The missing inflation puzzle: A synthetic control approach on the impact of the Extended Asset Purchase Programme on Euro-Area Inflation

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Abstract

This thesis studies the effects of the Extended Asset Purchase Programme (EAPP) introduced in 2015 by the European Central Bank (ECB) to fight the low inflation in the euro-area. I reassess the effects after including the owner-occupied housing (OOH) costs into the inflation index, at a monthly and yearly frequency, as recommended in the ECB's latest strategic review. At yearly frequency, with and without the OOH costs, disinflationary yet insignificant effects are found. At monthly frequency, when excluding the OOH costs, significant disinflationary effects are observed; while with the OOH costs, significantly short-term inflationary effects and long-term disinflationary effects are found. I employ and compare the approach of Harvey and Thiele (2021), the Synthetic Control of Abadie et al. (2010) and the Augmented Synthetic Control of Ben-Michael et al. (2021).

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1 Introduction

Excerpts from recent speeches of the current chair of the Federal Reserve System (Fed) and of the current president of the European Central Bank (ECB) summarise the common mandate of the two most influential central banks, especially relevant in macroeconomically-intricate, post-pandemic environment: promote price stability by keeping inflation at a predetermined target.[1] 'Thus, my main message today is that, as the outlook evolves, we will adjust policy as needed in order to ensure a return to price stability with a strong job market' (Powell, 2022). 'We will take whatever action needed to secure price stability and safeguard financial stability' (Lagarde, 2022). Although a straightforward task, central banks have struggled with their mandates. The reasons behind such challenges, the intricate functioning of the central banks and the unexpected policies' results on the real economy are extensively discussed in the next section. For now, the paper concentrates on the 'missing inflation' puzzle, a phenomenon characteristic to the euro-area, where inflation after the Great Financial Crisis (GFC) of 2008 failed to pick up as expected, especially when compared to other countries facing similar post-GFC conditions. The puzzle has severe implications for the efficiency of ECB's most powerful tools at its disposal, as the bank drastically cut interest rates from 3.25% in October 2008 to 0.25% in May 2009. Furthermore, Constâncio (2015) shows that not only has the ECB over-predicted euro-area inflation from 2012 onwards, but so have the IMF, the ECB Survey of Professional Forecasters (SPF), the Consensus Economics, the Euro Zone Barometer, the OECD and the European Commission. The fact that euro-area inflation was for a long time inexplicably lower intrigued the professionals, as they feared unconventional tools such as cutting interest rates and launching purchase programmes fail to produce the desired outcome of price stability and well functioning banking mechanisms. Existential questions on the efficiency of such tools and on general macroeconomic theory arose. In fact, Constâncio (2015) formulates the pivotal doubt of whether this disinflation was due to an aggregation of factors that determined a new, normal low-inflation regime or due to inappropriate timing, size, and channels of the adopted unconventional monetary policies.[2] Constâncio (2015) shows that few research and little consensus has been established regarding the missing inflation puzzle. Sharing the same doubts and a sense of urgency, the Economic System of Central Banks created the LIFT (Task Force on Low Inflation) expert research group on disentangling the low inflation phenomenon, encouraging more research ever since the LIFT launch in 2015.[3]

Yet immediate action was needed. Thus, the ECB launched the extended asset purchase programme (EAPP) for price stability and efficient transmission channels of monetary policy.[4]

[1]More specifically, the Fed has a 'dual mandate' , meaning that both price stability and maximum employment are its economic goals. However, the ECB has a single mandate of price stability.

[2]Based on Constâncio (2015), the factors are: demographic changes, or better integration of low-cost emerging countries' producers, or to the dominance of a service economy or finally, a declining power of trade unions.

[3]More information on the initiative, together with all the produced papers can be found at: https://www.ecb.europa.eu/pub/economic-research/research-networks/html/researcher_lift.en.html.

[4]The programme consists of a corporate sector purchase programme (CSPP), a public sector purchase programme (PSPP), asset-backed securities purchase programme (ABSPP) and third covered bond purchase pro-

The programme was ECB's largest large scale asset purchase (LSAP) until the pandemic, and ran from March 2015 until December 2018, but the majority of purchases were completed commencing 2018 (van der Zwan et al., 2021).[5] The decision to launch the EAPP was taken to address the risks of a too prolonged period of low inflation when 'most indicators of actual and expected inflation in the euro-area had drifted towards their historical lows ' (European Central Bank, 2015a). As such, the EAPP was not part of the global post-GFC unconventional monetary policies, but aimed to support a more effective policy transmissions after the GFC (Neri & Siviero, 2019).[6] This is why past research mainly investigates the transmission channels of the EAPP and their efficiency (e.g., Altavilla et al. (2015), Andrade et al. (2016), Ciccarelli et al. (2017), and Cour-Thimann and Winkler (2016)), especially because immediately actionable insights were needed to help the ECB adjust its forward guidance. Still, it is unclear and little researched whether the EAPP had the desired impact on the real economy (Papadamou et al., 2020). Only few recent papers looked back at the macroeconomic impact, estimating either positive (e.g. Gambetti and Musso (2017)), insignificant (e.g. Kucharčuková et al. (2016)) or negative (e.g. Zlobins (2021)) effects of the EAPP on euro-area inflation, as measured by the Harmonised Index of Consumer Prices (HICP). Thus, more focus on the macroeconomic effects of the EAPP is needed, especially since quantitative easing (QE) is not always completely understood and laudable.[7] When exploring the macroeconomic impact of the EAPP, Papadamou et al. (2020) also encourage different methodologies, as only Vector Autoregression (VAR) models and event studies were used. As such, a crucial yet unanswered question emerged: what would have happened to the real economy, had no EAPP been adopted? Since answering such question requires constructing a hypothetical scenario, the array of suitable methods spans over Difference-in-Difference, Synthetic Control Methods, or other techniques of building robust counterfactuals. Nonetheless, the latter two are preferred in this paper, as they should better exploit the data, offering better dynamic insights into the policy effects, whilst maintaining robustness. Employing the synthetic control method of Harvey and Thiele (2021), I question:

What is the impact of the ECB's EAPP on the HICP inflation in the euro-area, compared to a synthetic counterfactual where no such monetary policy was adopted?[8]

gramme (CBPP3). The packages included the following purchases: €60 billion from March 2015 to March 2016, €80 billion from April 2016 to March 2017, €60 billion from April 2017 to December 2017, €30 billion from January 2018 to September 2018, €15 billion from October 2018 to December 2018. While this programme was stopped in December 2018, it was reinstituted end 2019 and upscaled during the pandemic. More information is available at https://www.ecb.europa.eu/mopo/implement/app/html/index.en.html.

[5] As can be read here:https://www.ecb.europa.eu/press/key/date/2015/html/sp150630.en.html, the first transactions of the programme were completed in June 2015, which is taken as the intervention date when working with monthly frequency. For yearly frequency, the intervention date stays 2015.

[6] Note that Neri and Siviero (2019) claim that the 'decoupling principle ', which isolates balance sheet decisions from interest rate decisions, is characteristic of the ECB policy, where the EAPP was used as a complement, not substitute to interest rate cuts.

[7] Note that QE essentially means employing LSAPs. For example, Stroebel and Taylor (2012) and Thornton (2017) criticise the effectiveness of QE on the real economy, showing that economies react more to the signalling of QE than to its execution.

[8] Note that more precisely, 'on the 22^{nd} of January 2015 the Governing Council of the European Central Bank

The predominant doubt is whether inflation would have fared higher organically, thus making the EAPP redundant, given that it was adopted in different conditions than other unconventional monetary policies of other central banks (Papadamou et al., 2020). Characteristic to the EAPP are the size and the timing: throughout the GFC, central banks such as the Fed, the Bank of England (BoE), and the Swiss National Bank (SNB) introduced the largest LSAPs between 2008-2013, whilst the ECB only had modest quantitative easing attempts and mainly relied on providing liquidity and long-term refinancing operations (Beyer et al., 2017). Chiefly, the ECB aimed for similar results via different tools as it faced cross-country heterogeneity. Yet compared to the Fed, to the BoE and the SNB, EAPP was launched in a sturdier level of financial stress,[9] which may imply less efficiency of the EAPP or undesired consequences (Altavilla et al., 2015).

This thesis contributes to the existing literature in four ways. Firstly, to the best of my knowledge, no paper employed the synthetic control method to examine inflation evolution in the absence of the EAPP. For that, the employed methods construct a 'donor pool' that offers a counterfactual by matching the behaviour of the target variable pre-treatment, enabling policy evaluation. Secondly, past research on the EAPP has authors affiliated with the ECB (Papadamou et al., 2020), whereas this paper stands independent. Thirdly, I consider after-policy developments between 2015 until 2019, but past research mainly stops in 2017, when the LIFT ceased. Lastly, I recalculate the HICP as per the new forward guidance from the ECB.

The economic relevance of this thesis is three-fold. As Constâncio (2015) concludes, the missing inflation puzzle suggests a 'weakening of the link' between monetary policy, economic activity and inflation; warning that if inflation continues to remain low and misunderstood, monetary policy 'could lack effective instruments to stimulate economic activity'. Secondly, in March 2020 the ECB launched a similar programme to the EAPP, namely the Pandemic Emergency Purchase Programme (PEPP).[10] As Blot et al. (2020) captures, the EAPP and PEPP share similar characteristics, so inferences on the EAPP may instruct policy makers on expectations after the PEPP unwinding, started on March 2022. Thirdly, the ECB completed its strategic review in July 2021, the first one since 2003,[11] where two main points emerged. First, the ECB will no longer target a 'below, but close to 2% inflation target' as before but rather a 'symmetric 2% inflation target over the medium term' (European Central Bank, 2022). Second, the ECB's Governing Council 'recommends inclusion of owner-occupied housing (OOH) costs over time in the HICP' (European Central Bank, 2021). The ECB was the only central bank among considered donors that did not include the OOH costs. Thus, I readdress the research question by including the OOH costs into both the monthly and yearly inflation index.

My research uses the approach of Harvey and Thiele (2021), the Augmented Synthetic Control Model of Ben-Michael et al. (2021) and the Synthetic Control Model of Abadie et al. (2010).

(ECB) decided to launch an expanded asset purchase programme (APP) to address the risks of euro-area HICP inflation remaining too low for a prolonged period ' (Gambetti & Musso, 2017).

[9] This was based on how 'various yields and spreads were already compressed ' (Altavilla et al., 2015).

[10] For more information: https://www.ecb.europa.eu/mopo/implement/pepp/html/index.en.html.

[11] Full details are available here: https://www.ecb.europa.eu/press/pr/date/2021/html/ecb.pr210708 dc78cc4b0d.en.html

I show that for yearly data, compared to monthly data, a good counterfactual is harder to obtain. Then, irrespective of the OOH costs, with yearly data I find that the EAPP had negative but insignificant effects on inflation. Similar disinflationary yet significant effects are found when using monthly data without the OOH costs. When including the OOH costs for monthly data, I find significant immediate yet transitory inflationary effects, followed by significant long-term disinflationary effects. I show that the approach of Harvey and Thiele (2021) easily offers an insightful synthetic control method. The approach builds quickly counterfactuals that match the actual inflation the closest and explore well the intervention effects. Such improvements are enabled by using the time series properties of the data, even when few data points are available.

2 Institutional Details

This section discusses the role of central banks, together with the evolution of the inflation measurement and with the recent forward guidance to include the owner-occupied housing costs.

2.1 Central Banks' Role, Unconventional Policies and Two Economic Puzzles

The main role of central banks gravitates around conducting monetary policies to achieve price stability (low and stable inflation) and to address economic fluctuations, whilst promoting long-term employment and moderate interest rates (International Monetary Fund, 2016).[12] Broadly, there are four universal tools for achieving the described objectives: open market operations, minimum reserve requirements, the discount rate and forward guidance (International Monetary Fund, 2016).[13] Inflation targeting has mainly been used as monetary policy across the globe until the GFC, when central banks adopted unconventional monetary policies (International Monetary Fund, 2016). These policies were created as monetary authorities could no longer dampen the economic consequences of the GFC with traditional tools. The three main unconventional monetary practices are: cutting interest rates below the zero-lower bound (ZLB), LSAPs and finally, expectations management on reduced short-term rates, length and size of LSAPs.[14]

These unconventional tools impact the economy through five channels: portfolio rebalancing, signalling, confidence, liquidity, and bank-lending channels (Papadamou et al., 2020). Portfolio rebalancing, refers to how investors' portfolios accommodate changes in yields and risk premia of financial assets, given new monetary policies. The signalling channel describes how central banks use direct communication to influence investors' views on future policy stances, whilst the confidence channel is responsible for increasing investors' optimism in the economy. Both signaling and confidence channels rely on central banks' credibility for effective functioning.

[12] Please see earlier discussion on the distinction between Fed's dual mandate and ECB's single mandate.

[13] More details on how the ECB and the Fed use forward guidance are at https://www.ecb.europa.eu/mopo/implement/html/index.en.html and https://www.federalreserve.gov/monetarypolicy/policytools.htm.

[14] Note that Borio and Disyatat (2009) explain a key feature of the tools: the 'decoupling principle' :the decision on interest rates is independent from policies such as balance sheet extension via LSAP.

Finally, as central banks deploy money through the liquidity channel, the liquidity premium is reduced. The bank lending channel captures operating with consequently lower lending rates.

However, when assessing the effectiveness of the adopted unconventional policies, two puzzles emerge: the 'missing disinflation' and 'missing inflation' puzzles. Bobeica and Jarociński (2017) explain that the first puzzle pertains to the United States (US), where during the GFC, inflation did not fall as much as it was expected to, given the severity of the recession; while the second puzzle is characteristic to the euro-area, where inflation after the GFC failed to pick up as expected. Note that the unconventional monetary policies should revive inflation by stimulating consumption, as interest rates were cut and money was released into the economy, essentially. For example, a consequence of the expansive monetary policies taken during the pandemic is unarguably the high inflation observed currently worldwide. Constâncio (2015) offers an ample overview of explanations from the past literature as to why the missing disinflation was observed in the United States. In summary, the reasons belong to increased credibility of the Fed for anchoring inflation expectations,[15] downward wage rigidity and declining responsiveness to economic slack.[16] As explained before, the second puzzle remains under-researched and the research question in this thesis. Still, a valid doubt was whether inflation could have been so low due to mismeasurements. I explain next how euro-area inflation was calculated, and why a more accurate representation may arise when including the owner-occupied housing costs into the inflation measurement. I re-answer the research question with the recalculated inflation.

2.2 A Brief History of Inflation Measurement and Including the Owner-Occupied Housing Costs into the HICP

The idea to include the costs of owner-occupied housing (OOH) into the HICP inflation dates back to more than 30 years ago, when Astin (1999) built the HICP index to measure inflation and decided against including the owner occupied housing (OOH) costs.[17] However, Bonatti and Fracasso (2021) point out that the adoption of Regulation (EU) No 93/2013 offered a legal framework for compiling a standalone quarterly OOH price index, as Eurostat gathered country-data on OOH costs since 2000. Given that many central banks such as the Fed include the OOH costs into their inflation measures, Bonatti and Fracasso (2021) advised the ECB to do the same, as it clearly did not face data availability issues, but rather methodological disagreements. In the recent strategic review, the ECB settled for using the net acquisition approach in measuring the OOH costs, as it is based on the prices actually paid for the ownership of the house.[18] Empirically, Bonatti and Fracasso (2021) explain that even if inflation rate differences are small,

[15]This could hint towards improved signalling and confidence channels for the Fed.

[16]Economic slack refers to the resources in the economy that are not employed in generating output.

[17]Astin (1999) hinted that if the OOH costs are desired, than the assumption that housing purchases are equivalent to a consumer durable purchase is needed. This yielded philosophical debates and a general hesitancy to include the OOH costs.

[18]For understanding what different measurement approaches entail, please consult: https://www.ecb.europa.eu/pub/economic-bulletin/articles/2022/html/ecb.ebart202201$_0$1 $f643aad55c.en.html$.

they could be a decisive factor in unconventional monetary policy. For example, the ECB policies often may create a housing price bubble that is unaccounted for by the HICP.[19] Thus, the ECB may keep its unconventional policies for longer than needed if the HICP is underestimated. Bonatti and Fracasso (2021) also claim that if the HICP significantly reports less than what citizens perceive as their cost of living, then the credibility of the ECB is threatened. Ultimately, including the OOH costs into the HICP offers better cross-country comparability.[20]

2.3 A Brief Roadmap of the Thesis

I now present the organisation of my thesis in answering the research question. First, to validate the newly proposed approach of Harvey and Thiele (2021), a replication is run, for which results are compared to the original and reported in the Appendix. Then, the same methodology is applied to the HICP, without the OOH costs. After, the counterfactual is build via three methods: the approach of Harvey and Thiele (2021), the Synthetic Control Method (SCM) of Abadie et al. (2010) and the Augmented Synthetic Control Method (ASCM) of Ben-Michael et al. (2021). I inspect whether they arrive at similar donors' selection and similar intervention effects. These models will ultimately yield how inflation would have evolved without the EAPP and what the effect of the EAPP was on inflation. The validity and robustness of the conclusions is checked via placebo tests (Abadie et al., 2010). The next section unearths past research, while the applied methodology is detailed in the namesake section. The Results section presents the findings, while the Conclusion section reflects on limitations and finalises the paper.

