Economic Systems 47 (2023) 101053

Contents lists available at ScienceDirect

Economic Systems

journal homepage: www.elsevier.com/locate/ecosys

Unemployment shocks and material deprivation in the European Union: A synthetic control approach

Luis Ayala*,[1], Javier Martín-Román[2], Carolina Navarro[1]

Facultad de Derecho, UNED, C/ Obispo Trejo 2, 28040 Madrid, Spain

ARTICLE INFO

JEL classification in this article:
I32
J64

Keywords:
Material deprivation
Unemployment shocks
Synthetic control method
EUSILC

ABSTRACT

This paper analyzes how material deprivation responds to drastic changes in unemployment levels. We explore unemployment shocks registered in some European Union countries during the so-called Great Recession. To do so, we apply the synthetic control methodology, which has been rarely used in the field of distributive analyses. We use this approach to identify the impact of unemployment shocks on material deprivation and conduct different sensitivity analyses to test the results. We find that contrary to the traditional assumption of the low sensitivity of material deprivation measures to changes in the economic cycle, unemployment shocks have a significant and rapid impact on material deprivation. This conclusion holds even when extending the period of analysis, changing the indicator of material deprivation, or modifying the definition of unemployment shock.

1. Introduction

Should we expect a large increase in material deprivation and a worsening of living conditions right after an unemployment shock? Are material deprivation measures as sensitive to drastic changes in macroeconomic conditions as monetary poverty measures? In this paper, we try to determine the effects of an unemployment shock on a composite measure of material deprivation.

One of the greatest advances in the research on poverty has been the development of new methods for measuring material deprivation. As different authors have shown, the possibility of combining different partial indicators into an index that synthetically measures the level of deprivation can be more effective than a wide range of indicators to capture public and political attention. Some institutions have, in fact, incorporated the concept of material deprivation into their indicators of poverty and exclusion. The European Union, for instance, used the AROPE rate – the share of the total population at risk of poverty or social exclusion – as its main indicator for monitoring the EU 2020 Strategy poverty target. The measure corresponds to the sum of persons who are at risk of poverty, severely materially deprived or living in a household with very low work intensity.

While advances in the characterization of this phenomenon have been considerable, the evidence on its determining factors is less

* Corresponding author.
E-mail addresses: layala@cee.uned.es (L. Ayala), jmartin@cee.uned.es (J. Martín-Román), cnavarro@cee.uned.es (C. Navarro).
[1] (*UNED, Equalitas*)
[2] (*UNED*)

https://doi.org/10.1016/j.ecosys.2022.101053
Received 8 January 2022; Received in revised form 12 September 2022; Accepted 13 September 2022
Available online 22 September 2022
0939-3625/

robust. For instance, while numerous studies have explored inequality or certain forms of poverty, we still know very little about how these indicators change as the economic cycle changes. The extensive empirical literature on the effects of changes in macroeconomic conditions on income distribution (Blank and Blinder, 1986; Cutler and Katz, 1991; Jäntti, 1994; Smeeding et al., 2011; Meyer and Sullivan, 2011; Ayala et al., 2017) has had much less development in the case of material deprivation.

One of the reasons for this asymmetry lies in the a priori more static nature of material deprivation measures relative to those of income inequality or monetary poverty. As the extensive literature on capabilities has recognized, while the latter could be considered flow variables, the former are more similar to stock variables. However, this reasoning does not seem to correspond well with what happened in several countries during the so-called Great Recession. In many rich countries and especially in Europe, deprivation indicators grew remarkably (Duiella and Turrini, 2014).

Such a difference in the extent of this strand of the literature does not mean that the relationship between unemployment and material deprivation has not been addressed. Figari (2012) analyzed the drivers of deprivation in eleven European countries and found strong impacts of unemployment in most of them. Some studies have also used multilevel techniques to test the possible effects of unemployment on differences in multiple deprivation in EU countries (Whelan and Maître, 2012, 2013). Visser et al. (2014) found that the stronger the rise in the unemployment rate, the more economic deprivation individuals experience. Bárcena-Martín et al. (2014) found that long-term unemployment rates have a significant effect on deprivation when only macro-level variables are considered but that this effect vanishes when micro-level variables are introduced. Verbunt and Guio (2019) also used single- and multilevel methods to confront the respective within and between-country explanatory power of both types of models in measuring severe multiple deprivation. These authors also employed the Shapley decomposition method to compare the relative contributions of independent variables at the household and country levels and found that macroeconomic and institutional variables explain a large share of between-country differences in the risk of material deprivation. Cantó et al. (2020) included some indicators of deprivation in their analysis of the dimension and distribution of economic insecurity in European countries. They confirmed that there are significant differences by country that could be essentially linked to the characteristics of the labor market.

None of these studies specifically analyzed what happens when a significant change in the unemployment rate occurs over a very short time period, such as those changes that took place in the so-called Great Recession or in the more recent downturn resulting from COVID-19. During the Great Recession, unemployment rates in some European countries more than tripled and in some cases exceeded the 20% level. This paper analyzes how material deprivation responds to drastic changes in unemployment levels taking as reference the unemployment shocks registered in some European Union countries during the Great Recession.

The reasons for focusing on EU countries are varied. First, while most European countries were exposed to significant unemployment changes, in some its growth was much faster and unemployment rates reached their highs. Second, the European Monetary Union was designed by assigning the role of fiscal stabilization to national budgets with very few community counterparts. A common monetary policy was not enough to accommodate the needs of all states against asymmetric shocks. The fact that there was no common stabilizing mechanism in the form of a European unemployment insurance made the responses of social conditions to unemployment shocks very different in each country (Ábrahám et al., 2018).

To address this question, we apply the Synthetic Control Methodology (SCM). According to Athey and Imbens (2017) "the synthetic control approach (…) is arguably the most important innovation in the policy evaluation literature in the last 15 years." In order to correct the discretion that characterizes the choice of control units in many comparative case studies, SCM was born with the proposal by Abadie and Gardeazabal (2003) as an extension of the diff-in-diff methodology. Furthermore, some of the many distinct advantages SCM presents over regression-based methods and the aforementioned diff-in-diff approach can be found in King and Zeng (2006), Rubin (2008), Gobillon and Magnac (2016) or Abadie (2021). Since its first implementation in 2003, the dissemination of this technique has not stopped growing, and has already been extended to social, economic or public health interventions, among other areas. Nevertheless, it has not yet been widely used in the field of distributive studies.

We use this approach to identify the impact of unemployment shocks on material deprivation and conduct different sensitivity analyses to test the results. As our most important factual finding, we find that unemployment shocks have a rapid and significant effect on material deprivation in countries where they take place (Greece and Spain). This conclusion holds even when extending the period of analysis, changing the indicator of material deprivation, or modifying the definition of unemployment shock.

This paper is structured as follows. In the following section, we introduce our definitions of unemployment shocks and material deprivation. In the third section, we present our empirical strategy. In Section 4 we present the data. Section 5 presents our main results. The article ends with a brief list of conclusions.

2. Unemployment shocks and material deprivation in the EU-28

2.1. Unemployment shocks

As the main goal of this paper is to evaluate the effects of unemployment shocks on material deprivation rates within the EU-28, a necessary first step is to define this event. In practice, there is not a sufficient consensus on an empirically testable definition of an unemployment shock. It is worth mentioning, as an example, Burda and Hamermesh's (2010) tentative definition as the difference between the current year's unemployment rate and the unemployment rate averaged over the previous five years. The authors interpret this as the cyclical shock to the labor market in the corresponding area or country. In a similar vein, Dibooğlu and Enders (2001) use one standard deviation of the unemployment rate to test whether real wages asymmetrically respond to unemployment shocks.

Other studies that explicitly try to estimate the effects of unemployment shocks on dimensions of well-being do not use such specific definitions. Aaberge et al. (2000) take as a reference the general change in unemployment in Nordic countries from the early

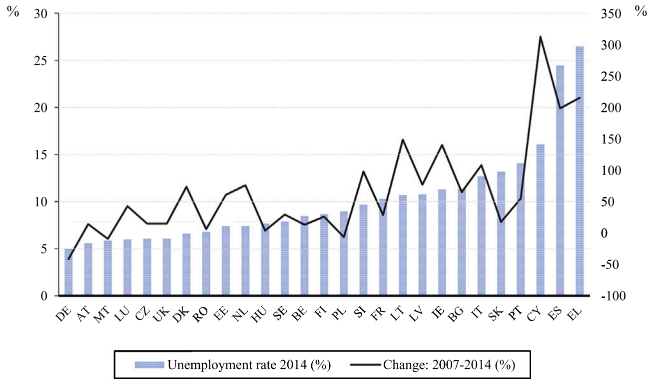


Fig. 1. Unemployment rates in EU countries
Source: Own elaboration from the Eurostat database. Notes: (1) The axis on the left denotes the unemployment rate in 2014; the one on the right denotes the change from 2007 to 2014; (2) BE: Belgium; BG: Bulgaria; CZ: Czech Republic; DK: Denmark; DE: Germany; EE: Estonia; IE: Ireland; EL: Greece; ES: Spain; FR: France; IT: Italy; CY: Cyprus; LV: Latvia; LT: Lithuania; LU: Luxembourg; HU: Hungary; MT: Malta; NL: Netherlands; AT: Austria; PL: Poland; PT: Portugal; RO: Romania; SI: Slovenia; SK: Slovakia; FI: Finland; SE: Sweden; UK: United Kingdom.

1980 s to the mid-1990 s Christelis et al. (2015) define an individual unemployment shock as a significant change in consumption with the transition to unemployment. Alt et al. (2017) define unemployment shocks by comparing expectations of unemployment for a calendar year – asking respondents to provide their best estimate of the probability that they will experience unemployment in a given year – to actual unemployment with a larger share of the year involving unemployment denoting a negative unemployment shock.

In the absence of a standard definition, we formulate a new proposal focused on the economic and financial crisis that started in 2007/2008 and our sample of countries (EU-28). As shown by Fig. 1, between 2007 and 2014, unemployment grew in practically all EU countries. However, differences in growth rates were considerable. While in Lithuania, Ireland, Cyprus, Spain and Greece, the rate more than doubled, in ten countries it grew by less than 20%. There is also broad variability in the resulting unemployment rates. While in Spain and Greece the unemployment rate increased to above 20%, in sixteen countries it remained at below 10%.

