EQUALITAS

Economics of Inequality and Poverty Analysis

EQUALITAS Working Paper No. 70

Unemployment Shocks and Material Deprivation in the European Union: A Synthetic Control Approach

Luis Ayala

Javier Martín-Román

Carolina Navarro-Ruiz

July, 2020

Unemployment Shocks and Material Deprivation in the European Union: A Synthetic Control Approach

Luis Ayala*
(*UNED*, *Equalitas*)
Javier Martín-Román
(*UNED*)
Carolina Navarro-Ruiz
(*UNED*, *Equalitas*)

* Facultad de Derecho, UNED, C/ Obispo Trejo 2, 28040 Madrid, SPAIN. Email: layala@cee.uned.es (corresponding author)

Luis Ayala and Carolina Navarro acknowledge financial support received from Comunidad de Madrid (H2019/HUM-5793).

Unemployment Shocks and Material Deprivation in the European Union: A Synthetic Control Approach

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 been 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.

JEL classification: I32, J64

Key words: material deprivation, unemployment shocks, synthetic control method, EUSILC

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 considerably less 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 on 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. More recently, 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 the measuring of severe multiple deprivation. The authors also employed the Shapley decomposition method to compare the relative contributions of independent variables at the household and country levels to find that macroeconomic and institutional variables explain a large share of between-country differences in the risk of material deprivation.

None of these studies specifically analyze 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 (Ábráham et al., 2018).

To address this question, we apply the synthetic control methodology, which 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 3 we present the data. Section 4 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 for unemployment shocks. 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 general changes in unemployment in Nordic countries from the early 1980s to the mid-1990s. 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.

[*Insert Figure 1 here*]

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 Figure 1, between 2007 and 2014, unemployment grew in practically all EU countries. However, differences in growth rates were considerable. While in Lithuania, Latvia, 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 2007-2014 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.[1] These countries are thus considered as the countries affected by the event studied. The remaining EU-27 countries will form the control group (*donor pool*) in our evaluation of the effects of unemployment shocks on material deprivation.

2.2. Material deprivation in EU countries

Relative to standardized relative measurement procedures for monetary poverty, the range of composite indices of material deprivation available is broad. In recent years, several works 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 (2010)]. These approaches have been developed in an attempt to answer to 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.

[1] We have not used the EU-28 as the focus of our analysis due to a lack of data for Croatia.

The policy-oriented nature of our research forces these elections 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 for 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 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 for whether the effect of an unemployment shock can be so great that it can increase an indicator with limited expected variations.

[*Insert Figure 2 here*]

Figure 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 Synthetic Control Methodology (SCM). The comparison unit in the SCM is selected as the weighted average of all potential comparison units that best resembles the characteristics of the case of interest. This technique was originally proposed by Abadie and Gardeazabal (2003) as a means 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 an evaluation of the economic impact of natural disasters (Cavallo et al., 2013) to an 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 consolidated 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.[2] (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

[2] See Abadie et al. (2010) for a more detailed explanation.

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.[3] In addition, these variables should have an approximately linear effect on the result. (3) It has 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 $j=2,\dots,J+1$ 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*).

We also assume that $1,2,\dots,T_0$ are the periods preceding the unemployment shock already referenced, and $T_{0+1},T_{0+2},\dots,T$ are the post-treatment periods. Two results in relation to the outcome of interest are possible: (1) Y_{1t}^N is the result observed for country i at time t if country i was not affected by the unemployment shock and (2) Y_{1t}^I is the observed result for country i at time t if country i was exposed to the event. The magnitude of the effect, impact (α), is simply the difference between the two potential results for the periods $T_{0+1},T_{0+2},\dots,T$:

$$\alpha_{1t} = Y_{1t}^I - Y_{1t}^N = Y_{1t} - Y_{1t}^N \quad (1)$$

For the affected country, 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 the treated country had not suffered 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 (1).

[3] We proceed this way to avoid interpolation bias and overfitting (Abadie et al., 2015; Grier and Maynard, 2016).

To find optimal weights, Abadie and Gardeazabal (2003) defined a $(K \times 1)$ vector X_1 of the preunemployment 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:

$$\parallel X_1 - X_0 W \parallel_v = (X_1 - X_0 W)' V (X_1 - X_0 W) \tag{2}$$

where $W^* = (w_1^*, w_2^*, \dots, w_{J+1}^*)'$ is a $(J \times 1)$ vector of non-negative weights that sums to one, and V is a symmetric, diagonal matrix of non-negative components that represents the relative importance of the selected predictors.

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 (1) to obtain the estimate of the effect of the unemployment shock:

$$\hat{\alpha}_{1t} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt} \tag{3}$$

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 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:

$$RMSPE = \sqrt{\frac{1}{T_0}\sum_{t=1}^{T_0}\left(Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt}\right)^2} \tag{4}$$

Ultimately, we must calculate the ratio between the postintervention RMSPE (the average for 2009-2014) 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).

4. DATA

We use annual country-level data from Eurostat for 2004-2014 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 2014 based on one of the two conditions we consider in defining the unemployment shock.