3 Literature Review

When investigating the effects of QE, research has been skewed towards the domestic and international effects of the Fed's LSAP, which were considerably disentangled by now (Papadamou et al., 2020). The focus on the Fed's LSAP might be because of the dual mandate the bank carries to promote both price stability and maximum employment. Thus, researching the macroeconomic effects of the adopted LSAPs was pivotal for the Fed in order to understand whether the latter goal of the mandate was also successfully addressed and to adjust its forward guidance. Concomitantly, the EAPP's impact is still assessed by researchers, mainly through two common routes. The first route looks at how the economy adopted the EAPP, investigating the transmission channels' efficiency. The second route analyses whether the desired effects (increase in inflation and in GDP growth) were reflected in the macroeconomy. This paper deals with the second route, which has been neglected thus far (Papadamou et al., 2020). The lack of research concerning the second route may be because studying the efficiency of the transmission channels offered immediate and necessary forward guidance in the ECB's single mandate of price stability.

[19]This happens as the ECB creates favourable conditions for citizens to buy houses through unconventional monetary policies, as it provides liquidity and low interest rates.

[20]Again, for example, the ECB is the only bank in the donor sample that does not include the OOH costs.

Nonetheless, it is worthwhile to discuss the first route of research as an intermediate step towards the second route. In that regard, it was found that given all channels' efficiency, the EAPP was successful in bringing inflation closer to the 2% target and in yielding a considerable impact on the real economy (Ciccarelli et al., 2017). One of the first contributions was achieved by an effective bank lending channel, which led the EAPP to have a sizeable effect on asset prices (Altavilla et al., 2015). Tangentially, the liquidity channel was also found to be highly effective in dampening the financial crisis aftermath, as it reinstituted the ECB's role as a 'lender of last resort' (Cour-Thimann & Winkler, 2016). Finally, the EAPP also proved to have a considerable impact in managing investors' expectations and their risk assessment (Andrade et al., 2016), through the signalling channel, sustained by the exchange rate behaviour (Ciccarelli et al., 2017).

As far as the second route is concerned, early tentative studies proved that EAPP yielded a higher GDP and higher goods prices (Darracq-Paries & De Santis, 2015). However, later studies show a more nuanced effect of the EAPP on real GDP and on inflation in the euro-area. In that sense, the EAPP effect on GDP was apparently sizeable during 2015, fading out throughout 2016, whilst for inflation, the opposite is true (Gambetti & Musso, 2017).[21] This delayed response of inflation is due to the increase in the financial stress before the adoption of the policies, which dissolves the expansionary effect (Lewis & Roth, 2019).[22] Such positive yet transitory effects on the macroeconomy were also shown on the sub-programmes of the EAPP, namely the PSPP and the CSPP (Belke & Gros, 2021; Demertzis & Wolff, 2016).[23]

On a more global perspective, the ECB's unconventional policies are often compared to its past conventional policies. In general, prices react quicker and stronger to unconventional policies, while economic output reacts slower and less (Kucharčuková et al., 2016).[24] Over the medium-term and long-term, inflation remains rather unaffected and given spillovers from other international policies, the ECB's unconventional tools could have been unwound sooner (Kucharčuková et al., 2016). Another dimension in the ECB's unconventional policy design regards the need to unanimously account for the countries' heterogeneity, which may undermine the overall efficiency of such policies (Burriel & Galesi, 2018). The desired output and inflation reactions are unobserved in countries with fragile banking systems (Burriel & Galesi, 2018).

The important conclusion that emerges from this overview is the lack of consensus on the impact of the EAPP on the macroeconomy, and less so on inflation, especially as the heterogeneity of the euro-area adds another layer of difficulty.[25] Also, the past model choices are quite homogeneous around a time-series approach based on various VAR formulations or event studies approaches, whilst some recent papers prefer actually a structural VAR (SVAR).

[21] This analysis used a VAR with time-varying parameters, which is another commonly employed method.

[22] Even though earlier it was mentioned that the ECB faced smoother economic conditions for implementing the EAPP that other central banks, I reiterate that nonetheless, it was considered a period of financial stress.

[23] As discussed in a previous footnote, PSPP stands for Public Sector Purchase Programme while CSPP stands for Corporate Sector Purchase Programme, both being part of the EAPP envelope.

[24] This was the case especially for six countries outside the euro-area, namely the Czech Republic, Denmark, Hungary, Poland, Sweden and the UK.

[25] The euro-area countries may have macroeconomic disparities as either emerging or developed economies.

Currently, recent research re-evaluating the EAPP and the impact of the new PEPP on the economy concludes that both EAPP and PEPP may increase economic output, but have a decreasing ability of lifting inflation (Zlobins, 2021). In fact, it may well be that the EAPP contributed towards disinflationary pressures. Since 2019, the signalling channel remained inert (Zlobins, 2021). Also recently, especially for Southern-European economies, unanimous country-level expansionary effects (increased growth and inflation) are found (van der Zwan et al., 2021).

These recent papers also introduce a new dimension to the everlasting research question, namely what would have happened with inflation, had no EAPP been introduced. A singular paper, namely Lhuissier and Nguyen (2021), uses a proxy SVAR to show via counterfactual simulations that in the absence of EAPP, output growth would have declined by one percentage point and inflation would have lowered by maximum 0.9 percentage points. Note that a wide array of studies use the SCM to examine how, for example, inflation targeting policies affected inflation, such as Angeriz and Arestis (2008). Although few, there are studies that use the SCM to address the impact of unconventional monetary policies on the macroeconomy. Aregger and Leutert (2017) use SCM to study the impact of unconventional monetary policy on the Euro-Swiss Franc exchange rate, while Neuenkirch (2020) use the same methodology to assess the impact of the BoE's LSAP on British GDP, concluding that QE positively affects the GDP, with a maximum effect of around 0.69 percentage points after 30 months. Particularly, to the best of my knowledge, no paper employs the suggested synthetic control methods (SCM, ASCM or the approach of Harvey and Thiele (2021)) to study the EAPP's impact on euro-area inflation.

4 Methodology

To answer the research question, a hypothetical inflation scenario has to be constructed. To do that, countries whose inflation behaves similarly to the euro-area inflation are considered as donors. These donors are used to built a counterfactual that should closely match the observed inflation pre-treatment (before the EAPP) and should accurately reveal what would have happened, had no EAPP been adopted, post-treatment. To build a reliable counterfactual, a good donor selection and a good estimation of the intervention effects are needed. For that purpose, three methods are employed and detailed in the next section. Then, I explain how the placebo tests together with Fisher's exact test (Fisher, 1992) can be performed as robustness checks.[26] Finally, I describe how to interpolate quarterly data into monthly data.[27]

4.1 Methodology for Analysing EAPP Impact on Inflation in the Euro-Area

Hereby I first discuss the approach of Harvey and Thiele (2021) and then the ASCM of Ben-Michael et al. (2021), comparing both models to the classic SCM of Abadie et al. (2010).

[26] Note that I simply use the one introduced by Abadie et al. (2010) combined with the methodology to build a synthetic control of Harvey and Thiele (2021).

[27] Why this technique is needed is discussed in the Data section.

4.1.1 The Synthetic Control Method with Structural Time Series Models

The counterfactual proxies how the outcome variable would have evolved, had the policy not been implemented. The Synthetic Control Method of Abadie et al. (2010) innovates through building a counterfactual by a 'data-driven' procedure selecting a pool of donors that share similar pre-treatment characteristics with the outcome variable. Then, it calculates an optimised weighted average across donors that closely matches the behaviour of the outcome variable as:

$$y_t^c = \sum_{i=1}^{N} w_i y_{it} = \mathbf{w}'\mathbf{y}_t, \quad t = 1, \ldots, T, \tag{1}$$

where y_t^c is the synthetic control (SC), y_{it} is donor i, while the w_i, $i = 1 \ldots . N$ are optimised weights for the N donors considered pre-treatment.[28] The policy effect is the difference between the target y_{0t} and the SC y_t^c, namely $y_{0t} - y_t^c$, for $t = \tau, \ldots, T$, with τ the intervention date.

I now reveal how the donors are selected. For Abadie et al. (2015), the variables on which the pre-treatment matching is performed may be either the outcome variable itself, across countries, or a set of covariates, economically related to the target variable. However, Harvey and Thiele (2021) adopt a time series approach, where they operate with the nonstationarity of the target variable and advise that valid controls must be on the same growth path as the target, hence cointegrated with and behaving similarly as the target. This assumption is especially appropriate when working with inflation, given that all central banks share similar mandates and comparable monetary policy tools through a common economic environment. Moreover, as Stock and Watson (2007) explain, inflation has become increasingly harder to predict with other than its own lagged values, which justifies the disregard of covariates, proposed by Harvey and Thiele (2021).

To assess the assumption of similar growth paths, a stationarity test on the contrast between the control and the target is performed. For that purpose, the KPSS test of Kwiatkowski et al. (1992) is recommended.[29] The KPSS tests are then applied consecutively to the contrast between each unit in the donor pool and the target variable. Then, the likely validity of donors is given by ordering them based on their KPSS statistics' magnitudes. Only those for which the null hypothesis of stationarity is not rejected are then considered.[30] The final validation step is to visually inspect the time series and to discard contrasts that have a large variance.

According to Harvey and Thiele (2021), simply calculating the intervention effect $y_{0t} - y_t^c$ ignores the dynamics of the time series data. To improve, restrictions may be imposed on donors, especially for time series with a few data points, and then the multivariate model becomes as:[31]

$$y_{0t} = \mu_t + \mu_0 + \varepsilon_{0t}, t = 1, \cdots, T, \tag{2}$$

[28] This equates to w being a N x 1 vector.

[29] For details on the tests' power in small samples and optimal lag selection, see Kwiatkowski et al. (1992).

[30] Note that Harvey and Thiele (2021) usually take the first three donors.

[31] Restrictions of Harvey and Thiele (2021) are similar, yet even less limiting to Abadie et al. (2015).

$$\mathbf{y}_t = \mathbf{i}\mu_t + \mu + \varepsilon_t, \tag{3}$$

where $\mathbf{y}_t, \mathbf{i}, \boldsymbol{\mu}$ and $\boldsymbol{\varepsilon}_t$ are $N \times 1$ vectors and μ_t is a common stochastic trend given by:

$$\mu_t = \mu_{t-1} + \delta_{t-1} + \eta_t, \delta_t = \delta_{t-1} + \zeta_t.$$

The vector $\mathbf{i}$ is a vector of ones, that equates the trend in $\mathbf{y_t}$ to the trend in y_{0t}, mathematically capturing that the donors are on the same growth path as the target. Then, both the donors and the target further add only a constant and a normal, identically distributed error term. Since there are no other different stochastic trends of the donors, except for those shared with the target, the above model is called the balanced growth model. This model then quantifies post-intervention movements in the target variable as follows:

$$y_{0t} - y_t^c = \mu_0 - \mathbf{w}'\mu + \left(1 - \mathbf{w}'\mathbf{i}\right)\mu_t + \varepsilon_{0t} - \mathbf{w}'\varepsilon_t, \quad t = 1, \cdots, T. \tag{4}$$

A requirement for balanced growth was the cointegration of each donor with the target. This is easily demonstrated above as $1 - \mathbf{w}'\mathbf{i}$ indeed makes the contrast $y_{0t} - y_t^c$ trend-stationary by equating $\mathbf{w}'\mathbf{i} = 1$. Thus, by definition, $1 - \mathbf{w}'\mathbf{i}$ is a cointegrating vector. Finally, wishing to minimise, for the pre-intervention period the distance between the target and the SC, the weights are obtained via a Restricted Least Squares (RLS) estimation, conditional on $\mathbf{w}'\mathbf{i} = 1$.

Nonetheless, a more efficient method than the described RLS-based one is obtained via allowing for a dynamic response in the structural time series models for the target variable. The new model assumes that there is an intervention at time $t = \tau$, whose effect is dispersed throughout m periods, $1 \leq m$. As such, intermediate effects are assumed to happen in the m periods, which lead to a permanent shift in the outcome variable, after $t = \tau + m$. To confirm when the level shift happened, visual inspection of the time series and a structural break test is needed. Mathematically, the intermediate effects are expressed via m pulse dummies as:

$$d_{j,t}^* = \begin{cases} 0 \text{ for } t \neq \tau + j - 1, \\ 1 \text{ for } t = \tau + j - 1 \end{cases}, j = 1, \ldots, m \ , \tag{5}$$

while the permanent effect, hence a permanent shift in y_{0t}, is modelled by:

$$d_t = \begin{cases} 0 \text{ for } t < \tau + m \\ 1 \text{ for } t \geq \tau + m \end{cases}, 1 < \tau + m \leq T \ . \tag{6}$$

Together, they yield the following specification for the outcome variable:

$$y_{0t} = \mu_t + \mu_0 + \lambda d_t + \sum_{j=1}^{m} \lambda_j d_{j,t}^* + \varepsilon_{0t}, t = 1, \ldots, T. \tag{7}$$

This specification favors the research question of this paper, as it enables observation of whether the introduction of EAPP triggered a hard break or a dynamic adjustment in inflation.

If the latter is selected, then it also quantifies the time frame for which the intermediate effects are present. In this specification, when computing the common trends, all T observations from the control groups and all $\tau-1$ pre-intervention observations of the target are employed, yielding the optimal estimators of the post-intervention target variable:

$$y_{0t|T} = \mu_0 + \mu_{t|T} + \varepsilon_{0t|T}, t = \tau, \dots, T, \tag{8}$$

and of the pulses:

$$\tilde{\lambda}_j = y_{0t} - y_{0t|T}, \quad j = 1, \dots, T - \tau + 1. \tag{9}$$

Harvey and Thiele (2021) present via a Monte Carlo simulation how this approach is more efficient than the RLS-based approach and explain how to carry out maximum likelihood (ML) estimation on the above estimators.[32] Thus, besides efficiency gains, compared to Abadie et al. (2015), this method may offer better donor selection and clearer post-intervention insights.

4.1.2 The Augmented Synthetic Control Method

The ASCM proposes an approach for when the pre-treatment fit via SCM is not very good. The ASCM first estimates the bias in the imperfect pre-treatment matching, and then removes the bias. Augmenting the SCM is preferably done via a ridge regression, yielding the Ridge ASCM (Ben-Michael et al., 2021).[33] Then, the Ridge ASCM can also be written as a weighted average of the controls as the SCM. Contrary to SCM, but similar to Harvey and Thiele (2021), the ASCM allows for negative weights to improve pre-intervention fit. Similarly to Abadie et al. (2010), the ASCM also allows for covariates. Without covariates, the donors follow the process:

$$y_{it}(0) = m_{it} + \varepsilon_{it}, \tag{10}$$

where m_{it} can be modelled as a linear combination of the lagged values of y_{it}, or of a set of latent time-varying factors of the donors. The ridge regression models m_{it} as a linear combination of both, resorting to negative weights only if the target variable is not in the convex hull of the outcomes of the untreated units, as needed in the SCM of Abadie et al. (2015).[34]

The ASCM should offer better pre-treatment fit than the SCM. If the above assumptions are redundant, the SCM and ASCM are asymptotically similar. Finally, the general ASCM is:

$$y_{0t}^{SC,aug} = \widehat{m}_T^{SC} + \sum_{i=0} \widehat{w}_i^{\text{scm}} \left(y_{iT} - \widehat{m}_{iT} \right), \tag{11}$$

[32] Note that Harvey and Thiele (2021) offer also an equivalent regression-based approach for estimating their proposed models; the only major difference being in the standard errors. This is exemplified for West Germany.

[33] The ASCM still corrects for bias without the ridge regression, whose properties are nonetheless preferred.

[34] In general, a convex hull is the smallest convex polygon that contains a given set of points in the plan. Specifically, for the SCM, the convex hull requirement states that the treated unit should belong to the convex hull of the control units. In other words, this means that there exists a weighted average of pre-intervention observations of the control variables that equates the pre-intervention observations of the treated variable.

where $\widehat{m}_{iT}$ is an estimator for m_{iT}, the model component of the post-treatment control, taken generally as a function of pre-treatment outcomes. Then, T denotes the post-treatment period, restricted to one here, for simplification purposes. The $\widehat{w}_i^{\text{scm}}$ are the SCM weights. For extensive details and a formulation with covariates please refer to Ben-Michael et al. (2021).

4.1.3 Robustness Checks

As Abadie et al. (2010), I perform placebo tests to assess whether the results could have been obtained at random. In that respect, the euro-area becomes part of the donor pool and each donor will iteratively act as the target variable.[35] If the gap between the target variable and the SC for the placebo-targets is larger than the original one obtained for the euro-area, then the results are not robust. This can further be quantified by the pre-treatment Mean Squared Prediction Error (MSPE) metric applied to the squared difference between inflation rate in the euro-area and its synthetic counterpart. Finally, I use Fisher's Exact Test (Fisher, 1992), which is a tangential method to the placebo tests, that also quantifies whether the euro-area effect remains sufficiently larger to be robust, when compared to the effect observed for the donors.

4.2 Methodology for Including the OOH Costs into the HICP

In general, measuring the OOH costs correctly is a methodological challenge, because it draws upon a conceptual discussion of whether purchasing houses should be treated as purchasing any other consumer durable goods. Past research has not agreed on a measurement technique, but the ECB, in its strategy review, advised for using the net acquisition approach, for which data is readily available. Thus, below I focus on documenting how to calculate the HICP that includes the OOH costs. The HICP is an annually chain-linked Laspeyres-type index (Eurostat, 2018).[36]

In basic representation, a Laspeyres-type index is a weighted average of relative prices:

$$P^{0t,mt} = \sum_{i=1}^{N} \frac{p_i^{mt}}{p_i^{0t}} \cdot w_i^{0t,t-1}, \tag{12}$$

where p_i denotes the price of product i, w_i denotes the associated weight of that expenditure in the index, $0t$ is the base period and mt is the comparison period, relative to the base period. This time approach is required by regulation, as the index should compare the prices of the current month to those of the reference period based on annual expenditure weights, but updated for each reference period. As such, for comparison period mt, m is the month of current year t.

