Charles University

Faculty of Social Sciences
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MASTER'S THESIS DRAFT

Who bears the costs of Brexit? A regional perspective

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Academic Year: **2022/2023**

Declaration of Authorship

I hereby proclaim that I wrote my master thesis on my own under the leadership of my supervisor and that the references include all resources and literature I have used.

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Abstract

One of the decisive elements for the Brexit referendum was the great regional inequality in the UK, the biggest among the G7 economies. In this thesis, we study whether spatial inequality increased due to Brexit. We successfully pioneer a Synthetic Control Method using Lasso to estimate the Brexit impact. Our results are consistent on the national level with other scholars, achieving a mild 2% drop in the real output in 2019 and a stunning 14% fall in 2020. At the regional level, our results hint bigger losses for London and Scottish regions than for rural areas. Thus, in contradiction to other studies, we show that Brexit could decrease spatial inequality.

JEL Classification	C54, O47
Keywords	Brexit, Regional inequality, Synthetic Control Method, Synthetic Control Method using Lasso, real GDP

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Abstrakt

Výsledok referenda o Brexite bol ovplyvnený aj regionálnou nerovnosťou ktorá je práve v UK najväčšou zo všetkých krajín G7. V tejto práci skúmame či sa táto nerovnosť ďalej zvyšuje kvôli Brexitu. Úspešne sme na odhad jeho dopadu aplikovali Syntetickú kontrolnú metódu využívajúcu Lasso. Na národnej úrovni sa naše výsledky zhodujú s prácami iných kolegov, zaznamenávajúc mierny pokles 2% reálneho HDP v 2019, a obrovský prepad 14 % v 2020. Na regionálnej úrovni naše výsledky ukazujú väčšie straty pre Londýnske a Škótske regióny než pre rurálne. Takže v kontradikcií s inými štúdiami, ukazujú že Brexit môže znížiť regionálne nerovnosti.

Klasifikace JEL	C54, O47
Klíčvá slova	Brexit, Regionálna nerovnosť, Syntetická kontrolná metóda, Synetická konrolná metóda využívajúca Lasso, reálne HDP

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Acronyms

EU European Union

GDP Gross Domestic Product

ITL International Territorial Level

NUTS Nomenclature of Territorial Units for Statistics

OLS Ordinary Least Squares regression

PM Prime Minister

SCM Synthetic Control Method

SCUL Synthetic Control Using Lasso

UK United Kingdom

Thesis Proposal

Author	Jakub Stuchlík
Supervisor	PhDr. Jaromír Baxa Ph.D.
Proposed topic	Who bears the costs of Brexit? A regional perspective

Preliminary scope of work

Motivation:

The UK is a quite heterogeneous country in economic structure and quality of life. It is very polarized in political opinions, like different western countries in the current era. This polarization has influenced also narrow Brexit referendum results. Alabrese (2018) explores how the voters for remain and to leave respectively had a distinctive pattern of education, age, and ethnicity which made it simple to predict the location results retrospectively.

The same differences between the regions could also provide an environment for heterogeneity in the impact of Brexit. For instance, McCombie (2018) hints out that Brexit will widen the regional disparities. As the "Leave" regions are mostly poorer, it could lead to a rather bizarre conclusion that the worse off after Brexit in economic terms is its supporters. This motive was corroborated by Fetzer (2020), which provided evidence that the Brexit enforced output decrease was correlated with the higher level of Leave support in the 2016 referendum. Moreover, there is also a significant relationship between employment rise and the referendum results, which the author interprets as having a long-term nature. Unfortunately, this interpretation could not be properly validated due to the unavailable data at the time of writing his paper.

Furthermore, since 2019 there is one structural change that cannot be overlooked. The omnipresent pandemics are one of the greatest changes of our era. The latest studies hint out that the impact of Covid often intervenes in opposite industries than Brexit (Pope (2021), Norman (2020)). One of the few industries that are predicted to be hit strongly by both shocks is automotive. Nevertheless, the inequality between regions is predicted to increase due to both treatments. How or weather have the process of the UK leaving the EU its own ability to resist the Covid-induced economic impact is, therefore, a very intuitive, yet by scholars unanswered questions.

Hypothesis:
1. Hypothesis 1: The impact of Brexit was varied significantly among UK regions
2. Hypothesis 2: The impact of Brexit was regionally correlated with referendum results
3. Hypothesis 3: The impact of Brexit has significantly influenced the impact of Covid on UK regions

Metodology:
At first, I shall collect more studies about the Brexit referendum and the division between regions before the referendum. The detailed overview of pre-referendum dynamics and votes will be followed with a deep-dive to scholars that measured the Brexit impact. Moreover, the literature review will also provide the recent estimations of Covid's impact on the UK at both national and regional levels.
Further for my estimation, I shall use the Synthetic control method created and further developed by Abadie (2003, 2010, 2015, 2021). This method aims to estimate the impact of specific treatment on a specific unit by the creation of this unit counterfactual. It is very suitable for the case of Brexit as a specific treatment that none different EU member country was exposed to. Furthermore, some scholars already applied it to this topic (Born 2017, Breinlich 2020, Fetzer 2020).
The method is suitable also for regional detail as the synthetic units of the UK can be consisted from the Eurostat NUTS database. The NUTS database consists of European regions (mostly EU). Even though other European regions were also affected by Brexit, various scholars use these units too, for instance, Born (2017). The reasoning behind this is that the impact on other EU regions was insignificant or negative. Although, it allows for robustness checks, from different regional databases. The missing key data (unemployment and GDP) for UK regional level in the Eurostat database is available at ARDECO online database.
The SCM usage on the regional level of Brexit is present as mentioned in Fetzer's (2020) paper. My thesis differs significantly in using data, where Fetzer (2020) uses combined NUTS 1 (12 units) and NUTS 3 (382 units) for his estimation. I propose a different approach with a more intuitive choice for SCM and also suitable for regression; NUTS 2 level (40 units). I argue that this

regional level is more adequate, as the control units will be also of the same level(in comparison to Fetzer (2020), as he created the doppelgangers of NUTS 3 UK regions from NUTS 2 Eurostat data and more). Moreover, due to the availability of data, I will inspect also the relationship between Brexit and Covid consequences.
The first and third hypotheses will be validated through the newest additions to SCM inference methods, which allow us to form t-tests and probability intervals even for SCM estimations (Chernozhukov, 2021a, 2021b; Cattaneo, 2021)). To test the second hypothesis I will construct a regression out of 40 UK regional units. This regression will inspect the relationship between referendum percentage results and my SCM estimated impact on unemployment and output.

Expected Contribution:
The application of SCM in the regional dimension will provide new insights into Brexit and regional inequalities that have not been revealed in previous scholars' work. The SCM has been applied to the within-UK regional inequalities by (Fetzer (2020)). I contribute with different methodology – the more intuitive and adequate NUTS 2 data selection, verification of his short-term interpretation of unemployment decrease, and examination of Brexit's influence on Covid impact. To my knowledge, no study estimates the synergy of Covid and Brexit with SCM methodology.

Outline:
1. Motivation: The setup of Brexit, its instant predictions, and further development of agreements and negotiations and their consecutive impact on uncertainty. Furthermore the I will briefly explore the regional differences and dynamics that shaped the Brexit process.
2. Studies: I will provide a literature review of studies concerning Brexit impact, UK regional inequality, Covid impact in the UK, and SCM application
3. Method: I will explain the SCM methodology and its recent developments
4. Data: I will explain and discuss the data selection of NUTS II and various covariates
5. Results: I will discuss my SCM results and consequent regression. I will provide the hypothesis evaluation and the results interpretation.
Concluding remarks: I will summarize my findings, validate of hypothesis and provide suggestions for further study and policy proposals.

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Chapter 1

Introduction

The currently governing conservative majority in the Parliament of the United Kingdom (UK) was elected in 2019 with an ambitious agenda; *"Get Brexit done and unleash Britain's potential"* (The Conservative Party 2019). The first half of the slogan is self-explanatory, concerning the back then ongoing negotiations about the date and form of the UK leaving the European Union (EU). It made sense to build a campaign around Brexit for the 2019 elections, as many pundits even renamed them as "second referendum "(Robert *et al.* 2021). The second, less obvious, refers to levelling up the economy and the opportunities across the UK regions. Positioning this issue within the election motto, next to the prominent topic of the election, suitably illustrates the relative importance and attractiveness of the problem in recent years. More importantly, there is evidence showing that both these topics, Brexit and regional inequality, are deeply interconnected (Gutiérrez-Posada *et al.* 2021).

The inner-state inequalities have been growing among most of the economically developed countries in Europe since the 1980s (Doran & Jordan 2013). Even within this pool of countries that share the same problem, the UK stands out as the country with the highest regional inequality among the G7 (McCann 2020) concerning output and productivity. Such essential macroeconomics unsurprisingly translates to spatially heterogeneous economic structures and demographic profiles within the UK. Coming back to the Brexit referendum, its results were highly polarized, especially among the lines of age, education or level of skilled labour. Thus, the scholars maintained a strong intuition to find a relationship between the plebiscite results and the spatial inequality. There is a lot of evidence supporting this claim as the results were distributed quite heterogeneously across the UK, with the Scottish regions, London and other urban areas tending to be more pro-remain in contrast to north England and rural regions (Goodwin & Heath 2016; Becker *et al.* 2017; Gutiérrez-Posada *et al.* 2021).

Simply said, the regions that fell behind in productivity and essentially all other eco-

nomic variables such as average income, output or investment in innovations voted overwhelmingly to leave the EU and eventually decided the referendum (Alabrese *et al.* 2019). Therefore, one could argue that spatial inequality was one of the most important reasons for the UK leaving the EU.
The consequent realization of Brexit caused one of the greatest structural shocks in the history of the modern UK (Martin & Gardiner 2019). Considering the heterogeneous nature of British regions facing this structural force, the intuitive hypothesis is that the impact has the potential to be non-uniformly distributed, similarly as the support for Leave was unevenly allocated among them. The essential question that withstands is: "Has Brexit further deepened the regional inequality that had contributed to Brexit in the first place?"
Even though the referendum is relatively recent and the transition ended in January 2021, plenty of studies are already estimating its impact. The studies are fairly consistent in the negative direction of impact on output and vary in proportion and generally focused on the national dimension(Tetlow & Pope 2021; Born *et al.* 2019; Serwicka & Tamberi 2018). The analysis for the regional level is mostly constructed as ex-ante estimations using a variety of approaches, although mainly with the same conclusion(Thissen *et al.* 2020). Los *et al.* (2017) estimates that regional inequality will widen due to Brexit, as the less productive regions enjoy a tighter trade connection to the EU regions. Similar results are provided by Petrie & Norman (2020) through estimation of the supply chain dynamics as the goods market is reacting stronger than the market with services to international market limitations. This conclusion is further provided by the only ex-post analysis to our knowledge by Fetzer & Wang (2020), which provides evidence that the negative impact of Brexit has been unevenly distributed among regions and the decrease has been positively correlated with the percentage of Leave voters.
To expand on this ongoing debate, we use the relatively recent but widely used approach to estimate the counterfactual scenario; the Synthetic control method developed by Abadie & Gardeazabal (2003), extended in later works (Abadie *et al.* 2010; 2015; Abadie 2021). The method is especially well suited for our case of Brexit, as the referendum was held on a particular date, and Brexit is geographically bounded to the UK and its context. The synthetic approach generally consists of constructing the counterfactual unit (UK regions without Brexit) from other units (regions in the EU) that did not experience the observed inference. Furthermore, the SCM was already successfully applied for this case by various scholars on national (Serwicka & Tamberi 2018; Opatrnỳ 2021) and regional level (Fetzer & Wang 2020).
The contribution of this thesis is further increased due to our specific choice of synthetic method; one of its most recent alternatives from Hollingsworth & Wing (2020) called Synthetic Control Method using Lasso (SCUL) that had not yet been used in

the Brexit case. Its biggest advantage, in this case, is the possibility to use an unlimited size of the mentioned donor pool without the risk of over-fitting the estimated synthetic region. This is one of the main self-critiques imposed in the Fetzer & Wang (2020). It is especially relevant for the regional level as there are significantly more possible donor regions as "optimal" number 20 for conventional SCM as defined by its creator Abadie (2021).
Concerning the estimation of UK regions, any synthetic approach requires that the intervention of Brexit does not expose the used donor pool. Therefore, one could claim that using EU regions in the common European market in the data pool is unsuitable for SCM. We argue otherwise, in line with Born *et al.* (2019) and Thissen *et al.* (2020), as the Brexit impact on different member states was insignificant or slightly negative. Besides the synthetic unit construction, we differ from Fetzer & Wang (2020) by the regional detail level and more recent data. We use the 41 UK regions from the NUTS 2 classification, which we consider more straightforward and suitable in comparison very detailed 382 NUTS 3 units and oversimplifying 12 regions from NUTS 1. Due to the data availability, we constructed two models; one contains more donor regions, and the other incorporates a smaller number of donors but with more detailed characteristics. At last, to observe the relationship between referendum results and the estimated impact of Brexit, we construct an OLS regression with 41 data points representing 41 British synthetic regions.
Our SCUL estimated models documented an enormous drop between the synthetic and real regions between 2019 and 2020. We interpret the drop mainly as a result of passing the bill with withdrawal agreement (Parliament 2020), as the countries also experienced the pandemic-related drop in the data pool. Model A, including fewer donor pool regions and more regional characteristics, perform unsatisfying as only 3 of its 41 regions are statistically significant. The resulting total impact of Brexit is a 0,8 % rise in the real output in 2019 and an eight % drop in 2020, which is inconsistent with the wide literature on the impact Brexit has on the national level. In contrast, Model B, including more regions summed impact, is consistent with this literature(Born *et al.* 2019) equal to the loss of 2 % in the real GDP per capita. Moreover, the drop in 2020 is equal to 13,6%, also in line with other literature (Springford 2022). This model's estimates are also more statistically relevant, with good p-value obtained for almost 25 % of the regions. Looking closer at the results, they seem quite contradictory to the other research constructed at the regional level. The biggest losses are recorded in London and Scottish regions, the relatively more productive regions that overwhelmingly voted to remain. On the contrary, the gains are estimated for the rural parts of England and Wales. This is to some extent approved by the regression where the percentage for Leave vote is the only significant variable with a positive relationship to Brexit impact on the real output equal to

0.91.

We stress that these results have to be taken with the grain of salt due to the very recent nature of Brexit. The Trade and Cooperation Agreement came to effect on the 1. January of 2021, which is unfortunately out of the data available today. The studies that analyze sector-specific data after the period hint that there was no significant impact on relative UK trade with the EU before the formalization of the Brexit process. However, the decline after the agreement is estimated to be a persistent 25 % close fall for imports from the EU to the UK since the start of 2021 (Freeman *et al.* 2022). This indicates that the mild drop in 2019 results explains only the economic uncertainty, and the significance in 2020 represents the fears from the hard Brexit materialized in the form of the work on the Trade and Cooperation Agreement.

Thus we recommend studying the regional impact in the upcoming years when more recent data will be available for the formal date of Brexit and possible bounce back from the pandemic. However, we evaluate the pioneering application of the new SCUL method as a success, as Model B has presented statistically significant results with a formalized selection from the donor pool. Moreover, the results are similar to other scholars' national estimates. Therefore we recommend this method as a suitable alternative for the synthetic approach in the case of relatively homogeneous great-sized donor pools.

The rest of the thesis is structured as follows. In the next chapter, we provide the context to describe the relationship between regional inequality and Brexit from both sides. The chapter serves as the socio-economic motivation behind this thesis and the literature review of Brexit impact estimation. In the third chapter, we provide the methodological description. We describe the conventional SCM in detail and introduce its Lasso version with a complex comparison and evaluation of benefits and risks. In the Data chapter, we present our data selection for SCUL models A and B and the OLS regression with the corresponding reasoning. In the fifth chapter, we offer and interpret the results of SCUL and OLS estimations. Last but not least, we conclude our SCUL application and its result in the conclusion chapter.

Chapter 2

The mutual connection between regional inequality and Brexit

In this chapter, we dive into the complex and significant relationship between regional inequality in UK and Brexit. We analyze both sides' connections before and after the structural shock in the form of the Referendum and the consequent complex process of the UK leaving the EU. This optics is essential for the entire thesis. We aim to establish to the reader that regional inequality is a rising issue among all developed economies and empirically proven throughout more prominent countries of the EU and G7. At the same time, these widening differences between cores and peripheries are the most striking, especially in the UK. As the referendum results were disproportionately dispersed spatially among the regions, it is pretty straightforward to look for a connection between the inner-country inequality and Brexit origin. And due to the geographical economic inequality, it also allows us to look at the possible heterogeneous impact of such structural force. In this chapter, we offer the reader the context of this mutual relation and empirical evidence for it in literature review form. There is an excellent scientific consensus in all three parts, as the spatial inequality in the UK is provable the biggest among G7; the referendum results were strictly divided on the demographics, education and work skill level, which are metrics that are overleaping with the key inequality metrics and the absolute majority of contemporary research on Brexit impact hint the heterogeneous and non-flat impact on the UK regions. The rest of the chapter is structured as follows; in the first sub-chapter, we introduce the relative level of UK regional inequality in the developed economies context; in the second part, we connect this phenomenon with the Brexit referendum results and last, not least, we provide the empirical estimations of other scholars on the impact of Brexit on a regional level.

2.1 The most significant regional inequality in G7

The rise of inner-country disparities is relevant to some extent for all economically developed countries over the globe, including the UK. Tackling this issue and fostering convergence among European regions was even one of the founding elementary aims of the EU(European Commission 2010). Depending on the specific approach (the level of the regions or the metric), we can obtain different results among the economically developed states, although the trend is imminent. According to OECD (2020), the inner-country regional differences in GDP per capita have risen among half of their members between the years 2000-2020, measuring in the Theil index[1]. These implications were consistent with any chosen level of regions.
Focusing on the more relevant set of countries in the EU, the European goals can be evaluated somewhat contra-dictionary. Using the Theil Index and concentrating on the EU14 (member states before 2004 enlargement), we can see the between states' regional income inequality decreasing between 1980 to 2009 by almost two-thirds(Doran & Jordan 2013). Such development is deservedly noted as an unprecedented success, but as we observe, the achievement is only one-dimensional. Because the entire regional inequality was rising through the same time period due to the widening income inequality within countries. The combination of these opposite directions hints that the more prosperous regions in poorer countries have managed to approach the areas in more affluent countries. At the same time, the peripheries of all countries are growing at a much lower rate. Other scholars explain the forces behind these phenomena through structural changes common in contemporary advanced economies. Maybe the most essential is the driving force of knowledge-based business activities that benefit the most out of proximity of people that happen in the urban centres of the countries (Bartolini *et al.* 2016; Group 2016). Thus there is a notion that the cohesion policy of the EU is missing out on some of the critical dynamics but is successful in others which already encourages scholars to submit policy change advice (Iammarino *et al.* 2019).
We have established that the rising discrepancies among inner-state regions are an issue among most OECD countries. Including also all of the EU's older member countries that are the, ones that are the most tied to the UK as economic partners. Now we want to build up on this narrative and emphasize that the UK regional inequality is exceptional even in this prominent club of developed economies that are also struggling with this issue. Arguably "one of the world's most highly cited spatial

[1] The Theil entropy index stands for $Theil = \sum_{i=1}^{N} \frac{y_i}{y} ln(\frac{y_i}{y})$ Where N stands for the number of regions and y_i is the variable of interest for the corresponding region. See the details and decomposition in OECD (2020).

economists and economic geographers" (BSG) Phillip McCann has characterised the regional inequality in the UK in the following words (McCann 2020):

> "Wide-ranging evidence suggests that the UK almost certainly has the highest level of regional inequality of any large wealthy country in the world. In many ways, the economic geography of the UK is reminiscent of a much poorer country at an earlier stage of economic development."

To illustrate what he described, we can observe the comparison of GVA among regions of OECD member countries in Figure 2.1. The most significant inequality in this metric among the OECD countries is driven mainly by two forces. One of those is London's superior, unchangeable position, driven primarily by its outstanding financial sector performance. The second one is the significant underperformance of all other UK regions in terms of productivity. Even after including the exceptional London region, the average regional productivity is the smallest out of the G7 nations, hitting the average of all OECD countries in 2014 (Gal & Egeland 2018). In other words, the London region is behaving as an island of prosperity, unable to transport its local success to the rest of the country nor create an economic synergy for the UK environment. Moreover, the extraordinary figures achieved in this urban core maintain the overall GDP per capita of the UK in the prominent club with northern richer EU economies, which may withstand the question of whether the UK even belongs to this group (McCann 2016). In the next sub-chapter, we shall explore how this continual significant increase in regional inequality that achieved the infamous first place among the advanced economies contributed to the Brexit referendum results.

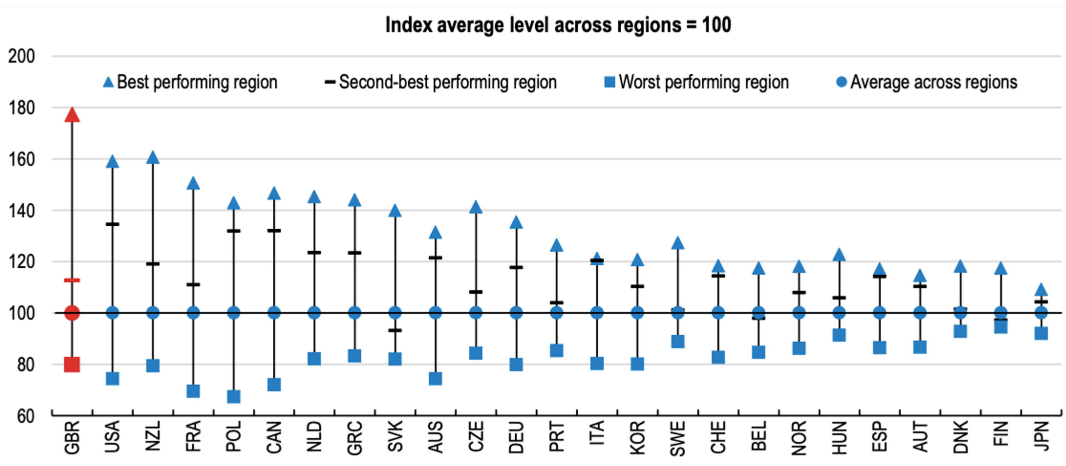


Figure 2.1: GVA per worker by region (NUTS1 level alternative) at 2014[2]

2.2 Referendum as an answer of those left behind

The various polarization traits that led to the infamous results of the Referendum were explored widely by different scholars. It is indispensable to dive into these characteristics before the spatial-based analysis. Most of these metrics highly differentiate among the British regions as we established the relative size of the regional inequality in the previous sub-chapter. There is a consistent consensus among scholars for the essential division lines being the following measurable factors; education, demographics, labour market context and relative importance of different economic sectors (Goodwin & Heath 2016; Becker *et al.* 2017; Gutiérrez-Posada *et al.* 2021). More specifically, the potential that an individual voted for Leave increased significantly with higher age and lower education of the citizen. Moreover, the skill level of their work is often correlated with their education level being also influential, with lower-skilled workers tending to vote for Leave. That is closely related to the local economic environment as low labour market conditions, or a high proportion of retail and manufacturing sectors were also strongly correlated with the share of the leave votes.

To visually illustrate the regional heterogeneously distributed in the Referendum, we can observe the results in the Figure 2.2. The results are visualized on the level of 41 UK regions in the percentage of votes that were cast for remaining in the EU. We can see the clear divide as the London, and the Scottish regions are well above 50 % in the company of North Ireland and the urban region of Merseyside. On the other part of the spectre, we observe the significant lead of the leave votes in Wales, the entire North England, with a stunning maximum achieving 65 % in the Lincolnshire region.

The motive of spatial inequality as one of the key forces in the Referendum is emphasized especially in deep analysis from Gutiérrez-Posada *et al.* (2021). Using the spatial Durbin model on a very detailed NUTS 4 data level, they found significant evidence for the importance of the relative spatial position. Thus, besides other factors already approved by previously mentioned studies, the relative income spatial position (relative to its members) also seems important. Moreover, this study also confirms the hypothesis on a lower level of data. They demonstrate the hypothesis from the national level and regional levels. Still, the differences between regions are so significant that they influence the motivation of the electorate, which can not be examined at the higher level of spatial organization.

[2]The figure was constructed from OECD regional database by Gal & Egeland (2018), with the following data-limitations. For Finish and Hungarian regions, the data refer to 2013. The data for Japan, New Zealand and Switzerland refer to 2012.

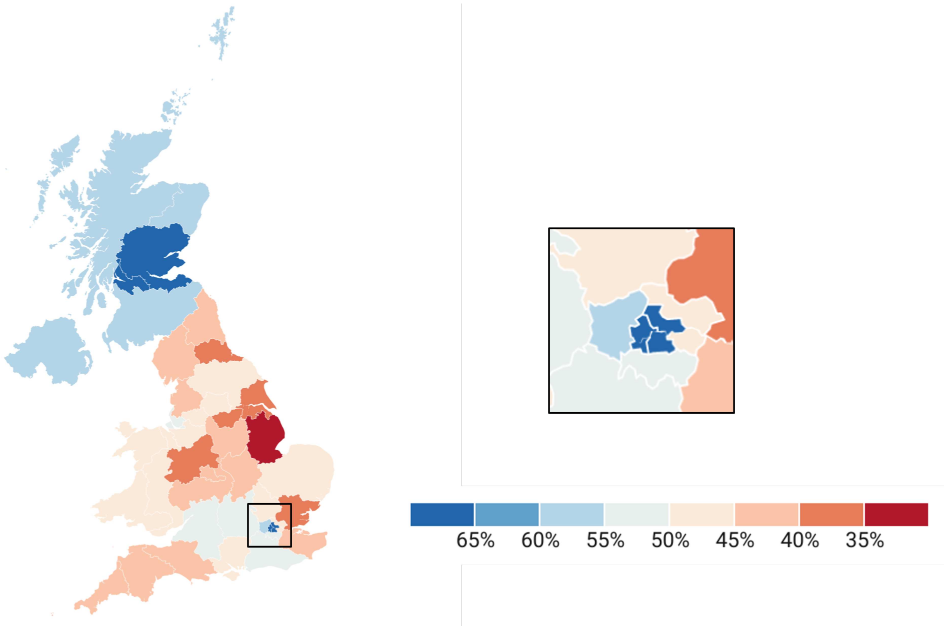


Figure 2.2: The EU referendum results by NUTS2 regions, votes cast for Remain (%)

On the other hand, the relationship with EU trade policies or migration which were part of popular wisdom and often mentioned by the Leave campaign (Gove *et al.* 2016) was not proved as significant. Neither the number of non-UK citizens living in the area nor relatively smaller economic connections to the EU were a significant boost for the Leave votes (Becker *et al.* 2017). Essentially, that does not mean that the biggest talking points of the "Take back control campaign" were ineffective. It just hints at how these messages were channelled to the voting booth. These narratives were less "real-life" driven and more based on the values and personality traits of the voters (Travis 2016). For instance, in the case of the trade connection, the results were the "irrational" opposite. As the regions with the most intense economic bonds with EU territories voted overwhelmingly for the leaving scenario of the Referendum. In other words, UK citizens from places where the economy was the most reliable on the trade connections emerging from the EU inner functioning were more likely to vote Leave and consequently risk the macro-economic situation of their region. There are various explanations for this behaviour. For instance, Garretsen *et al.* (2018) provides evidence of how individual personality traits can reveal the motives behind economically irrational behaviour. The one trait that comes as the most significant and influential is the individual tendency to "openness". Thus, the economic bond between the voter's region and the EU was often not the most decisive factor at all.

Goodwin & Heath (2016) summarizes the key universal differences on both socio-economical and personality levels:

> "The public vote for Brexit was anchored predominantly, albeit not exclusively, in areas of the country that are filled with pensioners, low-skilled and less well-educated blue-collar workers and citizens who have been pushed to the margins not only by the economic transformation of the country over recent decades but also by the values that have come to dominate a more socially liberal media and political class."

The social circles described in this quote can be found arguably in all modern and economically developed countries under various terms. For instance, they were named as those that "were left behind" or the "places that do not matter". As we explored the enormous economic and social differences in the previous chapter, it should be no surprise that these regions will change their behaviour somehow. In other words, it is very reasonable to assume that regional inequality in most of the relevant economic and social metrics is increasing; it will also reflect in the thinking and behaviour of inhabitants of these regions. Especially the rising division will appear not only in the wages but also in the people's interests. Although, the backlash in the form of elections was somewhat unexpected by the political elites. We can observe this backlash of those "left behind" in similar times around the democratic systems, especially in mostly majoritarian election cases. Essentially the entire topic of "geography of discontent" has caught traction after the EU membership referendum that is central to this thesis, the infamous Trump elections that took place the same year and the French presidential elections in 2017, where the votes for radical right candidate Le Penn were also mostly concentrated in the "places that do not matter".
To illustrate the disconnection of elite economic policymakers from the people living in weaker regions, we will mention two examples Rodríguez-Pose (2018) that explain the neo-liberal narrative. The economic scientists from World Bank acknowledged the rising issue of the "unbalanced economic growth" consolidating around urban centres (Rigg *et al.* 2009). Although, the suggested solution is natural adaption, as spatial redistribution would lead to ineffective transfers. Thus, the core idea is transferring labour from weaker regions to more productive ones rather than redistributing capital to narrow productivity inequality. This approach is presented in the UK context in its most straightforward form in Tim Leunig's speech in Liverpool Leunig (2008). Back then, an LSE professor and current government advisor identified productivity inequality as a problem, in this example, the economically deeply under-performing north of England around Liverpool and Manchester. His provided solution explicitly asked for moving people from these regions into the London area. In his argument, that is the most efficient way how the people from the north of England could share the fruits of economic rise in the urban core and contribute to it. Corresponding with the logic of Rigg *et al.* (2009) but more radically viewed the financial, spatial transfers as punishment for the parts of the country that yet

works economically efficiently. In a very simplified way, they were communicating to people that the region with which they are tied by community, family or other crucial self-identification features has lost its future.
This brief qualitative analysis aims to provide the narrative background to the empirically proofed connection between regional inequality and the Brexit referendum results. The combination of economic downfall and continuous neo-liberal patronising that did not consider social factors seems valid for an electoral backlash. Besides the value factors such as dignity, tearing up the community or other bonds to the spatial sectors, these policy suggestions also overlooked the different migration options among the population. The cost for migration, even inter-country ones, is much higher for lower-skilled workers, who also tend to have a smaller human capital network. The paradox of this understandable backlash is that the consequent populist policies impact the group that created it the most as they are the most fragile towards the economic instability and less efficient government policies often introduced by populists (Los *et al.* 2017). Whether that is the case also for Brexit and the consequent UK political climate is one of the questions we try to answer in this paper. We dedicate the next sub-chapter to reviewing other scholars' evidence and arguments on this matter.

2.3 Heterogeneous impact of Brexit

As we mentioned in the previous sub-chapter, the narrative that the most successful parts of the UK, especially the London area, is the region that profits the most out of the EU membership were present and exploited in the political campaign before the referendum. However, a few years afterwards, to our knowledge, there had not been published a piece of evidence that would hint this popular knowledge is based on facts. In direct contradiction, a huge set of different scholars argue and provide evidence for the polar opposite. Meaning that the regions already weaker before the referendum will be damaged quicker and stronger than the more productive ones (McCann & Ortega-Argilés 2021). The explanatory motive is rather straightforward - the level of dependence on the EU markets. In the case of the UK, the less prosperous regions in the Midlands and the North of England are far more connected by trade to their regional counter-EU counterparts than the more flourishing ones. In this sub-chapter, we will provide a literature review of analysis that observe the impact of Brexit on a regional level. To a lesser or bigger extent, these studies approve the narrative of heterogeneous regional impact that struck more regions already struggling. We want to emphasize that we have thematically divided the literature review into two parts; regional impact and data usage. The latter is presented as a part of the fourth data-related chapter. However, some papers are included in both as they are relevant for the impact and data usage simultaneously. The first one is presented here, mostly in chronological order.

One of the earliest papers from Los *et al.* (2017) has provided a prediction of the heterogeneous impact of Brexit based mainly on measuring the dependency of different regions on the EU market. The level of dependencies was estimated by the WOID data model, exploring the dependence among various sectors of the economy as industry, manufacturing, construction and services. This method indicated the previously mentioned narrative that the regions with predominantly support for Leave were more connected to the EU. Thus the impact will be stronger on them. The results hint that London is the least dependent on the EU as trade with the EU counts only for 7 points of London's GDP. Besides, Scottish regions were relatively loosely connected regarding trade to GDP ratio. But the rest of the regions reach 1,25-2 times more trade dependence on the EU than London. Almost half of them reach at least 10,5 points of their corresponding GDP. The paper does not estimate the specific scale of Brexit different scenarios' impact. Still, it concludes that the weaker regions will be struck disproportionately by the richer ones, with London hit the least.

Contrary to these conclusions Dhingra *et al.* (2017) argue that London and the South East will experience the most significant negative impact. Their estimates obtained by the structural trade model also hint at heterogeneous implications, but the opposite for both of their Brexit scenarios. The negative effect seems stronger in urban areas and those with higher wages. The analysis is focused at the Local authorities level. The authors explain the result through the heterogeneous specialisation of different sectors among the Local authorities. Significantly they predict the most significant blow for Business Activities and Financial Intermediation which is concentrated in London and other urban centres. The explanation for being contrary to other contemporary studies is a more profound and complex model that computes the sectoral effects also out of different changes in trade costs and different elasticises of substitution among destinations and sources. This is, to our knowledge, the only relevant study that implicitly hints that the Brexit impact could decrease the regional inequality among the regions of the UK.

McCombie & Spreafico (2018) is thus another study that, to some extent, contributes to the consensus of scholars. To achieve this conclusion, they analyze the early predictions of Her Majesty's Treasury, IMF and OECD using the Balance of payments constrained growth model applied to GVA. They argue that the first estimates of HMT were exaggerated, but the blow to the economy will still occur. Moreover, they hint that the regional disparities will grow further as the rise of non-tariff barriers decreases the income elasticities of demand in the model. Thus, the regions more connected to EU trade will significantly reduce. This approach reflects the same logic provided by Los *et al.* (2017) and results in the same conclusions; the division between the regions will grow further as the ones that are connected tighter by trade with the EU are also the ones that are staying behind in terms of productivity and GVA.

The impact of Brexit can be estimated using several different metrics. Nevertheless, most scholars, including those already mentioned, focus on macroeconomic optics. Brown *et al.* (2019) have explored the macroeconomic approach estimating through the perceptive impact on small and medium-sized enterprises. The data was collected from a series of surveys two years after the referendum. In those, the enterprises stated their concerns about the impact of Brexit on their business development. The most concerned ones were internationally oriented, medium-sized and knowledge-based, primarily located in London and other urban areas across the UK. They conclude that the enterprises that expect the most significant downturn are mostly the innovators and exporters that obtain high productivity levels. These findings go somewhat against the narrative, which shows that there could be underlying contrary forces that decrease the inequality in some particular niche industries that require a combination of highly skilled international workers with a focus on foreign markets, for instance, FinTech.

Steering back to the bigger picture Petrie & Norman (2020) provides a sectoral analysis that also indicates a heterogeneous impact on the British regions. Once again, we can observe the familiar pattern where the most significant drop is present in North East area followed by North West and Midlands. One can observe the most negligible impact on the opposing part of the spectre in London. The analysis is focused on the supply chain dynamics and different behaviour of service and goods-based local economies under Brexit. Goods are reacting more intensively to the introduced market divisions. Moreover, they often include a long supply chain that is struck with them as well.

Along with the consequences of the supply chain, there is important to observe the impacts of the value chain. As the paper Thissen *et al.* (2020) demonstrates, the global value chains are the channels for UK dependency on the EU. The measured outcome was the relative competitiveness of UK regions which is very suitable for the heterogeneous nature of the Brexit impact. The findings offer a clear message of increasing spatial inequality. As relatively weaker parts of the UK are getting weaker, relatively stronger ones are even gaining a relative competitive advantage against them. The pattern preserves even within the parts of the country. For instance,e, within the south of England, London and connected western areas to the Thames Valley are increasing their competitiveness compared to the rest of the region as Essex, Kent or Devon.

The further confirmation of Brexit increasing the spatial differences is presented by

Fetzer & Wang (2020). The critical distinction to previously stated scholars is that this work evaluates the impact ex-post compared to estimating the future losses and gains. Moreover, this paper requires considerable attention as its ambition is similar to ours; it connects the dots between referendum results and the heterogeneous impact of Brexit. The results of the synthetic control-based estimation confirm the findings of the other scholars, thus that Brexit had further widened the regional differences and that the impact of Brexit is not even remotely homogeneous among the regions. The authors explore various important patterns that contributed to the differences. From the sectoral point of view, the areas with higher shares of the manufacturing sector were experiencing a deeper economic fall in terms of output level. This finding is, to a large extent, in line with previously observed forces of supply and value chains Fetzer & Wang (2020) estimates of the rise in employment and accurate payroll correlated with the support of the Leave movement. Such findings somewhat contradict the spatial inequality increase. Nevertheless, the author still concludes in line with the estimation provided by other scholars.

To conclude on the heterogeneous impact, currently, there is a reasonably significant amount of evidence that the effects of Brexit damage economic activity more significantly than the regions already left behind. The estimates and evidence are available from a wide spectre of scholars, including analysing the governmental structure (McCann & Ortega-Argilés 2021). Thus, there withstands a fundamental question - how can this paper contribute to already existing robust estimates of fellow scholars? The first reason is that besides the work from Fetzer & Wang (2020), to our knowledge, all other studies are constructed only as an ex-ante economic impact modelling. In our opinion, that allows us to further validate or challenge the narrative from the other side with the usage of more recent data. Moreover, the only study presented as an ex-post analysis uses standard SCM methodology on regional data levels that seem either too complex (NUTS 3, which equals 382 districts for the UK) or too shallow (NUTS 1, which equals 12 regions for the UK). These reasons are in detail and covered in the corresponding chapters.

Chapter 3

Methodology

In this chapter, we present the features, assumptions and relevant use cases of the Synthetic Control Method (SCM), its Lasso variant, and Ordinary Least Squares (OLS) approaches. It contains the causal logic behind the models, their formal description, the reasoning behind their use in this study and the context of our application. We would like to emphasize to the reader, especially the differences between SCM and Synthetic Control Using Lasso (SCUL) and our argument for its innovative application. Our essential narrative is that the SCM is a practical, transparent and straightforward counterfactual method; however, its conventional versions are not entirely suitable for our regional-level data and corresponding enormous donor pool. That is why we prefer its SCUL alternative for this application, and we present in detail the core distinctions and implications for our model construction and interpretation in the upcoming paragraphs of this chapter.

3.1 Synthetic Control Method

The SCM is a method applicable for conducting comparative case studies created by Abadie & Gardeazabal (2003). The technique enables researchers to estimate the impact of policy interventions by synthetically predicting the outcome of a variable without the intervention and comparing it to the actual result for an exposed unit (e.g. country). SCM has become an extensively used method, as both the establishing paper of the method and the first extension from Abadie have been cited over 4000 times according to data obtained from Google Scholar. The method has been developed further by the original author (Abadie *et al.* 2010; 2015; Abadie 2021) providing researchers with more tools to get significant results. The SCM has been described Athey & Imbens (2017) as:

> "...arguably the most important innovation in the policy evaluation literature in the last 15 years."

The extensive adoption of the method stems from the flexibility of application in diverse domains of comparative studies. The research questions of high-profile SCM papers demonstrate this; from "How did the terrorist activity of the Basque separatist movement affect the regional economic performance?" to "What was the impact of California's new tobacco control laws on the local cigarettes consumption?" and "How did the reunification of Germany after the end of cold war affected the economic performance of West Germany?". Besides these method-establishing and essential method-expanding papers, there are plenty of more common applications that illustrate the variety of SCM use cases even more. For instance, this approach was used to estimate the impact of prostitution decriminalization (Cunningham & Shah 2018), to observe the pandemic development (Rehkopf & Basu 2018) or whether the quotes of celebrities can decrease society's prejudice (Alrababah *et al.* 2019).

The fundamental idea of SCM is the construction of counterfactual units. Those are derived from different units not exposed to the observed interest. This counterfactual unit consequently represents the unit of interest in a hypothetical scenario where it was not exposed to the corresponding treatment. It consists of a weighted combination of the non-treated units, where the weights are assigned in a way that minimizes the difference between the synthetic and natural units in time before the intervention for specified variables. From this arises one of the significant advantages - the model transparently presents what units and to which extent create the counterfactual and also which of the variables were significant in deriving this combination. Finally, the difference between the real-life unit and the counterfactual represents the impact of the intervention.

Arguably the biggest asset of the SCM in comparison to the conventional regression approach is the ability to overcome the trap of extreme extrapolation, as King & Zeng (2006) argued:

> "For example, with a sample of US time-series data, we could reasonably ask how much US presidential approval would drop if inflation increased by two percentage points, and we could generate a fairly certain answer. However, to take an absurdly radical alternative for the sake of clarity, we should not expect to get a precise empirically based answer from the same data, given any model, if we asked how much approval would drop if inflation increased by 200 percentage points."

The regressions' coefficients can theoretically be extrapolated to rather bizarre conclusions if we stretch them enough. In contrast, the SCM applications still present relevant results even after many time periods due to the construction pattern of the synthetic unit.

The SCM has various disadvantages. The most noticeable one is the absence of statistically conventional inference methods in the method. The standard tools such as confidence intervals and common errors are unavailable due to the lack of a randomization element in the time-series setup. Therefore the establishing paper(Abadie & Gardeazabal 2003) proposes a more "out of the box" method with the aim to value the relevancy of the estimation. For instance, so-called placebo tests simulate the intervention for data-pool units that were not exposed to it and inspected their development. If their development after the start of the absent intervention varies significantly, the robustness of the results is questionable. Fortunately, due to the dynamic development created by various scholars in recent years, this SCM characteristic is evolving and improving. Firpo & Possebom (2018) Introduces the modification of the inference method that allows for accurate hypothesis testing. Furthermore, there are lately available also t-tests for SCM results in the newest addition to the approach from Chernozhukov *et al.* (2021). The valuable addition of formalized inference method is functional in the form of a two-tailed p-value also for the SCUL methodology, which is used in this paper(Hollingsworth & Wing 2020).