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 form the control group (*donor pool*) in our evaluation of effects on material deprivation. 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 to 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 to satisfy one of the two proposed requirements for defining an unemployment shock.

According to the above definition, the unemployment shock took place in 2008, so we have a pretreatment period of five years (we observe effects from 2009 onwards) and a post-treatment period of six years. We study effects on the standard material deprivation rate and, as a measure of sensitivity, we also consider the severe material deprivation rate and use a *counting* approach.[4] For 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.

[*Insert Table A.1 here*]

Some authors have stressed that the SCM might be an adequate methodology with a fairly short preintervention 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, use a period of four years for their preintervention period, and Heim and Lurie (2014) also use 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 necessarily improve the fit, and similarly eliminating some of them inevitably worsens the fit (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. (2016)

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

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.[5] For Spain and Greece, the best model is the one that selects the lags of standard material deprivation rates corresponding to 2008, 2007 and 2005.

[*Insert Table 1a here*]

[*Insert Table 1b here*]

This initial specification helps us then choose the best model when we use two lags and when we only use one.[6]

[*Insert Table 2 here*]

5. 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.[7]

5.1. 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* 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 cases analyzed[8] with the first requirement

[5] We rule out using four or five lags for the reasons stated above.
[6] Table A.2 in the appendix shows the country weights in the synthetic units.
[7] 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.
[8] For both Spain and Greece, we only include the figure corresponding to specification [1], which presents the lowest RMSPE and which is the model we follow henceforth. The other figures are available upon request.

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.

[*Insert Figure 3a here*]

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

[*Insert Figure 3b here*]

Second, another precondition relates to the similarities of real predictor values for the treated country to those of the synthetic version. Table 3a 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.

[*Insert Table 3a here*]

For Greece, it is important to also note that the predictor means are again very close to the actual values. 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.

[*Insert Table 3b here*]

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. 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.[9] With the exception of this drop in 2011, in the remaining years the rate increased. In fact, between 2008 and 2014, there was a dramatic rise of 65%. Martínez

[9] See Figure 3a.

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 the 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, the authors 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 (2009-2014).

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 4.6% lower than that actually observed. In addition, and with the exception of 2011, the impact seems to follow a growing trend with 2014 being the year in which the impact reaches its maximum. This last finding is extensible to the three proposed models.

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 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% (almost 17 percentage points). On average, the impact is roughly 8% in the model with three lags, 9% in the model with two lags and close to 10% in the model including only one lag. All of them also share a remarkable feature: extraordinary growth from 2011 onwards reaching its greatest increase in 2014. For 2013 and 2014, the figures provided by all models exceed 10%.

[*Insert Table 4 here*]

5.2. 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 postunemployment shock

RMSPE and the preunemployment shock RMSPE allows us to evaluate the gap in Spain relative to those of the remaining countries of the *donor pool*. Only Poland, where the postevent RMSPE is roughly 70 times the RMSPE of the pre-event period, remains ahead of Spain, where the ratio is quite similar (68). This information confirms that the good fit shown by the *eyeball test* is not a product of chance. We can also check these figures by applying *placebo runs*.

[*Insert Figure 4a here*]

For the distribution of post-/preunemployment shock RMPSE using Greece as the unit of treatment, the calculations made place Greece in fourth position with a postevent RMPSE that is roughly 26 times that of the pre-event period. This ratio is higher than those observed in 20 countries of all 24 members of the *donor pool*. Therefore, these results also reveal that the probability of the effects being entirely attributable to chance is extremely low.

[*Insert Figure 4b here*]

5.3. 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.

Extension of the preunemployment 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).[10] Using information for a new sample of 12 countries[11], we reconstruct the series for 1996[12] to 2001. 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 2000-2001. Figures 5a and

[10] For the United Kingdom, data were drawn from the British Household Panel Survey (BHPS).
[11] The new sample includes the following countries: Belgium, Denmark, Ireland, France, Italy, the Netherlands, Austria, Portugal, Finland, the United Kingdom, Spain and Greece.
[12] We have not used data for 1994 and 1995 due to a large number of missing values.

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.

[*Insert Figure 5a here*]

[*Insert Figure 5b here*]

Alternative definition of unemployment shock

We also reformulate our definition of unemployment shock. As specified above, while unemployment grew in practically all of the countries studied, the magnitude of this growth and the resulting rates were very different. One way to isolate the treatment more precisely involves draw 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% to 20% in 2014 or a 50% to 200% increase in the unemployment rate from 2007-2014. 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.

[*Insert Figure 6a here*]

[*Insert Figure 6b here*]

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

Different outcome variables

The final sensitivity 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. 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 the *counting* approach proposed 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.

[*Insert Figure 7a.1 here*]

[*Insert Figure 7a.2 here*]

[*Insert Figure 7b.1 here*]

[*Insert Figure 7b.2 here*]

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 rate 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 these shocks 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 methods 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.