[35]Note that thus far, neither Harvey and Thiele (2021) nor Ben-Michael et al. (2021) have not formalised a procedure for carrying out placebo tests, yet I employ them also using the approach of the former, together with that of Abadie et al. (2010).

[36]According to Article 2(14) of Regulation (EU) 2016/792, the chain-linked Laspeyres-type index refers to: 'a price index that measures the average change in prices from the price reference period to a comparison period using expenditure shares from a period prior to the price reference period, and where the expenditure shares are adjusted to reflect the prices of the price reference period.'

Then, a Laspeyres-type index has the feature of 'consistency in aggregation' (Eurostat, 2018), meaning that the overall Laspeyres-type index is a weighted average of Laspeyres-type indices for each of the included products in the basket. Thus, the elementary approach to include the OOH costs is via the dedicated and readily-available Laspeyres-type OOH Price Index (OOHPI), and then aggregate the OOHPI into HICP. Indeed, this is the approach taken by past research such as Gros (2018) and Danske Bank (2020). In accordance to Gros (2018), this paper uses the national OOHPI and aggregates them in an euro-area OOHPI using the country weights also employed in the euro-area HICP, based on GDP weights. Then, the remaining dilemma of including the OOHPI into the HICP is what weight to give to the OOHPI. Gros (2018) argues that since the house ownership rates are similar across the euro-area and the US, the weight that the US gives their equivalent OOHPI into their inflation index should be also used for the HICP. Empirically, as per Gros (2018) and Muellbauer (2012) the OOHPI would receive a weight of 30%. However, Danske Bank (2020) and past ECB research consistently apply a weight of only 6.5%, as the HICP does for 'actual rent paid'.[37] Recently, Bonatti and Fracasso (2021) offer an involved methodology and arrived at a weight of the OOHPI into the HICP at 24%, which agrees with what other similar countries use and is also what this paper employs. Then, aggregating the euro-area OOHPI in the euro-area HICP is complete.

4.3 Interpolating Quarterly Data Into Monthly: A Cubic Spline Approach

Lastly, I aim to redo the analysis with monthly data, yet only quarterly data is available for the OOHPI. For that, I aim to interpolate monthly data between two quarters, say Quarter 1 (Q1) and Quarter 2 (Q2) of a certain year, which starts in January. The missing data is given by three intervals, namely the time periods of January to February, February to March and March to April, where January corresponds to Q1 and April to Q4. To do so, we use the cubic spline interpolation method introduced by de Boor (1978). This method builds a collection of n piece-wise polynomials, each of degree three, to retrieve monthly values of a desired variable on each interval given by two neighbouring quarters. This approach is preferred, as the smoothest curve can be obtained by imposing conditions on the first and second derivatives.

5 Data

The majority of needed data is readily available within the Eurostat (2022) database, which provides the corresponding data sets for the two pivotal variables in this thesis: the HICP and the OOHPI. Both data sets come with the weights calculated per country and per item. The country weights are based on the relative GDP of each country and are used to aggregate the respective euro-area indices. The item weights for the HICP are based on a pre-determined basket of goods, while the weight for the OOH costs, as explained before, stands at 24%.

[37] These papers that allow such a low weight find a limited impact of including the OOH costs into the HCIP.

The HICP is available at both monthly and yearly frequency, from 1^{st} of January 1996 until 29^{th} of April 2022, while the OOHPI is available at both quarterly and yearly frequency, from the first quarter of 2005 until last quarter of 2021. From first quarter of 2010 until today, all countries report consistently the quarterly and annual OOHPI. The other variables needed are the predictor variables, whose selection is explained in the next section. The used predictor variables are mainly available at yearly frequency, but spanning the same period as the HICP and OOHPI, and are sourced from OECD and the World Bank database. Reassuringly, the only impediment encountered is that the HICP is available at monthly frequency but the OOHPI only quarterly. I correct this by a cubic spline interpolation on the OOHPI, as explained before.[38]

5.1 Selecting the Predictors

Covariates must be economically related with inflation. As monetary policies target synchronously inflation and economic growth, the standard set of economic growth predictors are considered, as per Abadie et al. (2015): per capita GDP, final consumption expenditure (% of GDP), government expenditure (% of GDP) and trade openness. Unemployment (% of labour force) is added, given the inverse relationship with inflation, as captured by the Phillips curve.

5.2 Selecting the Time-Frame and the Donors

As explained before, Harvey and Thiele (2021) and Abadie et al. (2010) highlight that when constructing the donor pool, the donor units must share similar characteristics with the treated unit, before the treatment. Since the EAPP was introduced on the 22^{nd} of March 2015, it means that I expect a similar behaviour in inflation rates until that point, and a divergence thereafter. The countries adopting similar unconventional monetary policies and whose inflation rates behave similarly to the euro-area inflation rate are: Canada, Korea, Japan, New Zealand, Sweden, the United Kingdom and the United States; displayed in Figure 1. The euro-area inflation is consistently amongst the lowest. Japan is an interesting choice as with its past of deflation, it was expected to help build a better counterfactual for systematically lower euro-area inflation.[39] Yet in between 2013-2015, Japanese inflation is the highest amongst the donors. Interestingly, the Japanese inflation increased then due to the Fukushima disaster, which disrupted supply chains and industrial production, hence increasing consumer prices. Then, Japan and the rest of the countries engaged in unconventional monetary policies, mainly throughout 2008 until 2011. Around 2015 all inflation rates decrease but recover afterwards. Still, until 2016 the euro-area inflation rate remains flat and then one of the lowest until 2018.[40] We consider 2011 until 2015 as the pre-treatment period and 2015 until the beginning of 2018 as the post-treatment period.

[38] I preferred the cubic spline interpolation to take full advantage of the data. The other alternative was averaging the monthly inflation into quarterly inflation, but that disregards the important month-on-month variation.

[39] Acharya et al. (2021) compared the low euro-area inflation puzzle to Japan's 'lost decade' .

[40] The EAPP was stopped at the end of 2018, but it was restarted at the beginning of 2020, yet it was upscaled quickly to dampen the effects of the coronavirus pandemic.

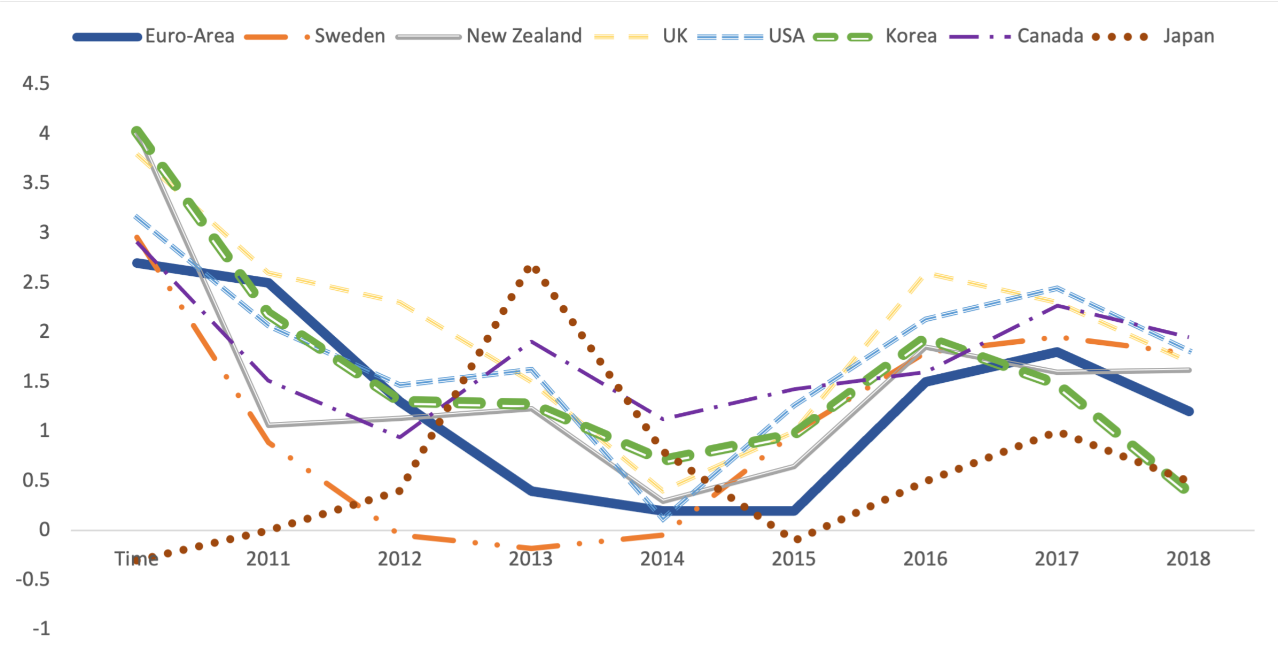

Figure 1. Total Inflation Rate (in % of Annual Change) Across Selected Donors

6 Results

In this section, I first discuss how euro-area inflation changes when including OOH costs. Then, to assess how inflation would have evolved, had no EAPP been adopted I compare the donor selection and the intervention effects estimated via the approach of Harvey and Thiele (2021) to the approach of Abadie et al. (2010) and the approach of Ben-Michael et al. (2021). Validity is assessed via robustness checks. For all results, both a monthly and a yearly data frequency is taken and I explore if including Japan gives a better counterfactual, as from 2013 to 2014, its inflation was the highest amongst the selected countries, but the lowest from 2011 to 2013.

6.1 Recalculating Euro-Area Inflation with the OOH Costs

As explained earlier, there exists ample debate on the weight given to the OOH costs into the HICP index. A 6.5% weight was applied when considering that the OOH costs should have the same weight as the 'actual rent paid' has into the HICP (Danske Bank, 2020; European Central Bank, 2017). When considering that the house ownership rates in the euro-area are similar to those in the United States, a weight of 30% should be taken by the ECB, as this is what the Fed assigned to the OOH costs into its respective inflation index (Gros, 2018; Muellbauer, 2012). Recently, Bonatti and Fracasso (2021) derived an optimal weight of 24% for the ECB.

For a yearly frequency, I considered both a weight of 24% and 6.5% to the OOH costs, as seen in Figure 2 below. Regardless of the assigned weight, the HICP with the OOH costs is lower than the HICP excluding them until 2014, and afterwards relationship reverses.[41] For yearly data, with a weight of 24% to the OOH costs, euro-area inflation would have increased on average by 0.12% and with a weight of 6.5%, only by 0.07%. For monthly data, the euro-area monthly inflation may be underestimated by almost 0.2% when excluding OOH costs, as shown in Figure A1 of Section 8.2.[42] Overall, with a weight of 24% to the OOH costs, the ECB would have achieved its inflation target in 2017 already, at both monthly and yearly frequency.

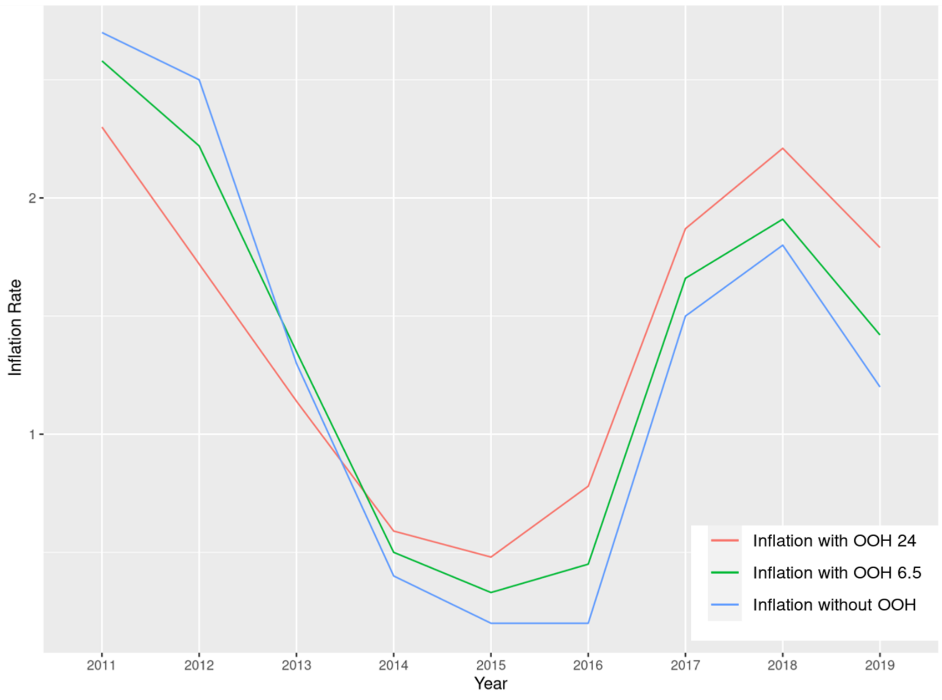

Figure 2. Yearly Inflation Rate Including the OOH Costs

6.2 Assessing the Selection of Countries in Building the Synthetic Control

The ultimate goal is to inspect which models produce a counterfactual closest to the actual inflation. For that, I analyse the composition of the counterfactual for seven models: the Harvey and Thiele (2021) approach (hereby denoted HT), the Abadie et al. (2010) approach (hereby named SCM), when excluding or including covariates, and finally the Ben-Michael et al. (2021) approach (hereby called ASCM) when including and excluding covariates and with and without employing a ridge regression (hereby denoted ASCM No Ridge and ASCM Ridge respectively).

[41]This happens because the OOH costs were low until 2014, due to the euro-area housing cycle achieving its lowest point at the end of 2013 (European Central Bank, 2015b). Then, the housing prices started to recover until 2016 and steadily increased afterwards (Bonatti & Fracasso, 2021).

[42]The underestimation is consistent with the findings of Bonatti and Fracasso (2021), Danske Bank (2020), and Gros (2018). Moreover, from now on, I keep only a 24% weight as a more extreme, representative scenario.

For the latter four, I compare the imbalance in the covariates, measured by the Euclidean norm. I scrutinise whether the models yield the same selection of donors and then I assess how the selection of donors varies when including Japan and the OOH costs.[43] Lastly, I inspect visually the difference between the counterfactual and observed inflation for all seven models.

Table 1: Selection of Donors with Yearly Inflation Rate excluding OOH Costs, excluding Japan

Countries/Models	HT	ASCM No Ridge		ASCM Ridge		SCM	
		without covariates	with covariates	without covariates	with covariates	without covariates	with covariates
Canada	-	-	0.476	-0.070	0.516	0.579	0.389
Korea	0.218	-	0.306	-0.075	0.362	-	0.611
United Kingdom	0.908	0.496	-	0.793	-	-	-
Sweden	-	0.420	0.221	0.755	0.263	-	-
New Zealand	-	-	-	-0.761	-	-	-
United States	-0.126	0.084	-	0.355	-	0.421	-
Scaled Imbalance	-	0.754	1.048	0.120	1.015	-	-

Note: This table reports the weights assigned to each donor in building the synthetic control. The weights should sum up to 1. Abbreviations: HT, Harvey and Thiele (2021); ASCM, Augmented Synthetic Control of Ben-Michael et al. (2021); SCM, Synthetic Control of Abadie et al. (2010).

Table 2: Selection of Donors with Yearly Inflation Rate excluding OOH Costs, including Japan

Countries/Models	HT	ASCM No Ridge		ASCM Ridge		SCM	
		without covariates	with covariates	without covariates	with covariates	without covariates	with covariates
Canada	-	-	0.407	-	0.561	0.141	0.344
Korea	0.218	-	0.490	-	0.758	0.126	0.397
United Kingdom	0.908	0.552	-	0.568	0.160	0.129	-
Sweden	-	0.408	0.101	0.423	0.452	0.140	-
New Zealand	-	-	-	-	-0.862	0.126	-
United States	-0.126	-	-	0.010	-0.069	0.138	-
Japan		0.040	0.066	-	-	0.201	0.259
Scaled Imbalance	-	0.689	0.980	0.657	0.585	-	-

Note: This table reports the weights assigned to each donor in building the synthetic control. They should sum up to 1. Abbreviations: HT, Harvey and Thiele (2021); ASCM, Augmented Synthetic Control of Ben-Michael et al. (2021); SCM, Synthetic Control of Abadie et al. (2010).

I first look at the yearly inflation without the OOH costs but both excluding Japan (as displayed in Table 1) and including Japan (as displayed in Table 2). Regardless of how Japan is considered, the HT always selects United Kingdom, Korea and the United States. This happens as the HT regards only the first three cointegrated donors with the lowest variance. Thus, although yearly Japanese inflation is cointegrated with the target, it displays the highest variance, as supported by Table A8, A9 and A10 in Section 8.3 and Section 8.4 of the Appendix. It is reassuring to see in Table A8 and Table A9 of Section 8.3 that all donors and the target behave as similar processes, justifying the balanced growth assumption explained in Methodology.

Moving on, for the SCM and the ASCM including or excluding Japan makes a considerable difference. When excluding Japan, neither SCM nor ASCM assigns a negative weight to the United States as the HT does, but when including Japan, the Ridge ASCM with covariates assigns a negative weight of -0.069 to the United States.[44] Nonetheless, amongst the ASCM models, the ASCM Ridge without covariates and without Japan achieves the lowest imbalance (0.120 in Table 1), highlighting that adding Japan as a donor does not benefit the counterfactual.

