2000 up to 2018 measuring regional gross value added.[5] The most recent release was published on 19 December 2019 covering data up to 2018. These data are classified as National Statistics, according to the Code of Practice for official statistics. The data measure estimates of balanced gross value added (GVA), allocated to local authorities in the UK on a workplace basis – that is, value added is attributed to the location of where economic activity takes place. We rely on the data that provides GVA in real terms using chained volume measures with values expressed in 2016 money value. The data are reported for each of the UK's 382 districts (using district boundaries as of January 2019) since 2000.

Donor pool data In order to construct synthetic control estimates of real GDP's evolution across the UK's regions and districts, we rely on multiple data sources. Specifically, for the analysis of quarterly data that we can construct for each of the 12 regions for which the UK data provide us with regional economic activity estimates, we naturally rely on donor pool data that is reported at the same frequency. We leverage real GDP data as reported in quarterly national accounts data collected by the Economists Intelligence Unit (EIU), which is mostly available only for a subset of countries. We put specific emphasis on data from the G20, the OECD and the EU economies in particular. The quarterly data is mostly available up until the end of 2019.

For the construction of *annual estimates* we rely on data from the EIU, the European Statistical Office (Eurostat), and the US's Bureau of Economic Analysis (BEA). We leverage both national- and subnational data for the annual estimates (very few countries – the UK is an exception producing experimental statistics –

[5]This data is available here https://www.ons.gov.uk/economy/grossdomesticproductgdp/bulletins/regionaleconomicactivitybygrossdomesticproductuk/1998to2018, 24.06.2020.

produce high frequency subnational economic accounts). The annual data from the Economists Intelligence Unit provides economic indicators for 204 countries, ranging from 1980 to 2019. We use real gross domestic product (GDP) data between 2000 and 2018 to construct the donor pools: G20, OECD, and EU, covering 18, 33, and 27 countries respectively.

At the subnational level, we obtain data for European countries for which data at the NUTS 2 region level are available from Eurostat.[6] This data covers 251 NUTS2 regions in Europe covering EU member countries, countries that are in accession talks with the EU along with members of the European Economic Area. To build the EU-NUTS2 donor pool, we use the gross value added at basic prices by NUTS 2 regions. Data for 175 of 251 regions are consistently available during 2000-2018. These regions can be used to construct the doppelganger.

We also leverage US subnational-level data. Specifically, we use real gross domestic product (GDP) by states from the Bureau of Economic Analysis.[7] This includes data for 50 US states and the District of Columbia. The real estimates of GDP are measured in chained 2012 dollars. We use this dataset to build the US-STATES donor pool. The motivation to draw particular emphasis on US subnational data in addition to EU subnational data is twofold: first, the US is one of the few countries that provide timely subnational data that is readily available up to 2018. Second, in Born et al. (2019) the US is the donor country with the largest weight contributing to the Doppelganger. Note that we restrict the set of units to be included to only include countries and regions for which real GDP is consistently available for each time period for which we also have UK data either quarterly or annual.

We next describe the various donor pool sets that we leverage.

2.2 Donor Pool Sets

We construct synthetic controls for each of the UK's 382 administrative districts using annual data. In addition, we also construct synthetic controls for each of the

[6]The closest comparable data is "Gross value added at basic prices by NUTS regions", which is accessible from https://ec.europa.eu/eurostat/web/products-datasets/-/nama_10r_3gva

[7]This data is available at https://apps.bea.gov/iTable/iTable.cfm?acrdn=5&isuri=1&reqid=70&step=1.

UK's 12 regions using quarterly data. In doing so, we we leverage on a broad set of donor pools.

For the region-level analysis leveraging quarterly data, we consider quarterly data coming from three donor pools: G20 (18 countries), OECD (33 countries), and EU member countries (27 countries). For the district-level analysis, we leverage annual data from five donor pools: G20 (18 countries), OECD (33 countries), and EU member countries (27 countries) in addition to data pertaining to NUTS2 regions in European countries (175 regions) and US states (50 states plus DC).

While the synthetic control method can be performed for a single donor pool set – indeed, Born et al. (2019) exclusively consider the set of OECD countries as donor pool to construct the counterfactual UK economy –, we take a step further. We proceed by constructing the full set of feasible combinations of donor pools that can be drawn from the sets of individual donor pools. For the quarterly analysis, that entails constructing synthetic control estimates for $\binom{3}{1} + \binom{3}{2} + \binom{3}{3} = 2^3 - 1 = 7$ donor pool sets (the EU, OECD, G20; the pairs EU and OECD, EU and G20, G20 and OECD; and the triplet EU, OECD and G20). Given that we have quarterly data for twelve UK regions, this entails constructing 12×7 synthetic control estimates.

For the district-level annual data, the potential set of combinations of donor pool data are even larger. In total, we can construct $\binom{5}{1} + \binom{5}{2} ... + \binom{5}{5} = 2^5 - 1 = 31$ possible combinations of the donor pool sets. The most comprehensive donor pool set would include annual data from OECD, G20, EU27 member countries as well as the subnational annual data at the NUTS2 data for EU member states and the data for the US States. In case a country has subnational data available, we retain the subnational data and exclude the national-level data. To illustrate: Germany is a member of the EU, the G20 and the OECD and reports data at NUTS2 level to Eurostat. As a result, in all the data sets that draw on NUTS2 data, we represent Germany as its NUTS2 regions exclusively. This is to ensure that we are not including the same political concept at multiple spatial resolutions. The above implies that for the 382 UK districts for which annual data is available, we construct a total of $382 \times 31 = 11,842$ different synthetic control estimates.

Appendix Table A2 provides the full set of combinations leveraged for the district-level analysis. Mechanically, the largest donor pool consists of the superset

of all potential donors (the combined set consisting of EU-NUTS2, US-STATES, G20, OECD and EU). This donor pool consists of 253 spatial units.

2.3 Constructing Synthetic Controls

To construct a synthetic control for each potential donor pool, we proceed as follows. We fix a UK region d, and one of the donor pool set $\mathcal{S}$. As explained above, the donor pool sets are all the possible combinations among NUTS2 regions in EU, states in the US, and G20, OECD and EU member countries for the district-level annual data as well as all combinations of donors that can be build when drawing quarterly data from the G20, OECD and EU countries quarterly-level data.

Let x_r be the real output of region r. This is either measured annually between 2000 and 2015, thus 16 data points; or for the quarterly data, the 18 data points from 2012Q1 to 2016Q2. For the annual data we consider 2015 as the last pre-vote period. For the quarterly data, we consider 2016Q2 as the last time period before the Brexit-vote as the EU referendum was held on 23 June 2016.

Let X_s denote a matrix of the real GDP of the units in the donor pool combination $s \in \mathcal{S}$. Thus X_s is of dimension $|T_0| \times n(s)$, where $n(s)$ is the number of units in donor pool s and $|T_0|$ indicates the number of time period prior to the EU referendum vote (i.e. $T_0 = \{2000, ..., 2015\}$ for the annual data and $T_0 = \{2012Q1, ..., 2016Q2\}$ for the quarterly data). The number of columns of X_s then varies from $n(s) = 18$, if s is relative to G20 countries only, to $n(s) = 253$ when s consists of the superset of all spatial units.

The weights $w_s^d \equiv \{w_1^d, \ldots, w_{n(s)}^d\}$, representing the importance of unit $\{1, \ldots, n(s)\}$ in the combined donor pool to approximate the UK region r, is selected to minimize the mean squared error criteria:

$$\hat{w}_s^d = \underset{w_s^d \in R}{\arg\min} \; (x_r - X_s w_s^d)' V (x_r - X_s w_s^d) \tag{1}$$

where R is defined as the compact space for which $w_j^d \geq 0$, $j \in \{1, \ldots, n(s)\}$ and $\sum_{j=1}^{n(s)} w_j^d = 1$. V is a symmetric positive semi-definite matrix that represents the relative importance of the each characteristic in the mean squared error minimization. Following Abadie and Gardeazabal (2003), Abadie et al. (2010), and Born

et al. (2019), we select V that minimizes the pre-intervention mean squared prediction error using code implementations in Matlab. Each $\hat{w}_s^d$ then allows us to construct a counterfactual series $\hat{y}_{d,t}^s$ for each region or district for 2016, 2017 and 2018 or for the quarterly period post 2016Q2 up to 2019Q3.

2.4 Model selection

Since we construct a total of 31 distinct synthetic controls for each district in the annual data – as well as seven distinct synthetic controls for the quarterly data – we can further identify among the set of synthetic controls a "best" representation of the UK region or district prior to the Brexit-vote. Naturally, one would expect that the "best" series among the set $\mathcal{S}$ may be the product of the most extensive donor pool. This is a mechanic result: a larger donorpool makes it easier to fit pre-treatment outcomes even when there are substantial discrepancies in factor loadings between the treated unit and the synthetic control.

We construct, for each district or region, the following measures of goodness of fit in the pre-Brexit sample according to three criteria:

$$\text{AAPE}_d^s = \frac{1}{T_0} \sum_{t \in T_0} |x_d^t - X_{t,s}\hat{w}_d^s| \tag{2}$$

$$\text{RMSPE}_d^s = \sqrt{\frac{1}{T_0} \sum_{t \in T_0} (x_d^t - X_{t,s}\hat{w}_s^d)^2} \tag{3}$$

$$\text{MAPE}_d^s = \max_{t \in T_0} |x_d^t - X_{t,s}\hat{w}_d^s| \tag{4}$$

where "AAPE" stands for "average absolute projection error", "RMSPE" stands for "root mean square projection error" and "MAPE" is the maximum projection error. These criteria are meant to capture the goodness of fit for a given donor pool set s, aggregating information across regions or district and pre-intervention periods T_0. Having constructed these measures for each district or region from the set of synthetic controls that have been constructed, we can select a "best" model that, among the set of synthetic controls, minimizes these three respective goodness-of-fit measures. Appendix Table A3 provides a tabulation of the 31 donor pool sets as well as the number of districts that have been selected to be "the best" model

using each of the three goodness-of-fit measures. This highlights that the "best model" among the 31 candidate models is not unanimously the one that is built with the most extensive donor pool set.

Ensemble model In addition to these more standard measures to identify a "best model" we also construct an *ensemble model*. The idea for using an ensemble method is inspired by the popularity of ensemble methods in machine learning (see e.g. Valentini and Dietterich (2002) on support-vector machines). Ultimately, ensemble methods use multiple learning algorithms to obtain better predictive performance than could be obtained from any of the constituent learning algorithms alone. The ensemble of models may average out biases that may be introduced due to overfitting. This is specifically relevant in our setting as naturally, when moving from national- to subnational data, naturally the donor pool becomes significantly larger. Abadie et al. (2010) show that the bias the bias bound of the synthetic control-based treatment effect estimate depends positively on the size of the donorpool. In the case of panel settings using synthetic control, Athey et al. (2019) found that the predictive accuracy of an ensemble method appears to dominate individual methods in terms of their predictive performance. That is, for each series we calculate the *ensemble average* as:

$$\hat{y}_{d,t}^{ENS} = \frac{1}{|\mathcal{S}_s|} \sum_{s \in \mathcal{S}} \hat{y}_{d,t}^{s}$$

This headline synthetic control estimator is computed as a simple average across the 31 (7) synthetic control for each series for the annual (quarterly) data.

2.5 Donor pool permutation tests

In addition to the ensemble estimator above, we further construct another ensemble estimator that is the result of a simulation approach. The simulation approach recognizes the potential issue whereby overfitting may introduce a bias in the out-of-sample projection. Such biases may be increasing in the size of the donor pool and decreasing in the pre-treatment period length.

In our setting, especially when studying subnational UK data at the district-level and when drawing in subnational data from other countries, we have a

rapidly exploding size of a donor pool (though spatial units are nested) and a relatively short pre-treatment period. To assess whether introduces a potential problem for our analysis we construct a further set of 70 synthetic control donor sets $\mathcal{S}_{\text{sim}}$ for the annual data. For each donor pool size ranging from 10, 15, 20, 25, 30, 35, and 40, we draw ten random samples random samples of potential donors and identify the weights the optimal weights in these artificially constrained donor pool. We draw these samples from the most comprehensive donor pool consisting of the superset of US States, NUTS2 regions, EU27, OECD and G20 countries, representing a country through subnational data whenever that data is available.

Similarly, we construct a set of 70 synthetic controls that are built using random samples of donor pools with the donor pool size ranging from 5, 10, 15, ..., 30 (note that the maximal number if constrained at 33 for the quarterly data).

The result is a further 70 counterfactual series that come from quite constrained and randomly selected donor pools. As such, each of these series individually is posed to be less accurate; yet, in their ensemble, they may have a relatively high degree of accuracy – that is we compute:

$$\hat{y}_{d,t}^{ENS_{sim}} = \frac{1}{|\mathcal{S}_{\text{s}}|} \sum_{s \in \mathcal{S}_{\text{sim}}} \hat{y}_{d,t}^{s}$$

This approach of restricting the donor pool size mechanically reduces concerns over biases introduced by mechanically overfitting as the donor pool size is ultimately constrained to include at most 40 units. This comes at the cost that constraining the donor pool may introduce biases due to the production of poor performance synthetic controls. The ensemble method again, while not having well-defined statistical properties, can help wash out these biases.

The simulation approach further, will let us study the empirical distribution of the "best" synthetic control estimate (either the ensemble model or the models identified using equations (2)-(4)) against the full set of other synthetic control estimates obtained from various donor pools. For the subnational data, we have a total of 101 synthetic control estimates. In some visual presentation we highlight the extent to which the "best" estimate appears to be an outlier vis-a-vis the estimates that can be obtained using alternative donor pools. This will highlight

the relative robustness of a specific estimate of the output gap induced by the Brexit-vote vis-a-vis the specific donor pool choice.

2.6 Placebo Brexit-votes in donor pool

We further conduct placebo Brexit-vote experiments. Given the relatively short pre-Brexit vote data periods, due to lack of historical subnational data availability, it makes little sense to conduct the type of placebos that shift a "placebo Brexit-vote" back in time. Rather, we conduct a set of placebo tests whereby we estimate synthetic controls for each of the donor pool spatial units, exposing each of them to a placebo "Brexit vote". If our benchmark estimate for the UK regions are capturing the causal impact of the referendum vote, its effect should dominate any possible impact of the fictitious Brexit votes in the synthetic control set.

We restrict the analysis to the *most comprehensive* donor pool set comprising the superset of NUTS2, US States, OECD, G20 and EU27 countries. Within that superset, that includes 253 spatial units, we only construct placebos for the set of spatial units that ever are included in the set of donor spatial units – this reduces down the set of regions to 138 donors. Further, we also ensure that different regions within a country are not serving as a donor to each other to mimic the fact that placebo "Brexit votes" are country-level events. We present visually the gaps between the synthetic controls and the actual values for each of the 138 donors, in addition, to the estimate for the actual district. This further allows the construction of a empirical p-value capturing the share of placebo Brexit-vote output gap estimates that are below (or above), the estimate pertaining to each specific UK region or district.

2.7 Top-down and bottom-up consistency

Lastly, we highlight that the results are consistent across different levels of spatial aggregation. We start by presenting results pertaining to synthetic control estimates across UK regions and constituent countries. The implied Brexit-vote costs aggregated up are very similar in comparison to estimates for the UK as a whole studied in Born et al. (2019) and Springford (2019). We conduct the analysis further across each of the UK's 382 local authority districts up to 2018. The district-level impact estimates, aggregated up to the region or country level are again, very

consistent with the region-level results as well as the country-level evidence from Born et al. (2019) and Springford (2019).

Throughout, we find very consistent estimates, highlighting the robustness of the results and further highlighting that we are likely to adequately capture the heterogeneity of the Brexit-vote economic impact across regions and districts.

2.8 Discussion

There are a number of limitations on the estimation of the counterfactual region $\hat{y}^d$. In particular, there is the risk of overfitting given the relative scarcity of consistent subnational data at the annual level and quarterly level prior to the EU referendum. This mechanically constrains the donor pool to a subset of countries. We address this potential problem several ways. First, in using the combined counterfactual measure as an ensemble $\hat{y}^d$, the estimates are condensing the projections across all of donor pools and are not being driven by a single choice. Second, as we show in the next subsection, the cost of Brexit is relatively stable across donor pools to begin with. Third, we arrive to very similar impact estimate compared to Born et al. (2019) if we aggregate the regional shocks to the national level. Lastly, we also adopt an ensemble method using a random donor pool permutations of different sizes which, again, produce very similar results. Overall, this points to a relative stability of our projections and that overfitting is not contributing significantly to the results we obtain.

Throughout the exercise, our identifying assumption is that the UK regional economy would have developed as the synthetic unit had it not been for the Brexit vote. This is assumption plausible given that Brexit vote was largely unexpected (see Born et al. (2019)). In turn, we can quantify the Brexit impact as the difference between the synthetic control and the realized values.

3 What are the costs of the Brexit-vote across UK's regions?

The UK's referendum on EU membership in 2016 saw majorities in favor of Leave only in England and marginally in Wales – though some analysis suggests

that the Welsh vote was tipped in favor of Leave due to English retirees settling there (see Dorling, 2018). Northern Ireland and Scotland overwhelmingly voted in favor of the UK remaining a member of the European Union. The tension that the split vote across the UK's constituent countries has created gives further rise to fears that the UK may disintegrate.

Visual results Figure 1 presents the results studying the evolution of real GDP over time across the UK's constituent countries: England, Scotland, Wales and Northern Ireland. The figure plots the ensemble synthetic control estimate constructed for the relevant country specific real GDP series. The figures suggest that the synthetic controls that are constructed are quite consistently tracking the UK's evolution prior to the EU referendum vote. With the exception of Wales, all of the UK's other constituent countries see significant divergence from their respective quarterly readings. On average, the English, Scottish and Northern Irish gross-value added appears to be 2.5, 2.1 and 4.0 percentage points smaller in 2018.

Figure 2 presents the synthetic control estimates for the remaining English regions. Throughout the synthetic control estimates quite closely track the evolution of the actual regional figures prior to the EU referendum vote, with most English regions experiencing significant divergence post 2016. Yorkshire and The Humber, the North West, the East and, to some extent, also the West Midlands, recorded a slightly delayed divergence – this may be due to these regions potentially temporarily benefiting from the devaluation of the pound as suggested by Broadbent et al. (2019).

Tabular results We next present the estimates of the size of the output losses in real terms. These are summarized in tabular format in Table 1 and Table 2. Table 1 presents the results in terms of the difference in the growth rates, while Table 2 presents the estimates capturing the Brexit-vote induced output loss measured in pounds.

In relative terms, the UK's most exposed region to the Brexit-vote costs so far is the West Midlands, followed by Northern Ireland, the South West and the South East respectively. The least exposed regions is, as indicated, Wales , Yorkshire &

the Humber and, at least in 2019, London. London saw a significant contraction in 2018 but was subsequently reducing some of the losses in 2019 – see Figure 2.

In absolute terms, Table 2, highlights that there is not a single overall region that can be classified as having gained in economic activity vis-a-vis their respective synthetic control. The absolute losses are largest in London and the South East in 2018 standing at £17 billion in London and 9.4 billion in the South East. We note that the aggregated losses estimated from regional data alone come reasonably close to estimates from Born et al. (2019): across the 12 regions, the losses add up to £50 billions in 2019 and £46 billion – or around 2.3 - 2.5 percent relative to the UK's 2015 GDP. Again, the numbers are very consistent with the figures in Born et al. (2019) and Springford (2019).

We next turn to the main focus of the analysis in this paper: the estimates of the district-level Brexit-vote cost to date. We will present main estimates and relate these to the exercise at the regional level conducted so far, highlighting again that these produce very similar results. Lastly, we speak to some of the underlying economic mechanisms and main correlates that explain the emerging gap between UK regional gross value added and those of the respective synthetic controls.