There are undoubtedly more disadvantages to the synthetic approach than only the lack of conventional inference methods, and we address them in the Method Limitations sub-chapter. Although, we want to emphasize one specific one as it's very relevant for this paper. The SCM options are pretty limited when using an enormously big donor pool. Especially when its size is significantly more extensive than the number of time periods before the intervention(Abadie & Vives-i Bastida 2022). Unfortunately, that is our case due to the nature of regional data. Moreover, the SCM lacks a formalized methodology for selecting its optimal donor-pool subset of a suitable size. This is essential for our motivation to use SCUL for our application, as it Hollingsworth & Wing (2020) offers us solutions through the Lasso approach.

Last but not least, the SCM has specific requirements as any other model out there. Most of them are equal to requirements for different approaches that aim to estimate the differences in comparative case studies. We address these needs of the SCM in the model requirements chapter. We do so with an emphasis on the model's suitability for our use-case of Brexit regional impact.r

3.1.1 Formal Model Description

We shall assume data for $J+1$ units[1] denoted by i in T time periods given by t. Furthermore, we shall divide the units by the occurrence of the treatment of interest[2]; without any loss of generality, we argue that the only single unit exposed to the analyzed treatment is the first one; $i = 1$.[3] Let us similarly split the time periods; let T_0 note the last period before the start of the treatment, where $1 \leq T_0 < T$.

[1]In our case, the units are regions of ITL 2 and NUTS 2 classification respectively
[2]Brexit
[3]The 41 ITL 2 regions of UK

We consider the treated unit is continuously exposed to the treatment throughout every time period such that $t \in [T_0 + 1, T]$ where $t \in \mathbb{Z}$. This gives us J units left unexposed to the treatment during all time periods. The resulting set of unexposed units constructs the control group. This set is referred to as the "donor pool" as defined in SCM establishing paper (Abadie & Gardeazabal 2003).
Now let us introduce the observed outcome[4] by Y_{it}^N, Y_{it}^I during the absence and during the presence of treatment, respectively, for the unit $i \in \{1, ..., J+1\}$ during the time periods $t \in \{1, ..., T\}$. Y_{it}^I is understandably relevant solely for the time periods between $T_0 + 1$ and T. Moreover, we assume the intervention is not influencing any outcomes in pre-treatment periods. In real-world cases, treatment usually has a pre-implementation impact on the unit (e.g. the markets react to the planned adoption of the euro by Slovakia even before the actual term of adoption, in case the currency reform is the treatment of interest). Although, we can always satisfy this assumption through the redefinition of T_0 to the last period before these pre-implementation effects appear.
Let us denote the effect of a treatment as $\alpha_{it} = Y_{it}^I - Y_{it}^N$ for unit i in period t. Trivially, in case all the stated assumptions are satisfied, this equation is equal to zero for every time period before the treatment of interest. To express the equation denoting the treatment effect formally: $\alpha_{it} = 0$ for every unit $i \in \{1, ..., J+1\}$ for all periods such that $t \in [1, t_0)$.
Therefore, the observed outcome for unit i for period t is in its general form equal to $Y_{it} = Y_{it}^N + \alpha_{it} D_{it}$, where D_{it} stands for the indication of unit i during period t is exposed to the treatment.
Hence, D_{it} is equal to 1 solely in case where $i = 1$ and $t > t_0$. Otherwise, it is always equal to zero. We aim to estimate α_{1t} for $t > t_0$, which we define as:

$$\alpha_{1t} = Y_{1t}^I - Y_{1t}^N \tag{3.1}$$

Y_{1t}^I is obviously already observed[5]. Therefore, to complete our task, we have to estimate Y_{1t}^N - the counterfactual doppelganger. To obtain the estimate, we apply the essential aspect of SCM; the construction of a specific synthetic unit with $i = 1$ formed by a weighted average of the rest of the J non-exposed units, the donor-pool members:

$$\hat{Y}_{1t}^N = w_2 Y_{2t} + ... + w_{J+1} Y_{J+1} \tag{3.2}$$

In this 3.2 equation holds holds $0 \leq w_i \leq 1$ and $\sum_{i=2}^{J+1} w_i = 1$ for all weights that: $w_i \in \{w_2, ..., w_{J+1}\}$. Afterwards, we have only one task remaining for the estimation of the treatment impact; we have to assign the optimal weights to the

[4]Real GDP, Unemployment
[5]The real UK regions

non-exposed units. For this task, we switch to a matrix notation in line with the method of establishing paper (Abadie & Gardeazabal (2003)). Let us denote the matrix of weights $\mathbf{W} = [w_2, ..., w_{J+1}]^T$ of size $(J \times 1)$. Let us assume we have collected K variables, essential unit characteristics that determine sufficiently the selected outcome variable Y and define suitably the essence of the units. Let us denote the matrix $\mathbf{X}_1$ of size $(K \times 1)$ gathering all these K essential characteristic variables for the first treated unit; $(i = 1)$. For the rest of the units, the donor pool, we define $\mathbf{X}_0$ of size $(K \times J)$ matrix gathering K characteristic variables for each of these units $i \in \{2, ..., J+1\}$. Now we obtain the optimal weights for the donor pool members by minimizing the following expression:

$$(\mathbf{X}_1 - \mathbf{X}_0\mathbf{W})^T\mathbf{V}(\mathbf{X}_1 - \mathbf{X}_0\mathbf{W}) \tag{3.3}$$

In this 3.3 equation $\mathbf{V}$ stands for the relative importance of the essential characteristics variables. Last but not least, we need to derive $\mathbf{V}^*$. Abadie *et al.* (2015) And other scholars provide various approaches. The weights can be set manually by the researcher (for instance, this approach could be necessary when studying the virus development and we adjust the value for the fatality ratio variable), or we can construct a simple regression of essential characteristic variables on the outcome variable and then plug in the resulting regression parameters as weights into the SCM. Although, we use a different approach for this theses, also demonstrated in the mentioned paper. It is at the same time the most commonly used approach in SCM applications. We determine the weights through the minimization of differences between the synthetic doppelganger and the original treated unit in periods before the treatment: $(Y^I_{1t} - Y^N_{1t})$.
We formalize these differences through the following equation:

$$MSPE = \frac{1}{T_0}\sum_{t=1}^{T_0}(Y_{1t} - \sum_{j=2}^{J+1} w^*_j Y_{jt})^2 \tag{3.4}$$

The MSPE in equation 3.2.3 stands for Mean Squared Prediction Error, and w^* is the function of $\mathbf{V}^*$, which generates a bilevel optimization problem. Therefore, for each value of $\mathbf{V}$, there existed an optimal w^* obtained from the minimization of equation (3.3). Proceeding with this process, we obtain the set of optimal values for unit weights and plug them into the MSPE. Consequent minimization of MSPE obtains both $\mathbf{V}^*$ with corresponding $\mathbf{W}^*$. The obtained $\mathbf{W}^*$ determines the final synthetic doppelganger by plugging in the equation 3.2. At last, now, through the comparison with the original exposed unit in equation , we estimate the treatment impact on the treated team, expressed in the outcome variable.

3.1.2 Model requirements

The model requirements are described in detail in the Abadie (2021) publication. In this section, we will behave according to categories that were defined in this paper. Most of these conditions are also necessary for different methodological approaches to comparative case studies. Abadie (2021) defines the following five types of contextual requirements; *Size of the Effect and Volatility of the Outcome*, *Availability of a Comparison Group*, *No Anticipation*, *No Inference*, *Convex Hull Condition* and *Time Horizon*. Let us inspect them one by one with our application in mind.
The first issue; ***Size of the Effect and Volatility of the Outcome*** covers two interconnected conditions. To begin with the size of the effect, this method is not suitable for the minor impacts of the treatment. It could be easily indistinguishable, with increased probability for highly volatile variables. The effect size is clearly detectable as various scholars provided evidence of significant changes in outcome. For instance, Born *et al.* (2019) show that the Brexit referendum caused output to decrease by 1.7% to 2.5% during the period of 2 years after voting took place. Moreover, the volatility of country output is rather suitable as it is a very common variable for the SCM applications, besides others, it was the case for the method-establishing paper(Abadie & Gardeazabal 2003). Although, in the light of the recent pandemic crisis, the volatility level of the outcome can be challenged. During the first lockdown period in the second quarter of 2020, the output of the UK dropped by a stunning and unprecedented 20.4%. It is literally the biggest quarterly output drop since this metric was introduced back in 1955(Partington 2020), which ought to be taken into account during the interpretation phase.
The ***Availability of a Comparison Group*** is obviously essential for the appropriate application of SCM. The donor pool has to contain units that are similar but at the same time have not been exposed to similar or identical interventions. We apply the approach to the units of ITL 2 regional level in the UK. That corresponds to the EU categorization of NUTS 2 regions used for European countries. Therefore the similarities criterion is easily met. Moreover, the UK being, until the recent time, in a mutual international organization with these regions helps a lot as the units shall be similar also in other main characteristics than the formal definition. In a similar fashion, Abadie *et al.* (2015) narrows the donor pool for estimation of German reunification in the OECD countries. The second requirement part concerning the absence of a similar treatment is very simple for our case, as the decision to leave the EU is a very specific one. No other European country has decided or presented the aim to leave the EU or a different similarly strongly integrated international institution in the 2016-2020 period.
No Anticipation feature warns the researcher that in case the intervention has any pre-implementation dynamics, the results could be biased. As in the example

mentioned earlier with the Slovak adoption of the Euro currency. Slovakia entered the Exchange Rate Mechanism already in 2005 and got approval for the adoption 5 months before the adoption, which took place on 1.1.2009 (European Comission 2016). In case we would be estimating this event, it would be necessary to consider a shift of the intervention period from the start of 2009 to earlier steps of the process as various private and public players could already start to act differently in light of upcoming intervention. Fortunately for our thesis, the Brexit referendum is quite opposite and, therefore, a suitable example. The results of the referendum came as a big surprise. Even 5 hours before the results clearly showed that UK voters had decided to leave the EU, the betting markets presented an 88% probability of the Remain vote winning(Cohn 2016). Therefore, the players had little intention to adapt before the referendum took place, and thus we argue no anticipation took place.

Furthermore, also ***No Inference*** ought to take place. This criterion represents the need for the donor pool members to be not influenced by any spillover effects of the observed intervention. Abadie (2021) especially mentions how the risk rises with the great geographic proximity of the intervention. This requirement is also in a slight contradiction to the availability of comparison group one. On one hand, we need to have available units whose dynamics have a similar pattern as the treated unit prior to the intervention. On the other hand, such similarities often arise out of geographical closeness or trade connections, which are not favourable by no inference criterion. Brexit has evidently also influenced the other remaining 27 member countries of the EU that remain in it to the recent day, without significant signs of further leavings(European Parliament 2018). We argue in line with Born *et al.* (2019), that even though there is an undeniable measurable impact on the rest of the member states, it is still suitable to use their regions in the donor pool. Because, in comparison to the impact of Brexit on the UK, the impact of the donor pool is insignificant and slightly negative. Moreover this narrative was proved also in regional level by Thissen *et al.* (2020). The logic provided in his paper is fairly simple. The UK value chain are significantly more connected to the EU economy then the other way around. The effects on the EU side should mirror the UK to some extent although due to the great asymmetry of the included sides it's magnitude shall be very different and thus much smaller on the EU side. Although we take this issue very seriously, and thus we dedicate more reflection and explanation in the Data devoted chapter, particularly the Donor-pool section.

Convex Hull Condition is once again a concept concerning the similarity between the treated unit outcome and the donor-pool member's outcomes. The main idea is that in case the observed outcome is too extreme, the synthetic estimate has the potential to be unavailable or irrelevant. As we mentioned earlier, the relative weights that eventually construct the synthetic unit must obey the following rule:

$0 \leq w_i \leq 1$. This rule protects the model from excessive out-of-donor-pool extrapolation. Thus in case the treated unit outcome is completely out of the interval of other unit's outcomes, the model is not able to present relevant results. However, the outcome variable can often be transformed in such a way which can resale these differences, for instance, by putting the variable in per capita form. In our case, this should not be an issue at least for the majority of British regions, as the regions in Europe provide similar heterogeneity as the UK itself, besides London. However, as this criterion is nonexistent in the SCUL approach, we will come back to it in the next chapter in greater detail.
Last but not least, there is the necessity for reasonable ***Time Horizon***. The relationship between treatment and outcome variables can have various patterns. Thus in some cases, the occurrence of the impact can take significantly more time than in others. The signals for Brexit are quite contradictory. On one hand, there is the instant reaction of the Pound as it fell 10% in comparison to the dollar just under a few hours after the closure of the polling stations (Allen *et al.* 2016). On the other hand, the formal processes have quite different dynamics; for instance, the UK left the Customs Union only in 2021. However, various scholars that we have already mentioned have found empirical evidence for measurable impact before 2020 (Born *et al.* 2019; Fetzer & Wang 2020; Fingleton *et al.* 2022). Thus we argue the Time Horizon should be sufficient, although the underlying processes ought to be used in interpretation.

3.1.3 Inference methods

As we already mentioned before, the inference methods are one of the weakest spots of the synthetic approach. However, in recent years, a lot of scholars have focused on this feature and developed various additions that are able to provide us with somewhat formalized inference results. In this sub-chapter, we briefly address some of these methodological extensions in a form of a literature review. Moreover, we introduce the reader also to the original inference methods. We do so with the aim to provide a relevant set of inference methods to compare with those ones offered by the SCUL extension and consequently applied in the empirical part of this thesis.
SCM inference methods were firstly introduced hand in hand with the method establishing paper(Abadie & Gardeazabal 2003). The so-called placebo tests consist of constructing the synthetic unit also on cases where the intervention did not take place. The logic behind the construction of placeboes is quite straightforward. In case the SCM has estimated a huge impact on the treatment, how rare is this impact? Some kind of answer can be provided by constructing the same method on the units of the donor pool that were not exposed to the treatment. In case there would be

an estimated impact also on these units, the researcher can not consider his results being robust. The other type of placebos is the so-called in-time placebos. What if we moved the start of the treatment a few time periods earlier? Will there still be an impact of similar altitude? In that case, once again, the relevancy of the results ought to be taken into question.
The trivial core idea of placebo testing will stay with the method in all future developments. In the core extension of SCM, the authors identified the notion that the donor pool that is ideal for estimation of the treated unit does not have to necessarily fulfil this function also for every single donor pool member(Abadie *et al.* 2010). This notion has a lot in common with the convex hull condition. The donor pool will always contain also the extreme border cases that co-create the interval of the outcome variable offered by it. Thus it is just logical that for these units, the original donor pool will be unsuitable. And those unit placebos results are then also quite irrelevant for the evaluation of the treated synthetic unit inference. They identify these poorly fitted placebos by their MSPE level in comparison to the treated unit MSPE. On various runs, they discard the units with MSPE 20 times higher, five times higher and two times higher. Moreover, they utilize this metric also for another inference approach. They compare the ratio of post-treatment and pre-treatment MSPE between the units in the so-called Ratio of the Mean Squared Predictions Error (RMSPE) metric. This gives the researcher insights into the relative size and robustness of the treated unit's estimated impact. The higher in comparison to the donor pool placebos is, the more relevant and robust the results are.
To this moment, we have observed only very informal and ad hoc inference methods. But as more scholars started to use this very simply applicable universal method, they identified the absence of systematic inference methods as one of its main weaknesses. Thus they aimed to develop something at least remotely similar to conventional inference methods, for instance, p-value (Dube & Zipperer 2015). They also execute the placebo tests for the donor and utilize them to construct a rank elasticity test. Comparing the standardized impact on the treated unit with the placebos provide a rank-based two-sided p-value. This means a step toward more conventional methods, although the quality of obtained p-value is strongly influenced by the size of the donor pool.
The p-value based on a similar principle with alteration of the weights parameter benchmark is also suggested Firpo & Possebom (2018). Moreover, they introduce in this paper also a framework for hypothesis testing. The key is the modification of the RMSPE test statistics Abadie *et al.* (2010). Their approach allows for testing of any sharp hypothesis, not only the most trivial one; that the treatment impact is equal to zero.
One of the most recent developments in the field of SCM inference methods that

demonstrates the possible future of the synthetic approach was offered in a paper by Chernozhukov *et al.* (2021). Their inference addition is concerning running a t-test on the average treatment effect of the synthetic unit. The t-statistic is obtained through a cross-fitting procedure for bias correction. The resulting t-test is robust against misspecification, functional with non-stationary data and executes especially well even for small samples. To sum up, there was a wide and strong development in the formalization of the inference methods. The majority of even the most sophisticated ones arise from the placebo tests. In this paper, we will execute the inference methods that are specific to the Lasso approach and are in detail addressed in the following chapter. However, from the ones presented in this sub-chapter, they are very similar to the ones presented in Dube & Zipperer (2015).

3.2 Synthetic Control Method using Lasso

In the previous chapter, we introduced the conventional SCM, its features, advantages and limitations. Thus now, we can proceed to the description of its Lasso-based alternative and their mutual comparison.

The SCUL method was developed very recently, Hollingsworth & Wing (2020) and its main difference is in the methods of obtaining weights. In contrast to the bilevel minimization of prediction errors for outcome variables and covariates, SCUL offers a regression approach. The lasso feature included protects the estimation from extensive over-fitting. Such integral difference also introduces the varied roles of donor-pool units and covariates. Since their impact on the creation of the synthetic unit is derived from regression, every covariate behaves as a solo donor pool unit. Such changes allow scholars to use a much bigger data pool without the fear of over-fitting. That is the main reason for the application of this alternative also for this study, as the size of the donor pool at a regional level is much greater than one at the state level.

The Hollingsworth & Wing (2020) with more added value in the formalized decision-making throughout the process and also in the inference methods. The donor-pool units formalized picks are obviously embedded into the regression process. The integration of Cohen's D statistics into every placebo unit grants us the opportunity to tackle the inference in a consistent way. As Cohen's D is transitional among different variables and does not rely only on the fit of the treated unit as MSPE. The derived p-value is then much more robust.

Although this approach also bears a few risks. The allowance for negative weights whose sum is not necessarily equal to zero introduces the risk of radical extrapolation. Furthermore, the method is very recent. And even though there already exists an R-package that eases the application, the method is yet waiting to be peer-reviewed.

However, this risk also bears the opportunity to induce additional added value in this paper, as it is one of the first applications of the innovative approach to this moment. The rest of the chapter is structured in the same nature as the previous one, dedicated to the conventional SCM with the final comparison. First, we present the formal descriptions, then the requirements of the model, in this case only the comparison, we follow up with the Inference methods and conclude with a discussion of the risks and benefits of this approach absolutely but also relative to more conventional SCM alternatives.

3.2.1 Formal description

In introducing the SCUL approach in a formal way, we will continue consistently with the notation provided in SCM formal description. As the principle of the model stays the same, we can follow up from equation 3.3. That equation denotes the formation of the synthetic unit out of a weighted sum of units unexposed to the intervention. Let us slightly alter the notation tough. As in the previous chapter, the j index stands for the donor-pool unit outcome variable indication, which in our case meant the real output of regions from NUTS 2 throughout Europe. The SCUL-related notation that we use in this sub-chapter still signs for the donor pool, but not only for the outcome variable of these units. Instead, let us suppose without the loss of generality that the $j = 1$ stands for the outcome variable of the treated unit, whereas the j between $(2, J + 1)$ stands for the outcome variable and covariates of the donor pool units. Thus in notation, this difference will not be very visible, but we emphasize this for the reader as it will be essential for the results part of this paper. Nevertheless, the most important and biggest change in the SCUL approach in comparison to conventional SCM is the way how are these weights derived and how they are no longer limited. Let us start with the weight derivation. Even Abadie & Gardeazabal (2003) offers alternative options to pick weights by a regression. Thus in case, we would go for simple ordinary least squares, the weights would be derived by minimizing:

$$\sum_{t=1}^{T_0} \left(Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt} \right)^2 \tag{3.5}$$

Which you can observe is the core part of MSPE, but in comparison to Abadie *et al.* (2010) approaching the simultaneous bilevel minimization is absent. That feature would not be relevant for the approach that takes the covariates as "independent" units. This straightforward regression-based way to obtain the weights is attractive, but there is a significant risk of uncontrolled extrapolation as the regression parameters can be negative, and also a higher probability of over-fitting (Ben-Michael *et al.* 2021). Moreover, the OLS bear further the inability to use more units than there was observed in pre-treatment periods, in cases where stays: $J > T_0$. Now let us change the OLS into the lasso regression. Then to obtain the optimal weights, we would have to minimize:

$$\sum_{t=1}^{T_0} \left((Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt})^2 + \sum_{j=2}^{J+1} \lambda |w_j^*| \right) \tag{3.6}$$

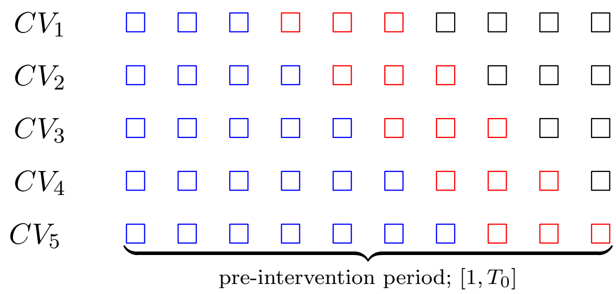
The difference between OLS and Lasso is the introduction of the penalty sum $\lambda|w_j^*$ as a companion to the squared prediction error. As we sum every weight's absolute value, we give the model incentive to decrease the complexity and force the large OLS-derived coefficient to decrease. For coefficients that were already small, there is a high possibility of shrinking them to zero. Thanks to that, the model is able to include more donor pool units than the number of pre-treatment periods. Moreover this us to drop the restrictions for all weights from previous the original SCM approach; $0 \leq w_i \leq 1$ and $\sum_{i=2}^{J+1} w_i = 1$. Now the weights can be negative for instance, for counter-cyclical units or to behave as an intercept.

The direction of minimizing force also in accordance with the sum of weights in absolute format is clear, however, the choice of λ is absolutely essential for the size of this power. In case it would be equal to zero, we will step back to the OLS estimator and not alter anything concerning the over-fitting or the maximum number of donor pool members. In case it is very high, it will drive every weight to zero. That is obviously also not a very welcomed output as the synthetic unit consists only of constant intercept. Hollingsworth & Wing (2020) offers us a cross-validation-based methodology to pick the optimal λ parameter. The method is chosen with the aim of maximizing the fit also out of the sample and in aim to limit the probability of over-fitting and possible auto-correlation issues.

Now let us proceed to the introduction of the cross-validation with rolling origin in more detail. Let us revise the notation of the time periods, where we observe periods between $[1, T]$. The last pre-intervention period is T_0 and for all mentioned holds following; $1 \leq T_0 < T$. In the aim for a more straightforward explanation, let us suppose that the time period length after treatment started taking place is equal to 3; $T - T_0 = 3$. Moreover, let us suppose that there are ten observed time periods before the intervention in the following visualization, where every square represents one time period:

$$\underbrace{\square\square\square\square\square\square\square\square\square\square}_{\text{pre-intervention period; } [1, T_0]} \qquad \underbrace{\square\square\square}_{\text{intervention period; } (T_0, T]} \tag{3.7}$$

The cross-validation procedure is based on dividing the time periods into various data subsets. The division happens only in the part prior to the intervention, so for the $t < To$. It divides the data primarily into two types of subsets: training data and test data. Although by the exclusion, also a subset of unused data is created in all cross-validation runs beside the last one. In the figure below, we observe only the ten time periods prior to the intervention. Every line represents one cross-validation run, denoted by CV_{1-5}. The periods that create the training sub-set are in blue, the ones contained in test are red and the not used pre-intervention periods are black. Every described sub-set, either test or training one is continuous in time periods. The length of the test sub-set is equal to the previously defined length of the treatment period for which we aim to estimate the counterfactual. The training one starts with the same length and gradually prolongs till it is possible. Let us emphasize that the here presented amount of cross-validation runs are defined by the assumptions made in equation 3.7 and would differ due to changes in any of those pre-defined variables.



After we recognize the pattern according to which the intervals are selected, we continue with their roles in the derivation of optimal λ. The optimal λ according to Hollingsworth & Wing (2020) is such one that performs very well also inside but also outside of the sample. The reasoning behind it is that maximizing only the fit inside of the sample (in intervals before the intervention) will assure an over-fitting feature to the estimation. The λ is picked from the interval between itself being zero and the smallest one that forces every weight to equal zero. A great number of different penalty parameters that lay in this interval are then tried on every training sub-set. Every of these λ introduces a different set of weights for every cross-validation training data. Then for each of these runs, the optimal weights are validated through the corresponding test data by minimizing their MSPE. The main idea is a series of in-time placebo tests with the fake treatment always beginning by the end of training data, and its length is the same as the real estimated treatment for the data. After we have obtained the ideal weights for every run, we will note the corresponding penalty parameters. Then out of these parameters, we choose the median λ out of these MSPE minimizing ones, and that serves as an optimal penalty parameter for the construction of our synthetic control. It is afterwards plugged into the equation 3.6, from which we derive the synthetic unit. Then, same as for the original SCM, we can evaluate the treatment impact after plugging the doppelganger into the equation

3.1.1.

3.2.2 Model requirements differences

The needs of SCUL are not very different from the conventional SCM requirements. Concerning the Size of the Effect and Volatility of outcome, Availability of a Comparison Group, and No Anticipation and No Inference conditions, there are no changes. As these criteria remain the same, we will not address them anymore in the SCUL section. As we believe, fulfilment of these criteria is well debated in the previous chapter. Thus we will dedicate this sub-chapter to the one requirement that differs from the Lasso weight derivation approach; ***Convex Hull Condition***.
This requirement is implied directly from two elementary restrictions on conventional SCM weights. Their inability to be negative, and that their combined sum is equal to one, as the following statements are required to hold for every w_i:

$$0 \leq w_i \leq \qquad 1 \sum_{i=2}^{J+1} w_i = 1 \tag{3.8}$$

These weight requirements are motivated by the protection before radical extrapolation Abadie *et al.* (2010; 2015). In simple words, the value of synthetic unit value must belong to the interval from lowest to highest donor-pool values. Then the unit is strictly bounded, and the risk of radical extrapolation is overcome. That is obviously a welcomed feature, although we must inspect what other dynamics are eradicated by these requirements. Because It actually eliminates any type of extrapolation out of the donor-pool set. Where the reasonable case of extrapolation does not have to be a necessary thing. In contrast, it can actually limit the performance of the SCM as the unit can not exceed the outcome of the highest or lowest donor pool member. For instance, in our case where the Inner London West region is reaching the highest real GDP per capita every year between 1998-2020 in comparison to any of the EU regions. This could negatively influence or even completely rule out the estimation of this region.
The violation of this condition also opens room for other possibilities than estimating the out-of-donor-pool interval variable, although they are not so relevant to our specific application. For instance, one can reasonably utilize the counter-cyclical variables thanks to the possibility of negative parameters. It also allows us to include in a better way other outcome variables that are not totally the same. For instance, to incorporate other tobacco products in the case of Californian cigarette consumption prominent paper (Abadie *et al.* 2010; Hollingsworth & Wing 2020)˙ Moreover, the convex hull condition protects only the radical extrapolation but lets the other face

of the same coin function unnoticed. By that, we mean extreme interpolation, which can harm the estimation in the same way (King & Zeng 2006).

3.2.3 Inference Methods

The SCUL approach differs similarly in inference methods to conventional SCM as it varies in the weights derivation. As the core ideas or narratives are very similar or even the same. But the devil lies in details. One of those is the way how to pick the placebo units that are relevant for the inference methods. To some extent, the logic is based on a similar foundation Abadie *et al.* (2010). As we mentioned before, the authors in this study have removed some of the placebos based on the ratio between the MSPEs of the placebos and the target synthetic unit. The reasoning behind this is that the comparison between the estimated unit and placebo units makes sense only in case the donor pool is suitable also for them. What necessarily does not have to be the case. The problematic feature of MSPE (see equation) is that it is only relevant in relative relationship to other MSPE, in this case to one of the estimated synthetic units. It does not carry any information itself as a statistic alone, it measures the fit of placebos in close relation to the treated unit fit. This Hollingsworth & Wing (2020) proposes a different metric of synthetic fit evaluation; Cohen's D statistic. This metric, in simplified terms, stands for the standardized mean difference in a baseline covariate between the donors and the treatment. In specific terms, the Cohen's D statistic used in SCUL is defined in the following way for every donor variable j:

$$D_j = \frac{1}{T_0} \sum_{t=1}^{T_0} |\frac{Y_{jt} - Y_* jt}{\sigma_j}| \tag{3.9}$$

Where the σ stands for the standard deviation of the corresponding variable j from its pre-treatment time period:

$$\sigma_j = \sqrt{\frac{1}{T_0} \sum_{t=1}^{T_0} (Y_{jt} - \overline{Y_t})^2} \tag{3.10}$$

As Cohen's D provides the researcher self-sufficient metric, the decision about which placebos to use for the inference methods is able to be consistent and systematic. The suggestion of Hollingsworth & Wing (2020) but also different scholars (Ho *et al.* 2007; King & Zeng 2006) is to use a rule of thumb equal to 0.25. That means that any covariate placebo that has a higher difference than a quarter of the standard deviation is eliminated from the inference evaluations. We are able to change Cohen's D, and with lower values, it would eradicate more placebo units with higher deviation. The

resulting set of placebo variables would have improved pre-treatment fit and thus a more relevant comparison. Although, it is not advised to set Cohen's D to zero because then very few placebo series would survive, and the inference legitimacy could struggle due to the small size of the resulting set. That's why we use the 0.25 rule of thumb for the selection of relevant placebo units.
Moving onward, after the construction of placebo tests for every covariate, removing the ones with too big Cohen's D, we can proceed to the construction of a two-sided p-value. In the aim for the inference to be relevant for the entire post-treatment estimation, we need a corresponding result metric. Let us define the author's original suggestion, the average treatment effect for the first treated unit $j = 1$ and the corresponding time period of the intervention $t \in (T_0 + 1, T)$:

$$ATT_{j=1,t\in(T_0+1,T)} = \frac{1}{T - T_0 - 1} \sum_{T_0+1}^{T} (Y_{1t} - Y_{1t}^*) \tag{3.11}$$

After the notation of the results format, we are able to design the two-sided p-value. The null hypothesis is created by setting the intervention impact to zero level. The p-value is rank-based applying the randomization inference from the inference method mentioned in the previous chapter Dube & Zipperer (2015). The pre-treatment period standard deviations are standardized in such a way that the corresponding average treatments estimations. Then they are not assigned to any specific unit and thus are comparable to each other. The p-value comes from a comparison of these standardized effects from both donor-pool variables and the treated unit. It is the percentile of the rank for the treated unit relative to the rest of the set.

3.2.4 Benefits and risks

Let us start with the benefits, which were the reason for implementing this young alternative of SCM. From our point of view, and especially for this application, the biggest advantage is the possibility of using an unlimited size of donor variables. As we are doing our estimation on the regional level, we happen to have much more donors available than other scholars often have. And in conventional SCM, it is not a straightforward advantage as stated by Abadie & Vives-i Bastida (2022):

> A larger donor pool is not necessarily better than a smaller one. Adopting a small donor pool of untreated units that are close to the treated unit in the space of the predictors helps reduce over-fitting and interpolation biases.

The notion that the bigger donor pool hurts the estimation through over-fitting was identified by various scholars in previous years (Abadie *et al.* 2015; Xu 2017). Yet, there is still no clearly formalized system on how to cut the donor pool to the desired quantity. There are only recommendations of not including donors that significantly differ from the unit of interest (Abadie *et al.* 2015). Thus after the elimination of units that are violating the model requirements, the scholars often step into ad hoc territory. Often it is represented with some specific heuristic criterion. For instance, to our knowledge, the only study that uses the SCM on UK regional level uses three different criteria, which damages the simplicity and transparency(Fetzer & Wang 2020). Moreover, it introduces a great amount of ad hoc like liberty to the scholar. The systematic selection of donor pool using the Lasso approach and rolling cross-validation element is both simple and transparent. Furthermore, it eliminates the over-fitting risk is, from our point of view, a key advantage and added value of the SCUL approach.

Another opportunity that SCUL gives us is the statistically formalized inference methods. We are aware that variations of the confidence intervals and the p-values are already well established in the synthetic control community (Dube & Zipperer 2015; Chernozhukov *et al.* 2021; Ben-Michael *et al.* 2021), so some could argue this shall already fit in the standard features territory. However, we see the addition of Cohen's D into the placebo process as sufficient reason for the advantage level.

Last but not least, out of the SCUL benefits, we have to dedicate a note for the stretching of the data requirements. As the approach erases the difference between the outcome variables and predictor variables. Thus the unit variables that would be in conventional SCM labelled as predictors are not required for the treated unit. This seems as a very small difference. But Brexit itself has also had an undesirable impact on the availability of data, especially for more niche ones such as the regional accounts. The UK has stopped sharing data with Eurostat by the end of the transition period (Eurostat 2020). As the British institutions were not able to compensate for these data losses, this advantage can not be overlooked.

However, this data feature also bridges us to the drawbacks and risk territory. Since every variable is functioning similarly to donor-pool members in conventional SCM, it is necessary to have the access to continuous data for every variable. In contrast, even in the SCM establishing paper (Abadie & Gardeazabal 2003), the researchers proposed how one can also add non-continuous, even one-period-long predictor variables. Equally or maybe more problematic issue is the necessity to have the observed predictor data for every variable till the end of the treatment period in comparison to its start. In other words, in conventional SCM, the scholar needed the predictor variables till the intervention started as it functioned for the optimization period only. In contradiction, SCUL also uses them as the parts of the resulting synthetic unit. Thus they need to be available till the last year of treatment. That can be very challenging, especially in cases like this which use very recent data. We dedicate

more details to the data issues in the corresponding chapter.
Probably the biggest disadvantage and risk in comparison to core SCM methods or other mainstream alternatives is the missing peer review and corresponding lack of uses. The number of citations, according to Google Scholar, is in the very low double digits, out of which even fewer are applications (Paraje *et al.* 2022). Thus a wide scholarly discussion is absent, and we have to satisfy ourselves with the self-critique of the author and our own analysis.
Even though the method is not yet adopted by the scientific community, the approach it has applied is not totally isolated from other's scholar's work. For instance: Athey *et al.* (2019) and Kellogg *et al.* (2021).
The different risk that we do not underestimate is the so many times mentioned before extrapolation issue. We argue in line Hollingsworth & Wing (2020), that the mainstream SCM is overlooking issues with potentially the same negative consequences as the radical extrapolation itself. However, the SCUL approach does not offer any solution for extreme interpolation either. Thus it is no zero-sum game. However, the method is at least controlling the risk with the tool of robust two-sided p-values.
Last but not least, we want to emphasize how this application differs us from the SCM applied on Brexit impact on the regional level provided by Becker *et al.* (2017). In their work, they have also struggled with the size of the available donor pool at the regional level. They have derived their own heuristics for picking the right donor pool which we argue is evaluating very limited options. They constructed various thematic-based groups (EU, OECD, G20, ...) and find all their combinations. The important part is they are not combining the specific units but rather already groups of units which are connected by narrative organisational logic rather than a model one. Afterwards, they evaluate these different models by three different criterion's; average absolute projection error, root mean square projection error and maximum projection error. In comparison to this method, we consider the SCUL creation of the synthetic method far more transparent and also logical as it encounters every single unit rather than a combination of artificially created sets of units. The authors also mentioned the over-fitting risk as the biggest issue in their discussion which is something that we aim to tackle through the above-mentioned abilities of the Lasso synthetic approach.
All in all, SCUL is a step in an interesting direction for SCM methods. To our knowledge, this spectre is yet not very developed as most scholars are working with more limited data in terms of the number of units. Besides the stated disadvantages and risks, there are various arguable benefits. We very much appreciated especially the formalization of various, often ad-hoc SCM procedures. However, the biggest advantage of this study introduced by SCUL is the donor pool size inclusively. Thus,

even though we do not ignore the limitations of this method, we perceive it as absolutely ideal for the estimation of Brexit's impact on regional real output throughout the UK.

3.3 OLS regression

In an aim to estimate the relationship between the Brexit referendum results and their synthetic estimates, we need to briefly address also different methodologies. As we have no goal of over-complicate we have chosen "one of the most common techniques used in multivariate analysis" (Dismuke & Lindrooth 2006). Of course, this quote is referring to the one and only Ordinary Least Squares approach. As this model does not need any further introduction we can move on to the data chapter. There we will provide more information on our specific application of both SCUL and the OLS.

Chapter 4

Data

In this chapter, we shall explore what type of data had different scholars chosen to estimate the impact of Brexit. We also delve into various relevant SCM applications at regional and national levels. Then we provide our data set with the corresponding reasoning for the selection choices. As regional data are more scarce, meaning less available, especially in recent years, we create two subsets. This is because not all countries have published relevant data about the economic structure of their regions for the year 2020. Besides others, there are included well economically developed countries such as Germany or Italy, which are very relevant for the estimation of the UK. Thus, we have decided to create two models. Their donor pool data sets overlap, but one contains European regions from more countries, and the other contains more relevant characteristics about a smaller number of specified areas. Furthermore, we provide descriptions for every donor pool variable and corresponding sources to ensure the repeatability of the study. Last but not least, we dedicate the last part to the data selection for the variables in our OLS, resulting in impact regression.

4.1 Literature review

In this section, we provide a brief literature review of different scholars' work related to British counterfactual construction in the case of Brexit and regional inequalities. We do so to give the reader sufficient background on our analysis-driven selection of the data pool and covariates in consequent sections. We emphasize the unfortunate fact that data accessibility highly differs between national and regional accounts. The resulting asymmetry is also clearly visible in the work of other scholars we present in this section.

4.1.1 National level

Let us start with the before-mentioned analysis that estimates the cost of economic nationalism with the synthetic approach (Born *et al.* 2019). The outcome variable is economic output. In the creation of the donor pool, the authors draw their focus on the OECD member countries. The only further restriction for these mostly developed economies is the availability of the outcome and predictor variables. Most of the covariates were standardized by being divided into the outcome variable. The ratios are derived for Consumption, Investment, Exports and Imports. Moreover, the authors also include the Employment share and Labour productivity growth, a variable that has implicitly included the outcome GDP.
Another already mentioned application of SCM on Brexit focuses on the reaction of the FDI inflows and outflows (Breinlich *et al.* 2020). Then the data outcome variable is represented through the count of MA and greenfield transactions. The covariates include the different sectors where this transaction takes place in considerable detail; business services, communications, financial services, healthcare, tourism, leisure, real estate, IT, transportation and others. We can see that the entire model is based "only" on the structure of the output variable. Concerning the donor-pool variables, they use the trade relationship between every non-EU OECD country and the EU as one unit. To dodge the over-fitting, they remove any member that does not reach more than five transactions over the entire period.
Providing a bit of diversity to our review of Brexit counterfactual is Celebi (2021) with their Panel Data Approach. However, the methodological link is close due to the Lasso regression combination. The output variables consist of GDP, gross fixed capital formation and export. The donor pool is once again created from the OECD countries, and the data carry quarterly periodicity. This paper also concludes our brief overview of national-level UK counterfactuals.
We can see that the scholars constructing the counterfactual for the UK are broadly satisfied with the offer of OECD member states. Moreover, they mainly consider only the outcome variable variation and data availability in decreasing the donor pool. Concerning the predictor variables, they vary in some detail. Although they often contain the essential economic metrics, unemployment or GVA. Moreover, the economy's structure in the sectors is also often used.

4.1.2 Regional level

Let us open the regional part with the paper we often use as a benchmark throughout this thesis. Fetzer & Wang (2020) created SCM-based counterfactual for the British alternatives of NUTS 1 and NUTS 3 regions. Especially the latter one was very ambitious and remarkable as 382 of these regions are in the UK, and the data

availability is lower with a higher level of regional detail. The researchers use quarterly data for the first one, which contains 12 reasonably significant regions. Those can be found in extensively big data pools in G20, OECD and EU countries. Thus they approach this level of region in the same way as it would be a sovereign state. For the second NUTS 3 level analyse, they expanded this donor pool with the 175 NUTS 2 regions and 51 US states and changed the data periodicity into an annual one. A combination of previously named groups obtains the final data set according to three specific criteria defined by the authors. Concerning the outcome variables, they construct models for accurate output rates. They present the results also for gross value added, employment, real payroll and productivity. Unfortunately, the authors do not share their combination of covariates for the data pool units. They address them only vaguely as "district-level characteristics that we explore".
Another study that inspected the heterogeneous impact of Brexit at the regional level is focused on competitiveness - (Thissen *et al.* 2020). The methodology highly varies from the synthetic approach, as it mainly uses inter-regional trade data for firms. Which elasticises to tariff barriers they study. Nevertheless, according to scholars, the appropriate level for such analysis is NUTS2. Due to their paper's nature, they also use the EU counterparts of these UK regions as they study the international inter-regional trade relationships between them.