We define a country as suffering an unemployment shock – starting in approximately 2007 – when the two following circumstances occur: (a) over 200% growth in the unemployment rate from 2007 to 2014, and (b) an unemployment rate exceeding 20% in 2014. When applying these criteria, two EU-27 countries are identified as being affected by an unemployment shock: Spain and Greece. These countries are thus considered as the countries affected by the event studied.[3] The remaining EU-27 countries, in turn, could be used as potential controls (*donor pool*[4]) for the evaluation of the effects of unemployment shocks on material deprivation.

2.2. Material deprivation in EU countries

Compared to the standardized relative measurement procedures for monetary poverty, the range of composite indices of material deprivation available is broad. Different landmark studies have aimed at more precisely identifying the extension and characteristics of multidimensional deprivation (Atkinson, 2003; Bourguignon and Chakravarty, 2003; Dutta et al., 2003; Deutsch and Silber, 2005; Alkire and Foster, 2011). These approaches have been developed in an attempt to answer the two main questions that the measurement of this phenomenon focuses on. The two standard ways of measuring material deprivation include the selection of partial deprivation indicators (*items*) and the calculation of a synthetic index that combines these partial indicators into a single value.

The policy-oriented nature of our research forces these selections to reflect as closely as possible the official items proposed by EU institutions and the indicators recommended by these institutions for monitoring the problem. We use the definition of standard material deprivation defined by the European Commission and the index currently employed under the Europe 2020 strategy (together with low income and very low work intensity). This definition – and our analysis – takes as a starting point a subset of material deprivation indicators available in *European Statistics of Income and Living Conditions* (EUSILC) and the

[3] If we had followed the criteria of Burda and Hammermesh (2010), there would be eight countries affected by the unemployment shock, which shows that our proposal allows for a more restrictive definition and takes advantage of the benefits of a much more specific "treatment", singular and distinctive to a few countries.

[4] The *donor pool* or "group of donors" is a set of units (countries) that can be used as potential controls, that is, a group of units (countries) not affected by the event under study that can have some incidence, that can receive a positive weighting, within the synthetic unit. In this paper, all the countries not influenced, neither partially nor totally by the unemployment shock, make up this *donor pool*. Thereby, all the EU-27 countries except Spain, Greece and Cyprus are part of the “group of donors”.

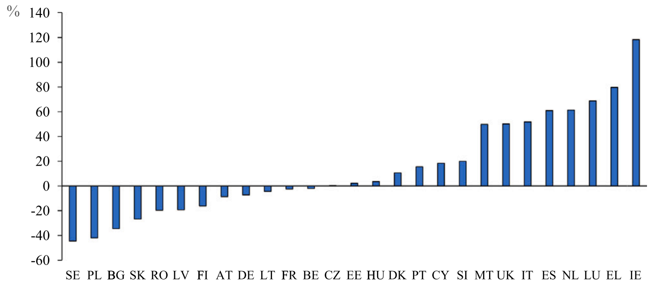


Fig. 2. Rate of growth in the standard material deprivation rate in EU countries (2007–2014)
Source: Own elaboration from the Eurostat database. Note: BE: Belgium; BG: Bulgaria; CZ: Czech Republic; DK: Denmark; DE: Germany; EE: Estonia; IE: Ireland; EL: Greece; ES: Spain; FR: France; IT: Italy; CY: Cyprus; LV: Latvia; LT: Lithuania; LU: Luxembourg; HU: Hungary; MT: Malta; NL: Netherlands; AT: Austria; PL: Poland; PT: Portugal; RO: Romania; SI: Slovenia; SK: Slovakia; FI: Finland; SE: Sweden; UK: United Kingdom.

deprivation index included in Eurostat statistics. This is defined as the percentage of the population that cannot afford at least three of the following nine items: (1) to pay their rent, mortgage or utility bills; (2) to keep their home adequately heated; (3) to pay for unexpected expenses; (4) to eat meat or protein regularly; (5) to go on holiday; and (6) to have a television set, (7) washing machine, (8) car, or (9) telephone.

This standard index presents certain limitations that reduce its usefulness for the analysis of levels and changes in material deprivation in European countries. On one hand, as stressed by Martínez and Navarro (2016), four of the nine indicators are consumer durables whose possession is highly generalized in Western Europe to the point at which their enforced lack is typically rare. The index has also been criticized for its inclusion of durable goods, which may reduce the index’s sensitivity to the economic cycle. In our case, this issue, more than posing a disadvantage, serves as an important argument to try to test whether the effect of an unemployment shock can be so great that it can increase an indicator with limited expected variations.

Fig. 2 shows how the rate of standard material deprivation changed over the period studied for the identification of unemployment shocks. The most important finding illustrated in the figure is the considerable heterogeneity of the indicator's behavior in EU countries in the period studied. It cannot be concluded that during the Great Recession deprivation increased in a generalized way nor that it was a problem of a fundamentally static nature. In a third of the countries the change was relatively minor and in almost the same number there was a significant reduction (greater than 15%) with a marked drop observed in Sweden and Poland. On the other hand, in a meaningful proportion of countries, deprivation increased by more than 50%; in particular, the rate of material deprivation more than doubled in Ireland.

3. Methodology

To assess the effects of unemployment shocks on material deprivation in EU countries, we apply the SCM. The comparison unit in the SCM is the weighted average of all potential comparison units that best resembles the characteristics of the case of interest during the preintervention period. This technique was originally proposed by Abadie and Gardeazabal (2003) to analyze the effects of terrorism on GDP per capita, and with Abadie et al. (2010) the generalized application of the methodology was established. Since this work, the method has been widely used to examine effects caused by a broad variety of specific events – see Craig (2015) for a review.

The SCM has been applied in numerous studies ranging from the evaluation of the economic impact of natural disasters (Cavallo et al., 2013) to the assessment of the effect of institutional interventions on a population's consumption and welfare (Abadie et al., 2010), among others. Within the framework of public policy evaluation, the SCM has been considered as one of the most powerful methodologies for conducting impact evaluations in the last decade. Nevertheless, and as far as we are concerned, practically no studies have implemented this method to study poverty and inequality (one exception is Grier and Maynard, 2016).

The most important advantages associated with the SCM are the following. (1) A number of public policy interventions affect aggregate units. The management of and access to macro-level data are more common and simple than the treatment of micro-level data, and there are many series available at that level of aggregation. (2) Regressions applied to samples of countries have been frequently questioned. Such regressions involve carrying out comparisons of entities with potentially different characteristics. In applying the SCM methodology, we resort to data-driven procedures that reduce the discretion in the choice of comparison control units and that allow us to create appropriate comparison groups. (3) The SCM does not involve making strict hypotheses to make precise estimations as with other quantitative techniques such as those of the difference-in-differences approach.[5] (4) Finally, the standard results inform us of the individual contributions of each *donor* units that form the synthetic control group.

Among restrictions applied, it is important to point out the following. (1) Some units in the *donor pool* should present both higher and lower values in predictor variables in comparison to that affected by the intervention. Otherwise, it would be impossible to appropriately recreate the unit of treatment. (2) In the preintervention period, units of control should have predictor values comparable to those of the treated unit.[6] In addition, these variables should have an approximately linear effect on the result. (3) It has

[5] See Abadie et al. (2010) for a more detailed explanation.
[6] We proceed this way to avoid interpolation bias and overfitting (Abadie et al., 2015; Grier and Maynard, 2016).

been recommended that using all preintervention outcomes together with covariates as predictors be avoided (Kaul et al., 2018). Otherwise, one would restrain the predictive power of the remaining covariates. (4) Finally, the statistical inference procedure is much less formal than those implemented by other quantitative methods and more traditional techniques.

3.1. Model formalization

Initially, let us assume that there are $J + 1$ countries where $j = 1$ denotes the country treated and $j = 2, \ldots, J + 1$ denote untreated or control countries (the EU-27 members not conditioned by the unemployment shock). It is thus assumed that a single country is affected by the event considered and that J units are available to contribute to the synthetic control (*donor pool*).

Let us assume that Y_{it}^N represents the outcome (material deprivation rate in the main results) for country i at time t without an unemployment shock, for units $i = 1, \ldots, J + 1$, and time periods $t = 1, \ldots, T$. We also suppose that T_0 is the number of pre-intervention periods, with $1 \leq T_0 < T$, and Y_{it}^I, the outcome that would be checked for unit i at time t if unit i is exposed to the event in periods T_{0+1} to T.[7]

Let us consider as well that $\alpha_{it} = Y_{it}^I - Y_{it}^N$ stands for the effect of the unemployment shock for unit i at time t, and D_{it} is an indicator taking value one when unit i suffers the effects of the unemployment shock, and value zero otherwise. Then, the observed outcome for unit i at time t could be described as follows:

$$Y_{it} = Y_{it}^N + \alpha_{it} D_{it} \tag{1}$$

Bearing in mind that only the first country is affected by the intervention analyzed, and only when $t > T_0$, we can state that:

$$D_{it} = \begin{Bmatrix} 1 \quad if \quad i = 1 \quad and \quad t > T_0 \\ 0 \quad otherwise \end{Bmatrix} \tag{2}$$

Ultimately, we intend to estimate α_{1t} for $t > T_0$. Thus, reordering terms in (1) we get:

$$\alpha_{1t} = Y_{1t}^I - Y_{1t}^N = Y_{1t} - Y_{1t}^N \tag{3}$$

For the country affected by the unemployment shock (treated unit), Y_{1t}^N cannot be observed in the post-treatment periods. Data are available for the actual path of the outcome (Y_{1t}^I), but it is unknown what would have happened with that trajectory if it had not suffered the effects of the unemployment shock. Therefore, we look for an estimate of Y_{1t}^N that, following Abadie et al. (2010), is given by a linear factor model. This is necessary to quantify the effect of the event by calculating the difference specified in (3).