4 What are the district-level cost of Brexit so far?

We construct counterfactuals for all the 382 districts in the United Kingdom in addition to the region-level analysis presented thus far. The district-level analysis will help shed some light on the underlying economic adjustments taking place. Naturally, we can not present 382 plots in this paper. The full visualizations are available on https://www.brexitcost.org. We next present some archetypes along with some stylized results.

4.1 Brexit-vote cost archetypes

In Figure 3 exemplifies the projected Brexit-vote effect for a small subset of districts. In Panel A and B, we show the case of two districts that can be called Brexit losers. This occurs because the actually realized real gross-value added series realized GDP value (dashed line) is significantly below the ensemble estimate of the synthetic control counterfactuals (solid line), but only after 2015. This suggests

that these districts experienced notably weaker growth or even contractions due to the "Brexit vote".

Panel A refers to the district of Northampton, in which 58.4% of voters supported Leave in 2016. This district saw noticeably slower growth vis-a-vis the synthetic control estimate.[8] In Panel B we show the corresponding output for the borough of Lewisham in London which, again, substantially not only grew slower but appears to have lost output in comparison to the non-Brexit counterfactual.[9] Finally, Panel C shows a Brexit winner (Dudley) and Panel D shows the impact on district that was unaffected in the most part (Newham Borough in London). The shaded area represents one standard deviation of the pre-treatment difference between the UK and its synthetic control.

As indicated, we are not able to include 382 full sets of graphs for each district in this paper. Rather the visualizations are provided http://www.warwickeconometrics.co/brexit-impact/. In Figure 4 we provide a summary of what type of information is presented on that webpage for each district using the example of Lewisham district. The top figure provides the ensemble synthetic control estimate along with the actual realized GDP growth relative to 2015. In the row below, we present on the left-hand side the full distribution of synthetic control estimates constructed using all different approaches as dark grey lines. These are shaded such that if multiple lines overlay, they appear visually darker. We overlay again, the ensemble synthetic control estimate (solid red) as well as the actual data that was reported by the ONS as a dashed blue line. The results highlight that the degree of uncertainty indicated by the confidence bands in the main figure are very similar vis-a-vis a host of other synthetic controls that could be constructed. Further, the results also will help shed a light to what extent the specific donor pool sample choice may be important or not important in shaping the results. For the year 2018, the difference between $\hat{y}^{ENS}_{d,2018} - y_{d,2018}$, i.e. the difference in the growth rates between the synthetic control estimate and the actual value for 2018 is indicated as a vertical line. The kernel density is indicating the distribution of this measure

[8] Local commentators attribute this to the Brexit-uncertainty, see https://www.lovebusinesseastmidlands.com/love-business-news/2019/10/12/businesses-in-northamptonshire-feel-the-impact-of-brexit-uncertainty/.

[9] See https://www.onlondon.co.uk/lambeth-southwark-and-lewisham-prepare-for-brexit-impacts/.

constructed for each of the 70 synthetic controls that are constructed using the randomly selected donor pools of fixed size. This highlights the extent to which the $\hat{y}^{ENS}_{d,2018} - y_{d,2018}$ is an outlier vis-a-vis the estimates that could be constructed using alternative donor pools.

Lastly, we also present visually the results from a set of placebo exercises described in Section 2.6. For each of the 138 potential donors that are ever included with non-zero weight we estimate a "fake Brexit" vote impact. We present these placebo estimates, plotting the normalized difference of $\hat{y}^{s}_{d,t} - y_{d,t}$ in the left figure for each 138 placebo Brexit-votes along with that measure for the "best synthetic control" estimate for Lewisham district as a red solid line. The right panel again, indicates the estimate of $\hat{y}^{s}_{d,2018} - y_{d,2018}$ for Lewisham district as a vertical line against the distribution of that difference for each of the placebo Brexit-vote districts. We would expect the estimate for Lewisham to clearly stand out relative to the empirical distribution of the placebo Brexit impacts, which are clearly centered around 0. This provides us with an alternative way of conducting inference as to whether treatment effects measured are statistically significant or not. In the case of Lewisham, 98% of placebo estimates are above the value of the Brexit-vote output gap for Lewisham.

In Subsection 4.3, we investigate the economic fundamentals that are correlated with the variation in the Brexit-vote cost or benefit across districts to date. We first proceed to explain how we classify the districts in a consistent manner regarding the estimated Brexit effects and present the summary of the results in tabular form as well as in regional aggregated forms.

4.2 Classification of districts as Winners and Losers

We classify individual districts as "Brexit winners" or "Brexit losers." To do so, we study the difference in the figures for Gross Value Added for 2018 vis-a-vis the synthetic control of each district constructed for each of the potential 101 donor pools (31 constructed with systematic donor pools, 70 constructed using the sampling approach). A district is classified as a "Brexit loser" if in at least 90% of the 101 synthetic control series, the 2018 Real Gross Value Added value is below the respective value of the synthetic control. Similarly, a district is classified

as a Brexit winner, if it meets the reverse conditions for positive outcomes. The remaining districts are classified as Unclear – i.e. appearing, by 2018 as neither winners nor losers.[10]

Figure 5 shows the result of this ensemble classification on a map. The figure on the left-hand side shows codes the districts that were Brexit losers (in red), Brexit winners (blue) and those that did not meet the criteria for either (in grey). The figure on the right-hand side displays the quintiles in the distribution of the real GDP losses (or gains) expressed in pounds per capita across districts in 2018 relative to the respective synthetic control. It is evident that the vast majority of districts, around 255 out of 382 districts report a negative value; with a minority of 127 districts reporting a positive output gap vis-a-vis the ensemble of synthetic controls. This means the number of district that record relative losses is twice as high as the number of districts that saw sizable gains.

We compare Brexit-vote winners and losers along a host of characteristics in Table A4. In terms of the classification, 168 districts are classified as clear "Brexit losers" according to the above rule, while only 78 districts are classified as clear "Brexit winners" in 2018. In Panel A of Appendix Table A4 it becomes clear that the above classification is quite successful in separating districts that appear to have lower or higher output relative to their respective synthetic controls, with districts classified as Brexit losers having notably lower gross-value added relative to their synthetic controls and districts classified as Brexit-vote winners having higher output.

The subsequent panels of Appendix Table A4 explore to what extent there are notable differences in socio-economic characteristics of districts classified as Brexit-vote losers or winners. Overall there are relatively few notable differences highlighting that the classification which is a result of the synthetic control estimates is not just capturing or confounding some other pre-EU referendum systematic differences across districts. Among the few notable differences, we see that districts classified as Brexit winners appear to exhibit an around 5 percentage points higher

[10] Broadbent et al. (2019) highlight that the depreciation of the pound in the wake of the Brexit vote in 2016 created a temporary positive windfall for exporters which may have had a positive temporary effect on local economies.

level of support for Leave in 2016, and also stand out as having higher turnout. They have a notably higher share of relatively young residents, were more exposed to the 2008/2009 financial crisis as measured by the unemployment rate increase between 2007 and 2009, and appear to be slightly more urban having a notably lower share of agriculture and mining employment.

In the next section we will study what are the main correlates that capture the variation across districts and within regions.

4.3 What drives the spatial distribution of the Brexit losses?

District-level estimates in detail Appendix Table A5 provides the full list of a host of measures capturing the Brexit-vote cost or economic gains across districts in detail. As indicated, in total, we note that out of the 382 districts, 168 (44 percent) emerge as Brexit losers and only 78 (20 percent) emerge Brexit winners. For every district that appears to be winning, there are two districts that are losing. In Table 3 we present a condensed version of the Appendix Table A5 focusing on the top 10 of districts that appear to be losing as a result of the Brexit vote according to the losses in gross-value added per capita. We also present the five districts that appear to have gained the most since the EU referendum vote – in keeping with the two-to-one ratio of losers to winners.

The table provides the Region and District name, along with the classification as per the above classification rule. We also provide the 2015 GVA baseline values expressed in real £million along with a per capita measure. The subsequent columns present the ensemble estimate of the output gap between a district and its ensemble estimated synthetic control expressed in absolute real £million; in percentage points; and expressed in per-capita terms. The subsequent additional columns provide additional estimates in absolute terms. Specifically, we provide a confidence band for the ensemble estimator gap (Low/High) that captures a one standard deviation of the pre-Brexit vote difference between the ensemble estimate and the synthetic control on either side. We further provide the central point estimates implied in the simulated donor pool ensemble estimate along with the best series identified according to the AAPE_s, RMSPE_s and MAPE_s criteria, as defined in Equations (2)-(4).

The losses in terms of gross-value added per capita are largest in Darlington, in the Northeast at £-11,133 per capita. On the other side, the gains are largest in Westminster, London, standing at £12,747 per capita. Though, on average and in total, the gains are usually much smaller compared to the losses.

Region-level distribution of Brexit losses In Table 4 we aggregate up the district-level estimates to the broad UK NUTS1 regions. The first three columns in Table 4 provide the numbers of districts classified as being Brexit winner or losers or with ambiguous assignment within each of the UK's 12 regions. The subsequent columns provide the aggregated district-level estimates in millions of pounds in real terms. The central estimate from the ensemble model across the 31 donor pools, along with the respective upper- and lower bounds are provided, along with the ensemble estimate that is constructed using the randomly sampled donor pools. In the last three columns, we present the losses that are obtained by a single donor pool, selected according to the AAPE_s, RMSPE_s and MAPE_s criteria, as in Equations (2)-(4). We note that the losses are consistent across donor pools selected by different criteria, and also with the ensemble classifier. Nevertheless, is notable heterogeneity across regions. In the South East , 39 out of 67 districts are classified as being Brexit losers. London equally exhibits a higher share of districts classified to be a Brexit loser. For every district that appears to be winning, there are two districts that are losing.

The aggregated district-level estimates are not that far off from the estimates in the previous section: the combined sum of the individual gaps adds up to £45.6 billion for 2018; the region-level estimates had a combined total effect summed up across regions of £46.1 billion. There are a few differences in the geographic attribution: the quarterly figures for 2018 suggested higher losses in the West Midlands, for example. Yet, the overall patterns are very comparable. The consistency in the estimates obtained across methods and across underlying datasets is indicative of the broader robustness of the results.

We next study patterns that appear to drive the variation across districts, *within regions*.

Empirical specification We next look at some of the correlates that are associated with higher, or lower, output losses due to the Brexit-vote. This is, to a significant extent, motivated by much of the ex-ante impact modelling which suggests that the regional economic impact of any Brexit-vote may actually exacerbate some of the inequalities that several studies have highlighted may have brought about the vote for Brexit to begin with (see e.g. Colantone and Stanig (2018) on the impact of trade integration; Fetzer (2018) on the role of welfare-reforms; and Becker et al. (2017) for a comprehensive correlational analysis).

To study inter-regional variation in the incidence of the Brexit-cost so far, we focus on the output loss measures expressed in % terms. This amounts to treating each district equally in terms of their respective size of the economy. We leverage a host of data drawn, among others, from Becker et al. (2017) to explore correlational patterns.

We estimate

$$\Delta\tilde{y}_{d,r(d),t} = \alpha_r + \beta' X_d + \epsilon_d \tag{5}$$

where $\Delta\tilde{y}_{d,r(d),t} = y_{d,r(d),t} - \hat{y}^{ENS}_{d,r(d),t}$ measures the difference in real growth rate between the district's actually recorded growth and the growth of the ensemble-method identified synthetic control. The variable X_d will capture a range of district-level characteristics that we explore. The above regression further controls for region level fixed effects, α_r to zoom in on the within-region variation across districts, given the significant heterogeneity that was identified in Figure A1. Standard errors uses robust standard errors.[11]

Brexit-vote cost and Leave support A natural first exercise is to study whether there exists a relationship between the district level output losses that we attribute to the Brexit-vote and the support for Leave in the 2016 EU referendum. In Figure 6 we present results summarizing the above regression model (5) as a binned scatter plot. The figure highlights that there is a notable gradient indicating that the districts that saw highest support for Brexit in 2016 experience noticeable larger

[11]Technically, a bootstrapping procedure may be more adequate given that the left-hand side regressor is a fitted regressor. It is, however, unclear what type of bootstrapping procedure to employ in the given setup.

output losses relative to their respective synthetic control. Summarizing this relationship, that is quite robust across all the output gap measures (see Appendix Table A6), we see that districts that, on average, had a 10 percentage point higher level of support for Leave, see a 0.9 percentage points higher output loss in 2018 due to the Brexit-vote.

This is not inconsistent with some ex-ante impact modeling that has expressed fears that the regions that most strongly came out in favour of Brexit may ultimately be the ones that may be most adversely affected by it (see e.g. Los et al., 2017). This suggests that regional economic inequalities that strongly came out in descriptive work around the Brexit vote (see e.g. Becker et al., 2017; Alabrese et al., 2019) may have already exacerbated as a result of the Brexit-vote.

Role of Local economic structure We next explore the role of local economic structure using two measures: the 2011 Census sector-level employment shares or the sector-level average real gross-value added share over the period from 2010-2015. The definitions of sectors slightly differ due to the data granularity. The results are presented in Tables 6 and 7.

They suggest that districts that exhibit higher employment and gross-value added shares in Manufacturing are strongly driving the reduction in Gross Value Added relative to the synthetic control. In Appendix Figure A2, we estimate the above cross-sectional regression for each year and note that this pattern is only emerging strongly post 2015.

Many ex-ante impact studies suggested that the economic cost of Brexit may be particularly pronounced in districts that have a high reliance on manufacturing sector.

District-level wages Wage levels serve as a common productivity estimate. In Table 8 we document some notable patterns around the structure of wages across districts and to what extent patterns prior to 2016 are affecting the evolution of the synthetic control after the Brexit-vote. Specifically, the results suggest that the output losses vis-a-vis a synthetic control are more pronounced in districts with higher median- and mean hourly pay levels. They are further larger in districts that

exhibit greater inequality in pay, measured as the interquartile range of hourly pay contrasting the difference between the 75th and the 25th percentile of pay. Districts that saw notable growth in lower quantiles of pay, specifically the 10th percentile from 2005 to 2015 seem to be more affected by the Brexit-vote.

Overall the patterns are quite mixed: the observation that Brexit-vote costs are most concentrated in districts with higher median or mean wage levels may suggest that the costs of the Brexit-vote may be born by the districts that have higher levels of productivity – this could help reduce regional inequalities across the UK. On the other hand, the patterns further suggest that the losses are concentrated among districts with a high degree of heterogeneity or inequality of pay structure and further, particularly in parts of the UK that saw sizable wage growth at the bottom end of the wage distribution. The latter could indicate that the Brexit-vote costs may have undermined catch-up of regions that may have lagged behind.

Other notable patterns Lastly, we turn to a few other notable patterns. Specifically, much of the work on Brexit has highlighted the dominant role that educational attainment or formal qualifications appears to drive the regional differences in voting patterns in the 2016 EU referendum vote. In Table 9 we document that the costs of Brexit appear to actually exacerbate the already existing regional economic cleavages. Specifically, columns (1) and (2) highlight that the contraction in economic activity vis-a-vis the respective ensemble synthetic control is more concentrated in districts with higher share of residents with no formal qualifications; conversely, the output losses are markedly smaller in districts which boasts a relatively well-educated resident population measured as of the 2011 Census. Turning to unemployment or economic participation, we observe that the average level of unemployment prior to 2015 does not appear to be correlated with the merging gap between districts and their respective synthetic controls. Rather, we see that districts that have higher rates of self-employment and experienced more notable increases in unemployment around the 2008 financial crisis exhibit less pronounced output losses due to the Brexit-vote.

Lastly, we also speak to the topic of immigration that was very prominently discussed during the EU referendum. We observe that the output losses and the

costs due to Brexit appear to be particularly concentrated in districts that exhibit higher levels of migration from EU Accession countries (the predominantly Eastern European countries joining the EU in 2004 and 2008 respectively). Throughout the above results do suggest that, quite possibly and consistent with much of the ex-ante impact modelling around the cost of Brexit to date, the economic impact of the Brexit-vote may have already served to exacerbate regional economic inequalities that came out in the EU referendum vote, despite Brexit – in the form of material changes to the terms of trade and market access – still not having materialized.

Appendix Figure A3 further highlights that there is a notable correlation between the output loss due to the Brexit-vote across districts and the share of workers on furlough in May 2020 as a result of the COVID19 pandemic. The estimate suggests that districts more exposed to Brexit cost to date have a sizeably higher share of workers currently furloughed. For every one percentage point higher output loss due to the Brexit-vote, the share of employees on furlough (using 2018 BRES employment data as a denominator) is 0.15 percentage points higher.

4.4 On the underlying mechanisms

Lastly, we present some stylized facts of what is happening to the economies in districts that seem to be losing in growth as a result of Brexit. As indicated, firms may rationally respond to the prospect of worsening market access by ultimately, freezing capital investment that may be difficult to salvage in case a hard Brexit materializes (see also Faccini and Palombo, 2019). Nevertheless, the short term incentives may be for firms to maintain output levels as ultimately, market access will still be the same until at least January 2021.[12]

The freeze in investment may result in firms having to expand their workforce and payrolls in order to maintain output. This should be felt in particular in districts were the investment freezes significantly contribute to the gap between the district GDP measure and its synthetic control. As firms operate now with ineffi-

[12] Broadbent et al. (2019) similarly highlight to the potential confounding effect that the depreciation of the pound in the wake of the Brexit vote in 2016 may have created as it provided a temporary windfall for firms that are exporting into the single market. This may have led to local economies appearing more resilient than they actually are.

cient capital-to-labor ratios and a slowly eroding capital stock, naturally, we would expect output per worker to decline – this decline should be most concentrated in districts that appear to be hardest hit vis-a-vis their respective synthetic control.

Figure 7 presents some evidence that speaks to this hypothesis by studying the data on gross-value added, along with employment and overall compensation of employees at the district level. The estimates underlying the figures are presented in Table 10. Panel A highlights that, on average, districts added significant employment relative to 2015 – on average, adding around 2.8 percentage points to the stock of employment. Even among the set of districts with relatively high exposure to the Brexit-vote costs in 2018 relative to 2015 – the Brexit-vote loser districts – employment growth was positive at 1.2 percentage points. Panel B highlights that there was sizable growth in payrolls. In Brexit-vote loser districts, overall payrolls expanded, in real terms, by 5.73 percentage points. This is only marginally smaller compared to the overall average of 6.47 percentage points. Lastly, panel C highlights what is happening to productivity measured as real Gross Value Added output per worker. This figure has drastically declined suggesting that among the "Brexit losers", productivity growth was -2.6 percentage points compared to an overall average growth of 1 percentage points between 2015 and 2018.

The observation that districts added employment and expanded payroll, while experiencing significant declines in productivity is suggestive that firms may have shifted away from capital to labor into a using more intensively a factor of production that can easily be discarded in the short-term once Brexit becomes a de-facto reality in form of changed market access from January 2020 onwards. This sets up the possibility of significant labor market dislocations should a hard Brexit become a political reality in 2020 as that employment growth is built on a shaky foundation.

5 Conclusion

This paper provides some first insights into the regional economic impact of Brexit to date. Much of the literature studying the economic impact of the Brexit-vote to date have exclusively focused on country-wide or sector-wide estimation

approaches. These broadly ignore the underlying economic geography. This is particularly important as the regional variation in socio-economic characteristics of the resident population has been identified as an important driver behind the regional differences in the extent of support for Leave in the 2016 EU referendum.

The research confirms existing work that has estimated that by 2018, Brexit has cost the UK economy at least two percent of real output. We find that these costs are far from evenly distributed across the UK. Within regions, districts whose regional economies depend heavily on manufacturing sector, appear to be particularly severely hit. Similarly, districts with relatively higher shares of residents with low educational attainment appear more exposed. Lastly, we also find that districts with higher support for Brexit in 2016 appear also more exposed to the Brexit-vote cost too date – this highlights that, quite likely, the cost of Brexit may exacerbate the already large regional economic disparities across regions in the UK. This is particularly concerning as growing economic inequalities may further accelerate a trend that may result in the political disintegration of the United Kingdom.