REFERENCES

Aaberge, R., Wennemo, T., Bjorklund, A., Jantti, M., Pedersen, P. J. and Smith, N. (2000): "Unemployment shocks and income distribution: how did the Nordic countries fare during their crises?" *Scandinavian Journal of Economics* 102: 77-99.

Abadie, A. and Gardeazabal, J. (2003): "The economic costs of conflict: A case study of the Basque Country." *American Economic Review* 93: 113-132.

Abadie, A., Diamond, A. and Hainmueller, J. (2010): "Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program." *Journal of the American statistical Association* 105: 493-505.

Abadie, A., Diamond, A. and Hainmueller, J. (2015): "Comparative politics and the synthetic control method.". *American Journal of Political Science* 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. and Foster, J. (2011): "Counting and Multidimensional Poverty Measurement." *Journal of Public Economics* 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. and Imbens, G. W. (2006): "Identification and inference in nonlinear difference-in-differences models." *Econometrica* 74: 431-497.

Atkinson, A. B. (2003): "Multidimensional deprivation: contrasting social welfare and counting approaches." *Journal of Economic Inequality* 1: 51-65.

Ayala, L., Cantó, O. y Rodríguez, J.G. (2017): "Poverty and the business cycle: The role of intrahousehold distribution of unemployment," *Journal of Economic Inequality* 15: 47-73.

Bárcena-Martín, E., Lacomba, B., Moro-Egido, A.I., and Pérez-Moreno, S. (2014): "Country Differences in Material Deprivation in Europe." *Review of Income and Wealth* 60: 802-820.

Barreix, A. D. and Corrales, L. F. (*eds*) (2019): *Reglas fiscales resilientes en América Latina* (Vol. 767). Inter-American Development Bank.

Blank, R.M. and Blinder, A.S. (1986): "Macroeconomics, Income Distribution, and Poverty," in S.Danziger (ed.): *Fighting Poverty: What Works and What Does Not*. Cambridge: Harvard University Press.

Bourguignon, F. and Chakravarty, S.R. (2003): "The measurement of multidimensional poverty", *Journal of Economic Inequality*, 1, 25-49.

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. and Pantano, J. (2013): "Catastrophic natural disasters and economic growth." *Review of Economics and Statistics* 95: 1549-1561.

Christelis, D., Georgarakos, D. and Jappelli, T. (2015): “Wealth shocks, unemployment shocks and consumption in the wake of the Great Recession.” *Journal of Monetary Economics* 72: 21-41.

Craig, P. (2015): “Synthetic Controls: A New Approach to Evaluating Interventions.” Working Paper. What Works Scotland.

Cutler, D.M. and Katz, L.F. (1991): “Macroeconomic Performance and the Disadvantaged,” *Brookings Papers on Economic Activity* 2: 1-74.

Deutsch, J. and Silber, J. (2005): “Measuring multidimensional poverty: An empirical comparison of various approaches”. *Review of Income and Wealth*, 51, 145-174.

Dibooğlu, S. and Enders, W. (2001): “Do real wages respond asymmetrically to unemployment shocks? Evidence from the US and Canada.” *Journal of Macroeconomics* 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. and 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.” *Journal of Economic Inequality* 10: 397–418.

Grier, K. and Maynard, N. (2016): “The economic consequences of Hugo Chavez: A synthetic control analysis”. *Journal of Economic Behavior & Organization* 125: 1-21.

Hamermesh, and Burda, M. (2010): “Unemployment, Market Work and Household Production,” *Economics Letters* 107: 131-133.

Heim, B. T. and Lurie, I. Z. (2014): “Does health reform affect self-employment?”. Evidence from Massachusetts. *Small Business Economics* 43: 917-930.

Jäntti, M. (1994): “A More Efficient Estimate of the Effects of Macroeconomic Activity on the Distribution of Income,” *The Review of Economics and Statistics* 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.

Martínez, R. and Navarro, C. (2014): “Has the Great Recession Changed the Deprivation Profile of Low Income Groups? Evidence from Spain.” *Hacienda Pública Española / Review of Public Economics*, 218-(3/2016): 79-104

Mayer, S. E. and Jencks, C. (1989): “Poverty and the distribution of material resources.” *Journal of Human Resources* 24: 88-113.

McClelland, R. and Gault, S. (2017): “The Synthetic Control Method as a Tool to Understand State Policy.” *Washington, DC: Urban-Brookings Tax Policy Center*.

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. and Papatheodorou, C. (2018): “The Greek Depression: Poverty Outcomes and Welfare Responses.” *Journal of Economics and Business* 21: 197–214

Smeeding, T., Thompson, J.P., Levanon, A. and Burak, E. (2011): “Income, Inequality, and Poverty over the Early Stages of the Great Recession,” in Grusky, D. and Western, B. and C. Wimer (eds.): *The Great Recession*, New York: Russell Sage Foundation.

