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The effects of Golden Visas on housing market prices

Applying a Synthetic control model to the Portuguese market

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Dissertation

presented as partial requirement for obtaining the Master Degree Program in Statistics and Information Management

NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
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THE EFFECTS OF GOLDEN VISAS ON HOUSING MARKET PRICES: APPLYING A SYNTHETIC CONTROL MODEL TO THE PORTUGUESE MARKET

By

Beatriz Isabel David Farinha

Master Thesis presented as partial requirement for obtaining the Master's degree in Statistics and Information Management, with a specialization in Risk Analysis and Management

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledge the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Lisbon, November 2023

DEDICATION

I dedicate this Master Thesis to my unyielding pursuit of knowledge, supported by the unwavering love of my family, whose encouragement and understanding have been steadfast companions on this academic journey. To my mentor, Bruno Damásio, whose guidance and wisdom have shaped my analytical skills and enriched my learning experience. Special thanks to my friends and colleagues whose support and insightful conversations have added depth to my research. This work stands as a testament to the collective resilience, determination, and camaraderie that have fueled my academic and personal growth. May this dedication express gratitude to those whose influence, both near and far, has played a crucial role in shaping this achievement.

ABSTRACT

Portugal contends with the controversial ramifications of its Golden Visa program on the dynamics of the housing market, especially since its establishment in 2012.The program's focal point lies in the substantial capital infusion into real estate, intensifying debates on its influence. This study employs a synthetic control method (SCM) to assess the impact of Portugal's Golden Visa program on the Housing Price Index (HPI). Our research constructs counterfactual scenarios for Portugal by leveraging SCM. The optimal weighted average of HPI values from other EU countries without Golden Visa programs serves as the basis for the counterfactual. Our findings indicate that, contrary to the concerns and debates surrounding the Golden Visa program, there is no statistically significant impact on Portugal's HPI from 2012 to 2021. Extending the analysis to other EU countries the Generalized Synthetic Control Method unveils nuanced insights, emphasizing the need for robust, complete datasets for accurate synthetic control construction. This study contributes to the growing literature on the causal effects of policy interventions by employing robust methodologies to address the complexities of economic impacts on housing markets.

KEYWORDS

Synthetic Control Method; House Price Index; Golden Visas; Counterfactual.

Sustainable Development Goals (SGD):

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LIST OF ABBREVIATIONS AND ACRONYMS

ARI	Authorization for Investment Activity
ATT	Average Treatment effect for those Treated
DiD	Difference-in-differences
EU	European Union
GDP	Gross Domestic Product
HPI	House Price Index
IFE	Interactive Fixed Effects
INE	Instituto Nacional de Estatística – Statistics Portugal
GEPF	Gabinete de Estudos, Planeamento e Formação
GSCM	Generalized Synthetic Control Method
MSPE	Mean Square Prediction Error
RMSPE	Root Mean Square Prediction Error
SCM	Synthetic Control Method
SC	Synthetic Control
SEF	Serviços de Estrangeiros e Fronteiras
TE	Treatment Effect

1 INTRODUCTION

The political measures aimed at attracting non-European citizens to invest in European countries are believed to be strongly linked to an increase in prices and the cost of living in some European Union (EU) countries. However, it is hard to tell how European economies would have growth in the absence of these political interventions. This article investigates the impact of the Golden Visas in the real estate prices, by using the impact of Residence by Investment Programmes in Portugal as a case study. The case of Portugal is particularly intriguing from an economic standpoint. The housing market holds a pivotal role in the Portuguese economy. Its significance extends beyond financial supervision authorities, central banks, and investors, as it profoundly impacts the living standards of the population. As per data from Statistics Portugal (INE), during the 2nd quarter of 2022, the Housing Price Index (HPI) witnessed a year-on-year surge of 13.2%, marking a 0.3 percentage point increase compared to the preceding quarter (INE, 2023).

Between 2007 and 2008, a severe global financial crisis erupted, marking one of the most significant economic downturns since the Great Depression of the 1930s, known as the Great Recession. This financial turmoil was triggered by the collapse of the real estate market in the United States and culminated in the bankruptcy of Lehman Brothers, a major global bank, in 2008. Concurrently, in December 2008, the Portuguese Government, in collaboration with the EU, introduced what would later be recognized as the European Recovery Plan. This comprehensive initiative aimed to boost public investments, provide support to small and medium-sized enterprises, and offer assistance to the unemployed. By 2009, Portugal faced a budget deficit of 9% of its Gross Domestic Product (GDP) (Luciano Amaral, 2022). Subsequently, the worsening scenario of external debt prompted the implementation of austerity measures. In April 2011, Portugal found itself compelled to seek external assistance, leading to the involvement of the troika. The troika's program encompassed a series of structural reforms designed to stimulate economic growth. The global economic crisis had an especially adverse effect on Portugal, prompting European governments to implement initiatives focused on tourism and urban redevelopment in order to mitigate the severe repercussions of the crisis on both the economy and society (Sequera & Nofre, 2019). In 2012, the government introduced a range of measures aimed at attracting foreign investment in real estate and luring high-income individuals to Portugal. These initiatives featured various incentives, most notably tax advantages and the issuance of residency permits, notably known as the Golden Visas program.

The Residence Authorization for Investment Activity (ARI) regime, commonly referred to as the Golden Visas, has been in operation since October 8, 2012. It is designed to entice non-European citizens to invest in Portugal, typically in real estate, by providing them with a residence permit. This special regime for residence permits related to investment activities, often denoted as ARI, grants a temporary residence permit without the need for a residence visa. Nonetheless, there are several requirements outlined in the Immigration Law and associated regulations that applicants must satisfy. All non-European citizens who engage in an investment activity, either individually or through a company established in Portugal or another EU state with a permanent presence in Portugal, and who meet the criteria stipulated in the Immigration Law and related regulations, are eligible to seek a Residence Permit for Investment Activity. This can be obtained by investing in at least one of the following options, as outlined by SEF - Serviços de Estrangeiros e Fronteiras in 2022:

i) The capital transfer of at least 1,5 million euros.
ii) The creation of at least 10 job positions.
iii) The purchasing of real estate properties with a minimum value amount of 500 thousand euros.
iv) The purchasing of real estate properties, for which the construction was completed at least 30 years ago or located in an urban rehabilitation area and carrying out rehabilitation works on the acquired real estate, in a global amount of at least 350 thousand euros.
v) Capital transfer of at least 500 thousand euros, applied in research activities carried out by public or private institutions of scientific research, integrated with the national scientific and technological system.
vi) Capital Transfer of at least 250 thousand euros, applied in investment or support to artistic production, recovery, or maintenance of the national cultural heritage, (…).
vii) Capital Transfer of at least 500 thousand euros, applied in the acquisition of participation units in investment funds or venture capital funds aimed at the capitalization of companies, which are constituted under Portuguese legislation, whose maturity, at the time of the investment, for at least five years and at least 60% of the value of the investments is made in commercial companies headquartered in the national territory.

viii) Capital Transfer of at least 500 thousand euros, invested in the incorporation of a commercial company with headquarters in national territory, combined with the creation of five permanent jobs, (…).

According to the RIFA 2021 (Relatório de Imigração, Fronteiras e Asilo 2021) published by SEF/GEPF, at the end of 2021, 814 first residence permits were granted to investors, along with 1092 permits issued to their family members (Joaquim Estrela et al., 2022). In 2021, the program led to the creation of only three job positions but resulted in a substantial influx of capital, totalling 460 million euros. A significant portion of this investment, amounting to 409 million euros (89%), was directed towards the purchase of real estate properties. These findings indicate that the Golden Visas program tends to attract investors who utilize the program to multiply their wealth and generate profits (Surak & Tsuzuki, 2021).

The Golden Visa program in Portugal has long been a popular choice for non-EU citizens seeking residency within the country. These programs have particularly piqued the interest of nationals from China, the United States, Brazil, and Russia. However, a turning point came after a ministerial meeting on February 16, 2023, when the Portuguese government introduced a comprehensive set of measures aimed at addressing various concerns associated with housing policy. It was within this context that a pivotal decision regarding the potential discontinuation of the Golden Visa program was brought to the forefront as a means to counteract real estate speculation. Prime Minister Antonio Costa emphasized a critical aspect of this move: most of the golden visas that had been granted were primarily directed towards real estate investments, with minimal contributions to job creation and other economic activities. Subsequently, the Assembly of the Republic of Portugal convened on July 19, 2023, leading to the approval of significant revisions to the Golden Visa regime. Three of the requirements mentioned above, specifically points i), iii), and iv), were officially revoked and nullified by Law No. 56/2023 on October 6th, 2023. (SEF, 2023).

A limited body of literature has explored the economic implications of golden visas. Lopes (2014) employs hedonic models to assess the relative significance of various property attributes concerning house prices in Cascais, Portugal. His findings indicate that the Golden Visa program exerts a positive and statistically significant influence on property values. Nevertheless, the author urges caution when interpreting this outcome due to the restricted dataset and analysis period. The study's sample is confined to the latter half of 2013, a period marked by a surge in Golden Visa applications, primarily driven by investor concerns of potential policy alterations.

Taking a comparative quantitative approach, Surak & Tsuzuki (2021) assert that the impact on real estate markets is generally negligible. This is substantiated by the fact that the proportion of Golden Visas within real estate transactions in the domestic market remains marginal in most cases, with Greece being a notable exception.

To date, as this dissertation takes shape, there remains a notable absence in the empirical literature regarding the impact of Golden Visas on the economic growth, at a country level, employing the Synthetic Control Method (SCM). Since 2012, Portugal has implemented various political and economic measures aimed at mitigating the financial crisis, resulting in substantial investments in the country. It's worth noting that Golden Visas represent only 3% of the total investments in real estate purchases in Portugal (SEF, 2023). Consequently, establishing a direct causal link between the Golden Visa program and housing market prices remains uncertain. This study seeks to address the following key questions: i) How does the implementation of the Golden Visa program influence the evolution of housing prices in Portugal? ii) Does this impact warrant the termination of the program? To bridge this knowledge gap, this research conducts the first comparative case study, utilizing the SCM, to examine the repercussions of a political and economic intervention in Portugal. The principal aim of this study is to assess the influence of the Golden Visa program on housing prices. This will be accomplished by analysing the trajectory of real estate prices in Portugal in the absence of the Golden Visas program intervention. Synthetic Portugal is meticulously constructed through a linear combination of countries within the control group. This synthetic counterpart behaves as though it were the actual Portugal in the period preceding the intervention. Subsequently, the behaviour of synthetic Portugal following the implementation of the Golden Visas program serves as a counterfactual scenario depicting what might have occurred if the 2012 intervention had not taken place. To estimate the effect of economic variables resulting from the Golden Visas, a comparative analysis is conducted between the post-intervention economic indicators of actual Portugal and synthetic Portugal. The SCM offers a robust and flexible approach for analysing these effects, creating a synthetic counterpart, tailored to reflect the pre-intervention characteristics of the treated unit. This allows for more accurate and context-specific causal inference.