4.2 UK regional data for SCUL

Let us proceed with the definition of the data used for our treated units - the regions of the UK. There are two different classifications among the regional divisions of the UK. This complicated pattern emerged due to the specific construction of Britain out of four different states. However, we choose the one compatible with the NUTS classifications of Eurostat. The so-called International territorial level (ITL) was renamed NUTS after British statistical institutions withdrew from Eurostat. Depending on the detail of regions, there are three possibilities for the data set selection. The highest layer consists of 12 units: Wales, North Ireland, Scotland and England, divided into nine regions. The middle layer consists of 41 regions, with much more detailed stratification as the only state that remains a sovereign unit in Northern Ireland. The highest possible level comparable to European regions consists of 382 relatively small spatial units. However, this detailed stratification lacks the relevant data for covariates on their European counterparts, which we describe in detail in the next section. On the other hand, the least detailed layer is quite shallow as it does not even have a suitable option to differentiate between more urban and rural parts of the country. Moreover, the resulting 12 points would not be ideal for constructing the OLS regression. Thus, we have decided to continue with the NUTS2 categorised

regions as, in our opinion, they are a sufficient amount of regional dynamics detail. At the same time, the data for them are available. Moreover, we are in line with the analysis of the EU, as their inter-regional analyses are based on the same layered data set (Mercenier *et al.* 2016).
Afterwards, there is the choice of the outcome variable. To represent the complex picture of the British economy after Brexit, we decided to go for the conventional choice of real GDP. We are well aware that this metric cannot comprehend all the underlying essential notions, such as which industries were struck or benefited and how the labour market reacted to the migrant outflow. There are two types of reasons. For the economy's structure, the data are not yet documented on the side of the UK. Moreover, we found out the volatility is too great for the SCUL application in our case for such variables as unemployment or growth-based metrics. Too often, we're the units equal to a constant average over time. Thus we analyse only the impact on the real regional output.
Concerning retrieving the data, we exploit the advantages of SCUL presented in the previous chapter. As we already mentioned, because every covariate acts like an "independent" donor pool unit, the only necessary data series for the treated unit is the outcome variable. Many regional UK data sets are no longer shared and publicly published since the withdrawal from Eurostat. We very much welcome this feature. Moreover, this metric is available only from 1998-2020, which very straightforwardly predefined the maximum potential interval for our analysis. After the research of the possible donor pool units, it has also become the finite time horizon for this study. It fits the time-horizon requirement and the Lasso rolling cross-validation technique. The four years since the referendum were sufficient for other scientists to find empirical evidence of the Brexit impact (Born *et al.* 2019; Fetzer & Wang 2020). Moreover, this time horizon offers the SCUL data set with 19 pre-treatment periods and four intervention-filled ones. Thus, the Lasso can find the optimal penalty parameter λ based on a solid number of 12 cross-validation runs. In the following figure, we can observe this outcome variable's heterogeneity across all the UK regions. On the left map, we can see the differences between the average value of the real GDP in the time period 1998-2020. On the right half of the figure, we can observe the close of the London metropolitan area. Colour intervals of 5 000 pounds in length visualise the values. That also stands for regions in outer breaks beside Inner London. The visual demonstrates that heterogeneity and regional inequality are wide and visible. The division between the prosperous south of England, successful Scotland and the rest is striking. Moreover, the central London regions are extreme, which is not visible from the visual due to the Inner London West being an absolute outlier with more than 150 000 pounds of real GDP per capita. With this visualisation of our UK outcome variable, we can move on to the donor pool selection.

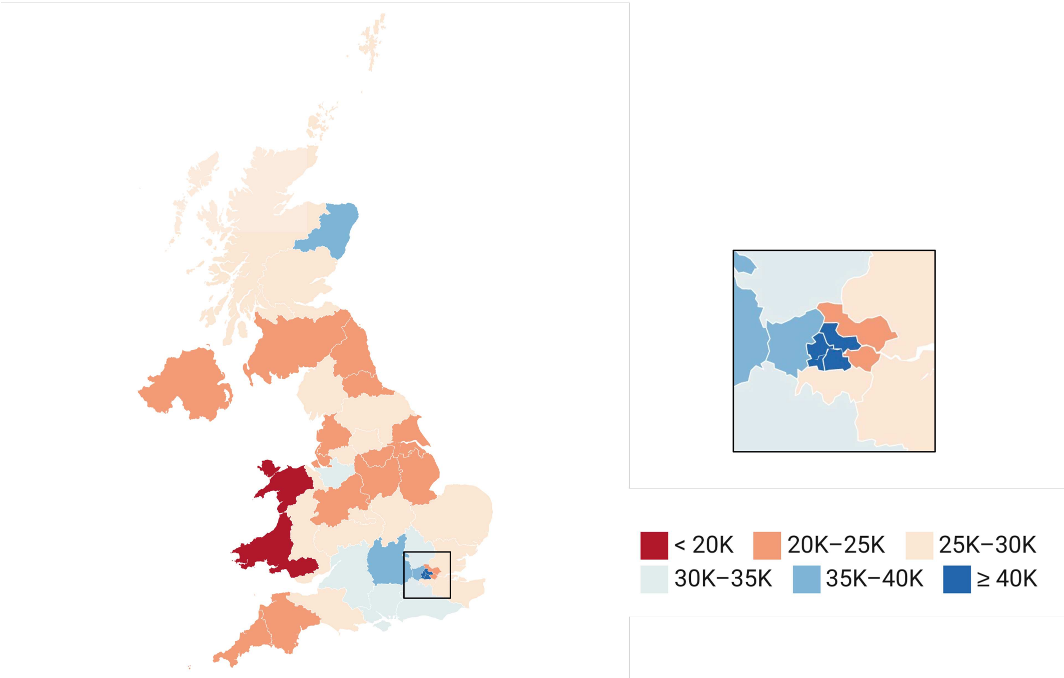


Figure 4.1: Average real GDP in British regions of NUTS 2 level between 1998-2020

4.3 Donor Pool selection

The core idea of the SCUL, which eased the data collection process for the treatment unit, is playing the opposite role for the Donor pool. In conventional SCM, the covariates' role is to help set the ideal weights that maximise the pre-treatment fit of both outcome and covariates variables. Thus, the need for their observed values ends at the start of the intervention. In SCUL, they instead work as donor pool units in the conventional SCM. Thus, they are part of the resulting synthetic unit. Therefore, they are necessary for every period in which the calibration and counterfactual estimation take place. Such constraints significantly curb our possible donor pool selection, eventually leading to the construction of two donor pools and two corresponding models. Let us introduce you to their detailed structure and the reasons that brought us to this unconventional solution.

To our knowledge, the biggest available database for regional economic data in economically developed countries is the Eurostat NUTS database. The biggest advantage overall is that the data are consistent across the states. We work with the already second-time re-processed data supplemented by sectoral disaggregation from the Annual Regional Database of the European Commission's Directorate General for Regional and Urban Policy, shortly ARDECO(Gardiner 2022). This database also consists of countries that are not member states of the EU, including Switzerland, Albania and Turkey. In sum, there are 296 regions of the NUTS2 regional

level available in this database. However, only restricting the availability of outcome variables for the years 1998-2020 decreases the amount of 254. We can add a few variables without a further radical decrease in the donor pool units, as we can still count on the 240 different regions around Europe. These variables are Gross Value Added (GVA), GDP growth rate, capital formation, productivity, employment, hours worked, population and real wages. The labour market is thus covered comfortably. However, we miss the economic structure of the regions. And here the complications begin. Even the widest available metric that stores this information decreases the number of regions in the donor pool to 88. This metric is GVA divided into six different sectors. However, until now, we were not defining which regions belong to which of these groups.
Thus let us visually provide this information in Figure 4.2. In this map of Europe in NUTS2 detail, we can see a clear colour division in relation to our model architecture. The grey regions are included in the ones included in the ARDECO data set, which already fail the outcome variable and the most important covariates. The yellow ones have available data for real GDP and other crucial covariates, and the green regions have all available information for all time periods. To sustain transparency, the offshore territories are not visible on the map, although their data availability is consistent with their European counterparts of; Portugal, Spain and France. Moreover, to provide the reader with a complete and transparent overview of the data used, please explore the **??**, where you can see the name, metric and model usage of every characteristic we use in consequent SCUL applications. Now we can see the data division, their respective definitions and possibilities for the donor pool creation a proceed to the data pool definition.

4.3.1 Model A - more characteristics

The first model is a very straightforward pick. Even after all the systematic elimination of regions, we still hold into account a substantial number of observations - 88 areas. Moreover, the parts are pretty heterogeneous as there are representative countries almost from every European sector. Central Europe is well engaged; the south region is represented by Spain, whereas the French and areas of Belgium depict the west. To sum up, Model A consists of 88 European parts out of 10 different European countries. Besides the outcome variable of actual output and the beforementioned significant covariates, it also operates with the local economy's structure. The representative variables for those are the division of GVA on Agriculture, Industry, Construction, Financial services, non-market services and the rest of the services. Together this makes 14 characteristics, which, combined with mentioned regions, produce 1056 donor pool variables.

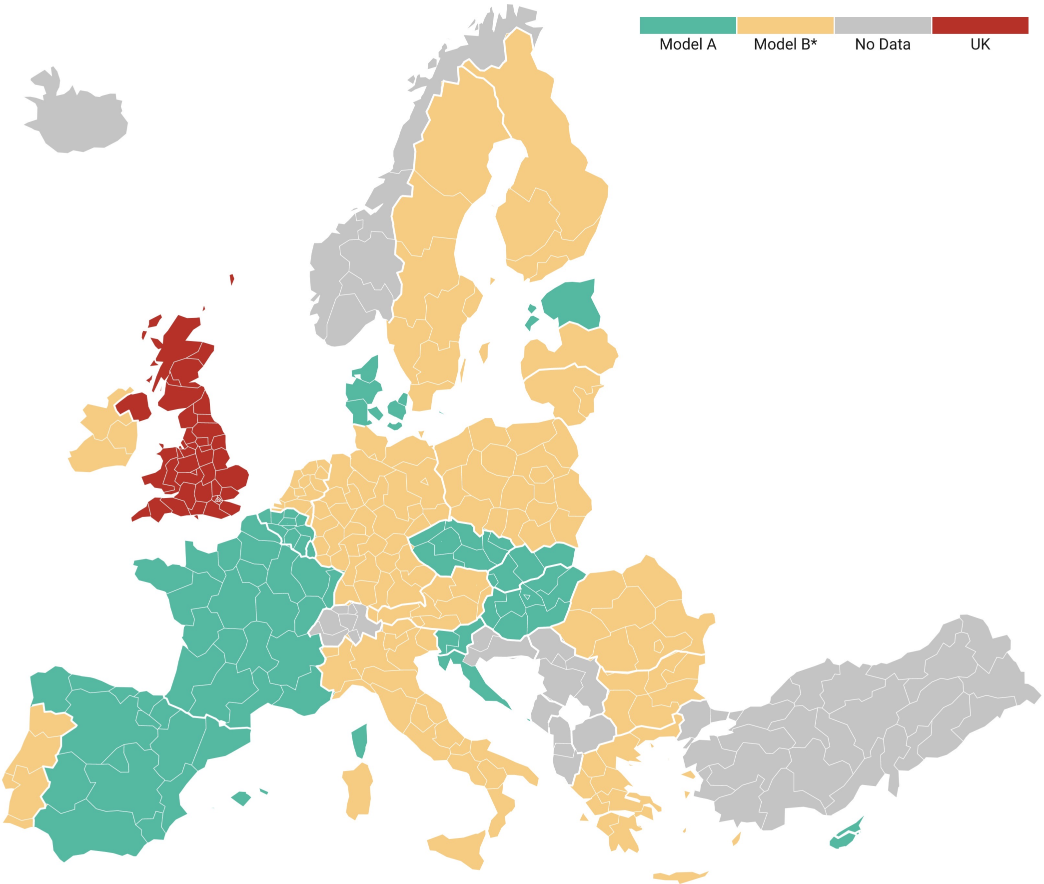


Figure 4.2: European regions of NUTS 2 classification and their data available in the context of our two data pools

4.3.2 Model B - more regions

However, we have decided to create also a less detailed characteristic-wise model. In our opinion, omitting German, Italian and Austrian regions could potentially sabotage the aim to construct a robust synthetic unit for UK regions. Especially for those most developed. Moreover, we have tools to differentiate the models with systematic inference methods. The model can count on 241 different regions across Europe. In line with the previously stated number and the combination of yellow and green territories, we have included the analysis's three Irish areas. We are aware of its potential conflict with the No inference condition described earlier (Abadie *et al.* 2015). The geographical proximity is a good factor, although one could argue similarly about the regions that belong to France. However, it must be noted that Ireland is the only land border with the EU country and UK. From our point of view, the role of Ireland in the entire post-referendum process is much more crucial. Due to the detailed and delicate history between Ireland and the UK, the Irish question was quite a hot topic during the negotiations (Considère-Charon 2020). As in the

Variable	Metric	Model
Gross Domestic Product	Million of Euros	Both
Gross Domestic Product growth	index (2015 = 100)	Both
Gross Value Added Total	Million of Euros	Model B
Gross Value Added (NACE sector A)	Million of Euros	Model A
Gross Value Added (NACE sectors B-E)	Million of Euros	Model A
Gross Value Added (NACE sector F)	Million of Euros	Model A
Gross Value Added (NACE sectors G-J)	Million of Euros	Model A
Gross Value Added (NACE sectors K-N)	Million of Euros	Model A
Gross Value Added (NACE sectors O-U)	Million of Euros	Model A
Total Population	Persons	Both
Total Employment	1000 jobs	Both
Worked Hours	1000 hours	Both
Wages	Million of Euros	Both
Productivity	Euros	Both
Capital Formation	Euros	Both

Table 4.1: Summary of Variables used in Models A and B from ARDECO database

case of incautious steps, there was a risk of civil unrest based on nationality topics. However, even the Thissen *et al.* (2020) that inspected the impact of Brexit on the EU regions explicitly had not found any distinguishing effect on the competitiveness of Ireland regions. The competitive struggles introduced by Brexit were shared with specific areas of Hungary and the Netherlands based on the relative sectoral economic compositions.

Last, we include these in line with previous SCM applications on the Leave referendum(Born *et al.* 2019; Fetzer & Wang 2020). The resulting model then consists of the outcome variable and significant covariates; GVA, GDP growth (2015 value normalized to 100), capital formation, productivity, employment, number of worked hours, population and real wages. The GVA is a single metric representing the entire sum of the sectors used in Model A. Together this makes nine characteristics and consequent 2169 donor pool variables. The fact that the amount of these inputs is even higher than for model A serves as another motivation for us to persuade both approaches.

4.4 OLS Regression

In the last data-dedicated sub-chapter, we will present the data selection for the OLS regression. This regression aim's to validate the hypothesis that the regional impact of Brexit was correlated with the referendum results. Thus, the first variables are implicitly pre-defined. The figures for the impact will be derived from our

SCUL estimation, and the referendum results are a self-defined variable as well. In selecting the other explanatory variables, we wanted to construct a model in line with the argumentation of the other scholars. Concerning the time structure of the user data, we implied it from the date of the pre-defined explanatory variable, the referendum. As the EU referendum took place in June of 2016, we decided to use all the explanatory variables from the prior year due to the data's annual structure, 2015.

The interconnecting narrative through which other scholars explored the estimation of heterogeneity was the differences in the relative industrial structure (Los *et al.* 2017; Brown *et al.* 2019; TUC 2020). Thus, similarly, as for Model A of our SCUL analysis, we use the data for the GVA as divided by the NACE sectors. However, there is more extensive detail of this industrial stratification available for the UK-only level. That we plan to utilize. Thus we use 20 different sectors instead of the 6 for the synthetic unit creation. Please see all the specific sectors in Table 4.2 and the other variables used for our OLS regression.

Moreover, the GVA data also serves as a more direct measurement of regional inequality. Thus we construct another variable from the region's relative GVA in comparing the GVA for the entire UK. We use The more detailed data available for the inner-country level and the demographic variables, which played a significant role in the referendum results (Goodwin & Heath 2016; Becker *et al.* 2017). Instead of the lone sum of the inhabitants, we can offer the stratification into five groups; between 0-24 years, 25-39 years, 40-54 years, 55-59 years and above 70 years. We expand the demographic dimension also to the other variable used in the synthetic estimation; of the labour market variables. Even though we could not find a clear unemployment cut specifically for the younger generation, we found a different approach. We use two variables for unemployment. Whereas one explores the unemployment for a population from 25 onwards, the other one does it for a bigger pool from 15-year old's forward.

Last but not least, the variable that was also mentioned in many interpretations of the regional inequality, referendum results as well the heterogeneous impact; the education(Goodwin & Heath 2016; Gutiérrez-Posada *et al.* 2021). We construct three representative variables that contain the relative amount of the region's population that has achieved the primary, secondary or tertiary level of education. The sources for all the upper mentioned variables were Eurostat and Office for National Statistics. The specific sources can be seen in the OLS data summarizing Table 4.2.

Monitored element	Specific variables and metrics	Data source
Brexit impact	The percentage difference between actual and synthetic region output.	Our analysis
Referendum results	The percentage of voters for Leaving the EU in the corresponding region.	Office for National Statistics
Demography	The percentages for the following age groups of population: 0-24 years, 25-39 years, 40-54 years, 55-69 years, 70+ years	Eurostat
Education	The percentage for a population that has achieved the following level of education: primary education, secondary education, tertiary education	Eurostat
Labour market	The amount of unemployed workforce among the following age groups of population: 15+ years, 25+years	Eurostat
Economic structure	Percentage of GVA created in following sectors according to NACE classification: **A** - Agriculture, **B** - Mining, **C** - Manufacturing, **D** - Electricity, **E** - Water supply and waste management, **F** - Construction, **G** - Wholesale and Retail, **H** - Transport and storage, **I** - Information and communication, **J** - Accommodation and food, **K** - Finance and Insurance, **L** - Real estate, **M** - Professional and technical activities, **N** - Administrative and support services, **O** - Public administration, **P** - Education, **Q** - Health and social work **R** - Entertainment, **S** - Other services, **T** - Households as employers	Office for National Statistics
Inner-country relative economic position	GVA of the region as a percentage of UK's GVA	Office for National Statistics

Table 4.2: Summary of Variables used in OLS regression and corresponding data sources

Chapter 5

Results

In this chapter, we shall present our empirical results. We offer the generated synthetic controls from the two corresponding SCUL models in the first two sections. For every one of these models, we offer the estimated impact for the latest available years, 2019 and 2020. We also provide the results of the inference methods and comment consequently on the robustness of our results. The inference methods explicitly hint that Model B is statistically superior to Model A.
Moreover, we acknowledge the radical drop in output during the pandemic year 2020, although the donor-pool members also experienced the lockdowns. Furthermore, in that year also, the final version Withdrawal agreement was signed by UK PM. Thus in the second part of this chapter, we introduce the regression-based only on the impact estimated in the year 2020 on the results of Model B.

5.1 Synthetic Model A

Let us start with the model results that included a smaller number of regions in its donor pool but utilized more essential characteristics about them. The synthetics in Model A were also created based on the information on the economic structure represented by GVA divided by the NACE sectors. In Figure 5.1, we can observe the visualised results for all 41 British regions for 2019 and 2020. The colour spectrum represents the difference between the real GDP development of the actual areas and their synthetic counterparts. The difference is presented in colour spectre percentage points intervals. The intervals enlarging further away from zero lay the resulting difference. The exact intervals can be seen on the legend between the two years. First, we need to address the elephant in the room; the enormous difference between 2019 and 2020. Almost two-thirds of British regions in 2019 showed a rise in output thanks to the referendum results. Where 14 out of 41 reach above three percent rise. On the contrary, only two regions sustained values above their synthetic counterparts in

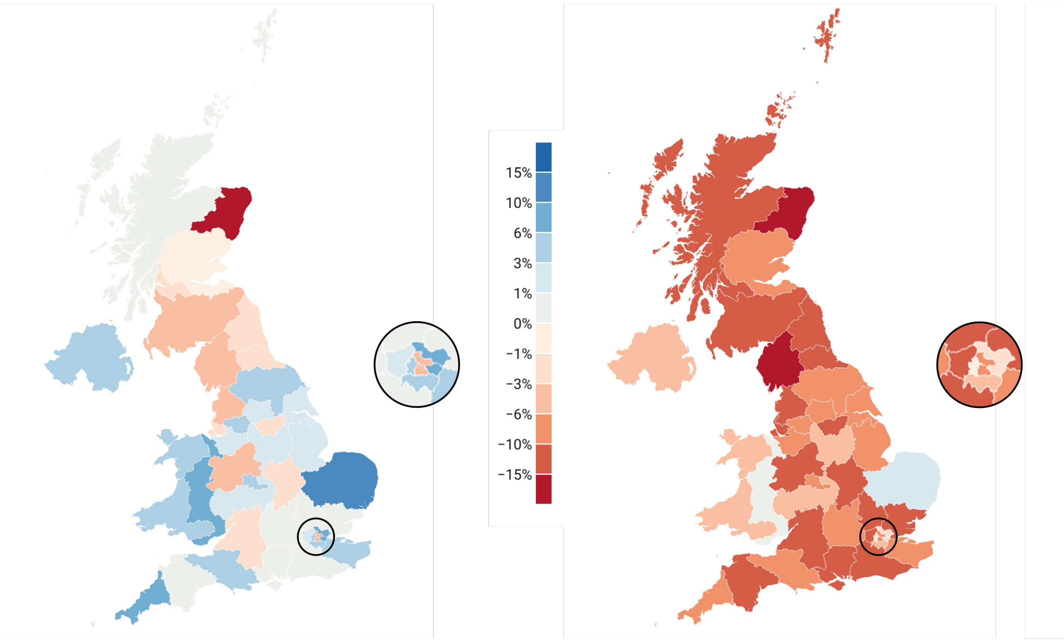


Figure 5.1: Model A Results, difference in percents between real UK and synthetic UK, the year 2019 on the left and 2020 on the right

2020: East Anglia and East Wales. The results for every single area and the United Kingdom as a whole achieved by simply summing the 41 regions can be seen in Table 5.1.

The pattern of massive fall of the real region output compared to the synthetic counterpart in between these two years is also present in Model B (see Figure 5.4). We argue that the spread of coronavirus has struck the countries heterogeneously to some degree, accordingly to different reactions to the pandemic. That does not contradict the notion that the exposure to Brexit has also mediated the consequences of the pandemics (TUC 2020; Petrie & Norman 2020; Tetlow & Pope 2021). We acknowledge that the over-leaping impact might be difficult to estimate and is limited by the short-data coverage of the pandemics. However, we proceed in the interpretation of both final years that are available in our models.

In the case of Model A, the results for the entire sum of all the regions are not in line with the previous literature for 2019. In Born *et al.* (2019) or Fetzer & Wang (2020) is the country-wide impact of Brexit reaching negative values around close to 2 percent of the output in 2019. Our model indicates a positive effect equal to 0,8 percent of the real output, which puts the robustness of the model in question even before the interpretation of the inference methods. The estimates for the pandemic year are equal to an 8.5% drop in the real output.

5.1.1 Inference

One of the attractive features of the SCUL methodology was the possibility of obtaining a conventional inference score. The obtained ranked p-values for model A can be seen in Table 5.1 for differentiation for both ends of the estimation in the year 2019 and the consequent 2020. Unfortunately, the obtained p-values hint that our estimates are far from significant. Even after stretching the standard threshold for p-value up to 0.1, we observe only seven statistically relevant assessments out of 41 for the model that ended in 2019. It isn't easy to find any common traits among them to find any pattern where the model functions robustly. It includes more urban areas such as Outer London, East and North East but also rural ones such as Cornwall and Isles of Scilly, which we explore further in the following region example. All but one of the more robust estimates conclude a positive impact of the Brexit referendum. The one being North Eastern Scotland, with an estimated 29.8 percent decline implied by the referendum. We consider the inference methods further pointing out the in-robustness of the model as only 17 percent of the region can be labelled as statistically significant for the 2019 year. The p-values are even worse for the pandemic year, with only three statistically substantial regions; Outer East and North East London, North Eastern Scotland and East Anglia. Due to the obtained low values, we consider the model fit unsatisfying. The smoke plots that more closely illustrate the system of getting ranked p values can be seen in the Appendix.

5.1.2 Region example - Cornwall and Isles of Scilly

To further explore the dynamics of the Model and the inference methods, we have also decided to present a region example. We know that selecting a single region can create an illegitimate conclusion. Thus we emphasize to the reader that the aim of including the specific case has more of an illustrative and qualitative analysis aim than a complex quantitative one. For the latter one, please explore Table 5.1 and corresponding chapters in Appendix; A.1.1 for the synthetic vs Actual comparison charts and A.1.2 for the smoke plots for the here discussed Model A.

For Model A, we have selected the Cornwall and Isles of Scilly case. The selection of this region is driven by a combination of its statistical relevance, rural character, Brexiter nature and radical fall introduced by the pandemics. Concerning the inference, the Cornwall region belongs to the seven statistically significant ones obtaining a p-value equal to 0,1, which hits the border of our stretched ten percentage significance interval for 2019. Unfortunately, it misses the spot with the p-value for the latter year equal to 0,16. However, we are still observing a relatively well-fitted SCUL model. Following up on the region's profile, it is a rural one where the Leave

Location	2019				2020			
	Difference	Actual	Synthetic	P value	Difference	Actual	Synthetic	P value
Bedfordshire and Hertfordshire	0,1%	35 075	35 035	0,42	-10,2%	31 108	34 287	0,83
Berkshire Buckinghamshire and Oxfordshire	0,5%	45 360	45 137	0,78	-7,7%	41 072	44 219	0,46
Cheshire	2,4%	40 661	39 681	0,35	-7,8%	36 410	39 247	0,59
Cornwall and Isles of Scilly	6,8%	23 110	21 542	0,1*	-8,0%	19 832	21 426	0,16
Cumbria	-5,1%	28 314	29 768	0,32	-20,6%	24 372	29 399	0,11
Derbyshire and Nottinghamshire	3,0%	26 543	25 757	0,3	-4,3%	23 685	24 715	0,46
Devon	0,7%	25 376	25 209	0,49	-12,8%	21 906	24 713	0,45
Dorset and Somerset	3,2%	26 607	25 758	0,09*	-9,4%	23 438	25 648	0,45
East Anglia	10,0%	29 814	26 831	0,08*	1,4%	26 539	26 178	0,08*
East Wales	6,8%	29 711	27 700	0,12	0,9%	26 465	26 216	0,12
East Yorkshire, Northern Lincolnshire	1,7%	26 781	26 339	0,55	-6,7%	23 880	25 480	0,88
Eastern Scotland	-0,6%	32 885	33 073	0,94	-8,9%	29 272	31 878	0,45
Essex	0,9%	27 675	27 437	0,28	-10,5%	24 218	26 770	0,99
Gloucestershire Wiltshire, BathBristol	-2,3%	34 666	35 451	0,57	-12,9%	30 958	34 957	0,2
Greater Manchester	3,4%	30 168	29 140	0,31	-7,6%	26 916	28 973	0,6
Hampshire and Isle of Wight	0,8%	34 460	34 176	0,86	-10,8%	30 517	33 800	0,45
Herefordshire, Worcestershire, Warwickshire	2,0%	32 182	31 553	0,2	-5,3%	28 053	29 530	0,29
Highlands and Islands	0,3%	28 931	28 848	0,88	-10,1%	25 566	28 150	0,53
Inner London East	-4,0%	51 643	53 733	0,66	-6,5%	46 385	49 422	0,46
Inner London West	5,7%	187 627	176 888	0,17	-0,2%	170 695	171 029	0,18
Kent	3,0%	28 499	27 635	0,17	-7,5%	25 189	27 068	0,46
Lancashire	-3,9%	26 218	27 250	0,85	-14,5%	23 061	26 396	0,26
Leicestershire, Rutland, Northamptonshire	-1,4%	29 129	29 532	0,81	-12,1%	25 946	29 096	0,24
Lincolnshire	1,6%	24 003	23 612	0,26	-9,2%	21 042	22 969	0,73
Merseyside	-2,4%	25 395	26 017	0,74	-13,2%	22 550	25 517	0,31
North Eastern Scotland	-29,8%	38 824	50 407	0,09*	-40,8%	34 667	48 799	0,05**
North Yorkshire	3,8%	29 808	28 674	0,13	-9,7%	25 981	28 489	0,28
Northern Ireland	4,3%	26 551	25 422	0,1*	-4,4%	23 738	24 791	0,15
Northumberland, Tyne and Wear	-2,2%	26 010	26 595	0,97	-13,5%	22 576	25 620	0,41
Outer London, East and North East	9,6%	24 214	21 900	0,07*	-3,0%	20 919	21 542	0,09*
Outer London, South	3,7%	30 078	28 967	0,23	-5,3%	26 554	27 971	0,41
Outer London, West and North West	1,2%	39 525	39 059	0,29	-10,5%	34 095	37 671	0,73
Shropshire and Staffordshire	-3,3%	25 244	26 082	0,73	-14,0%	22 323	25 452	0,2
South Yorkshire	-2,3%	23 183	23 709	0,7	-11,0%	20 535	22 793	0,28
Southern Scotland	-3,1%	24 189	24 932	0,74	-12,0%	21 783	24 404	0,27
Surrey East and West Sussex	0,2%	34 504	34 436	0,8	-10,0%	30 732	33 815	0,28
Tees Valley and Durham	-1,6%	22 404	22 756	0,55	-11,1%	19 921	22 127	0,28
West Central Scotland	-1,5%	30 404	30 869	0,99	-10,3%	27 137	29 923	0,45
West Midlands	4,5%	27 050	25 834	0,07*	-7,6%	23 858	25 663	0,12
West Wales and The Valleys	3,4%	22 421	21 651	0,23	-5,1%	19 666	20 666	0,35
West Yorkshire	1,6%	28 371	27 903	0,45	-6,3%	25 181	26 777	0,88
United Kingdom (SUM)	0,8%	1 383 613	1 372 298		-8,5%	1 228 741	1 333 586	

Table 5.1: Complete results of Model A for years 2019 and 2020

option in the referendum has won by a gain of 56,5 percent points. This implies that Cornwall appears in the top third of the 41 regions distribution, ranked by the support for the leave. It even obtains the lowest portion of the population that has reached tertiary education among all the regions, equal to 32 percent of its inhabitants. Moreover, it has the smallest GVA among all the other 41 regions in the UK in the year before the referendum. Thus we are observing a quite stereotypical pro-leave region with lower productivity, a lower ratio of high-education inhabitants, and a reasonably fitted model.
In Figure 5.3, we can observe that the variation between Cornwall and its synthetic counterpart is relatively high, at least for the first three years till 2019. In the so-called "smoke plot", the difference between the region and its counterpart is visualized by the thick green line. When it reaches values above zero, the real region has over-performed its synthetic counterpart and vice versa. The black line mess represents this relationship for all the placebos constructed from all the donor regions used for this Model. This figure visualizes the reasoning behind the obtaining of the ranked p-value. Also, it lets us easily explore the fitting before the intervention of the referendum, which is very suitable, as the gap between the synthetic and real units has started growing since the referendum year. Now we can move on to Figure 5.2 to observe the motive behind the significant drop in the last year of estimation. As we can see, the output of the real unit is significantly greater than the synthetic one up to 2019. The synthetic one stagnates through the period and does not alter substantially even during the last year of our estimation, which also happens to be the first year of the Covid pandemic. In the previous period between 2019 and 2020, the synthetic output falls by 0,53 percent. Instead, the real Cornwall region records a much more significant fall in the same period. It is equal to stunning 14 percentage points. We do not aim to deny the hypothesis that was also presented by other scholars (TUC 2020), that Brexit had an impact on the ability of the UK to handle the pandemics. However, we believe the introduced drop might also be caused by the fact that the Withdrawal deal was finally passed by parliament (Parliament 2020), which ended the period of economic uncertainty with a specific defined formal agreement one year before its activation.

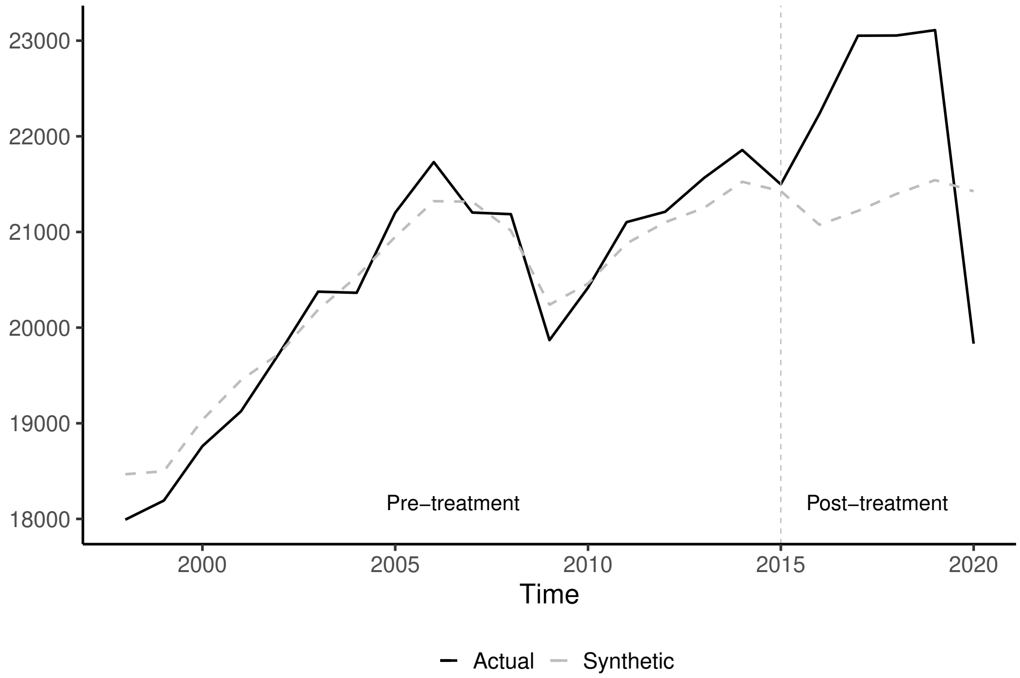


Figure 5.2: Model A region example - Cornwall and Isles of Scilly, difference between the real region and synthetic region

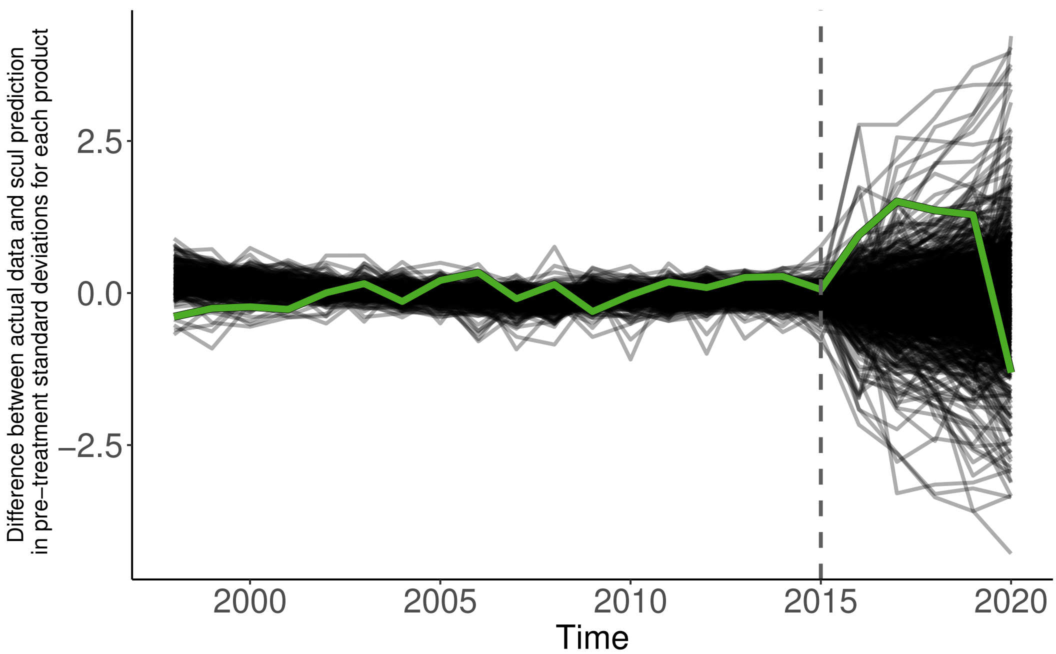


Figure 5.3: Model A region example - Smokeplot of Cornwall and Isles of Scilly

5.2 Synthetic Model B

Model B includes 241 regions, 153 more than its A alternative. Although the comparison it lacks the variables describing the division of GVA between the NACE sectors. The visualized results can be observed in Figure 5.4. The figure is consistent with the previous model's visualisation, using the same colour scheme and dividing the Model into two years. The difference between the estimate covering the period ending in 2019 and the one ending in 2020 has the same negative direction as in model A. However, the specific values differ widely. In the pandemic year, there is not a single region in the UK. The actual output would be higher than the one of its synthetic counterpart. In other words, after passing the withdrawal agreement bill, there is not a single region that would benefit from the UK leaving the EU.

The overall synthetic UK, obtained by the simple sum of all estimated 41 regions,

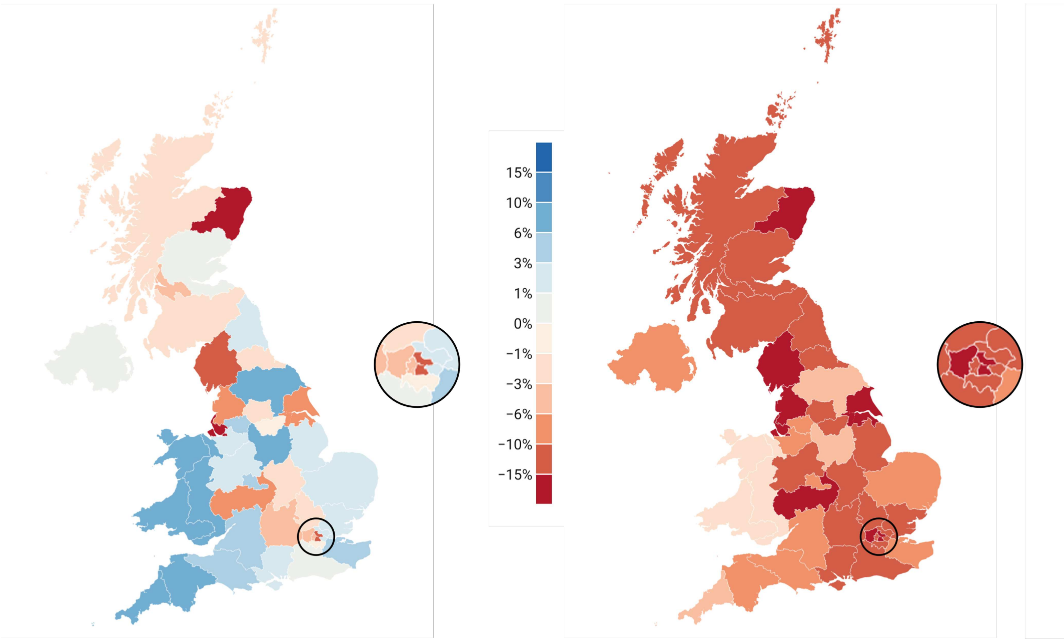


Figure 5.4: Model B Results, difference in percents between real UK and synthetic UK, the year 2019 on the left and 2020 on the right

is 1,8 percent higher than the actual output of the UK in 2019. This is consistent with other scholars' estimates for the same period mentioned before that obtained the results of around 2 percent loss (Born *et al.* 2019; Fetzer & Wang 2020). For the upcoming year 2020, the drop in the real output of the summed UK is equal to 13,6%. That is very much in the range of the estimation of Springford (2022) that shows the Brexit introduced loss in the similar time around 13%. Thus we consider the results for both years robust ones.

They are divided almost precisely into two halves on the level of regions. As for 22 regions, their synthetic estimate is lower than their factual output, and 19 regions'

estimates act the other way around for 2019. The regions that were advantaged the most from the results of the referendum, according to this estimate, are East Wales, North Yorkshire and West Wales, where all achieved more than a 9 percent rise against the synthetic regions. Such results are a bit contra-intuitive in the context of the rural-urban divide we mentioned earlier. All three are mostly rural regions. The majority voted for Brexit. On the other side of the spectrum, we can observe four regions; Inner London East, Cumbria, Merseyside and North Eastern Scotland. All lose more than one-tenth of their outputs, with the Scottish region losing a stunning one-third of its real GDP.
The drop for this region expands to almost one-half in the year 2020. Overall, among all regions, the 2020 year means drop by an average of 10%, without considering their previous score. We present all the results for the 41 areas in table 5.2.

5.2.1 Inference methods

The obtained p-values are relatively better than Model A. Almost 31 percent of the estimated regions have a p-value below 10 point threshold for 2019, and nearly one-quarter of the variables hit the entry for 2020. This time the pattern is relatively more straightforward, although not in the structural way of the regions. All the statistically significant areas besides Essex are achieving relative extremes in impact. In other words, if we would order the 41 areas in line by the level of difference between the synthetic unit and the actual unit, the bottom three and the top nine with the highest gain from Brexit are the ones with a significant p-value. The pattern can be econometric-ally discussed to which degree the ranked nature of the p-value implies it in this SCUL application. However, we consider that Model B has achieved sufficient robustness to approve the hypothesis that Brexit had a heterogeneous impact on the British regions, as we can observe that the statistical significance is shallow with a less radical effect. The importance can be found at the extreme that proves this hypothesis. Moreover, we will take these results to the next step; to test whether there is some relationship between the voting in the referendum and Brexit's structural impact.

5.2.2 Region example - North Eastern Scotland

To further explore the dynamics of the model and the inference methods, we are repeating the same approach as for model A, observing the regional example closely. The reasoning and limitations are the same as we have mentioned in the previous case. Thus we stress again that this one region case study is provided to further qualitatively analyse the dynamics of the model and specific narratives rather than a complex quantitative one.