To find optimal weights, Abadie and Gardeazabal (2003) defined a $(K \times 1)$ vector X_1 of the pre-unemployment shock values of K predictors of the outcome variable and a $(K \times J)$ matrix X_0, which measures the values of the same variables for the *donor pool*. The vector of optimal weights referring to the control countries, W^*, is the one that minimizes the following problem:

$$\|X_1 - X_0 W\|_v \quad = (X_1 - X_0 W)' V (X_1 - X_0 W) \tag{4}$$

where $W^* = (w_1^*, w_2^*, \ldots, w_{J+1}^*)'$ is a $(J \times 1)$ vector of non-negative weights that sums to one, and V is a diagonal matrix with nonnegative components. The values of the diagonal elements of V show the relative importance of the different growth predictors. Considering that W^* depends on V, it seems appropriate to clarify that the choice of V could be subjective, reflecting the previous knowledge of the researchers about the relative importance of each particular growth predictor. However, the most common practice, and the one applied in this paper, consists of implementing a more operational method, choosing V such that the material deprivation rate path for Spain (Greece) during the pretreatment period is best reproduced by the resulting synthetic Spain (synthetic Greece).

Once we have obtained the matrix $W^*(V^*)$ formed by the estimated optimal weights that each country of the control group receives for the design of the synthetic control unit, it is enough to apply these weights in (3) to obtain the estimate of the effect of the unemployment shock:

$$\hat{\alpha}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt} \tag{5}$$

3.2. Inference

With the SCM methodology, neither confidence intervals nor statistical significance parameters are calculated, which are typical procedures in an inference analysis. Alternatively, the SCM offers complementary options also known as *falsification* tests. With "in-space" placebos, each country integrating the original *donor pool* is separately conceived as a treated entity and the SCM is applied as if countries were affected by the unemployment shock (Abadie et al., 2010; Abadie et al., 2015).

By applying this iterative mechanism, we obtain a distribution of estimated placebo treatment effects for all countries in which no event occurred. Considering that none of these control countries has been influenced by the unemployment shock studied, we should only observe great disparities between these *placebo* countries and their corresponding synthetic control randomly and in sporadic

[7] We assume that there is no effect of the unemployment shock on the outcome of interest before its occurrence, that is, $Y_{it}^I = Y_{it}^N$ when $t \leq T_0$.

cases. A more accurate mechanism for identifying the significance of the results is based on the Root Mean Squared Prediction Error (RMSPE), which is the index typically used to assess the goodness of fit when applying the SCM. It measures for a given unit of analysis the fit – or lack thereof – between the actual outcome variable and its synthetic counterpart. In other words, it represents the distance or discrepancy between the path drawn by each variable. Formally, it is defined as follows:

$$RMSPE = \sqrt{\frac{1}{T_0}\sum_{t=1}^{T_0}\left(Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}\right)^2} \tag{6}$$

Ultimately, we must calculate the ratio between the postintervention RMSPE (the average for 2009–2019) and preintervention RMSPE (the average for 2004–2008) and determine how many control countries present an effect as large as that observed in the treated country (Spain or Greece). Within this ratio, the numerator quantifies the magnitude of the impact (the higher the RMSPE, the greater the impact) and the denominator quantifies the goodness of fit (the lower the RMSPE, the better the fit).

3.3. Data

We use annual country-level data from Eurostat for 2004–2019 for EU-27 countries. As EU-SILC begins in 2004 (corresponding to 2003 income data), we include the five years preceding the event analyzed. The endpoint is set to 2019, the last year with full availability of data for the outcome variables.

The two countries considered to be affected by the event – unemployment shock – are Greece and Spain. First, we use Spain as our unit of treatment. Next, the same analysis is conducted for Greece. The remaining EU-27 countries stand as possible candidates to take part in the control group (*donor pool*). The defined event – the unemployment shock – captures the effects of the economic cycle in all EU-27 countries, but we can quantify the intensity of impacts in the countries where there is a differential increase in the evolution of the two parameters chosen as a reference to define the unemployment shock.

As stressed above, the successful use of the SCM requires an important assumption to be fulfilled: it is essential to dispense with all units suffering the effects of a similar event in some years of the preintervention period – in our case, 2004–2008. If these were included, they could interfere with and condition the true effects of the intervention examined. Of the considered countries, Cyprus is excluded from the group of potential controls as it satisfies one of the two proposed requirements for defining an unemployment shock –a growth in the unemployment rate higher than 300% during 2007–2014.

According to the definition introduced in Section 2, the unemployment shock took place in 2008, so we have a five-year pre-treatment period, and eleven post-treatment years to measure the impact – we observe effects from 2009 onwards. In the main model, we study the effects on the standard material deprivation rate. Furthermore, as a robustness check, we also present results for the nine items used in the definition of material deprivation. Later, in the sensitivity analysis subsection, we study the impact on two additional outcome variables: the severe material deprivation rate and a *counting* index.[8] Regarding the predictors considered, we use the Gini index, work intensity, GDP per capita, social protection benefits as a percentage of GDP, and the lagged outcome variable for several periods preceding the unemployment shock.

The selection of these variables as the main predictors of the recent evolution of the material deprivation rate finds justification in the statistical associations found in previous studies between the synthetic indicators of deprivation and other macro variables.[9] Income variables, for instance, have a strong and positive effect on deprivation in Martínez and Navarro (2014). Other macro-level determinants, such as macroeconomic conditions, poverty and social expenditure, have also been highlighted by the comparative literature on the determinants of deprivation (Bárcena-Martín et al., 2014; Figari, 2012).

Some authors have stressed that the SCM might be an adequate methodology with a fairly short pre-intervention time period inasmuch as the duration of the post-treatment period is reasonably long and the fit between the synthetic and treated units is adequate (Carling and Li, 2016), as is the case in our empirical exercise. Barreix and Corrales (2019), for instance, used a period of four years for their preintervention period when studying the effectiveness of fiscal rules in Peru and Colombia, and Heim and Lurie (2014) also used a relatively short pretreatment period (eight years) to analyze the effects of a Massachusetts health reform on self-employment.

With respect to the number of predictors used, it should be underscored that increasing their number does not always improve the fit, and similarly eliminating some of them does not necessarily worsen it (McClelland and Gault, 2017). Additionally, regarding the predictors considered, one of the most common practices in the application of this methodology involves the use of the lagged outcome variable (Abadie et al., 2010). By including several lags of the outcome variable, we measure the effect of other predictors. This strategy somehow mitigates the effects of not incorporating relevant predictors into the analysis. However, there is no consensus on what a suitable number of lags is.

Some authors have drawn attention to the desirability of encompassing all outcome lags available as predictors. Furthermore, they believe that including other covariates has hardly any influence on the final estimates (Athey and Imbens, 2006). On the other hand, other scholars claim that only using the lags of the outcome variable is not the best solution (Kaul et al., 2016). Without any additional predictor, the estimated model cannot be supported by economic theory and does not have any justification. Ferman et al.

[8] This option simply involves counting the number of items a household is deprived of while assigning the same weight to each item (Mayer and Jencks, 1989; Atkinson, 2003).

[9] See Table A.1.

(2016) recommend working with different specifications, using several combinations of lags and generating all possible results. This latter option is the one we use in this investigation.

We initially determined which model provides a better fit (the one that presents the lowest RMSPE) when selecting a maximum of three lags of the outcome variable from the set of predictors.[10] For Spain and Greece, the best model is the one that picks the lags of standard material deprivation rates corresponding to 2008, 2007 and 2005.[11]

This initial specification, the model including as predictors the Gini index, an indicator of work intensity, the GDP per capita, social protection benefits as a percentage of GDP, and the lagged outcome variable of 2008, 2007 and 2005 (model 1 or main model), helps us then choose the best model when we use two lags (model 2) and when we only use one (model 3).

Proceeding the same way – minimizing the RMSPE – model 2 comprises the four standard predictors indicated above plus the lags of the dependent variable corresponding to 2007 and 2005. Finally, model 3 appends the lag of the standard material deprivation of 2005 to the set predictors used in all the three models.[12]

4. Results

We are interested in determining how the standard material deprivation rates of Spain and Greece would have evolved in absence of the unemployment shock that, according to the definition set out in the above section, took place in 2008. For this purpose, we use a combination of different European countries to construct a synthetic control unit for each of these countries that resembles as much as possible the actual evolution of the material deprivation rate before the outset of the shock. The subsequent track of this counterfactual Spain (and Greece) without effects of the treatment is then compared to the actual path.[13]

4.1. Main results

Regarding what constitutes a good fit or how to appraise similarities, the most direct and immediate option is to resort to the *eyeball test* – Figs. 3a and 3b – by comparing the evolution of the material deprivation rate in the treatment country (Spain and Greece) to that of the control group. Starting with Spain, our first result is that the evolution of actual Spain and its synthetic counterpart practically overlap in the three models analyzed[14] with the first requirement being met if we want to rely on estimates of the causal impact of the unemployment shock. From the moment that the unemployment shock occurs, the two curves separate.

As observed for Spain, what first draws our attention when examining Greece is the accuracy of the pretreatment fit across the different specifications. The two figures reveal extraordinarily homogeneous behavior, providing an initial guarantee for subsequent estimates.[15]

Second, another precondition relates to the similarities of real predictor values for the treated country to those of the synthetic version. Tables 1a,1b shows these values for the three models under analysis – the specifications with the lowest RMSPE including one, two and three lags. While not all of them match exactly, the approximation can be accepted as reasonably good.

For Greece, it is important to also note that the predictor means are again very close to the actual values, as can be checked in Table 1b. On the other hand, we find that some models that in principle provide a better fit – a lower RMSPE – show a greater mismatch in their predictor values. This is due to the predictive power assigned to each of them, since it varies depending on the specification used and with the total number of variables involved in the estimate. Achieving the best possible fit regardless of these considerations is what truly matters.

The indicators on the fit of the estimates therefore confirm the validity of our evaluation of the impact of the unemployment shock in both countries on the standard material deprivation rates. The gap between the actual rates and those of the synthetic units reports and quantifies the impact in percentage points. The drastic increase in unemployment denotes a significant and rapid increase in material deprivation in both Spain and Greece.

For Spain, the double-rip recession and its W-shaped recovery path seem to be the main explanatory factor behind the sharp fall in the actual material deprivation rate observed for 2011. In the short term – between 2008 and 2014 –, there was a dramatic rise of 65%. Martínez and Navarro (2014) drew attention to this issue – the sudden increase in the material deprivation rate during the Great Recession – and highlighted the early impact of material deprivation on the main indicators. According to these authors, one of the first and most intense effects of the crisis involved a reduction in the capacity to face unexpected expenses. This item increased from 36% in 2008 to 42% in 2009 and then continued to grow until it reached 48% in 2013. Likewise, they find that the number of families declaring they could not go on holiday at least one week a year increased from 30% in 2008 to 36% in 2009 and then to 42% in 2013. These factors caused a notable increase in the material deprivation rate during the treatment period.