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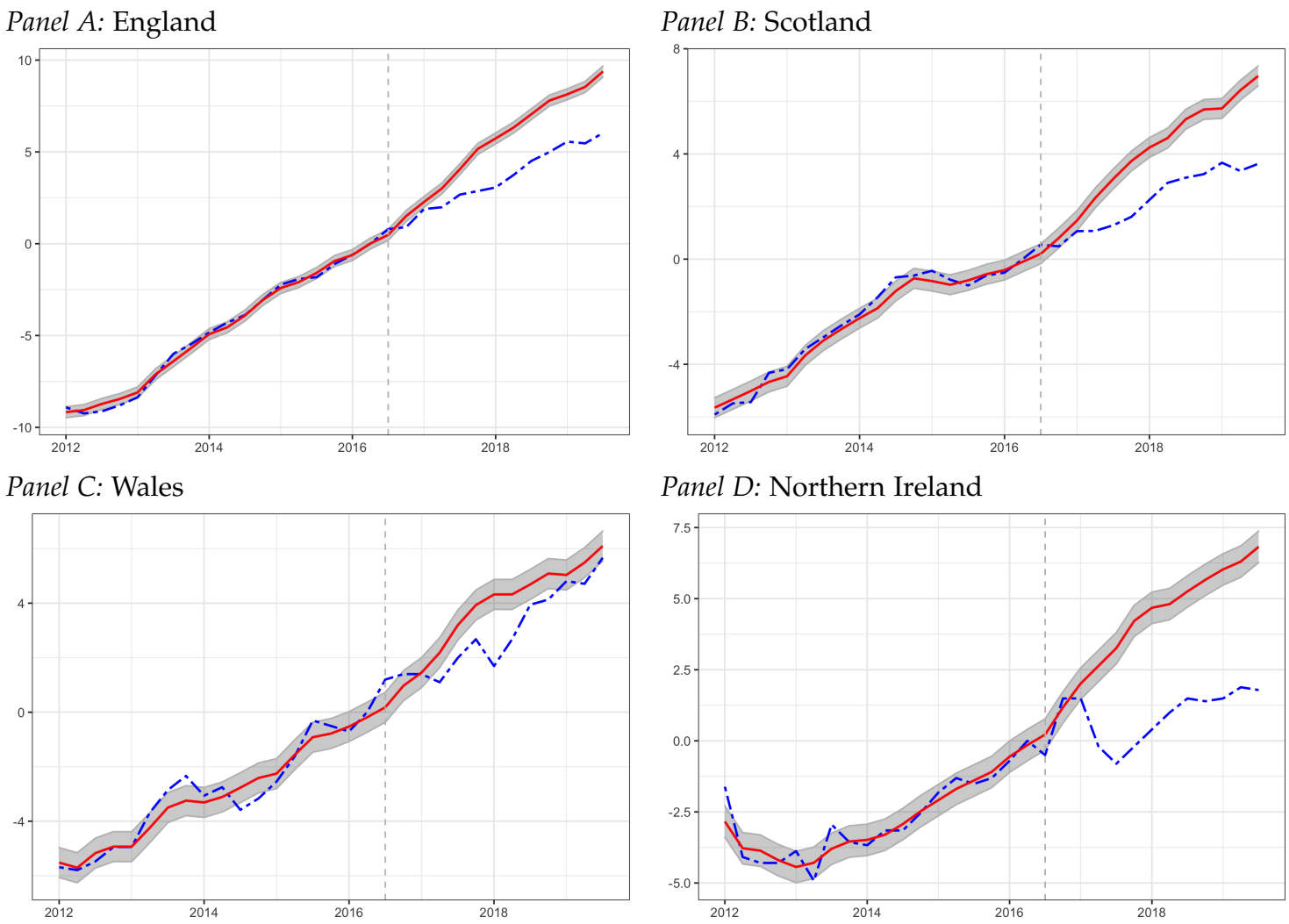
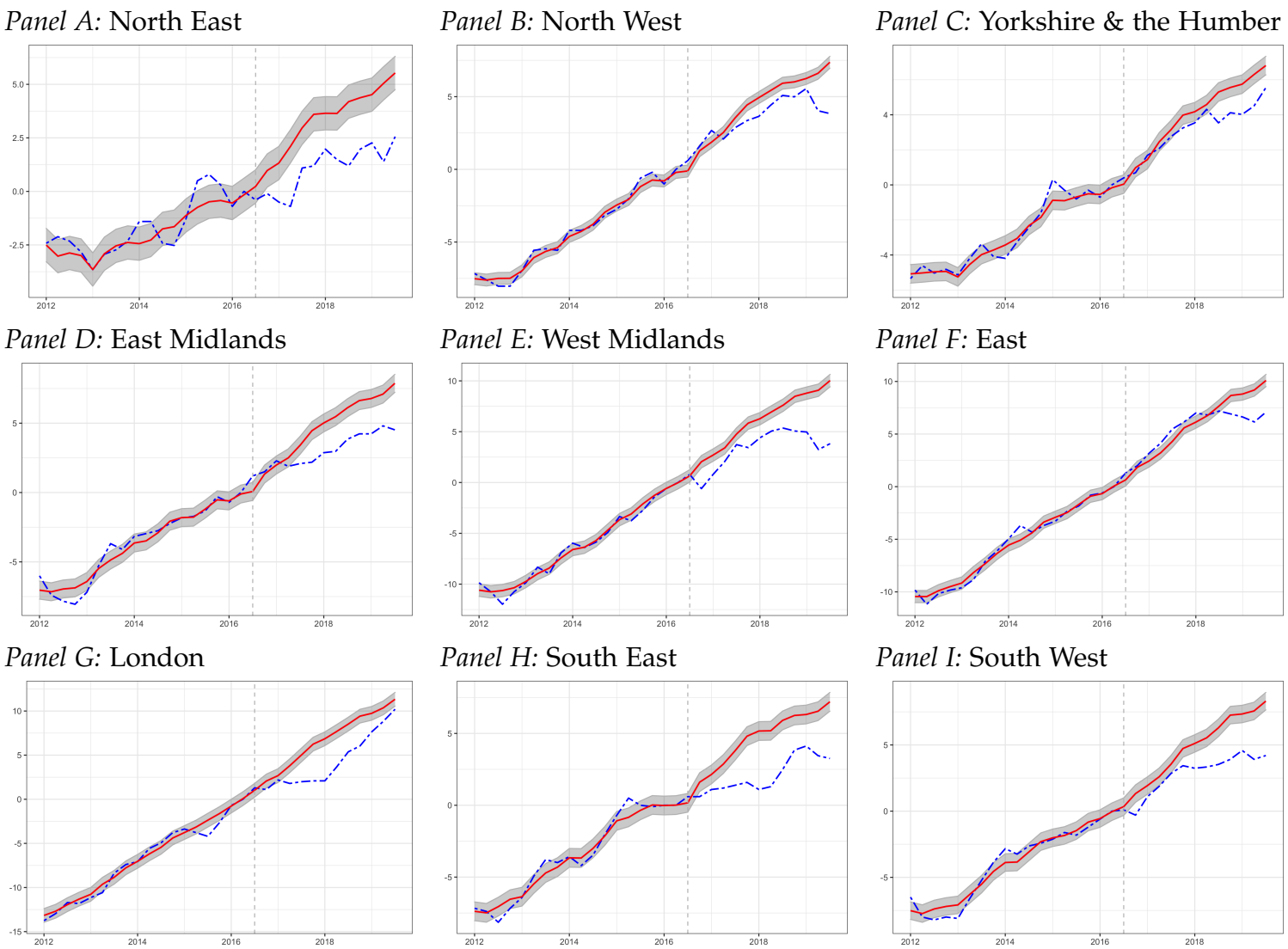
Valentini, G. and T. G. Dietterich (2002). Biasâvariance analysis and ensembles of SVM. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) 2364*, 222–231.

Figure 1: Ensemble estimate of the impact of Brexit-vote on UK constituent countries real GDP



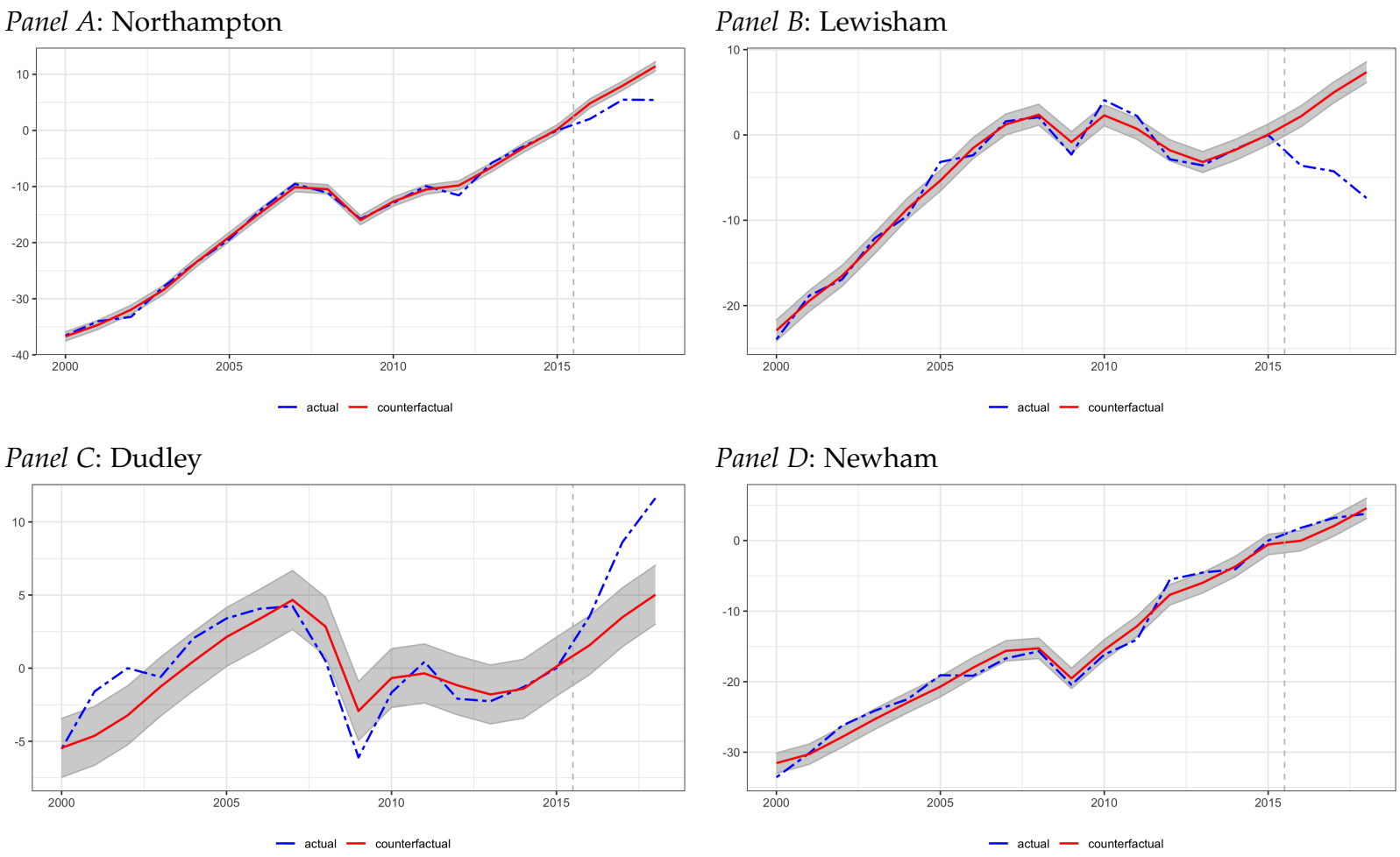
Notes: Figure plots the synthetic control value of the deviation of real GDP relative to 2015 constructed using different donor pools indicated in the figure panels against the actually realized UK real GDP over time.

Figure 2: Quarterly Region-Level Synthetic Control Estimates Across Other English Regions



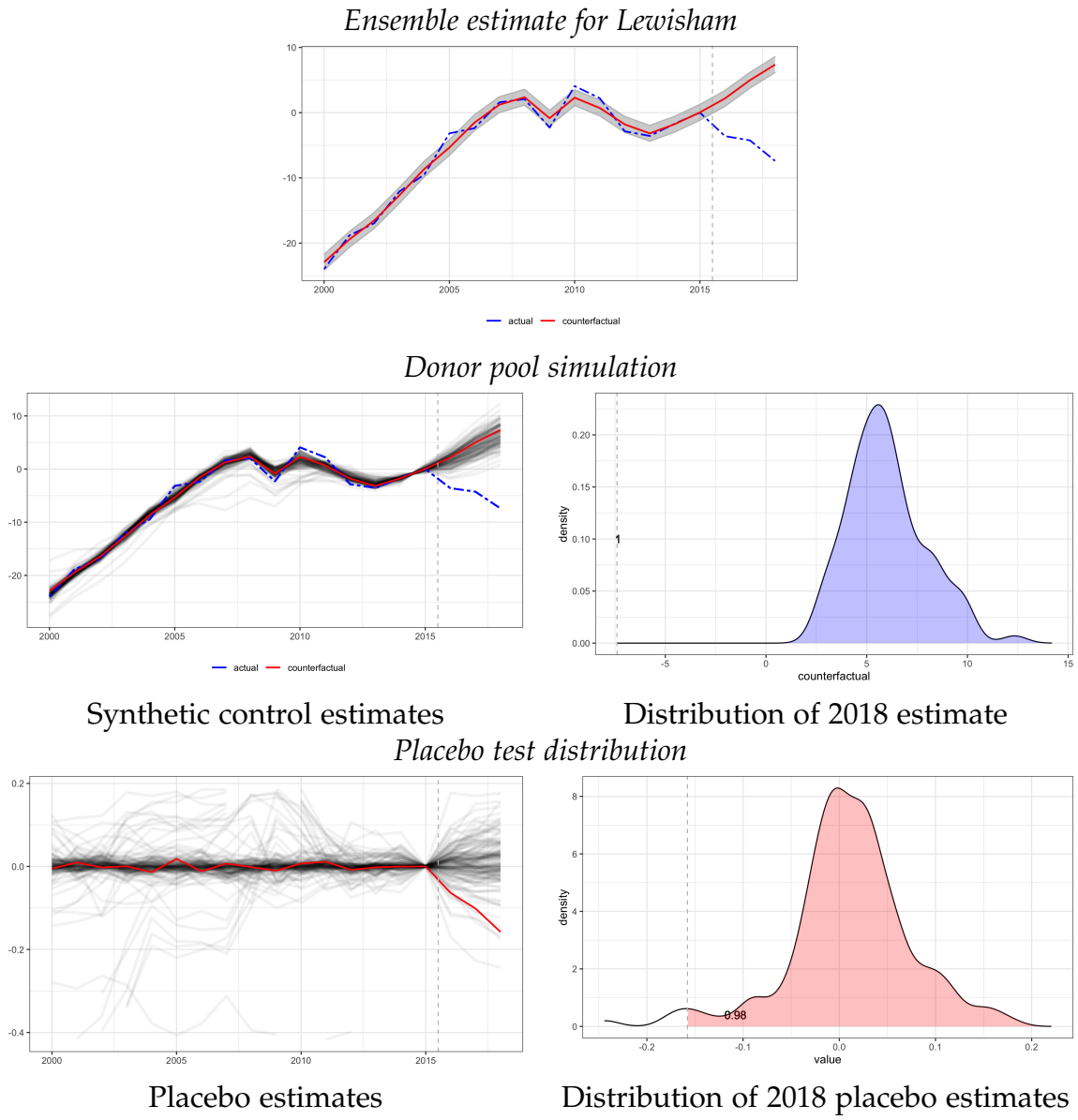
Notes: Figure plots the synthetic control value of the deviation of real quarterly GDP relative to 2016 Q2 constructed for each of the nine English NUTS1 regions. The dotted line indicates the regions realized real GDP growth relative to 2016Q2 while the red line indicates the ensemble synthetic control estimate.

Figure 3: Example Curves for a Select Set of Districts



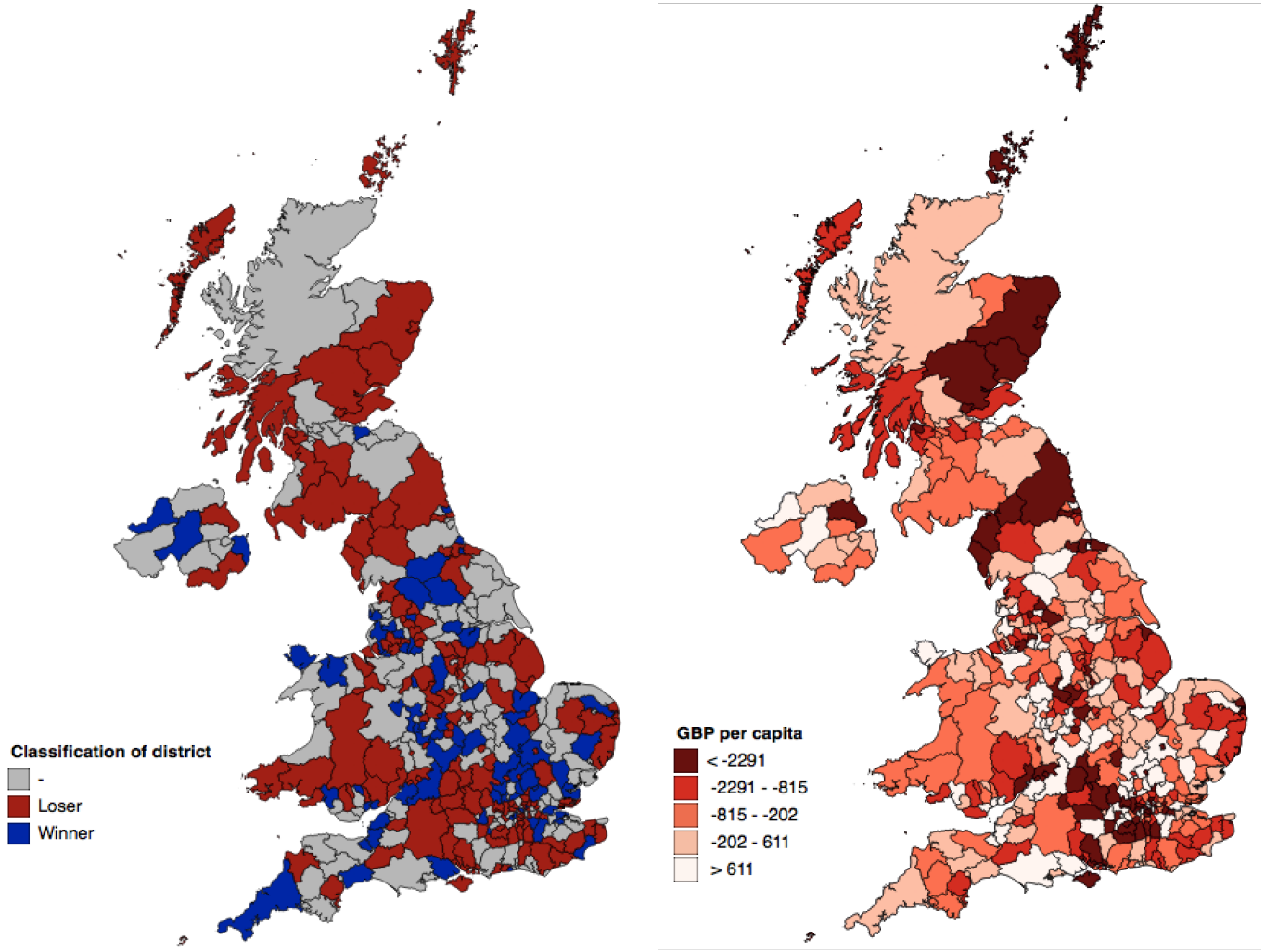
Notes: Figures plot the realized (blue) and counterfactual path (red) of real GDP relative to 2015 across regions in the UK highlighting Northampton and Lewisham as examples of districts classified as "Brexit losers" in Panels A and B; Dudley, for a positive impact of Brexit in Panel C; and neutral effect on the London borough of Newham. The counterfactual path is the ensemble average across the 31 synthetic controls constructed across different donor pools.