This paper operates at the intersection of two prominent branches in the literature. Firstly, from a methodological perspective, it aligns with a growing body of research employing the synthetic control (SC) approach to analyse the consequences of political interventions. For instance, Surak & Tsuzuki (2021) investigated the effects of the intervention on real estate markets but employed a regression analysis as their method of analysis. The second key contribution relates to the broader literature investigating the ramifications of Portugal's Golden Visas intervention in 2012. While numerous authors, including Lopes (2014), Tripathi (2019), Mihaljek & Balazs (2007), Sabal (2005), and Taltavull Paz (2003), have delved into the determinants of house prices in various European countries, there remains a dearth of research specifically examining the direct impact of Golden Visas on house prices in Portugal. To bridge this gap, this study integrates a unique database encompassing multiple countries and an extensive time frame, offering a comprehensive overview of the economic landscape. We have started by using a combination of all countries belonging to the EU to construct a SC country which resembles relevant economic characteristics of Portugal before the implementation of the Golden Visas in 2012. The housing prices evolution of the "counterfactual" Portugal without Golden Visas is compared to the actual Portugal. All the European countries chosen to create the counterfactual have never implemented any type of residency permit. We find that, after implementation of the Golden Visas, the growth rate of the Housing Price Index in Portugal follows the SC Portugal. Moreover, the gap between Portugal and the counterfactual is approximately 0 along the time observed. On the second part, we have applied the generalized synthetic control method (GSCM), which is in theory more efficient since it allows us to add more treated units. In this way, the counterfactual is instead compared to the 6 countries belonging to the EU that have implemented Golden Visas, namely Spain, Cyprus, Ireland, Malta, Greece, and Portugal.

The paper is structured as follows: Section 2 offers a comprehensive review of the applications of the SCM; In Section 3, the SCM is elucidated, along with a description of the data employed in this study, and a presentation of the generalization of the SCM; Section 4 delves into the empirical results derived from the SCM and its generalized application; Finally, Section 5 presents the ultimate conclusions drawn from the study.

2 LITERATURE REVIEW

The comparative case study is a well-established method within the field of social science, often employed to address inquiries concerning the causal impact of policy interventions on a single unit or aggregate units, like countries, regions, or cities. As Abadie et al. (2011) points out, in a comparative case study the investigators compare the outcomes for the unit(s) affected by an event or intervention (the treated group) to the outcomes for one or more unaffected and similar units (the control group). The rationale behind this method is to use the control group's outcome to approximate the outcome that would have been observed for the treated group in the absence of treatment.

The SCM is considered one of the most important contributions for the qualitative comparative case studies from the last decades. The SC methods uses a given SC unit that most approximates from the treated unit during the pre-treatment period. Then, the post-intervention outcomes for the SC unit are the ones that would have been observed for the treated unit in the absence of the intervention. (Abadie et al., 2011). Abadie and Gardeazabal (2003) have developed a comparative case study to investigate the economic effects of conflicts, by using the terrorist conflict in the Basque Country as a case study. The article allowed them to find that the per capita GDP in the Basque Country declined about 10 percentage points relative to a SC region without terrorism, after the outbreak of terrorism in the late 1960's (Abadie and Gardeazabal, 2003).

Since most of the policy interventions take place at an aggregate level such as countries, regions and cities, and usually affect single aggregate unit, the potential applicability of SC methods to comparative case studies is very large (Abadie et al., 2010). Following the Basque Country study, the SCM has become quite famous within the academic literature and has been applied in a large range of applications in economics and political science (Gilchrist et al., 2023). In 2010, Abadie, Diamond, and Hainmeller developed an article to further investigate the application of SC methods to comparative case studies and to discuss its advantages, by applying the method to study the effects of Proposition 99, a large-scale tobacco control program that California implemented in 1988. They were able to demonstrate that, after Proposition 99 implementation tobacco consumption fell markedly in California relative to a comparable SC region (Abadie et al., 2010). Later, in 2015, the same authors mentioned above published an article applying the SCM to estimate the impact of the 1990 German reunification.

The main objective was to discuss the SCM as a potentially useful tool for researchers of both traditions (Abadie et al., 2015).

Several other authors have conducted comparative case studies to examine the effects of political and economic interventions. Campos et al. (2019) in his paper applies the SCM to analyse the growth effects of European integration, by constructing counterfactuals for countries that joined the EU from 1973 to 2004. The author estimates that without European integration, per capita incomes would have been, on average, approximately 10% lower in the first ten years after joining the EU. Spruk (2019) analyse the impact of institutional breakdowns to long-run development, using Argentina as a case study. The author generates a counterfactual scenario to examine the trajectory of Argentina's long-run development in the absence of breakdowns on the eve of World War I. He finds that in the absence of institutional breakdowns, Argentina would largely have avoided the decline and joined the ranks of rich countries with an income level similar to New Zealand (Spruk, 2019). Ando (2015) examines how the establishment of nuclear power facilities (NPFs) in Japan in the 1970s and 1980s has affected local per capita income levels in the municipalities in which they were located. The author finds that the estimated effects are often economically meaningful and, in some cases, huge: the income level was 11% higher on average and 62% higher in one municipality in 2002 when compared with counterfactual units (Ando, 2015). Possebom (2017) applies the SCM to evaluate the economic impact of the Free Trade Zone of Manaus (FTZM) in the economic growth during the twentieth century, by using a Brazilian city (Manaus) as a case study. The author finds that the enterprise zone had significantly positive effects on real GDP per capita and Services Total Production per capita, but it also had significantly negative effects on Agriculture Total Production per capita.

Regarding the examination of the impact of Golden Visas on housing prices, there is a notable scarcity of studies applying the SCM. Cunha & Lobão (2022) employ a difference-in-differences (DiD) approach, utilizing a feasible generalized least squares (FGLS) estimator. Their research centers on investigating the consequences of increased tourism-driven short-term rentals (STR) on housing prices in municipalities located within Portugal's two largest Metropolitan Statistical Areas, namely Porto and Lisbon. Their findings reveal a noteworthy impact on housing prices in municipalities where a higher proportion of housing transitioned into tourism-driven short-term rentals. This transition resulted in a leftward shift in housing supply, consequently leading to a notable surge in housing prices. Although Golden Visas do not inherently equate to tourism, it's important to note that a greater influx of tourists in a country is often associated with an increased number of Golden Visa applicants (Surak & Tsuzuki, 2021).

3 MATERIALS AND METHODS

To assess the impact of the Golden Visas intervention on housing market prices in Portugal, our study employs a robust statistical methodology. Specifically, we rely on the SCM proposed by Abadie and Gardeazabal (2003). This study seeks to project a counterfactual scenario representing Portugal's hypothetical trajectory had the Golden Visas program not been introduced in 2012. As an extension of the SCM, we use the GSCM, an advancement introduced by Xu (2017). This extension is tailored to accommodate multiple treated units and variable treatment periods, overcoming the constraints of the traditional SCM, which is designed for single treated units. Furthermore, the GSCM seeks to enhance the interpretation of uncertainty estimates, addressing a key challenge in the original SCM.

It is important to acknowledge that predicting the outcomes of a counterfactual scenario is a challenging task, given that it requires envisioning an alternative reality where historical events transpired differently. In our case, this means simulating a Portugal that exhibits the same economic behaviours as the actual Portugal in the years leading up to 2012 but without the influence of the Golden Visas intervention that occurred in that year. This approach allows us to isolate and estimate the specific impact of the intervention on housing market prices.

3.1 METHODS

3.1.1 Synthetic control method

The SCM represents an advanced technique that assigns weights to a set of comparable units. These weights, when applied to the respective units, collectively construct an optimally estimated counterfactual, known as the "synthetic unit." The synthetic unit essentially delineates the hypothetical trajectory of the treated unit in the absence of the treatment. This method, although remarkably robust, is a logical extension of the DiD strategy (Cunningham, 2021). In a typical DiD analysis, a control unit is contrasted with a treated unit before and after an intervention. This analysis hinges on the premise that the control unit and the treated unit must exhibit similarity in virtually all aspects or, at the very least, share a substantial degree of similarity prior to the intervention. The crux of this approach is that the intervention, or treatment, exerts its influence solely on the treated unit while leaving the control unit unaffected. Consequently, any observed discrepancies between these two units following the intervention can be ascribed to the causal impact of the intervention (Sadeghi & Kibler, 2022).

In this section, we expound upon the empirical methodology employed, centred around the SCM. We define the intervention of the Golden Visas as the “treatment”, Portugal as the “treatment unit,” and countries other than Portugal as the “control unit.” Within the framework of SCM, we also define the House Price Index (HPI) as the “outcome” variable (Y_{jt}) which is expressed as an annual average index with a base year of 2015=100. Y_{jt} is the outcome of interest in country j at time t for $J + 1$ aggregate units, and the treatment group is $j = 1$.

Suppose that we observe $J + 1$ aggregate units over the period from time 1 to time T ($t = 1$, $\cdots$, T_0, $T_0 + 1 \cdots$, T). Y_{1t} denote the observed outcome for Portugal at time t and Portugal be exposed to the treatment at time $T_0 + 1$. Let T_0 denote the number of pre-treatment periods, with $1 \leq T_0 \leq T$. The SC estimator models the effect of the intervention at time $T_0 + 1$ on the treatment group ($j = 1$) using a linear combination of optimally chosen units as a SC (Cunningham, 2021).

For the post-intervention period, the SC estimator measures the treatment effect as:

$$Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt} \tag{1}$$

Which is represented by the difference between the values of actual Portugal Y_{1t} and synthetic Portugal $\sum_{j=2}^{J+1} w_j^* Y_{jt}$. And the w is a vector of optimally chosen weights.

Let $(J \times 1)$ be the vector of weights $\mathrm{W} = (\mathrm{w}_2, \cdots, \mathrm{w}_{\mathrm{J}+1})'$ such that $\mathrm{w}_1 \geq 0$ for j = 2, $\cdots$, J + 1 and $w_2 + \cdots + w_{\mathrm{J}+1} = 1$. In essence, it should be noted that no unit is assigned a negative weight; however, it is permissible for a unit to be assigned a weight of zero. Furthermore, the cumulative sum of all assigned weights must invariably amount to unity. By choosing the optimal weight w_j^*, we assure the SC can accurately fit the trajectory of the actual outcome before the intervention of the Golden Visas because, theoretically and ideally, the difference between Y_{1t} and $\sum_{j=2}^{J+1} w_j^* Y_{jt}$ must be zero for the pre-treatment period. Thus, Abadie, Diamond, and Hainmueller (2010) propose the following:

$$||X_1 - X_0 W|| = \sqrt{(X_1 - X_0 W)' V (X_1 - X_0 W)} \tag{2}$$

The optimal weight vector $W^*$is chosen to minimize the following distance between X_1 and X_0W, where X_1 is a $(k \times 1)$ vector of pre-treatment values of k housing market prices predictors for Portugal Country and, X_0 is a $(k \times J)$ matrix which contains the values of the same variables for the J control countries. The selection of weights is undertaken with the primary objective of ensuring that the Synthetic Portugal closely approximates the characteristics of the actual Portugal in the period preceding the implementation of the Golden Visas policy.