[10] We rule out using four or five lags for the reasons stated above.

[11] See online appendix Table OA.1. y Table OA.2.

[12] See online appendix Table OA.3.

[13] In cases where multiple units are affected by the event of interest, as is the case that concerns us, the SCM can be applied to each affected unit separately or to an aggregate of all units involved (Abadie et al., 2015). As it would not make much sense to consider Spain and Greece as a single unit of treatment, we developed two exercises in parallel.

[14] For both Spain and Greece, we only include the figure corresponding to specification or model [1], which presents the lowest RMSPE and which is the model we follow henceforth. The rest of figures are available upon request.

[15] Table A.2 shows the country weights in the synthetic units of control used as a group of comparison.

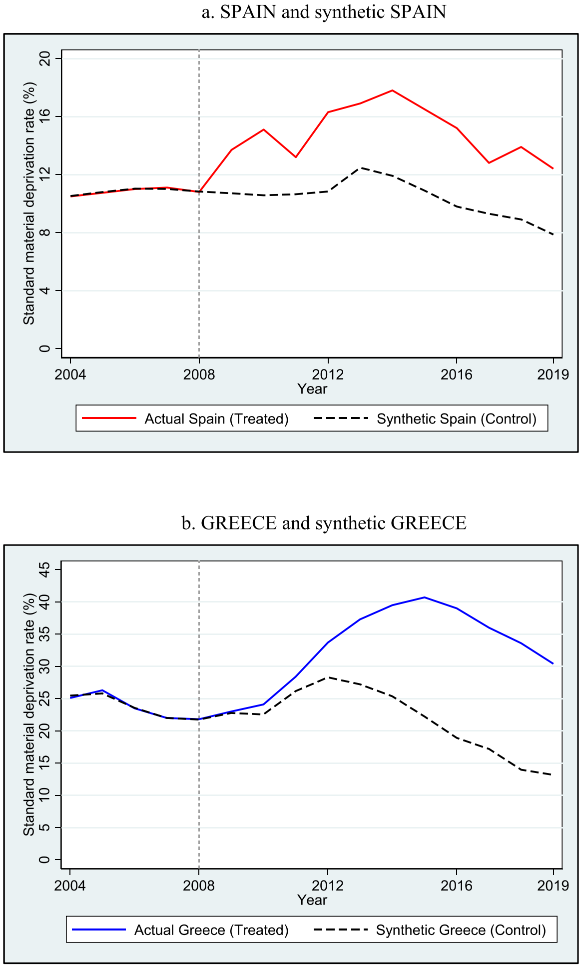


Fig. 3. Trends of the material deprivation rate: SPAIN and GREECE. a. SPAIN and synthetic SPAIN. b. GREECE and synthetic GREECE, Source: Own elaboration using EUSILC 2004–2019.

Table 1a
Predictor means: SPAIN and GREECE. Results for SPAIN.

Predictor variables	Actual Spain	Synthetic Spain		
		[1]	[3]	[7]
Gini index	0.319	0.283	0.293	0.274
Work intensity (%)	59.73	60.29	59.73	59.73
Ln (GDP per capita)	10.02	10.38	10.36	10.18
Social protection benefits (% GDP)	19.98	25.49	24.32	21.46
Standard material deprivation rate 2008	10.80	10.83	—	—
Standard material deprivation rate 2007	11.10	11.01	10.69	—
Standard material deprivation rate 2005	10.74	10.80	10.74	10.97

Source: Own elaboration using EUSILC and Eurostat database.
Notes: (1) Gini index and Ln (GDP per capita) are averaged for the 2004–2008 period. Work intensity is averaged between 2006 and 2008 and social protection benefits (% GDP) is averaged during 2005–2008. (2) Model [1] includes three lags of the outcome variable as predictors: 2008, 2007 and 2005; Model [3] includes two: 2007 and 2005; Model [7] only includes 2005.

Table 1b
Results for GREECE.

Predictor variables	Actual Greece	Synthetic Greece		
		[1]	[3]	[7]
Gini index	0.336	0.318	0.336	0.334
Work intensity (%)	58.60	62.66	61.87	61.22
Ln (GDP per capita)	9.88	9.87	9.86	9.89
Social protection benefits (% GDP)	23.55	19.75	19.86	20.56
Standard material deprivation rate 2008	21.80	21.76	—	—
Standard material deprivation rate 2007	22.00	21.99	22.22	—
Standard material deprivation rate 2005	26.30	25.80	25.71	25.74

Source: Own elaboration using EUSILC and Eurostat database.
Note: (1) Gini index and Ln (GDP per capita) are averaged for the 2004–2008 period. Work intensity is averaged between 2006 and 2008 and social protection benefits (% GDP) is averaged during 2005–2008. (2) Model [1] includes three lags of the outcome variable as predictors: 2008, 2007 and 2005; Model [3] includes two: 2007 and 2005; Model [7] only includes 2005.

Table 2
Impact results (estimated gap in percentage points).

Year	Treatment unit: SPAIN			Treatment unit: GREECE		
	[1]	[3]	[7]	[1]	[3]	[7]
2009	**2.99** ***	**2.97** **	**2.02** **	0.23	0.13	0.37
2010	**4.53** ***	**4.13** **	**3.89** **	1.56	-0.82	-0.71
2011	**2.56** *	2.11	0.77	2.24	-0.78	-1.09
2012	**5.47** ***	**5.52** *	3.29	5.41	3.17	3.26
2013	**4.43** ***	**4.70** *	**3.48** *	10.08	**8.96** **	**8.95** *
2014	**5.89** ***	**5.52** **	**4.63** *	**14.15** *	**13.14** **	**13.28** ***
2015	**5.61** ***	**5.48** *	**5.31** *	**18.47** *	**16.55** **	**16.28** ***
2016	**5.41** ***	**5.10** *	**6.20** *	**20.09** **	**17.58** **	**17.12** ***
2017	**3.51** ***	3.44	**5.23** *	**18.81** **	**17.17** **	**16.92** ***
2018	**5.00** ***	**5.33** **	**6.45** **	**19.63** **	**16.42** **	**16.01** ***
2019	**4.54** ***	**4.74** **	**5.70** **	**17.24** **	**15.81** **	**15.77** ***
Average	4.54	4.46	4.27	11.63	9.76	9.65

Source: Own elaboration using EUSILC and Eurostat database.
Notes: (1) Asterisks indicate level of significance: ***pseudo standardized p-value < 0.01, **pseudo standardized p-value < 0.05, *pseudo standardized p-value < 0.1. (2) Model [1] includes three lags of the outcome variable as predictors: 2008, 2007 and 2005; Model [3] includes two: 2007 and 2005; Model [7] only includes 2005.

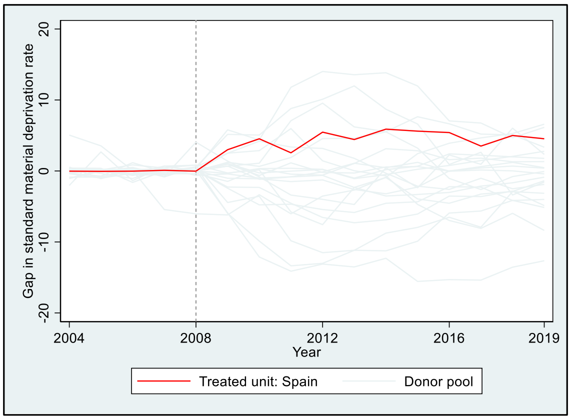
In the absence of the 2008 unemployment shock and according to the estimates made, the scenario could have been a very different one. The results of the best model show that, on average, the standard material deprivation rate would have been 4.5% points lower than that actually observed. In addition, the impact seems to follow a growing trend from 2012 onwards with five years in which the impact is over 5% points. On the other hand, it should also be noted that the results are significant for practically all the years analyzed in the three models (see Table 2).

For Greece, Papanastasiou and Papatheodorou (2018), in the same way as Martínez and Navarro (2014) did for Spain, found that more than half of the population in 2015 experienced difficulties paying unexpected financial expenses and could not afford a week-long holiday. Both studies coincide in finding that these two items were the most sensitive to the effects of the crisis and heavily conditioned the evolution of the actual material deprivation rate. Here, an exception is observed in 2009 when the effects of the Great Recession on the deprivation rate were barely noticeable. Nonetheless, the growth occurring from 2009 to 2014 rose to 72%. Considering all the post-treatment period, the impact is, on average, close to 12% points in the model with three lags, and approximately 10% points in the models including two lags and only one lag, respectively. All of them also share a remarkable feature: an extraordinary growth from 2012 onwards reaching its greatest increase in 2016. Between 2014 and 2019, the impact was always higher than 13% points.

On the other hand, we have also examined other indicators as the outcome variable of reference: the nine items defining the material deprivation – according to Eurostat – examined one by one (see Figure A.1).[16] In the case of Spain, we found a moderately reasonable fit for 5 out of 9 items: to pay rent, mortgage or utility bills, to keep the home adequately heated, to face unexpected expenses, to go on holiday, and to eat meat or protein regularly, although in the latter case the order of magnitude of the observed changes is notably lower than that of the rest of the items. In all of them, it is evident that in the absence of the unemployment shock studied here, the percentage of the population that cannot cope with these items would have been notably lower.