Figure 4: District-specific Brexit-vote information card: the case of Lewisham



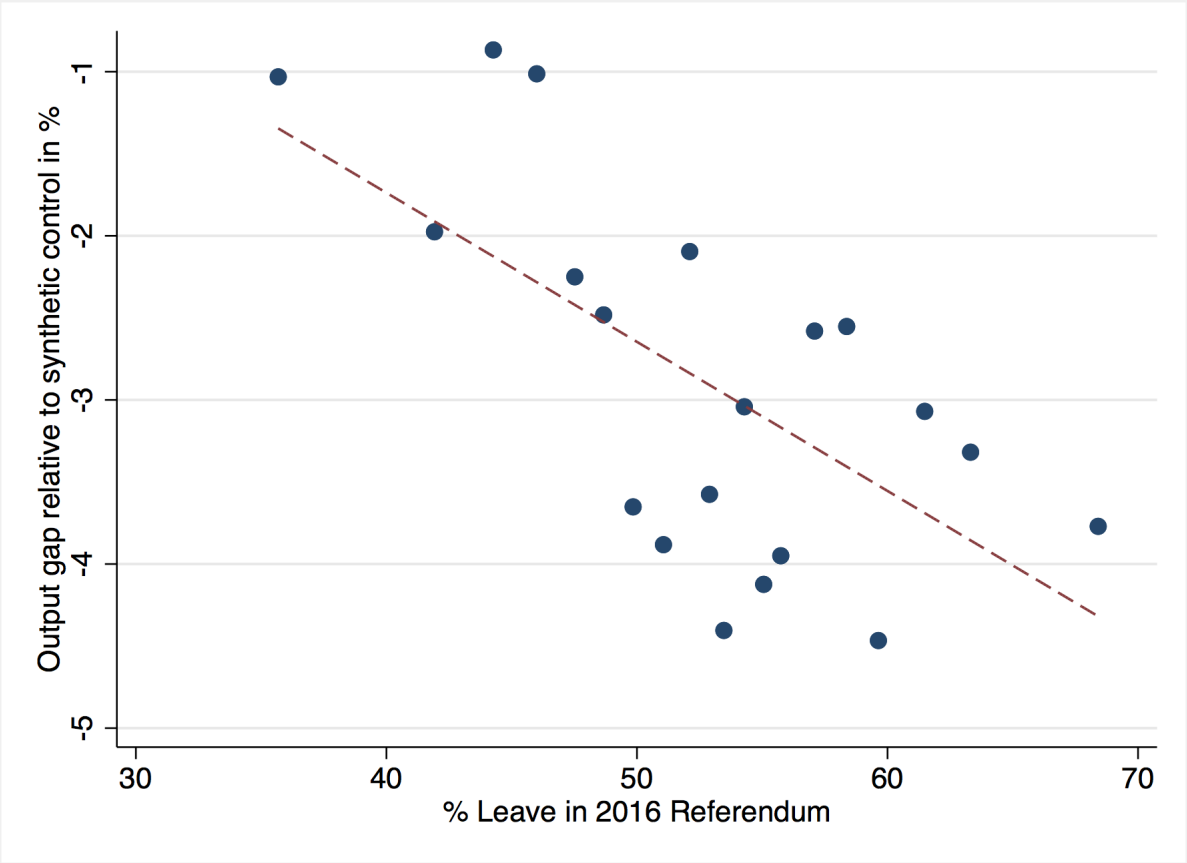
Notes: Figures plot sample information provided on https://www.brexitcost.org. The top panel presents the ensemble synthetic control estimate (solid) of real gross value added relative to 2015 as well as the actual series (dashed). The "donor pool simulation" presents the full distribution of all synthetic control estimates constructed through the permutation test whereby synthetic control estimates are constructed using 70 donor pools of different sizes that are randomly selected. The right figure presents the kernel density estimate of the distribution of the actual gap between the ensemble estimate and the actual line in 2018 vis-a-vis the distribution of that measure for all other synthetic control estimates constructed. The bottom row presents results from a placebo tests whereby synthetic control estimates are constructed for 138 donors that are ever drawn upon in the estimate vis-a-vis the estimate of the Brexit-output gap for the actual district. The right panel presents again the empirical distribution of the 2018 gap vis-a-vis the placebo "Brexit" measures.

Figure 5: District Level Classifications and Output Losses By 2018



Notes: Left figure plots the classification of districts into losers, winners or no clear based on the estimate of the output gap obtained from the ensemble synthetic control that was constructed using the 101 potential synthetic control estimates constructed for each district. The right figure plots out the distribution of gross-value added losses measured in pounds per capita across UK districts as of 2018 expressed in real 2015 units.

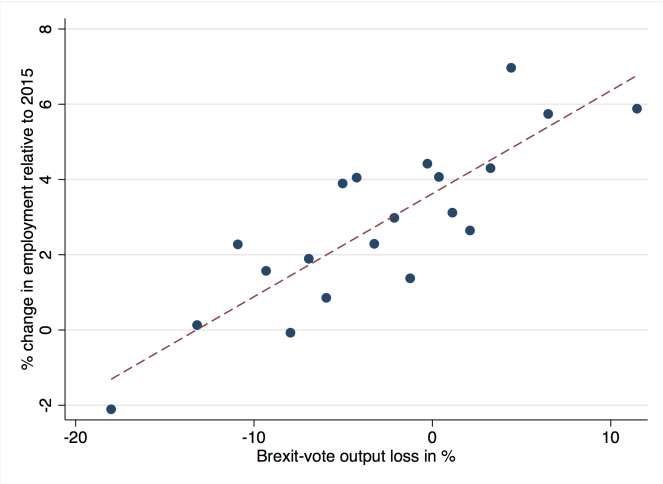
Figure 6: Relationship between support for Leave and District-Level Output Losses By 2018 relative to 2015



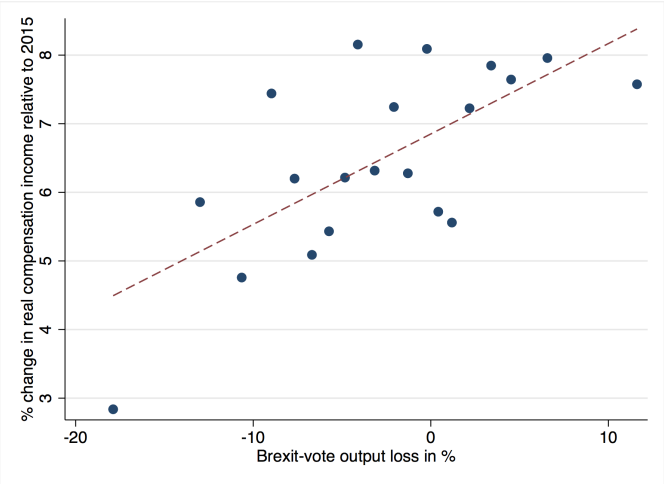
Notes: Figure plots a binned scatter plot of the ensemble synthetic control estimate of the output loss by 2018 (in % relative to 2015). The underlying regression partials out NUTS1 region fixed effects.

Figure 7: Mechanism driving Brexit-vote output losses: Employment- and payroll growth despite falling output per worker

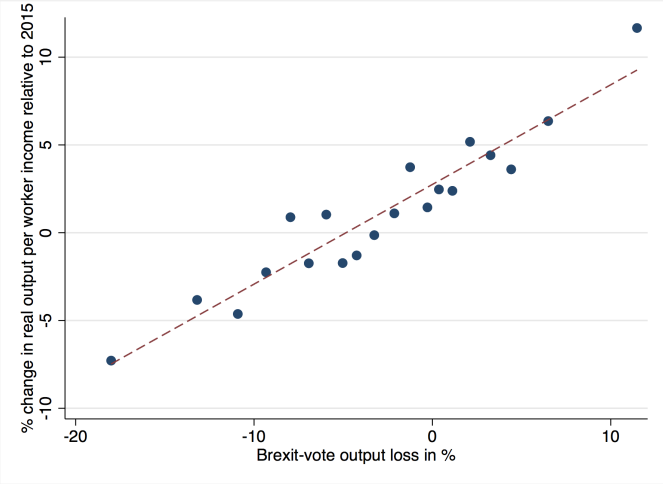
Panel A: Employment growth



Panel B: Real Payroll growth



Panel C: Productivity declines



Notes: Figure plots a binned scatter plot of the ensemble synthetic control estimate of the output loss by 2018 (in % relative to 2015) on the horizontal axis against real employment growth (in %) relative to 2015 in panel A; real wage growth in % relative to 2015 in panel B and real changes in output per worker in % in panel C. The underlying regressions are all statistically significant at the 1% level and control for NUTS1 region fixed effects with coefficients presented in Appendix Table 10.

Table 1: Region Level Brexit-vote Cost Estimates from Quarterly Data for 2018 and 2019

	Ensemble estimate			*implied by "best synthetic control"*			
Region	Ensemble	Lower CI	Upper CI	$\hat{y}_d^{ENS_{sim}}$	AAPE$_s$	RMSPE$_s$	MAPE$_s$
Panel A: *Based on quarterly data (average for) 2018*							
North East	-2.31	-3.09	-1.53	-2.37	-2.46	-1.80	-0.76
North West	-1.04	-1.45	-0.63	-0.99	-1.71	-1.67	-1.15
Yorkshire & ...	-1.03	-1.56	-0.50	-1.04	-1.41	-1.88	-2.00
East Midlands	-2.33	-2.98	-1.68	-2.26	-3.63	-3.50	-3.63
West Midlands	-2.37	-2.98	-1.75	-2.31	-3.57	-3.56	-1.07
East	-0.33	-0.92	0.25	-0.29	-0.86	-0.91	-1.70
London	-3.83	-4.61	-3.05	-3.81	-3.47	-4.57	-4.81
South East	-3.45	-4.10	-2.80	-3.46	-3.88	-3.45	-3.52
South West	-2.55	-3.21	-1.89	-2.45	-2.77	-3.82	-3.34
Northern Ireland	-4.03	-4.58	-3.48	-4.03	-4.81	-4.55	-4.52
Scotland	-2.09	-2.47	-1.72	-2.09	-2.67	-2.67	-2.74
Wales	-1.49	-2.04	-0.94	-1.54	-0.56	-0.94	-0.72
Panel B: *Based on quarterly data (average for) 2019*							
North East	-2.96	-3.74	-2.18	-3.06	-3.40	-1.88	-1.02
North West	-2.27	-2.67	-1.86	-2.22	-2.77	-2.97	-2.58
Yorkshire & ...	-1.59	-2.12	-1.07	-1.57	-2.33	-2.82	-2.59
East Midlands	-2.73	-3.38	-2.08	-2.65	-4.59	-4.01	-4.59
West Midlands	-5.29	-5.90	-4.68	-5.25	-6.88	-6.88	-3.74
East	-2.74	-3.32	-2.16	-2.68	-3.37	-3.50	-4.83
London	-1.59	-2.37	-0.81	-1.56	-0.87	-2.77	-2.89
South East	-3.08	-3.73	-2.43	-3.11	-3.13	-2.57	-2.66
South West	-3.50	-4.16	-2.84	-3.42	-3.60	-4.59	-4.55
Northern Ireland	-4.67	-5.22	-4.11	-4.64	-5.41	-5.18	-5.42
Scotland	-2.82	-3.20	-2.44	-2.80	-3.93	-3.93	-4.03
Wales	-0.48	-1.03	0.07	-0.54	1.19	0.48	0.54

Notes: Table presents region-level estimates of the cost of Brexit expressed in the difference in growth rates relative to 2016Q2 between the actual UK region and the synthetic control estimate. The data capture the average difference in the respective year indicated in the column head. The preferred estimate is the ensemble average across the whole set of synthetic control estimates. We further provide the ensemble estimate constructed using the 70 synthetic controls using the sampling approach, along with the estimates that are obtained when picking the best series among the set of synthetic control according to the best pre-treatment fit as defined by equations (2)-(4).

Table 2: Region Level Brexit-vote Cost Estimates from Quarterly Data in Real GVA for 2018 and 2019

	Ensemble estimate			*implied by "best synthetic control"*			
Region	Ensemble	Lower CI	Upper CI	$\hat{y}_d^{ENS_{sim}}$	AAPE$_s$	RMSPE$_s$	MAPE$_s$
Panel A: *Based on quarterly data (average for) 2018*							
North East	-1236	-1659	-817	-1271	-1321	-961	-406
North West	-1856	-2590	-1126	-1764	-3059	-2980	-2054
Yorkshire & ...	-1234	-1873	-599	-1243	-1695	-2268	-2418
East Midlands	-2484	-3184	-1787	-2412	-3897	-3751	-3897
West Midlands	-3277	-4134	-2425	-3205	-4971	-4967	-1479
East	-542	-1477	387	-477	-1397	-1467	-2754
London	-17056	-20608	-13531	-16973	-15399	-20446	-21526
South East	-9421	-11241	-7612	-9444	-10602	-9425	-9600
South West	-3489	-4407	-2577	-3358	-3805	-5276	-4594
Northern Ireland	-1644	-1875	-1414	-1644	-1969	-1858	-1846
Scotland	-2905	-3436	-2376	-2894	-3716	-3716	-3818
Wales	-941	-1293	-592	-969	-350	-593	-453
UK combined	-46085	-57777	-34467	-45654	-52181	-57707	-54845
Panel B: *Based on quarterly data (average for) 2019*							
North East	-1597	-2025	-1173	-1651	-1837	-1011	-545
North West	-4061	-4803	-3322	-3968	-4976	-5340	-4631
Yorkshire & ...	-1932	-2580	-1288	-1903	-2831	-3437	-3153
East Midlands	-2950	-3660	-2243	-2865	-5001	-4361	-5001
West Midlands	-7357	-8231	-6488	-7307	-9653	-9644	-5154
East	-4423	-5377	-3474	-4329	-5462	-5666	-7873
London	-7317	-10954	-3708	-7166	-4003	-12852	-13414
South East	-8523	-10364	-6695	-8604	-8656	-7088	-7339
South West	-4857	-5790	-3929	-4732	-4990	-6390	-6336
Northern Ireland	-1922	-2156	-1689	-1912	-2235	-2140	-2243
Scotland	-3955	-4493	-3418	-3921	-5545	-5545	-5684
Wales	-307	-662	46	-347	755	304	345
UK combined	-49201	-61096	-37383	-48705	-54433	-63169	-61027

Notes: Table presents region-level estimates of the cost of Brexit expressed in millions of real pounds of gross-value added in 2018. The table aggregates the district level estimates. Losers, winners and ambigous cases are defined as per the classification in Section 4.2. The preferred estimate is the ensemble average across the 31 synthetic control estimates. We further provide the ensemble estimate constructed using the 70 synthetic controls using the sampling approach, along with the estimates that are obtained when picking the best series among the 31 synthetic control according to the best pre-treatment fit as defined by equations (2)-(4).

Table 3: District Level Estimates of the Economic Cost of the Brexit-vote for the ten districts with largest losses and the 5 districts with most gains in per capita real Gross Value Added

District			*GVA in 2015*		$\hat{y}_d^{ENS}$ *ensemble*			*other estimates in £million*					
Region	LA	Type	£million	capita	£million	%	capita	Low	High	ENS_{sim}	$AAPE_s$	$RMSPE_s$	$MAPE_s$
North East	Darlington	Loser	5782	54548	-1180	-20.10	-11133	-1409	-959	-1029	-1161	-1161	-1316
London	Islington	Loser	17759	78059	-2209	-11.49	-9711	-2406	-2014	-1861	-2708	-3195	-3195
London	Tower Hamlets	Loser	31190	106151	-2809	-8.23	-9559	-3403	-2225	-2924	-4500	-4500	-5749
Scotland	Aberdeen City	Loser	11351	49277	-2062	-18.19	-8951	-2445	-1690	-2802	-3043	-3043	-1155
South East	Reigate &Banst...	Loser	7071	49175	-1263	-19.38	-8783	-1462	-1070	-1258	-1302	-1302	-1302
East	Broxbourne	Loser	2671	27733	-712	-26.39	-7390	-807	-619	-620	-789	-779	-789
South East	Mole Valley	Loser	4007	46069	-589	-14.87	-6766	-740	-442	-742	-459	-459	-459
W Midlands	East Staffords...	Loser	3829	32953	-786	-21.74	-6760	-887	-687	-757	-798	-790	-767
London	Kensington &Ch...	Loser	10183	64210	-1066	-9.92	-6721	-1520	-629	-1413	-887	-887	-887
Scotland	Shetl&Islands	Loser	794	34224	-154	-19.86	-6628	-173	-135	-161	-131	-142	-142
North East	North Tyneside	Winner	7550	37243	1048	12.62	5168	862	1229	898	1263	1193	1193
South East	Wokingham	Winner	5846	36266	1021	15.20	6332	928	1112	894	1184	1184	1234
W Midlands	Solihull	Winner	7659	36327	1607	18.34	7621	1366	1840	1732	1485	1485	1485
East	Three Rivers	Winner	3485	37964	704	16.49	7670	498	900	855	586	586	586
London	Westminster	Winner	56957	239268	3034	4.69	12747	2162	3895	2883	111	70	70

Table 4: Region Level Aggregated District Level Brexit-vote Cost Estimates in Real GVA in 2018

	# of districts classified as			*District-level aggregation*			*implied by "best synthetic control"*			
Region	losers	winners	unclear	Ensemble	Lower CI	Upper CI	$\hat{y}_d^{ENS_{sim}}$	AAPE_s	RMSPE_s	MAPE_s
North East	6	3	3	-4450	-6506	-2440	-4384	-3134	-3352	-3739
North West	19	11	9	-2902	-6154	269	-1760	-2462	-2782	-3076
Yorkshire & ...	5	5	11	-1276	-3032	448	-683	-1231	-1111	-885
East Midlands	16	4	20	-3863	-5651	-2116	-3136	-4173	-4225	-3897
West Midlands	10	11	9	644	-2555	3748	1837	1044	660	28
East	13	17	16	1419	-2049	4794	3409	2171	1637	1725
London	19	4	10	-12321	-20831	-4001	-11237	-19712	-21462	-19785
South East	39	8	20	-13193	-18869	-7659	-12582	-11634	-11753	-12640
South West	12	6	11	-1948	-4156	216	-2118	-2058	-2366	-2071
Wales	10	5	7	-508	-1658	617	-672	61	25	26
Scotland	17	1	14	-6008	-8526	-3539	-6683	-6933	-6677	-4416
Northern Ireland	2	3	6	-1289	-2093	-507	-718	-1495	-1392	-1318
UK combined	168	78	136	-45695	-82079	-10169	-38728	-49557	-52799	-50049

Notes: Table presents region-level estimates of the cost of Brexit expressed in millions of real pounds of gross-value added in 2018. The table aggregates the district level estimates. Losers, winners and ambigous cases are defined as per the classification in Section 4.2. The preferred estimate is the ensemble average across the 31 synthetic control estimates. We further provide the ensemble estimate constructed using the 70 synthetic controls using the sampling approach, along with the estimates that are obtained when picking the best series among the 31 synthetic control according to the best pre-treatment fit as defined by equations (2)-(4).