[43] To reiterate, Japan was an intriguing donor as it has both the highest and lowest inflation rate in the pretreatment sample, for roughly equal amounts of time, from 2011 until 2013 and from 2013 until 2015, respectively.

[44] In Figure 1, the United States displays an increasing peak from 2013 to 2015, compared to the slumps exhibited by the countries that were assigned positive weights by the models.

This is confirmed by the fact that apart from the SCM, all the other models assign a zero weight to Japan when the country is considered as a donor. When looking at Figures A8 of Section 8.7.3 of the Appendix, it is clear that the SCM matches the actual inflation the worst, making the assigned weight to Japan redundant.[45] The synthetic control of the Ridge ASCM matches the actual inflation better than the SCM (see Figure A9 of Section 8.7.3). Yet, the HT approach matches the actual inflation the best, as its counterfactual has no kinks (see Figure A10 of Section 8.7.3). As such, adding Japan does not improve counterfactuals across the models.

For yearly inflation with the OOH costs, the conclusion regarding the importance of including Japan is not altered much, as Table 3 and Table 4 below show that the HT again disregards Japan, replacing the United Kingdom with Canada but keeping the other donors.[46] This time, including or excluding Japan makes no difference in achieving the lowest imbalance, yielded again by the ASCM Ridge without covariates (0.599 when excluding Japan versus 0.597 when including Japan), although Japan does not receive a zero weight by all the models.

Table 3: Selection of Donors with Yearly Inflation Rate including OOH Costs, excluding Japan

Countries/Models	HT	ASCM No Ridge		ASCM Ridge		SCM	
		without covariates	with covariates	without covariates	with covariates	without covariates	with covariates
Canada	0.326	-	0.644	0.016	0.663	0.188	0.497
Korea	0.474	-	-	-0.043	0.015	0.135	0.338
United Kingdom	-	-	-	0.025	0.036	0.163	-
Sweden	-	0.421	0.355	0.454	0.385	0.174	0.165
New Zealand	-	-	-	-0.069	-0.055	0.141	-
United States	0.198	0.579	-	0.616	-0.045	0.198	-
Scaled Imbalance	-	0.663	0.821	0.599	0.792	-	-

Note: This reports the weights assigned to each donor, summing up to 1. Abbreviations: HT, Harvey and Thiele (2021); ASCM, Augmented Synthetic Control of Ben-Michael et al. (2021); SCM, Synthetic Control of Abadie et al. (2010).

Table 4: Selection of Donors with Yearly Inflation Rate including OOH Costs, including Japan

Countries/Models	HT	ASCM No Ridge		ASCM Ridge		SCM	
		without covariates	with covariates	without covariates	with covariates	without covariates	with covariates
Canada	0.326	-	0.514	-	0.653	0.129	0.419
Korea	0.474	-	0.233	-	0.550	0.104	0.198
United Kingdom	-	0.389	-	0.401	0.178	0.108	-0.097
Sweden	-	0.433	0.226	0.416	0.588	0.128	-
New Zealand	-	-	-	-	-0.976	0.104	-
United States	0.198	-	-	-	-0.060	0.123	-
Japan	-	0.177	0.024	0.183	0.066	0.304	0.286
Scaled Imbalance	-	0.624	1.058	0.597	0.719	-	-

Note: This reports the weights assigned to each donor, summing up to 1. Abbreviations: HT, Harvey and Thiele (2021); ASCM, Augmented Synthetic Control of Ben-Michael et al. (2021); SCM, Synthetic Control of Abadie et al. (2010).

Finally, Figure A11 of Section 8.7.4 of the Appendix demonstrates that HT achieves the counterfactual closest to the actual inflation. Although the counterfactual has a visible kink that makes the matching less precise, it is smoother than the counterfactual produced by the SCM and by the Ridge ASCM with and without covariates (consult Figure A11 of Section 8.7.4). Overall, Table 3 and Table 4 also indicate that the selection of donors is more homogeneous across models when including the OOH costs.[47]

[45] This is concluded by looking at how closely the synthetic control matches actual inflation pre-treatment. When excluding Japan, no significant differences were found, thus the picture was omitted.

[46] In Figure 1, the higher euro-area inflation would no longer be matched by British inflation, which decreases drastically after 2013. Higher Korean inflation moves steadily parallel to the euro-area inflation after 2013.

[47] Homogeneous refers to the fact that the same countries are repeatedly chosen by the models.

The main conclusion from the comparison for the yearly data is that the HT arrives at the donor selection immediately, whilst the other models take more steps: covariates have to be considered and Japan has to be a candidate donor only to conclude that it receives almost zero weight from all models and that covariates do not improve the pre-treatment matching.[48] At the same time, for the HT, the fact that the inflation rate of Japan had the highest variance excluded the country as a viable donor from the beginning. Thus, as Harvey and Thiele (2021) claim, their proposed approach is an easier method to build a synthetic control. Furthermore, another conclusion is that when including the OOH costs, there is more homogeneity in the selection of the donors across models. As a side note, besides the HT, the SCM and the Ridge ASCM without covariates are overall preferred. A reason for not preferring covariates may be offered by Stock and Watson (2007), who explain that inflation is only heavily dependent on past inflation, thus covariates do not reduce the imbalance. Table A11 of Section 8.5 reports the weights assigned by the SCM to the covariates. In all instances, zero weight is attributed to past inflation, favoring unemployment as a predictor when Japan is excluded,[49] and government expenditure when Japan is included.[50] The pre-treatment matching and the post-treatment differences can be inspected for all models in Sections 8.7 of the Appendix.[51]

I now analyse how the countries are selected at a monthly frequency. Few covariates are available at yearly frequency. I only consider the SCM and ASCM without covariates.[52] Disregarding covariates agrees with the fact that previously the models without covariates were chosen. Furthermore, the inflation rate for New Zealand was excluded due to missing and corrupted data, so Japan is included instead, as finding another suitable donor was infeasible.[53]

Table 5: Selection of Donors with Monthly Inflation Rate excluding OOH Costs

Model\Country Weights	Canada	Korea	United Kingdom	Japan	Sweden	United States	Imbalance
HT	-	-	-	-0.369	0.731	0.637	-
ASCM No Ridge	-	-	0.643	-	0.356	-	0.534
ASCM Ridge	-	0.067	0.640	-0.210	0.436	0.064	0.306
SCM	0.135	0.152	0.330	0.116	0.106	0.161	-

Note: This reports the weights assigned to each donor in building the synthetic control. The weights should sum up to 1. Abbreviations: HT, Harvey and Thiele (2021); ASCM, Augmented Synthetic Control of Ben-Michael et al. (2021); SCM, Synthetic Control of Abadie et al. (2010).

[48] This may be the case only for the inflation data, as I discuss later that past research has proven inflation to be extremely hard to be predicted by anything other than its past values.

[49] This is consistent with the Philips relationship between inflation and unemployment.

[50] This is because Japan has one of the highest government expenditure proportion across the globe, closely followed by the euro-area.

[51] The figures in the Appendix plot the synthetic versus observed inflation for the HT and the SCM and the difference between observed and synthetic for the ASCM, facilitating the interpretation of the models. Note that similar visual analysis can be carried for the subsequent tables and may be used to infer whether the considered model offers a satisfying matching. This is for now a suggested comparison across models, together with assessing the donor selection, as it is not yet possible to compute the imbalance for the HT and for the SCM.

[52] One may argue that further interpolation may be done. Yet doing so from yearly to monthly data would yield too noisy estimates. Then, having both the target and the donor interpolated may cause unreliable estimates.

[53] This is increasingly hard as the QE after the GFC affected the entire world, yet I already considered all the most important central banks for whom the adopted unconventional policies satisfy the underlying assumptions of the synthetic control method.

Table 6: Selection of Donors with Monthly Inflation Rate including OOH Costs

Model\Countries	Canada	Korea	United Kingdom	Japan	Sweden	United States	Scaled Imbalance
HT	-	-	-	-0.133	0.674	0.458	-
ASCM No Ridge	-	-	0.517	-	0.482	-	0.431
ASCM With Ridge	-	-	0.521	-	0.489	-	0.422
SCM	0.108	0.476	0.090	0.065	0.133	0.128	-

Note: This reports the weights assigned to each donor in building the synthetic control. The weights should sum up to 1. Abbreviations: HT, Harvey and Thiele (2021); ASCM, Augmented Synthetic Control of Ben-Michael et al. (2021); SCM, Synthetic Control of Abadie et al. (2010).

Table 5 shows that excluding the OOH costs at a monthly frequency makes the HT select Japan, Sweden and the United States, where Japan receives negative weight. When including the OOH costs, the same selection of donors by the HT is maintained, as they are the only feasible donors, given that only they are cointegrated with the target. Table A6 and Table A7 of Section 8.3 of the Appendix confirm that the selected donors are cointegrated and that except for Sweden, they can be modelled as similar processes as the target, namely the euro-area inflation. Nonetheless, it is reassuring to see all models selecting Sweden, regardless of the treatment of the OOH costs. Moreover, an imminent conclusion is that at a monthly frequency, the models select almost the same donors regardless of the OOH costs, suggesting that having more data points for pre-treatment matching yields a less erratic matching, as expected by Abadie et al. (2010).[54] Furthermore, Figure A4 and Figure A7 of Section 8.7 of the Appendix prove that the counterfactual produced by the HT matches the actual inflation the closest once again.

A few remarks concerning the SCM and the ASCM emerge. First, the SCM is the only one that considers all the countries in the sample as the donors with and without the OOH costs. Nonetheless, as Figure A2 of Section 8.7.1 highlights, the SCM struggles to obtain a good pre-treatment match when excluding the OOH costs, but performs relatively well when including the OOH costs (consult Figure A5 of Section 8.7.2 of the Appendix). The ASCM seems to produce a counterfactual that is only marginally better than the one resulted from the SCM. Yet particularly, the Ridge ASCM manages well to correct imbalance in the pre-treatment matching, considering that the euro-area inflation has been systematically lower. This explains the relatively pronounced peak in the pre-treatment difference between observed and synthetic inflation for the Ridge ASCM (see Figure A6 of Section 8.7.2 of the Appendix).

A pivotal conclusion of the section is the superiority of the HT in three aspects, namely: in building counterfactuals that match the actual inflation the best, in selecting the donors in an easier manner than other models and finally, in offering a reliable pre-treatment matching when the time series have very few data points. Moreover, using a monthly frequency determines a more homogeneous donor selection across models. Lastly, the Ridge ASCM overall manages well to correct for the pre-treatment donor imbalance, but offers counterfactuals that match the actual inflation worse than the HT. The next section discusses the observed intervention effects.

[54] Still, as seen earlier, the HT produced the closest counterfactual for the yearly data, reinforcing the claim of Harvey and Thiele (2021) that their approach is particularly suitable for when only having a few data points available in the pre-intervention period.

6.3 Assessing the Impact of the EAPP

Previously I showed that the HT builds a better counterfactual than the ASCM and the SCM.[55] I now inspect the estimated intervention effects of the HT and compare them to the other models. Finally, I perform placebo tests for robustness of the results. To begin with, Table 7 reports the obtained estimation results of the HT for yearly data with and without the OOH costs, where it is assumed that the EAPP determined a permanent shift in inflation around 2018,[56] towards which inflation adjusted itself towards from 2015 until including 2017.[57]

Table 7: Estimated Intervention Effects with Yearly Inflation Data

	Yearly Inflation with OOH				Yearly Inflation without OOH			
Year	Multivariate		RLS Synthetic Control		Multivariate		RLS Synthetic Control	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
2015	-0.122	1.797	-0.084	0.646	-0.216	1.325	-0.302	0.822
2016	-0.833	0.984	-0.478	0.646	-1.458	1.023	-0.760	0.822
2017	-0.233	1.190	-0.048	0.646	-0.650	1.121	-1.016	0.822
2018	**-0.678**	**1.409**	**0.116**	**0.457**	**-0.745**	**1.420**	**-0.250**	**0.581**

Note: This table reports the observed intervention effects when the approach of Harvey and Thiele (2021) is used. The step dummy, given by the level break, is at 2018. Abbreviations: RLS, Restricted Least Squares.

Clearly, Table 7 exhibits that no significant effects were found at a yearly frequency, even when including the OOH costs. This lack of significance is also found by Kucharčuková et al. (2016), who showed that inflation does not respond to unconventional monetary policies. When looking at the sign of the estimates, the predominantly negative intervention effects would mean that the EAPP induced disinflationary pressures, bringing the euro-area inflation down by on average 25 basis points (bps) (-0.250) to around 70 bps lower (-0.678 and -0.745).[58] These disinflationary pressures are confirmed by the recently growing research on the so-called 'flattening of the Phillips curve' phenomenon. The Phillips curve would predict that inflation lowers when the unemployment rate rises. Nonetheless, in the recent years this relationship seemed to fade, thus the Phillips curve flattened, encapsulating a decreased sensitivity of inflation towards unemployment and economic conditions in general (Occhino, 2019).[59]

Zlobins (2021) also finds an immediate muted response of the economy and long-term disinflationary effects to the ECB's EAPP and may offer a more comprehensive explanation to this. Zlobins (2021) not only attributes these findings to the flattening of the Phillips curve, but also to inactive confidence and reanchoring channels. As such, the liquidity and bank-lending channels were mainly responsible for recovering the economy. This meant that firms benefited from lower interest rates, which helped them cut down their costs and decreased their price pressures.

[55] Specifically, better refers to the pre-treatment matching. The ASCM also performed better than the SCM.

[56] To capture that, a step dummy (for which the results are in bold) is taken for 2018 as a structural break is found then via the Chow test for structural breaks in time series data (Chow, 1960).

[57] This was, as explained before, modelled by pulse dummies. Only the HT offers the possibility to model a gradual response building up to a permanent response, which is why this approach was preferred in the first place.

[58] The positive step dummy of 0.116 is addressed later.

[59] To understand the factors behind the flattening, see Occhino (2019).

Ultimately the lower rates increased the 'productive capacity' of the economy,[60] yet with limited impact on the private consumption. Zlobins (2021) labelled this described mechanism as the 'capacity utilization channel', which recently appeared in the euro-area. Another explanation to the disinflationary pressures comes from Acharya et al. (2021), who shows that the EAPP, which may be seen as an 'ultra-accommodative monetary policy' worked against the ECB's goals of reinforcing price stability. Acharya et al. (2021) explains this happens by creating a 'zombie credit channel'. Such a channel is activated when the unconventional monetary policies are adopted in a weak financial sector, determining cheap lending to 'non-viable' companies, creating an excess capacity in the economy and hence also a supply-side disinflation.[61] Acharya et al. (2021) offers an ample discussion on how the zombie credit channel may well be responsible for the missing inflation puzzle in the euro-area and specifically shows that the fraction of the zombie firms increased by more than 2% when the ECB carried the EAPP.

Another remark is that the RLS when including the OOH costs produces a positive step dummy, as denoted in the last row of Table 7. One may argue this hints at a delay in inflation picking up, as suggested by Darracq-Paries and De Santis (2015) and Lewis and Roth (2019). On the other side, as Harvey and Thiele (2021) claim, it may be another example of the RLS failing to capture well the dynamics of the time series data, as the multivariate model does. In fact, only the multivariate model yields similar magnitudes of the disinflationary effects regardless of the OOH costs treatment. Then, including the OOH costs suggests that the disinflationary pressure would have dampened by almost 0.07% (-0.745 minus -0.678).

Finally, I plot the synthetic inflation versus the observed inflation for the SCM (top) and for the HT (middle) in Figure 3 below. Figure 3 also plots the difference between the observed and actual inflation for the ASCM (bottom).[62] The ASCM is consistent with the finding of the multivariate model of HT regarding the negative effects, as the difference is negative at all times, meaning that the synthetic control is above the observed inflation. Finally, the SCM and the HT perform fairly similar, showing that after 2018 the actual inflation overtakes the synthetic inflation. Yet, the plot for the HT captures only the RLS-based estimation, which is admittedly similar to the SCM following the explanations of Harvey and Thiele (2021).[63]

Nonetheless, given the insignificance of the coefficients, conclusions are limited, as reiterated by Fisher's exact test in Table A15 and A16 of Section 8.8, showing that euro-area inflation does not stand out against the placebos, and does not achieve the highest MSPE, as expected.[64]

[60] As the interest rate is lower, firms now may invest more into capital, shifting away from employing more labour and thus decreasing private consumption since workers are paid less or laid off.

[61] The same supply-side inflation is essentially found by Zlobins (2021), but they focus on firm-level mechanisms, whereas Acharya et al. (2021) investigates what happens beyond the firm-level, at a macroeconomic level.

[62] When the ASCM line is above zero, the observed inflation is above the synthetic inflation.

[63] Harvey and Thiele (2021) also plot the synthetic control only when estimating an RLS-based synthetic control.

[64] This is because the Fisher's p-value is too high and the z-score suggests insignificance.