[16] These nine items are described in Table A.1.

a. Standard material deprivation gaps (in percentage points) in Spain and placebo gaps in 23 EU control countries



b. Standard material deprivation gaps (in percentage points) in Greece and placebo gaps in 23 EU control countries

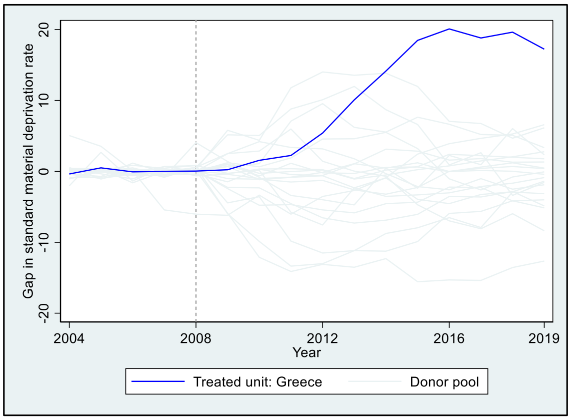
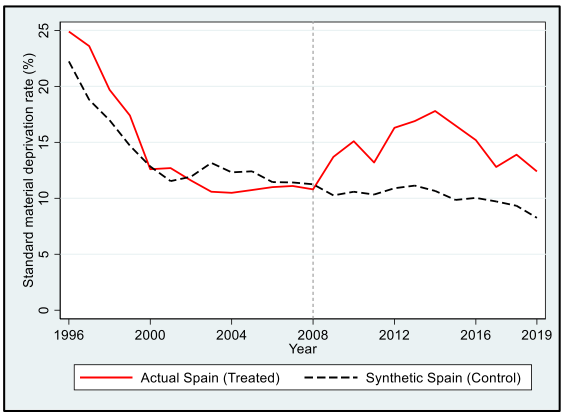


Fig. 4. "In-space" placebos: SPAIN and GREECE. a. Standard material deprivation gaps (in percentage points) in Spain and placebo gaps in 23 EU control countries. b. Standard material deprivation gaps (in percentage points) in Greece and placebo gaps in 23 EU control countries,
Source: Own elaboration using EUSILC 2004–2019.

a. SPAIN and synthetic SPAIN



b. GREECE and synthetic GREECE

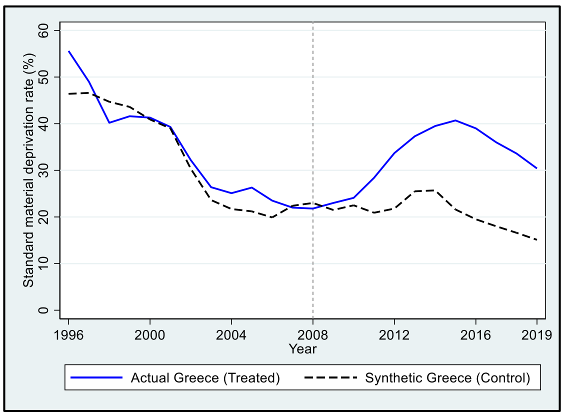


Fig. 5. Extension of the pre-unemployment shock time period: 1996–2019. a. SPAIN and synthetic SPAIN b. GREECE and synthetic GREECE,
Source: Own elaboration using EUSILC 2004–2019.

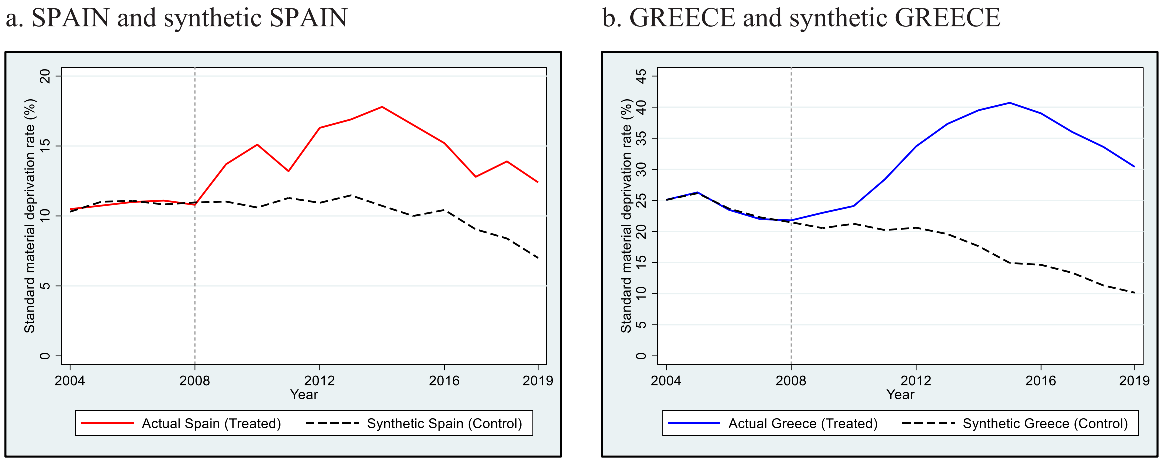


Fig. 6. A stricter criterion for the unemployment shock definition. a. SPAIN and synthetic SPAIN b. GREECE and synthetic GREECE, Source: Own elaboration using EUSILC 2004–2019.

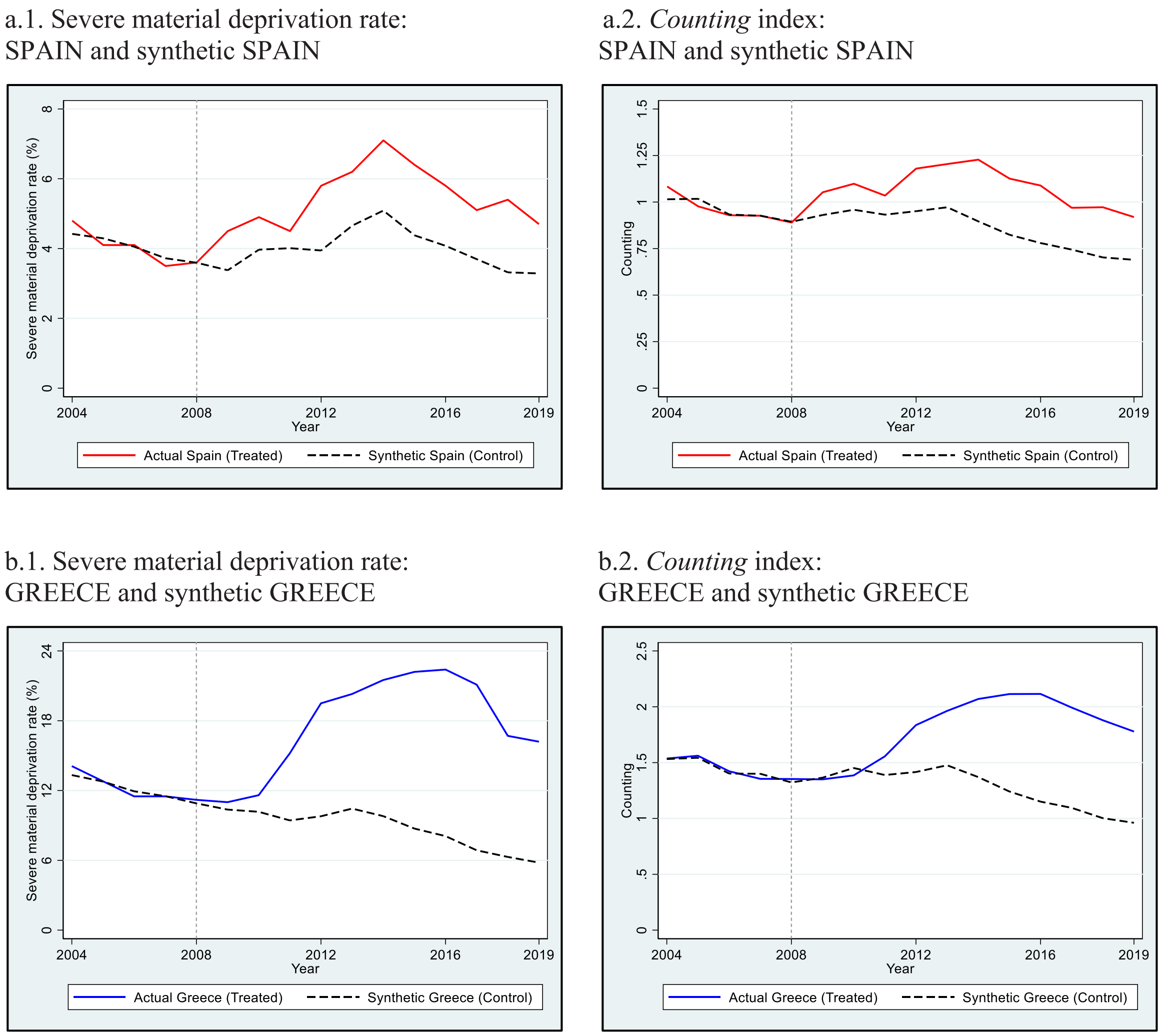


Fig. 7. Different outcome variables. a.1. Severe material deprivation rate: SPAIN and synthetic SPAIN a.2. b.1. Severe material deprivation rate:GREECE and synthetic GREECE. b.2.
(a) *Counting* index: SPAIN and synthetic SPAIN, Source: Own elaboration using EUSILC 2004–2019. (b) *Counting* index: GREECE and synthetic GREECE, Source: Own elaboration using EUSILC 2004–2019.

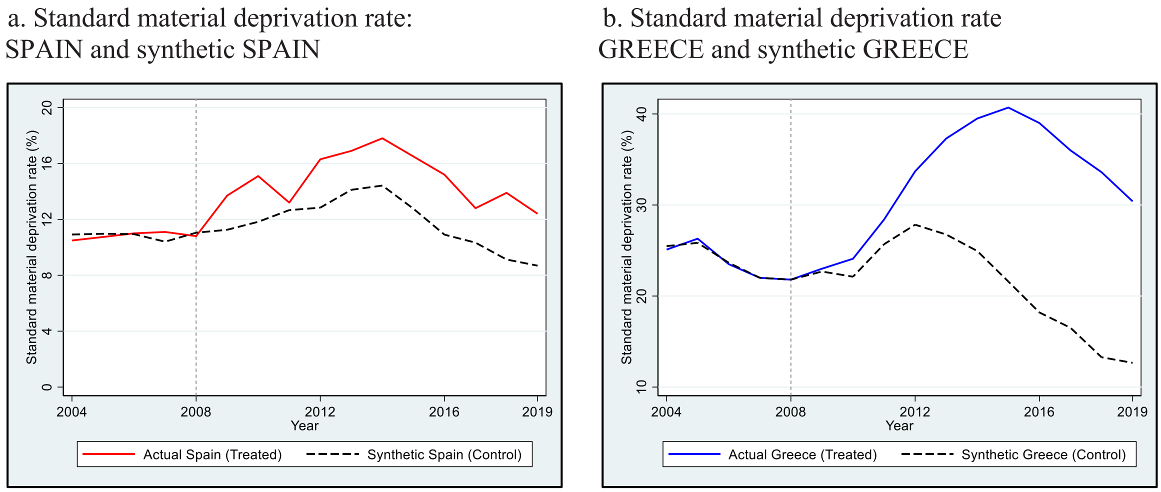


Fig. 8. Similar subset of countries in the *donor pool.* a. Standard material deprivation rate:SPAIN and synthetic SPAIN. b. Standard material deprivation rate GREECE and synthetic GREECE,
Source: Own elaboration using EUSILC 2004–2019.