Table 5: Correlation between 2010-2015 district-level sector average Gross Value Added and the estimated loss in GVA by 2018 relative to 2015

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Primary (Agriculture, Forestry, Fishing, Mining)	-3.052							
	(9.596)							
Manufacturing		-10.598**						
		(4.802)						
Construction			11.899					
			(15.438)					
Wholesale and Retail				-17.213				
				(12.750)				
Transportation and Storage					-13.405			
					(8.609)			
Public, education, health						-5.201		
						(5.604)		
Finance and Insurance							10.504	
							(6.408)	
Professional, scientific, technical and other services								20.229*
								(10.952)
Mean of DV	-2.9	-2.83	-2.83	-2.83	-2.83	-2.85	-2.85	-2.85
R2	.0879	.103	.0934	.0967	.0961	.0934	.0979	.1
Local authority districts	381	422	422	422	422	420	420	420

Notes: All regressions include NUTS1 region shifters. The dependent variable is the ensemble estimate of the output gap in percent relative to 2015. The ensemble has been constructed from 31 synthetic controls constructed using different sets of donor pools. Robust standard errors are provided in the parentheses. Stars indicate *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 6: Correlation between 2011 census level sector and district-level employment shares at the estimated loss in GVA by 2018 relative to 2015

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Agriculture and Mining employment share (2011)	-46.647**							
	(18.241)							
Manufacturing employment share (2011)		-35.253***						
		(12.630)						
Construction employment share (2011)			-36.278					
			(27.176)					
Retail employment share (2011)				-0.733				
				(21.142)				
Hotel/Restaurant employment share (2011)					-11.869			
					(19.505)			
Transport employment share (2011)						20.627		
						(17.041)		
Finance employment share (2011)							32.120*	
							(16.676)	
Other Service sector employment share (2011)								19.034*
								(9.785)
Mean of DV	-3.03	-3.03	-3.03	-3.03	-3.03	-3.03	-3.03	-3.03
R2	.0918	.0982	.0857	.0804	.0812	.0838	.0898	.0903
Local authority districts	370	370	370	370	370	370	370	370

Notes: All regressions include NUTS1 region shifters. The dependent variable is the ensemble estimate of the output gap in percent relative to 2015. The ensemble has been constructed from 31 synthetic controls constructed using different sets of donor pools. Robust standard errors are provided in the parentheses. Stars indicate *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 7: Correlation between 2010-2015 district-level sector average Gross Value Added and the estimated loss in GVA by 2018 relative to 2015

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Primary (Agriculture, Forestry, Fishing, Mining)	-3.052							
	(9.596)							
Manufacturing		-10.598**						
		(4.802)						
Construction			11.899					
			(15.438)					
Wholesale and Retail				-17.213				
				(12.750)				
Transportation and Storage					-13.405			
					(8.609)			
Public, education, health						-5.201		
						(5.604)		
Finance and Insurance							10.504	
							(6.408)	
Professional, scientific, technical and other services								20.229*
								(10.952)
Mean of DV	-2.9	-2.83	-2.83	-2.83	-2.83	-2.85	-2.85	-2.85
R2	.0879	.103	.0934	.0967	.0961	.0934	.0979	.1
Local authority districts	381	422	422	422	422	420	420	420

Notes: All regressions include NUTS1 region shifters. The dependent variable is the ensemble estimate of the output gap in percent relative to 2015. The ensemble has been constructed from 31 synthetic controls constructed using different sets of donor pools. Robust standard errors are provided in the parentheses. Stars indicate *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 8: Correlation between hourly pay levels, inequality and changes from 2005 to 2015 and the estimated loss in GVA by 2018 relative to 2015

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mean hourly pay (2015)	0.331**						
	(0.168)						
Median hourly pay (2015)		0.455*					
		(0.253)					
Interquartile range hourly pay (2015)			0.374**				
			(0.164)				
10th percentile hourly pay growth (2015-2005)				-9.132*			
				(4.828)			
25th percentile hourly pay growth (2015-2005)					-3.334		
					(4.828)		
Mean hourly pay growth (2015-2005)						-1.876	
						(1.590)	
Median hourly pay growth (2015-2005)							-5.284
							(4.612)
Mean of DV	-3.03	-3.03	-2.95	-2.99	-3.02	-3.03	-3.03
R2	.0914	.0909	.0912	.0891	.0817	.0821	.0836
Local authority districts	370	370	364	367	369	370	370

Notes: All regressions include NUTS1 region shifters. The dependent variable is the ensemble estimate of the output gap in percent relative to 2015. The ensemble has been constructed from 31 synthetic controls constructed using different sets of donor pools. Robust standard errors are provided in the parentheses. Stars indicate *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 9: Correlation between other social- and economic characteristics and the estimated loss in GVA by 2018 relative to 2015

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share of Res. Pop. No Qualification (2011)	-18.404**							
	(7.912)							
Share of Res. Pop. Qualification 4+ (2011)		11.694**						
		(5.843)						
Unemployment rate APS (2015)			0.014					
			(0.172)					
Self-employment rate APS (2015)				0.224**				
				(0.102)				
Unemployment rate increase 2007-2009					0.351*			
					(0.187)			
Migrant Stock from EU8 Accesssion countries (2011)						-57.817**		
						(27.828)		
Migrant Stock from EU15 countries (2011)							8.166	
							(32.832)	
Migrant Stock Non-EU (2011)								-3.166
								(7.251)
Mean of DV	-3.03	-3.03	-3.03	-3.03	-3.1	-3.03	-3.03	-3.03
R2	.0945	.0909	.0816	.0914	.0926	.0908	.0805	.0807
Local authority districts	370	370	368	368	336	370	370	370

Notes: All regressions include NUTS1 region shifters. The dependent variable is the ensemble estimate of the output gap in percent relative to 2015. The ensemble has been constructed from 31 synthetic controls constructed using different sets of donor pools. Robust standard errors are provided in the parentheses. Stars indicate *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 10: Mechanisms: Employment and Payroll Growth and Productivity Losses point towards capital decumulation

	(1)	(2)	(3)
	Real growth relative to 2015 in		
	Employment	Payroll	Output per worker
Brexit-vote output loss in %	-0.274***	-0.132***	-0.568***
	(0.044)	(0.038)	(0.053)
Mean of DV	2.8	6.47	1.05
R2	.186	.235	.358
Local authority districts	362	377	362

Notes: All regressions include NUTS1 region fixed effects. The regression coefficient capture the impact of a 1 percentage point *lower* growth of a district vis-a-vis its respective ensemble synthetic control estimate on real employment growth in % relative to 2015 in column (1); real payroll growth in % relative to 2015 in column (2) and real changes in output per worker in % in column (3). Robust standard errors are provided in the parentheses. Stars indicate *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Online Appendix

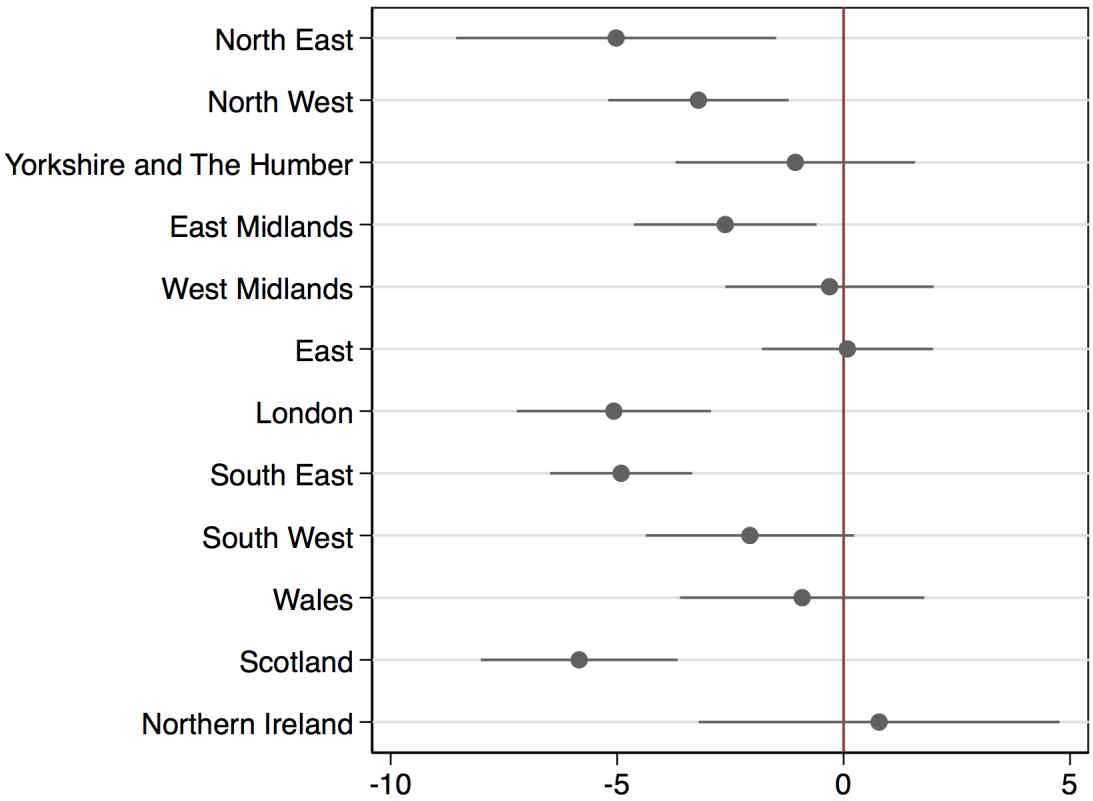
"Measuring the Regional Economic Cost of Brexit: Evidence up to 2019"

For Online Publication

Thiemo Fetzer and Shizhuo Wang

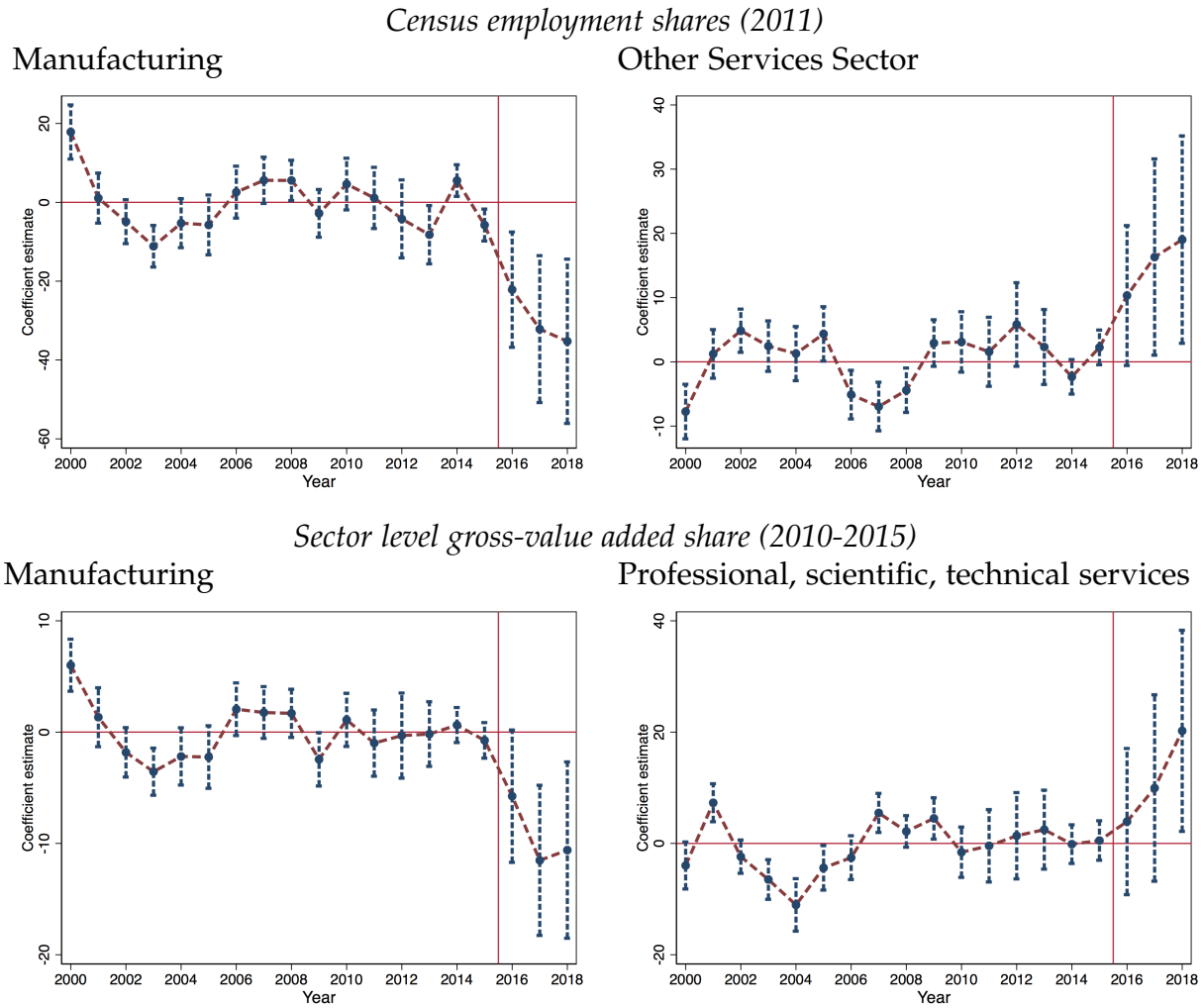
July 6, 2020

Figure A1: Average District-Level Real GVA Output Gap in % relative to 2015 By 2018 Across Regions



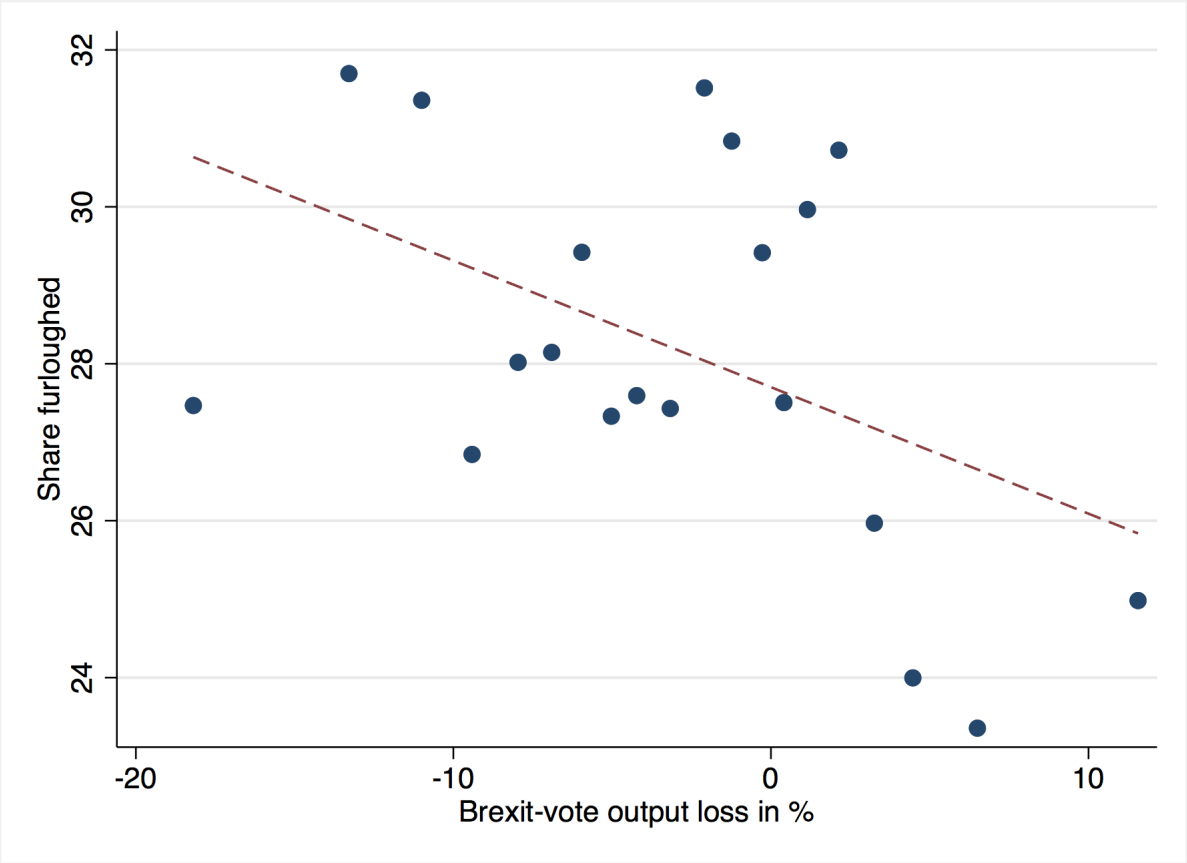
Notes: Figure plots the average output loss, comparing the difference between the UK realised real GDP relative to 2015 and the ensemble estimate of the synthetic control using the ensemble. The estimated coefficients are computed by a regression of the output gap on region dummies, which are presented here, and bars correspond to the 90% confidence intervals.

Figure A2: Relationship between economic structure and Brexit-vote output losses emerges post 2016: Exploring Manufacturing and Some Services



Notes: Figures present results from estimating regression specification 5 for each year, plotting out the coefficient β that is estimated for each year. The figure highlights that the increasing gap between the synthetic control and actual recorded output is only emerging after the Brexit vote. 90% confidence intervals are indicated constructed from estimating clustered standard errors at the district level.

Figure A3: Share of employees furloughed as of May 2020 due to COVID19 and Brexit-vote output losses by 2018 across districts



Notes: Figures present results from a binned scatter plot regression, controlling for NUTS1 region fixed effects. The regression line indicates that for every one percentage point lower output due to the Brexit-vote vis-a-vis a the ensemble synthetic control estimate the share of employees currently furloughed is 0.15 percentage points higher. This relationship is significant at the one percent level using robust standard errors.

Table A1: UK-level estimates of Brexit-vote cost to date using synthetic controls constructed from various donor pools in this paper and Born et al. (2019)

		Brexit cost estimates				*quality of pre Brexit fit*		
Donor Pool	#	Gap	Upper	Lower	GBP bn	$AAPE_s$	$RMSPE_s$	$MAPE_s$
EU	27	-4.46	-3.97	-4.94	-87.23	0.39	0.23	0.06
G20	18	-1.49	-0.62	-2.35	-29.13	0.67	0.71	0.12
OECD	33	-2.75	-2.43	-3.06	-53.80	0.25	0.10	0.04
G20, EU	42	-2.26	-1.94	-2.57	-44.22	0.23	0.09	0.05
G20, OECD	41	-2.77	-2.45	-3.09	-54.22	0.25	0.10	0.04
OECD, EU	40	-2.55	-2.26	-2.84	-49.88	0.22	0.08	0.04
G20, OECD, EU	48	-2.55	-2.26	-2.84	-49.90	0.22	0.08	0.04
Ensemble $\hat{y}_d^{ENS}$		-2.28	-2.02	-2.54	-44.67	0.14	0.03	0.02
Ensemble $\hat{y}_d^{ENS_{sim}}$		-1.97	-1.32	-2.63	-38.63	0.38	0.21	0.06
$RMSPE_d$		-2.76	-2.70	-2.81	-54.00	0.04	0.00	0.01
$AAPE_d$		-2.14	-2.09	-2.20	-42.00	0.04	0.00	0.01
$MAPE_d$		-2.76	-2.70	-2.81	-54.00	0.04	0.00	0.01

Notes: Table shows Brexit cost at the national level. These are the results when constructing synthetic controls using the various donor pools indicated from Annual Real Gross Value Added data (Panel A). "#" refer to the number of units in the donor pool set. "Gap" is the estimated cost of Brexit expressed in percentage drop in real 2015 GDP. "Upper" and "Lower" being the upper and lower limits of the confidence intervals. "GBP bn" translates into real billion pounds. Finally, $MAPE_s$, $RMSPE_s$, $AAPE_s$ are measures of goodness of fit, see Equations (2)-(4).