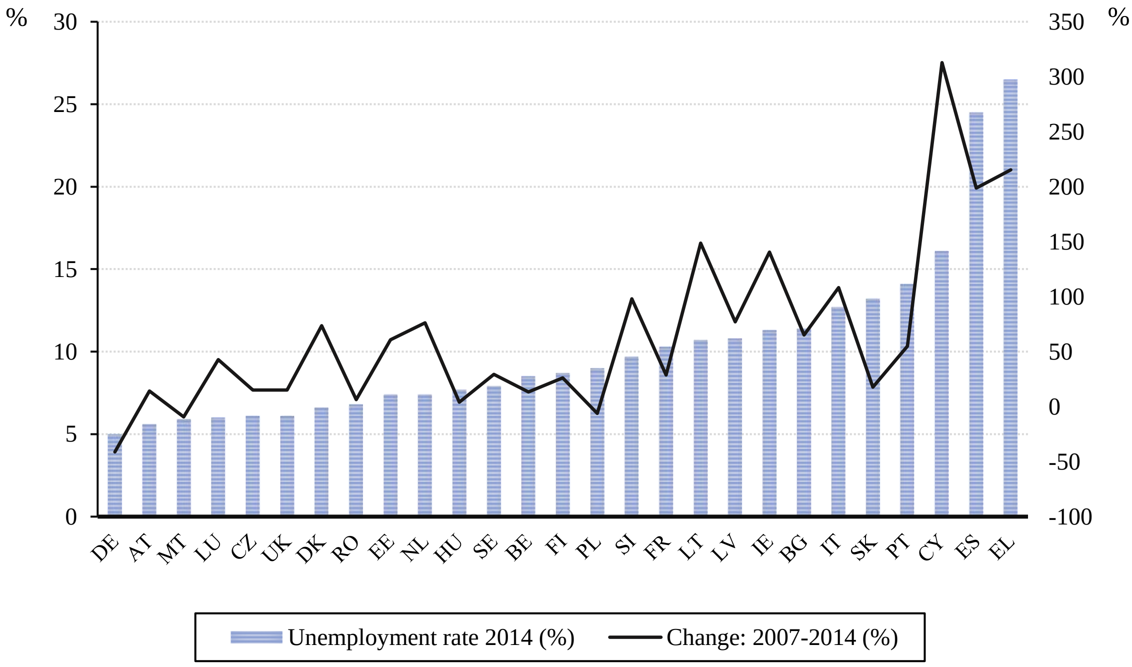
Verbunt, P. and Guio, A.C. (2019): “Explaining Differences Within and Between Countries in the Risk of Income Poverty and Severe Material Deprivation: Comparing Single and Multilevel Analyses.” *Social Indicators Research* 144: 827-868.

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.” *Social Indicators Research* 115: 1179–1203.

Whelan, C.T. and Maître, B. (2012): “Understanding Material Deprivation in Europe: A Multilevel Analysis.” *Research in Social Stratification and Mobility* 30: 489–503.

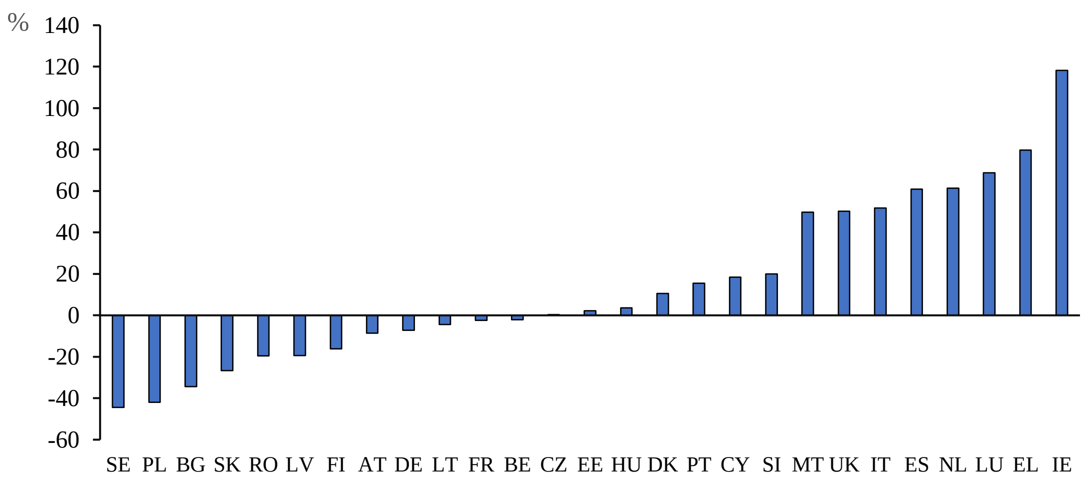
Whelan, C.T. and Maître, B. (2013): “Material Deprivation, Economic Stress and Referencing Groups in Europe: An Analysis of EU-SILC2009.” *European Sociological Review* 29: 1162-1174

Figure 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 2007-2014; (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.

Figure 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.