In the case of Greece (see Figure A.2), the results seem very conclusive for the following items: to keep the home adequately heated, to go on holiday, to eat meat or protein regularly, and to have a car. Again, the order of magnitude is important and very different in the latter cases.

The peculiar trajectories observed for some of the remaining items in both countries can be partially justified on two grounds. First, it is important to bear in mind that the *donor pool* used here is significantly lower than that used in the standard material deprivation analysis. Specifically, the number of countries included in the control group here was only 11. Second, four of the nine items are classified as consumer durables – items 6, 7, 8 and 9 –, and these are goods whose possession is within the reach of most citizens in Western European countries. In short, its lack is very rare, a fact proven by the magnitude of the percentages of people deprived – extremely low. In Spain, for instance, almost none of the families interviewed by the *Instituto Nacional de Estadística* (Spanish Statistical Office) in 2012 had to do without a television, a telephone or a washing machine due to lack of income.

According to our results, the durables indicators are much more stable.[17] This result, together with the low incidence of deprivation in these indicators, means that the synthetic deprivation rate is mainly associated with changes in the ability to afford items included in the economic strain dimension.

4.2. Inference

As stated above, we are interested in measuring similarities between the actual trajectory of the material deprivation rate and the path described by the same variable for the comparison group or synthetic unit. The ratio between the post-unemployment shock RMSPE and the pre-unemployment shock RMSPE in the treated countries allows us to evaluate the significance of the results by comparing them to those of the remaining countries of the *donor pool*. When considering Spain as the unit of treatment (see Fig. 4a), it emerges in first position with a ratio around 100. Poland ranks second, where the post-event RMSPE is roughly 70 times the RMSPE of the pre-event period. This information confirms that the good fit shown by the *eyeball test* is not a product of chance. This quotient is the analytical result of one of the most well-known resources in the analysis of synthetic controls: the *placebo runs*[18] – an iterative method showing the distribution of the estimated gaps for the countries in which no unemployment shock occurred.

[17] Before the unemployment shock, some of these durables showed some increase in the percentage of population that could afford them, which can be attributed to the fact that in the years prior to the shock Greece recorded some of the largest GDP increases since the early 1980 s. In Spain there was also a strong economic expansion from the mid-1990 s until the 2008 crisis.

[18] The *placebo runs* consist of estimating the same model on each untreated country taking part of the *donor pool*, assuming it was a treated unit when, in fact, it was not. By applying this procedure to all the untreated countries individually ("iterative method"), we get a distribution of "in-place" placebo effects. The actual treated unit must be removed from being considered for the synthetic controls of all these other units. Ultimately, if we observe that the distribution of placebo effects produces too many effects as large as the main estimate, the one linked to the actual treated unit, then it is likely that the estimated effect was checked by chance.

For the distribution of post-/pre-unemployment shock RMPSE using Greece as the unit of treatment (see Fig. 4b), the calculations made place Greece in third position with a post-event RMPSE that is about 52 times that of the pre-event period. This ratio is higher than those observed in 20 of all 23 members of the *donor pool*. Therefore, these results also reveal that the probability of the effects being entirely attributable to chance is exceptionally low.

4.3. Sensitivity analysis

To test the validity of our finding of a large impact of unemployment shocks on material deprivation, we propose different alternative scenarios that evaluate their sensitivity to changes in the length of the pretreatment period and in the number of control countries used (*donor pool*) and to a new definition – a stricter one – for unemployment shock.

4.3.1. Extension of the pre-unemployment shock time period: 1996–2004

Our first sensitivity exercise involves extending the number of years included in the pretreatment period. We start our analysis in 2004 because this is the year for which data for all EU-27 countries are available. Obtaining information on previous years implies restricting the number of countries in the *donor pool*. This is what we do here. We exploit microdata from the European Community Household Panel (ECHP).[19] Using information for a new sample of 12 countries,[20] we reconstruct the series for 1996–2001.[21] For 2002 and 2003, years in which there is "a survey gap," we link the series by applying, for the different variables used, the rate of variation observed from 2000 to 2001. Figs. 5a and 5b show the new results for Spain and Greece, respectively. Despite having eliminated some countries with a positive contribution to the corresponding synthetic unit of the original model and in spite of the methodological problems outlined above, a similar effect of increasing levels of material deprivation due to the unemployment shock is observed. It is also true that the fit in the pre-treatment period is not as precise as that observed in the main model.

4.3.2. Alternative definition of unemployment shock

We also reformulate our definition of unemployment shock. As specified above, while unemployment grew in practically all the countries studied, the magnitude of this growth and the resulting rates were very different. One way to isolate the treatment more precisely involves drawing a more radical divide between countries exposed to the shock and those not exposed. To do so, we discard as potential controls countries registering an unemployment rate of 10–20% in 2014 or a 100–200% increase in the unemployment rate from 2007 to 2014 (see Fig. 6a and b). In applying these more rigorous new criteria, the list of countries excluded from the donor pool is extended to the following: Slovenia, France, Lithuania, Latvia, Ireland, Bulgaria, Italy, Slovakia and Portugal. The similarities between the new figures and the original ones are remarkable.[22]

4.3.3. Different outcome variables

Another test conducted involved replacing the standard material deprivation rate with two alternative measures. First, we replicate the above estimates using the severe material deprivation rate (see Fig. 7a.1 and b.1). This measure was the first official measure of deprivation used in the EU and is more restrictive than the original one – the percentage of the population that cannot afford at least four rather than three items. We also use a *counting* approach (see Fig. 7a.2 and b.2) implemented, among others, by Atkinson (2003).

The fits obtained are quite good and the effects, despite being slightly smaller for Spain, do not present major changes from what was previously found.

4.3.4. Similar subset of countries in the "donor pool"

The control countries to build the corresponding synthetic control units (synthetic Spain and synthetic Greece) are selected from a *pool* of potential candidates (*donor pool*) that have not been affected by the event under study. Originally, we used a sample of 23 control countries. As a final robustness test, we only keep those most similar to the treated countries. To do this we exclude the Nordic countries and some of the Eastern ones from the *donor pool*. Specifically, the following countries were removed as potential controls: Bulgaria, Denmark, Estonia, Latvia, Lithuania, Romania, Finland and Sweden. The fit with this more restricted *donor pool* is still quite good for both treated countries (see Fig. 8a and b) and the results are in line with the previous findings.[23]

[19] For the United Kingdom, data were drawn from the British Household Panel Survey (BHPS).

[20] The new sample of control countries includes Belgium, Denmark, Ireland, France, Italy, the Netherlands, Austria, Portugal, Finland, the United Kingdom, Spain and Greece.

[21] We have not used data for 1994 and 1995 due to a large number of missing values.

[22] We have also tested the data by considering other time intervals (2006–2013, 2008–2015, 2007–2012) to identify the countries that suffered the shock. Greece and Spain are the only two countries that meet the conditions regardless of the period of unemployment growth analyzed or are very close to it.

[23] The synthetic Spain with the restricted *donor pool* is formed by the Netherlands (45.5%), Germany (23.7%), Ireland (15.8%) and Portugal (15.0%). In the case of Greece, the synthetic unit is made by Ireland (39.9%), Poland (27.6%), Italy (22.1%) and Hungary (10.4%).

In brief, the new evidence exposed in this section is broad and strong enough to show that the unemployment shock analyzed in the paper did indeed have a strong and significant impact on material deprivation in the countries considered.

5. Conclusion

Unlike the extensive literature on the relationship between income distribution and macroeconomic conditions, the evidence on the sensitivity of material deprivation indicators to unemployment changes is much more limited. The less dynamic nature of deprivation measures compared to monetary indicators has meant that interest in relationships to the economic cycle has traditionally been less widespread. The remarkable increase in material deprivation observed during the Great Recession puts this assumption at risk.

In this paper, we have tried to establish causality relationships between changes in material deprivation and unemployment shocks. In focusing on the recent EU experience, we use a combination of European countries to construct a synthetic control unit for each country that as much as possible resembles the actual evolution of outcome variables before the outset of the shock.

An important and novel element of our approach relates to our proposed definition of an unemployment shock. A lack of consensus in the literature has led us to propose a specific definition that could be used in other studies. The use of the double criterion of the growth of the unemployment rate and its level has allowed us to differentiate two countries in which such shocks took place (Spain and Greece). However, this is a relative criterion in which the demarcation of countries affected by an event depends on the severity of the problem involved. Fortunately, through our sensitivity analyses we have been able to use more stringent criteria in defining these shocks, which has served to more clearly delimit the countries affected by them and those that were not.

Our results show that in the countries for which the proposed criteria confirm the existence of an unemployment shock, a significant increase in material deprivation occurred. Based on the natural limits for establishing causal relationships, these results refute the traditional assumption of the low sensitivity of material deprivation measures to changes in the economic cycle.

This conclusion holds when other alternatives are used to identify the observed effect. To cover a broader pretreatment period, we extended the series by combining it with ECHP data. Even at the cost of reducing the number of countries analyzed, the effect of the unemployment shock on material deprivation remains. The same occurs when other material deprivation measures are considered and above all when countries relatively similar to Spain and Greece based on any of the criteria used to define the unemployment shock are removed from the analysis.

Our results, in short, allow us to anticipate how drastic changes in the unemployment rate can lead to rapid well-being losses among households, which are not limited to increased monetary poverty and insufficient income but extend to material well-being and living conditions. Such results, derived from this study of what happened in the so-called Great Recession in a high-income area such as the European Union, could be even more severe in the face of even greater and rapid increases in unemployment such as those registered in these same countries due to the COVID-19 crisis.

Declarations of interest

none.

Acknowledgments

The authors acknowledge financial support received from the Ministerio de Ciencia e Innovación (PID2021–125710OB-C21. Luis Ayala and Carolina Navarro acknowledge financial support received from Comunidad de Madrid (H2019/HUM-5793). Javier Martín-Román acknowledges financial support received from Universidad de Valladolid (Movilidad Doctorandos UVa 2017).

APPENDIX

See Figs. A1 and A2 and Tables Tables A1 and A2.