Let V be a $(k \times k)$ symmetric matrix with nonnegative values that captures the relative importance of the different predictors. As Abadie & Gardeazabal (2003) points out, arguably, the choice of V could be subjective. Nevertheless, in practice, it becomes evident that most researchers tend to opt for a configuration that minimizes the mean squared prediction error.

$$\sum_{t=1}^{T_0}\left(Y_{1t} - \sum\nolimits_{j=2}^{J+1} w_j^*(V)Y_{jt}\right)^2 \tag{3}$$

To evaluate the suitability of the SC in replicating the trajectory of the actual outcome for the treated unit before the intervention, we compute the root mean squared prediction error (RMSPE) of the SC, coupled with a visual inspection for further assessment. The mean squared prediction error (MSPE) measures the mean squared difference between the actual values and the predicted values of the HPI variable. A lower MSPE indicates better accuracy of the SCM in predicting the outcome variable.

According to Abadie (2021), the integrity of the results rests significantly on the scrupulousness with which the methodology is executed and the on the fulfilment of the requisite contextual and data criteria. This holds especially true in the context of statistical procedures geared towards estimating causal effects. The assumptions necessary for the proficient application of the SCM encompass the following: (i) Size of the effect and volatility of the outcome; (ii) Availability of a comparison group; (iii) No anticipation; (iv) No interference. In other words, it must be discarded from the control group those units with outcomes possibly affected by the intervention on the treated unit; (v) Convex hull condition. In other words, the differences between the characteristics of the treatment unit and the characteristics of the SC should be small. A potential way to proceed in those cases is to transform the outcome to time differences or growth rates; (vi) Time horizon. In other words, there must be a sufficient post intervention period. (vii) Aggregate data on predictors and outcomes. Hence, considering these criteria, we will carefully designate control units, delineate pre-treatment periods, and ascertain predictive variables to facilitate the estimation of a reliable counterfactual outcome.

SCM provide a valuable advantage by facilitating the implementation of placebo tests, which enable researchers to assess the validity of their results. Placebo tests involve applying the SCM by reallocating the intervention in the data to different units and time periods where the actual intervention did not occur. The objective is to determine whether the trajectories of the SC and the treated unit remain consistent beyond that specific point in time. Furthermore, researchers may consider conducting placebo tests using outcome variables that should theoretically remain unaffected by the treatment (Abadie et al., 2011). We will employ placebo tests to evaluate the quality of the previously generated SC. When comparing the trajectory of a particular unit where the actual intervention did not occur with its SC, a minimal gap suggests a high-quality SC.

3.1.2 Generalized synthetic control method

As an application extension of the SCM, we use the GSCM recently developed by Xu et al. (2017) to estimate the impact of the Golden Visas on the housing prices. Yiqing Xu's work aims to address limitations in the SCM, which is constrained to single treated units and presents challenges in interpreting uncertainty estimates. He emphasizes the advantages of the GSCM over SCM. Firstly, The GSCM offers frequentist uncertainty estimates, enhancing efficiency under the right model specifications. It uses a parametric bootstrap approach based on simulated data, ensuring valid inference under reasonable assumptions. Unlike the synthetic matching method, it utilizes all control group data, maximizing efficiency with correct model specifications. Additionally, it features a built-in cross-validation mechanism that automatically selects the number of factors for the Interactive Fixed Effects (IFE) model, simplifying implementation. This data structure leverages observations from treated units in pre-treatment periods for model selection, reducing overfitting risks when ample data is available. For more information on how these factors are estimated, please see the original article by Xu (2017).

In this section, we delve into the empirical methodology centred on the GSCM. Suppose Y_{it} is the outcome of interest of country *i* at time *t*. Let $\mathcal{T}$ and C denote the sets of units in treatment and control groups, respectively. The total number of units is $N = N_{tr} + N_{co}$, where N_{tr} and N_{co} are the numbers of treated and control units, respectively. All units are observed for T periods (from time 1 to time *T*). Let $T_{0,i}$ be the number of pre-treatment periods for country *i*, which is exposed to the treatment at time $(T_{0,i}+1)$ and subsequently observed for $q_i = T - T_{0,i}$ periods. Units in the control group are never exposed to the treatment in the observed time span. For notational convenience, we assume that all treated units are first exposed to the treatment at the same time, i.e., $T_{0,i} = T_0$ and $q_i = q$; variable treatment periods can be easily accommodated (Xu, 2017)

The primary focus of this method is the Average Treatment effect for those Treated (ATT) at time t (when $t > T_0$):

$$ATT_{t,t>T_0} = \frac{1}{N_{tr}} \sum_{i \in T} [Y_{it}(1) - Y_{it}(0)] \tag{4}$$

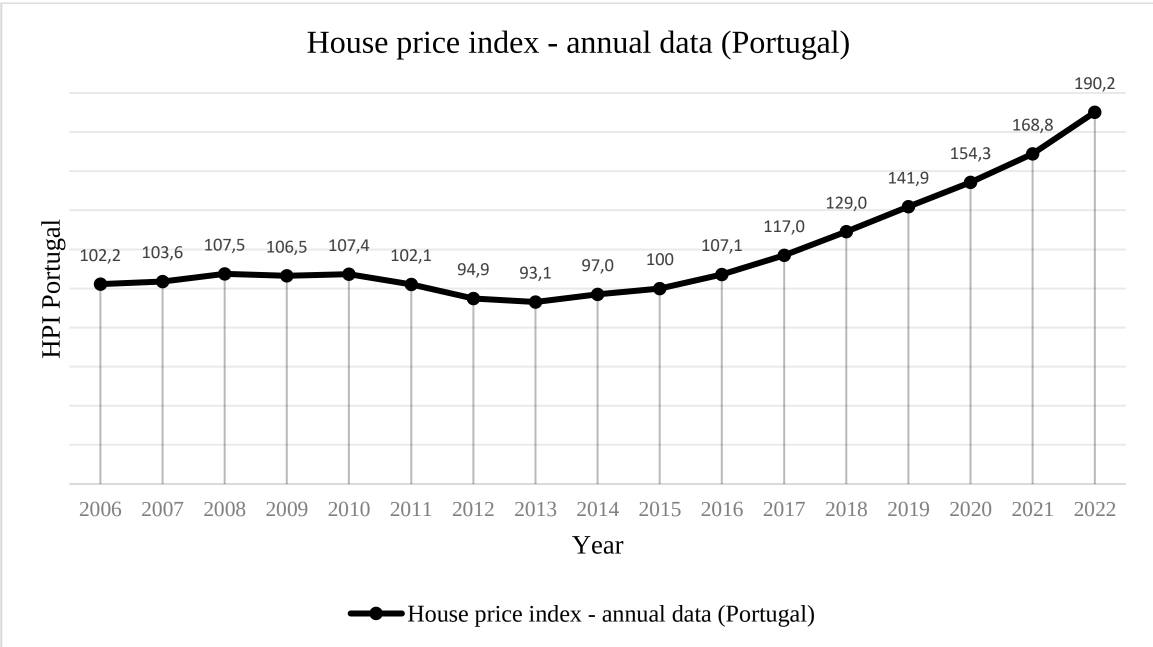
Let $Y_{it}(1)$ be the observed outcome for the treated units in post-treatment periods, and $Y_{it}(0)$ the counterfactual outcome for the treated units in the post-treatment periods. The main objective of the method is to construct counterfactuals for each treated unit in post treatment periods. Differences between $Y_{it}(1)$ and $Y_{it}(0)$ are used to estimate unit-time period-specific ATTs. These differences can be combined to generate ATTs specific to each time period in the post-treatment phase, as well as total ATTs spanning the entire post-treatment period.

3.2 DATA

Similar to the DiD approach, the SCM necessitates several key components for its application. These components include an intervention, a treated unit, a control group, and an outcome variable. By comparing the changes in the outcome variable for both the treated and control units, SCM assesses the causal impact of the intervention. In our SCM model, the intervention corresponds to the introduction of Golden Visas in Portugal in 2012. The treated unit is exclusively Portugal, which experienced this intervention. The control unit is synthetically constructed based on a control group consisting of 21 EU countries that did not implement the Golden Visas program during the study period. Given that none of the countries in the control group adopted Golden Visas, the intervention's effects are solely attributable to the treated unit, Portugal. The study's timeframe spans 15 years, encompassing the period from 2007 to 2021. In constructing the control group, we specifically focus on selecting EU countries with a similar developmental status as Portugal. Additionally, recognizing the significance of contextual variables in understanding housing market dynamics, we have included various control variables that may influence housing market activity.

To scrutinize the trajectory of housing prices, this study employs the HPI as the chosen outcome variable, measured in terms of the annual average index. The global real estate market boasts a staggering total worth of 217 trillion dollars, representing a significant 60 percent of the world's assets (Stein, 2019). The continual conversion of capital into real estate properties, encompassing both buildings and lands, has contributed to the sustained escalation of global real estate prices. The HPI is a widely utilized metric for gauging fluctuations in housing prices, designed to encapsulate the price dynamics of all residential properties acquired by households, spanning diverse types like flats, detached houses, and terraced houses, encompassing both new and pre-existing properties, irrespective of their ultimate purpose and previous owners. Notably, only market prices are factored into this analysis, thus excluding self-built dwellings, while the land component is integrated. The data is presented as an annual average index with a baseline year of 2015 set at 100 (Eurostat, 2023).

Figure 1: House Price Index evolution for Portugal (2006-2022)



Source of data: Eurostat

Figure 1 illustrates the progression of the HPI, expressed as an annual average index with a base value of 100 for the year 2015, within Portugal over the timeframe spanning from 2006 to

2022. A decline was observed from the onset of the 2008 crisis until 2012, coinciding with the initiation of incentives and external aid. Subsequently, there was a notable acceleration in 2015, marked by an exponential surge in the HPI.

Housing prices are intricately linked to various factors, including location, area, and population. To predict individual housing prices accurately, it becomes imperative to consider a broader spectrum of information beyond the HPI itself (Quang et al., 2020). This necessitates the inclusion of additional variables within the dataset. Notably, variables such as GDP and unemployment rates are theoretically influential factors that exert an impact on housing prices, rendering them pivotal for enhancing the dataset. A comprehensive exploration of these control variables will be undertaken in the subsequent section, specifically in point 3.2.3.

3.2.1 Synthetic control group

The process of selecting countries for the SC group is a pivotal step, underpinned by data and contextual specific requirements, as previously mentioned. As highlighted by Abadie (2021), a key consideration is the need to confine the SC to units sharing akin characteristics with the impacted unit, aligning with the Convex Hull Condition.

The EU's market integration project, in force since 1993, has transformed the economic activity leading to a European business reorganization. The changes in the economy have produced a truly transnational European society and a creation of a European identity, popular culture, and politics (Fligstein, 2009). To capture similarities in terms of culture, economy, and politics, I have chosen a set of 21 countries within the EU, deliberately excluding those where the Golden Visa program had previously been instituted (Ireland, Malta, Greece, Cyprus, and Spain). In adhering to this approach, I have satisfied the requirements concerning 'no interference (iv)' and 'the availability of a comparison group (ii)'. The assembled control group encompasses the following countries: Austria, Belgium, Bulgaria, Croatia, Denmark, Slovakia, Slovenia, Estonia, Finland, France, Germany, Netherlands, Hungary, Italy, Latvia, Lithuania, Luxembourg, Poland, Czech Republic, Romania, and Sweden (Table 1).