Figure 3. Trends of the material deprivation rate: SPAIN and GREECE

Figure 3a. SPAIN and synthetic SPAIN [1]

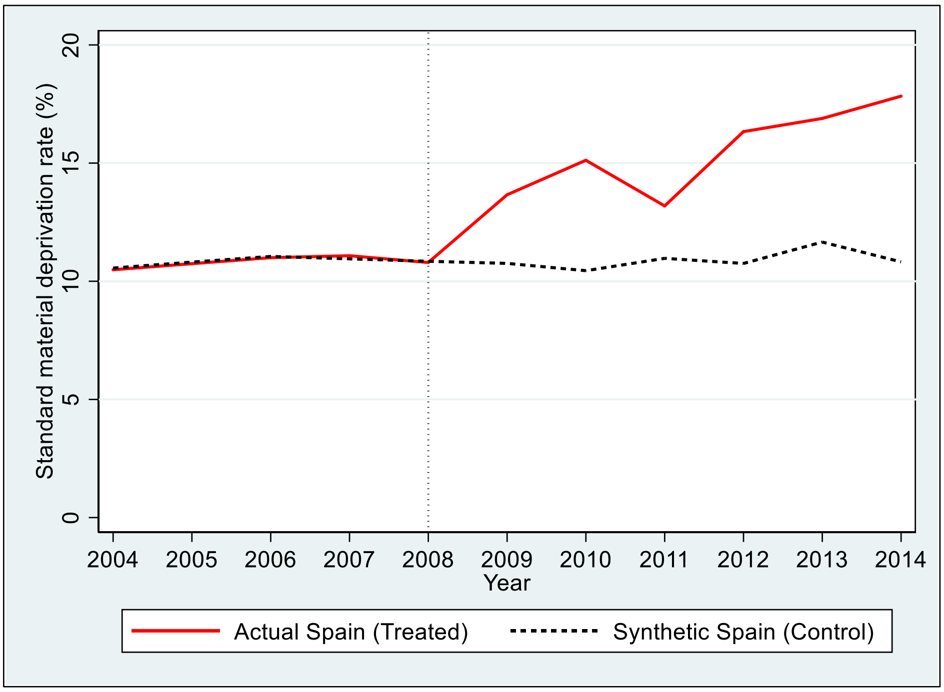
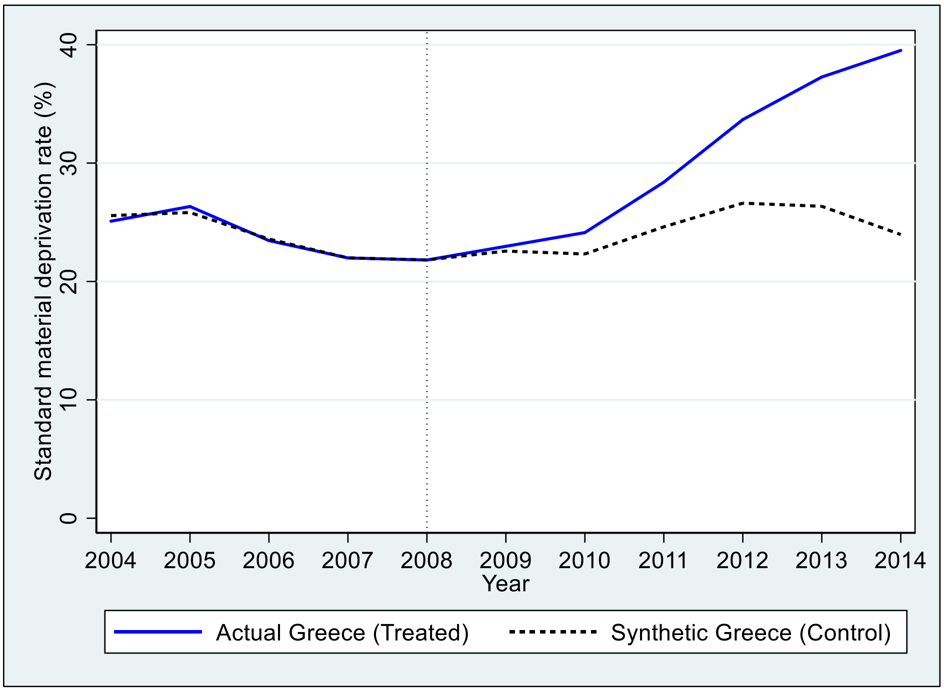


Figure 3b. GREECE and synthetic GREECE [1]



Source: Own elaboration from the Eurostat database.

Figure 4. "In-space" placebos: SPAIN and GREECE

Figure 4a. Gaps in the *donor pool* (treated unit: SPAIN) [1]