Table A2: Total Sets of Combinations of Donor Pools

Pool 1	Size 1	Pool 2	Size 2	Pool 3	Size 3	Pool 4	Size 4	Pool 5	Size 5
EU-NUTS2	175	EU-NUTS2 US-STATES	226	EU-NUTS2 US-STATES G20	241	EU-NUTS2 US-STATES G20 OECD	250	EU-NUTS2 US-STATES G20 OECD EU	253
US-STATES	51	EU-NUTS2 G20	191	EU-NUTS2 US-STATES OECD	242	EU-NUTS2 US-STATES G20 EU	247		
G20	18	EU-NUTS2 OECD	192	EU-NUTS2 US-STATES EU	233	EU-NUTS2 US-STATES OECD EU	245		
OECD	33	EU-NUTS2 EU	182	EU-NUTS2 G20 OECD	200	EU-NUTS2 G20 OECD EU	203		
EU	27	US-STATES G20	68	EU-NUTS2 G20 EU	197	US-STATES G20 OECD EU	98		
		US-STATES OECD	83	EU-NUTS2 OECD EU	195				
		US-STATES EU	78	US-STATES G20 OECD	91				
		G20 OECD	41	US-STATES G20 EU	92				
		G20 EU	42	US-STATES OECD EU	90				
		OECD EU	40	G20 OECD EU	48				

Notes: Table presents full set of potential combinations of donor pools drawn from the set of five potential donor sets. Cells colored light blue include donor pools only constructed of subnational data; cells colored light red include only country-level donors; non-colored cells capture a donor pool set comprised of a mix of country-level and subnational data. The counts indicated in the columns with the respective sizes represent the maximum number of spatial units included in the respective donor pool.

Table A3: District-Level "best model" selected from the set of 31 synthetic controls constructed for each district

	Donor pool		*implied by "best synthetic control"*		
Donor pool set	Type	Size	$RMSPE_s$	$AAPE_s$	$MAPE_s$
NUTS2	Subnational only	1.00	0	0	0
US States	Subnational only	1.00	0	0	0
G20	Country only	1.00	0	0	0
OECD	Country only	1.00	0	0	0
EU	Country only	1.00	1	1	5
NUTS2, US States	Subnational only	2.00	27	25	41
NUTS2, G20	Mixed	2.00	0	0	0
NUTS2, OECD	Mixed	2.00	0	0	0
NUTS2, EU	Mixed	2.00	0	0	0
US States, G20	Mixed	2.00	2	8	7
US States, OECD	Mixed	2.00	9	12	12
US States, EU	Mixed	2.00	21	14	18
G20, OECD	Country only	2.00	0	0	0
G20, EU	Country only	2.00	0	0	0
OECD, EU	Country only	2.00	0	0	0
NUTS2, US States, G20	Mixed	3.00	25	39	21
NUTS2, US States, G20	Mixed	3.00	25	39	21
NUTS2, US States, OECD	Mixed	3.00	22	24	12
NUTS2, US States, EU	Mixed	3.00	40	33	36
NUTS2, G20, OECD	Mixed	3.00	1	2	0
NUTS2, G20, EU	Mixed	3.00	1	1	1
NUTS2, OECD, EU	Mixed	3.00	0	0	0
US States, G20, OECD	Mixed	3.00	6	10	15
US States, G20, EU	Mixed	3.00	18	22	19
US States, OECD, EU	Mixed	3.00	16	12	21
G20, OECD, EU	Country only	3.00	2	2	3
NUTS2, US States, G20, OECD	Mixed	4.00	38	33	33
NUTS2, US States, G20, EU	Mixed	4.00	44	44	34
NUTS2, US States, OECD, EU	Mixed	4.00	36	35	31
NUTS2, G20, OECD, EU	Mixed	4.00	1	1	2
NUTS2, G20, OECD, EU	Mixed	4.00	1	1	2
US States, G20, OECD, EU	Mixed	4.00	14	17	17
NUTS2, US States, G20, OECD, EU	Mixed	5.00	58	40	27

Notes: Table presents the number of districts whose "best fit" has been determined according to equations (2)-(4) from the set of 31 synthetic control candidates tabulated against the respective donor pools.

Table A4: Characteristics of districts classified as Brexit-vote losers or winners

	Overall	*Losers*		*Unclear*		*Winners*	
	Mean	Mean	p	Mean	p	Mean	p
Panel A: Output losses							
Output loss relative to y_d^{Ens}	-2.83	-8.54	0.00	-0.78	0.00	6.43	0.00
	(6.95)	(4.96)		(2.13)		(4.02)	
Output loss relative to $y_d^{ENS_{sim}}$	-2.32	-8.34	0.00	-0.39	0.00	7.29	0.00
	(7.20)	(4.90)		(1.93)		(4.31)	
Output loss relative to y_d^{MAPE}	-2.62	-8.40	0.00	-0.50	0.00	6.70	0.00
	(7.32)	(5.23)		(3.17)		(4.86)	
Output loss relative to y_d^{AAPE}	-2.68	-8.50	0.00	-0.45	0.00	6.50	0.00
	(7.38)	(5.64)		(2.90)		(4.60)	
Output loss relative to y_d^{RMSE}	-2.81	-8.58	0.00	-0.65	0.00	6.38	0.00
	(7.36)	(5.64)		(2.90)		(4.63)	
Panel B: EU preferences							
% Leave in 2016 Referendum	47.72	47.31	0.69	45.86	0.12	52.11	0.01
	(18.41)	(19.11)		(18.71)		(15.47)	
% Turnout in 2016	66.33	65.22	0.36	65.31	0.49	70.75	0.01
	(22.12)	(22.88)		(23.46)		(16.88)	
Panel C: Demographics (2011)							
Share with No Qualification (2011)	0.31	0.31	0.63	0.31	0.29	0.32	0.52
	(0.05)	(0.06)		(0.05)		(0.06)	
Share with Qualification 4+ (2011)	0.27	0.27	0.71	0.27	0.50	0.27	0.74
	(0.08)	(0.08)		(0.08)		(0.08)	
Population 0 - 19 yrs	0.25	0.25	0.42	0.25	0.18	0.25	0.50
	(0.02)	(0.02)		(0.02)		(0.02)	
Population 20 - 29 yrs	0.12	0.12	0.24	0.12	0.54	0.11	0.01
	(0.03)	(0.03)		(0.03)		(0.02)	
Population 30 - 44 yrs (2011)	0.22	0.23	0.70	0.22	0.61	0.22	0.91
	(0.02)	(0.02)		(0.02)		(0.02)	
Population 45 - 59 yrs (2011)	0.20	0.19	0.21	0.19	0.84	0.20	0.05
	(0.02)	(0.02)		(0.02)		(0.02)	
Population 60 older (2011)	0.21	0.21	0.33	0.22	0.53	0.22	0.64
	(0.03)	(0.03)		(0.03)		(0.04)	
Panel D: Incomes							
Median hourly pay (2015)	13.49	13.47	0.87	13.46	0.84	13.59	0.66
	(2.14)	(2.08)		(2.19)		(2.20)	
Mean hourly pay (2015)	16.12	16.10	0.87	16.02	0.63	16.36	0.44
	(2.92)	(2.99)		(2.81)		(2.98)	
Unemployment rate increase 2007-2009	2.31	2.10	0.12	2.26	0.76	2.87	0.02
	(2.29)	(2.35)		(2.25)		(2.18)	
Unemployment rate APS (2015)	5.27	5.29	0.89	5.27	0.98	5.24	0.90
	(2.11)	(2.12)		(2.02)		(2.28)	
Panel E: Employment shares (2011)							
Agriculture & Mining	0.02	0.02	0.17	0.01	0.74	0.01	0.08
	(0.02)	(0.02)		(0.02)		(0.01)	
Manufacturing	0.09	0.09	0.97	0.09	0.75	0.09	0.65
	(0.04)	(0.04)		(0.04)		(0.03)	
Construction	0.08	0.08	0.65	0.08	0.41	0.08	0.68
	(0.02)	(0.02)		(0.02)		(0.02)	
Retail	0.16	0.16	0.15	0.16	0.76	0.16	0.17
	(0.02)	(0.02)		(0.02)		(0.02)	
Hotel/Restaurant	0.06	0.06	0.69	0.06	0.34	0.05	0.08
	(0.02)	(0.02)		(0.02)		(0.02)	
Transport & Storage	0.09	0.09	0.19	0.08	0.18	0.09	0.97
	(0.03)	(0.03)		(0.03)		(0.02)	
Finance	0.04	0.04	0.36	0.04	0.51	0.04	0.71
	(0.03)	(0.03)		(0.03)		(0.02)	
Other Service sector	0.46	0.46	0.69	0.46	0.50	0.46	0.76
	(0.04)	(0.04)		(0.04)		(0.04)	

Notes: Table presents summary statistics for the three districts classified into Brexit-vote winners, losers and ambigous using the method presented in section 4.2. The respective overall and group-level means are presented with the p-values indicating whether a group-specific mean is statistically different from the overall mean.

Table A5: District Level Estimates of the Economic Cost of the Brexit-vote Across 382 districts in 2018 relative to 2015 Real Gross Value Added

District			*GVA in 2015*		$\hat{y}_d^{ENS}$ *ensemble*			*other estimates*					
Region	LA	Type	£million	capita	£million	%	capita	Low	High	ENS_{sim}	$AAPE_s$	$RMSPE_s$	$MAPE_s$
North East	Hartlepool	Winner	2618	28303	77	2.84	838	30	125	94	125	110	110
North East	Middlesbrough	Winner	5254	37714	279	4.99	2001	228	329	265	393	378	409
North East	Redcar &Clevel...	Loser	3596	26573	-578	-16.46	-4273	-657	-501	-586	-597	-550	-660
North East	Stockton-on-Te...	Loser	9796	50203	-1085	-11.05	-5558	-1180	-990	-1108	-995	-1044	-1000
North East	Darlington	Loser	5782	54548	-1180	-20.10	-11133	-1409	-959	-1029	-1161	-1161	-1316
North East	County Durham	-	16714	32183	-17	-0.10	-34	-203	166	-247	41	41	40
North East	Northumberland	Loser	10102	31923	-826	-8.15	-2609	-969	-684	-605	-686	-686	-690
North East	Newcastle upon...	-	17174	59065	-211	-1.21	-727	-489	62	-491	356	333	336
North East	North Tyneside	Winner	7550	37243	1048	12.62	5168	862	1229	898	1263	1193	1193
North East	South Tyneside	Loser	3850	25927	-665	-17.14	-4477	-750	-581	-655	-664	-595	-631
North East	Sunderland	-	13592	49102	-631	-4.33	-2278	-1006	-264	-369	-734	-734	-892
North East	Gateshead	Loser	8040	39856	-661	-7.97	-3277	-961	-371	-552	-476	-637	-637
North West	Halton	Winner	3857	30437	199	4.80	1573	137	261	150	221	221	202
North West	Warrington	Loser	7040	33882	-697	-9.26	-3353	-840	-556	-517	-821	-714	-727
North West	Blackburn with...	-	2927	19796	-163	-5.19	-1100	-209	-117	-56	-214	-215	-213
North West	Blackpool	Winner	2411	17202	190	7.22	1353	81	294	243	187	187	187
North West	Cheshire East	-	12880	34281	-118	-0.82	-314	-650	395	102	192	45	-250
North West	Cheshire West ...	-	8855	26516	304	3.21	909	194	412	169	410	436	436
North West	Allerdale	Loser	1943	20081	-374	-19.34	-3870	-419	-331	-339	-395	-414	-414
North West	Barrow-in-Furn...	Loser	1557	23007	-74	-4.49	-1090	-144	-6	-114	-25	-25	-141
North West	Carlisle	Loser	2782	25733	-382	-13.08	-3534	-429	-336	-312	-361	-367	-431
North West	Copeland	Loser	1703	24437	-264	-15.79	-3786	-324	-206	-304	-255	-260	-220

Table A5: District Level Estimates of the Economic Cost of the Brexit-vote Across 382 districts in 2018 relative to 2015 Real Gross Value Added

District			*GVA in 2015*		$\hat{y}_d^{ENS}$ *ensemble*			*other estimates*					
Region	LA	Type	£million	capita	£million	%	capita	Low	High	ENS_{sim}	$AAPE_s$	$RMSPE_s$	$MAPE_s$
North West	Eden	Loser	1393	26495	-100	-6.93	-1894	-125	-75	-88	-103	-103	-103
North West	Burnley	Winner	1964	22507	66	2.99	758	34	98	93	29	57	79
North West	Chorley	Winner	1882	16660	57	2.87	505	25	88	68	60	77	75
North West	Fylde	Winner	1870	24132	64	3.18	823	-68	188	102	70	73	73
North West	Hyndburn	Loser	1539	19210	-216	-13.82	-2700	-233	-200	-205	-230	-230	-230
North West	Lancaster	Loser	2709	19242	-282	-10.14	-2004	-413	-157	-228	-313	-353	-353
North West	Pendle	Loser	2232	24821	-214	-9.35	-2384	-299	-133	-164	-238	-238	-238
North West	Preston	-	4012	28518	126	2.97	896	84	168	100	167	187	184
North West	Ribble Valley	Loser	1481	25308	-119	-7.47	-2029	-163	-76	-111	-82	-82	-137
North West	Rossendale	Loser	1109	15976	-115	-10.15	-1655	-132	-98	-115	-111	-108	-110
North West	South Ribble	-	3371	30733	-247	-6.62	-2253	-422	-80	-59	-301	-365	-372
North West	West Lancashir...	Winner	2243	19941	173	7.24	1540	145	201	179	195	192	188
North West	Wyre	-	1530	13967	-4	-0.28	-40	-35	26	3	6	8	15
North West	Bolton	Winner	5435	19285	157	2.67	557	85	228	289	20	9	42
North West	Bury	-	3010	16029	22	0.73	119	-29	73	-45	80	80	72
North West	Manchester	Winner	19382	36583	997	4.69	1882	892	1102	863	1010	935	935
North West	Oldham	Loser	3485	15139	-186	-5.07	-809	-225	-148	-102	-184	-235	-235
North West	Rochdale	Loser	3346	15613	-160	-4.76	-746	-212	-109	-162	-140	-146	-156
North West	Salford	Loser	7206	29390	-687	-8.88	-2803	-852	-525	-587	-629	-618	-597
North West	Stockport	Winner	5955	20665	339	5.35	1177	271	407	325	429	366	369
North West	Tameside	Loser	3302	14907	-329	-9.70	-1485	-366	-293	-285	-316	-314	-290
North West	Trafford	Winner	7958	34158	324	3.75	1391	226	421	358	191	229	273

Table A5: District Level Estimates of the Economic Cost of the Brexit-vote Across 382 districts in 2018 relative to 2015 Real Gross Value Added

District			*GVA in 2015*		$\hat{y}_d^{ENS}$ *ensemble*			*other estimates*					
Region	LA	Type	£million	capita	£million	%	capita	Low	High	ENS_{sim}	$AAPE_s$	$RMSPE_s$	$MAPE_s$
North West	Wigan	Loser	4995	15501	-321	-6.20	-997	-407	-237	-190	-428	-429	-429
North West	Knowsley	Winner	3245	22036	33	0.92	225	-19	85	119	41	26	26
North West	Liverpool	Loser	12719	26450	-408	-3.11	-849	-607	-213	-517	-264	-366	-297
North West	St. Helens	Loser	2709	15254	-190	-6.85	-1069	-221	-159	-132	-185	-185	-191
North West	Sefton	-	3863	14094	27	0.66	99	-48	101	91	-3	4	47
North West	Wirral	Loser	4918	15288	-340	-6.83	-1056	-404	-276	-330	-217	-206	-206
North West	South Lakeland	-	2440	23512	10	0.39	93	-34	52	-52	45	60	60
E Midlands	Derby	Loser	6747	26576	-290	-4.15	-1144	-396	-187	-324	-392	-392	-256
E Midlands	Leicester	Loser	7768	22579	-553	-6.74	-1608	-631	-476	-522	-463	-545	-545
E Midlands	Rutland	-	710	18513	1	0.08	15	-19	19	12	6	3	3
E Midlands	Nottingham	Loser	9535	29896	-939	-9.28	-2944	-1017	-861	-830	-1004	-984	-984
E Midlands	Amber Valley	-	2355	18963	-63	-2.52	-506	-94	-32	-10	-91	-94	-94
E Midlands	Bolsover	Loser	1808	23204	-154	-7.91	-1972	-193	-115	-106	-192	-193	-190
E Midlands	Chesterfield	-	2244	21481	-61	-2.59	-586	-98	-25	-69	-109	-81	-81
E Midlands	Derbyshire Dal...	Winner	1326	18597	87	5.88	1214	-13	180	93	84	53	53
E Midlands	Erewash	-	1480	12905	-10	-0.67	-90	-31	10	-7	-23	-14	1
E Midlands	High Peak	-	1368	14947	1	0.08	12	-33	34	29	-19	-19	-19
E Midlands	North East Der...	Loser	1358	13626	-150	-10.60	-1501	-176	-124	-119	-150	-141	-153
E Midlands	South Derbyshi...	Loser	2449	24651	-430	-16.68	-4331	-582	-286	-403	-367	-367	-454
E Midlands	Blaby	-	3422	35477	29	0.79	301	-33	90	-52	40	40	40
E Midlands	Charnwood	-	3270	18668	59	1.73	338	0	117	78	72	70	71
E Midlands	Harborough	-	1980	22211	-20	-0.99	-229	-74	32	18	-71	-93	-100

Table A5: District Level Estimates of the Economic Cost of the Brexit-vote Across 382 districts in 2018 relative to 2015 Real Gross Value Added

District			*GVA in 2015*		$\hat{y}_d^{ENS}$ *ensemble*			*other estimates*					
Region	LA	Type	£million	capita	£million	%	capita	Low	High	ENS_{sim}	$AAPE_s$	$RMSPE_s$	$MAPE_s$
E Midlands	Hinckley &Bosw...	Loser	2215	20395	-261	-11.02	-2407	-304	-220	-196	-233	-233	-274
E Midlands	Melton	-	1130	22176	15	1.31	303	-8	38	30	33	-5	-8
E Midlands	North West Lei...	-	3262	33595	-126	-3.45	-1295	-175	-77	-39	-142	-142	-40
E Midlands	Oadby &Wigston	Loser	845	15094	-54	-6.39	-957	-71	-37	-53	-41	-50	-35
E Midlands	Boston	Loser	1335	19962	-127	-8.89	-1895	-158	-96	-107	-145	-151	-149
E Midlands	East Lindsey	Loser	2140	15500	-176	-8.23	-1276	-215	-138	-165	-198	-187	-187
E Midlands	Lincoln	Loser	2632	27235	-130	-4.71	-1344	-168	-92	-141	-142	-127	-142
E Midlands	North Kesteven	-	2046	18238	15	0.67	130	-17	46	17	64	-27	-17
E Midlands	South Holland	Winner	1818	19924	106	5.25	1157	65	146	117	130	102	118
E Midlands	South Kesteven	Loser	2655	19049	-126	-4.60	-906	-175	-78	-155	-95	-95	-95
E Midlands	West Lindsey	Loser	1403	15093	-121	-8.12	-1305	-156	-87	-86	-159	-155	-155
E Midlands	Corby	-	1453	21723	-3	-0.16	-39	-20	14	17	-22	-1	-1
E Midlands	Daventry	Winner	1963	24601	146	6.68	1825	118	173	166	168	138	140
E Midlands	East Northampt...	-	1258	13966	5	0.38	56	-7	17	26	13	23	-7
E Midlands	Kettering	-	1971	20194	16	0.77	168	-9	41	-22	51	64	76
E Midlands	Northampton	Loser	6946	31358	-454	-6.01	-2051	-517	-392	-342	-615	-545	-504
E Midlands	South Northamp...	-	1739	19516	-36	-1.91	-407	-64	-9	-0	-39	-41	-13
E Midlands	Wellingborough	-	1653	21413	-23	-1.32	-300	-38	-8	-10	-28	-20	-30
E Midlands	Ashfield	Loser	2518	20376	-284	-10.48	-2300	-352	-218	-223	-321	-320	-307
E Midlands	Bassetlaw	Loser	2111	18406	-47	-2.16	-409	-72	-22	-58	-55	-57	-26
E Midlands	Broxtowe	-	2285	20432	13	0.55	117	-36	61	21	35	35	35
E Midlands	Gedling	-	1649	14198	-15	-0.87	-127	-100	66	8	5	5	53