The data period is from 1995 to 2022, annual observations. The main analysis focuses on the time frame spanning from 2007 to 2021. This interval is chosen due to data limitations, as data for certain treatment units is unavailable prior to 2007 or beyond 2021. Within this dataset, we divide the data into two distinct periods: the pre-treatment period spans from 2007 to 2012, while the post-treatment period extends from 2012 to 2021. The pre-intervention period is sufficiently large to enable the application of the SCM. As Abadie (2021) emphasizes, the credibility of the SC estimator hinges significantly on its capacity to consistently trace the trajectory of the outcome variable for the treated unit before the intervention. Given that the effects of certain interventions may require time to manifest or reach a quantifiable level in the data, the post-intervention period, spanning nine years, is substantial in line with the previously mentioned requirement '(vi) Time horizon'.

Table 1: The list of the countries in the analysis for SCM

Country	Country code	Unit number	Golden Vista
Austria	AT	1	N
Belgium	BE	2	N
Bulgaria	BG	3	N
Czech Republic	CZ	4	N
Germany	DE	5	N
Denmark	DK	6	N
Estonia	EE	7	N
Finland	FI	8	N
France	FR	9	N
Croatia	HR	10	N
Hungary	HU	11	N
Italy	IT	12	N
Lithuania	LT	13	N
Luxembourg	LU	14	N
Latvia	LV	15	N
Netherlands	NL	16	N
Poland	PL	17	N
Portugal	PT	18	Y
Romania	RO	19	N
Sweden	SE	20	N
Slovenia	SI	21	N
Slovakia	SK	22	N

Golden Vista: N = included in the 21 countries in the main control group, Y= included in the treatment group.

3.2.2 Control Variables

To construct a SC that effectively aligns with the actual outcome trajectory for Portugal during the pre-treatment period, the identification of predictive variables is imperative. Control variables are elements used in the application of the SCM to create a SC group that can be comparable to the treatment group - Portugal. Variables are selected based on their relationship to the outcome variable, the HPI.

Based on an extensive review of the existing literature concerning the determinants of housing prices, certain variables consistently emerge as key contributors. Notably, the most frequently cited determinants of housing prices include the GDP (Cunha et al., 2021; Hossain et al., 2009; Tripathi, 2019; Kaulihowa et al., 2019; O'Donovan et al., 1997; Mihaljek et al., 2007), interest rates (Lourenço & Rodrigues, 2017; Cunha et al., 202; Nistor et al., 2018; Sabal, 2005; Tupenaite et al., 2017; Algieri, 2013; Mihaljek et al., 2007), income (Taltavull Paz, P., 2003; Reichert, 1990; Nistor et al., 2018; Tripathi, 2019; Czinkan et al., 2019; Algieri, 2013; Taghizadeh-Hesary et al., 2020), population (Taltavull Paz, P., 2003; Reichert, 1990; Tripathi, 2019; Sabal, 2005; Droes et al., 2017; Czinkan et al., 2019; O'Donovan et al., 1997), inflation rates (Hossain et al., 2009; Tripathi, 2019; Tupenaite et al., 2017; Algieri, 2013; Taghizadeh-Hesary et al., 2020), mortgage loans (Reichert, 1990; Sabal, 2005; Tupenaite et al., 2017; Ge, 2009; Kaulihowa et al., 2019; Mihaljek et al., 2007), unemployment (Reichert, 1990; Nistor et al., 2018; Ge, 2009; Liu et al., 2021; Kalabiska et al., 2022), tourism (Cunha et al., 2021; Biagi et al. 2015), money supply (Taghizadeh-Hesary et al., 2020), construction activity (Cunha et al., 2021; Tupenaite et al., 2017; Ge, 2009), wage (Kalabiska et al., 2022;), and migration (Nistor et al., 2018; Sabal, 2005; Kalabiska et al., 2022; Gok et al., 2015). For comprehensive details regarding the variables, please consult Appendix A.

These control variables will enable us to conduct a comparative analysis between the two groups: Portugal and its counterfactuals. To enhance the analysis and facilitate result interpretation, we applied logarithmic transformations to all variables except for HICP, which represents the inflation rate. This transformation serves to establish linearity in the data, enabling the variables to be interpreted as growth rates. As a result, we satisfy the 'Convex Hull Condition (v)' requirement previously mentioned.

3.2.3 Generalized Synthetic Control Method

We will expand the application of the SCM to accommodate multiple treated units by employing the GSCM. Like the SCM, the GSCM serves as an econometric tool to estimate the causal impact of an event, such as the introduction of Golden Visas, on a specific variable of interest. It offers the potential for greater efficiency and the flexibility to incorporate several treatment units, each with distinct treatment start dates. We will construct a new database that includes six treatment units, corresponding to the six EU countries that have implemented Golden Visas: Ireland, Portugal, Greece, Cyprus, Spain, and Malta (as depicted in Table 2). These treatment units will have varying treatment initiation dates. The control units, however, will remain consistent and comprise the same 21 countries within the EU that have never implemented Golden Visas. The list of countries included in the GSCM analysis is presented in Table 3. The data period is from 2009 to 2022, annual observations. The main analysis focuses on the time frame spanning from 2011 to 2021. This specific time frame is selected due to data constraints, as information for some treatment units is either unavailable before 2011 or after 2021.

Table 2: The list of treated unites in the analysis for GSCM

Country (i)	Country Code	Treatment year $(T_{0,i}+1)$
Ireland	IE	2012
Portugal	PT	2012
Greece	EL	2013
Cyprus	CY	2013
Spain	ES	2013
Malta	MT	2014

Table 3: The list of the countries in the analysis for GSCM

Country	Country code	Unit number	Golden Vista
Austria	AT	1	N
Belgium	BE	2	N
Bulgaria	BG	3	N
Cyprus	CY	4	Y
Czech Republic	CZ	5	N
Germany	DE	6	N
Denmark	DK	7	N
Estonia	EE	8	N
Greece	EL	9	Y
Spain	ES	10	Y
Finland	FI	11	N
France	FR	12	N
Croatia	HR	13	N
Hungary	HU	14	N
Ireland	IE	15	Y
Italy	IT	16	N
Lithuania	LT	17	N
Luxembourg	LU	18	N
Latvia	LV	19	N
Malta	MT	20	Y
Netherlands	NL	21	N
Poland	PL	22	N
Portugal	PT	23	Y
Romania	RO	24	N
Sweden	SE	25	N
Slovenia	SI	26	N
Slovakia	SK	27	N

Golden Vista: N = included in the 21 countries in the control group, Y= included in the 6 countries in the treatment group.

4 RESULTS AND DISCUSSION

Customizing the code from Abadie et al. (2011) to our specific dataset, as detailed in the Appendix B, requires adhering to Synth's workflow. This entails initial data preparation utilizing the 'dataprep' function, wherein we define the treatment and control variables. Within our database, referred to as the "FinalTable," the 'predictors' correspond to those variables recognized as possessing substantial causal relevance to the dependent variable, as ascertained through the literature review. The 'time.predictors.prior' refers to the period before the intervention of Golden Visas in Portugal. It will be over this period that the values for the predictors must be estimated since there was no intervention. The 'time.optimize.ssr' refers to the period of the dependent variable over which the loss function should be minimized, that is, the period over which the MSPE, which is the sum of the residuals squares between the treatment unit (Portugal) and the SC unit (Synthetic Portugal), will be minimized.

The application of the SCM encompassed all EU countries that had never implemented the Golden Visa program. Initially, 22 countries were considered however, Romania (unit number = 19) was excluded from the application of the SC due to insufficient data, rendering the application of the SC infeasible. Importantly, we conduct a balance check by comparing our treated unit (Portugal) and our SC unit (Synthetic Portugal) before the intervention. This step is essential to ensure their relative similarity. Any differences observed between these units after the intervention can be attributed to the causal effect of the intervention. Find the balance check results in Table 4.

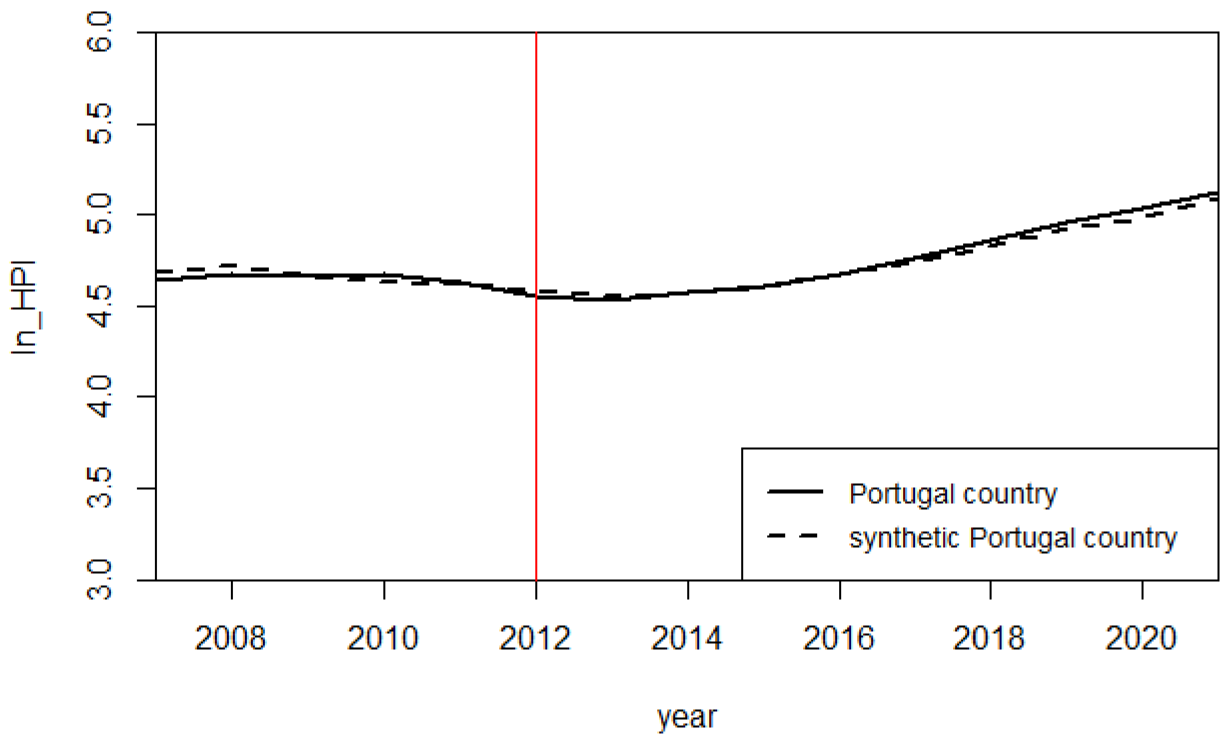
Table 4: Yearly gaps between Portugal and synthetic Portugal

Pre-treatment		Post-treatment	
Year	Gap	Year	Gap
2007	-0.04172	2013	-0.01687
2008	-0.03670	2014	0.01555
2009	0.00750	2015	0.00000
2010	0.04513	2016	0.00354
2011	0.00866	2017	0.02329
2012	-0.03357	2018	0.03596
		2019	0.02976
		2020	0.05840
		2021	0.04197

Analysing the variations in the gaps between the results of the SC and the treatment group over time (Table 4), it becomes evident that the trajectory of Portugal's ln_HPI closely mirrors that of synthetic Portugal throughout the entire period of pre-Golden Visas intervention. Abadie's work does not include a specific numerical test for determining the acceptability of the gaps between the treated and synthetic units. Instead, the issue is addressed by calculating the RMSPE without a predefined threshold for acceptance. Likewise, in the placebo tests, the author relies on graphical output rather than employing a numerical test. I follow this approach in my study. Consequently, we can proceed to the next analytical step, which focuses on the post-treatment period.