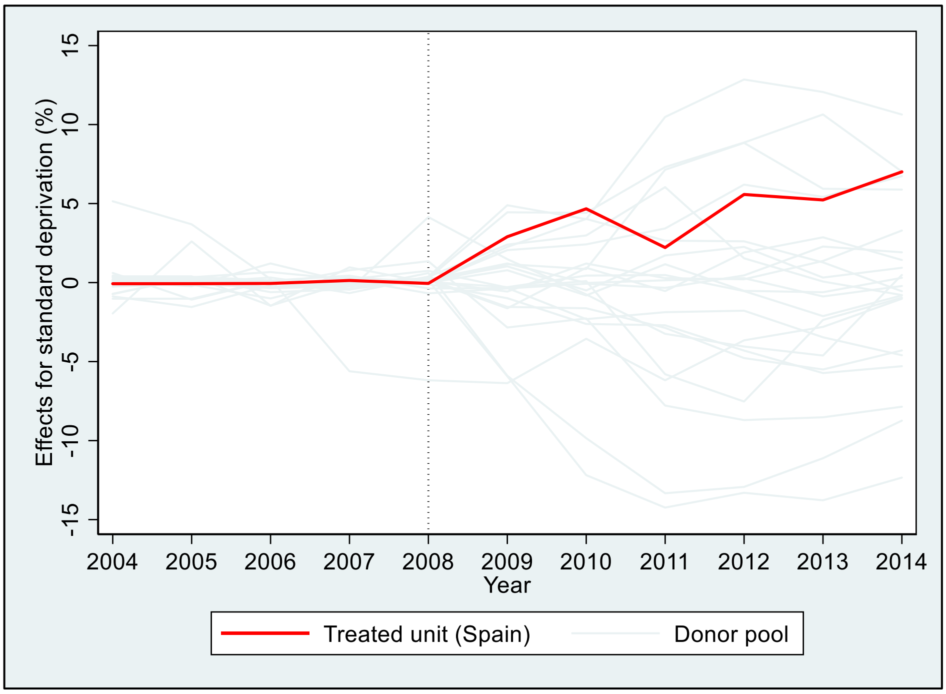
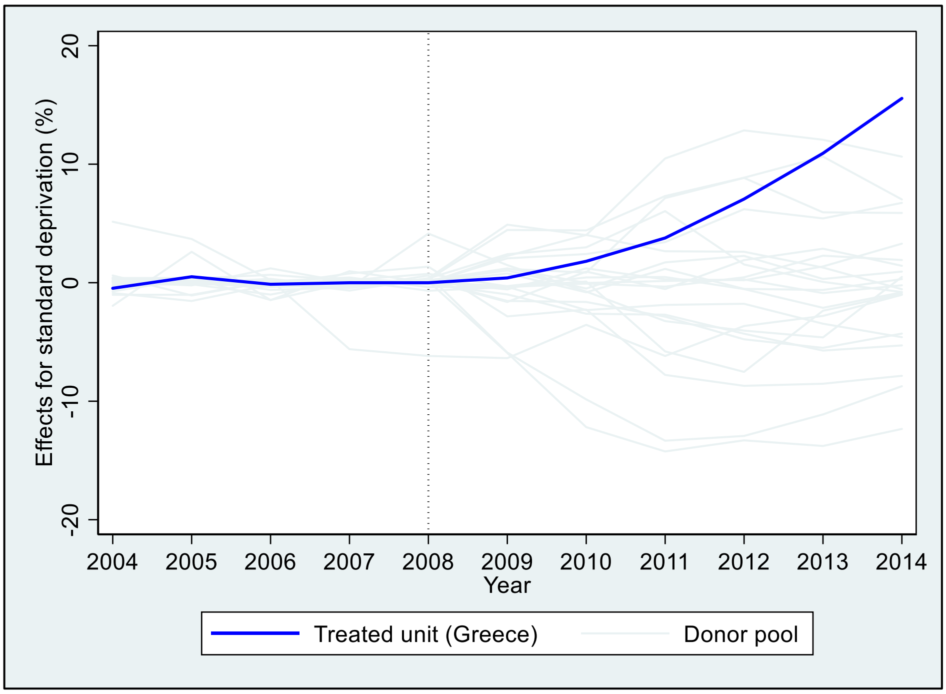


Figure 4b. Gaps in the *donor pool* (treated unit: GREECE) [1]



Source: Own elaboration from the Eurostat database.

Figure 5. Extension of the preunemployment shock time period: 1996-2008

Figure 5a. SPAIN and synthetic SPAIN [1]

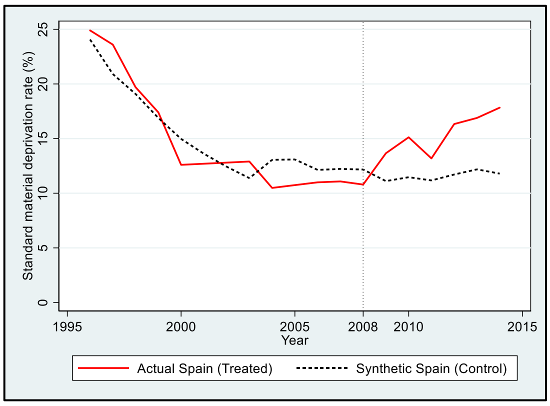
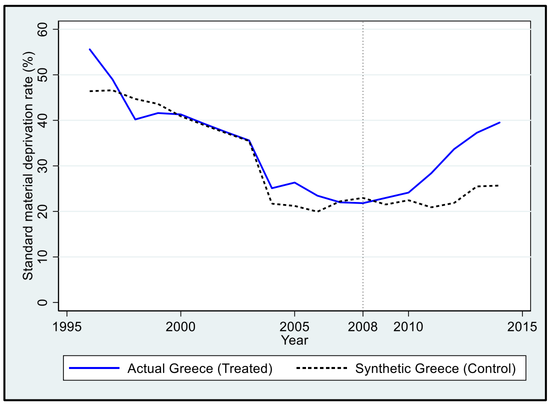


Figure 5b. GREECE and synthetic GREECE [1]



Notes: Numbers enclosed in square brackets refer to the econometric specifications used.
Source: Own elaboration from the Eurostat database.