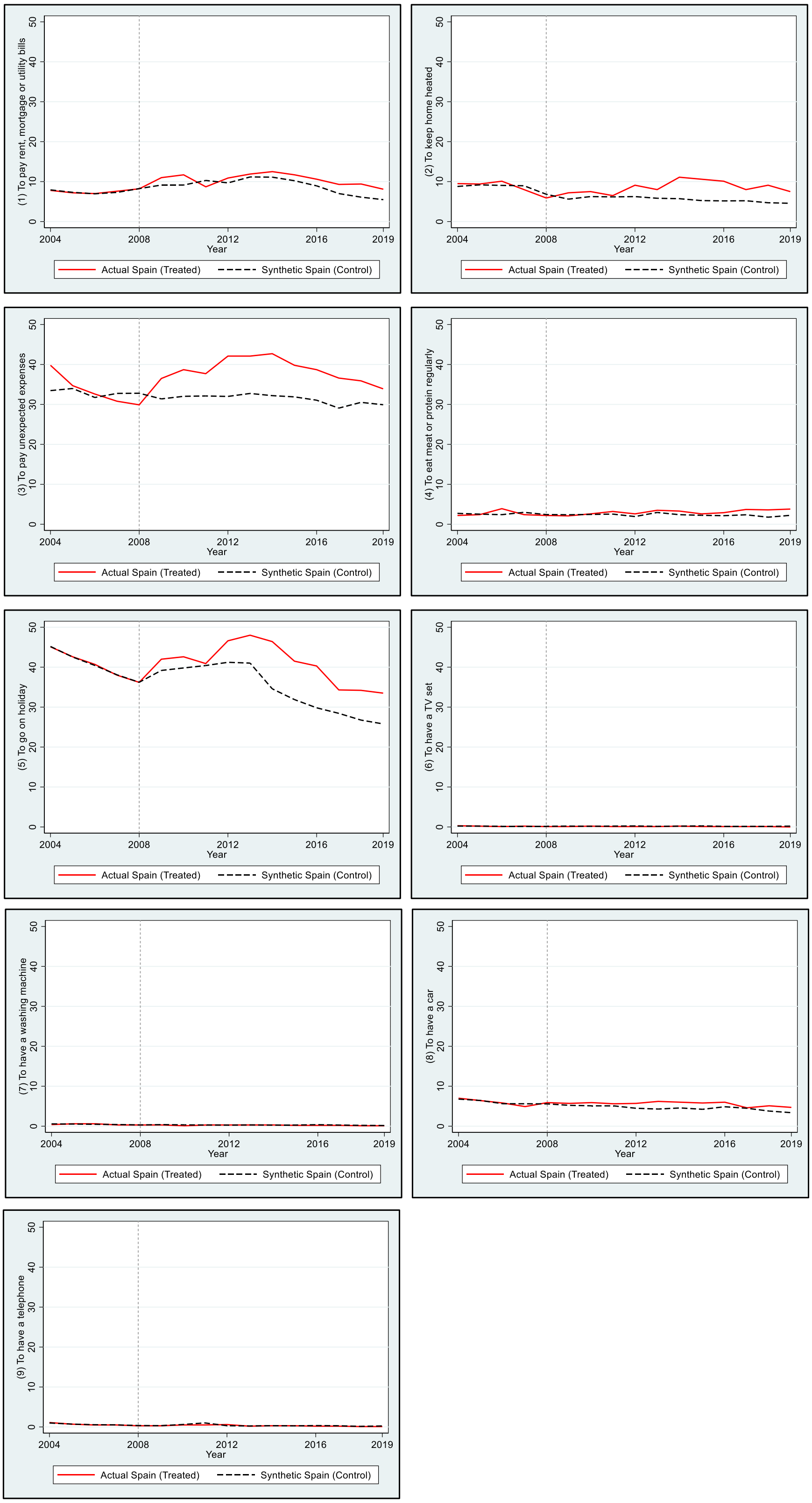


Fig. A.1. Trends of the nine items of the material deprivation rate: SPAIN. Percentage of population that cannot afford each one of the nine items. Source: Own elaboration using EUSILC 2004–2019.

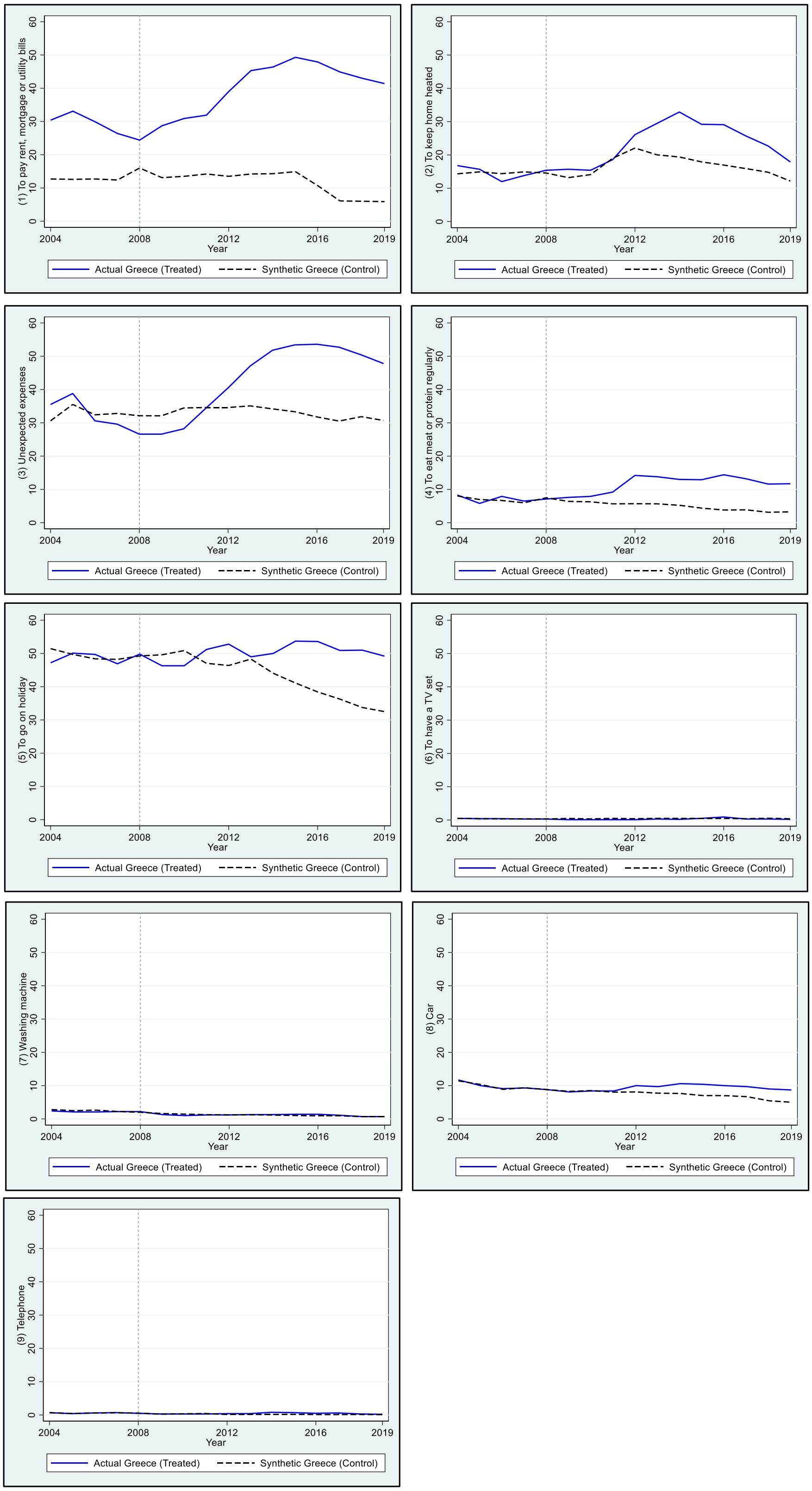


Fig. A.2. Trends of the nine items of the material deprivation rate: GREECE. Percentage of population that cannot afford each one of the nine items. Source: Own elaboration using EUSILC 2004–2019.

Table A.1
Description of the variables.

	Variables	Definition
Outcome/Dependent variables	Standard material deprivation rate (%)	Measures the percentage of the population that cannot afford at least three of the following nine items: (1) to pay their rent, mortgage or utility bills; (2) to keep their home adequately heated; (3) to pay for unexpected expenses; (4) to eat meat or protein regularly; (5) to go on holiday; and (6) to have a television set, (7) washing machine, (8) car, (9) or telephone.
	Individual items making up the definition of material deprivation	The nine ones mentioned above examined one by one.
	Severe material deprivation rate (%)*	Measures the percentage of the population that cannot afford at least four of the following nine items: (1) to pay their rent, mortgage or utility bills; (2) to keep their home adequately heated; (3) to pay for unexpected expenses; (4) to eat meat or protein regularly; (5) to go on holiday; and (6) to have a television set, (7) washing machine, (8) car, or (9) telephone.
	Counting index (%)*	Number of dimensions under which people suffer deprivation.
Predictor variables	Gini index	Indicator measuring the extent to which the distribution of income within a country deviate from a perfectly equal distribution.
	Work intensity (%)	The ratio of the total number of months in which all working-age household members worked in the income reference year and the total number of months in which the same household members theoretically could have worked in the same period.
	Temporary employment (%)*	Employees who cannot find a permanent or full-time job.
	Ln (GDP per capita)	Ratio of real GDP to the average population of a specific year in natural logarithm form.
	Social protection benefits (% GDP)	Transfers to households, in cash or in kind, intended to relieve them of the financial burden of several risks and needs as defined in ESSPROS[24]. These include disability, sickness/healthcare, old age, survivor, family/child, unemployment, housing and social exclusion provisions not covered elsewhere.

Source: Own elaboration from the Eurostat database.
Notes: (1) The asterisk (*) is denoting variables used in sensitivity tests; (2) *Temporary employment* has been used instead of *Work intensity* when extending the pre-unemployment shock time period.
[24] ESSPROS refers to the European system of integrated social protection statistics.

Table A.2
Country weights in the synthetic units: SPAIN and GREECE.