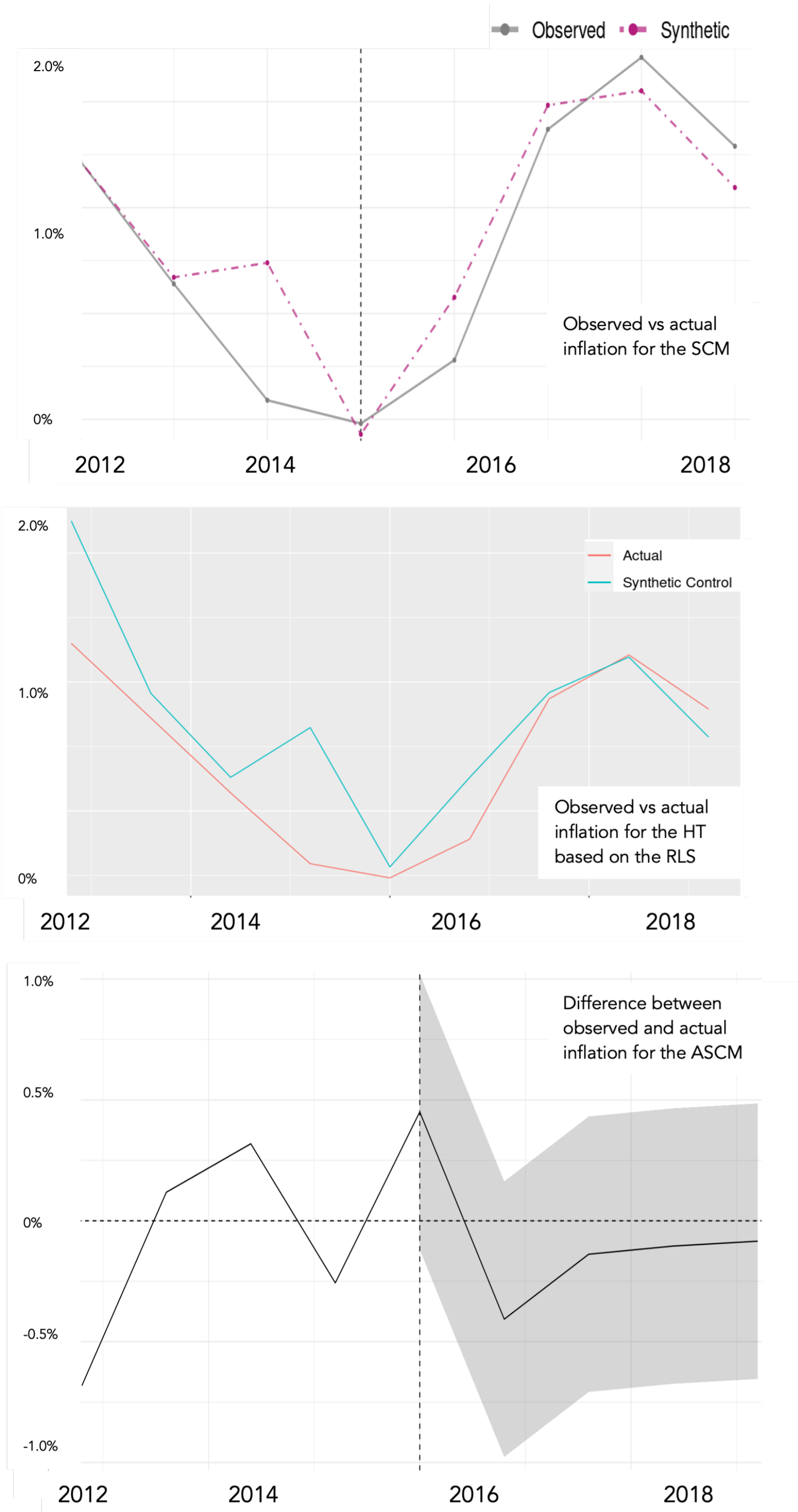

Figure 3. Observed versus Synthetic Inflation for Yearly Inflation with OOH Costs across Models

I now proceed to understand how the conclusions of my analysis change when the monthly inflation rate is used. The intervention effects of the HT are presented below in Table 8.

Table 8: Estimated Intervention Effects with Monthly Inflation Data

Month	Monthly Inflation with OOH				Monthly Inflation without OOH			
	Multivariate		RLS Synthetic Control		Multivariate		RLS Synthetic Control	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
06/2015	0.740*	0.281	0.661*	0.278	0.308	0.274	0.3066	0.267
07/2015	0.573*	0.281	0.469*	0.278	-0.012	0.278	-0.01731	0.267
08/2015	0.469*	0.281	0.373	0.278	-0.097	0.276	-0.10215	0.267
09/2015	0.276	0.280	0.145	0.278	-0.400	0.283	-0.40897	0.267
10/2015	0.322	0.280	0.206	0.278	-0.246	0.280	-0.25192	0.267
11/2015	-0.017	0.281	-0.107	0.278	-0.735**	0.276	-0.741***	0.267
12/2015	-0.005	0.281	-0.079	0.278	-0.753**	0.274	-0.760***	0.267
01/2016	-0.661*	0.283	-0.745**	0.278	-1.717***	0.277	-1.730***	0.267
02/2016	-0.535*	0.281	-0.614**	0.278	-1.551***	0.274	-1.560***	0.267
03/2016	-0.644*	0.281	-0.767**	0.278	-1.739***	0.282	-1.752***	0.267
04/2016	-0.961*	0.283	-1.066**	0.278	-2.235***	0.280	-2.251***	0.267
05/2016	-0.749**	0.283	-0.849**	0.278	-1.981***	0.279	-1.997***	0.267
06/2016	-0.836**	0.283	-0.967**	0.278	-2.014***	0.285	-2.031***	0.267
07/2016	-0.684**	0.283	-0.829**	0.278	-1.843***	0.288	-1.861***	0.267
08/2016	-0.805**	0.284	-0.941**	0.278	-2.043***	0.287	-2.063***	0.267
09/2016	-0.705**	0.285	-0.795**	0.278	-1.951***	0.279	-1.969***	0.267
10/2016	-0.818**	0.283	-0.913**	0.278	-1.929***	0.278	-1.944***	0.267
11/2016	-0.850**	0.282	-0.955**	0.278	-1.884***	0.279	-1.898***	0.267
12/2016	-0.977**	0.284	-1.082***	0.278	-1.948***	0.281	-1.966***	0.267
01/2017	-0.505**	0.286	-0.553*	0.278	-1.270***	0.275	-1.284***	0.267
02/2017	-0.668**	0.288	-0.729*	0.278	-1.544***	0.278	-1.562***	0.267
03/2017	-0.461	0.287	-0.509*	0.278	-1.402***	0.276	-1.417***	0.267
04/2017	-0.388	0.284	-0.494*	0.278	-1.287***	0.281	-1.305***	0.267
05/2017	-0.498*	0.283	-0.618*	0.278	-1.508***	0.283	-1.525***	0.267
06/2017	-0.380*	0.282	-0.515*	0.278	-1.411***	0.285	-1.429***	0.267
07/2017	-0.654*	0.284	-0.818*	0.278	-1.784***	0.294	-1.805***	0.267
08/2017	-0.580*	0.283	-0.725*	0.278	-1.601***	0.288	-1.620***	0.267
09/2017	-0.705*	0.283	-0.825*	0.278	-1.679***	0.283	-1.695***	0.267
10/2017	-0.548*	0.284	-0.653**	0.278	-1.662***	0.281	-1.680***	0.267
11/2017	-0.571*	0.284	-0.676*	0.278	-1.617***	0.281	-1.635***	0.267
12/2017	-0.442	0.282	-0.541*	0.278	-1.464***	0.278	-1.477***	0.267
01/2018	**-0.432*** **	**0.068**	**-0.542*** **	**0.071**	**-1.545*** **	**0.101**	**-1.561*** **	**0.068**

Note: This table reports the observed intervention effects when the approach of Harvey and Thiele (2021) is used. The step dummy, given by the level break, is at 2018. Abbreviations: RLS, Restricted Least Squares. The standard errors (SE) are the same across estimates for RLS, but differ for multivariate, in line with Harvey and Thiele (2021).

Interestingly, at a monthly frequency, regardless of the model, the step dummy (captured in the last row of the table) and the pulse dummies remain predominantly significant for both the RLS and multivariate formulations.[65] Thus, regardless of how the OOH costs are treated, the results across models are homogeneous and significant, suggesting that this sampling frequency is preferred. This shows that the yearly inflation ignores intra-monthly variation and leaves too small of a pre-treatment and post-treatment sample for reliable results. Moreover, monthly inflation carries more interest for policy formulation, as it is poignantly perceived by consumer.

It is remarkable that when excluding the OOH costs, the EAPP appears to have significantly lowered inflation, given by the negative intervention effects in Table 8, found for all the months.[66]

[65]With a similar procedure, the level break was found again for the beginning of January 2018.

[66]Indeed, Figure A2, A3 and A4 of Section 8.7.1 of the Appendix show that the synthetic inflation is always higher than the observed inflation after the EAPP went through.

When including the OOH costs into the monthly inflation, the first pulse dummies of both the RLS and the multivariate model show immediate yet temporary and decreasing significant positive effects (from around 0.661 or 0.740 to 0.206 or 0.322). From the beginning of 2016 it seems that the disinflationary pressures have been gradually induced, all throughout 2018. This temporary increase in inflation is consistent with past findings, that also claimed that the EAPP had immediate positive effects on inflation, which dissipated quickly as the EAPP was held for too long (Gambetti & Musso, 2017; Lhuissier & Nguyen, 2021). Still, the main conclusion is that overall the EAPP actually lowered inflation in the euro-area. The explanations behind this phenomenon were widely discussed earlier.[67] However, it is worth nothing that similarly to the yearly frequency, when including the OOH costs, the disinflationary effects dampen, as the estimates decrease in magnitude for both the pulse dummies and the step dummies. For example, the step dummy of -1.545 for the multivariate model when excluding the OOH costs becomes -0.432 when including the OOH costs. Similar effect is observed for the RLS model.

Figure 5 below compares the observed against the synthetic inflation for the SCM (top), the HT (middle) and the difference between the observed and the counterfactual for the ASCM (bottom). By the SCM and the ASCM, it appears that after 2018 the observed inflation climbed higher than the synthetic control, showing inflationary pressures in the euro-area. Yet for the SCM, this mild and delayed inflationary effect found is undermined by the obvious failure to produce a good counterfactual, as the counterfactual exhibits an increased peak after 2013, when the actual inflation went down. The HT builds a synthetic control that traces well the movements in the actual inflation, although it is somewhat actually lower than the observed inflation.[68] Furthermore, for the ASCM, Table A13 of Section 8.6 of the Appendix shows that with the OOH costs, some positive yet insignificant effects are found, limiting the possible inference. To sum up, the HT approach is the only one that manages to find significant results, suggesting that as Harvey and Thiele (2021) claim, their models capture well the intervention effects by exploring the time series properties of inflation, but the SCM and the ASCM do not.[69]

Nonetheless, I once again plot the results of the placebo tests for the SCM and for the HT as a robustness check.[70] Table A14 and A15 of Section 8.8 highlight that for the SCM once again the euro-area inflation does not distinguish itself amongst the donors when applying the placebo tests, contrary to what was expected, irrespective of whether the OOH costs are included.[71]

[67]This discussion was introduced when presenting the disinflationary effects at a yearly frequency. Notwithstanding, it applies at the monthly frequency too.

[68]Note that the counterfactual may be lower for the HT as the model attributed the majority of weight to Sweden. Yet, Swedish inflation was significantly lower than euro-area inflation until 2014.

[69]Interestingly, the ASCM does capture significant disinflationary effects when the OOH costs are excluded. Yet when the OOH costs are included and the euro-area inflation is closer to its peers, it seems that the ASCM cannot capture the more subtle difference between the post-treatment actual and synthetic inflation. This is shown in Table A13 of Section 8.6 of the Appendix.

[70]At the moment, it is not possible to perform placebo tests for the ASCM. Also, for the HT, although no formal procedure on how to carry out placebo tests was given, I combined the methodology of Harvey and Thiele (2021) with that of Abadie et al. (2010).

[71]No such tests are yet available for the ASCM and the HT.

Then, Figure A12 and A13 of Section 8.8 of the Appendix also graphically shows that the euro-area inflation again does not stand out against the others when performing placebo tests. Thus, although the results are significant, the inference from the obtained results may be limited.

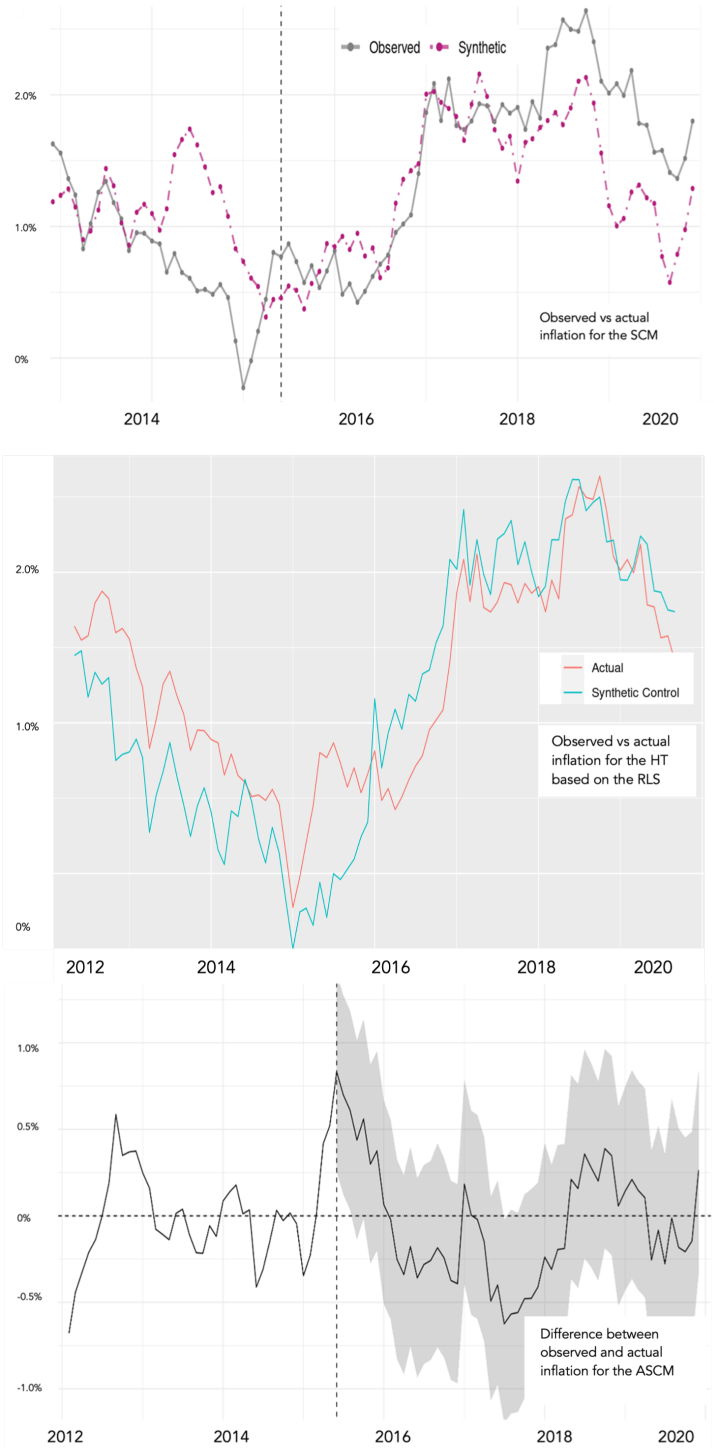

Figure 4. Comparison For Monthly Data with OOH Costs of Observed and Synthetic Inflation

7 Conclusion

This thesis investigates what would have happened to the euro-area inflation in the absence of the EAPP, introduced by the ECB in 2015. Suspecting that the euro-area inflation may also have been lower than expected due to mismeasurement, as recommended in the latest strategic review of the ECB, I include the OOH costs into the HICP inflation. Consequently, I reanswer the research question with the newly calculated inflation measurement. I also inspect how the sampling frequency of the inflation rate changes the results. As such, I work with both yearly and monthly inflation, to provide clearer economic insights and to better explore the available data, whilst adding an additional robustness check. Note that inflation including the OOH costs at a monthly frequency was obtained via a cubic spline approach. To address the main research focus, three main methods are employed and compared, namely the time-series method of Harvey and Thiele (2021), the classic Synthetic Control Method proposed by Abadie et al. (2010) and the Augmented Synthetic Control Method of Ben-Michael et al. (2021). For the latter two methods, different variations are used, yielding together with the approach of Harvey and Thiele (2021) a total of seven models. As both Harvey and Thiele (2021) and Ben-Michael et al. (2021) claim to improve the approach of Abadie et al. (2010), the methods are compared based on the way they select the donors needed to build the counterfactual and on the produced intervention effects. Lastly, I assess the validity of results via placebo tests and Fisher's exact test. It is worth mentioning that I construct the placebo tests also for the approach of Harvey and Thiele (2021), although no methodology in doing so was previously proposed. On the side, upon initiating the analysis of this thesis, I replicated the approach of Harvey and Thiele (2021).

Simply including the OOH costs into the HICP index shows that the yearly inflation would have increased by 0.12% and by 0.2% at a monthly frequency. Thus, the ECB would have achieved its inflation target around 2017. Then, for the yearly inflation, regardless of the OOH costs treatment, predominantly negative yet insignificant effects of the EAPP are found, indicating that the programme has triggered a delayed response in inflation picking up, if not even furthering the abnormally low euro-area inflation. At monthly frequency, the disinflationary pressures are confirmed when the OOH costs are excluded by the estimated significant negative effects. Yet, when including the OOH costs, first significant yet temporary and decreasing positive effects are found, meaning that the EAPP drove inflation higher for a short while. Afterwards, long-term negative effects are found for the monthly inflation with the OOH costs. The yielded effects align with the conclusions of Acharya et al. (2021) and Zlobins (2021).