Figure 6. A stricter criterion for the unemployment shock definition

Figure 6a. SPAIN and synthetic SPAIN [1]

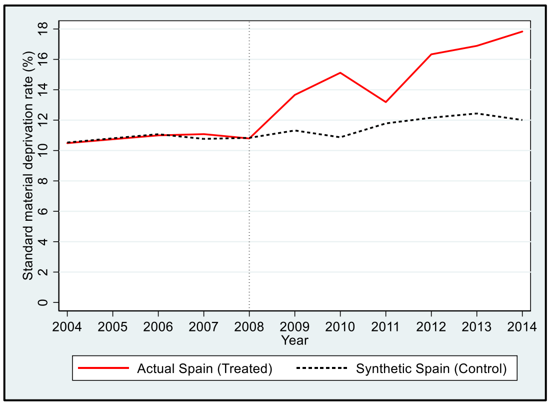
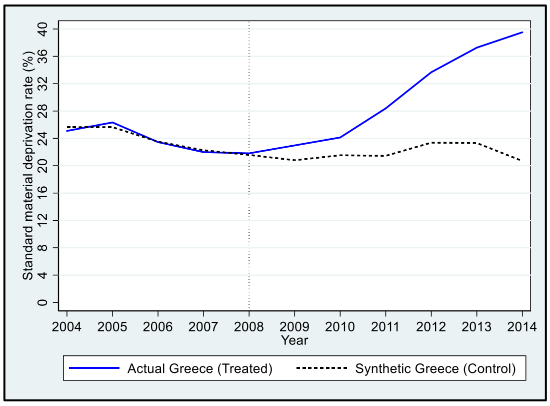


Figure 6b. GREECE and synthetic GREECE [1]



Source: Own elaboration from the Eurostat database.

Figure 7. Alternative outcome variables

Figure 7a.1. Severe material deprivation rate:
SPAIN and synthetic SPAIN [1]

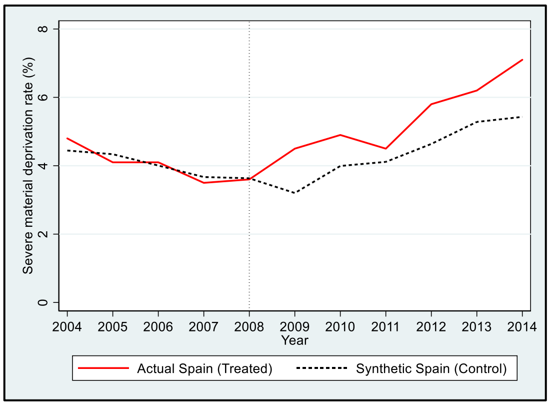
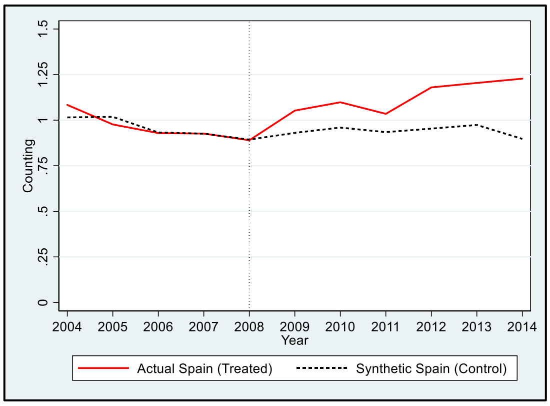


Figure 7a.2. *Counting* approach:
SPAIN and synthetic SPAIN [1]



Source: Own elaboration from the Eurostat database.

Figure 7b.1. Severe material deprivation rate:
GREECE and synthetic GREECE [1]