EU-27 countries	Composition of the *donor pool*					
	Synthetic SPAIN			Synthetic GREECE		
	[1]	[3]	[7]	[1]	[3]	[7]
Austria	0	0	0	0	0	0
Belgium	0	0	0	0	0	0
Bulgaria	0	0	0	0	0	0
Cyprus*	—	—	—	—	—	—
Czech Republic	0	0	0	0	0	0
Denmark	0.336	0	0	0	0	0
Estonia	0	0	0	0	0	0
Finland	0	0	0	0	0	0
France	0	0	0	0	0	0
Germany	0.220	0.373	0.377	0	0	0
Greece* *	—	—	—	—	—	—
Hungary	0	0	0	0.122	0	0
Ireland	0	0	0	0.355	0.140	0.069
Italy	0	0	0	0.264	0.525	0.662
Latvia	0	0	0	0	0.259	0.270
Lithuania	0	0	0	0.025	0.005	0
Luxembourg	0.118	0.162	0.234	0	0	0
Malta	0	0	0.389	0	0	0
Netherlands	0	0.281	0	0	0	0
Poland	0	0	0	0.233	0	0
Portugal	0.226	0.184	0	0	0.071	0
Romania	0	0	0	0	0	0
Slovakia	0	0	0	0	0	0
Slovenia	0	0	0	0	0	0
Spain* *	—	—	—	—	—	—
Sweden	0.100	0	0	0	0	0
United Kingdom* **	—	—	—	—	—	—

Source: Own elaboration using EUSILC and Eurostat database.
Notes: (*) Conflicting country excluded; (**) Countries of treatment; (***) Country excluded due to lack of data in the outcome variable of interest. Model [1] includes three lags of the outcome variable as predictors: 2008, 2007 and 2005; Model [3] includes two: 2007 and 2005; Model [7] only includes 2005.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ecosys.2022.101053.

References

Aaberge, R., Wennemo, T., Bjorklund, A., Jantti, M., Pedersen, P.J., Smith, N., 2000. “Unemployment shocks and income distribution: how did the Nordic countries fare during their crises?”. Scand. J. Econ. 102, 77–99.
Abadie, A., 2021. “Using synthetic controls: Feasibility, data requirements, and methodological aspects.”. J. Econ. Lit. 59 (2), 391–425.
Abadie, A., Gardeazabal, J., 2003. “The economic costs of conflict: A case study of the Basque Country.”. Am. Econ. Rev. 93, 113–132.
Abadie, A., Diamond, A., Hainmueller, J., 2010. “Synthetic control methods for comparative case studies: Estimating the effect of California’s tobacco control program.”. J. Am. Stat. Assoc. 105, 493–505.
Abadie, A., Diamond, A., Hainmueller, J., 2015. “Comparative politics and the synthetic control method.”. Am. J. Political Sci. 59, 495–510.
Ábrahám, Á., Brogueira de Sousa, J., Marimón, R. and Mayr, L. (2018): “On the Design of a European Unemployment Insurance System”. ADEMU WP2018/105.
Alkire, S., Foster, J., 2011. “Counting and multidimensional poverty measurement.”. J. Public Econ. 95, 476–487.
Alt, J.E., Barfort, S. and Lassen, D.D. (2017): “The effects of income and unemployment shocks on political preferences.” NBER Political Economy Conference. Cambridge, MA, USA.
Athey, S., Imbens, G.W., 2006. “Identification and inference in nonlinear difference-in-differences models.”. Econometrica 74, 431–497.
Athey, S., Imbens, G.W., 2017. “The state of applied econometrics: Causality and policy evaluation.”. J. Econ. Perspect. 31 (2), 3–32.
Atkinson, A.B., 2003. “Multidimensional deprivation: contrasting social welfare and counting approaches.”. J. Econ. Inequal. 1, 51–65.
Ayala, L., Cantó, O., Rodríguez, J.G., 2017. “Poverty and the business cycle: The role of intrahousehold distribution of unemployment,”. J. Econ. Inequal. 15, 47–73.
Bárcena-Martín, E., Lacomba, B., Moro-Egido, A.I., Pérez-Moreno, S., 2014. “Country Differences in Material Deprivation in Europe.”. Rev. Income Wealth 60, 802–820.
Reglas fiscales resilientes en América Latina. In: Barreix, A.D., Corrales, L.F. (Eds.), Inter-American Development Bank Vol. 767.
Blank, R.M., Blinder, A.S., 1986. “Macroeconomics, Income Distribution, and Poverty,”. In: Danziger, S. (Ed.), Fighting Poverty: What Works and What Does Not. Harvard University Press, Cambridge.
Bourguignon, F., Chakravarty, S.R., 2003. “The measurement of multidimensional poverty”. J. Econ. Inequal. 1, 25–49.
Burda, M., Hamermesh, D., 2010. “Unemployment, Market Work and Household Production,”. Econ. Lett. 107, 131–133.
Cantó, O., García-Pérez, C., Romaguera-de-la-Cruz, M., 2020. “The dimension, nature and distribution of economic insecurity in European countries: A multi-dimensional approach”. Econ. Syst. 44, 1–19.
Carling, K. and Li, Y. (2016): “The power of the synthetic control method.” Working papers in transport, tourism, information technology and microdata analysis. No. 2016:10, Dalarna University.
Cavallo, E., Galiani, S., Noy, I., Pantano, J., 2013. “Catastrophic natural disasters and economic growth.”. Rev. Econ. Stat. 95, 1549–1561.
Christelis, D., Georgarakos, D., Jappelli, T., 2015. “Wealth shocks, unemployment shocks and consumption in the wake of the Great Recession.”. J. Monet. Econ. 72, 21–41.
Craig, P. (2015): “Synthetic Controls: A New Approach to Evaluating Interventions.” Working Paper. What Works Scotland.
Cutler, D.M., Katz, L.F., 1991. “Macroeconomic performance and the disadvantaged,”. Brook. Pap. Econ. Act. 2, 1–74.
Deutsch, J., Silber, J., 2005. “Measuring multidimensional poverty: An empirical comparison of various approaches”. Rev. Income Wealth 51, 145–174.
Dibooğlu, S., Enders, W., 2001. “Do real wages respond asymmetrically to unemployment shocks? Evidence from the US and Canada.”. J. Macroecon. 23, 495–515.
Duiella, M. and Turrini, A. (2014): “Poverty developments in the EU after the crisis: a look at main drivers.” ECFIN Economic Brief nº31.
Dutta, I., Pattanaik, P.K., Xu, Y., 2003. “On Measuring Deprivation and the Standard of Living in a Multidimensional Framework on the Basis of Aggregate Data”. Economica 70, 197–221.
Ferman, B., Pinto, C. and Possebom, V. (2016): “Cherry Picking with Synthetic Controls.” FGV Working Paper 420. São Paulo, Brazil: Sao Paulo School of Economics.
Figari, F., 2012. “Cross-national differences in determinants of multiple deprivation in Europe.”. J. Econ. Inequal. 10, 397–418.
Gobillon, L., Magnac, T., 2016. “Regional policy evaluation: Interactive fixed effects and synthetic controls.”. Rev. Econ. Stat. 98 (3), 535–551.
Grier, K., Maynard, N., 2016. “The economic consequences of Hugo Chavez: A synthetic control analysis”. J. Econ. Behav. Organ. 125, 1–21.
Heim, B.T., Lurie, I.Z., 2014. “Does health reform affect self-employment?”. Evidence from Massachusetts. Small Bus. Econ. 43, 917–930.
Jäntti, M., 1994. “A More Efficient Estimate of the Effects of Macroeconomic Activity on the Distribution of Income,”. Rev. Econ. Stat. 76, 372–378.
Kaul, A., Klößner, S., Pfeifer, G. and Schieler, M. (2018): “Synthetic Control Methods: Never Use All Pre-Intervention Outcomes as Economic Predictors.” Working Paper. Saarbrücken, Germany: Saarland University.
King, G., Zeng, L., 2006. “The dangers of extreme counterfactuals.”. Political Anal. 14 (2), 131–159.
Martínez, R., Navarro, C., 2014. “Pobreza y privación: tendencias y determinantes.”. Documento de Trabajo 2. Fundación FOESSA,, Madrid, pp. 2.
Martínez, R., Navarro, C., 2016. “Has the Great Recession Changed the Deprivation Profile of Low Income Groups? Evidence from Spain. Hacienda Pública Esp. / Rev. Public Econ. 218 (3/2016), 79–104.
Mayer, S.E., Jencks, C., 1989. “Poverty and the distribution of material resources.”. J. Hum. Resour. 24, 88–113.
McClelland, R., Gault, S., 2017. “The Synthetic Control Method as a Tool to Understand State Policy.”. Urban-Brookings Tax Policy Center, *Washington, DC*.
Meyer, B.D., and Sullivan, J.X. (2011): “Consumption and Income Poverty Over the Business Cycle,” Research in Labor Economics, in: Herwig Immervoll & Andreas Peichl & Konstantinos Tatsiramos (ed.), Who Loses in the Downturn? Economic Crisis, Employment and Income Distribution, volume 32: 51–82.
Papanastasiou, S., Papatheodorou, C., 2018. “The greek depression: poverty outcomes and welfare responses.”. J. Econ. Bus. 21, 197–214.
Rubin, D.B., 2008. “For objective causal inference, design trumps analysis.”. Ann. Appl. Stat. 2 (3), 808–840.
Smeeding, T., Thompson, J.P., Levanon, A., Burak, E., 2011. “Income, Inequality, and Poverty over the Early Stages of the Great Recession,”. In: Grusky, D., Western, B., Wimer, C. (Eds.), The Great Recession. Russell Sage Foundation, New York.
Verbunt, P., Guio, A.C., 2019. “Explaining Differences Within and Between Countries in the Risk of Income Poverty and Severe Material Deprivation: Comparing Single and Multilevel Analyses.”. Soc. Indic. Res. 144, 827–868.
Visser, M., Gesthuizen, M., Scheepers, P., 2014. “The impact of macro-economic circumstances and social protection expenditure on economic deprivation in 25 European Countries, 2007–2011.”. Soc. Indic. Res. 115, 1179–1203.
Whelan, C.T., Maître, B., 2012. “Understanding material deprivation in Europe: a multilevel analysis. *Res. Soc. Stratif. Mobil.* 30, 489–503.
Whelan, C.T., Maître, B., 2013. “Material deprivation, economic stress and referencing groups in Europe: an analysis of EU-SILC2009.”. Eur. Sociol. Rev. 29, 1162–1174.