Location	2019				2020			
	Difference	Actual	Synthetic	P value	Difference	Actual	Synthetic	P value
Bedfordshire and Hertfordshire	-1,9%	35 075	35 754	0,34	-12,7%	31 108	35 072	0,75
Berkshire Buckinghamshire and Oxfordshire	-3,5%	45 360	46 929	0,31	-13,1%	41 072	46 465	0,17
Cheshire	1,1%	40 661	40 198	0,45	-9,3%	36 410	39 787	0,91
Cornwall and Isles of Scilly	8,3%	23 110	21 184	0,07*	-5,9%	19 832	21 004	0,09*
Cumbria	-11,1%	28 314	31 466	0,1*	-28,2%	24 372	31 236	0,04**
Derbyshire and Nottinghamshire	7,2%	26 543	24 628	0,09*	-3,4%	23 685	24 491	0,12
Devon	8,9%	25 376	23 128	0,07*	-6,2%	21 906	23 266	0,11
Dorset and Somerset	5,5%	26 607	25 151	0,04**	-7,1%	23 438	25 093	0,09*
East Anglia	2,5%	29 814	29 080	0,34	-8,4%	26 539	28 777	0,87
East Wales	10,0%	29 711	26 741	0,07*	-1,5%	26 465	26 866	0,07*
East Yorkshire, Northern Lincolnshire	-7,6%	26 781	28 826	0,23	-16,7%	23 880	27 873	0,08*
Eastern Scotland	0,6%	32 885	32 677	0,59	-11,6%	29 272	32 670	0,53
Essex	1,3%	27 675	27 303	0,07*	-10,3%	24 218	26 713	0,13
Gloucestershire Wiltshire, BathBristol	3,7%	34 666	33 369	0,21	-7,2%	30 958	33 174	0,43
Greater Manchester	3,5%	30 168	29 110	0,31	-8,8%	26 916	29 275	0,75
Hampshire and Isle of Wight	1,4%	34 460	33 967	0,91	-12,2%	30 517	34 248	0,36
Herefordshire, Worcestershire, Warwickshire	-6,4%	32 182	34 236	0,4	-20,4%	28 053	33 778	0,11
Highlands and Islands	-1,4%	28 931	29 340	1	-12,9%	25 566	28 863	0,37
Inner London East	-11,1%	51 643	57 382	0,25	-20,7%	46 385	55 998	0,12
Inner London West	-4,4%	187 627	195 847	0,84	-14,8%	170 695	195 880	0,35
Kent	5,5%	28 499	26 918	0,08*	-6,8%	25 189	26 909	0,17
Lancashire	-7,6%	26 218	28 203	0,59	-19,1%	23 061	27 473	0,13
Leicestershire, Rutland, Northamptonshire	-1,7%	29 129	29 629	0,73	-14,5%	25 946	29 706	0,17
Lincolnshire	1,6%	24 003	23 621	0,16	-10,5%	21 042	23 241	0,53
Merseyside	-17,1%	25 395	29 736	0,07*	-36,2%	22 550	30 723	0,03**
North Eastern Scotland	-34,2%	38 824	52 088	0,06*	-48,9%	34 667	51 635	0,03**
North Yorkshire	9,5%	29 808	26 978	0,05**	-3,9%	25 981	26 982	0,06*
Northern Ireland	0,5%	26 551	26 406	0,18	-7,5%	23 738	25 523	0,36
Northumberland, Tyne and Wear	1,5%	26 010	25 624	0,68	-14,2%	22 576	25 777	0,55
Outer London, East and North East	1,1%	24 214	23 938	0,21	-11,0%	20 919	23 230	0,78
Outer London, South	-0,4%	30 078	30 207	0,5	-11,1%	26 554	29 509	0,4
Outer London, West and North West	-4,5%	39 525	41 299	0,67	-17,2%	34 095	39 972	0,3
Shropshire and Staffordshire	1,1%	25 244	24 965	0,31	-11,3%	22 323	24 844	0,79
South Yorkshire	-1,0%	23 183	23 405	0,27	-12,2%	20 535	23 043	0,89
Southern Scotland	-2,7%	24 189	24 846	0,76	-11,9%	21 783	24 372	0,26
Surrey East and West Sussex	0,3%	34 504	34 392	0,79	-11,7%	30 732	34 314	0,21
Tees Valley and Durham	-1,0%	22 404	22 639	0,53	-14,6%	19 921	22 824	0,2
West Central Scotland	-5,1%	30 404	31 940	0,61	-14,4%	27 137	31 039	0,22
West Midlands	3,9%	27 050	26 008	0,06*	-7,5%	23 858	25 658	0,1*
West Wales and The Valleys	9,3%	22 421	20 331	0,06*	-2,9%	19 666	20 231	0,07*
West Yorkshire	-2,2%	28 371	28 995	0,97	-13,8%	25 181	28 649	0,26
United Kingdom (SUM)	-1,8%	1 383 613	1 408 484		-13,6%	1 228 741	1 396 183	

Table 5.2: Complete results of Model B for years 2019 and 2020

In the previous case, we observed a Brexit-supported region; thus, we have chosen the opposite here. We have also sustained the decision factors; the statistical significance, economic productivity and clear stance on the referendum results. These were the variables that persuaded us to zoom in on the region of North Eastern Scotland. From the statistical point of view, the significance is supported by the p-value that obtains 0,06 for the estimation ending in the year 2019 and even bigger significance in the pandemic year 2020, resulting in 0,03. The support of the EU in the region is the 6th highest in the country, with a 58 percent share of votes for remain. That is not a surprising result, concerning that the support for the EU was higher across Scotland, and this region contains two urban centres, Aberdeen and Dundee. This is also reflected in the educational statistics, where more than half of the regional inhabitants achieved tertiary education. The 52 percent share of people who achieved tertiary education implies that North Eastern Scotland is in the top 5 regions concerning high education statistics. This further translates also to the economic figures. The region is the 6th most successful in the output per capita metrics. These figures illustrate quite a consistent story about well-above-average educated and productive regions with urban centres that have voted in the referendum according to these statistics.
Concerning the results, let us observe figures 5.5 and 5.6. The perfect fit can be seen from both figures as in the 5.5 we can see both the dotted grey line representing synthetic unit and the black actual representing region ultimately overlapping till the intervention hits. The same can be seen from the constant difference equal to zero in figure 5.6. Staying in this figure, we can see a clear and consistent drop since the referendum took place. The difference is, at the same time, significantly higher than for the placebo units throughout the after-referendum years. The black lines' mess represents the placebo unit's development. We can observe the dynamics behind significant p-value over the entire estimated period. The resulting difference between synthetic North Eastern Scotland and the real region obtains the highest difference among all the estimated regions, reaching negative 34,2 percentage points in 2019 and 48,9% in the final year. The estimated impact is an outlier compared to the rest of our pool. On the other hand, the direction of the effect is characteristic of the regions that voted overwhelmingly to remain in the referendum. We can see the negative impact around the London region and most other Scottish ones. We will aim to inspect these counter-intuitive relationships in the next sub-chapter that presents the results of the OLS regression.

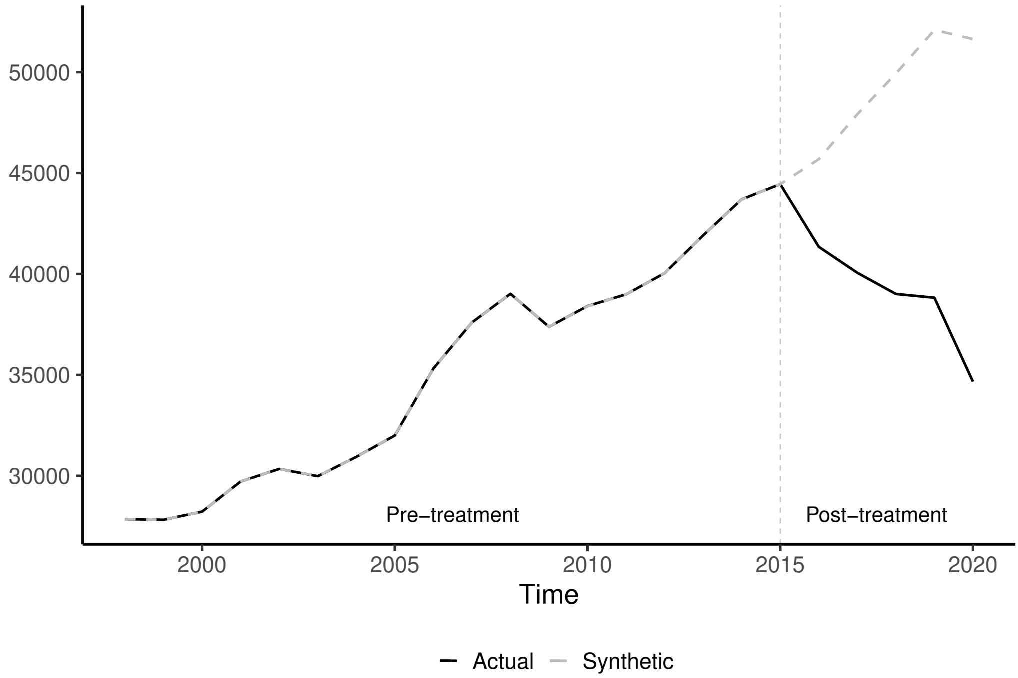


Figure 5.5: Model B region example - North, Eastern Scotland, the difference between the real region and synthetic region

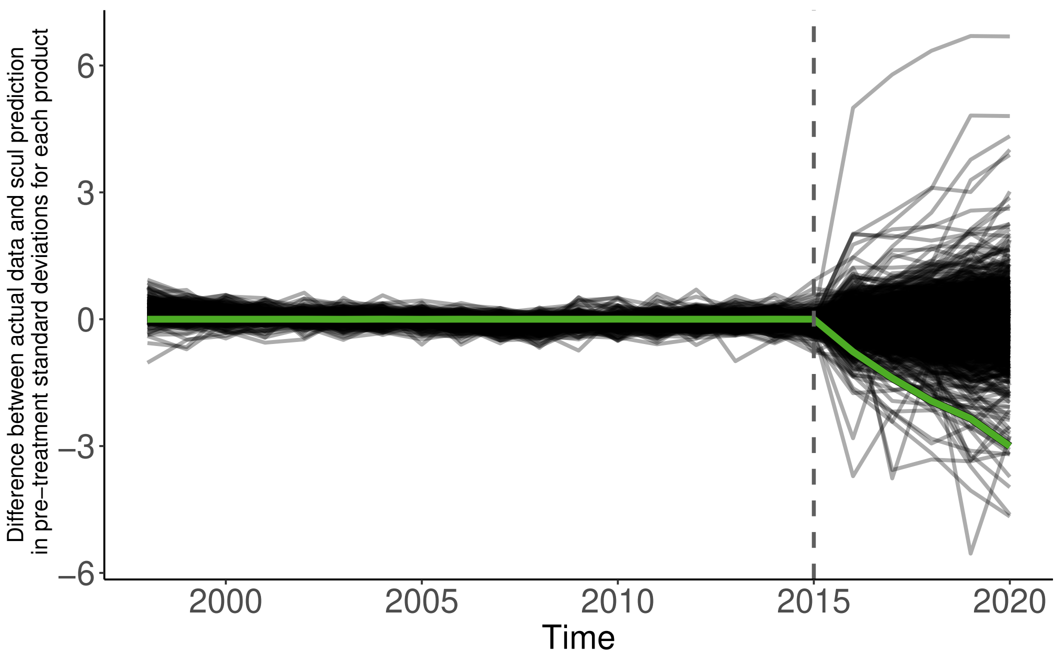


Figure 5.6: Model B region example - Smoke plot of North, Eastern Scotland

5.3 OLS results

In this sub-chapter, we present the results of our OLS regression. We have constructed three models out of the variables we have introduced in the data corresponding sub-chapter. All include the referendum result variable and the proxy for regional economic inequality. Model 1 is also constructed from the GVA stratification according to NACE sectors. The second one includes, instead of the economic structure, the regional demographic profile, information about the achieved education and labour market information. The last model includes all variables. As we explained previously, we use the results only from Model B as they are much more statistically significant and robust when compared to other scholars' work. To be precise, we use the impact estimated for the year 2020.

The results for all three model variations can be seen in table 5.3. The R squared is the biggest for the last model, achieving 0.91, although it is relatively big for the model that contains the NACE sectors distribution. This hints that the economy's structure is relatively more important than the demographic information to explain the Brexit impact. However, one could also argue that this information's also, to some extent, included in the Brexit referendum results variable as it was strongly correlated with the level of education and distribution of the age groups in the region. The results are quite poor concerning the significance of the specific variables in the models. There are only two variables whose corresponding p-value is below 0.05; the percentage of people between the ages of 25-39 for Model 2 and the referendum results for Model 3. First, let us briefly comment on the first significant variable. Its relevance is very disputable as the model's R squared is low, and all other age groups obtained a negative parameter even within the standard distribution range. Moving on to the referendum variable in Model 3, "Lper" represents the percentage of points that were voted for the Leave in the referendum. The parameter equal to 0.86 hints at a positive relationship between the Brexit votes and consequent impact. Both the impact on economic output and the referendum are provided in percentage points. Thus, the parameter can be interpreted in the following way. For every percent economy's structure is a 0.91 percent rise in the output gap between the real leaving the UK region and the synthetic remained UK region. Studying this relationship was one of the three essential hypotheses of this thesis.

These results are quite contrary to all ex-ante and the one ex-post study focused on regional differences in the impact of Brexit. On the other hand, it is consistent and entirely predictable with the SCUL results explored in the previous sub-chapter. We have already briefly commented on the opposite nature of our estimation, where the rural areas ought to benefit from the act of leaving the EU. However, the parameter from Model 3 has to be taken with the amount of salt. No other variable in the

model could be considered statistically significant.
Moreover, the intercept and all the variables representing the economic structure have more than one hundred times higher magnitude with highly volatile outcomes. However, we consider the results of this OLS regression as an approval of our qualitative interpretation of the SCUL estimates. It indicates that our estimated impact of Brexit in the first two years contradicts other research, as the regions that voted to remain in the EU seem to suffer more economically. Moreover, contrary to other scholars, such results indicate that Brexit's impact might decrease regional inequality.

	Model 1	Model 2	Model 3
(Intercept)	466.29 (287.09)	−16.87 (25.13)	499.36 (316.78)
Leave (%)	0.27 (0.21)	0.10 (0.27)	0.91* (0.37)
GVA of UK (%)	1.36 (1.74)	1.17 (1.23)	1.94 (2.65)
0-24 years		−3.66 (2.47)	2.61 (4.78)
25-39 years		−5.46* (2.27)	0.51 (3.62)
40-54 years		−4.94 (2.76)	1.31 (3.72)
55-69 years		−7.41 (4.52)	1.21 (8.25)
primary education		21.16 (24.89)	28.64 (26.88)
secondary education		20.93 (24.68)	28.45 (26.49)
tertiary education		21.38 (24.90)	30.09 (26.60)
unemployed 15+		5.21 (3.54)	7.49 (4.26)
unemployed 25+		−4.82 (4.50)	−10.09 (5.62)
GVA_A	−467.96 (286.79)		−530.42 (313.71)
GVA_B	−468.62 (286.82)		−532.56 (313.34)
GVA_C	−467.00 (287.07)		−530.82 (313.76)
GVA_D	−464.64 (287.09)		−529.52 (313.59)
GVA_E	−466.03 (287.66)		−534.06 (313.49)
GVA_F	−467.20 (287.09)		−528.82 (314.01)
GVA_G	−466.46 (287.20)		−531.48 (313.62)
GVA_H	−467.05 (286.99)		−530.78 (313.36)
GVA_I	−463.10 (286.79)		−525.68 (313.47)
GVA_J	−467.00 (287.02)		−530.67 (313.76)
GVA_K	−466.41 (287.11)		−530.13 (313.78)
GVA_L	−466.46 (287.12)		−532.37 (313.69)
GVA_M	−467.44 (287.24)		−532.34 (314.13)
GVA_N	−465.17 (286.87)		−529.14 (313.46)
GVA_O	−465.73 (287.72)		−531.90 (314.21)
GVA_P	−466.14 (286.64)		−531.17 (313.05)
GVA_Q	−466.53 (286.79)		−526.94 (313.48)
GVA_R	−473.48 (288.77)		−541.92 (315.89)
GVA_S	−462.30 (286.44)		−524.17 (312.63)
GVA_T	−453.09 (289.96)		−485.52 (325.18)
R^2	0.78	0.46	0.92
Adj. R^2	0.51	0.25	0.62
Num. obs.	41	41	41

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 5.3: OLS models (Model 1 - economic structure, Model 2 - demographic structure, Model 3 - combined)

Chapter 6

Conclusion

In this thesis, we have applied a new, recently developed methodology SCUL to the impact of Brexit on the regional level of the UK. The data availability limits the obtained results till the first pandemic year in 2020. We have constructed two models, one containing more information about the donor pool members and the other with more regions with fewer characteristics variables. The latter has produced much more robust results, with 10 out of 41 regions obtaining a ranked p-value below 0.1. Moreover, the sum of the Brexit impact on the real GDP in 2019 is consistent with other studies on a national level, equal to a drop in the output by 2 percent. The results hint at an enormous drop in 2020, the year the withdrawal agreement bill was passed, equal to 13,6%.

On the other hand, the results contradict other literature on the regional level, as the regions that experienced the biggest loss introduced by Brexit are the London and the Scottish areas. This is in direct opposition to the literature dedicated to estimating the spatially heterogeneous impact of Brexit, where the less productive ones that overwhelmingly voted for Brexit end up being the most economically beaten up by the referendum results. In our estimation, these regions, as those in rural England or Wales, benefit from leaving the EU. We have further approved this relationship by the OLS regression, where we have found a significant positive parameter next to the Leave percentage vote as an explanatory variable for Brexit impact equal to 0.91.

We conclude that the resulting difference in 2019 is introduced not by Brexit itself but by the uncertainty that the referendum introduced. The drop in 2020 reflectsreflects the response to finally passing a bill containing the formal description of Brexit, mixed with pandemics. In our opinion, the impact of the formal Brexit dynamics can be fully observed only after 2021, which was out of the scope of this thesis due to the data availability. Only after this term, the withdrawal agreement was activated, and the UK economy had the opportunity to bounce back from the lockdown period.

Concerning the pioneering methodology we have applied, we consider it a successful and suitable application of a novel approach. It has ideal in formalized matters dealing with the issue of over-fitting and the great size of the donor pool. Moreover, the statistically more significant model has provided results consistent with the national research, which is much richer and thus more robust than the regional one. For future applications, we recommend preferring more donor pool units than the details of their characteristics. Therefore we recommend this methodology for future usage of regional studies and possibly also for studying the heterogeneous economical impact on British regions in the future, which will create much more contribution with the availability of data after the year 2021.

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Appendix A

SCM results

A.1 Model A

A.1.1 SCM Results

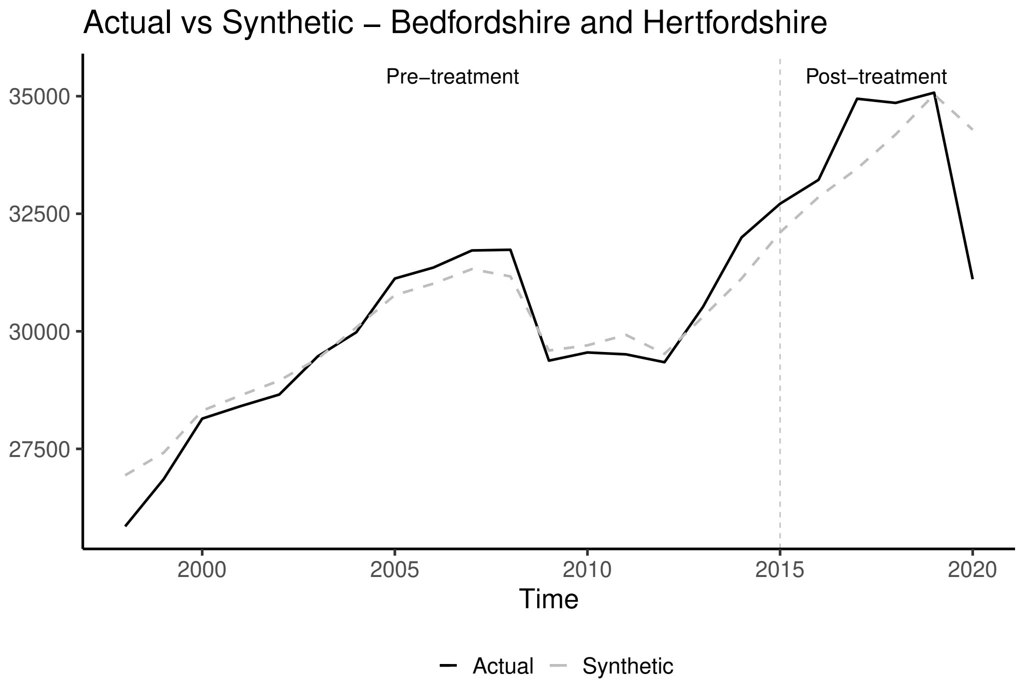

Figure A.1: Model A: Development of Actual and Synthetic GDP of Bedfordshire and Hertfordshire

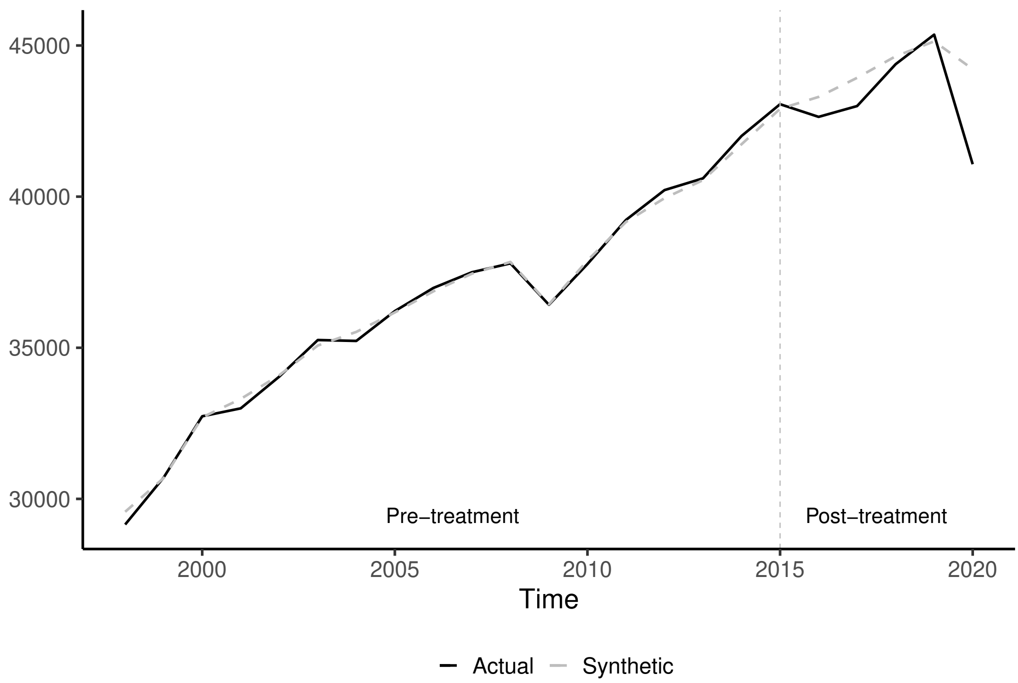

Figure A.2: Model A: Development of Actual and Synthetic GDP of Berkshire Buckinghamshire and Oxfordshire

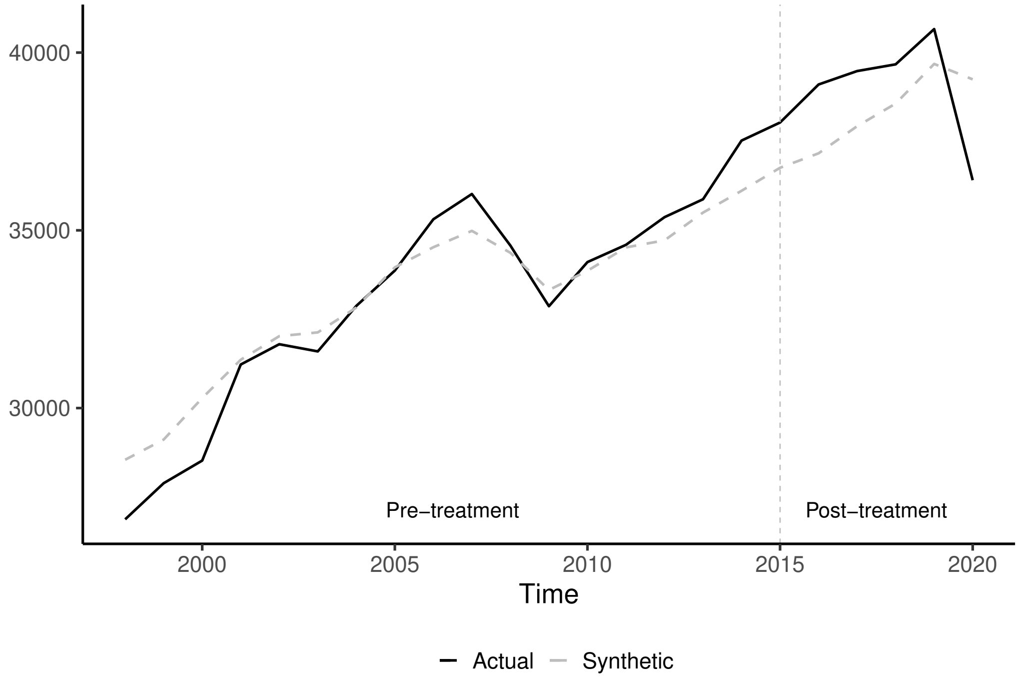

Figure A.3: Model A: Development of Actual and Synthetic GDP of Cheshire

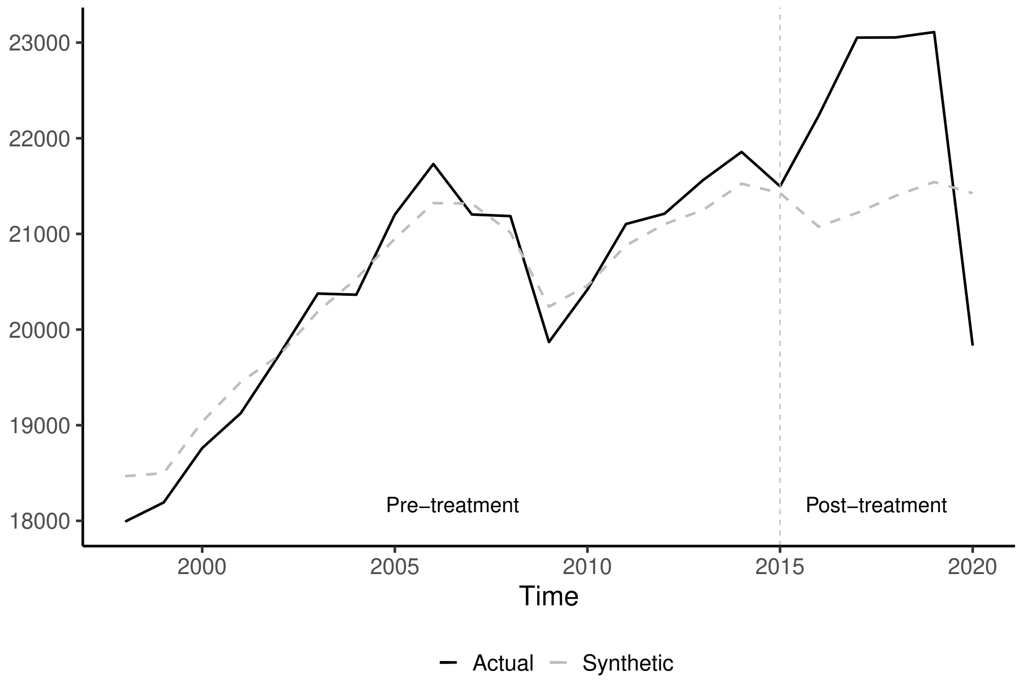

Figure A.4: Model A: Development of Actual and Synthetic GDP of Cornwall and Isles of Scilly

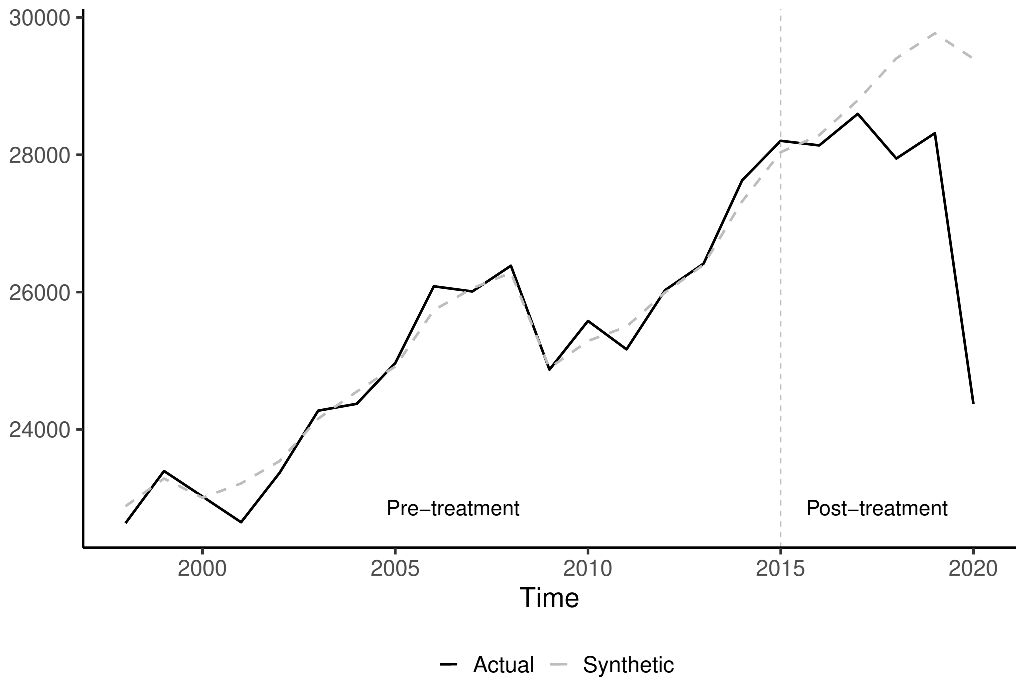

Figure A.5: Model A: Development of Actual and Synthetic GDP of Cumbria

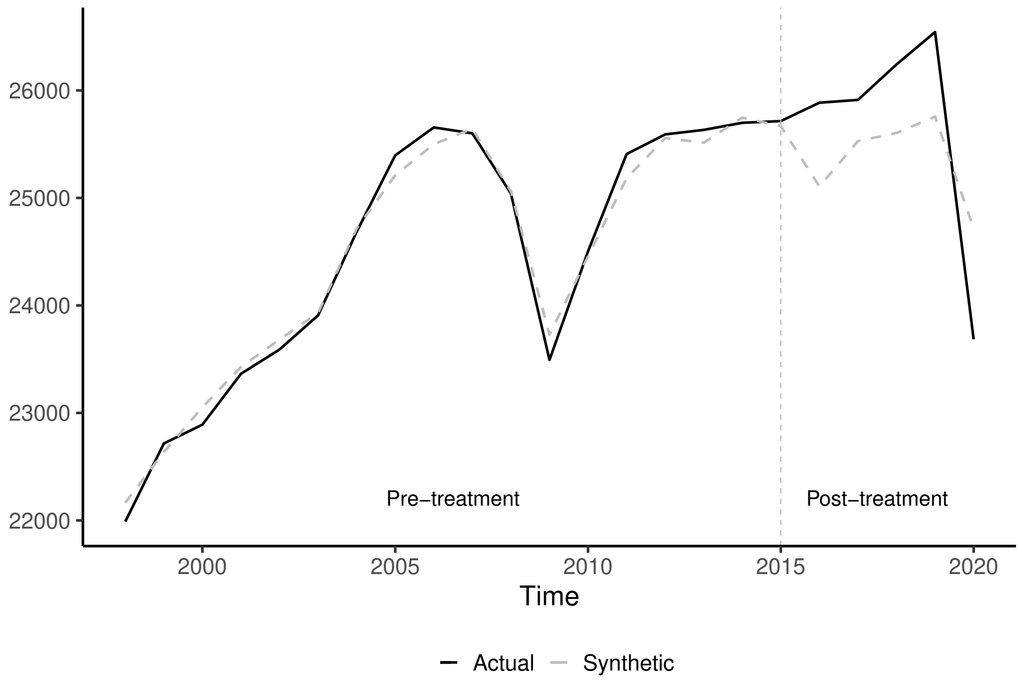

Figure A.6: Model A: Development of Actual and Synthetic GDP of Derbyshire and Nottinghamshire

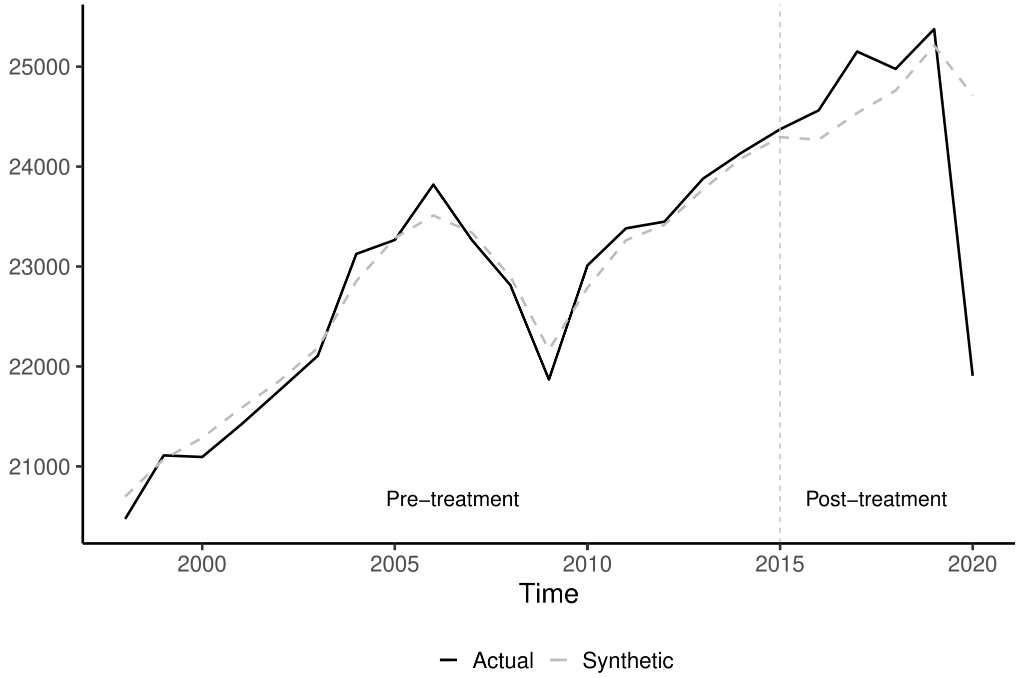

Figure A.7: Model A: Development of Actual and Synthetic GDP of Devon

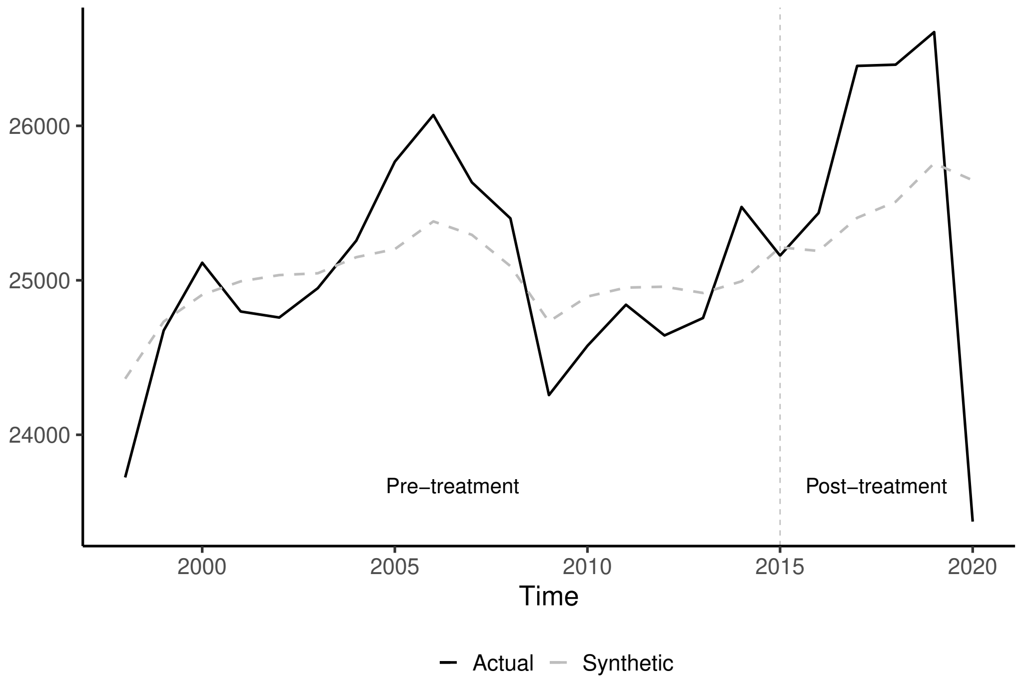

Figure A.8: Model A: Development of Actual and Synthetic GDP of Dorset and Somerset

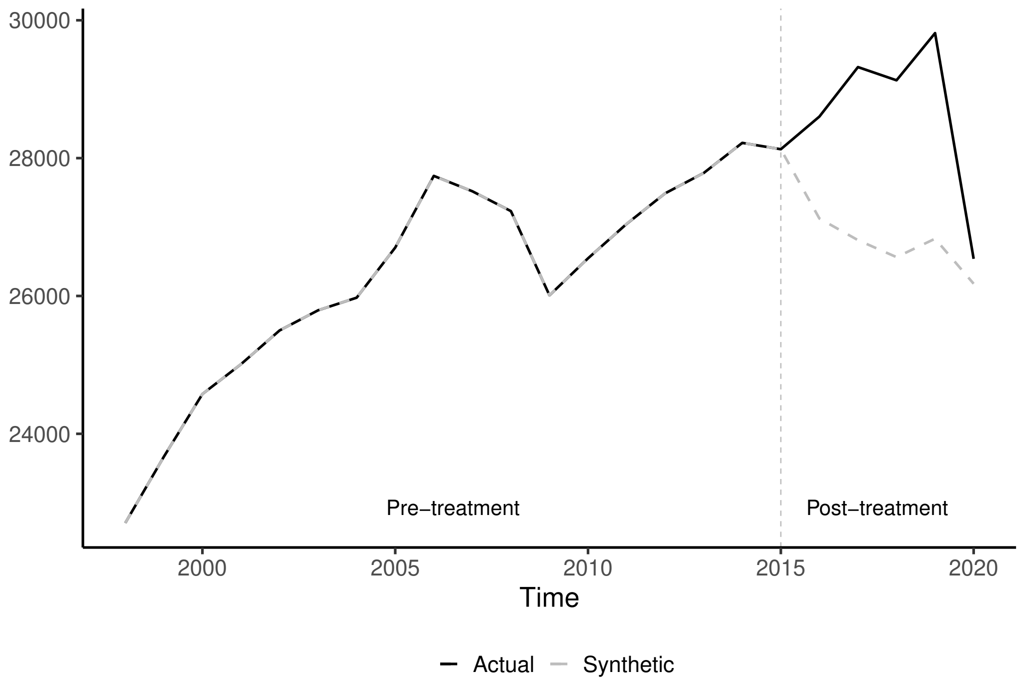

Figure A.9: Model A: Development of Actual and Synthetic GDP of East Anglia

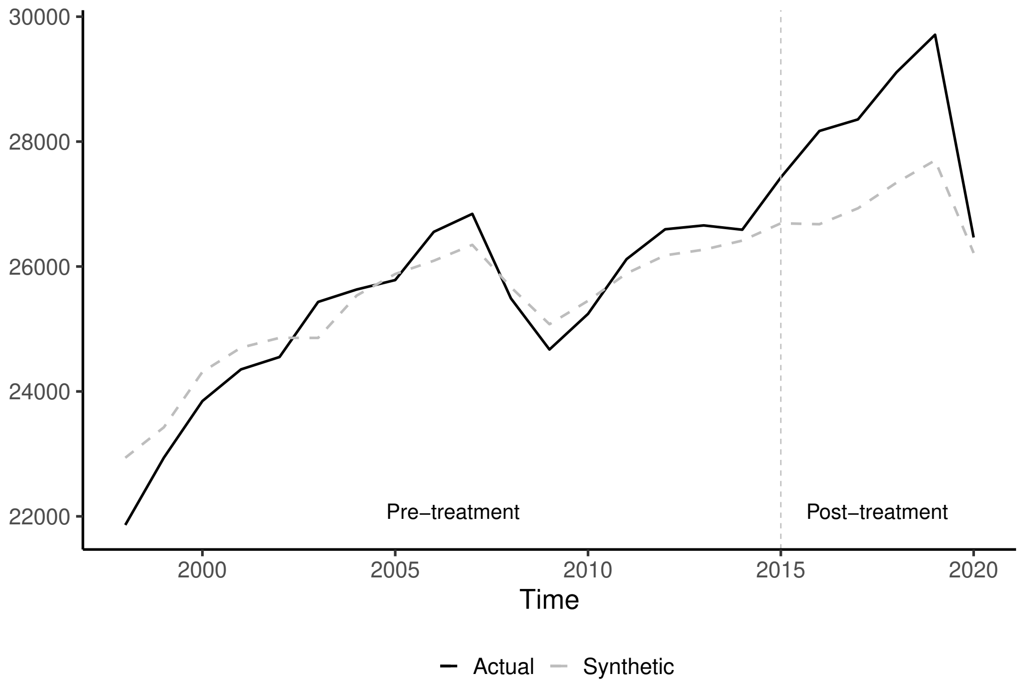

Figure A.10: Model A: Development of Actual and Synthetic GDP of East Wales

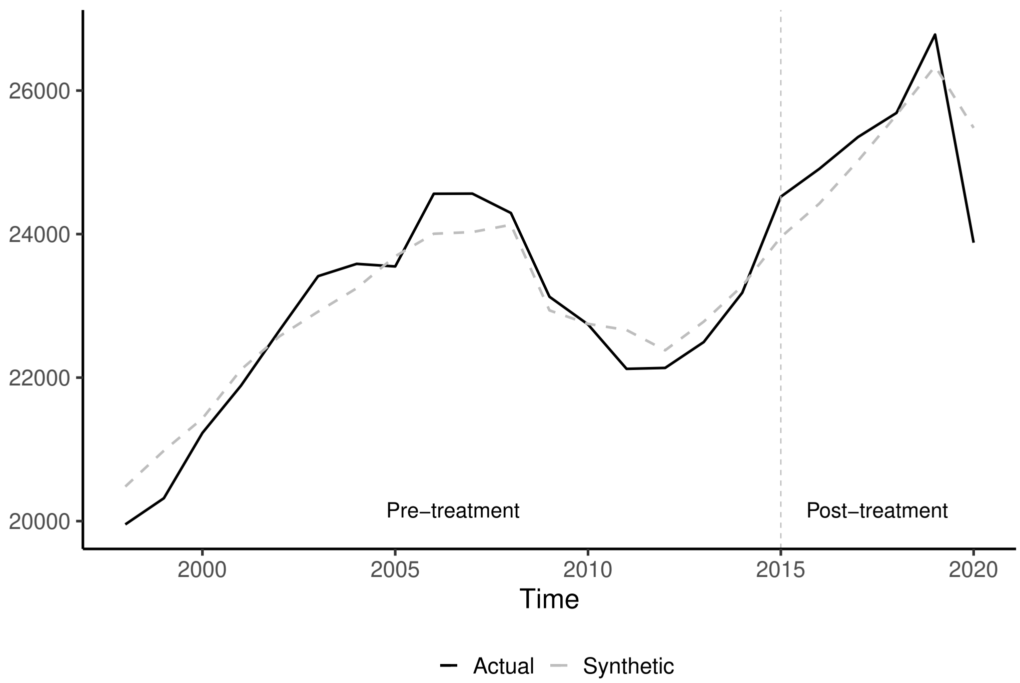

Figure A.11: Model A: Development of Actual and Synthetic GDP of East Yorkshire and Northern Lincolnshire