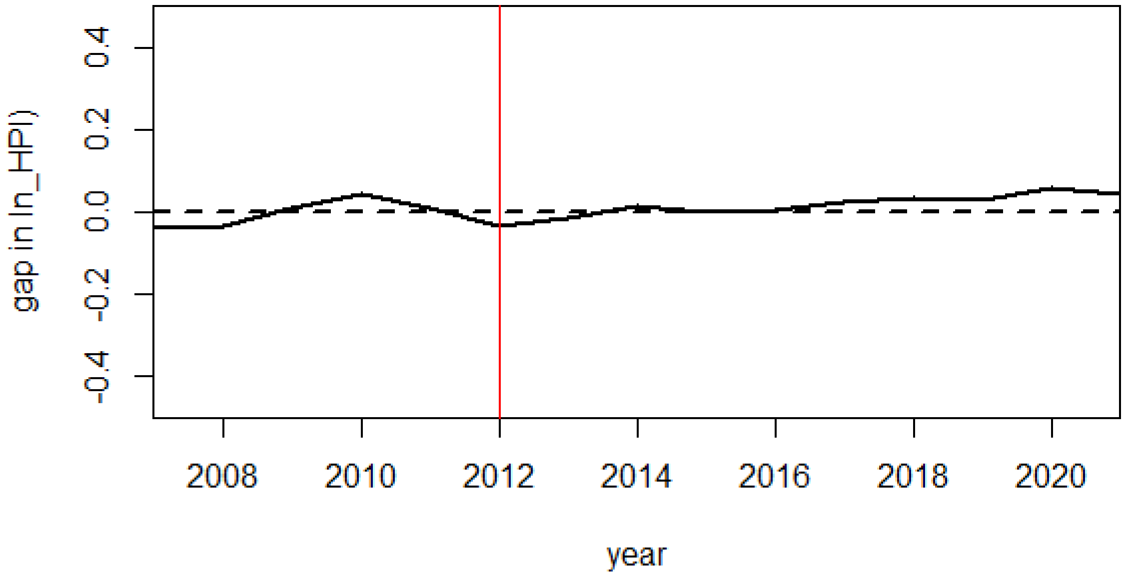
As depicted in Figure 2, Portugal and synthetic Portugal exhibit remarkably similar behaviour during the pre-treatment period, displaying nearly parallel trends. An essential guiding principle in SCM model design is to maximize the length of the pre-treatment period, with longer periods being preferable. Given the sufficient duration of the pre-treatment period and the minimal pre-treatment disparities between Portugal and synthetic Portugal and, our SCM model effectively addreses these aspects.

Figure 2: Portugal vs. Synthetic Portugal



In the next step, we will examine how the disparities between the results of the SC and the treatment group evolve over time using the gaps.plot() function (Figure 3). It is evident that Portugal's ln_HPI trajectory closely mirrors that of synthetic Portugal throughout the entire period, both pre-treatment and post-treatment. This suggests a minimal or non-significant effect on the Housing Price Index.

Figure 3: Gaps between Portugal and Synthetic Portugal



4.1 PLACEBO TESTS

Conducting robustness tests, also known as placebo tests following Abadie and his co-authors' approach, is an essential step in our analysis. These tests aim to assess the quality of the SC estimated. Specifically, we seek to compare the HPI's evolution in a country similar to Portugal, one that has not implemented Golden Visas, with its synthetic country. The objective of these placebo tests is to examine whether the observed gap illustrated in Figure 2 might be attributed to factors other than the introduction of Golden Visas. To identify the country most similar to Portugal in terms of the control variables (GDP, income, population, inflation, mortgage loans, unemployment, tourism, money supply, construction, wages, and migration), we analysed the weight of each country in the model (Table 5).

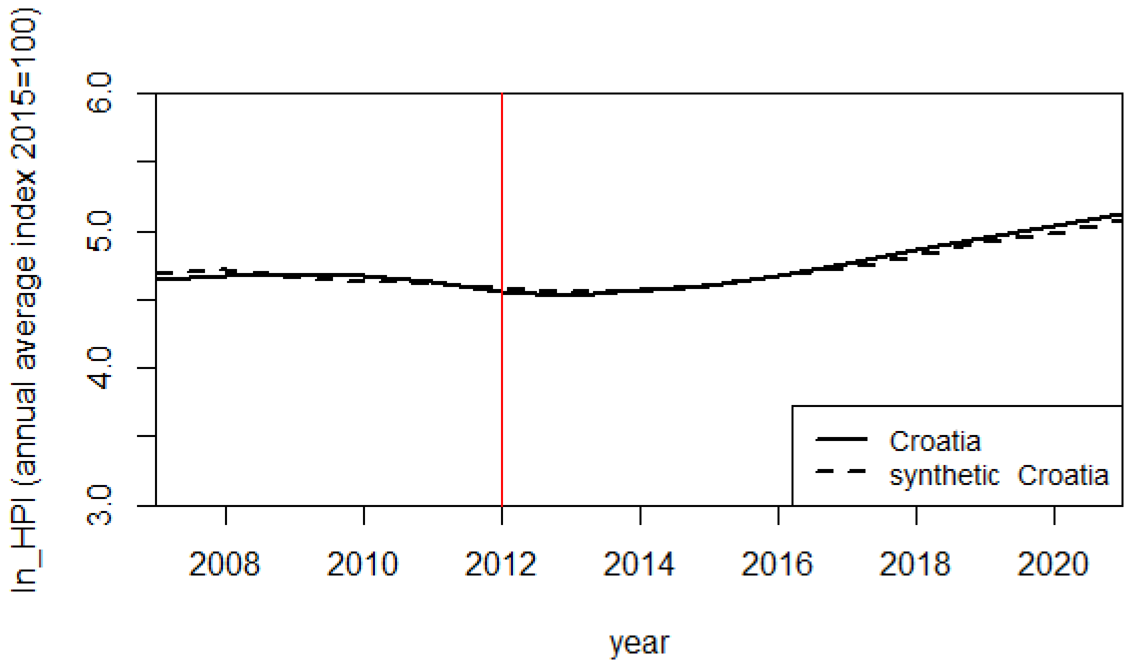
Table 5: SCM weights for the countries in the control group

Weight	Country	Country code	Unit number
0.001	Austria	AT	1
0.002	Belgium	BE	2
0.004	Bulgaria	BG	3
0.003	Czech Republic	CZ	4
0.001	Germany	DE	5
0.001	Denmark	DK	6
0.004	Estonia	EE	7
0.002	Finland	FI	8
0.004	France	FR	9
0.260	Croatia	HR	10
0.423	Hungary	HU	11
0.141	Italy	IT	12
0.002	Lithuania	LT	13
0.000	Luxembourg	LU	14
0.003	Latvia	LV	15
0.095	Netherlands	NL	16
0.001	Poland	PL	17
0.001	Sweden	SE	20
0.001	Slovenia	SI	21
0.047	Slovakia	SK	22

To conduct the placebo study, we focus on Hungary and Croatia as they are the countries with the largest weights in the SC for Portugal. Hungary contributes 42% and Croatia contributes 26% to the construction of synthetic Portugal, while all other countries have minimal or approximately 0% weight, and Luxembourg has no contribution to the SC. Croatia and Hungary share several characteristics with Portugal, some of which may not be directly captured by our data. Croatia, like Portugal, falls under the category of moderately developed countries within the EU. Its economy relies significantly on sectors such as tourism, services, and agriculture. Situated in Southern Europe, Croatia shares climate and opportunities for tourism, agriculture, and trade that are similar to those of Portugal. Figure 4 displays the real growth rate path of the Housing Price Index (HPI) for Croatia alongside the growth rate path suggested by a "synthetic Croatia." This synthetic country is constructed as a weighted combination from various other

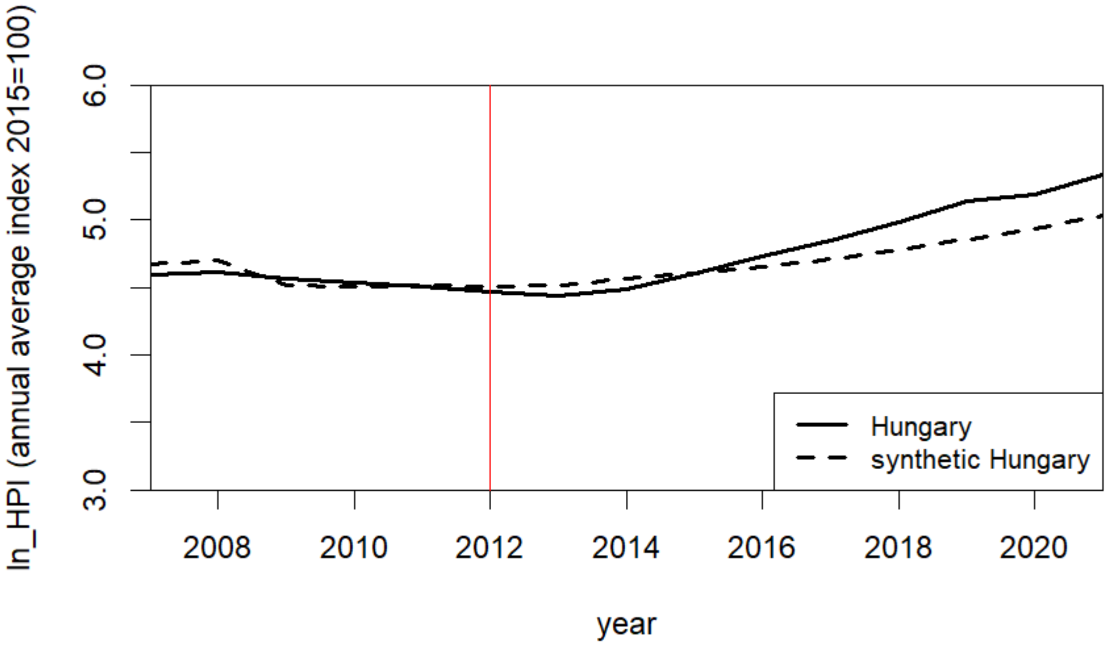
EU countries (without Croatia), as detailed earlier. Croatia presents a trajectory very similar to that of their synthetic model, reinforcing the quality of the SC applied.