The fact that the sampling frequency may matter is another remark. This may be as yearly inflation aggregates over the informative month-on-month variation. Furthermore, consumers and policy makers alike tend to track the monthly inflation closer than the yearly inflation. Thus, this approach is further encouraged when assessing the impact of the taken unconventional policies. Nonetheless, more research using similar techniques to the synthetic control methods is encouraged. New research could disentangle the effects of the PEPP ceased few months ago.

If the EAPP induced supply-side disinflation, while the PEPP induced supply-side inflation (Nersisyan & Wray, 2022), it is worthwhile to see why such a different economic response arose.

A final remark is the superiority of the approach of Harvey and Thiele (2021). Overall, the model arrives simply at a reliable donor selection that produces counterfactuals which match the actual inflation the closest. Furthermore, the model continues to perform well, especially for the pre-treatment matching, even when few data points are available. Lastly, the model captures best the intervention insights by using the time series properties of the data, compared to the models of Ben-Michael et al. (2021) and of Abadie et al. (2010).

However, the synthetic control methods are fairly new, thus some suggested methodological improvements are as follows. For the approach of Harvey and Thiele (2021), it would be useful to investigate how covariates may be included in the approach and how to econometrically determine the optimal number of selected donors that have minimal variance and are cointegrated with the target. Nonetheless, in terms of the pre-treatment fit, Harvey and Thiele (2021) assure that even if it is suboptimal, valid inference can still be carried out and the estimated intervention effects are robust. The approach of Ben-Michael et al. (2021) also yields valid results with a poor pre-treatment fit, as it precisely uses the ridge regression to correct for that. Still, together with the approach of Harvey and Thiele (2021), it would benefit from having a specified methodology on how to conduct placebo tests in that particular case. As Ben-Michael et al. (2021) highlight, thus far no robust inferential methods have been developed for when pre-treatment SCM fit is imperfect. For that, a potential innovation is to tweak the ASCM with the proposed method of Arkhangelsky and Imbens (2021), allowing for doubly robust estimation.[72]

Finally, Keynes once said that 'by a continuing process of inflation, governments can confiscate, secretly and unobserved, an important part of the wealth of their citizens' (Keynes, 1919). This then creates an 'arbitrary rearrangement of riches that strikes at both the security and confidence that people have in the economic system' (Keynes, 1919). This quote supports the need for better inflation understanding and strenuously encourages further research in the area.

[72]This may pose computational challenges.

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8 Appendix

8.1 Replication Results

Below I present the results obtained with the analysis proposed by Harvey and Thiele (2021) for two datasets, covering the German reunification and the smoking policy introduced in California. The figures have been omitted, as they are easily reproducible.

8.1.1 German Reunification

For this dataset, the logarithm of the annual GDP per capita was a necessary transformation, mentioned by the authors as well. The first step was to inspect the trend and slope properties of the time series data and to quantify whether the assumption of similar growth paths for the target and the donors is plausible. The results are reported in the table below, where the first column tests the hypothesis of a deterministic trend against a stochastic trend, while the second column addresses whether a fixed slope of a I(1) process or a stochastic slope of a I(2) process is present. The third column directly answers for which countries the balanced growth assumption is valid, indicating that for those countries we should observe a p-value equal or greater than 0.1, as selected by Harvey and Thiele (2021).

Table A1: Replication of Table 5 in Harvey and Thiele (2021) denoting KPSS(2) tests for log annual per capita GDP from 1971 to 1990

	I(0) statistic	I(0) p-value	I(1) statistic	I(1) p-value	Coint(level)	Coint(level) p-value	Variance
West Germany	0.192	0.019	0.432	0.063	-	-	-
USA	0.197	0.017	0.536	0.034	0.145	0.100	0.000
UK	0.205	0.014	0.596	0.023	0.203	0.100	0.001
Austria	0.196	0.018	0.516	0.038	0.479	0.046	0.000
Belgium	0.193	0.019	0.460	0.051	0.074	0.100	0.000
Denmark	0.191	0.020	0.551	0.030	0.593	0.023	0.002
France	0.192	0.019	0.461	0.051	0.078	0.100	0.000
Italy	0.193	0.019	0.446	0.057	0.659	0.017	0.001
Netherlands	0.194	0.018	0.417	0.070	0.688	0.015	0.002
Norway	0.195	0.018	0.508	0.040	0.664	0.017	0.006
Switzerland	0.135	0.070	0.146	0.100	0.610	0.022	0.005
Japan	0.177	0.025	0.319	0.100	0.723	0.011	0.003
Greece	0.200	0.016	0.578	0.025	0.642	0.019	0.005
Portugal	0.126	0.088	0.137	0.100	0.223	0.100	0.002
Spain	0.177	0.024	0.397	0.078	0.288	0.100	0.002
Australia	0.192	0.019	0.468	0.049	0.639	0.019	0.002
New Zealand	0.150	0.047	0.363	0.093	0.608	0.022	0.009

Note: A p-value greater than 0.1 indicates a failure to reject the null of cointegration at the 10% significance level.

All results match the ones by Harvey and Thiele (2021), except Austria and the United Kingdom. It appears that the statistic of the cointegration test reported for Austria, namely 0.203 is that of the United Kingdom and vice-versa. Nonetheless, since both are greater than 0.1, Austria remains a valid choice and is preferred as donor to the United Kingdom because of its lower variance. Portugal and Spain would qualify, but the larger variance excludes them.

Then, once the donors have been selected as described above, the next step is to estimate the models proposed, namely the Restricted Least Square Synthetic Control (SC) of Equation (6) in Harvey and Thiele (2021) and the multivariate model of Equations (7)-(9) of Harvey and Thiele (2021). In estimating both models, a set of pulse dummies and a step dummy is needed. Since we similarly take the level break to occur in year 1999, corresponding to the step dummy, and given that the German reunification took place in 1990, eight pulse dummies covering the period from 1991 to 1998 are constructed and the estimated intervention effects are reported in Table 2 below. Overall, the estimated intervention effects and the standard errors closely resemble those obtained by Harvey and Thiele (2021), with the exception of the standard errors in the multivariate model, which in this paper, are slightly bigger, and rounded. The reason behind this is that I follow the recommended regression approach, compared to the ML approach employed by the authors. The latter allows for an estimation error in the weights while the former does not. Overall, I also report the significance of the intervention effects, which the authors omitted.

Table A2: Replication of Table 6 in Harvey and Thiele (2021) denoting the estimated intervention effects for Germany with a level break in 1999

	Multivariate		SC	
Year	Estimate	SE	Estimate	SE
1991	0.027*	0.010	0.027**	0.009
1992	0.013	0.010	0.013	0.009
1993	-0.021	0.010	-0.018	0.009
1994	-0.042***	0.011	-0.038***	0.009
1995	-0.0495***	0.011	-0.046***	0.009
1996	-0.059***	0.011	-0.055***	0.009
1997	-0.084***	0.010	-0.082***	0.009
1998	-0.093***	0.010	-0.091***	0.009
1999	**-0.116*****	**0.005**	**-0.114*****	**0.004**

Abbreviations: SC, synthetic control; SE, standard error.

8.1.2 Smoking in California

I follow a similar approach, but the first remark is that although the authors do not state, the stationarity tests are performed on the logarithm of the per capita cigarette consumption, not on the raw data. Nonetheless, the models are estimated using the raw data. The table below presents the obtained variance, test statistics and p-values, with the mention that my reported variance of Colorado does not match the one obtained by the authors, but it is close and the test statistic is nonetheless identical. Since my formula produces consistent results for all the other states, I assume it was a mere typing error.

Table A3: Replication of Table 3 in Harvey and Thiele (2021) denoting the stationarity tests statistics from 1990 to 1988

	Coint(level)	p-value	Variance
Alabama	0.742	0.010	252.514
Arkansas	0.734	0.010	313.073
Colorado	0.286	0.100	20.298
Connecticut	0.593	0.023	95.284
Delaware	0.531	0.035	55.117
Georgia	0.730	0.011	211.004
Idaho	0.218	0.100	24.949
Illinois	0.697	0.014	40.614
Indiana	0.547	0.031	67.416
Iowa	0.669	0.016	76.865
Kansas	0.658	0.017	116.672
Kentucky	0.506	0.040	375.162
Louisiana	0.685	0.015	109.475
Maine	0.748	0.010	50.230
Minnesota	0.677	0.016	116.647
Mississippi	0.752	0.010	162.511
Missouri	0.749	0.010	104.602
Montana	0.309	0.100	19.373
Nebraska	0.688	0.015	62.779
Nevada	0.422	0.068	183.677
New Hampshire	0.624	0.020	589.730
New Mexico	0.696	0.014	36.287
North Carolina	0.249	0.100	364.528
North Dakota	0.522	0.037	123.404
Ohio	0.679	0.015	152.895
Oklahoma	0.614	0.021	154.016
Pennsylvania	0.725	0.011	144.535
Rhode Island	0.721	0.012	125.985
South Carolina	0.748	0.010	184.484
South Dakota	0.696	0.014	93.000
Tennessee	0.741	0.010	325.158
Texas	0.652	0.018	137.528
Utah	0.625	0.020	56.655
Vermont	0.606	0.022	191.004
Virginia	0.708	0.013	100.533
West Virginia	0.684	0.015	60.008
Wisconsin	0.722	0.012	83.243
Wyoming	0.334	0.100	129.917

Note: A p-value greater than 0.1 indicates a failure to reject the null of cointegration at the 10% significance level.

This time, the possibilities of selecting appropriate donors are numerous. I replicate the three combinations considered by the authors and reported in Table 4 below, namely Colorado-Montana-Idaho, Colorado-Wyoming-Idaho and Colorado-North Carolina-Idaho.

Table A4: Replication of the weights assigned to different donor selections

RLS weights	Colorado	Montana	Idaho	Wyoming	North Carolina
Colorado-Montana-Idaho	0.385	0.327	0.288	-	-
Colorado-Wyoming-Idaho	0.609	-	0.409	-0.019	-
Colorado-North Carolina-Idaho	0.645		0.318		0.036

Note: This are the different countries' weights assigned in building the synthetic control.

The obtained weights in all scenarios match the ones reported by the authors. Finally, Colorado, Montana and Idaho are selected as the donors based on which the synthetic control is constructed. Then, the following models are estimated: the equation for the target minus the synthetic control, namely equation (6) labelled as the SC model, the first equation in Equation (10) labelled as the univariate model and lastly the multivariate model of Equation (7)-(9). For the SC model, the reported coefficients and their standard errors are similar to those obtained by the authors. For the univariate model, while the intervention effects match those of Harvey and Thiele (2021), the standard errors do not, for the same reason as discussed earlier, in the example concerning Germany. Nonetheless, due to different assumptions than for Germany, the bivariate and multivariate model could not be estimated as proposed by the authors. I believe that this is due to the lack of having a powerful software that can handle multivariate systems of state space models, which is needed for estimating the shared trend. This fully justifies the use of the STAMP software by the authors. Still, when implementing manually their suggested approach, I was able to obtain estimates for the multivariate model that are somewhat similar, but do not fully match the original ones. To further clarify, in my thesis investigating the impact of the EAPP on inflation in the euro-area, I employ the models in accordance to the example of West Germany, due to the mentioned reasons.

Table A5: Replication of Table 4 in Harvey and Thiele (2021) denoting the estimated intervention effects for California when a level change was assumed in 1995

	Multivariate		Univariate		SC	
Year	Estimate	SE	Estimate	SE	Estimate	SE
1989	-1.103	3.345	-1.1617	4.2766	-0.813	3.676
1990	-10.567*	3.971	-7.2731	4.7098	-7.751*	3.676
1991	-17.088***	3.276	-15.668***	4.0777	-15.986***	3.676
1992	-19.484***	3.444	-17.538***	4.4027	-17.58***	3.676
1993	-24.138***	3.458	-21.876***	4.3898	-22.06***	3.676
1994	-33.033***	3.886	-29.153***	4.8882	-29.586***	3.676
1995	-29.824***	3.107	-28.408***	4.1386	-27.822***	1.678

Abbreviations: SC, synthetic control; SE, standard error.

8.2 Extension Appendix: Monthly Annualised Inflation Rate Including the OOH Costs

The figure below plots the monthly annualised inflation rate when excluding the OOH costs (blue) and when including the OOH costs (red). Similarly for the yearly data, inflation without the OOH costs fares higher until around 2014, and afterwards the relationship reverses. The tables' titles specify whether the OOH costs are included and the data frequency.

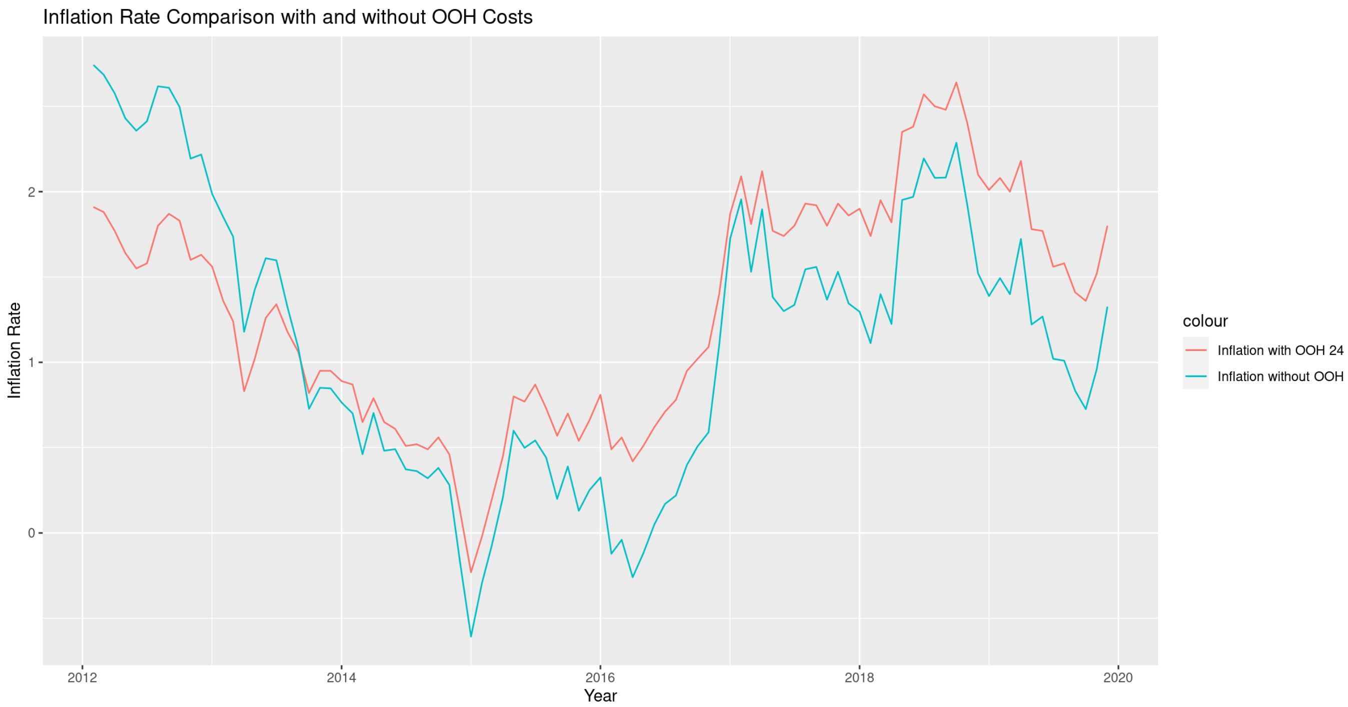

Figure A1. Monthly annualised inflation rate including the OOH costs

8.3 Extension Appendix: Results of the Cointegration Tests

The tables below present the KPSS tests for the three null hypotheses denoted below, in agreement with the approach of Harvey and Thiele (2021). The only countries that have a p-value of at least 0.1 in the last column of the table are suitable for selection. Afterwards, out of the set of cointegrated donors, the first three ones with the smallest variance are selected, as Harvey and Thiele (2021) suggest. This is why the variances are reported in Section 8.4.

Table A6: Results of cointegration tests for monthly data, without the OOH costs

	I(0) statistic	I(0) p-value	I(1) statistic	I(1) p-value	Coint(level)	Coint(level) p-value
Euro-Area	0.193	0.019	0.188	0.100	-	-
Sweden	0.133	0.073	0.392	0.080	0.341	0.100
United Kingdom	0.162	0.036	0.385	0.083	0.374	0.088
United States	0.158	0.040	0.195	0.100	0.344	0.100
Korea	0.150	0.047	0.172	0.100	0.365	0.092
Canada	0.133	0.073	0.481	0.046	0.354	0.097
Japan	0.283	0.010	0.326	0.100	0.162	0.100

Note: A p-value greater than 0.1 indicates a failure to reject the null of cointegration at the 10% significance level.

Table A7: Results of cointegration tests for monthly data, with the OOH costs

	I(0) statistic	I(0) p-value	I(1) statistic	I(1) p-value	Coint(level)	Coint(level) p-value
Euro-Area	0.193	0.019	0.256	0.100	-	-
Sweden	0.140	0.061	0.392	0.080	0.338	0.100
United Kingdom	0.162	0.036	0.385	0.083	0.376	0.087
United States	0.158	0.040	0.195	0.100	0.345	0.100
Korea	0.150	0.047	0.172	0.100	0.365	0.092
Canada	0.133	0.073	0.481	0.046	0.352	0.098
Japan	0.283	0.010	0.326	0.100	0.170	0.100

Note: A p-value greater than 0.1 indicates a failure to reject the null of cointegration at the 10% significance level.