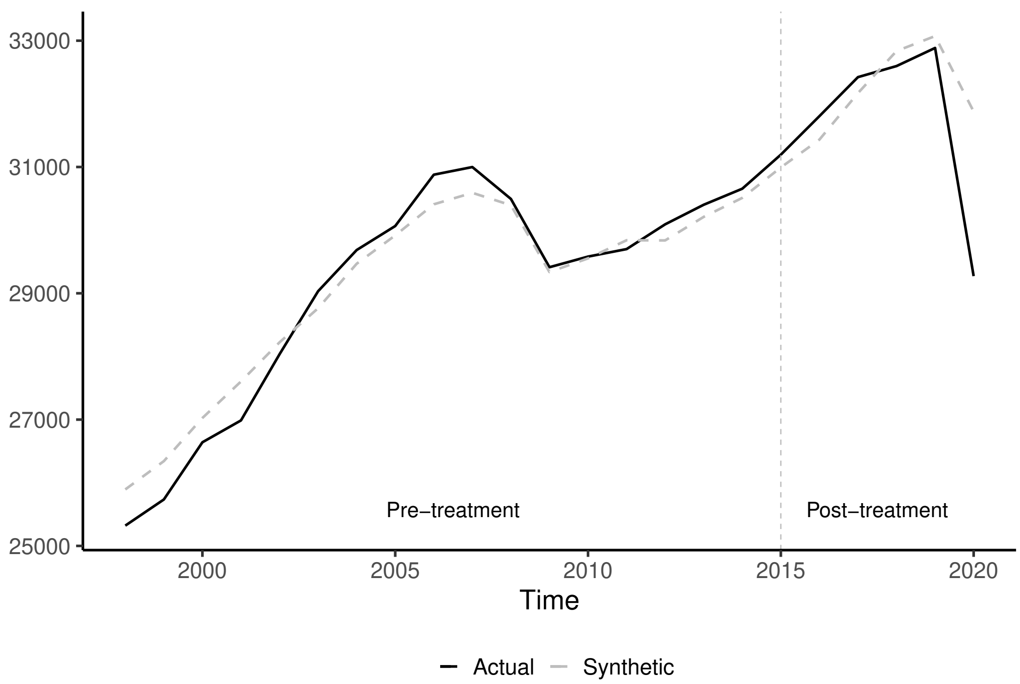

Figure A.12: Model A: Development of Actual and Synthetic GDP of Eastern Scotland

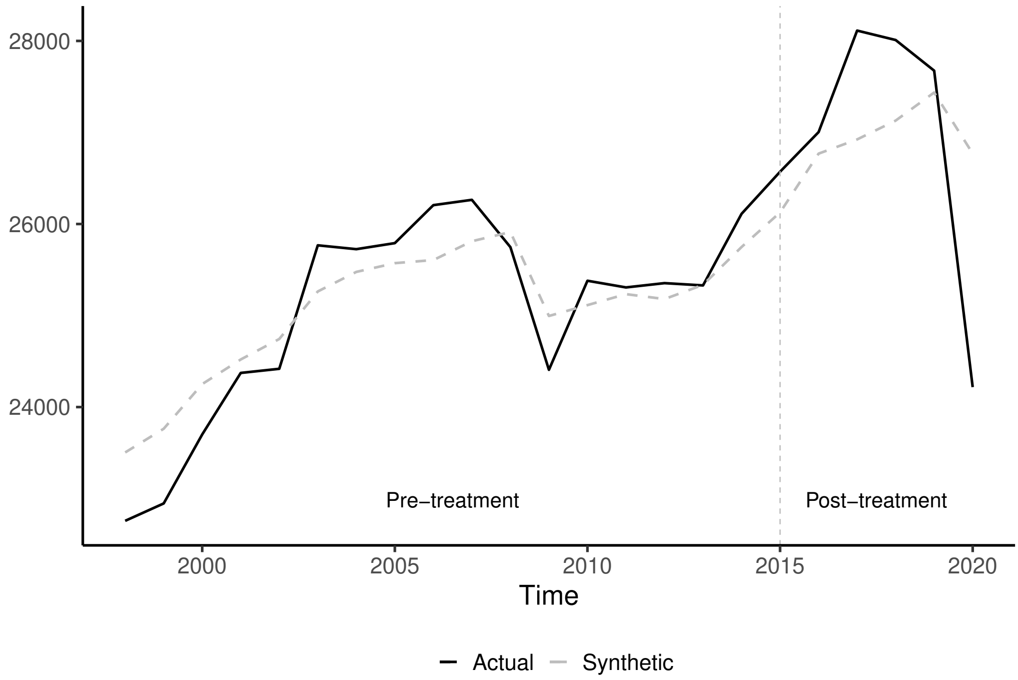

Figure A.13: Model A: Development of Actual and Synthetic GDP of Essex

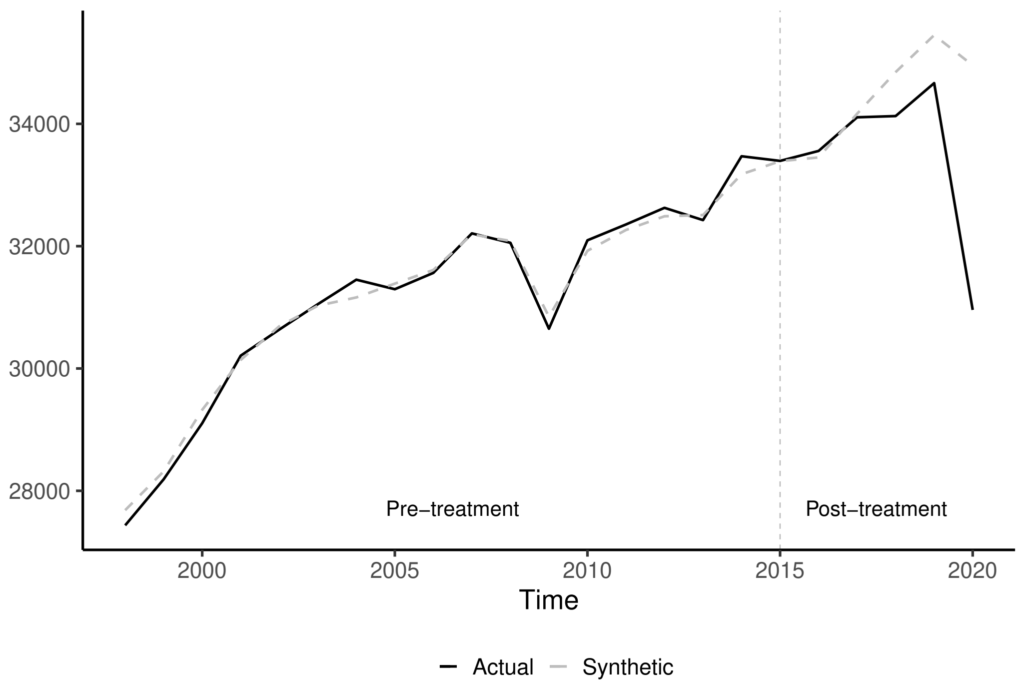

Figure A.14: Model A: Development of Actual and Synthetic GDP of Gloucestershire, Wiltshire and BathBristol

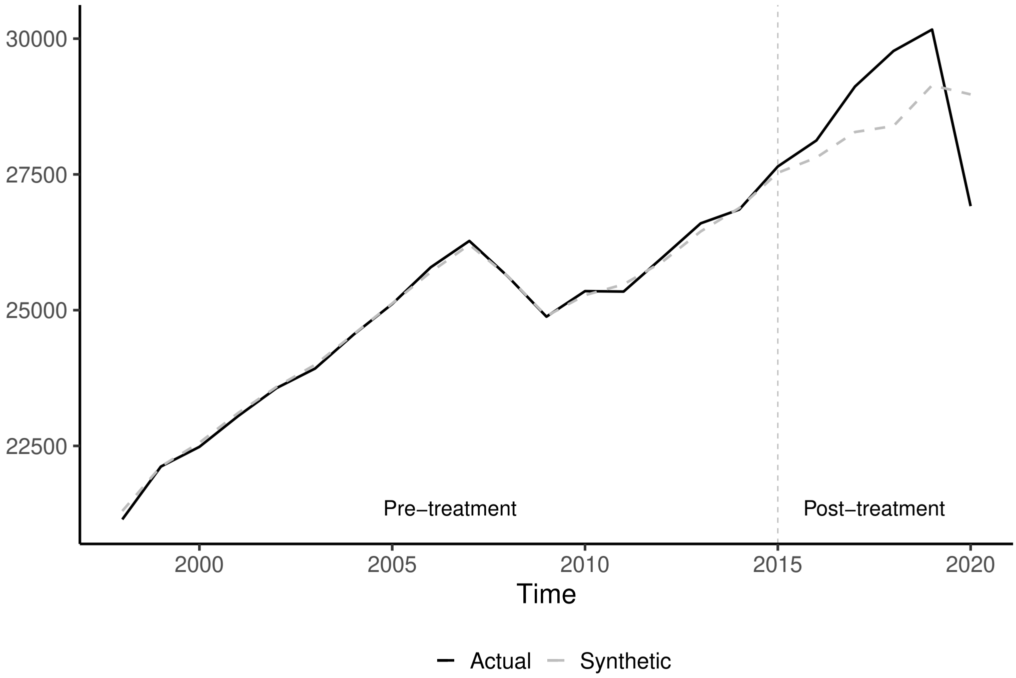

Figure A.15: Model A: Development of Actual and Synthetic GDP of Greater Manchester

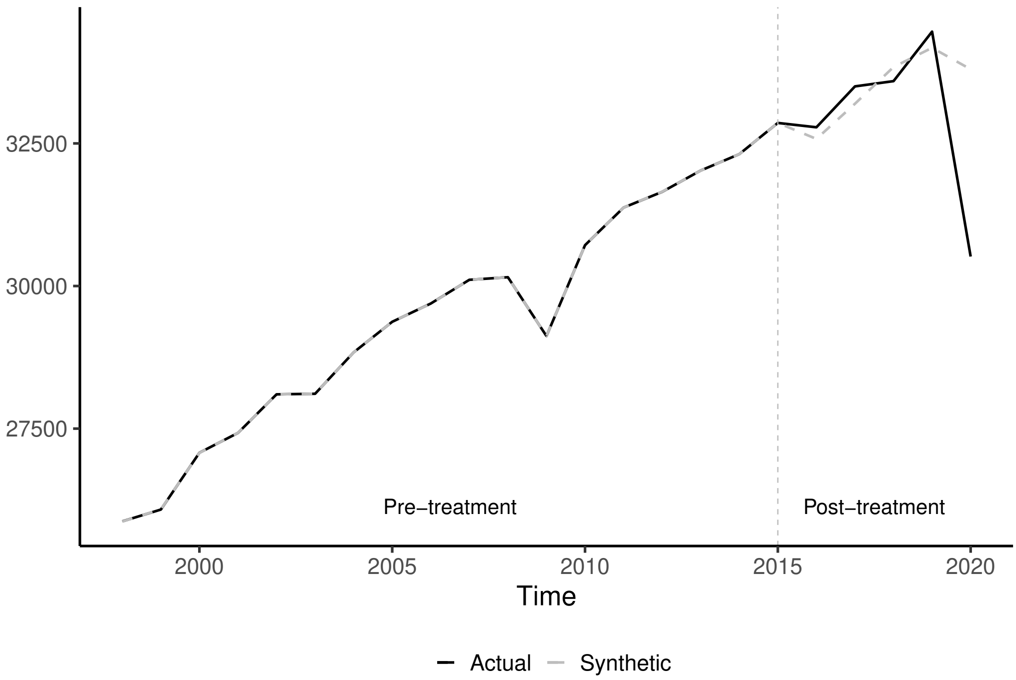

Figure A.16: Model A: Development of Actual and Synthetic GDP of Hampshire and Isle of Wight

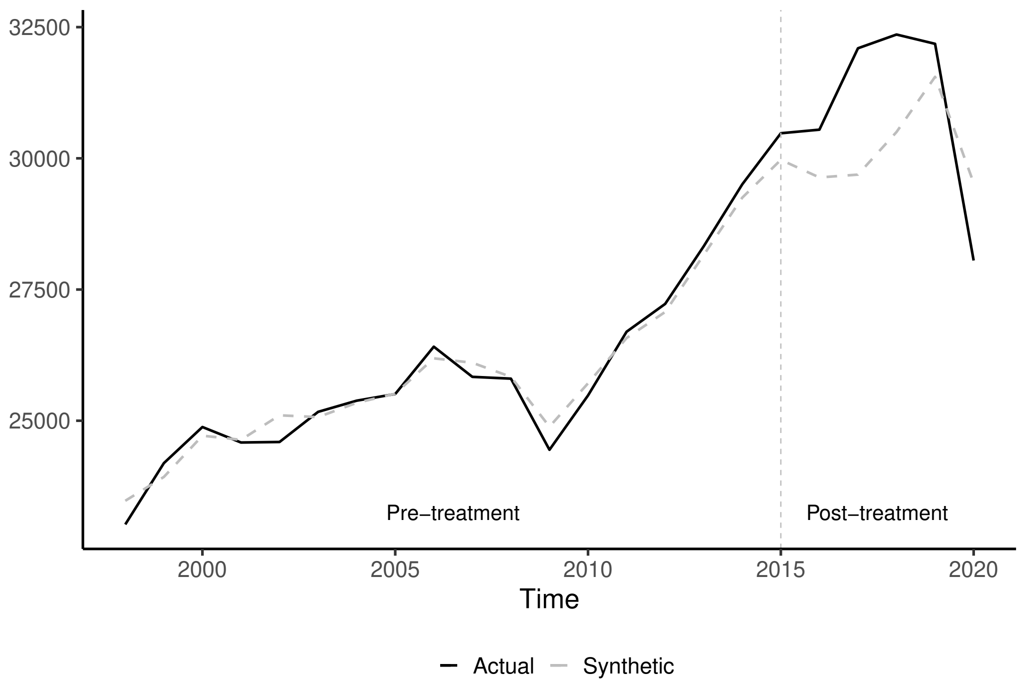

Figure A.17: Model A: Development of Actual and Synthetic GDP of Herefordshire, Worcestershire and Warwicksh

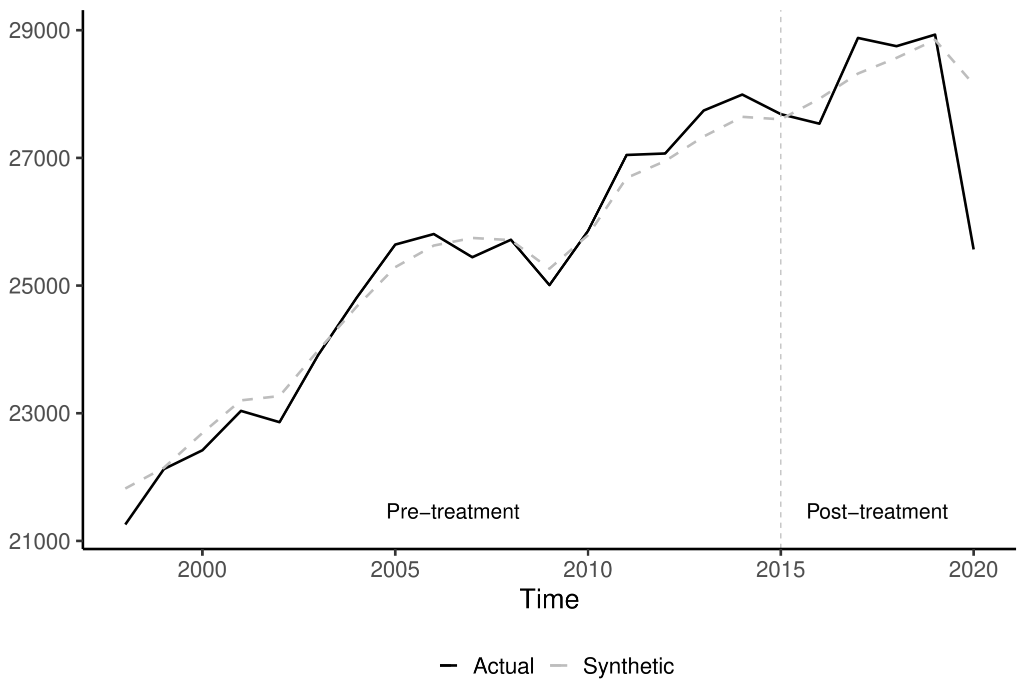

Figure A.18: Model A: Development of Actual and Synthetic GDP of Highlands and Islands

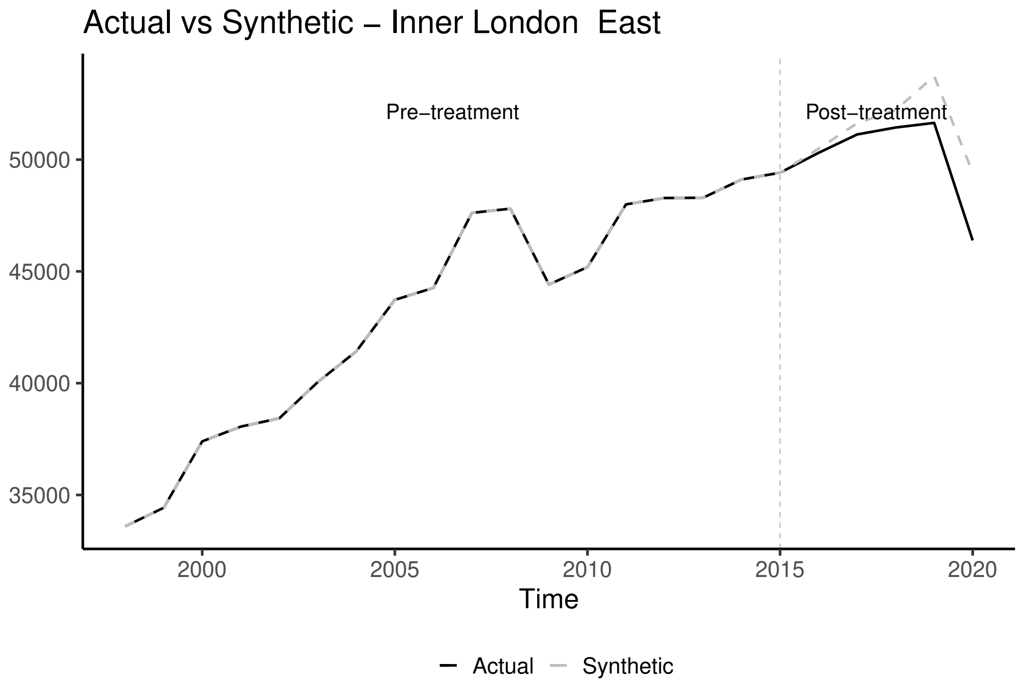

Figure A.19: Model A: Development of Actual and Synthetic GDP of Inner London, East

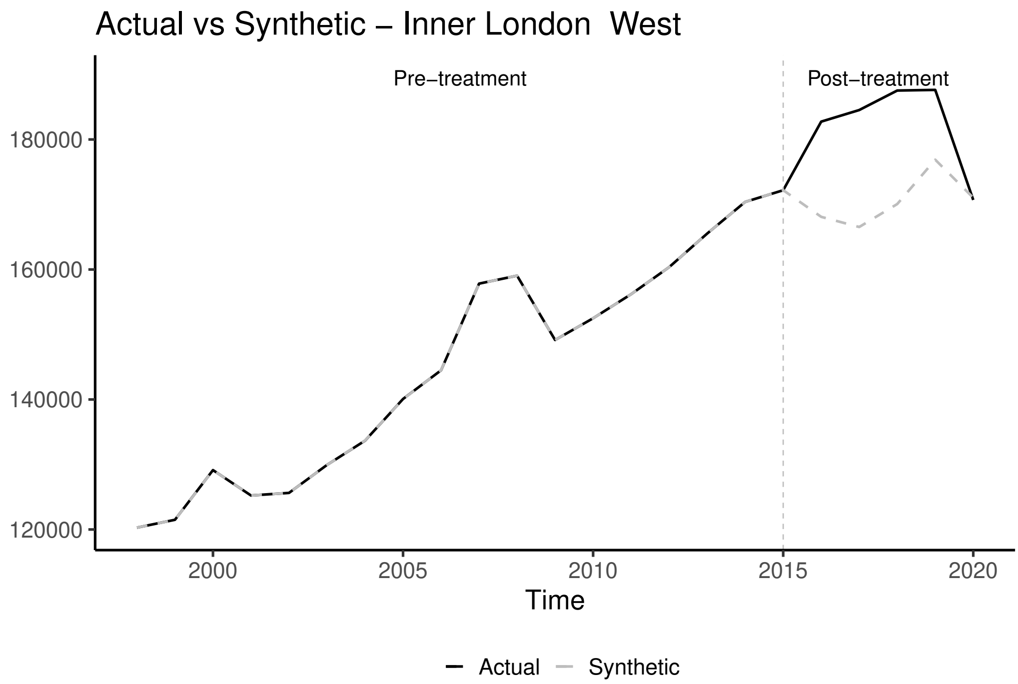

Figure A.20: Model A: Development of Actual and Synthetic GDP of Inner London, West

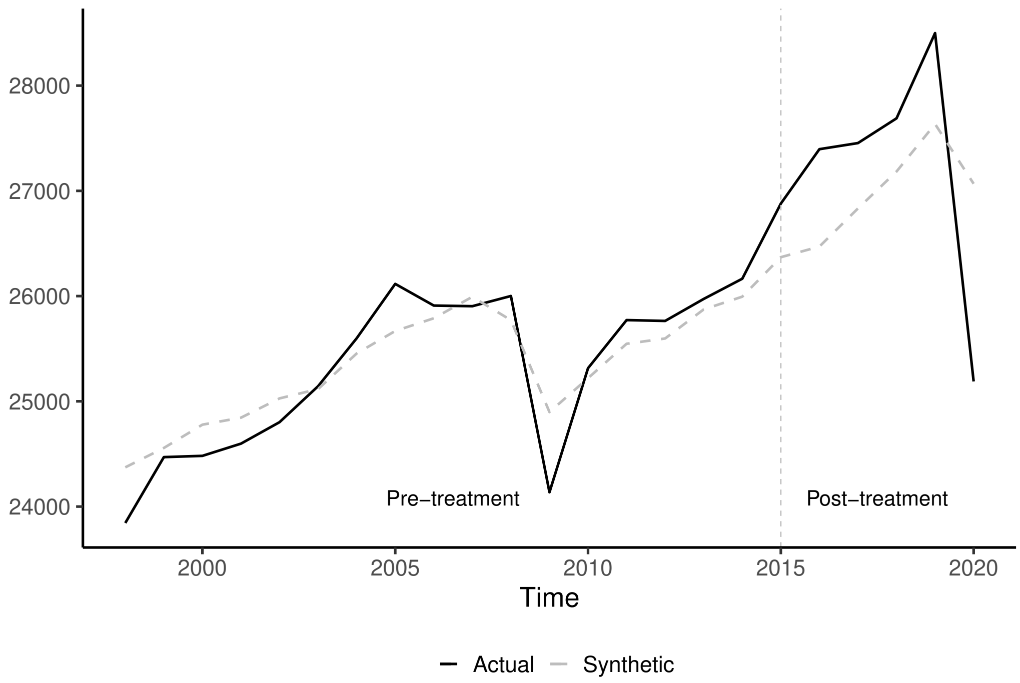

Figure A.21: Model A: Development of Actual and Synthetic GDP of Kent

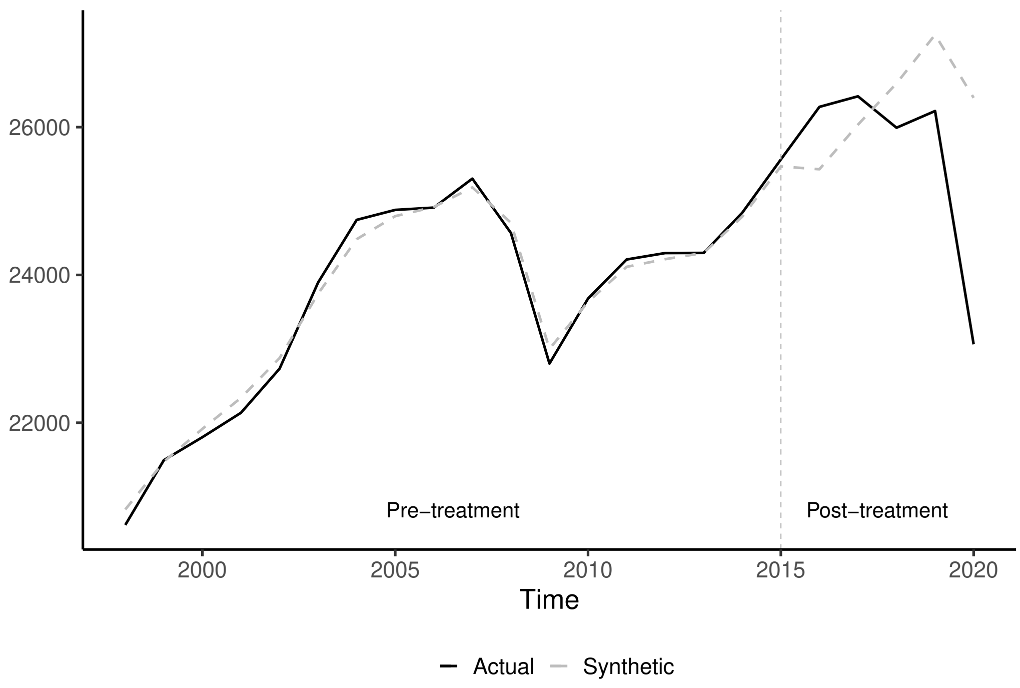

Figure A.22: Model A: Development of Actual and Synthetic GDP of Lancashire

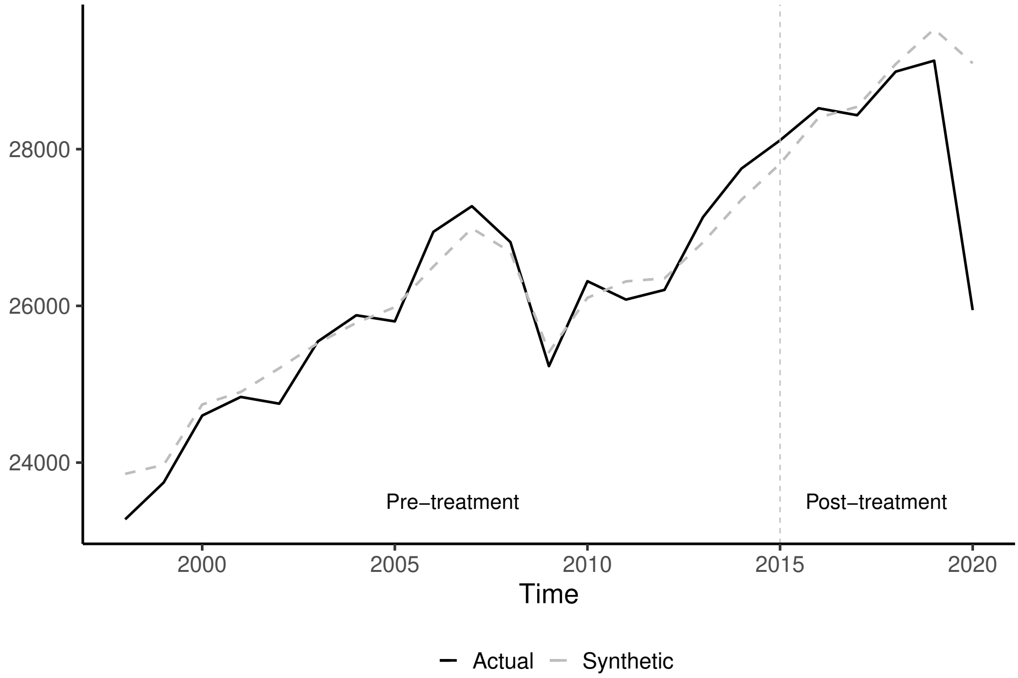

Figure A.23: Model A: Development of Actual and Synthetic GDP of Leicestershire, Rutland and Northamptonshire

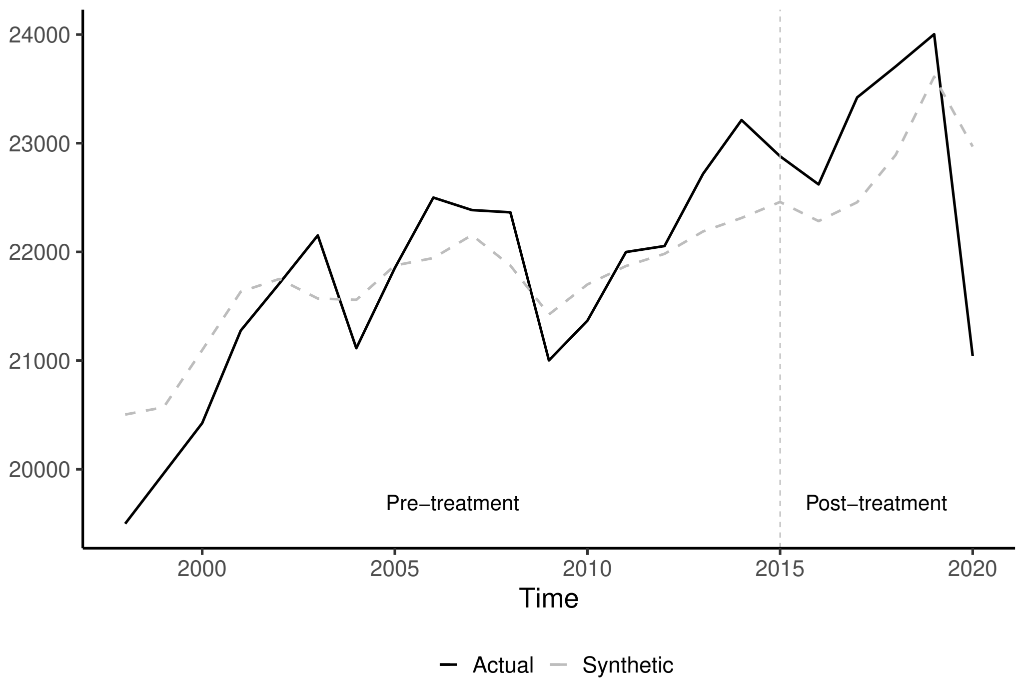

Figure A.24: Model A: Development of Actual and Synthetic GDP of Lincolnshire

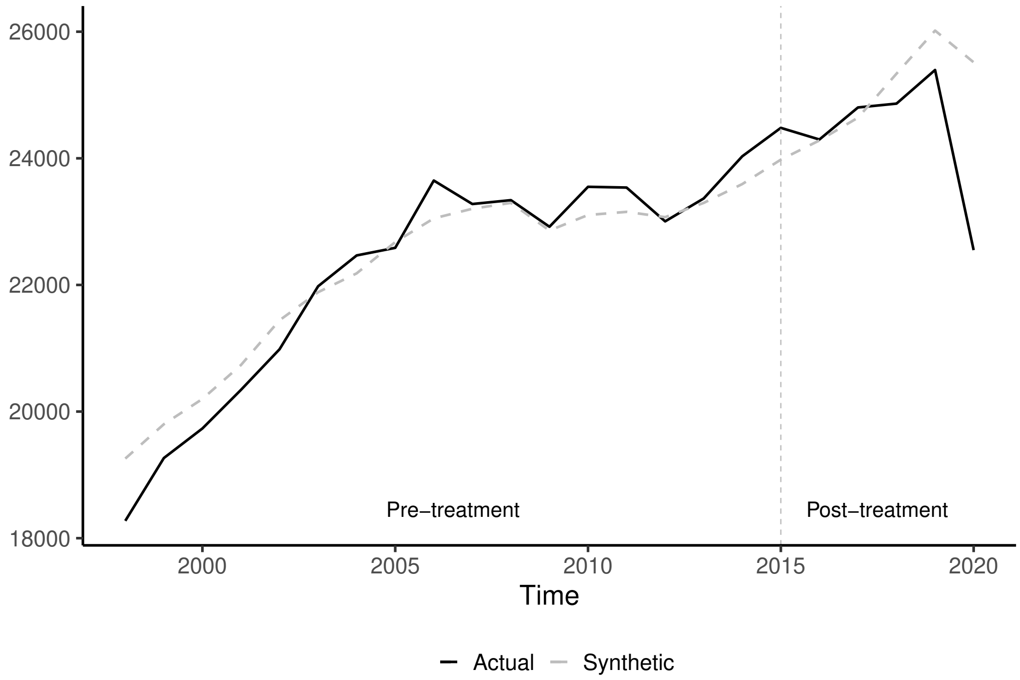

Figure A.25: Model A: Development of Actual and Synthetic GDP of Merseyside

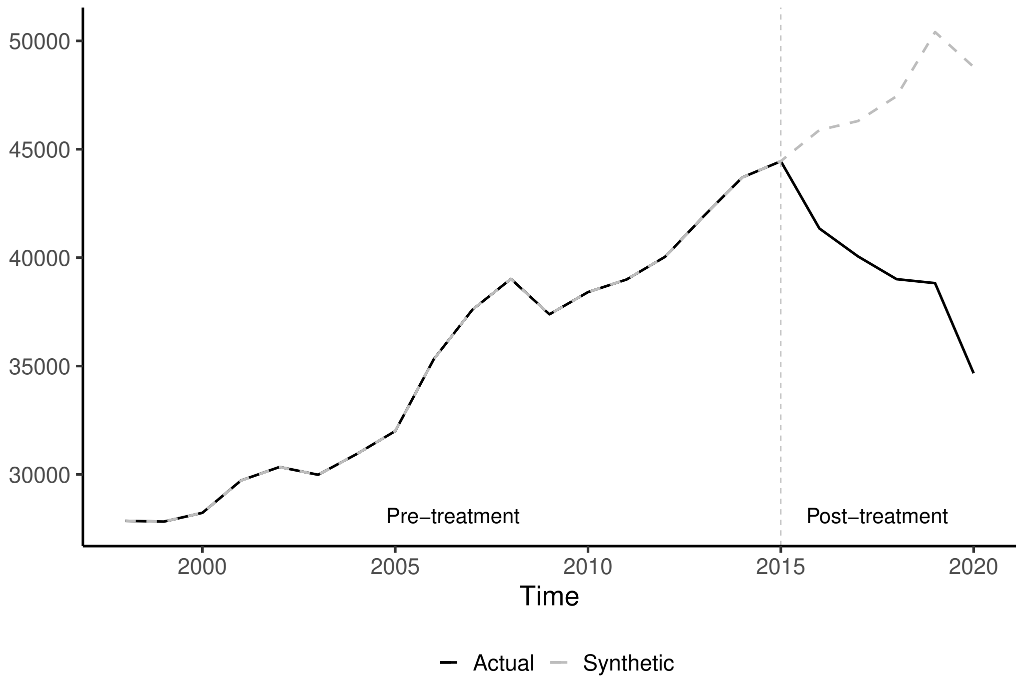

Figure A.26: Model A: Development of Actual and Synthetic GDP of North Eastern Scotland

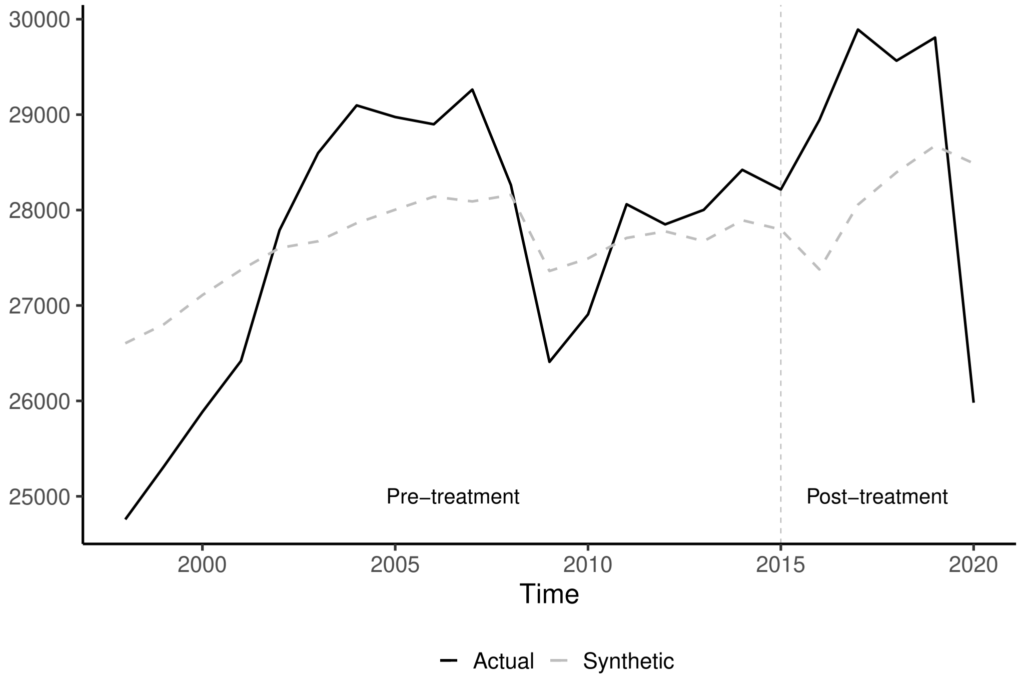

Figure A.27: Model A: Development of Actual and Synthetic GDP of North Yorkshire

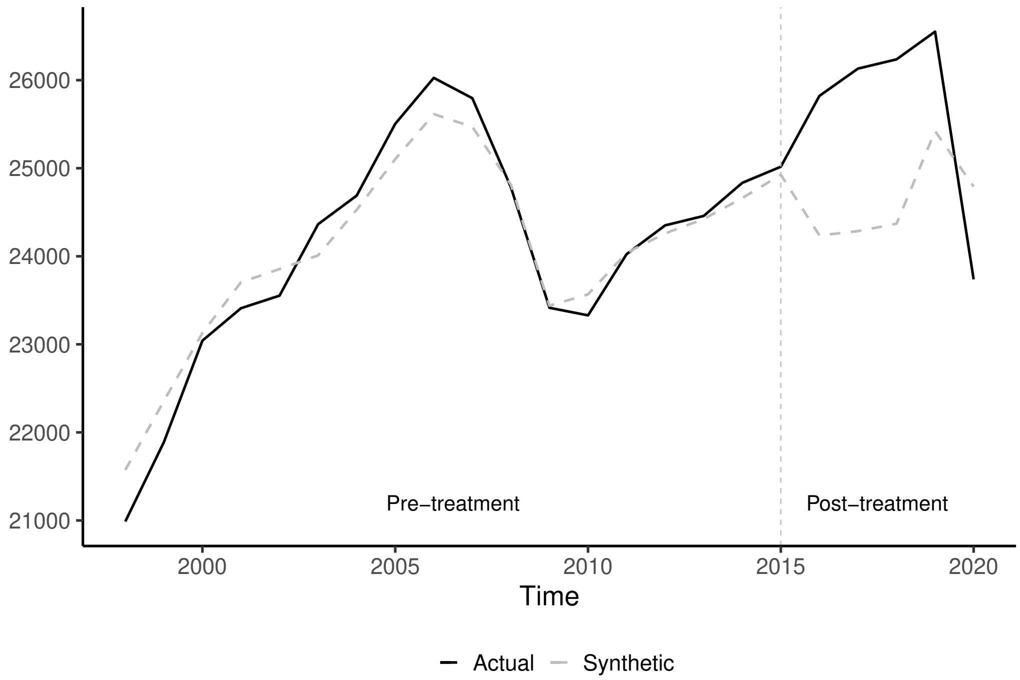

Figure A.28: Model A: Development of Actual and Synthetic GDP of Northern Ireland