Figure 4: Placebo Study ln_HPI for Croatia



The weighted combination of EU countries accurately reproduces Hungary's HPI growth rate until 2017 (Figure 5). However, between 2017 and 2021, Hungary exceeded the SC by an average of 21 percent in HPI growth rate (Appendix C). Upon closer examination, this divergence can be attributed to Hungary's significantly elevated inflation rates during that period, stemming from common external shocks such as COVID-related disruptions in the supply chain and surges in commodity prices, particularly in energy and food. These factors were further exacerbated by Russia's conflict in Ukraine (Cohn Bech et al., 2023). Hungary experienced notably higher inflation rates compared to the average levels in other EU countries (refer to the annexes). Given that Hungary is a key component of the SC for Portugal, the abnormally high inflation rates in Hungary starting in 2017 may artificially widen the gap in HPI for Portugal, as depicted in Figure 2 and Figure 3. Consequently, our placebo study suggests that while Hungary's HPI growth rate can be reasonably replicated using our methodology, the gap in Portugal's HPI growth rate during the same period, relative to its SC, may have been smaller than what is indicated in Figure 3.

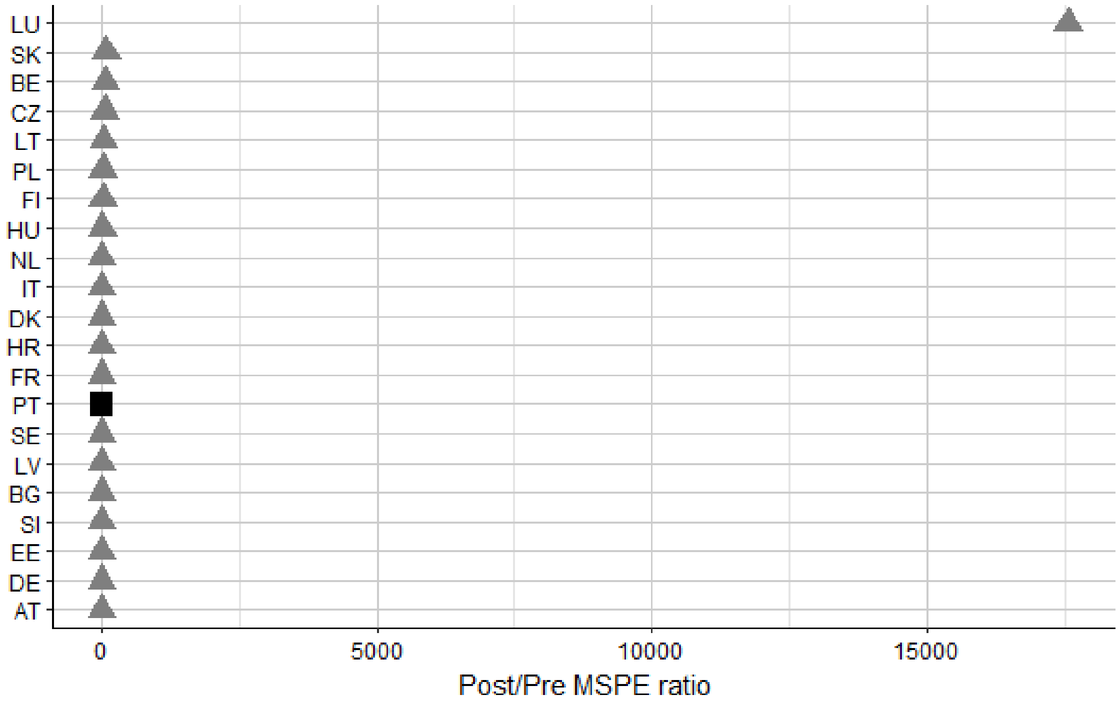
Figure 5: Placebo Study ln_HPI for Hungary



4.2 Mean Square Prediction Error

The primary purpose of the MSPE is to assess the quality and robustness of the SC model. It evaluates the accuracy of the SCM by comparing the actual values of the outcome variable (HPI) in the treated unit (Portugal) with the values predicted by the SC in the pre-treatment period. Researchers can use it to determine whether the SC accurately reproduces the pre-intervention outcomes for the treated unit and whether the differences between predicted and actual values are statistically significant. Figure 6 provides insight into the effectiveness of the SCM by presenting the Post/Pre Ratio MSPE, a key statistic for assessing the model's performance before and after the treatment or intervention. This ratio hinges on two crucial components: (i) Pre-Treatment MSPE. This metric evaluates how accurately the SC model predicts the outcomes for the treated unit during the pre-treatment period. It essentially measures the model's ability to replicate the actual results for the treated unit before any intervention transpires; (ii) Post-Treatment MSPE. This component quantifies the SC model's predictive accuracy for the treated unit during the post-treatment period. It gauges how well the model can replicate the actual post-intervention outcomes for the treated unit.

Figure 6: Post/Pre MSPE ratio



A Post/Pre-Ratio MSPE significantly greater than 1 may imply a noticeable alteration in the treated unit's outcomes following the intervention. Conversely, a value close to 1 indicates that the SC model effectively predicts post-intervention outcomes that closely resemble those observed before the intervention. A Post/Pre Ratio MSPE close to 0 suggests that the model is effective in predicting pre-intervention outcomes.

In Figure 6, all the treatment units display Ratio MSPE values of approximately 0. This suggests that the SCM exhibits good precision in replicating the outcomes of the treated units during the pre-treatment period. In other words, the model effectively captures the historical trajectories of these treated units before any interventions occurred. However, it's worth noting that Luxembourg stands out with a Ratio MSPE significantly greater than 1, approximately around 17500 units. This result is not surprising, considering the information obtained earlier in Table 5. A weight of 0 is assigned to Luxembourg in the construction of the SC model, meaning Luxembourg was not a significant contributor to the creation of the SC for Portugal. Luxembourg and Portugal exhibit notable disparities in various aspects, including their economic size, economic structure, and income levels (refer to the annexes). This substantial Ratio MSPE value underscores that Luxembourg is an inappropriate reference point for simulating the effects of the treatment in Portugal.

4.3 Generalized Synthetic Control Method

Motivated by Xu Yiqing pioneering research in 2017 and further refined by the collaborative efforts of Yiqing Xu and Licheng Liu in 2021, the R package "gsynth" offers a tool for applying the GSCM. This method effectively generates counterfactual scenarios for each treated unit by leveraging the control group's data. Adapting this package to our unique dataset entails the inclusion of a binary variable. This binary treatment indicator plays a pivotal role, with the value 1 signifying treatment and 0 indicating no treatment.

To embark on our analysis, our initial step is to gain a comprehensive understanding of the data structure and identify any instances of missing values. Figure 7 illustrates that our dataset comprises six treated units and 21 control units (N_{tr} = 6; N_{co} = 21; T = 11). As we proceed through the gsynth workflow, certain treated units have been automatically excluded due to insufficient pre-treatment periods. Specifically, 5 treated countries—Spain, Portugal, Ireland, Cyprus, and Greece—have been removed from our analysis. The shaded region in gray (Figure 7) represents all the treated units that were excluded from our sample. This exclusion occurred as a result of the GSC method's implementation, which identified insufficient pre-treatment periods in these units. Consequently, only Malta remained in our sample for further analysis.

Figure 7: Data Structure after application of the Gsynth

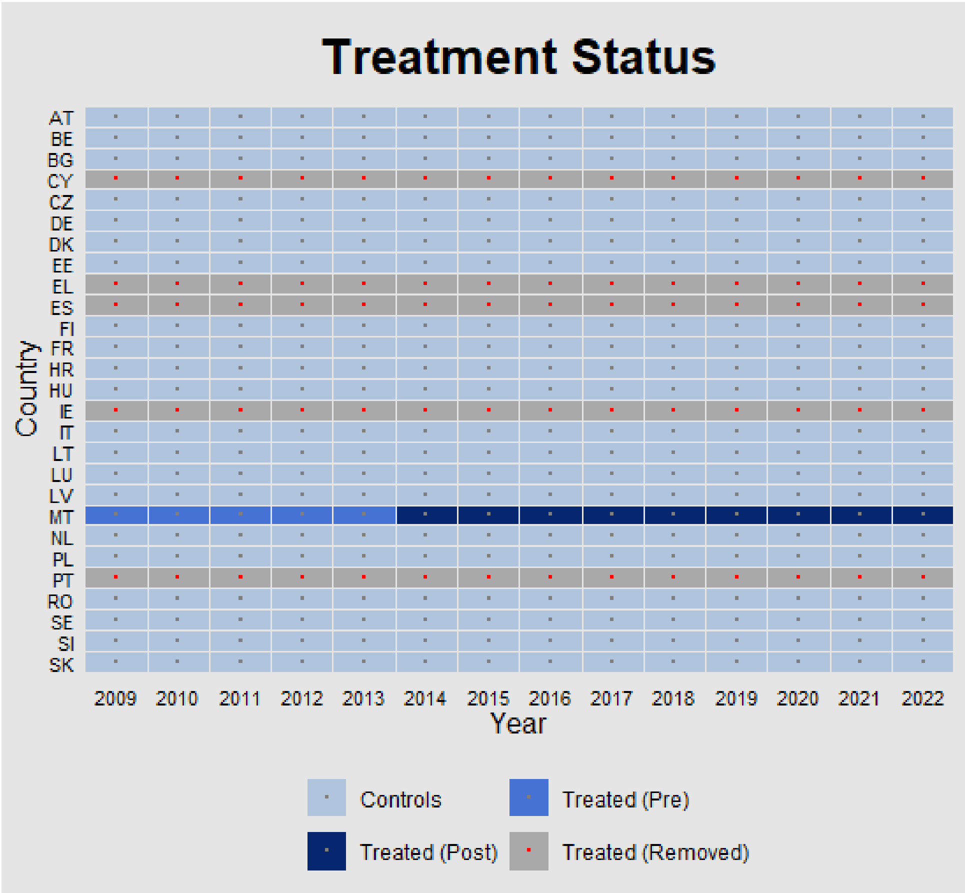


Figure 8 illustrates the impact of Golden Visas on the evolution of the Housing Price Index growth rate (ln_HPI) over time for each unit in the dataset. The x-axis represents time relative to the intervention, while the y-axis denotes the treatment effect. These visualizations incorporate 95 percent confidence intervals represented by the shaded region. The intervals are based on block bootstraps, repeated 1,000 times. Notably, the gaps remain nearly flat during the pre-treatment periods. Using the GSC method, there is a close match between the average actual HPI growth rate and the average predicted index in the pre-treatment periods. However, a noticeable divergence occurs after the implementation of Golden Visas, with an ATT of approximately -0.251, accompanied by a standard error of 0.365 (Table 6). This indicates that the implementation of Golden Visas is linked to a slight decrease in the HPI growth rate in Malta.