Table A8: Results of cointegration tests for yearly data, without the OOH costs

	I(0) statistic	I(0) p-value	I(1) statistic	I(1) p-value	Coint(level)	Coint(level) p-value
Euro-Area	0.150	0.047	0.170	0.100	-	-
Sweden	0.134	0.072	0.331	0.100	0.143	0.100
New Zealand	0.142	0.057	0.250	0.100	0.143	0.100
United Kingdom	0.144	0.054	0.180	0.100	0.177	0.100
United States	0.139	0.062	0.185	0.100	0.146	0.100
Korea	0.145	0.052	0.284	0.100	0.143	0.100
Canada	0.137	0.067	0.218	0.100	0.239	0.100
Japan	0.133	0.073	0.253	0.100	0.312	0.100

Note: A p-value greater than 0.1 indicates a failure to reject the null of cointegration at the 10% significance level.

Table A9: Results of cointegration tests for yearly data, with the OOH costs

	I(0) statistic	I(0) p-value	I(1) statistic	I(1) p-value	Coint(level)	Coint(level) p-value
Euro-Area	0.150	0.047	0.320	0.100	-	-
Sweden	0.148	0.048	0.331	0.100	0.228	0.100
New Zealand	0.142	0.057	0.250	0.100	0.243	0.100
United Kingdom	0.144	0.054	0.180	0.100	0.372	0.089
United States	0.139	0.062	0.185	0.100	0.313	0.100
Korea	0.145	0.052	0.284	0.100	0.309	0.100
Canada	0.137	0.067	0.218	0.100	0.188	0.100
Japan	0.133	0.073	0.253	0.100	0.312	0.100

Note: A p-value greater than 0.1 indicates a failure to reject the null of cointegration at the 10% significance level.

8.4 Extension Appendix: The Variance of Contrasts for Selected Donors

The tables here document the variance of the contrasts for all the countries in the donor sample. The smaller the variance, the better. The first three cointegrated donors with the smallest variance of their respective contrasts are selected as the donors to build the counterfactual with.

Table A10: The variance of the contrasts of the considered donors, for different data selections

Data	Sweden	New Zealand	United Kingdom	United States	Korea	Canada	Japan
Yearly, including Japan, with OOH	0.499	0.851	0.346	0.297	0.403	0.417	3.359
Yearly, including Japan, without OOH	0.597	1.119	0.255	0.392	0.433	0.983	4.815
Monthly, without OOH	0.817	-	0.222	0.372	0.444	0.795	2.307
Monthly, with OOH	0.221	-	0.151	0.295	0.179	0.693	3.528

Note: The cointegrated donors with the smallest variance are preferred.

8.5 Extension Appendix: Weights of Predictor Variables within SCM

The tables below report the weight received by each predictor variable, in order to match the actual inflation the best by the synthetic control before the intervention, when employing SCM. For the ASCM the predictor weights could not be retrieved given the software limitations. Even though this is a limitation, the imbalance and the plotted difference between the observed inflation and the counterfactual in Section 8.7 and 8.8 of the Appendix visually show whether including covariates improve the pre-treatment matching between the observed inflation and the counterfactual. As I argued, in general, covariates do not improve the pre-treatment matching.

Table A11: The weights assigned by the SCM to the considered predictor variables for all donors

Data	GDP per Capita	Government Expenditure	Housing Expenditure	Unemployment	Trade	Past Inflation
Yearly, exlcuding Japan, without OOH	0.404	0.003	0.262	0.766	0.009	0.014
Yearly, excluding Japan, with OOH	0.043	0.036	0.129	0.174	0.276	0.012
Yearly, including Japan, with OOH	0.016	0.916	0.001	0.003	0.000	0.026
Yearly, including Japan, without OOH	0.005	0.890	0.005	0.046	0.000	0.051

8.6 Extension Appendix: Estimated Intervention Effects for ASCM Models

These tables report the intervention effects obtained by the ASCM,[73] to which the effects obtained via the HT approach are compared. For the yearly data, since the Ridge ASCM was always preferred, only the results for this model are reported. Note that the exact intervention effects of the SCM also could not be retrieved, but the plots in Section 8.7 and 8.8 show observed and synthetic inflation at each time point.[74]

[73]They accompany the figures reported in Section 8.7 and 8.8.

[74]Nonetheless, more reliable measures of comparison are needed, yet thus far no methodology has been documented in that scope and I report this as a limitation of my study.

Table A12: Estimated intervention effects for chosen ASCM models with yearly data

	Yearly Inflation with OOH				Yearly Inflation without OOH			
Year	Ridge ASCM Excl. Cov, Excl. Japan		Ridge ASCM Excl. Cov, Incl. Japan		Ridge ASCM Excl. Cov, Excl. Japan		Ridge ASCM Excl. Cov, lncl. Japan	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
2015	0.431	1.000	0.203	0.800	0.228	0.800	-0.600	0.200
2016	-0.365	0.400	-0.018	1.000	-1.123	0.200	-0.959	0.800
2017	-0.119	1.000	-0.009	1.000	-1.013	0.200	-0.287	1.000
2018	-0.027	1.000	0.291	0.800	-0.887	0.200	-0.047	1.000
2019	-0.010	1.000	0.266	0.800	-0.747	0.600	0.036	1.000

Note: This table reports the observed intervention effects when the approach of Ben-Michael et al. (2021) is used. The step dummy, given by the level break, is at 2018.

Table A13: Intervention effects for monthly inflation rate with chosen ASCM models

	Monthly Inflation with OOH				Monthly Inflation without OOH			
Month	No Ridge ASCM		Ridge ASCM		No Ridge ASCM		Ridge ASCM	
	Estimate	p-value	Estimate	p-value	Estimate	p-value	Estimate	p-value
06/2015	0.824	0.024	0.832	0.024	0.461	0.415	0.526	0.073
07/2015	0.697	0.024	0.699	0.024	0.311	0.683	0.300	0.341
08/2015	0.609	0.073	0.610	0.049	0.245	0.805	0.221	0.488
09/2015	0.438	0.122	0.438	0.122	0.047	0.902	0.010	0.976
10/2015	0.557	0.073	0.560	0.073	0.231	0.805	0.222	0.488
11/2015	0.300	0.293	0.299	0.317	-0.149	0.829	-0.198	0.512
12/2015	0.378	0.268	0.375	0.195	-0.090	0.878	-0.174	0.561
01/2016	0.080	0.683	0.064	0.732	-0.401	0.488	-0.614	0.049
02/2016	-0.013	0.951	-0.021	0.878	-0.647	0.244	-0.775	0.049
03/2016	-0.239	0.366	-0.252	0.317	-0.843	0.098	-1.017	0.024
04/2016	-0.320	0.293	-0.340	0.268	-0.992	0.049	-1.258	0.024
05/2016	-0.157	0.537	-0.178	0.488	-0.793	0.122	-1.066	0.024
06/2016	-0.339	0.293	-0.359	0.220	-0.894	0.049	-1.152	0.024
07/2016	-0.260	0.366	-0.281	0.317	-0.785	0.122	-1.030	0.024
08/2016	-0.233	0.366	-0.258	0.317	-0.765	0.146	-1.061	0.024
09/2016	-0.154	0.537	-0.185	0.463	-0.760	0.146	-1.120	0.024
10/2016	-0.222	0.415	-0.244	0.341	-0.747	0.146	-1.023	0.024
11/2016	-0.355	0.268	-0.374	0.220	-0.867	0.049	-1.079	0.024
12/2016	-0.366	0.268	-0.393	0.171	-0.675	0.195	-0.969	0.024
01/2017	0.208	0.439	0.183	0.463	0.004	1.000	-0.308	0.341
02/2017	0.038	0.829	0.004	0.976	-0.158	0.829	-0.547	0.073
03/2017	0.011	1.000	-0.021	0.878	-0.393	0.488	-0.752	0.049
04/2017	-0.119	0.585	-0.150	0.537	-0.433	0.415	-0.763	0.049
05/2017	-0.464	0.122	-0.493	0.098	-0.965	0.049	-1.268	0.024
06/2017	-0.373	0.293	-0.400	0.171	-0.904	0.049	-1.176	0.024
07/2017	-0.592	0.073	-0.624	0.049	-1.105	0.049	-1.445	0.024
08/2017	-0.537	0.098	-0.568	0.073	-1.002	0.049	-1.330	0.024
09/2017	-0.532	0.073	-0.559	0.073	-0.971	0.049	-1.241	0.024
10/2017	-0.446	0.122	-0.480	0.098	-1.009	0.049	-1.345	0.024
11/2017	-0.450	0.220	-0.477	0.122	-0.968	0.049	-1.224	0.024
12/2017	-0.395	0.244	-0.412	0.171	-1.037	0.049	-1.187	0.024
01/2018	-0.230	0.366	-0.239	0.341	-0.972	0.049	-1.000	0.024
02/2018	-0.302	0.293	-0.310	0.317	-1.031	0.049	-1.083	0.024
03/2018	-0.180	0.512	-0.195	0.463	-0.783	0.122	-0.929	0.024
04/2018	-0.164	0.512	-0.189	0.463	-0.826	0.098	-1.093	0.024
05/2018	0.237	0.366	0.211	0.439	-0.219	0.805	-0.496	0.073
06/2018	0.185	0.488	0.158	0.512	-0.259	0.756	-0.555	0.073
07/2018	0.379	0.293	0.358	0.244	-0.029	0.976	-0.262	0.488
08/2018	0.290	0.317	0.276	0.317	-0.178	0.829	-0.326	0.341
09/2018	0.221	0.415	0.201	0.439	-0.165	0.829	-0.400	0.244
10/2018	0.404	0.171	0.389	0.171	0.060	0.902	-0.117	0.732
11/2018	0.369	0.268	0.348	0.220	-0.133	0.854	-0.372	0.244
12/2018	0.084	0.659	0.056	0.756	-0.493	0.366	-0.800	0.049
01/2019	0.167	0.512	0.142	0.561	-0.450	0.415	-0.707	0.049
02/2019	0.234	0.366	0.210	0.439	-0.347	0.610	-0.581	0.049
03/2019	0.167	0.512	0.148	0.537	-0.424	0.415	-0.608	0.049
04/2019	0.120	0.585	0.105	0.683	-0.322	0.659	-0.465	0.195
05/2019	-0.237	0.366	-0.255	0.317	-0.765	0.146	-0.947	0.024
06/2019	-0.067	0.732	-0.083	0.707	-0.582	0.244	-0.748	0.049
07/2019	-0.261	0.366	-0.277	0.317	-0.846	0.098	-1.005	0.024
08/2019	0.006	1.000	-0.013	0.927	-0.593	0.244	-0.773	0.049
09/2019	-0.164	0.512	-0.182	0.488	-0.771	0.146	-0.924	0.049
10/2019	-0.187	0.488	-0.207	0.439	-0.812	0.098	-1.010	0.024
11/2019	-0.128	0.561	-0.145	0.537	-0.646	0.244	-0.825	0.049
12/2019	0.279	0.341	0.265	0.341	-0.139	0.829	-0.306	0.390

8.7 Extension Appendix: Graphs of the Synthetic Control Versus Observed for SCM and ASCM

These are the figures showing the evolution of the counterfactual against the observed inflation, for both pre-treatment and post-treatment. They are reported for all the preferred sub-models, although initially I used them to confirm that a chosen model was preferred by observing whether the pre-treatment matching was improved, compared to the other alternatives. I display the figures for both yearly and monthly data for: the HT, the SCM with and without covariates and with and without Japan, the ASCM with and without ridge, with and without covariates and with and without Japan, respectively. An important distinction is that for the models of the ASCM family, the computed difference between the observed inflation minus the synthetic control is plotted together with the confidence intervals (in grey). If the grey shaded area is far from the zero line, it means that the estimated effects are significant. For the SCM and the HT,the counterfactual against the observed are plotted. In general, the Ridge ASCM improves slightly the matching but oftentimes the scaled imbalance is a better informative measure than the pictures, as such I only present the pictures for the selected Ridge ASCM.

8.7.1 Monthly Data, Excluding OOH Costs

Below are the pictures of the observed versus synthetic inflation without the OOH costs for monthly data, where the vertical dotted line represents the time the EAPP took place.

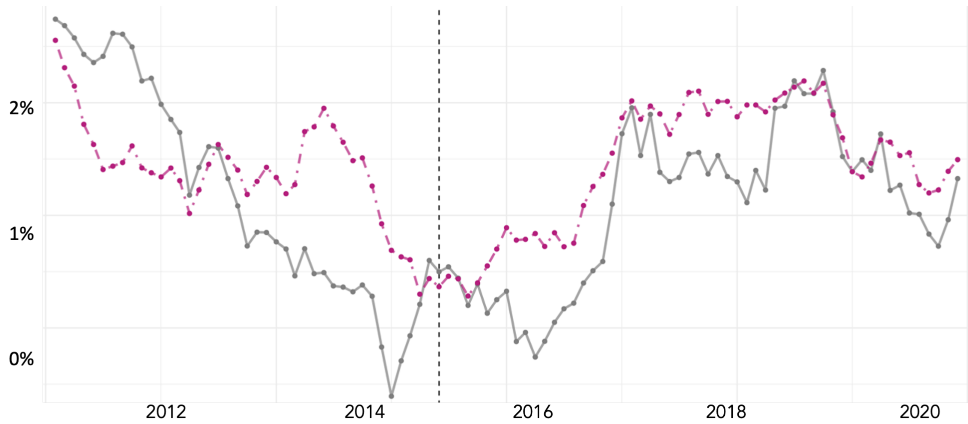

Figure A2. Synthetic inflation (pink) versus observed inflation (grey) for SCM

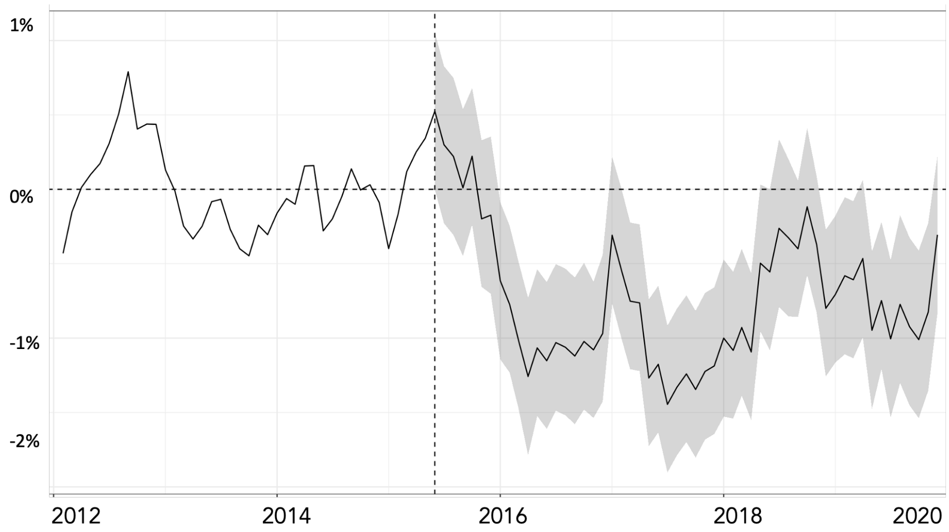

Figure A3. Synthetic and observed inflation difference for ASCM with ridge

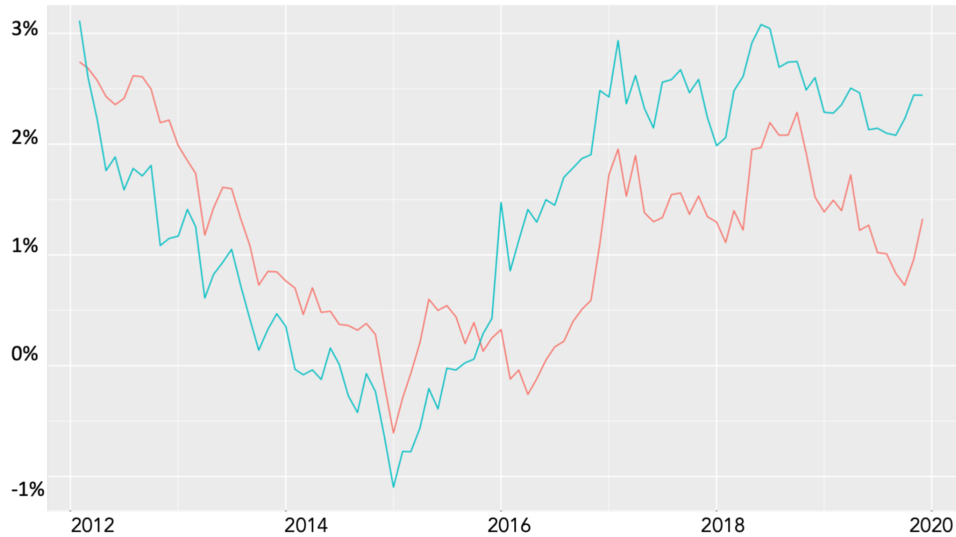

Figure A4. Observed (red) versus synthetic inflation (blue) for HT excluding OOH costs

8.7.2 Monthly Data, Including OOH Costs

Below are the pictures of the observed versus synthetic inflation with the OOH costs for monthly data, where the vertical dotted line represents the time the EAPP took place. Compared to the previous section, the SCM and the ASCM match the pre-treatment inflation better, suggesting that including the OOH costs facilitates an easier matching as inflation across donors is closer.