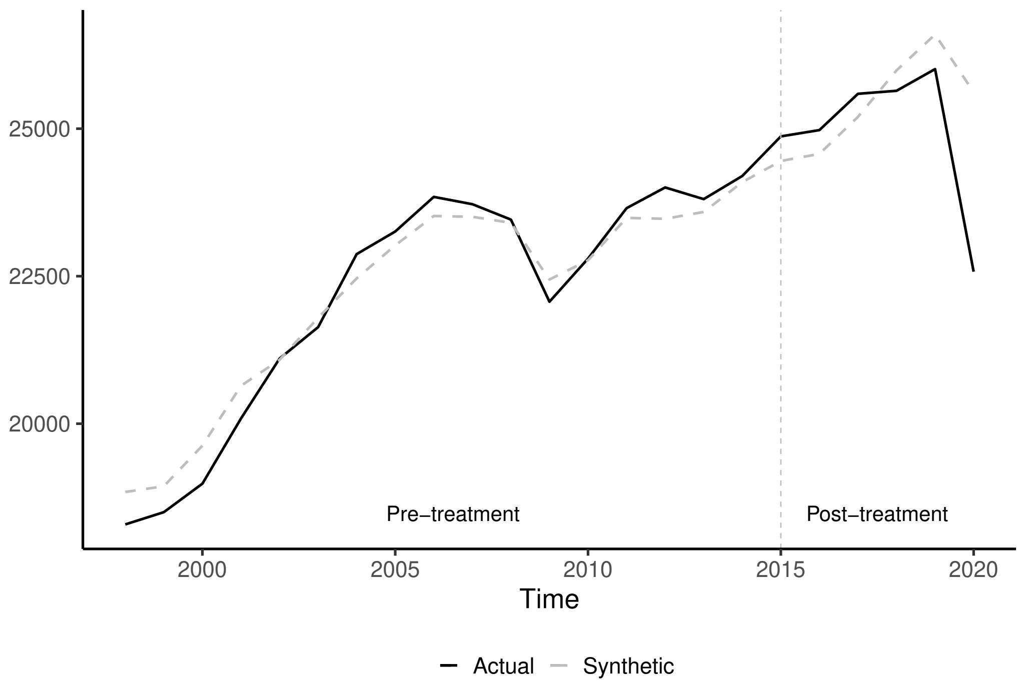

Figure A.29: Model A: Development of Actual and Synthetic GDP of Northumberland and Tyne and Wear

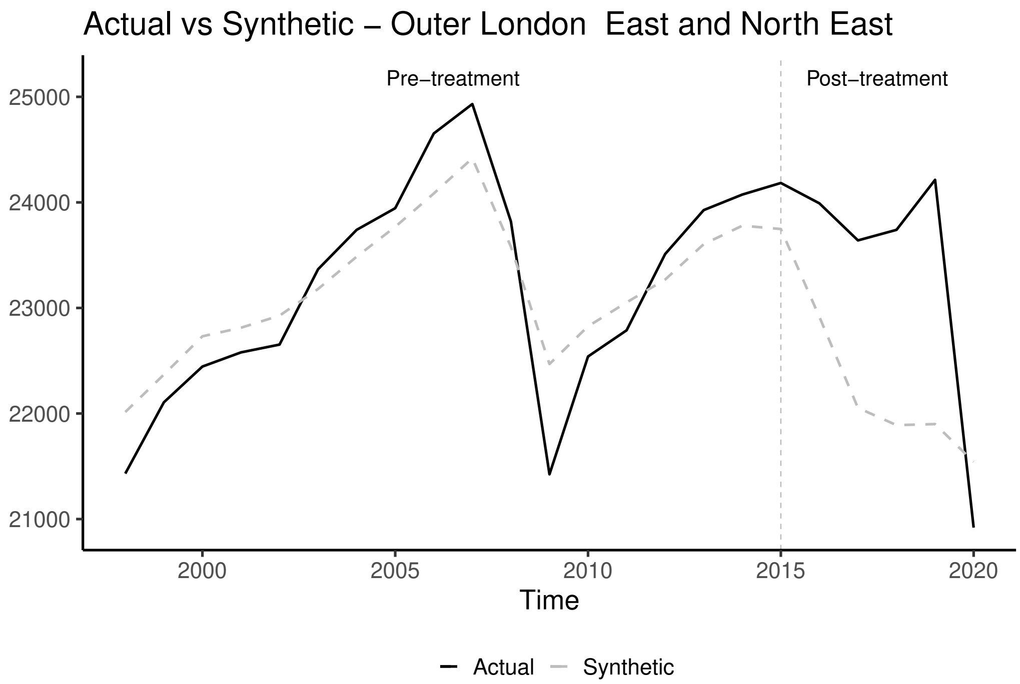

Figure A.30: Model A: Development of Actual and Synthetic GDP of Outer London, East and North East

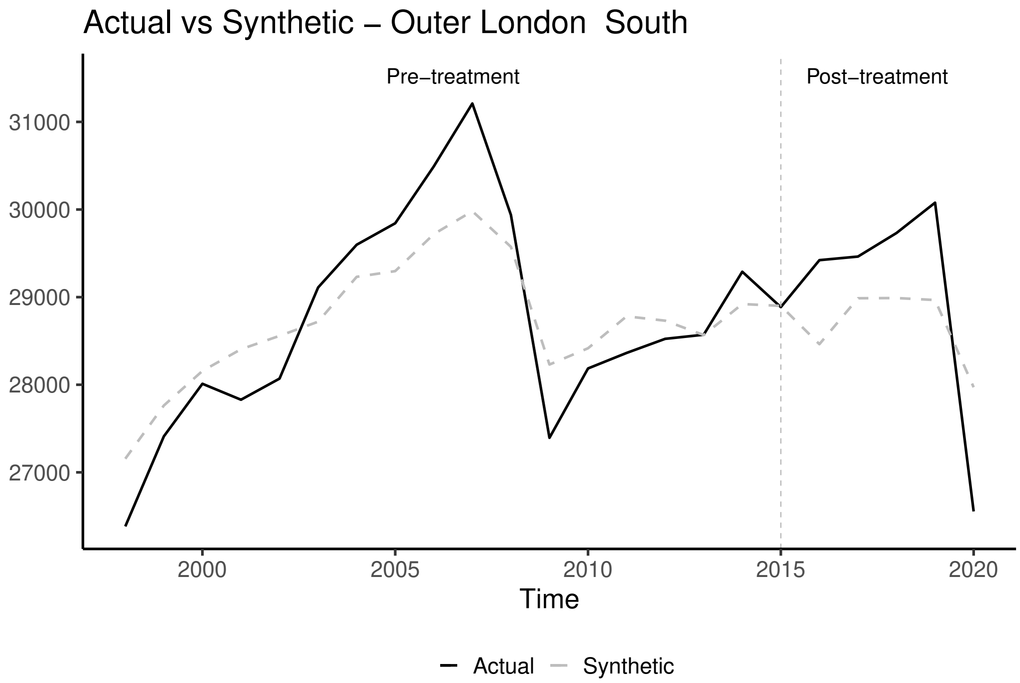

Figure A.31: Model A: Development of Actual and Synthetic GDP of Outer, London South

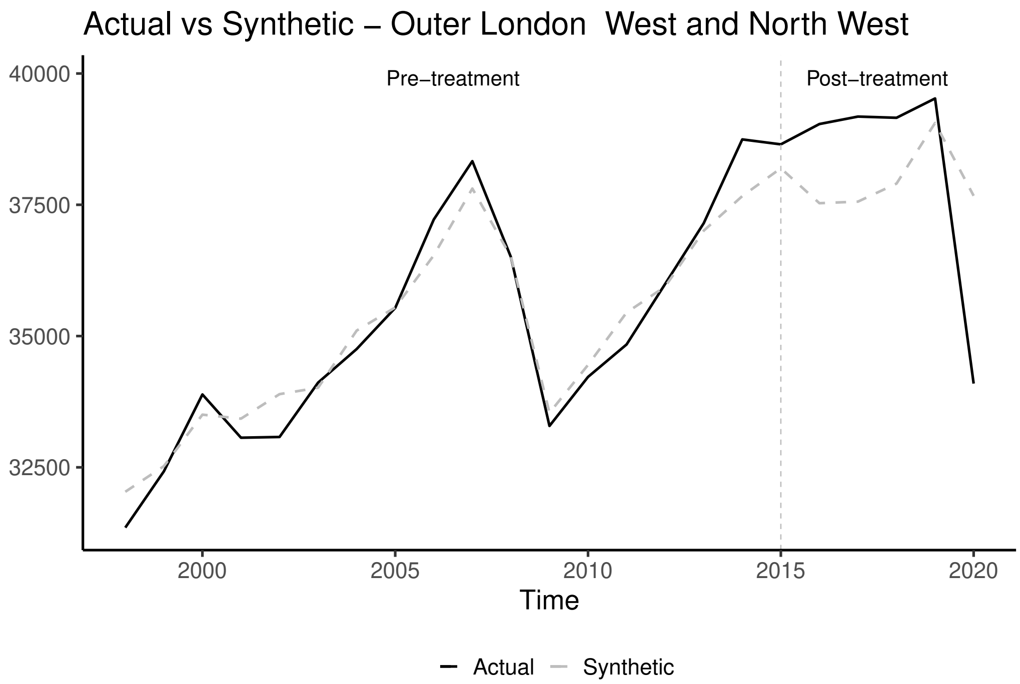

Figure A.32: Model A: Development of Actual and Synthetic GDP of Outer London, West and North West

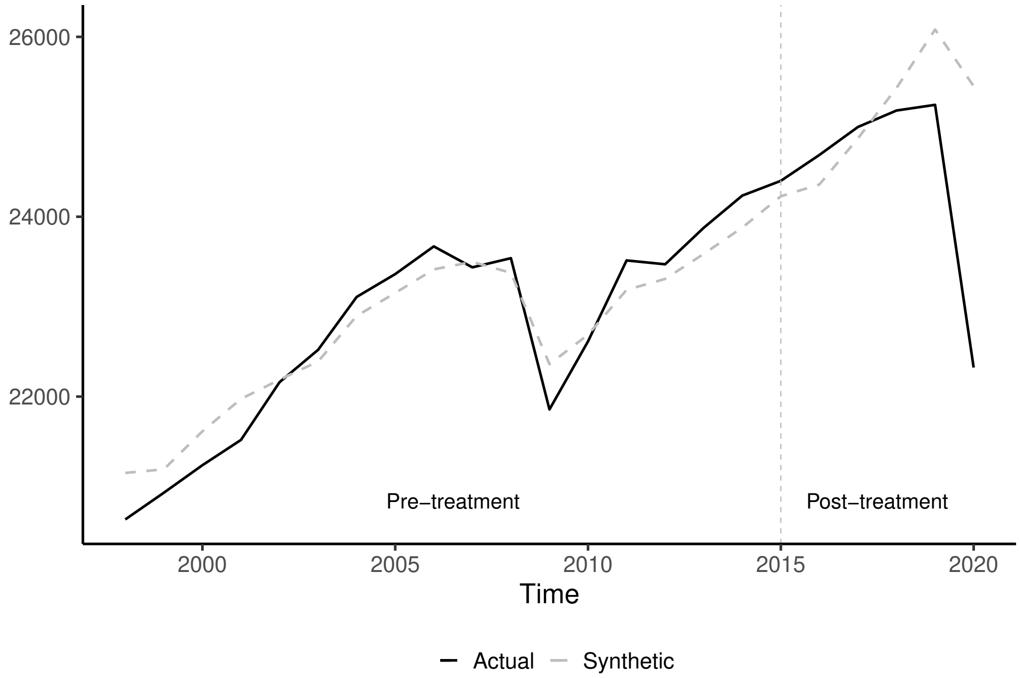

Figure A.33: Model A: Development of Actual and Synthetic GDP of Shropshire and Staffordshire

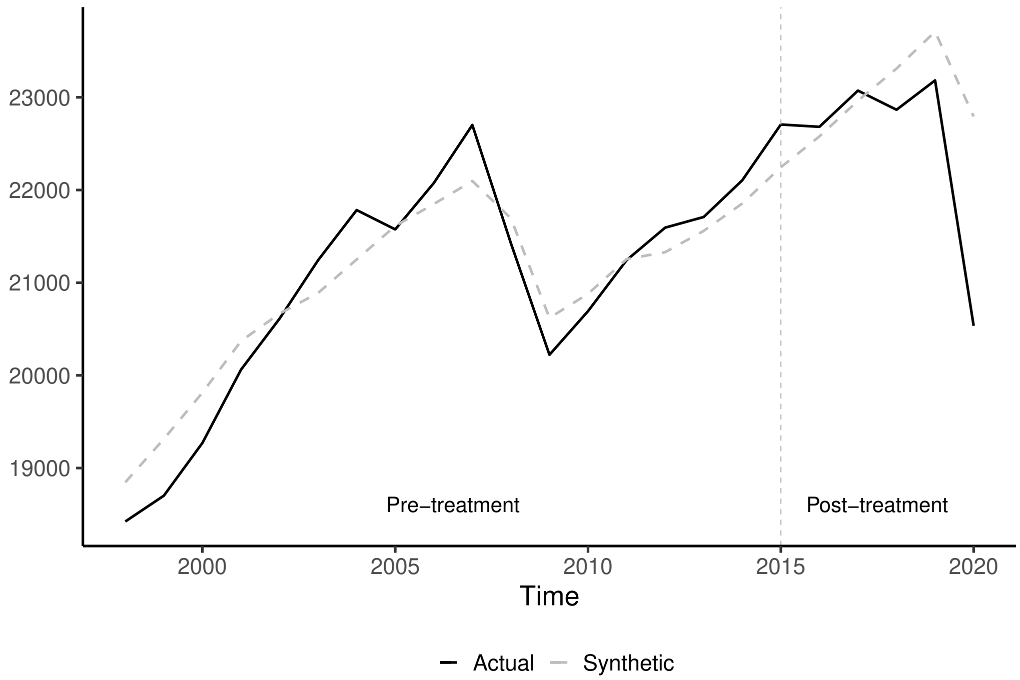

Figure A.34: Model A: Development of Actual and Synthetic GDP of South Yorkshire

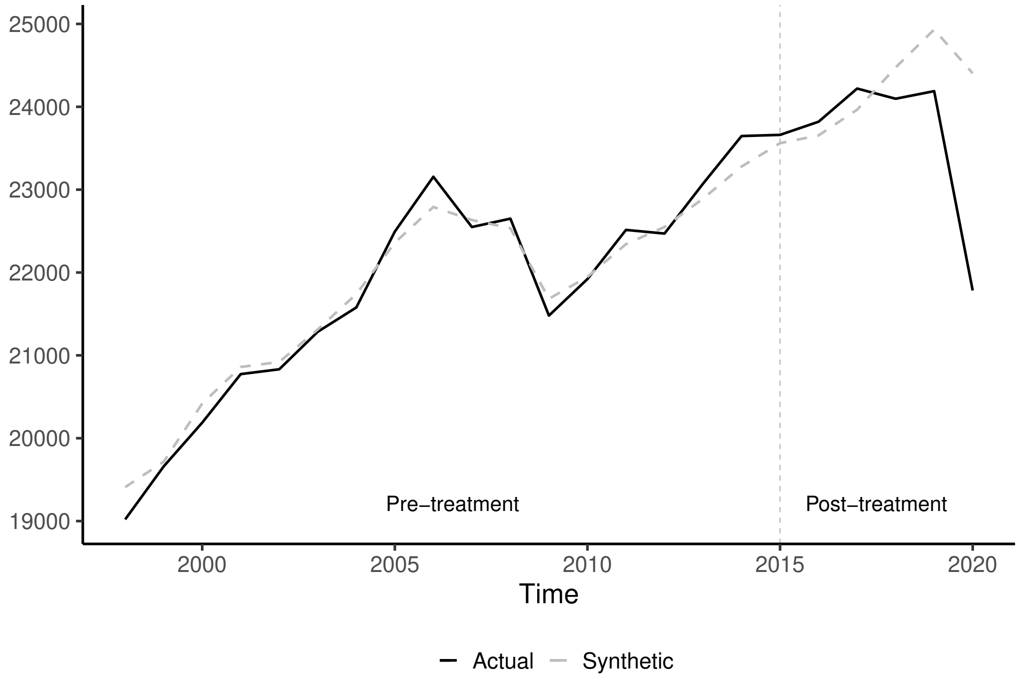

Figure A.35: Model A: Development of Actual and Synthetic GDP of Southern Scotland

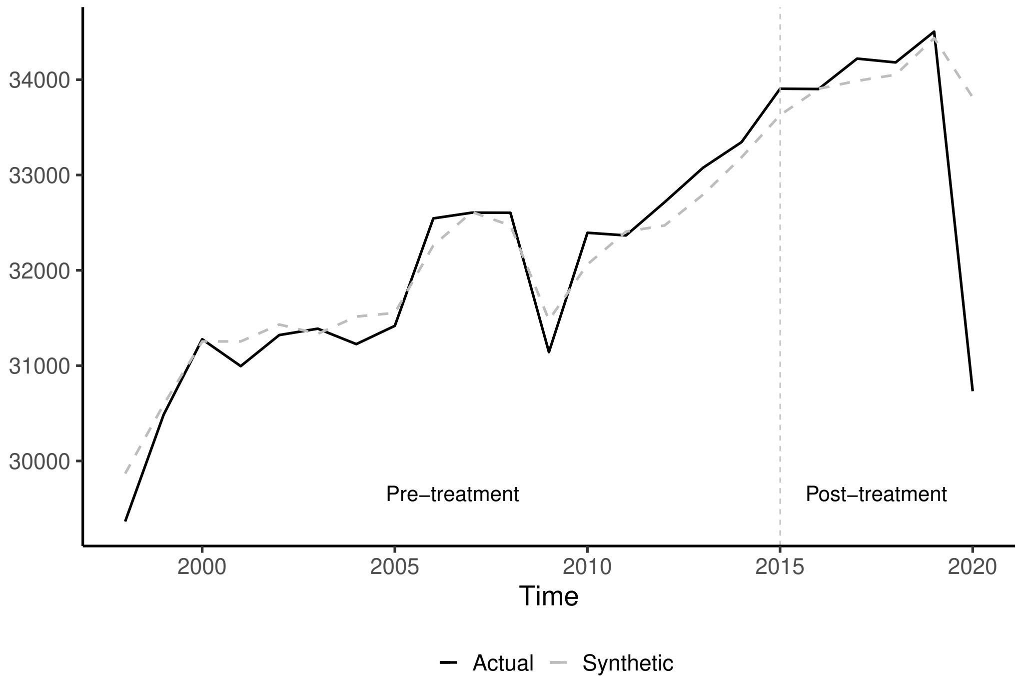

Figure A.36: Model A: Development of Actual and Synthetic GDP of Surrey East and West Sussex

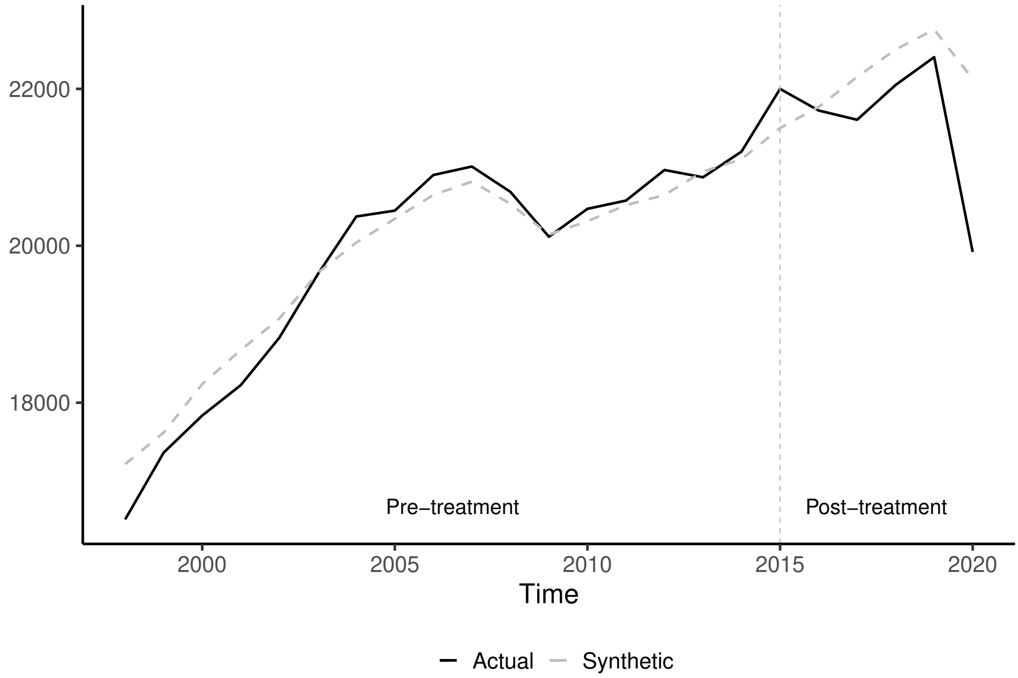

Figure A.37: Model A: Development of Actual and Synthetic GDP of Tees Valley and Durham

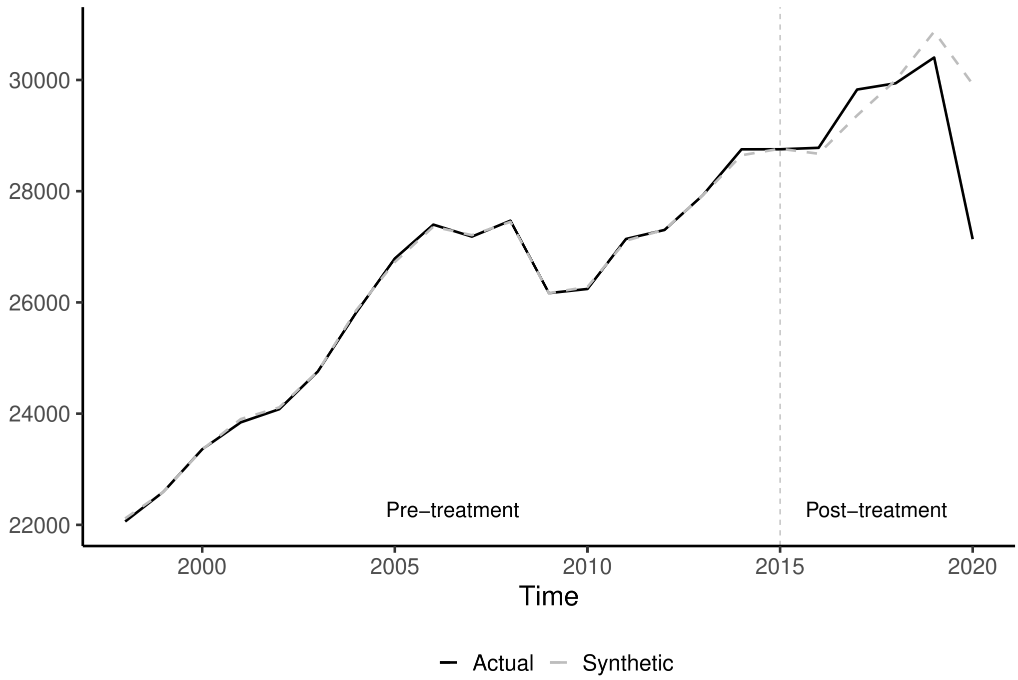

Figure A.38: Model A: Development of Actual and Synthetic GDP of West Central Scotland

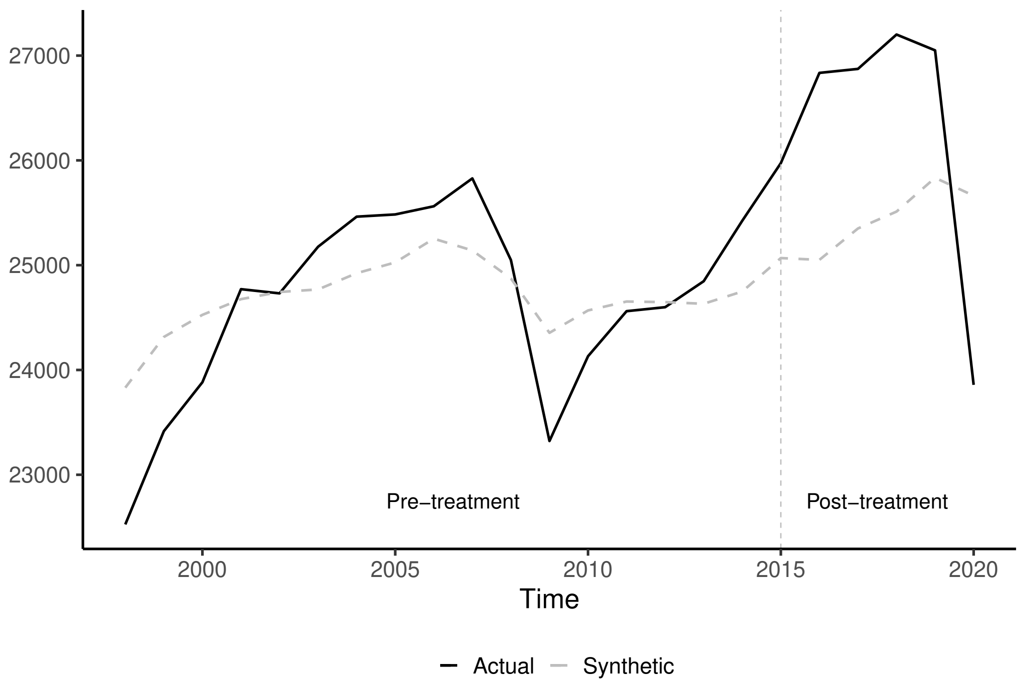

Figure A.39: Model A: Development of Actual and Synthetic GDP of West Midlands

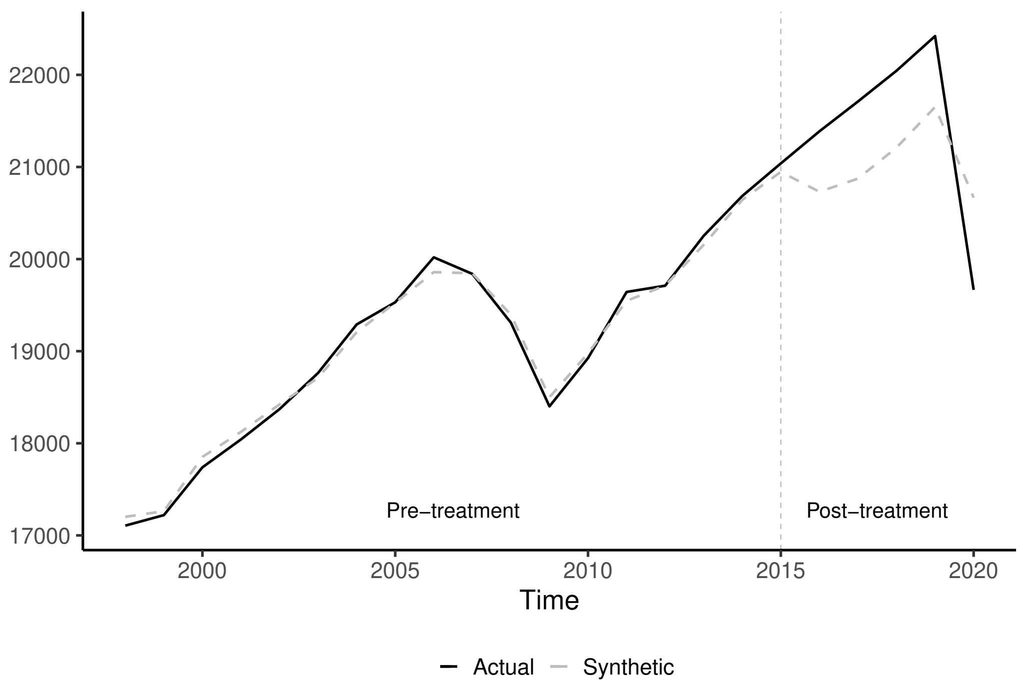

Figure A.40: Model A: Development of Actual and Synthetic GDP of West Wales and The Valleys

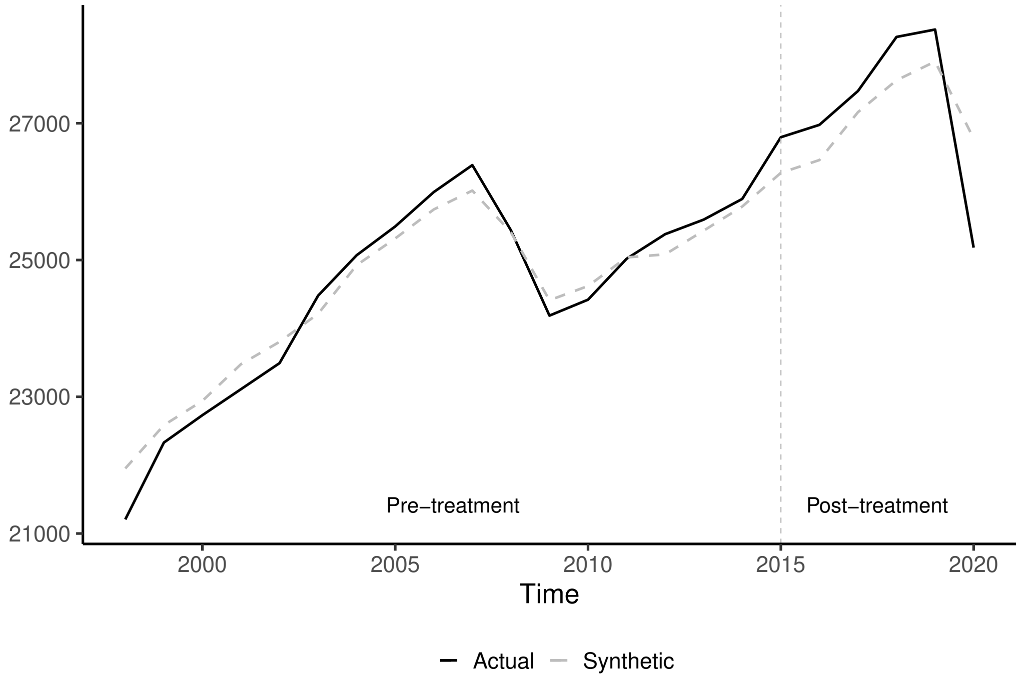

Figure A.41: Model A: Development of Actual and Synthetic GDP of West Yorkshire

A.2 Model B

A.2.1 SCM Results

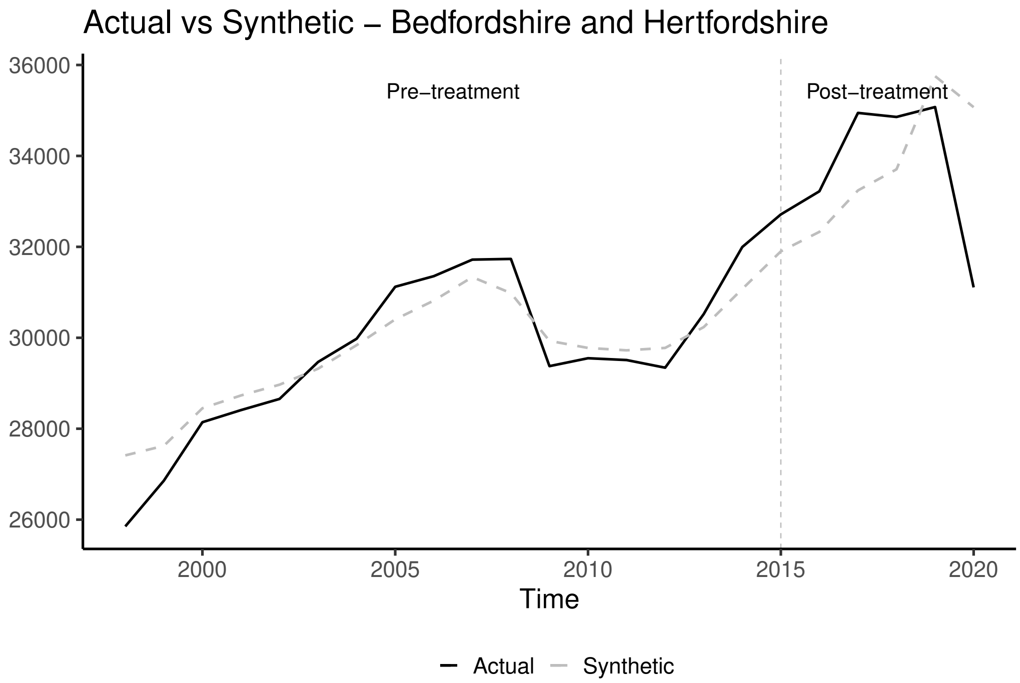

Figure A.42: Model B: Development of Actual and Synthetic GDP of Bedfordshire and Hertfordshire

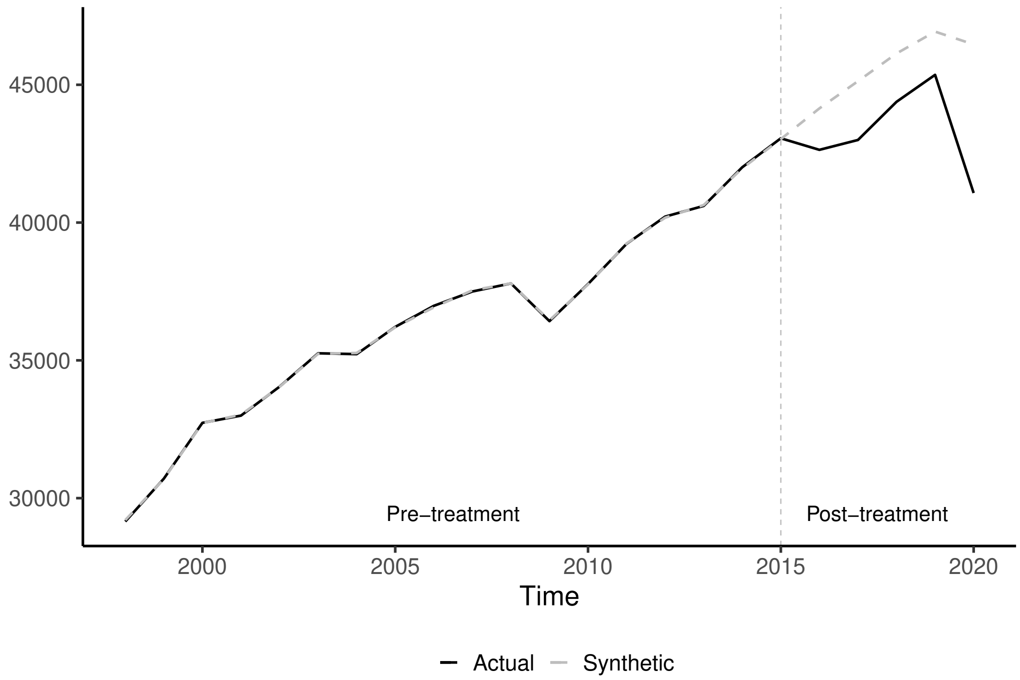

Figure A.43: Model B: Development of Actual and Synthetic GDP of Berkshire Buckinghamshire and Oxfordshire

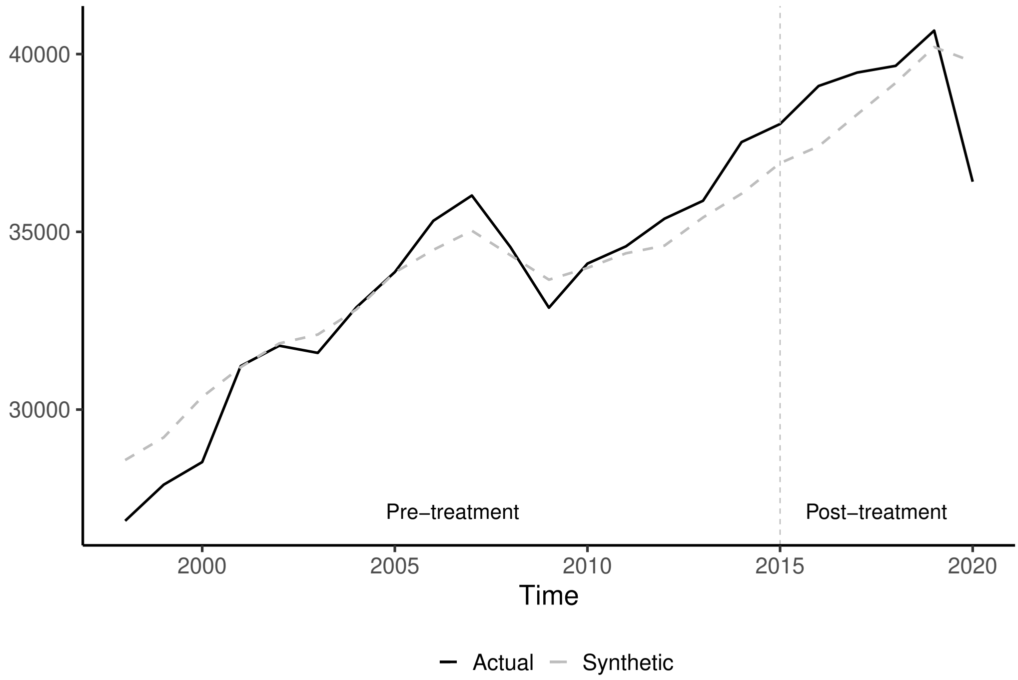

Figure A.44: Model B: Development of Actual and Synthetic GDP of Cheshire

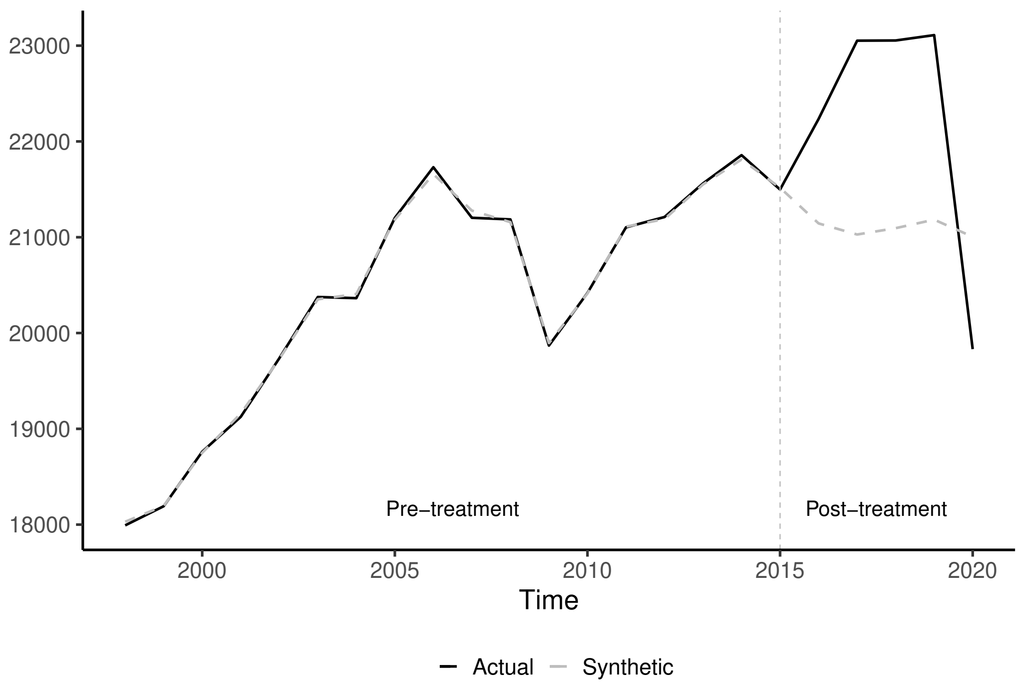

Figure A.45: Model B: Development of Actual and Synthetic GDP of Cornwall and Isles of Scilly

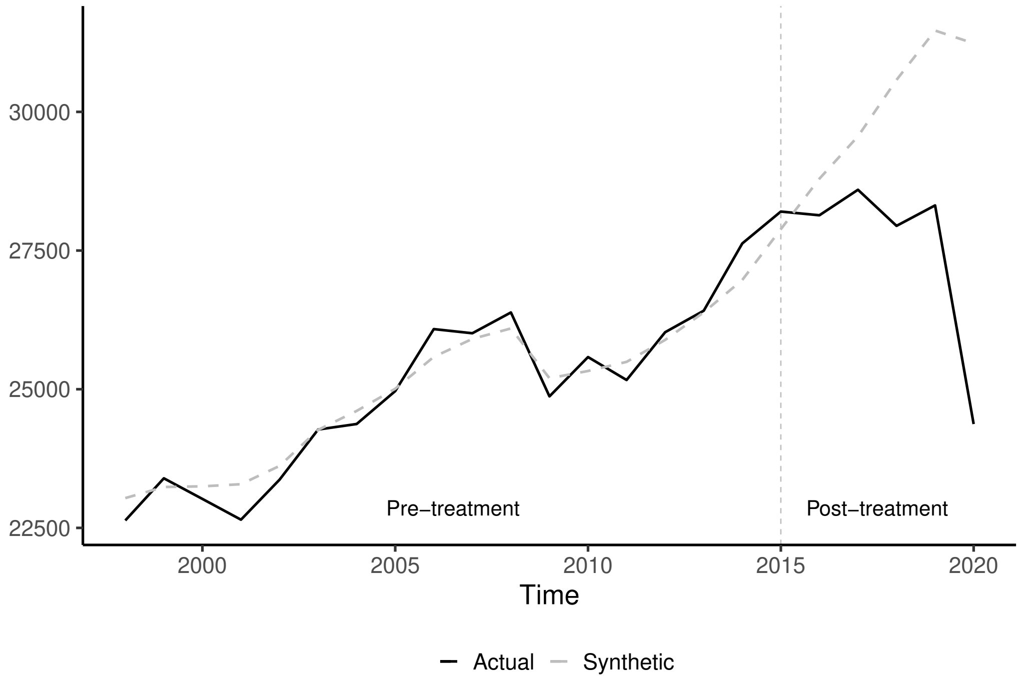

Figure A.46: Model B: Development of Actual and Synthetic GDP of Cumbria

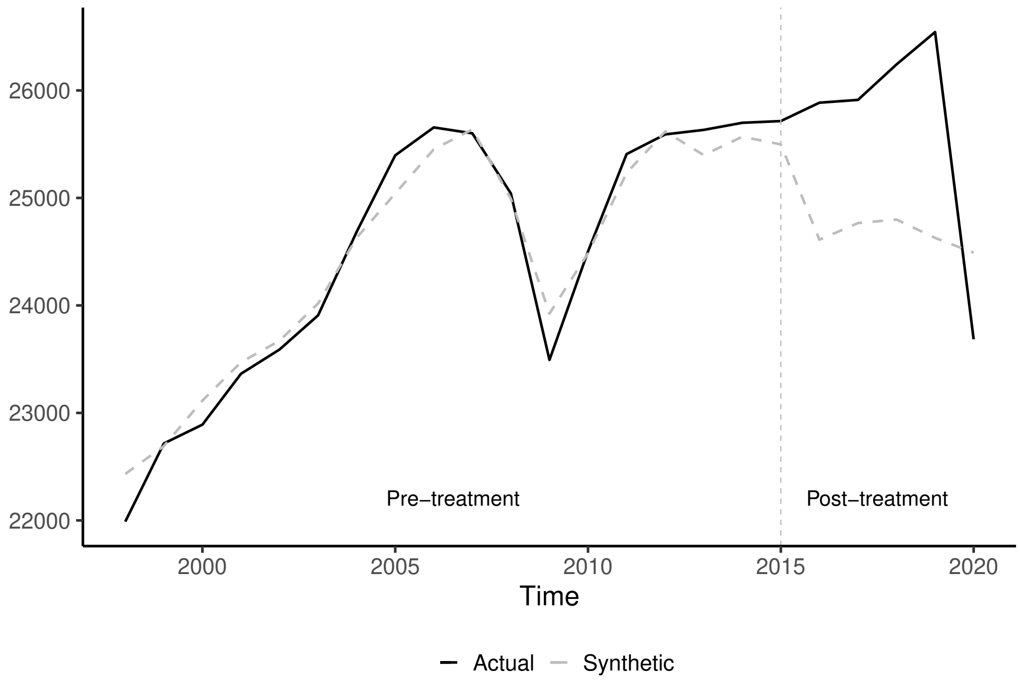

Figure A.47: Model B: Development of Actual and Synthetic GDP of Derbyshire and Nottinghamshire