Figure 8: GSCM - Estimated ATT

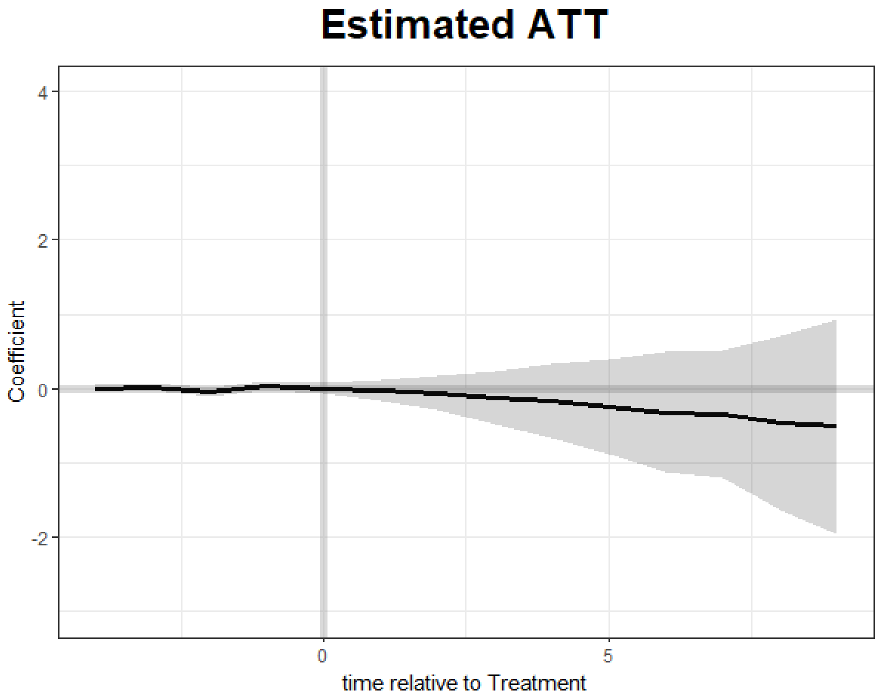
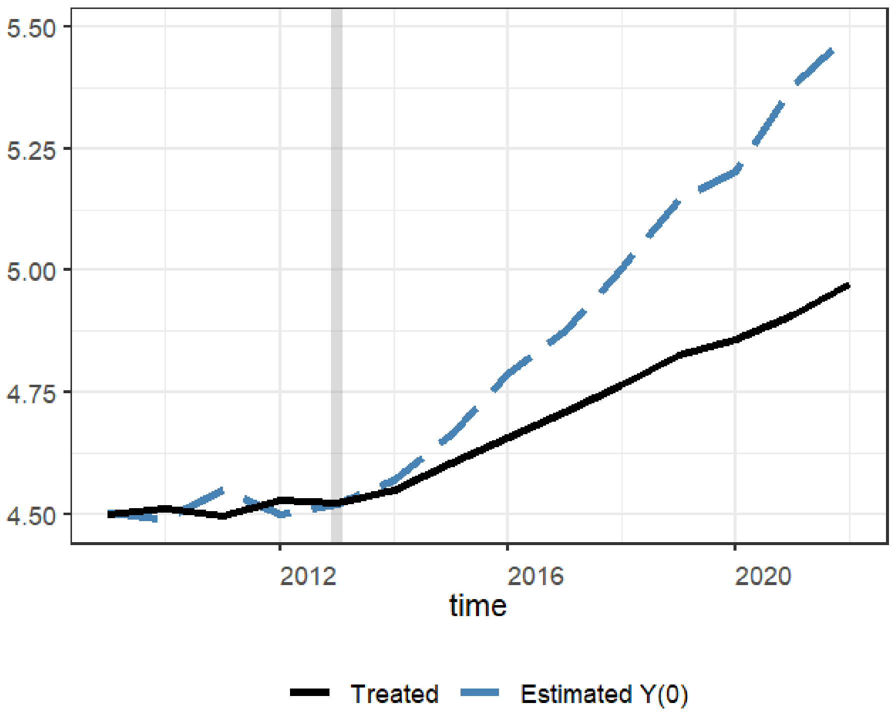


Table 6: ATT

Estimate	S.E.	CI.lower	CI.upper	p.value
0.251	0.365	0.966	0.465	0.492

Figure 9 displays the counterfactual paths of outcomes for the treated units in the absence of Golden Visas. The visualization enables us to observe how the Housing Price Index (HPI) growth rate would have evolved without the policy intervention. Using the GSC method, we can see that prior to the Golden Visas' implementation, the gaps between the two lines are almost flat, signifying that the predicted and actual outcomes align well in pre-treatment periods. However, following the Golden Visas intervention, there is a noticeable divergence. In the graph, the solid bold line represents the average HPI growth rate of Malta, while the dashed bold line represents the average predicted outcome for Malta in the absence of the treatment. As noted earlier, the figure illustrates that, according to the GSC method, the HPI growth rate predicted without the policy is higher than the actual outcome. This suggests that, in the absence of the Golden Visas policy, the HPI growth rate would have been higher.

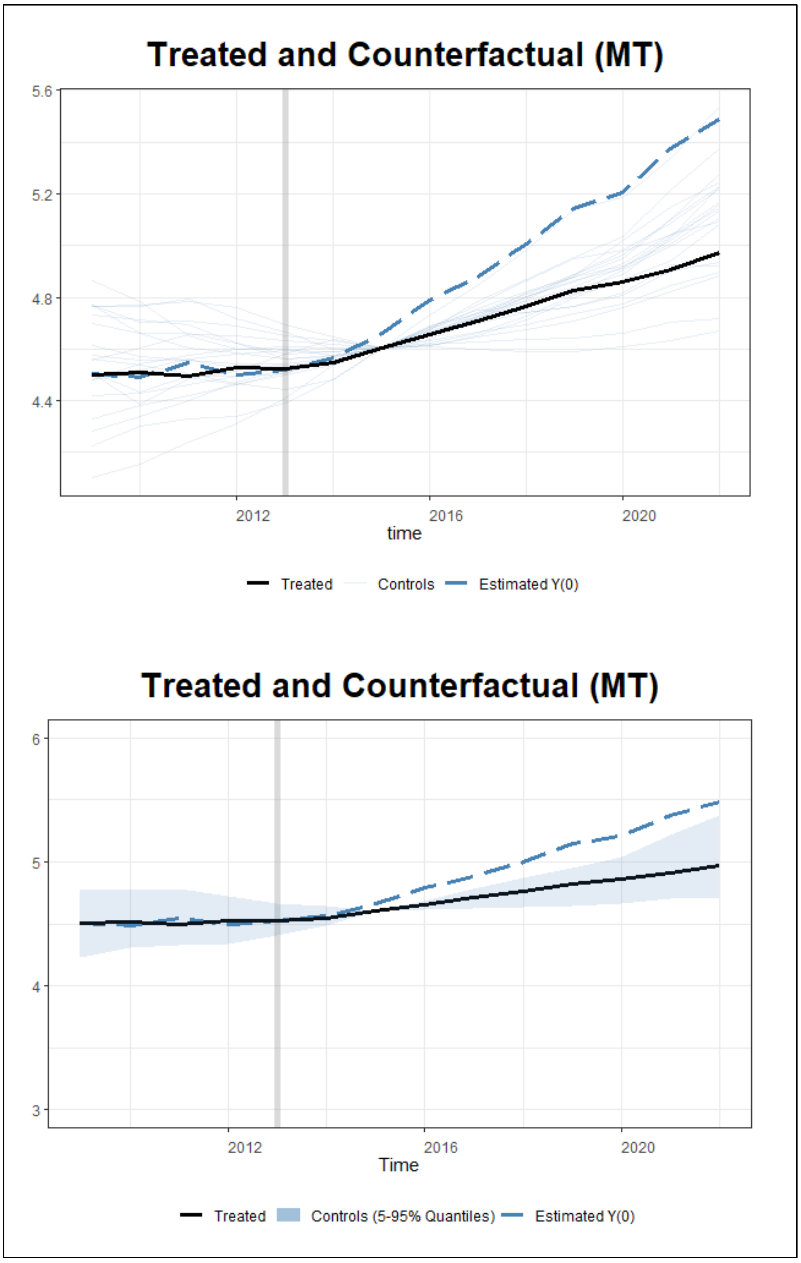
Figure 9: GSCM - Estimated Counterfactual



Additionally, we can incorporate two 5 to 95% quantile bands of the treated and control outcomes as reference points. This helps ensure that the estimated counterfactuals are not simply the product of extreme extrapolations and align with the broader distribution of data (Figure 10).

The observation of a counterfactual outcome being higher than the actual treated outcome for the HPI in Malta, as well as a negative impact of Golden Visas on HPI growth rate in Malta, may seem counterintuitive at first. However, such outcomes can occur due to the specific characteristics of the data and the way the GSCM constructs the counterfactuals. After a thorough analysis of the dataset for, no outliers or highly unexpected values were found that could explain this behaviour. This leads to the hypothesis that the observed discrepancy may be related to the sample size and missing information due to data constraints. The pre-intervention period may not be sufficiently large to enable the proper application of the GSCM. The credibility of the SC estimator heavily depends on its capacity to consistently replicate the trajectory of the outcome variable for the treated unit before the intervention. The absence of sufficient pre-intervention data may lead to counterfactual trajectories that deviate from actual outcomes.

Figure 10: GSCM - Estimated Counterfactual with Controls



5 CONCLUSIONS

Portugal has been witnessing significant political polarization in relation to the impact of the Golden Visas on the housing market prices ever since their inception in 2012. This polarization is underpinned by the notable observation that a substantial portion of the capital injected into Golden Visas has been channeled towards the purchase of real estate properties. This concentration of investment in real estate has been a focal point in the ongoing debate surrounding the program's impact on the Portuguese housing market. This issue reached a critical juncture in the 2nd quarter of 2022 when the Housing Price Index (HPI) registered a substantial year-on-year increase of 13.2% (INE, 20223). This surge in housing prices placed considerable pressure on the government to address the issue of real estate speculation. Consequently, in response to this context, a pivotal decision emerged regarding the potential discontinuation of the Golden Visa program as a means to counteract this speculation. Subsequently, on July 19, 2023, the Assembly of the Republic of Portugal convened to deliberate on this matter, leading to the approval of substantial revisions to the Golden Visa regime. Three specific requirements to obtain the ARI, namely: i) The capital transfer of at least 1.5 million euros; ii) The acquisition of real estate properties with a minimum value of 500 thousand euros; and iii) The purchase of real estate properties, either constructed at least 30 years ago or situated in an urban rehabilitation area, along with the execution of rehabilitation works on the acquired real estate, with a combined value of at least 350 thousand euros; were officially revoked and nullified by Law No. 56/2023 on October 6th, 2023 (SEF, 2023). This marked a significant shift in Portugal's approach to its Golden Visa program in response to the mounting concerns over real estate speculation and its socio-economic implications.

This paper seeks to address a pivotal question that carries significant policy implications: Does the implementation of Golden Visas have a discernible association with the fluctuations in housing market prices? Furthermore, is this impact statistically significant enough to warrant consideration for discontinuation to curtail speculation surrounding housing prices? In order to explore these questions, our study investigates the impact of the Golden Visa program on housing market prices, with a specific focus on the Housing Price Index in Portugal. To forecast how housing prices in Portugal might have evolved had the Golden Visa program not been introduced, we employ the SCM. This approach involves creating a synthetic counterpart of Portugal by combining data from countries in the control group. In order to extend the analysis, we expand our study to encompass other EU countries that have adopted the Golden Visa programs, by using the GSCM. This approach involves creating a synthetic counterpart for each country and produce an ATT for each unit of time.