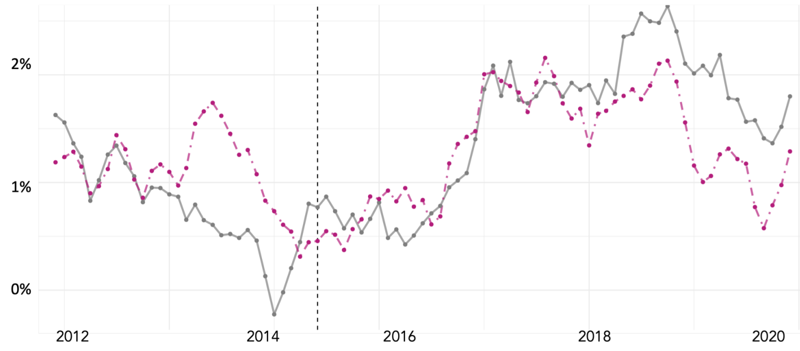

Figure A5. Observed (grey) versus synthetic inflation (pink) for SCM

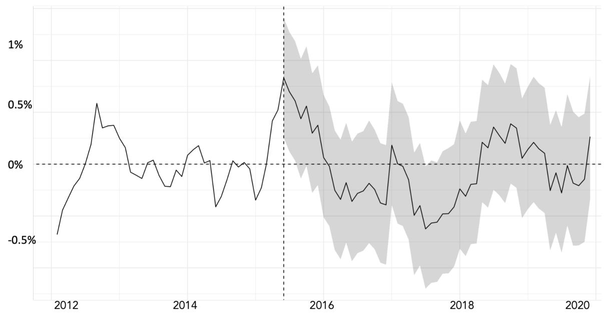

Figure A6. Difference of observed and synthetic inflation for Ridge ASCM, no covariates

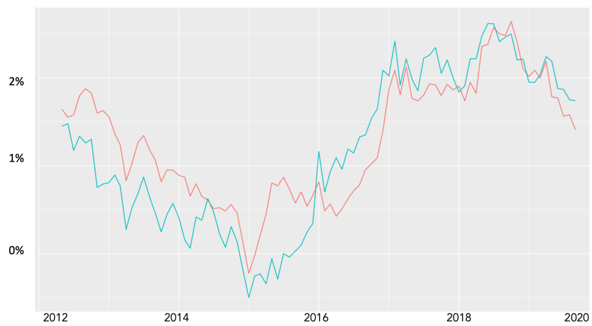

Figure A7. Observed (red) versus synthetic inflation (blue) difference for HT

8.7.3 Yearly Data, Excluding OOH Costs

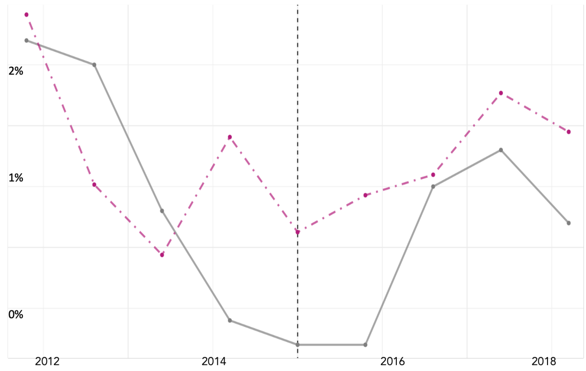

Figure A8. Observed (grey) and synthetic inflation (pink) for the SCM without covariates

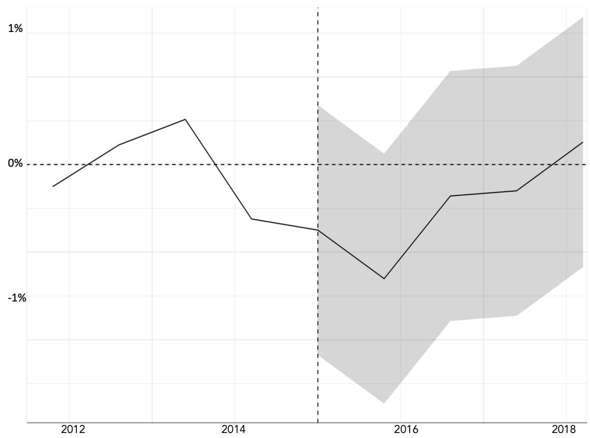

Figure A9. Difference of observed and synthetic inflation for the Ridge ASCM, no covariates

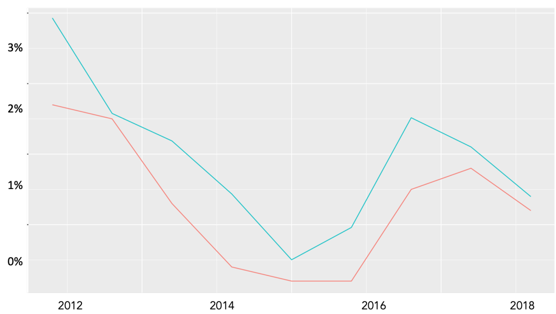

Figure A10. Observed (red) and synthetic inflation (blue) for the SCM with covariates

8.7.4 Yearly Data, Including OOH Costs

This is the same picture as presented in the thesis, but it was easier to refer to this picture here, as in the thesis I only introduce it later.

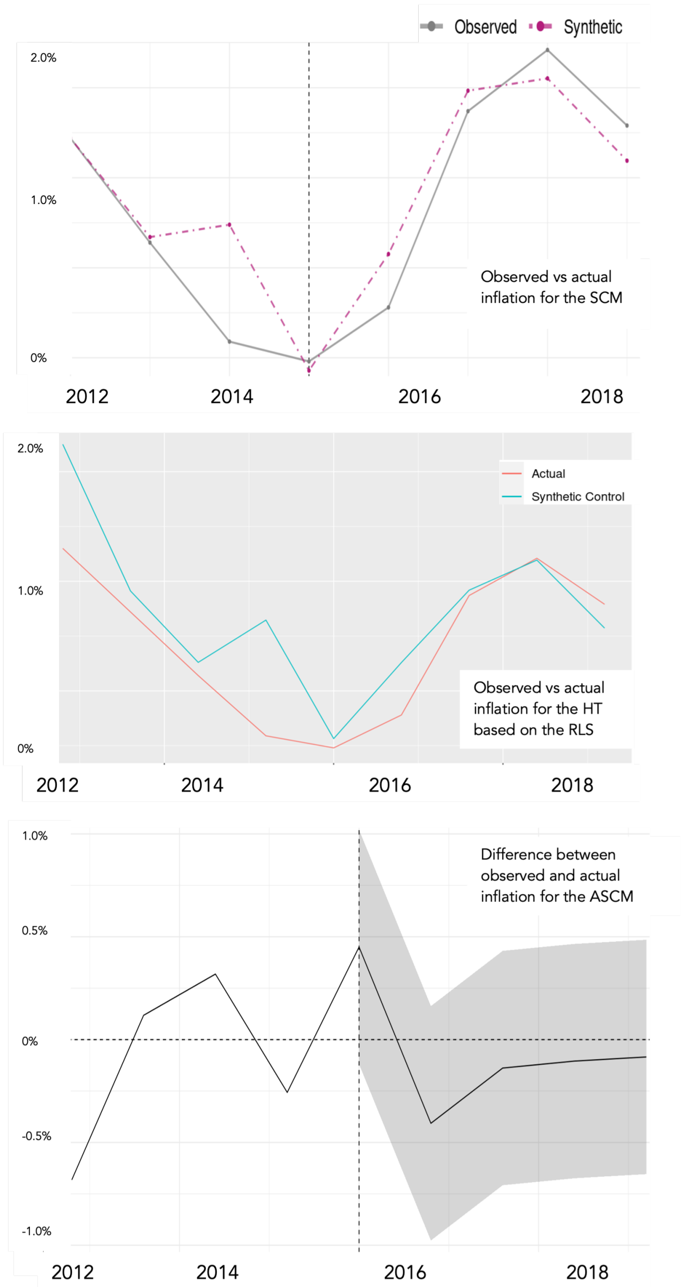

Figure A11. Observed versus Synthetic Inflation for Yearly Inflation with OOH Costs across Models

8.8 Results of the Fisher's Exact Test for the Selected Models

Table A14: Robustness checks for SCM with monthly inflation rate, excluding OOH costs

	Country	Type	Pre-MSPE	Post-MSPE	MSPE Ratio	Rank	Fisher's Exact p-Value	Z-Score
1	Korea	Donor	0.25	0.49	1.96	1	0.14	2.04
2	Canada	Donor	0.50	0.44	0.86	2	0.29	0.38
3	United Kingdom	Donor	0.57	0.35	0.61	3	0.43	-0.01
4	Euro-Area	Treated	0.57	0.26	0.46	4	0.57	-0.24
5	New Zealand	Donor	0.45	0.09	0.20	5	0.71	-0.63
6	United States	Donor	0.86	0.17	0.19	6	0.86	-0.64
7	Sweden	Donor	1.13	0.02	0.02	7	1.00	-0.90

Note: This table reports different robustness checks statistics for the chosen SCM with the monthly inflation rate excluding the OOH costs. No significant effect is found for Euro-Area.

Table A15: Robustness checks for SCM with monthly inflation rate, including OOH costs

	Country	Type	Pre-MSPE	POST-MSPE	MSPE Ratio	Rank	Fisher's Exact p-Value	Z-Score
1	Korea	Donor	0.15	0.83	5.73	1	0.14	2.11
2	United States	Donor	0.12	0.27	2.26	2	0.29	0.35
3	Canada	Donor	0.30	0.39	1.32	3	0.43	-0.13
4	Euro-Area	Treated	0.27	0.20	0.75	4	0.57	-0.42
5	United Kingdom	Donor	0.38	0.18	0.47	5	0.71	-0.57
6	Japan	Donor	3.58	1.35	0.38	6	0.86	-0.62
7	Sweden	Donor	2.48	0.45	0.18	7	1.00	-0.72

Note: This table reports different robustness checks statistics for the chosen SCM with the monthly inflation rate including the OOH costs. Significant effect is found for Euro-Area at 80% confidence level, yet the fact that also Korea displays a significant effect, hinders the possible conclusions.

Table A16: Robustness checks for SCM with yearly inflation rate, excluding OOH costs

	Country	Type	Pre-MSPE	Post-MSPE	MSPE Ratio	Rank	Fisher's Exact p-Value	Z-Score
1	Korea	Donor	0.16	0.39	2.46	1	0.12	2.25
2	New Zealand	Donor	0.22	0.24	1.11	2	0.25	0.61
3	Canada	Donor	0.71	0.33	0.46	3	0.38	-0.19
4	United States	Donor	0.15	0.04	0.31	4	0.50	-0.38
5	United Kingdom	Donor	0.36	0.10	0.28	5	0.62	-0.41
6	Euro-Area	Treated	0.80	0.13	0.16	6	0.75	-0.55
7	Japan	Donor	4.34	0.56	0.13	7	0.88	-0.60
8	Sweden	Donor	1.18	0.01	0.01	8	1.00	-0.74

Note: This table reports different robustness checks statistics for the chosen SCM with the monthly inflation rate excluding the OOH costs. No significant effect is found for the Euro-Area.

Table A17: Robustness checks for SCM with yearly inflation rate, including OOH costs

	Country	Type	Pre-MSPE	Post-MSPE	MSPE Ratio	Rank	Fisher's Exact p-Value	Z-Score
1	United States	Donor	0.14	0.21	1.51	1	0.12	1.11
2	Korea	Donor	0.29	0.41	1.41	2	0.25	0.93
3	New Zealand	Donor	0.29	0.41	1.41	3	0.38	0.92
4	Canada	Donor	0.20	0.24	1.17	4	0.50	0.48
5	United Kingdom	Donor	0.49	0.34	0.69	5	0.62	-0.40
6	Euro-Area	Treated	0.30	0.17	0.55	6	0.75	-0.66
7	Japan	Donor	2.96	1.44	0.49	7	0.88	-0.78
8	Sweden	Donor	1.11	0.04	0.04	8	1.00	-1.61

Note: This table reports different robustness checks statistics for the chosen SCM with the monthly inflation rate including the OOH costs. No significant effect is found for the Euro-Area.

In both Figure A12 (for the HT) and Figure A13 (for the SCM) below, the euro-area does not distinguish itself amongst donors, which suggests no robust results.

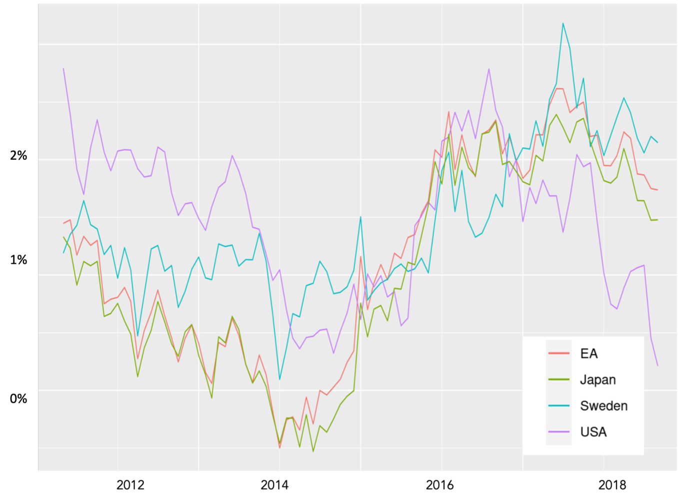

Figure A12. Placebo tests for the HT with monthly data including the OOH costs.

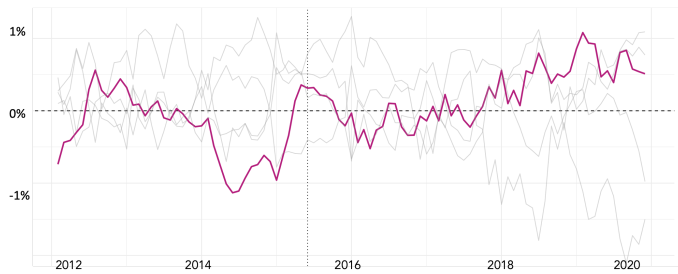

Figure A13. Placebo tests for the SCM with monthly data including the OOH costs.

The lack of robustness if further supported by this picture, where ideally the euro-area should have had the highest MSPE.

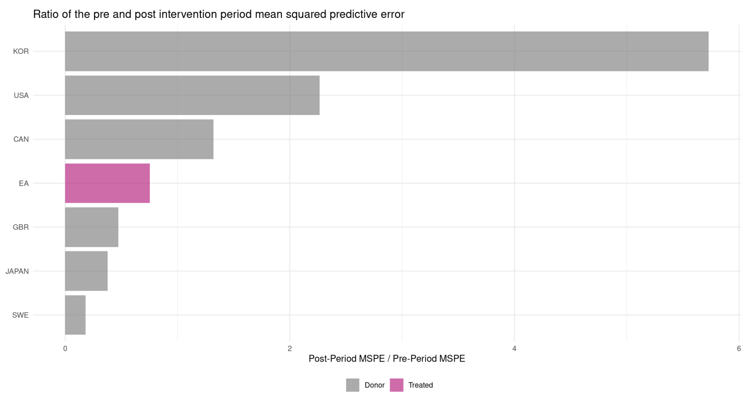

Figure A14. MSPE across countries for the SCM with monthly data including the OOH costs.

8.9 Software and Code

This thesis was coded via the R Core Team (2022). The Synthetic Control of Abadie et al. (2010) was coded via the package of Dunford (2021) while the Augmented Synthetic Control of Ben-Michael et al. (2021) was coded via the package of Ben-Michael (2022). For the approach of Harvey and Thiele (2021), the packages of Pfaff (2008) and of Henningsen and Hamann (2007) were of great importance. Finally, for including the OOH costs into the inflation index, the packages of Ryan and Ulrich (2020) and of Zeileis and Grothendieck (2005) were of pivotal use.

As far as the coding files are concerned, there are two main folders: Extension and Replication. The Replication folder contains two sub-folders, California and Germany that each provide the necessary code and data for reproducing the examples of Harvey and Thiele (2021). Then, the Extension folder contains four sub-folders: two deal with including the OOH costs into the inflation index at a monthly and yearly frequency (namely OOH into HICP annually and OOH into HICP monthly); whilst the other two deal with conducting the analysis either with monthly data or with yearly data (namely Extension with Monthly Data and Extension with Yearly Data). Both the sub-folders Extension with Monthly Data and Extension with Yearly Data contain two other sub-folders: with OOH and without OOH, for which two final sub-folders are contained: Harvey and Thiele, and Synthetic Control + Augmented Synthetic Control. Thus, to run the models of interest, one has to first think at the desired data frequency, then at the desired treatment of the OOH costs and then at the desired class of models: HT, SCM or ASCM. In general, the needed data for the models is provided in the respective sub-folders such that it is easy to run upon opening the file of interest, where the necessary packages are loaded in the beginning. Note that I advise working with the files in R Studio Cloud, which is where I did the analysis, as it facilitates easier data upload. Upon opening R Studio Cloud, one only has to click Files, then Upload and then Import Dataset with the dataset of choice. Then, going through the files line by line should yield the desired results, whilst the comments should help keep track of the steps of the analysis.