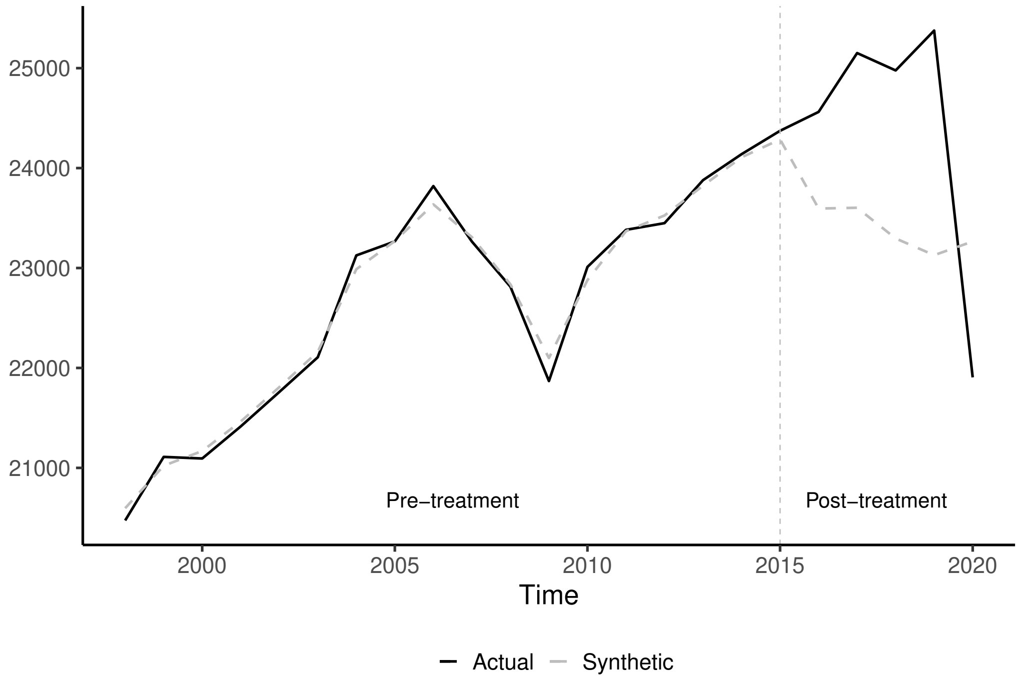

Figure A.48: Model B: Development of Actual and Synthetic GDP of Devon

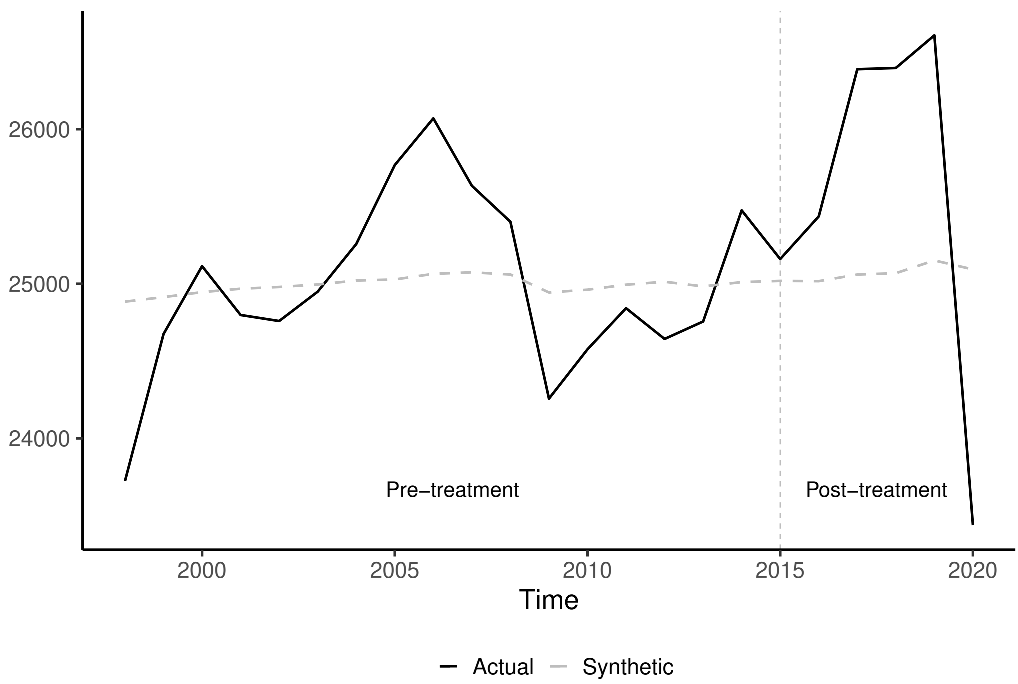

Figure A.49: Model B: Development of Actual and Synthetic GDP of Dorset and Somerset

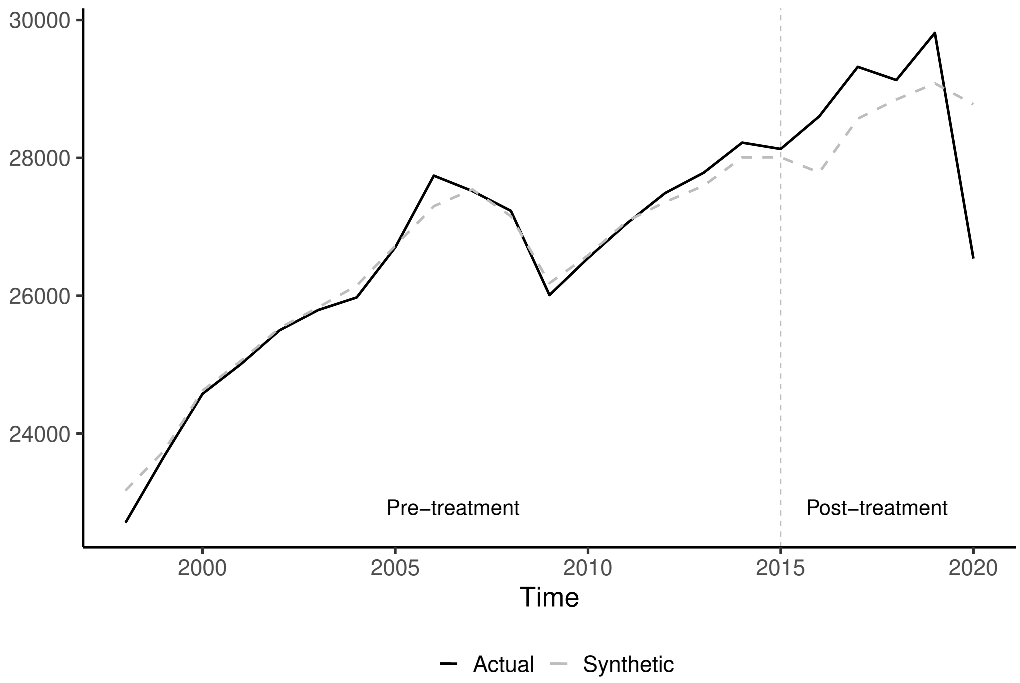

Figure A.50: Model B: Development of Actual and Synthetic GDP of East Anglia

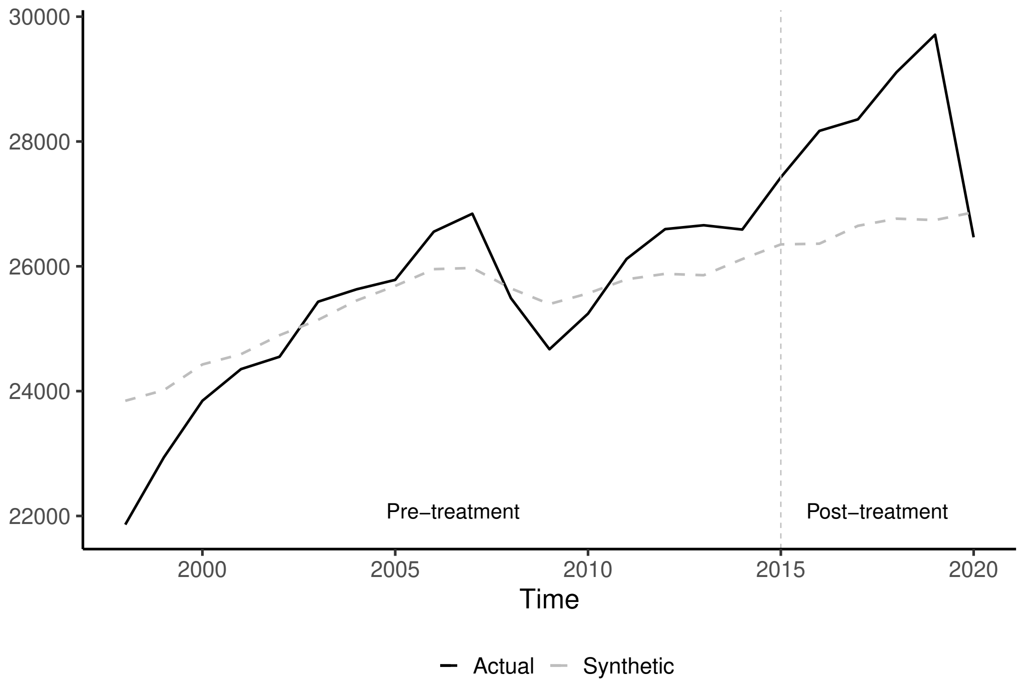

Figure A.51: Model B: Development of Actual and Synthetic GDP of East Wales

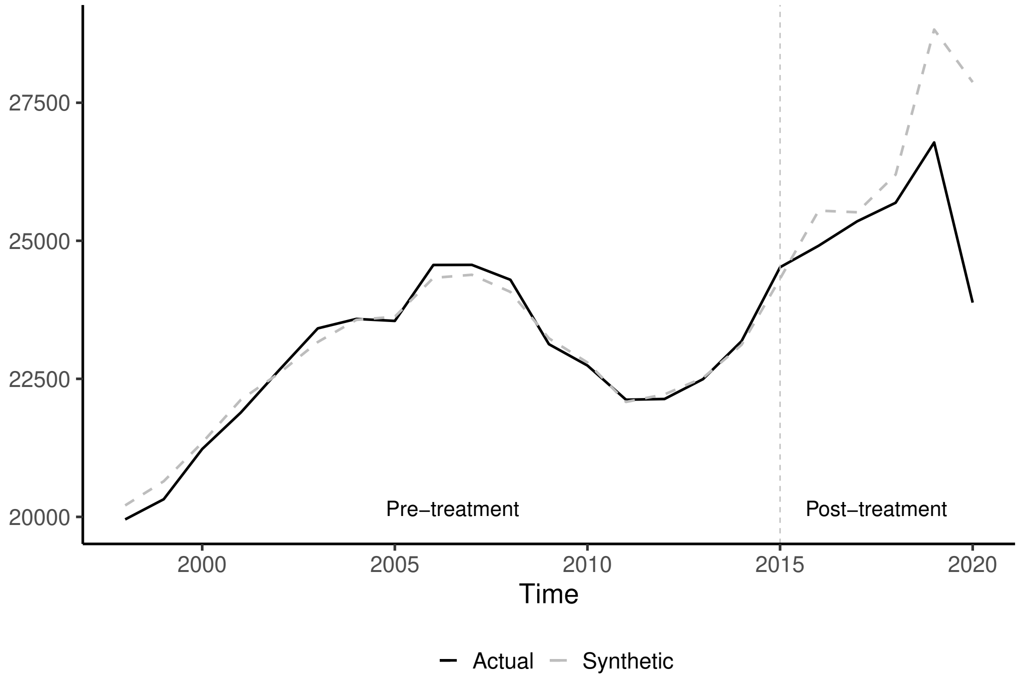

Figure A.52: Model B: Development of Actual and Synthetic GDP of East Yorkshire and Northern Lincolnshire

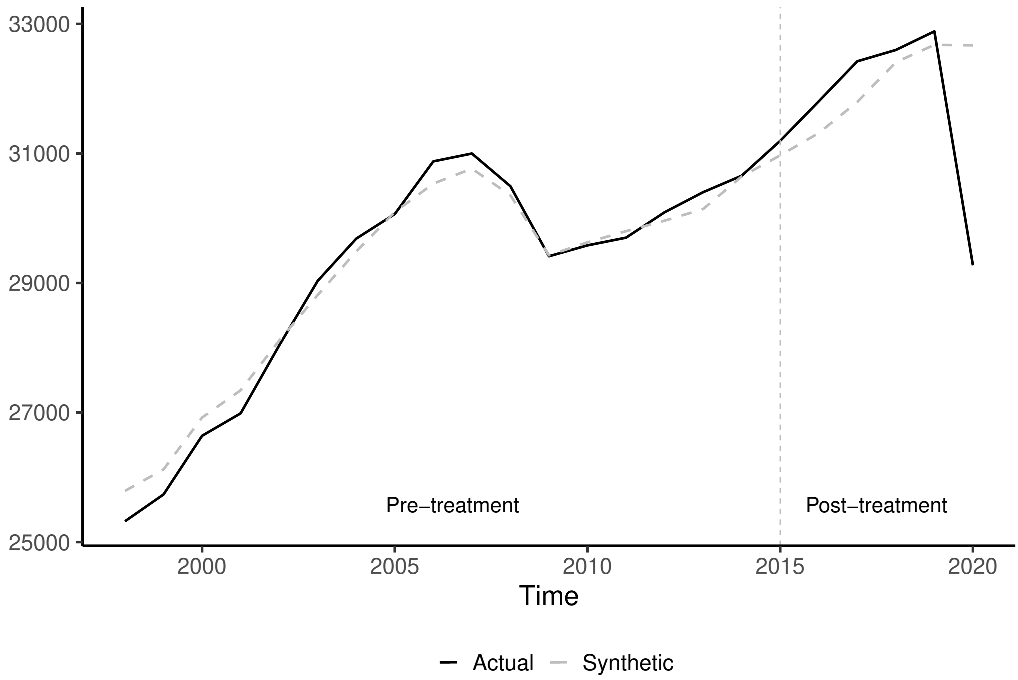

Figure A.53: Model B: Development of Actual and Synthetic GDP of Eastern Scotland

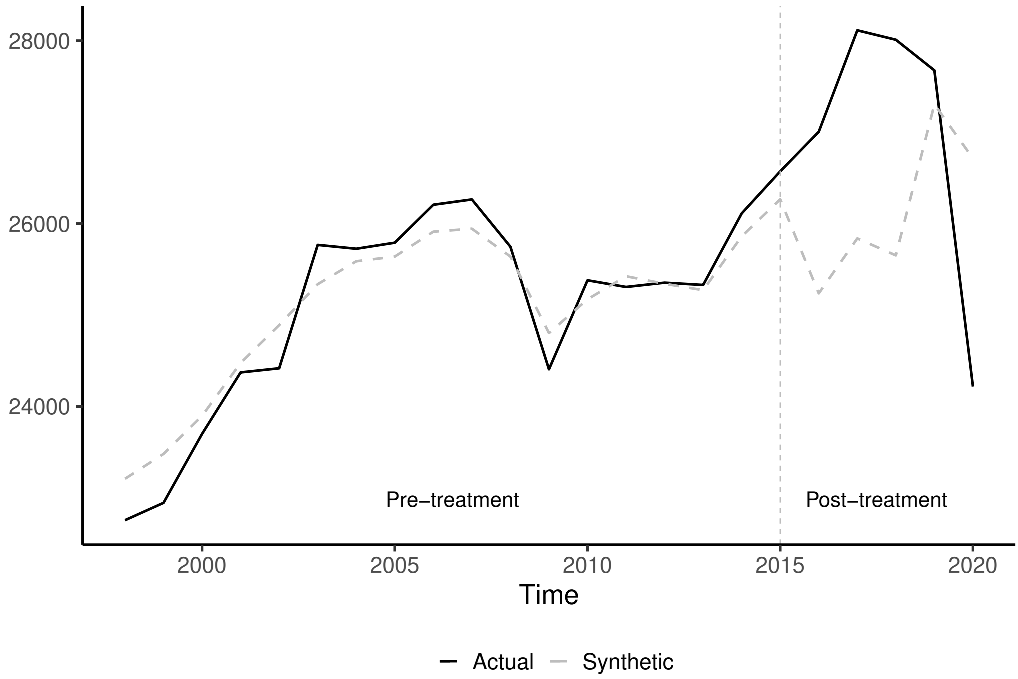

Figure A.54: Model B: Development of Actual and Synthetic GDP of Essex

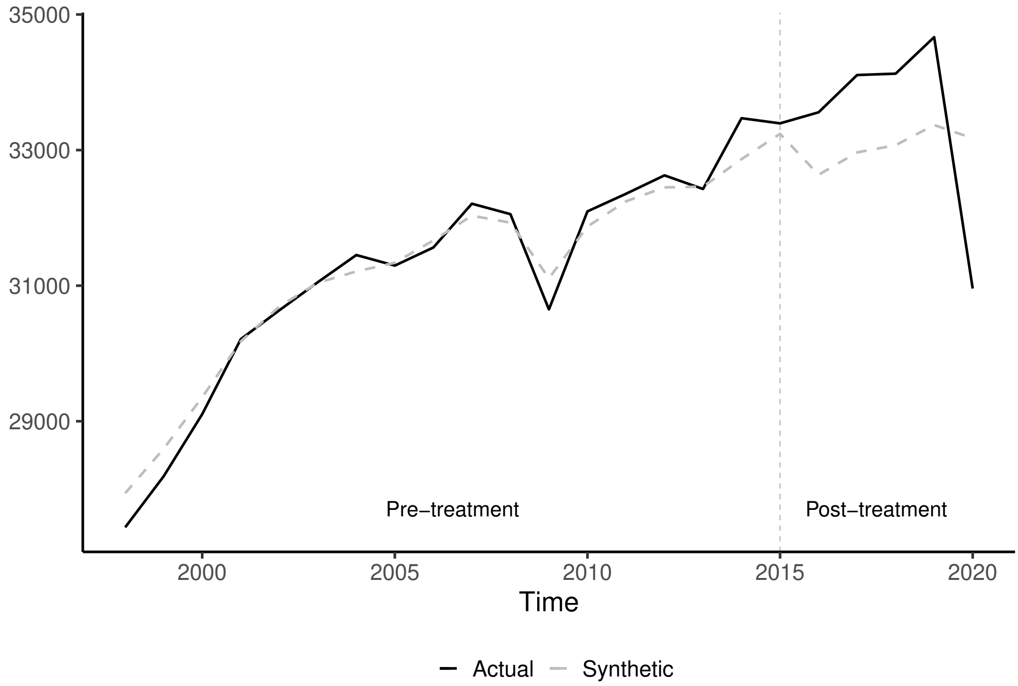

Figure A.55: Model B: Development of Actual and Synthetic GDP of Gloucestershire, Wiltshire and BathBristol

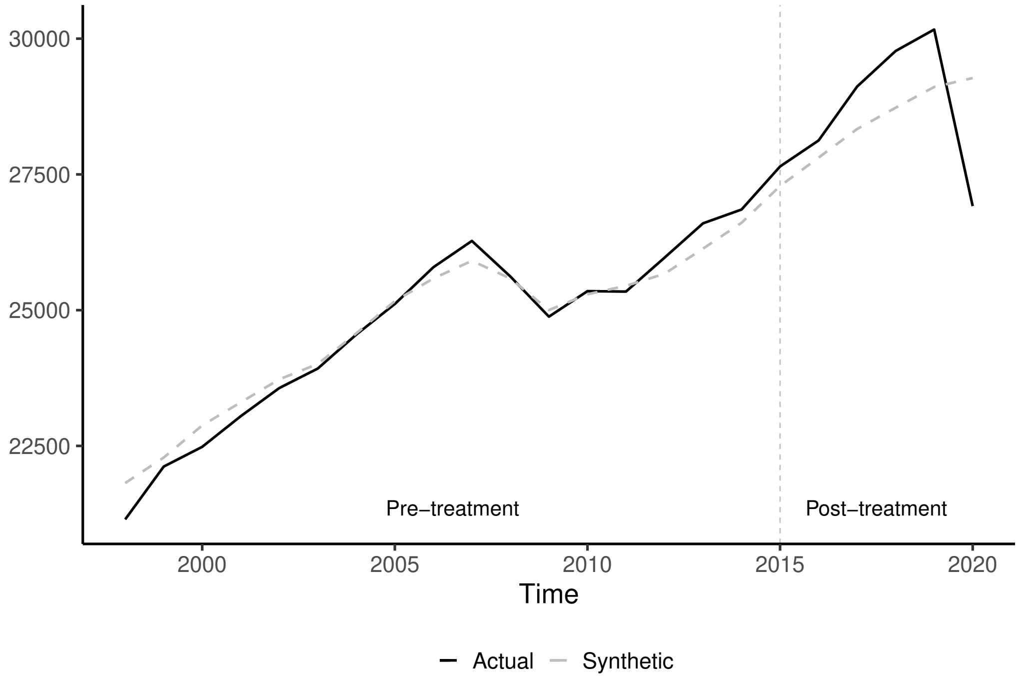

Figure A.56: Model B: Development of Actual and Synthetic GDP of Greater Manchester

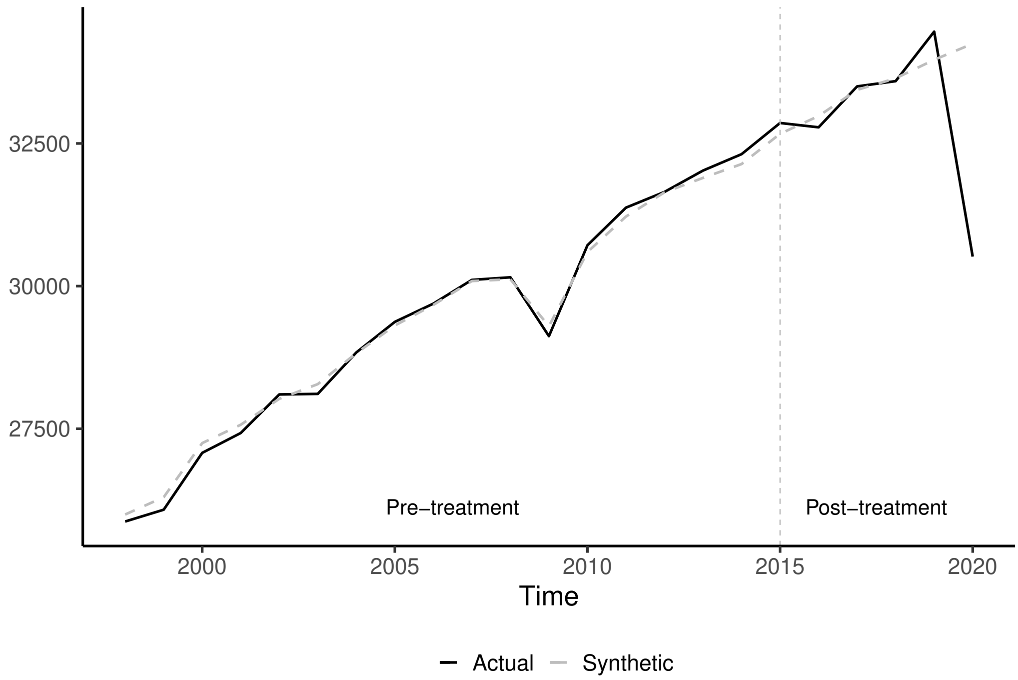

Figure A.57: Model B: Development of Actual and Synthetic GDP of Hampshire and Isle of Wight

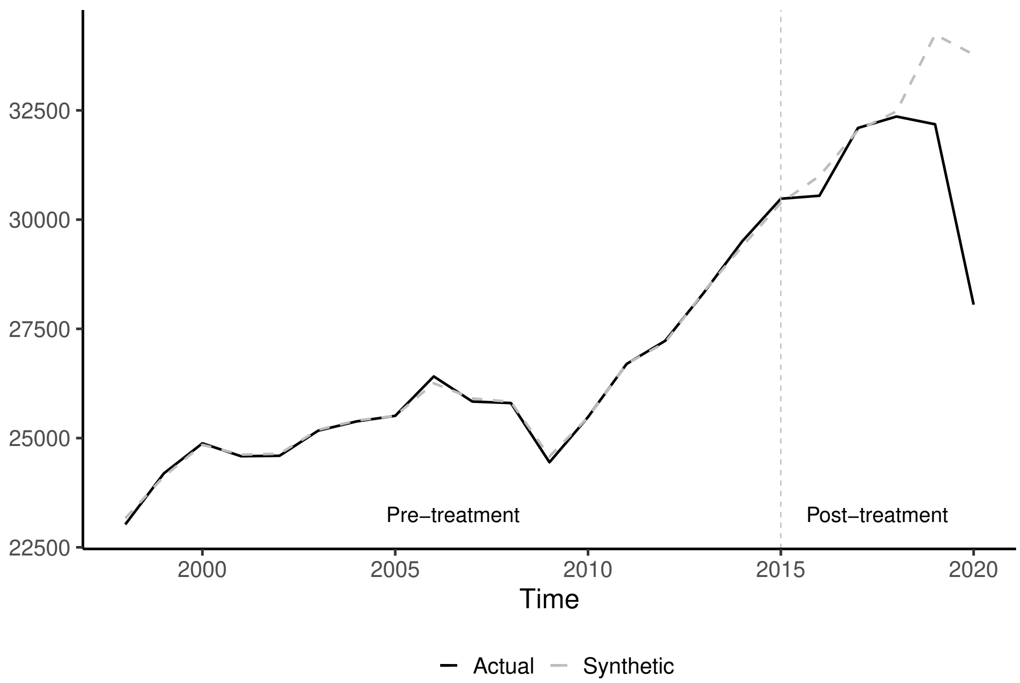

Figure A.58: Model B: Development of Actual and Synthetic GDP of Herefordshire, Worcestershire and Warwicksh

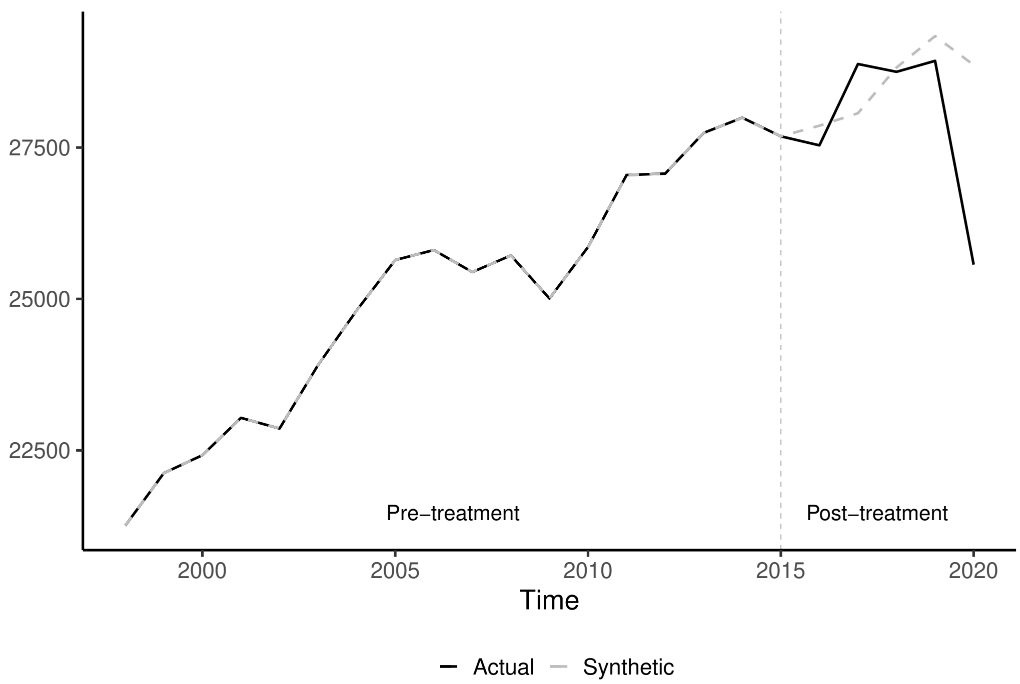

Figure A.59: Model B: Development of Actual and Synthetic GDP of Highlands and Islands

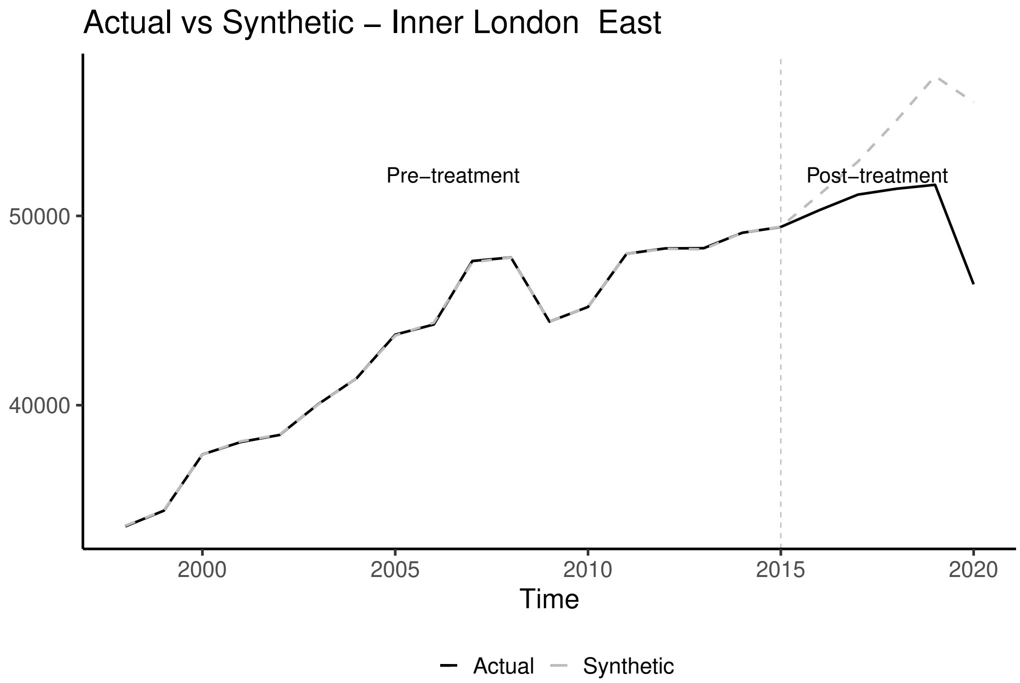

Figure A.60: Model B: Development of Actual and Synthetic GDP of Inner London, East

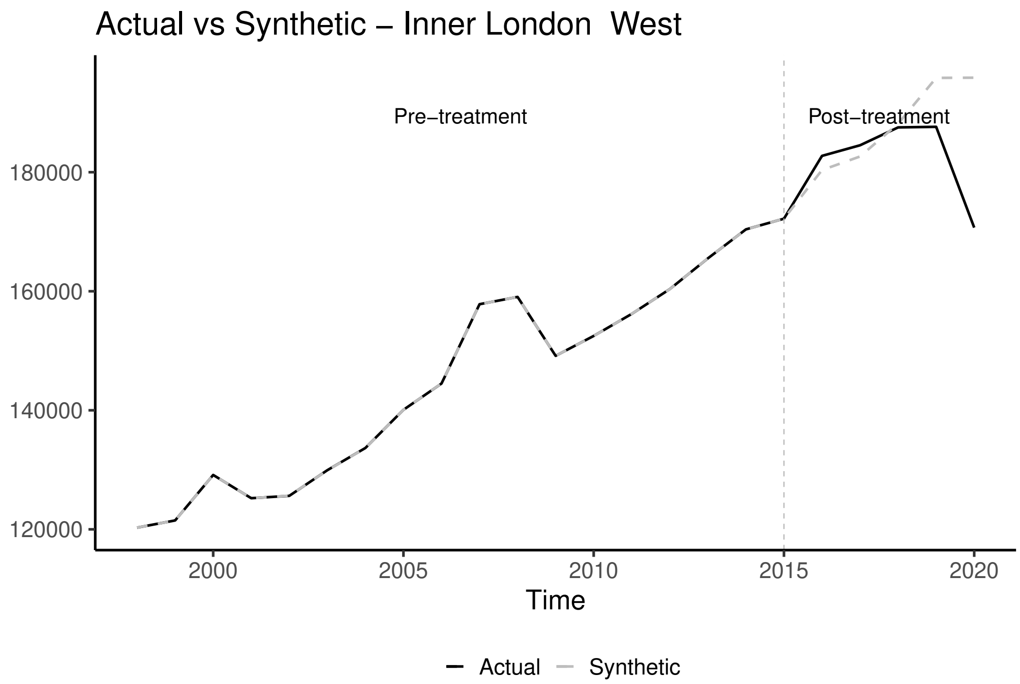

Figure A.61: Model B: Development of Actual and Synthetic GDP of Inner London, West

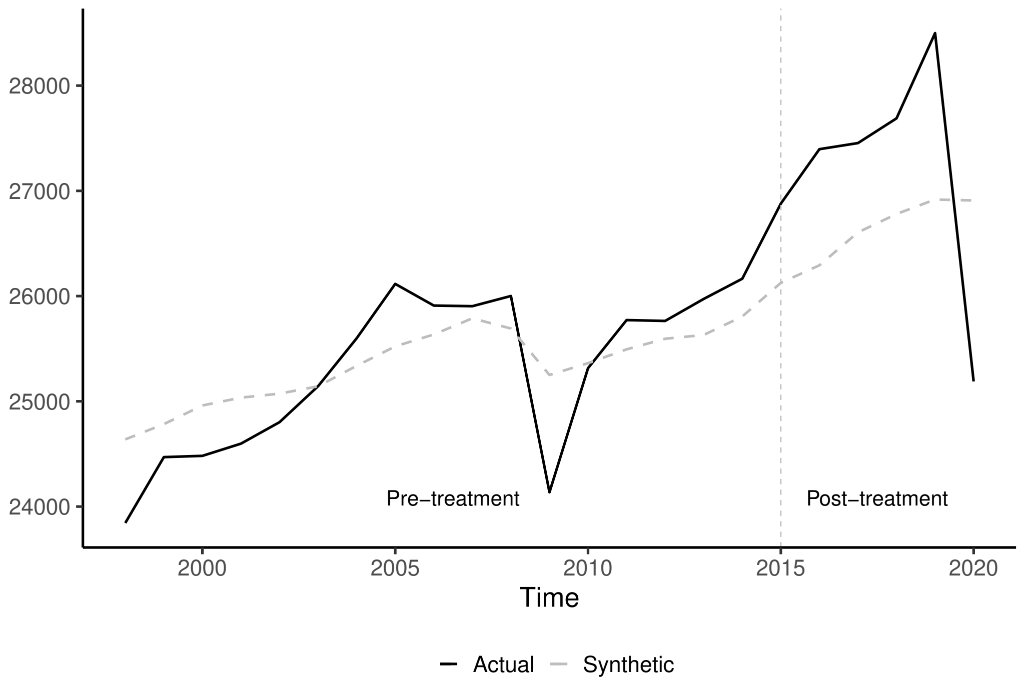

Figure A.62: Model B: Development of Actual and Synthetic GDP of Kent

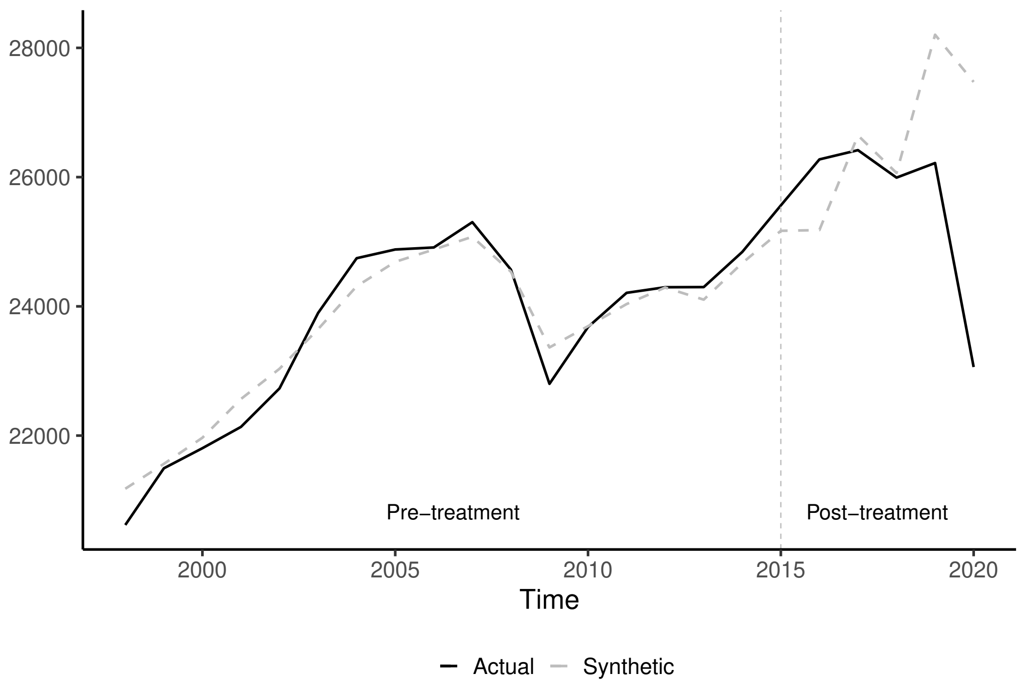

Figure A.63: Model B: Development of Actual and Synthetic GDP of Lancashire

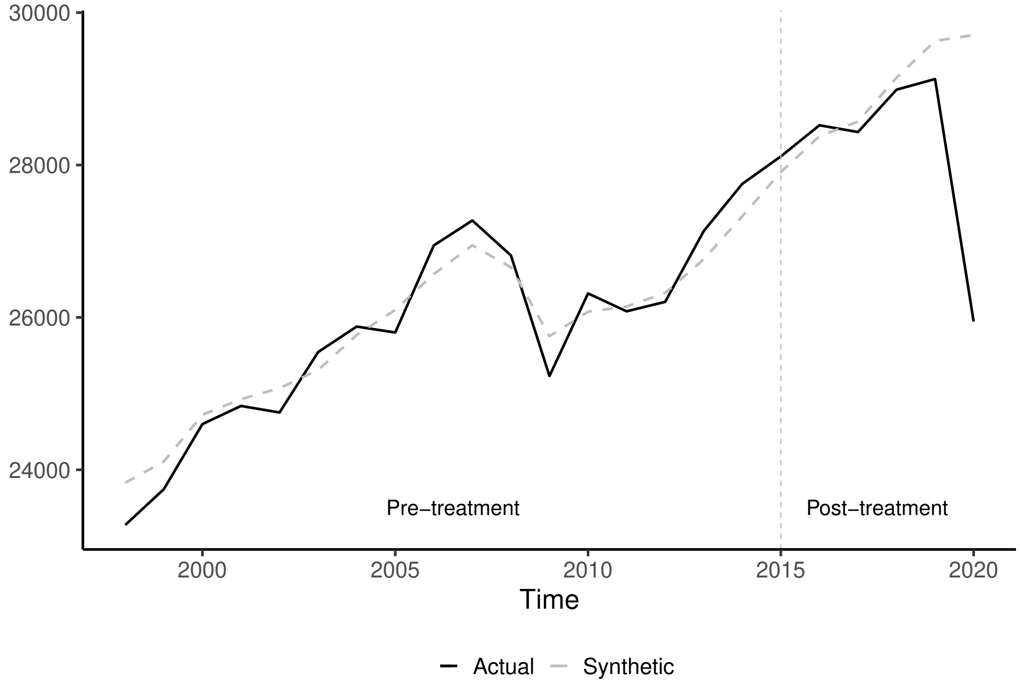

Figure A.64: Model B: Development of Actual and Synthetic GDP of Leicestershire, Rutland and Northamptonshire