This study suggests that the implementation of Golden Visas had no discernible impact on the trajectory of Portugal's Housing Price Index throughout the entire duration of its intervention. The gap between Portugal and its counterfactual is approximately zero across the entire investigative period from 2012 to 2021. According to the SCM, the Golden Visas had no statistically significant effects on the housing market prices at a country level. Our analysis has revealed that Hungary and Croatia exhibit behavior analogous to Portugal within the context of EU countries, contributing 42% and 26%, respectively, to the construction of the synthetic Portugal. This indicates a high degree of similarity in terms of control variables, particularly with respect to the Housing Price Index (HPI), tourism, and GDP (as detailed in Appendix D). Conversely, our findings indicate that Luxembourg carries no weight in the contribution to the SC, suggesting that Luxembourg's outcomes for the predictors significantly differ from those observed in Portugal.

When extending our analysis to the other EU countries that have implemented Golden Visas, using the GSCM, we have discovered that the estimated outcome for the growth rate of the HPI is higher without the intervention. The ATT is approximately -0.251, with a standard error of 0.365. It's important to note that this slight divergence observed after the implementation of Golden Visas in Malta does not necessarily imply a negative impact on the growth rate of the HPI. We will provide a more detailed explanation of this point in the limitations section of our study, specifically addressing the application of the GSCM for this particular case.

Our study is subject to certain limitations. Firstly, our research approach does not enable us to draw conclusions regarding the impact of Golden Visas in specific cities within Portugal, notably in Lisbon, Cascais, Oeiras, and Porto, which are among the most affected cities in terms of price speculation (INE, 2023). The SCM necessitates the availability of data pertaining to outcomes and predictors of the outcome for the unit or units exposed to the intervention of interest, along with a set of comparison units (Abadie, 2021). Consequently, the predictors and outcomes are often reported as time series data by government agencies and multilateral organizations. These outcomes are typically represented at the state or country level, such as GDP per capita, unemployment rate, or inflation rate. Therefore, we cannot draw definitive conclusions about the significant impact, or lack thereof, of Golden Visas in specific cities like Lisbon or Porto, due to the limitations inherent to our research methodology.

Furthermore, in the application of the GSCM, we encountered issues related to missing data for certain variables in some periods across the countries included in the treatment group. This situation led to a reduction in the time horizon of our dataset. It is important to highlight that a dataset characterized by a restricted number of pre-intervention periods may compromise the capability to consistently trace the trajectory of the outcome variable for the treated unit before the intervention. In such cases, the resulting SC may fail to accurately replicate the trajectory of the outcome for the treated unit in the absence of the intervention (Abadie, 2021). The results derived from our analysis of Malta underscore the critical significance of having a high-quality dataset characterized by an adequate number of pre-intervention periods and the absence of missing data. This requirement is essential for ensuring that the counterfactual is accurately estimated, thereby guarding against the potential for inaccurate results. These findings serve as a valuable reminder of the importance of data integrity and completeness, particularly within the context of our research.

In conclusion, our study addresses critical policy questions surrounding Portugal's Golden Visa program. We investigated whether the implementation of Golden Visas is associated with discernible fluctuations in housing market prices. Surprisingly, our findings reveal that the program had no statistically significant impact on Portugal's Housing Price Index from 2012 to 2021, challenging prevailing perceptions. Also, we questioned whether this impact, or lack thereof, is substantial enough to justify considerations for discontinuation to mitigate speculation surrounding housing prices. Contrary to the debates and concerns, our analysis suggests that the observed fluctuations in housing prices cannot be attributed to the Golden Visa program. This implies that discontinuation may not be warranted solely based on its impact on housing market prices. These insights contribute significantly to the ongoing discourse on the program's implications, offering valuable considerations for policymakers and stakeholders.

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APPENDIX A. VARIABLES DETAILS

Data on the control variables and the outcome variable were sourced from EUROSTAT, accessible via the following website: https://ec.europa.eu/eurostat/en/. Information for each variable was collected using the "eurostat" package in R. The interest rate variable has been omitted from the dataset due to a lack of data for the majority of the units.

Variable	Eurostat indicator	Time period
Gross Domestic Product (GDP)	GDP per capita in PPS	2010-2021
Income	Adjusted gross disposable income of households per capita	2000-2021
Population	Active population aged 15-64 - annual averages	2003-2022
Inflation	Inflation rate	2011-2022
Mortgage loans	Cost overload rate [1]	2011-2022
Unemployment	Total unemployment rate	2010-2021
	Long-term unemployment, % of active population aged 15-74	2003-2021
Tourism	Arrivals of residents/non-residents at tourist accommodation establishments	2011-2022
Construction	Residential construction - annual data, % of GDP	1995-2022
Migration	Immigration	2009-2020
House Price Index (HPI)	House price index (2015 = 100) - annual data	2000-2021

[1] The percentage of the population living in a household in which total housing costs (net of housing subsidies) represent more than 40% of income total available household income (net of housing benefits)

APPENDIX B. SCM R CODE

```
dataprep.out <- dataprep(
  foo = FinalTable,
  predictors = c("ln_construct","ln_immigratn", "ln_overburden_rt", "ln_tourism",
                 "ln_unemploymt_rt", "ln_unemploymt_rt_AP"),
  predictors.op = "mean",
  time.predictors.prior = 2006:2012,
  special.predictors = list(
    list("ln_HPI", 2000:2021 ,"mean"),
    list("ln_population", seq(2009, 2022), "mean"),
    list("ln_incom", seq(2000, 2021), "mean"),
    list("hicp", seq(2011, 2022), "mean"),
    list("ln_GDP", seq(2011, 2022), "mean")),
  dependent = "ln_HPI",
  unit.variable = "loc_number",
  unit.names.variable = "geo",
  time.variable = "time",
  treatment.identifier = 18,
  controls.identifier = c(1:17, 20:22),
  time.optimize.ssr = 2008:2013,
  time.plot = 2007:2021)
  synth.out <- synth(data.prep.obj = dataprep.out, method = "BFGS")

gaps <- dataprep.out$Y1plot - (dataprep.out$Y0plot %*% synth.out$solution.w)

path.plot(synth.res = synth.out, dataprep.res = dataprep.out,
          Ylab = "ln_HPI", Xlab = "year",
          Ylim = c(3, 6), Legend = c("Portugal country",
                                     "synthetic Portugal country"),
          Legend.position = "bottomright")
```

APPENDIX C. ANNUAL GAPS HUNGARY AND SYNTHETIC HUNGARY

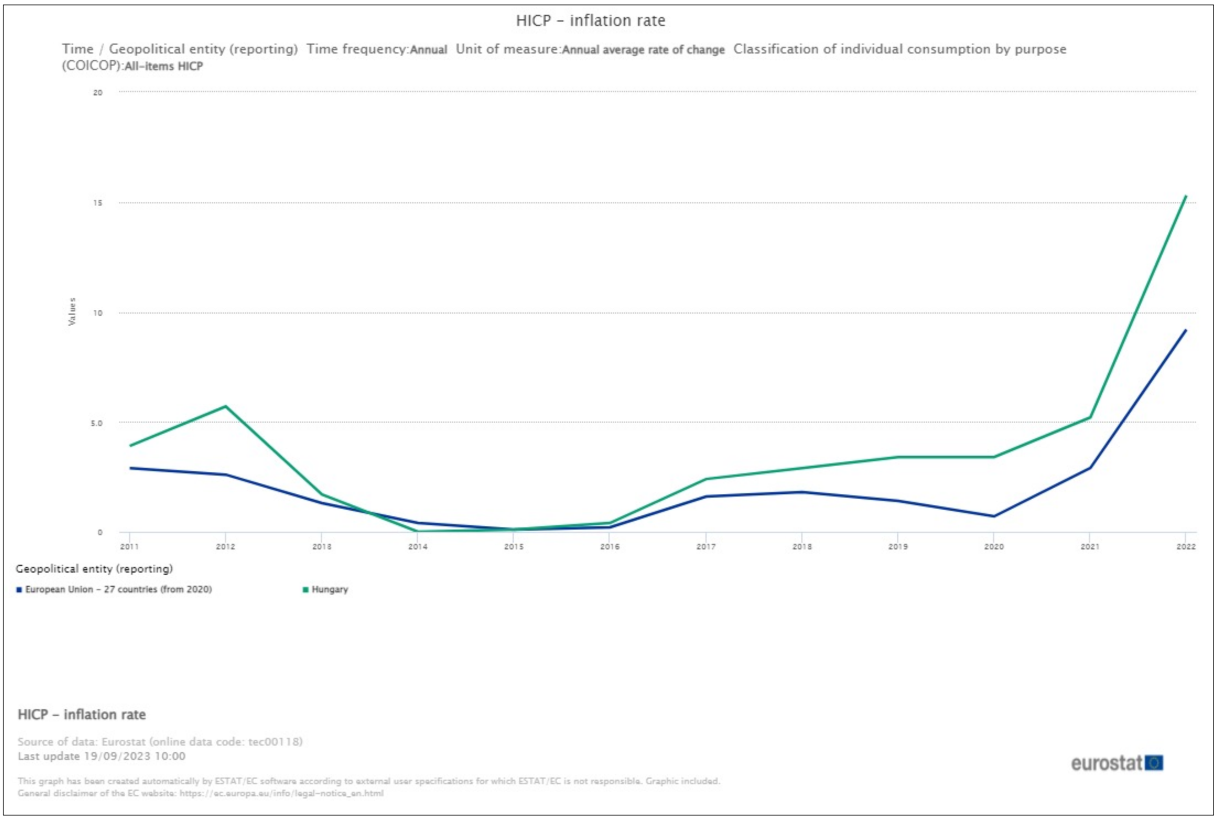
Year	Gap
2007	-7.296636e-02
2008	-8.265956e-02
2009	4.690814e-02
2010	3.444993e-02
2011	-1.363087e-02
2012	-4.141571e-02
2013	-7.731144e-02
2014	-7.832230e-02
2015	1.952976e-09
2016	7.889214e-02
2017	1.403078e-01
2018	2.057392e-01
2019	2.836407e-01
2020	2.497868e-01
2021	3.024945e-01

APPENDIX D. SCM WEIGHTS FOR THE PREDICTORS

Predictor	Weight
House Price Index	0.403
Tourism	0.247
Gross Domestic Product	0.217
Migration	0.058
Construction	0.029
Unemployment rate (%Active population)	0.016
Population	0.014
Mortgage loans	0.008
Unemployment rate	0.005
Income	0.001
Inflation rate	0.001

ANNEXES

Evolution of the HICP – Inflation rate, for the European Union and Hungary. Retrieved from https://ec.europa.eu/eurostat/en/



Evolution of the Adjusted gross disposable income of households pe capita, for Luxembourg and Portugal. Retrieved from https://ec.europa.eu/eurostat/en/