Table A5: District Level Estimates of the Economic Cost of the Brexit-vote Across 382 districts in 2018 relative to 2015 Real Gross Value Added

District			*GVA in 2015*		$\hat{y}_d^{ENS}$ *ensemble*			*other estimates*					
Region	LA	Type	£million	capita	£million	%	capita	Low	High	ENS_{sim}	$AAPE_s$	$RMSPE_s$	$MAPE_s$
E Midlands	Mansfield	-	1455	13626	0	0.00	0	-12	12	-4	-15	-18	-6
E Midlands	Newark &Sherwo...	-	2272	19141	36	1.50	300	9	62	15	60	60	84
E Midlands	Rushcliffe	Winner	2056	17957	263	11.37	2300	218	308	263	195	279	298
W Midlands	Herefordshire,...	Loser	3775	20024	-313	-7.95	-1663	-450	-181	-290	-358	-358	-172
W Midlands	Telford &Wreki...	Winner	3680	21436	845	19.74	4925	750	938	891	862	862	862
W Midlands	Stoke-on-Trent	Winner	4880	19385	322	6.16	1280	292	353	190	387	387	391
W Midlands	Shropshire	-	5732	18358	-13	-0.22	-42	-74	47	-44	122	67	-81
W Midlands	Cannock Chase	-	1951	19809	-50	-2.43	-513	-104	1	-4	-77	-67	-77
W Midlands	East Staffords...	Loser	3829	32953	-786	-21.74	-6760	-887	-687	-757	-798	-790	-767
W Midlands	Lichfield	Loser	2313	22551	-226	-9.72	-2203	-330	-126	-132	-189	-173	-189
W Midlands	Newcastle-unde...	Loser	2107	16608	-163	-7.58	-1282	-182	-143	-159	-168	-168	-180
W Midlands	South Stafford...	Winner	1533	13847	171	10.27	1544	142	199	170	157	157	176
W Midlands	Stafford	-	2812	21268	86	2.80	647	31	139	47	155	155	155
W Midlands	Staffordshire ...	Loser	1415	14437	-70	-4.73	-718	-96	-46	-69	-66	-61	-61
W Midlands	Tamworth	Winner	1339	17365	90	6.12	1171	68	113	124	111	105	105
W Midlands	North Warwicks...	Winner	2522	40182	215	7.81	3425	139	289	182	239	239	275
W Midlands	Nuneaton &Bedw...	Loser	2048	16177	-174	-7.88	-1377	-291	-63	-163	-36	-59	-59
W Midlands	Rugby	Winner	2707	25915	188	6.40	1803	126	249	146	234	234	88
W Midlands	Stratford-on-A...	Winner	4215	34426	187	4.02	1530	58	313	157	264	240	134
W Midlands	Warwick	-	5486	39498	-65	-1.05	-468	-248	112	89	242	-62	-311
W Midlands	Bromsgrove	Winner	2460	25678	142	5.47	1481	30	249	130	167	173	167
W Midlands	Malvern Hills	-	1440	18914	-20	-1.33	-263	-50	10	-36	-3	-3	-3

Table A5: District Level Estimates of the Economic Cost of the Brexit-vote Across 382 districts in 2018 relative to 2015 Real Gross Value Added

District			*GVA in 2015*		$\hat{y}_d^{ENS}$ *ensemble*			*other estimates*					
Region	LA	Type	£million	capita	£million	%	capita	Low	High	ENS_{sim}	$AAPE_s$	$RMSPE_s$	$MAPE_s$
W Midlands	Redditch	Loser	2063	24322	-227	-10.03	-2677	-329	-129	-141	-354	-277	-277
W Midlands	Worcester	Loser	3032	30024	-452	-15.31	-4480	-509	-396	-487	-357	-357	-421
W Midlands	Wychavon	-	2426	19933	-11	-0.43	-91	-41	19	-9	-5	-19	-27
W Midlands	Wyre Forest	-	1349	13544	7	0.49	70	-11	24	14	7	6	6
W Midlands	Birmingham	-	25735	23123	298	1.07	267	-63	653	738	12	-62	-177
W Midlands	Coventry	Loser	9305	27027	-1119	-11.53	-3249	-1356	-887	-953	-1076	-1076	-1216
W Midlands	Dudley	Winner	4826	15256	346	6.60	1095	243	447	416	384	378	378
W Midlands	Sandwell	Winner	5421	16988	328	5.57	1028	114	534	438	185	185	185
W Midlands	Solihull	Winner	7659	36327	1607	18.34	7621	1366	1840	1732	1485	1485	1485
W Midlands	Walsall	Loser	4400	15949	-390	-8.59	-1415	-475	-307	-349	-408	-408	-288
W Midlands	Wolverhampton	-	4213	16515	-109	-2.38	-426	-420	183	-36	-73	-73	-73
East	Peterborough	Winner	5172	26707	744	12.39	3841	605	879	890	696	696	880
East	Luton	Loser	5579	26121	-429	-6.99	-2011	-660	-207	-131	-626	-626	-626
East	Southend-on-Se...	Loser	2832	15801	-83	-2.84	-461	-104	-61	-108	-49	-54	-58
East	Thurrock	Winner	3555	21411	232	6.04	1396	137	324	343	224	237	241
East	Bedford	-	3731	22425	46	1.14	274	-18	108	109	35	35	-1
East	Central Bedfor...	Winner	5383	19760	415	6.73	1524	336	493	501	488	348	348
East	Cambridge	Loser	5921	47328	-401	-6.49	-3207	-518	-287	-436	-27	-27	-301
East	East Cambridge...	-	1791	20403	-60	-3.20	-685	-97	-24	-34	-26	-25	-37
East	Fenland	Loser	1733	17538	-94	-5.08	-947	-130	-58	-128	-28	-43	-24
East	Huntingdonshir...	Winner	3977	22682	98	2.29	559	72	124	120	132	103	103
East	South Cambridg...	Winner	4488	29051	558	10.98	3610	518	597	495	571	571	616

Table A5: District Level Estimates of the Economic Cost of the Brexit-vote Across 382 districts in 2018 relative to 2015 Real Gross Value Added

District			*GVA in 2015*		$\hat{y}_d^{ENS}$ *ensemble*			*other estimates*					
Region	LA	Type	£million	capita	£million	%	capita	Low	High	ENS_{sim}	$AAPE_s$	$RMSPE_s$	$MAPE_s$
East	Basildon	-	5349	29398	-144	-2.47	-791	-259	-31	-66	-120	-120	-58
East	Braintree	Winner	2967	19710	317	9.57	2106	221	410	380	378	344	344
East	Brentwood	-	2898	37930	-162	-5.08	-2120	-292	-37	-62	-20	-120	-120
East	Castle Point	Loser	1000	11213	-43	-4.14	-477	-63	-23	-35	-43	-42	-26
East	Chelmsford	-	4471	25886	-66	-1.39	-381	-171	37	-31	-153	-74	53
East	Colchester	-	3860	20874	-74	-1.83	-403	-130	-19	-49	-50	-65	-63
East	Epping Forest	Winner	3188	24661	662	18.18	5122	587	736	733	777	777	849
East	Harlow	Winner	2019	23660	62	2.87	727	-61	178	89	65	65	65
East	Maldon	Winner	958	15249	28	2.72	440	-0	55	38	31	33	40
East	Rochford	Loser	1090	12795	-52	-4.52	-609	-78	-27	-48	-16	-16	-16
East	Tendring	-	1674	11806	10	0.54	69	-29	48	27	-14	-14	-14
East	Uttlesford	Loser	2137	25081	-47	-2.16	-554	-84	-11	-80	-6	-6	-6
East	Broxbourne	Loser	2671	27733	-712	-26.39	-7390	-807	-619	-620	-789	-779	-789
East	Dacorum	Winner	3812	25234	303	7.31	2007	256	350	364	269	269	270
East	Hertsmere	Winner	3598	34879	227	5.59	2198	141	311	327	122	171	171
East	North Hertford...	Winner	3047	23152	221	6.81	1682	173	269	234	201	201	203
East	Three Rivers	Winner	3485	37964	704	16.49	7670	498	900	855	586	586	586
East	Watford	-	4461	46301	-95	-1.86	-989	-247	52	89	-155	-36	137
East	Breckland	Loser	2258	16640	-151	-6.37	-1115	-199	-105	-139	-167	-167	-167
East	Broadland	Winner	2763	21820	165	5.39	1304	122	208	182	239	197	121
East	Great Yarmouth	Loser	1984	20119	-395	-20.70	-4002	-421	-368	-455	-354	-354	-355
East	King's Lynn &W...	-	2841	18782	-15	-0.53	-102	-43	11	-95	46	46	47

Table A5: District Level Estimates of the Economic Cost of the Brexit-vote Across 382 districts in 2018 relative to 2015 Real Gross Value Added

District			*GVA in 2015*		$\hat{y}_d^{ENS}$ *ensemble*			*other estimates*					
Region	LA	Type	£million	capita	£million	%	capita	Low	High	ENS_{sim}	$AAPE_s$	$RMSPE_s$	$MAPE_s$
East	North Norfolk	-	1478	14314	-14	-0.89	-132	-30	3	-27	-2	1	-2
East	Norwich	-	3905	28277	-93	-2.22	-673	-156	-31	-87	-17	-17	-100
East	South Norfolk	Loser	2508	19116	-158	-6.00	-1201	-201	-115	-156	-138	-138	-138
East	Babergh	-	1653	18387	-32	-1.80	-353	-52	-12	-16	-56	-56	-14
East	Ipswich	-	4079	29624	-171	-3.94	-1243	-318	-29	-66	-155	-217	-217
East	Mid Suffolk	Winner	1836	18314	105	5.33	1043	86	123	91	102	109	109
East	St Albans	-	3940	26952	-52	-1.22	-355	-118	13	90	-54	-253	-254
East	Welwyn Hatfiel...	Winner	3774	32042	306	7.14	2597	118	485	424	291	193	193
East	East Hertfords...	Winner	3564	24666	384	9.68	2657	249	515	457	484	484	484
East	Stevenage	Loser	2657	30689	-327	-11.91	-3773	-429	-228	-232	-319	-392	-392
East	East Suffolk	Loser	4871	20024	-234	-4.69	-963	-308	-162	-262	-143	-143	-286
East	West Suffolk	-	4964	28105	52	1.00	293	12	91	-0	69	69	72
East	Somerset West ...	-	3132	21054	-115	-3.45	-771	-159	-71	-65	-112	-115	-145
London	City of London	-	59418	8885599	393	0.60	58760	-602	1373	-488	-1077	-883	-993
London	Barking &Dagen...	Loser	3621	17829	-467	-13.08	-2299	-534	-401	-452	-414	-426	-391
London	Barnet	-	8237	21746	-264	-2.95	-696	-402	-127	-144	-214	-209	-209
London	Bexley	Loser	6024	24853	-676	-10.91	-2788	-886	-472	-653	-710	-710	-710
London	Brent	Loser	8306	25680	-722	-8.14	-2233	-879	-569	-431	-939	-939	-939
London	Bromley	Winner	7224	22207	322	4.09	990	168	473	417	287	340	387
London	Camden	-	28348	116258	1132	3.44	4642	262	1979	1747	502	229	680
London	Croydon	Loser	8561	22525	-680	-7.57	-1789	-912	-453	-404	-831	-879	-879
London	Ealing	Loser	9366	27204	-1283	-13.16	-3726	-1502	-1069	-1037	-1454	-1454	-1389

Table A5: District Level Estimates of the Economic Cost of the Brexit-vote Across 382 districts in 2018 relative to 2015 Real Gross Value Added

District			*GVA in 2015*		$\hat{y}_d^{ENS}$ *ensemble*			*other estimates*					
Region	LA	Type	£million	capita	£million	%	capita	Low	High	ENS_{sim}	$AAPE_s$	$RMSPE_s$	$MAPE_s$
London	Enfield	Loser	7077	21528	-305	-4.11	-929	-348	-263	-301	-303	-319	-359
London	Greenwich	-	5022	18292	-106	-1.99	-384	-137	-74	-52	-162	-198	-198
London	Hackney	Winner	6622	24651	474	6.18	1765	358	588	551	441	439	1002
London	Hammersmith &F...	-	9588	52628	-208	-1.99	-1140	-489	67	-306	456	75	75
London	Haringey	Loser	4232	15776	-669	-15.88	-2493	-716	-622	-697	-596	-611	-611
London	Harrow	Loser	5034	20396	-417	-7.92	-1690	-541	-296	-286	-399	-456	-467
London	Havering	-	5225	20952	-120	-2.16	-483	-207	-35	-57	-227	-152	-144
London	Hillingdon	Loser	13793	46589	-1487	-10.23	-5023	-1889	-1095	-1076	-1744	-1744	-1769
London	Hounslow	-	16304	61198	-669	-3.68	-2510	-1481	110	-770	128	-288	-288
London	Islington	Loser	17759	78059	-2209	-11.49	-9711	-2406	-2014	-1861	-2708	-3195	-3195
London	Kensington &Ch...	Loser	10183	64210	-1066	-9.92	-6721	-1520	-629	-1413	-887	-887	-887
London	Kingston upon ...	-	4534	26421	63	1.28	368	1	125	115	35	98	105
London	Lambeth	Loser	11974	37333	-1881	-14.49	-5865	-2081	-1684	-1511	-2104	-2712	-852
London	Lewisham	Loser	3913	13264	-578	-14.76	-1960	-630	-527	-523	-620	-559	-559
London	Merton	Loser	5713	27738	-757	-12.76	-3677	-877	-640	-571	-996	-870	-854
London	Newham	-	5992	17820	-48	-0.78	-144	-139	41	-186	127	127	126
London	Redbridge	Loser	4810	16145	-237	-4.73	-796	-302	-174	-248	-264	-204	-213
London	Richmond upon ...	Winner	6259	32242	713	10.07	3674	586	838	685	755	755	826
London	Southwark	-	17571	56968	709	3.76	2299	230	1175	46	-145	-145	-145
London	Sutton	Loser	4067	20348	-145	-3.41	-725	-208	-83	-101	-107	-97	-97
London	Tower Hamlets	Loser	31190	106151	-2809	-8.23	-9559	-3403	-2225	-2924	-4500	-4500	-5749
London	Waltham Forest	Loser	4187	15469	-305	-6.93	-1125	-349	-260	-283	-280	-272	-284

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District			*GVA in 2015*		$\hat{y}_d^{ENS}$ *ensemble*			*other estimates*					
Region	LA	Type	£million	capita	£million	%	capita	Low	High	ENS_{sim}	$AAPE_s$	$RMSPE_s$	$MAPE_s$
London	Wandsworth	Loser	7684	24052	-1054	-12.97	-3300	-1157	-953	-907	-875	-887	-875
London	Westminster	Winner	56957	239268	3034	4.69	12747	2162	3895	2883	111	70	70
South East	Medway	Winner	4987	18123	144	2.72	523	113	174	79	258	260	259
South East	Bracknell Fore...	Loser	5219	43782	-273	-5.06	-2294	-344	-204	-190	-309	-295	-254
South East	West Berkshire	Loser	7373	46825	-365	-4.93	-2318	-468	-264	-493	-267	-267	-267
South East	Reading	-	7538	46617	-25	-0.32	-154	-115	64	-213	154	160	152
South East	Slough	Loser	7926	54274	-720	-8.98	-4933	-809	-632	-941	-547	-547	-570
South East	Windsor &Maide...	-	6633	44734	178	2.48	1199	30	323	57	310	327	180
South East	Wokingham	Winner	5846	36266	1021	15.20	6332	928	1112	894	1184	1184	1234
South East	Milton Keynes	Loser	12549	47682	-1087	-7.73	-4129	-1498	-687	-625	-381	-381	-1651
South East	Brighton &Hove	-	7594	26733	20	0.24	70	-102	140	-32	-0	125	185
South East	Portsmouth	Loser	5389	25596	-216	-3.91	-1027	-265	-167	-378	-210	-210	-260
South East	Southampton	Loser	7756	31522	-688	-8.81	-2797	-862	-518	-659	-805	-805	-831
South East	Isle of Wight	Loser	2505	17923	-381	-15.07	-2723	-407	-355	-360	-390	-390	-390
South East	Aylesbury Vale	Loser	4286	22760	-77	-1.73	-407	-174	19	-115	-60	-49	-49
South East	Chiltern	Winner	2440	25776	222	8.19	2346	167	276	253	175	190	190
South East	South Bucks	Loser	2282	32926	-170	-7.27	-2448	-203	-137	-150	-148	-144	-144
South East	Wycombe	Loser	5423	31018	-526	-9.73	-3010	-581	-472	-496	-498	-498	-493
South East	Eastbourne	-	1666	16301	-9	-0.50	-86	-29	12	-21	3	3	3
South East	Hastings	-	1438	15641	-40	-2.66	-434	-59	-21	-16	-57	-63	-24
South East	Lewes	-	1764	17483	-92	-5.04	-908	-134	-51	-51	-135	-165	-165
South East	Rother	Loser	1272	13649	-160	-12.52	-1718	-183	-138	-126	-133	-207	-201

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District			*GVA in 2015*		$\hat{y}_d^{ENS}$ *ensemble*			*other estimates*					
Region	LA	Type	£million	capita	£million	%	capita	Low	High	ENS_{sim}	$AAPE_s$	$RMSPE_s$	$MAPE_s$
South East	Wealden	Loser	2420	15435	-99	-3.99	-632	-138	-61	-67	-218	-217	-217
South East	Basingstoke &D...	-	6762	38786	152	2.14	869	-28	326	4	217	217	217
South East	East Hampshire	-	2368	19950	-18	-0.74	-153	-79	41	16	40	11	45
South East	Eastleigh	Loser	3876	30052	-255	-6.06	-1973	-348	-163	-217	-332	-230	-230
South East	Fareham	Loser	2746	23841	-465	-15.37	-4040	-615	-322	-375	-417	-417	-248
South East	Gosport	Loser	955	11268	-39	-3.87	-462	-60	-19	-34	-32	-41	-48
South East	Hart	Loser	3445	36496	-500	-13.75	-5294	-573	-428	-410	-483	-510	-549
South East	Havant	Loser	2956	24009	-559	-19.46	-4541	-606	-513	-577	-571	-571	-560
South East	New Forest	Winner	3905	21782	168	4.01	937	28	303	224	158	157	228
South East	Rushmoor	Winner	3185	33468	104	2.95	1092	69	138	140	128	105	102
South East	Test Valley	Loser	3129	25784	-226	-6.86	-1861	-276	-177	-191	-190	-217	-214
South East	Winchester	Loser	5001	41081	-493	-9.23	-4050	-533	-453	-396	-580	-594	-584
South East	Ashford	Loser	2845	22935	-228	-7.57	-1834	-262	-194	-151	-288	-293	-293
South East	Canterbury	Loser	3106	19453	-209	-6.50	-1311	-238	-180	-229	-214	-215	-207
South East	Dartford	Loser	3682	35564	-380	-9.81	-3670	-472	-290	-276	-407	-397	-487
South East	Dover	Loser	2451	21605	-201	-8.18	-1775	-250	-154	-200	-246	-197	-197
South East	Gravesham	-	1510	14284	-20	-1.26	-193	-38	-3	-23	-8	-24	-25
South East	Maidstone	-	3777	23028	-129	-3.18	-786	-174	-85	-82	-93	-108	-216
South East	Sevenoaks	Winner	3498	29603	181	4.84	1530	110	250	91	293	293	296
South East	Folkestone &Hy...	Winner	1989	18108	64	3.05	583	27	100	75	63	62	62
South East	Swale	-	2507	17597	-32	-1.23	-227	-144	75	15	-31	-39	-39
South East	Thanet	-	1938	13860	-26	-1.27	-186	-42	-10	-11	-26	-26	-26