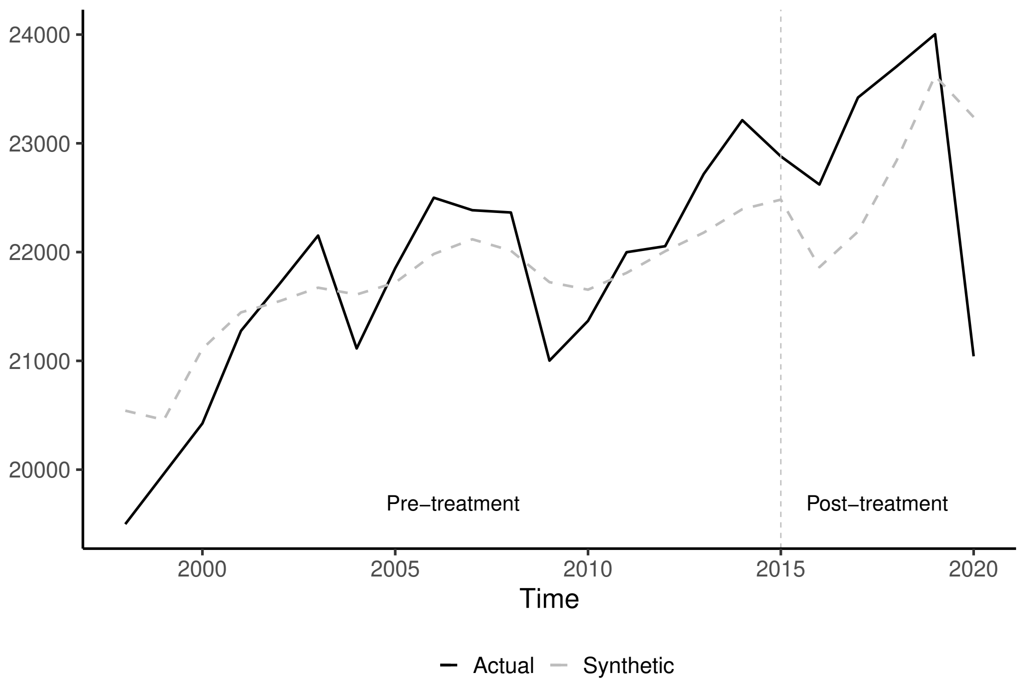

Figure A.65: Model B: Development of Actual and Synthetic GDP of Lincolnshire

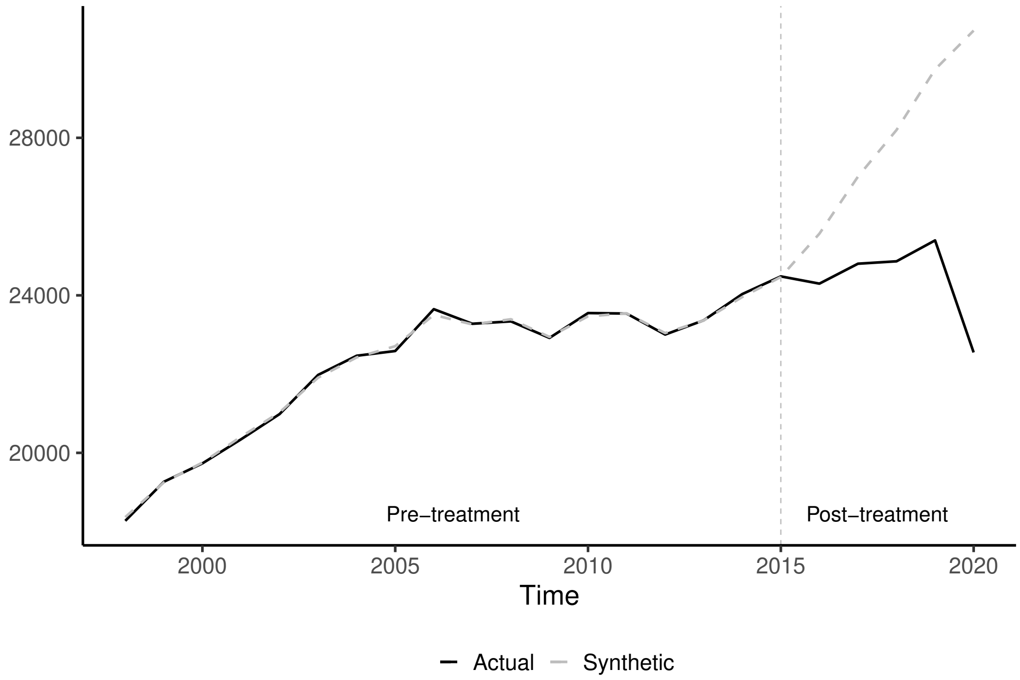

Figure A.66: Model B: Development of Actual and Synthetic GDP of Merseyside

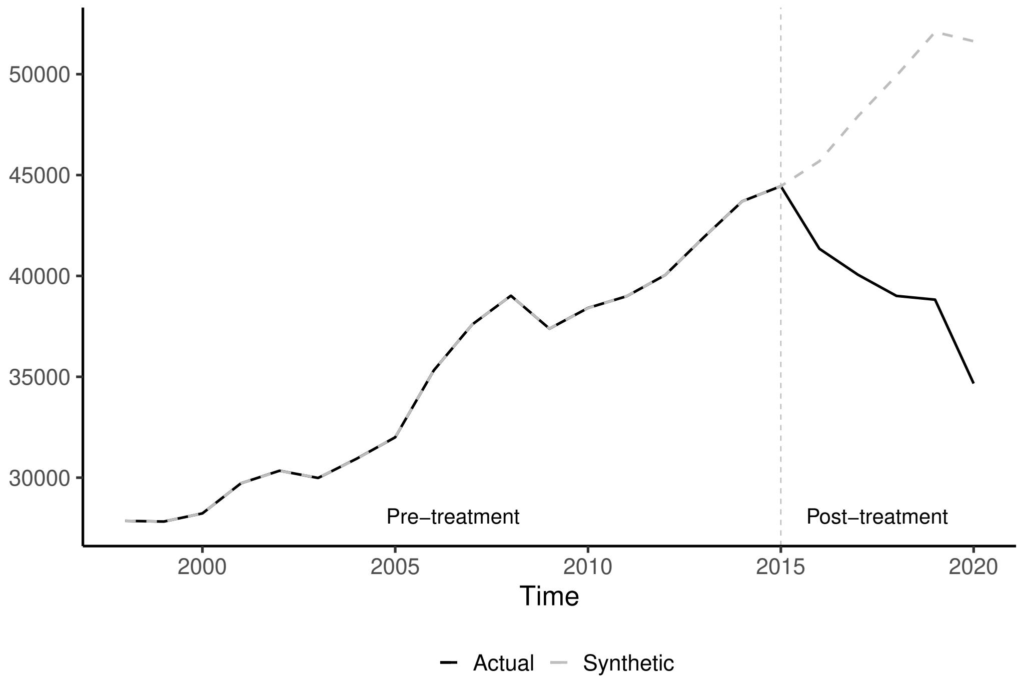

Figure A.67: Model B: Development of Actual and Synthetic GDP of North Eastern Scotland

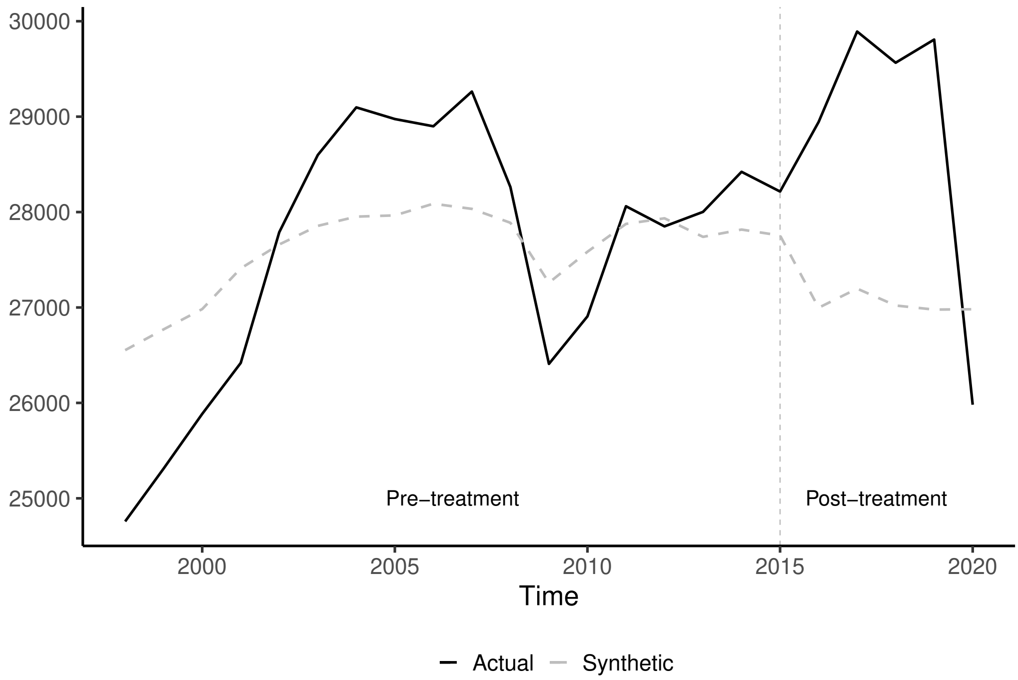

Figure A.68: Model B: Development of Actual and Synthetic GDP of North Yorkshire

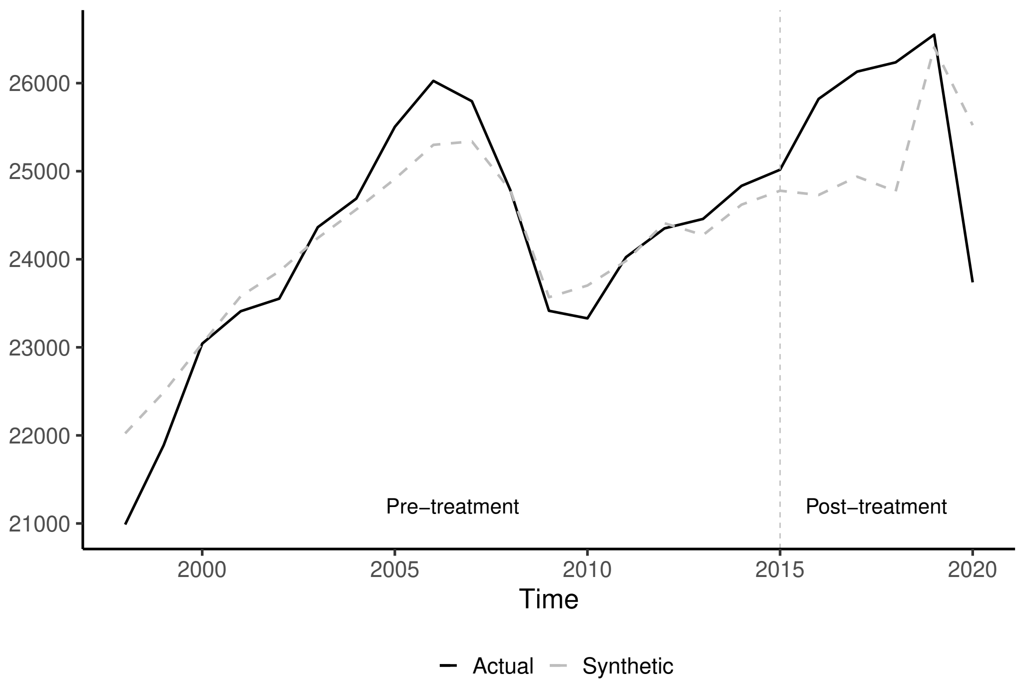

Figure A.69: Model B: Development of Actual and Synthetic GDP of Northern Ireland

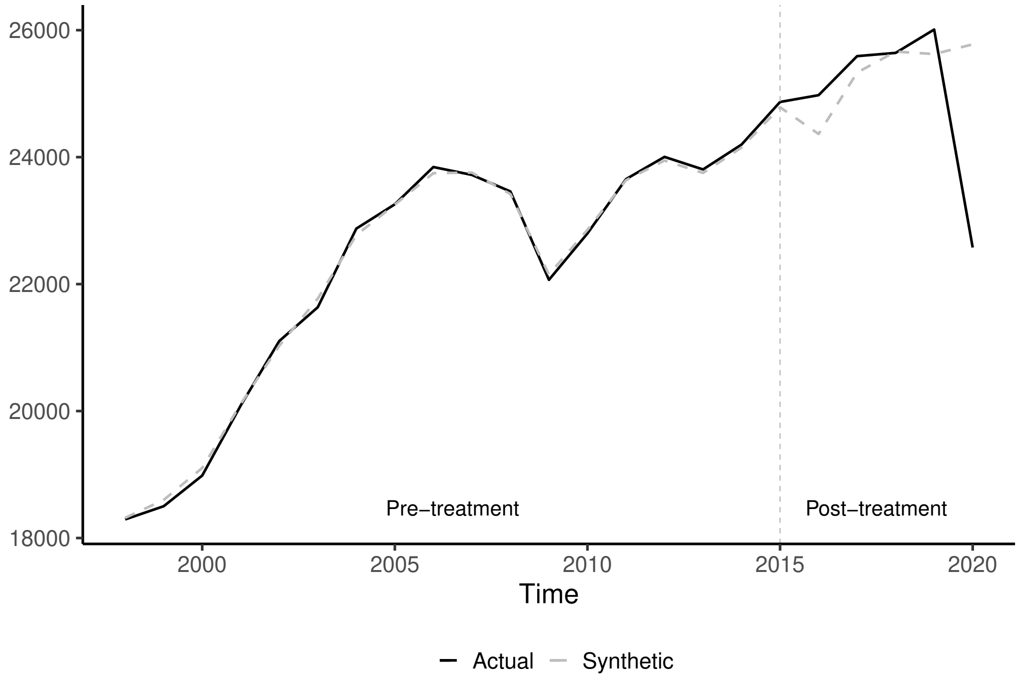

Figure A.70: Model B: Development of Actual and Synthetic GDP of Northumberland and Tyne and Wear

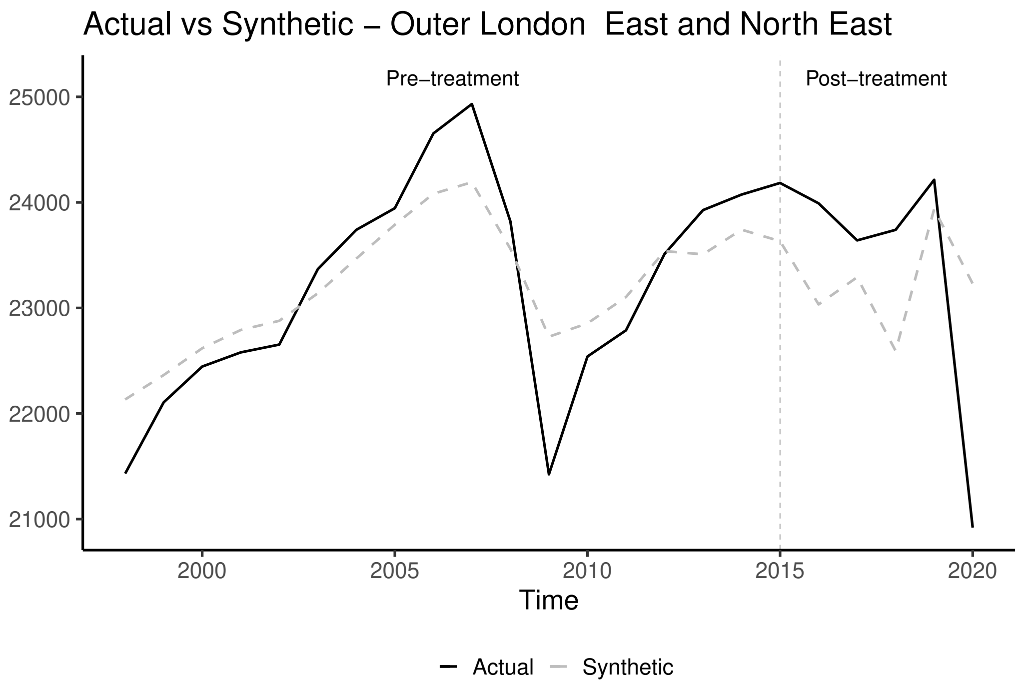

Figure A.71: Model B: Development of Actual and Synthetic GDP of Outer London, East and North East

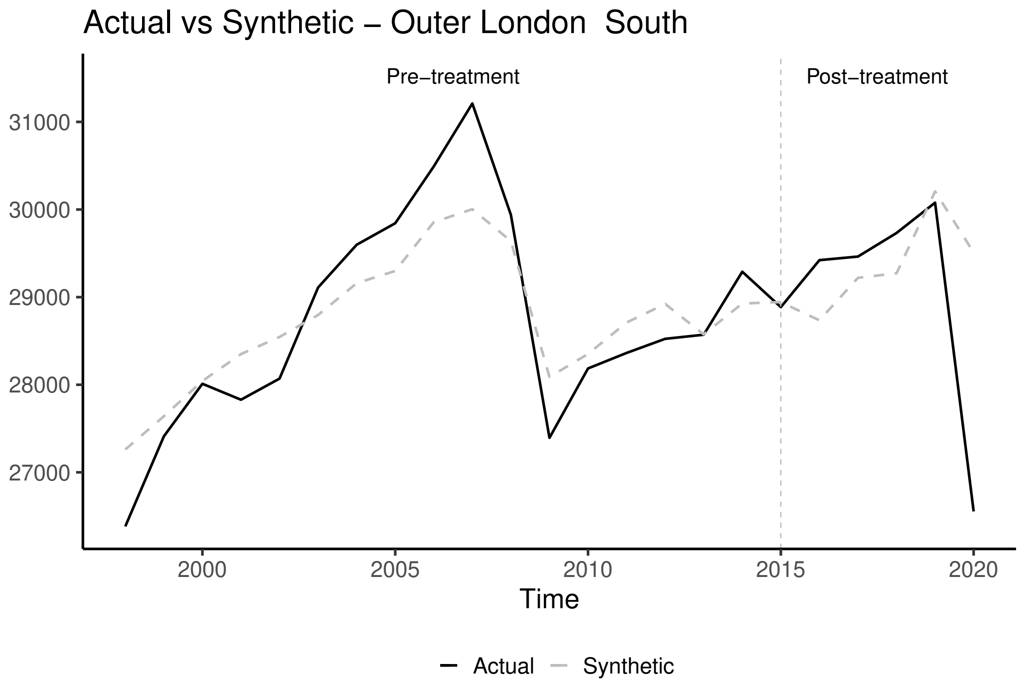

Figure A.72: Model B: Development of Actual and Synthetic GDP of Outer, London South

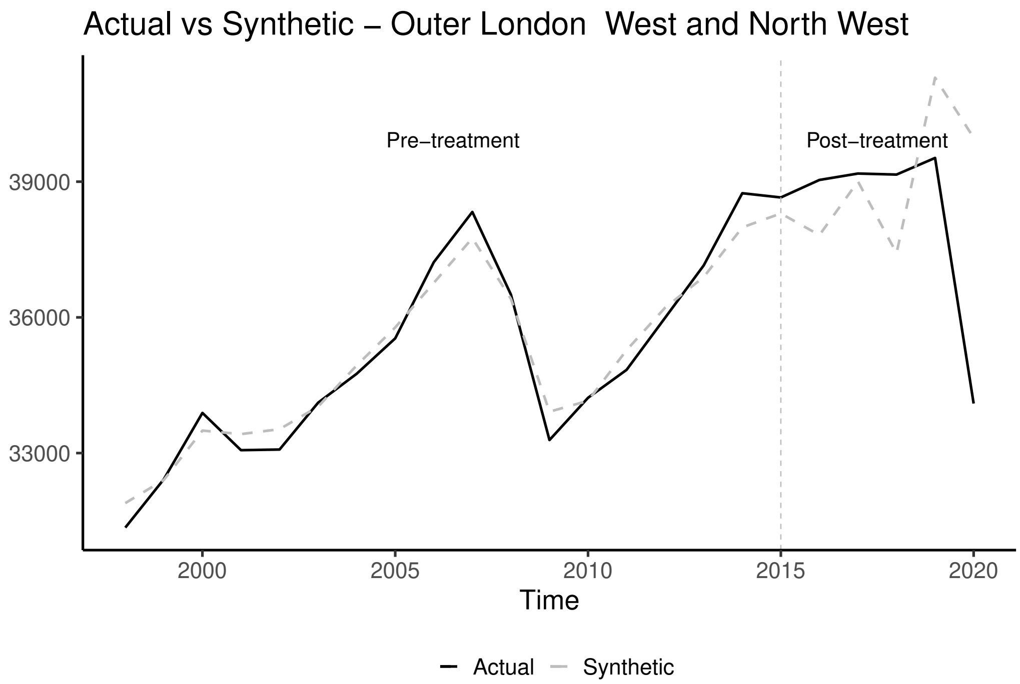

Figure A.73: Model B: Development of Actual and Synthetic GDP of Outer London, West and North West

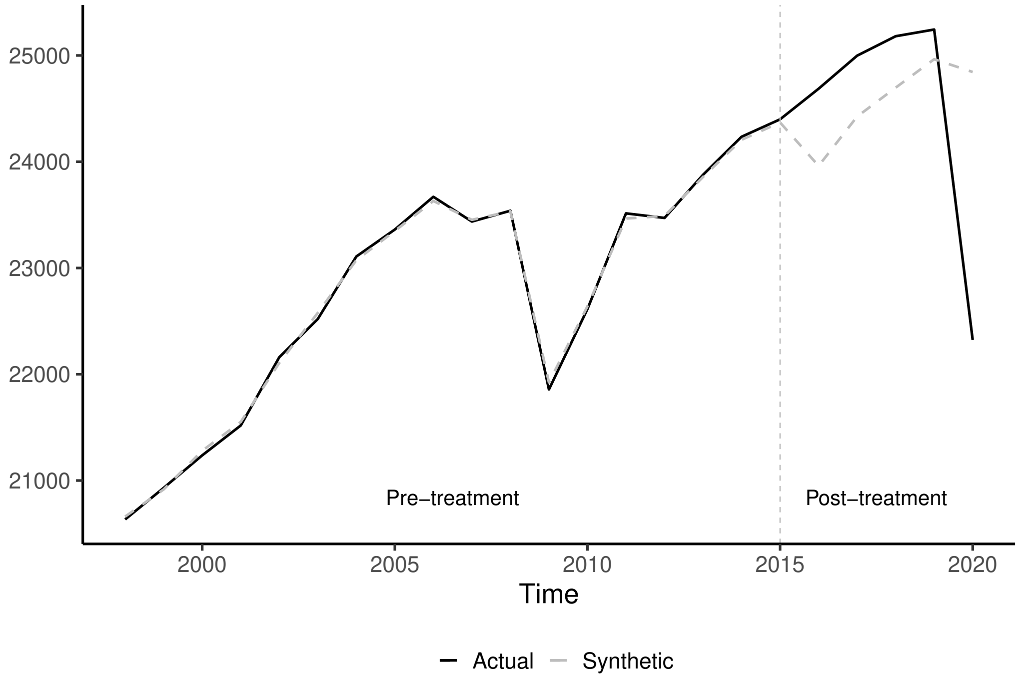

Figure A.74: Model B: Development of Actual and Synthetic GDP of Shropshire and Staffordshire

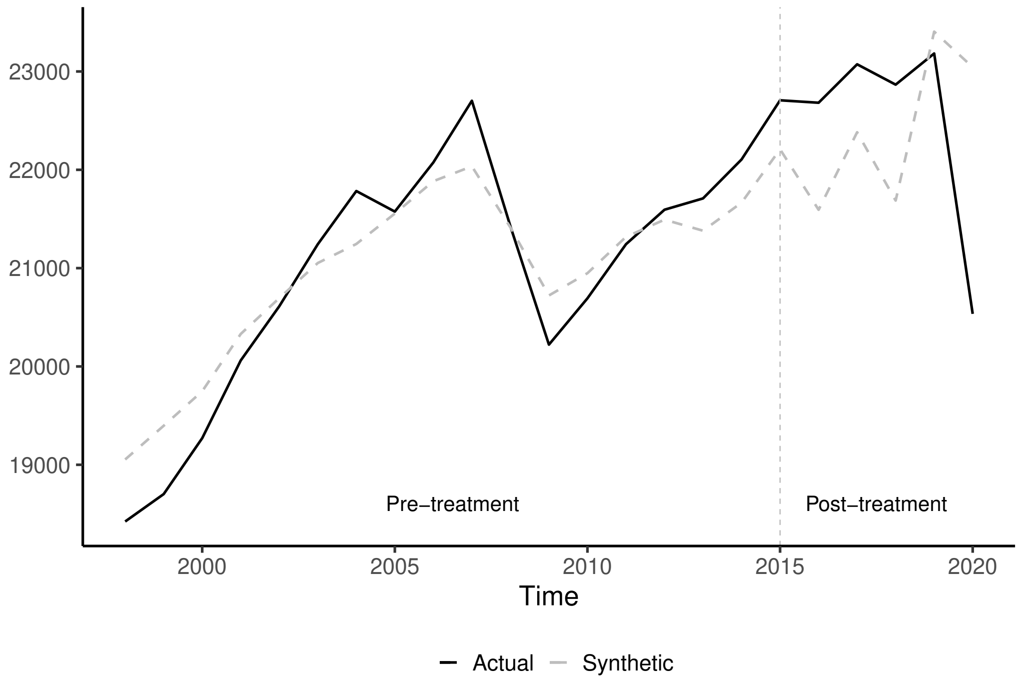

Figure A.75: Model B: Development of Actual and Synthetic GDP of South Yorkshire

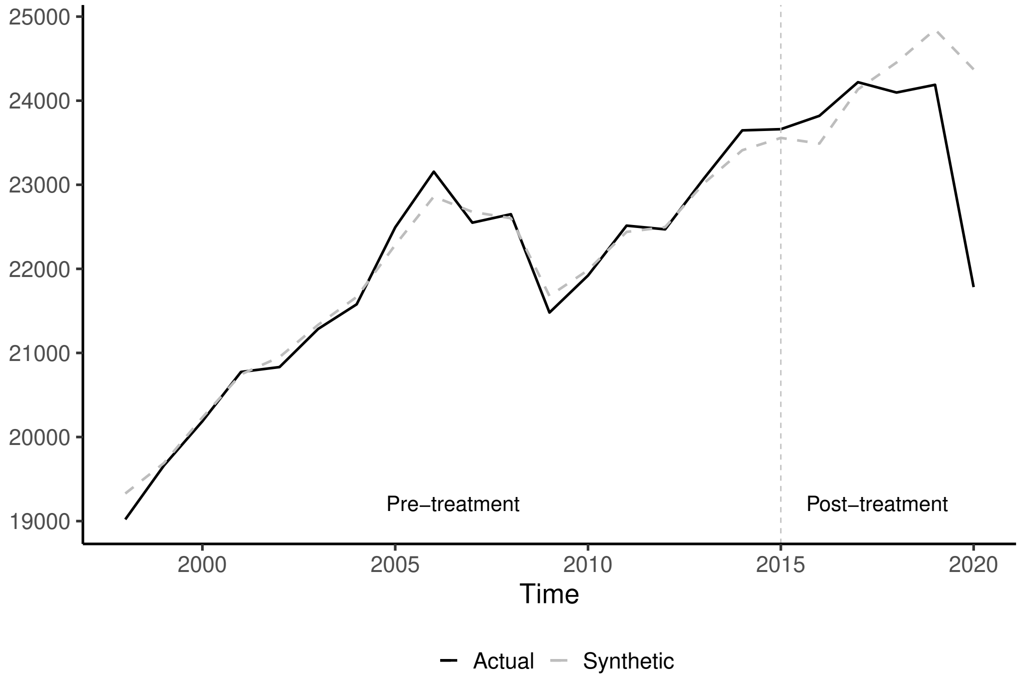

Figure A.76: Model B: Development of Actual and Synthetic GDP of Southern Scotland

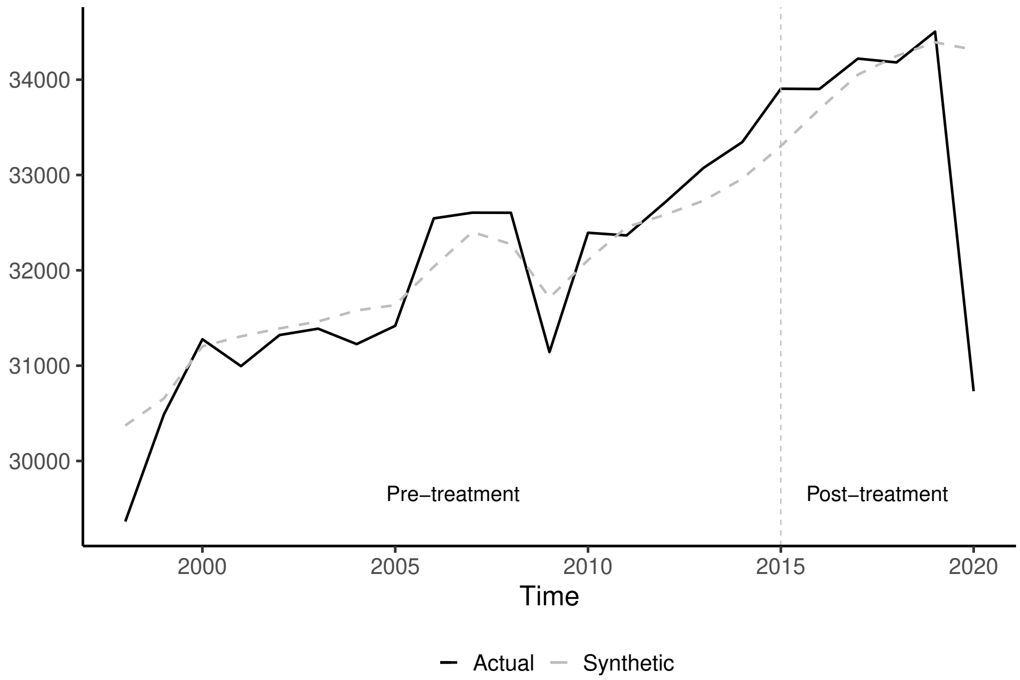

Figure A.77: Model B: Development of Actual and Synthetic GDP of Surrey East and West Sussex

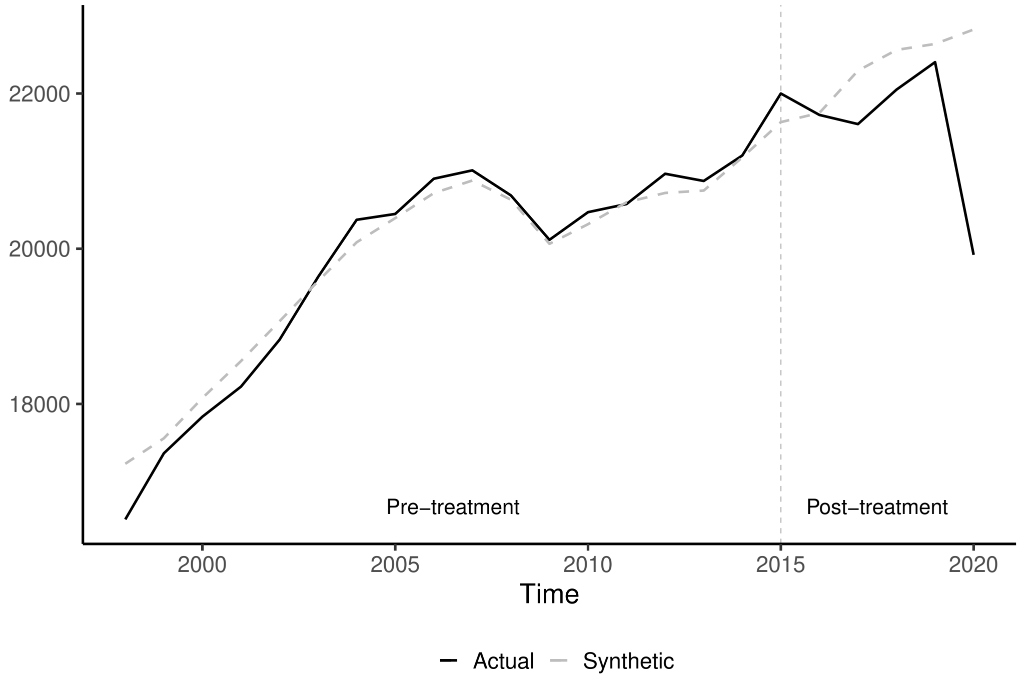

Figure A.78: Model B: Development of Actual and Synthetic GDP of Tees Valley and Durham

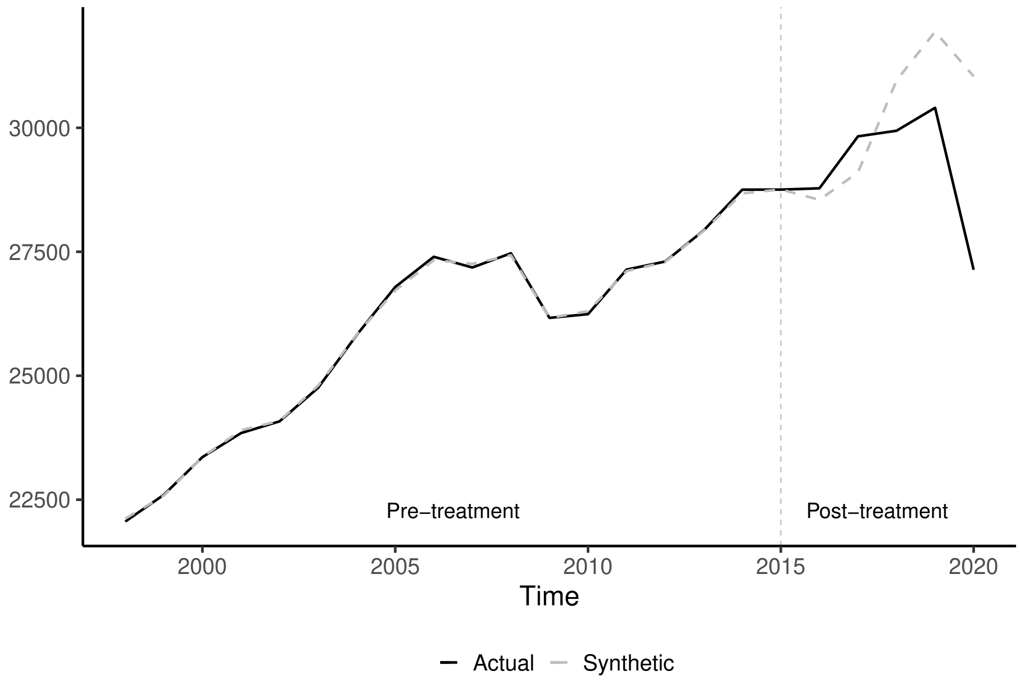

Figure A.79: Model B: Development of Actual and Synthetic GDP of West Central Scotland

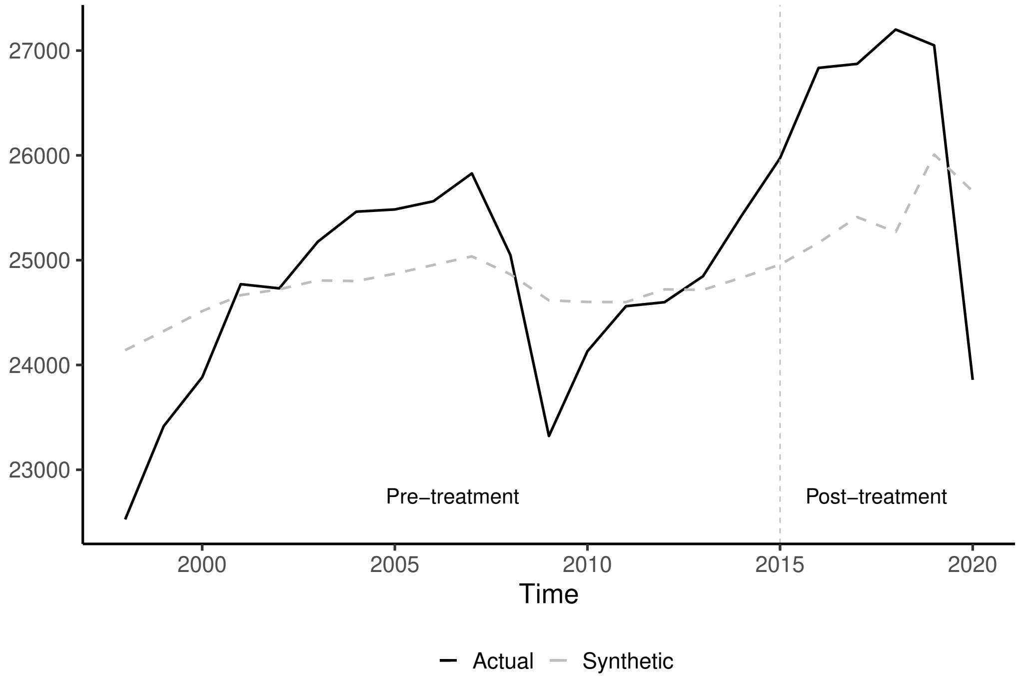

Figure A.80: Model B: Development of Actual and Synthetic GDP of West Midlands

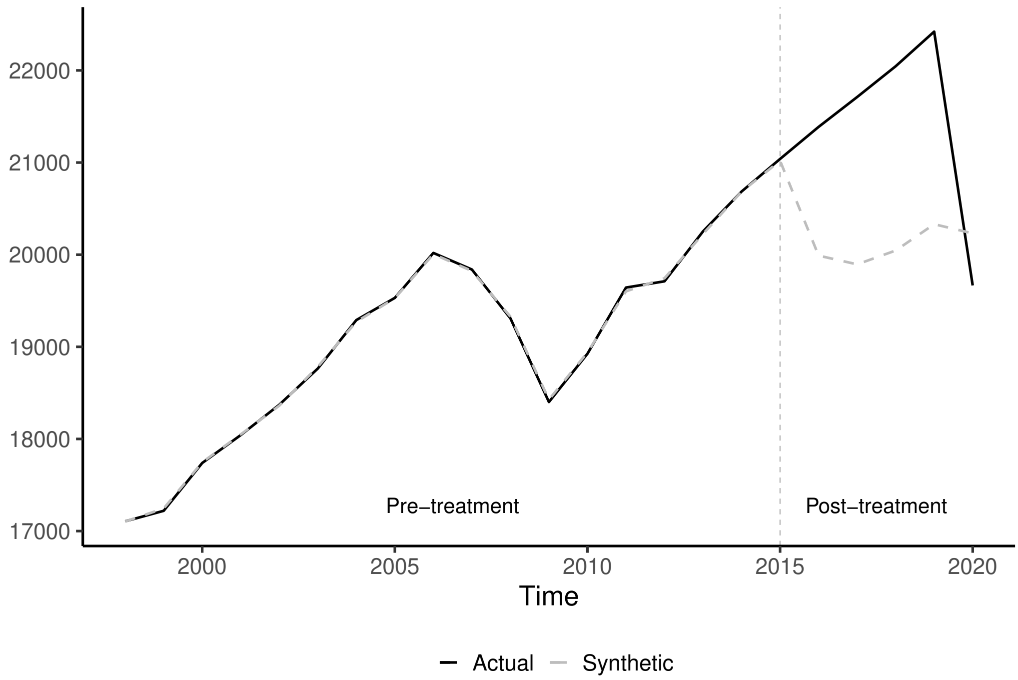

Figure A.81: Model B: Development of Actual and Synthetic GDP of West Wales and The Valleys

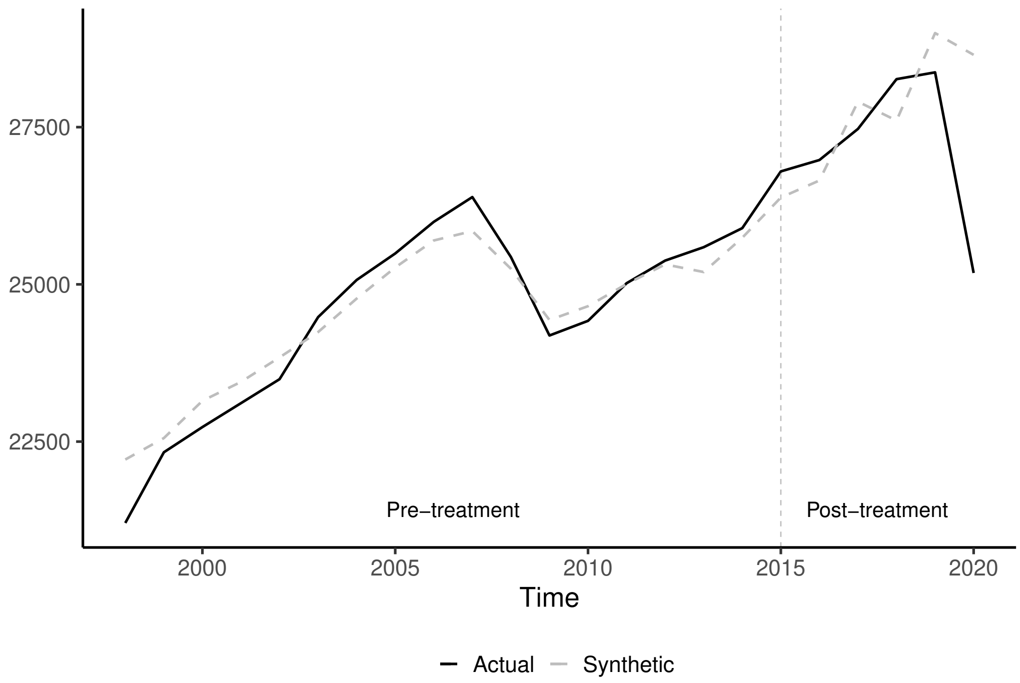

Figure A.82: Model B: Development of Actual and Synthetic GDP of West Yorkshire