Table A5: District Level Estimates of the Economic Cost of the Brexit-vote Across 382 districts in 2018 relative to 2015 Real Gross Value Added

District			*GVA in 2015*		$\hat{y}_d^{ENS}$ *ensemble*			*other estimates*					
Region	LA	Type	£million	capita	£million	%	capita	Low	High	ENS_{sim}	$AAPE_s$	$RMSPE_s$	$MAPE_s$
South East	Tonbridge &Mal...	-	3806	30259	-63	-1.56	-499	-93	-33	-13	-7	-0	-25
South East	Tunbridge Well...	Loser	3463	29697	-260	-7.42	-2232	-351	-172	-110	-152	-174	-174
South East	Cherwell	Loser	4621	31748	-401	-8.50	-2758	-462	-342	-346	-378	-378	-373
South East	Oxford	Loser	6081	39304	-889	-14.46	-5746	-1022	-759	-898	-680	-690	-690
South East	South Oxfordsh...	Loser	4125	29853	-538	-12.83	-3897	-604	-474	-515	-538	-538	-548
South East	Vale of White ...	Loser	3877	30640	-104	-2.58	-818	-184	-25	-151	-61	-61	-59
South East	West Oxfordshi...	Loser	2381	21923	-322	-12.93	-2962	-395	-250	-328	-362	-329	-211
South East	Elmbridge	-	5324	39321	-604	-10.20	-4458	-968	-259	-336	-908	-937	-937
South East	Epsom &Ewell	Loser	1716	21871	-161	-9.46	-2047	-200	-122	-163	-118	-130	-127
South East	Guildford	Loser	4983	34352	-564	-11.30	-3887	-641	-488	-490	-539	-601	-601
South East	Mole Valley	Loser	4007	46069	-589	-14.87	-6766	-740	-442	-742	-459	-459	-459
South East	Reigate &Banst...	Loser	7071	49175	-1263	-19.38	-8783	-1462	-1070	-1258	-1302	-1302	-1302
South East	Runnymede	-	5306	62429	118	2.00	1385	-51	282	-139	305	246	250
South East	Spelthorne	Loser	2948	29954	-47	-1.52	-476	-101	7	-59	-60	-91	-91
South East	Surrey Heath	-	3218	36409	64	1.92	727	-20	146	6	107	87	233
South East	Tandridge	Loser	1865	21708	-305	-16.31	-3550	-351	-260	-260	-376	-376	-287
South East	Waverley	Loser	3287	26506	-307	-9.52	-2475	-381	-235	-296	-260	-260	-220
South East	Woking	Loser	3340	33077	-337	-9.71	-3336	-475	-204	-313	-570	-570	-570
South East	Adur	-	1089	17143	-7	-0.59	-103	-30	17	2	-36	-4	14
South East	Arun	Loser	2142	13749	-52	-2.27	-333	-87	-17	-44	-35	-36	-35
South East	Chichester	-	3165	26871	-28	-0.86	-235	-76	20	-21	34	8	12
South East	Crawley	-	5589	50403	-89	-1.50	-802	-259	77	-4	-134	-149	-149

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District			*GVA in 2015*		$\hat{y}_d^{ENS}$ *ensemble*			*other estimates*					
Region	LA	Type	£million	capita	£million	%	capita	Low	High	ENS_{sim}	$AAPE_s$	$RMSPE_s$	$MAPE_s$
South East	Horsham	-	3000	22017	-12	-0.38	-87	-120	93	48	55	55	-81
South East	Mid Sussex	Loser	3156	21621	-193	-5.96	-1319	-220	-165	-139	-245	-243	-261
South East	Worthing	Winner	3222	29750	213	6.20	1963	60	359	246	182	202	331
South West	Bath &North Ea...	Loser	4056	22009	-281	-6.76	-1526	-348	-215	-239	-329	-329	-329
South West	Bristol, City ...	-	13120	29114	105	0.74	233	-47	255	-11	-28	-168	-139
South West	North Somerset	Winner	4098	19520	50	1.13	239	-30	129	94	104	13	37
South West	South Gloucest...	-	10386	37912	-6	-0.06	-24	-191	176	-132	-484	-333	-398
South West	Plymouth	-	5032	19251	-88	-1.67	-336	-145	-31	-187	-103	-103	-103
South West	Torbay	Loser	2008	15008	-229	-11.32	-1715	-273	-187	-205	-247	-247	-251
South West	Swindon	Loser	9242	42476	-906	-9.33	-4163	-1042	-772	-814	-869	-902	-916
South West	Cornwall	Winner	9633	17506	310	2.99	564	219	401	315	236	226	226
South West	Isles of Scill...	Loser	68	29122	-2	-3.41	-1010	-5	0	-3	-1	-0	-0
South West	Wiltshire	Loser	10901	22316	-246	-2.14	-504	-464	-32	-431	-58	-58	-68
South West	Bournemouth, C...	-	9456	24191	122	1.22	311	33	210	136	145	94	145
South West	Dorset	-	7301	19646	241	3.14	650	92	388	184	397	397	421
South West	East Devon	Winner	2468	17835	66	2.55	477	-1	132	79	90	90	35
South West	Exeter	-	4977	39601	5	0.10	43	-82	92	-29	39	36	17
South West	Mid Devon	-	1184	14878	23	1.86	290	5	41	29	18	21	25
South West	North Devon	-	2067	21952	14	0.66	152	-9	37	13	15	13	13
South West	South Hams	-	1920	22619	-20	-0.98	-233	-57	17	-31	9	9	-1
South West	Teignbridge	Loser	2177	16889	-143	-6.18	-1111	-197	-91	-102	-140	-140	-158
South West	Torridge	Loser	894	13482	-17	-1.86	-260	-32	-2	-24	-18	-14	-13

Table A5: District Level Estimates of the Economic Cost of the Brexit-vote Across 382 districts in 2018 relative to 2015 Real Gross Value Added

District			*GVA in 2015*		$\hat{y}_d^{ENS}$ *ensemble*			*other estimates*					
Region	LA	Type	£million	capita	£million	%	capita	Low	High	ENS_{sim}	$AAPE_s$	$RMSPE_s$	$MAPE_s$
South West	West Devon	-	751	13779	-27	-3.47	-495	-44	-11	-16	-14	-23	-23
South West	Cheltenham	Loser	3047	26134	-474	-15.39	-4068	-631	-325	-441	-568	-642	-312
South West	Cotswold	Winner	2983	34869	330	10.00	3859	272	387	356	307	331	290
South West	Forest of Dean	Loser	1540	18208	-227	-14.39	-2690	-312	-147	-264	-149	-149	-149
South West	Gloucester	Loser	3255	25596	-334	-10.28	-2626	-393	-275	-268	-235	-286	-285
South West	Stroud	Winner	2257	19328	181	7.31	1550	119	242	195	205	172	210
South West	Tewkesbury	Loser	2714	31243	-392	-14.11	-4509	-483	-303	-345	-387	-387	-438
South West	Mendip	-	2058	18366	-21	-0.95	-184	-44	2	14	-61	-62	21
South West	Sedgemoor	Winner	2112	17579	281	11.95	2341	252	310	248	356	363	363
South West	South Somerset	Loser	3261	19703	-263	-7.72	-1586	-315	-211	-239	-289	-289	-289
Wales	Isle of Angles...	Winner	908	12975	59	6.02	850	26	92	75	52	52	52
Wales	Gwynedd	-	2539	20665	-84	-3.23	-688	-133	-37	-30	-69	-58	-186
Wales	Conwy	Winner	1736	14937	48	2.55	415	5	90	58	59	60	60
Wales	Denbighshire	-	1650	17425	1	0.04	7	-36	37	-4	10	-24	-24
Wales	Flintshire	Loser	3419	22191	-84	-2.40	-548	-125	-45	-84	-23	-23	-68
Wales	Wrexham	Loser	3038	22232	-71	-2.29	-522	-121	-23	-104	-65	-45	-39
Wales	Ceredigion	-	1297	17376	-17	-1.32	-231	-49	14	-26	-12	-11	33
Wales	Pembrokeshire	Loser	2175	17616	-92	-4.16	-746	-198	9	-80	-60	-60	-60
Wales	Carmarthenshir...	Loser	2944	15903	-54	-1.77	-293	-93	-16	-94	-4	-1	-5
Wales	Swansea	Loser	5039	20789	-283	-5.32	-1169	-356	-212	-330	-244	-245	-201
Wales	Neath Port Tal...	Winner	2271	16107	216	8.65	1533	129	300	214	260	258	260
Wales	Bridgend	-	2919	20543	13	0.42	93	-38	64	53	19	-20	-28

Table A5: District Level Estimates of the Economic Cost of the Brexit-vote Across 382 districts in 2018 relative to 2015 Real Gross Value Added

District			*GVA in 2015*		$\hat{y}_d^{ENS}$ *ensemble*			*other estimates*					
Region	LA	Type	£million	capita	£million	%	capita	Low	High	ENS_{sim}	AAPE_s	RMSPE_s	MAPE_s
Wales	Vale of Glamor...	-	2363	18520	-158	-6.30	-1235	-249	-69	-204	-91	-89	-60
Wales	Cardiff	-	10576	29611	358	3.21	1003	267	449	163	581	562	589
Wales	Rhondda Cynon ...	Loser	3600	15164	-375	-10.30	-1581	-406	-345	-420	-343	-349	-338
Wales	Caerphilly	-	2699	14981	-67	-2.36	-371	-118	-16	-22	-83	-65	-125
Wales	Blaenau Gwent	Winner	812	11676	39	4.49	555	15	62	47	20	31	55
Wales	Torfaen	Loser	1488	16203	-67	-4.40	-726	-92	-41	-71	-39	-39	-52
Wales	Monmouthshire	Loser	2020	21844	-99	-4.73	-1068	-141	-57	-65	-85	-85	-84
Wales	Newport	Winner	3394	22968	356	9.51	2406	287	422	401	341	341	341
Wales	Powys	Loser	2206	16631	-90	-4.02	-676	-151	-30	-107	-84	-84	-52
Wales	Merthyr Tydfil	Loser	989	16671	-56	-5.38	-936	-82	-30	-42	-78	-78	-41
Scotland	Clackmannanshi...	Loser	948	18458	-124	-11.96	-2416	-146	-103	-79	-118	-112	-112
Scotland	Dumfries &Gall...	Loser	2763	18461	-55	-1.89	-368	-99	-12	-48	-29	-27	-37
Scotland	East Ayrshire	Loser	1553	12723	-77	-4.80	-629	-101	-53	-62	-48	-48	-48
Scotland	East Lothian	-	1584	15371	-29	-1.70	-281	-56	-2	-43	-23	-22	3
Scotland	East Renfrewsh...	-	986	10609	-55	-5.20	-589	-99	-13	-53	-60	-60	5
Scotland	Na h-Eileanan ...	Loser	546	20170	-32	-5.69	-1168	-43	-20	-39	-8	-15	-58
Scotland	Falkirk	-	3682	23236	1	0.04	9	-76	77	-42	-16	-16	-16
Scotland	Fife	Loser	7159	19450	-727	-9.94	-1974	-821	-633	-634	-765	-807	-966
Scotland	Highland	-	5909	25240	-31	-0.51	-134	-128	64	-175	70	70	25
Scotland	Inverclyde	Loser	1266	15925	-225	-18.12	-2826	-265	-186	-210	-228	-228	-235
Scotland	Midlothian	-	1447	16558	-71	-4.47	-811	-135	-10	-42	17	17	-87
Scotland	Moray	-	2030	21254	-21	-0.98	-216	-64	22	-71	58	5	-5

Table A5: District Level Estimates of the Economic Cost of the Brexit-vote Across 382 districts in 2018 relative to 2015 Real Gross Value Added

District			*GVA in 2015*		$\hat{y}_d^{ENS}$ *ensemble*			*other estimates*					
Region	LA	Type	£million	capita	£million	%	capita	Low	High	ENS_{sim}	$AAPE_s$	$RMSPE_s$	$MAPE_s$
Scotland	North Ayrshire	Loser	1954	14354	-130	-6.56	-958	-164	-98	-140	-140	-140	-140
Scotland	Orkney Islands	Loser	628	28980	-85	-13.49	-3905	-111	-60	-71	-107	-107	-69
Scotland	Perth &Kinross	Loser	4320	28813	-495	-11.24	-3299	-566	-425	-558	-469	-471	-471
Scotland	Scottish Borde...	-	1893	16601	-3	-0.16	-29	-37	30	26	33	16	16
Scotland	Shetl&Islands	Loser	794	34224	-154	-19.86	-6628	-173	-135	-161	-131	-142	-142
Scotland	South Ayrshire	-	1847	16432	6	0.29	49	-32	42	21	-6	-28	132
Scotland	South Lanarksh...	Loser	5153	16295	-157	-2.92	-498	-224	-91	-192	-93	-86	-174
Scotland	Stirling	-	2483	26748	15	0.58	160	-36	65	21	42	7	12
Scotland	Aberdeen City	Loser	11351	49277	-2062	-18.19	-8951	-2445	-1690	-2802	-3043	-3043	-1155
Scotland	Aberdeenshire	Loser	7381	28176	-1322	-17.00	-5047	-1467	-1180	-1288	-1710	-1406	-946
Scotland	Argyll &Bute	Loser	1802	20739	-91	-4.88	-1048	-125	-58	-121	-49	-67	-67
Scotland	City of Edinbu...	Winner	21294	42690	1393	6.03	2792	1076	1705	1130	1346	1469	1469
Scotland	Renfrewshire	Loser	3874	22193	-309	-7.64	-1773	-379	-241	-269	-251	-251	-362
Scotland	West Dunbarton...	-	1566	17480	-58	-3.47	-643	-89	-27	-52	-65	-35	-42
Scotland	West Lothian	-	4571	25601	-177	-3.73	-993	-273	-83	-1	-153	-179	-241
Scotland	Angus	Loser	1953	16707	-302	-15.13	-2584	-342	-263	-305	-273	-273	-306
Scotland	Dundee City	Loser	3426	23116	-101	-2.87	-680	-171	-32	-162	-37	-37	-25
Scotland	North Lanarksh...	-	6756	19973	-373	-4.99	-1102	-525	-223	-138	-378	-361	-378
Scotland	East Dunbarton...	-	1281	11976	-2	-0.17	-23	-45	38	26	-3	-3	-3
Scotland	Glasgow City	-	18830	31055	-156	-0.79	-257	-367	53	-151	-297	-297	5
N Ireland	Antrim &Newtow...	-	2835	20183	-77	-2.57	-549	-118	-37	-54	-34	-34	-64
N Ireland	Armagh City, B...	-	3324	15996	13	0.34	61	-37	61	76	-85	11	-29

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District			*GVA in 2015*		$\hat{y}_d^{ENS}$ *ensemble*			*other estimates*					
Region	LA	Type	£million	capita	£million	%	capita	Low	High	ENS_{sim}	$AAPE_s$	$RMSPE_s$	$MAPE_s$
N Ireland	Belfast	-	11932	35207	160	1.24	472	14	305	301	84	84	267
N Ireland	Causeway Coast...	-	1960	13692	-14	-0.66	-97	-67	38	21	-27	-25	-25
N Ireland	Derry City &St...	Winner	2303	15407	202	8.04	1352	165	238	199	224	224	205
N Ireland	Fermanagh &Oma...	-	1968	17067	-30	-1.42	-260	-65	5	17	-37	-43	-48
N Ireland	Lisburn &Castl...	-	3010	21469	-6	-0.20	-46	-71	57	-0	3	3	28
N Ireland	Mid &East Antr...	Loser	4402	32097	-1720	-51.31	-12541	-1939	-1512	-1596	-1803	-1776	-1815
N Ireland	Mid Ulster	Winner	2676	18583	268	8.83	1859	189	344	340	227	230	227
N Ireland	Newry, Mourne ...	Loser	2625	14884	-125	-4.47	-710	-170	-81	-95	-99	-90	-85
N Ireland	Ards &North Do...	Winner	1764	11109	41	2.12	257	6	75	73	50	22	22
Yorkshire& ...	Kingston upon ...	-	5773	22325	-144	-2.40	-556	-237	-52	-39	-161	-179	-181
Yorkshire& ...	East Riding of...	-	6299	18705	-134	-2.00	-397	-248	-21	29	-75	-71	-66
Yorkshire& ...	North East Lin...	Loser	3119	19497	-454	-14.53	-2839	-487	-422	-422	-438	-423	-533
Yorkshire& ...	North Lincolns...	-	3726	21938	-81	-2.07	-479	-160	-5	18	-146	-146	-7
Yorkshire& ...	York	-	5759	27986	132	2.18	643	-71	329	81	367	367	367
Yorkshire& ...	Craven	Winner	1276	22857	89	6.31	1601	71	107	85	96	85	85
Yorkshire& ...	Hambleton	Loser	2134	23692	-112	-5.09	-1247	-175	-51	-76	-122	-122	-111
Yorkshire& ...	Harrogate	Winner	3758	23500	82	2.00	514	-8	170	152	-47	-47	-47
Yorkshire& ...	Richmondshire	Winner	757	14401	32	4.04	618	13	51	24	52	52	52
Yorkshire& ...	Ryedale	-	1156	21676	-34	-2.68	-642	-83	13	-24	-37	-37	6
Yorkshire& ...	Scarborough	-	1864	17245	62	3.16	571	36	87	46	97	97	96
Yorkshire& ...	Selby	-	1974	22896	-2	-0.10	-24	-47	42	35	-39	-39	48
Yorkshire& ...	Barnsley	-	3550	14801	52	1.38	219	11	93	47	95	95	106

Table A5: District Level Estimates of the Economic Cost of the Brexit-vote Across 382 districts in 2018 relative to 2015 Real Gross Value Added

District			*GVA in 2015*		$\hat{y}_d^{ENS}$ *ensemble*			*other estimates*					
Region	LA	Type	£million	capita	£million	%	capita	Low	High	ENS_{sim}	AAPE_s	RMSPE_s	MAPE_s
Yorkshire& ...	Doncaster	Winner	5227	17110	623	10.37	2039	569	676	773	600	604	602
Yorkshire& ...	Rotherham	Loser	4636	17767	-252	-5.24	-967	-324	-182	-256	-331	-329	-331
Yorkshire& ...	Sheffield	Loser	12041	21155	-343	-2.79	-603	-538	-151	-571	-176	-176	-188
Yorkshire& ...	Bradford	-	9019	17021	-167	-1.81	-316	-276	-60	-168	-256	-188	-256
Yorkshire& ...	Calderdale	Loser	4581	22042	-798	-16.25	-3842	-942	-658	-507	-954	-954	-852
Yorkshire& ...	Kirklees	-	6929	16008	20	0.27	45	-48	87	45	48	42	48
Yorkshire& ...	Leeds	-	24009	31051	-62	-0.24	-80	-185	61	-239	107	107	125
Yorkshire& ...	Wakefield	Winner	6712	20095	216	3.07	647	97	333	284	89	151	151

Table A6: Correlation between 2016 % Leave support and the estimated loss in GVA by 2018 relative to 2015

	(1)	(2)	(3)	(4)	(5)
		implied by "best synthetic control"			
	Ensemble	Ensemble_{sim}	AAPE_s	RMSPE_s	MAPE_s
% Leave in 2016 Referendum	-0.091*	-0.079	-0.099*	-0.099**	-0.087*
	(0.049)	(0.050)	(0.052)	(0.048)	(0.050)
Mean of DV	-2.9	-2.32	-2.63	-2.66	-2.8
R2	.0971	.112	.0876	.0961	.0944
Local authority districts	381	381	381	381	381

Notes: All regressions include NUTS1 region shifters. The dependent variable is the ensemble estimate of the output gap in percent relative to 2015. The ensemble has been constructed from 31 synthetic controls constructed using different sets of donor pools. Support for Leave is estimated in percentage points. Robust standard errors are provided in the parentheses. Stars indicate *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.