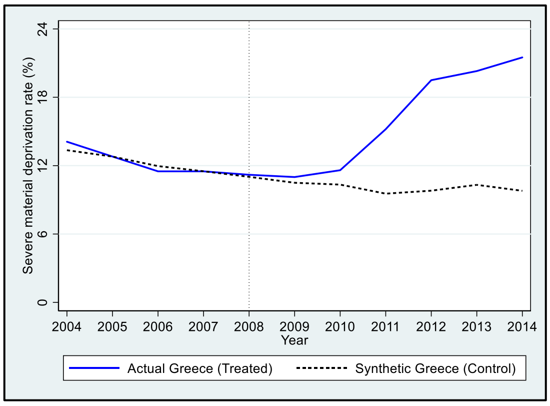
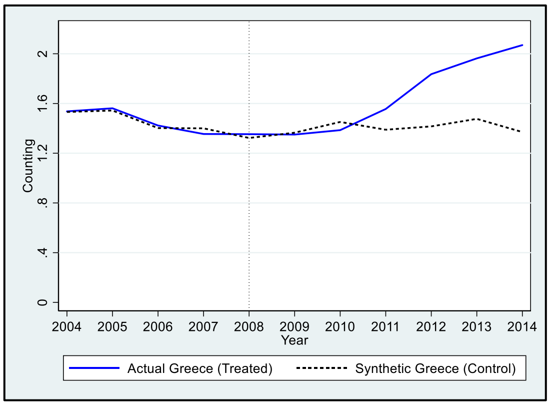


Figure 7b.2. *Counting* approach:
GREECE and synthetic GREECE [1]



Source: Own elaboration from the Eurostat database.

Table 1a. Best fit for the standard material deprivation rate as the outcome of interest using three lags (SPAIN)

	Predictor variables	All possible combinations of choosing 3 lags from the 5 years of the preunemployment shock period									
		[ES_1]	[ES_2]	[ES_3]	[ES_4]	[ES_5]	[ES_6]	[ES_7]	[ES_8]	[ES_9]	[ES_10]
Standard material deprivation	Gini index	X	X	X	X	X	X	X	X	X	X
	Work intensity (%)	X	X	X	X	X	X	X	X	X	X
	Ln (GDP per capita)	X	X	X	X	X	X	X	X	X	X
	Social protection benefits (% GDP)	X	X	X	X	X	X	X	X	X	X
	Standard material deprivation rate 2008	X	X	X	X	X	X	—	—	—	—
	Standard material deprivation rate 2007	X	X	X	—	—	—	X	X	X	—
	Standard material deprivation rate 2006	X	—	—	X	X	—	X	X	—	X
	Standard material deprivation rate 2005	—	X	—	X	—	X	X	—	X	X
	Standard material deprivation rate 2004	—	—	X	—	X	X	—	X	X	X
	RMSPE	0.170	0.078	0.104	0.162	0.163	0.187	0.210	0.146	0.226	0.211

Note: ES = Spain.
Source: Own elaboration.

Table 1b. Best fit for the standard material deprivation rate as the outcome of interest using three lags (GREECE)

	Predictor variables	All possible combinations of choosing 3 lags from the 5 years of the preunemployment shock period									
		[EL_1]	[EL_2]	[EL_3]	[EL_4]	[EL_5]	[EL_6]	[EL_7]	[EL_8]	[EL_9]	[EL_10]
Standard material deprivation	Gini index	X	X	X	X	X	X	X	X	X	X
	Work intensity (%)	X	X	X	X	X	X	X	X	X	X
	Ln (GDP per capita)	X	X	X	X	X	X	X	X	X	X
	Social protection benefits (% GDP)	X	X	X	X	X	X	X	X	X	X
	Standard material deprivation rate 2008	X	X	X	X	X	X	—	—	—	—
	Standard material deprivation rate 2007	X	X	X	—	—	—	X	X	X	—
	Standard material deprivation rate 2006	X	—	—	X	X	—	X	X	—	X
	Standard material deprivation rate 2005	—	X	—	X	—	X	X	—	X	X
	Standard material deprivation rate 2004	—	—	X	—	X	X	—	X	X	X
	RMSPE	0.454	0.314	0.461	0.387	0.564	0.564	0.571	0.639	0.592	0.766

Note: EL = Greece.
Source: Own elaboration.

Table 2. Choice of model: sensitivity test to different specifications

	Predictor variables	3 lags	2 lags			1 lag		
		[1]	[2]	[3]	[4]	[5]	[6]	[7]
Standard material deprivation (SPAIN)	Gini index	X	X	X	X	X	X	X
	Work intensity (%)	X	X	X	X	X	X	X
	Ln (GDP per capita)	X	X	X	X	X	X	X
	Social protection benefits (% GDP)	X	X	X	X	X	X	X
	Standard material deprivation rate 2008	X	X	—	X	X	—	—
	Standard material deprivation rate 2007	X	X	X	—	—	X	-—
	Standard material deprivation rate 2005	X	—	X	X	—	—	X
	RMSPE	0.078	2.391	0.211	0.209	3.237	2.979	0.211
Standard material deprivation (GREECE)	Gini index	X	X	X	X	X	X	X
	Work intensity (%)	X	X	X	X	X	X	X
	Ln (GDP per capita)	X	X	X	X	X	X	X
	Social protection benefits (% GDP)	X	X	X	X	X	X	X
	Standard material deprivation rate 2008	X	X	—	X	X	—	—
	Standard material deprivation rate 2007	X	X	X	—	—	X	-—
	Standard material deprivation rate 2005	X	—	X	X	—	—	X
	RMSPE	0.313	1.559	0.876	0.752	1.180	1.866	0.876

Source: Own elaboration.

Table 3. Predictor means: SPAIN and GREECE

Table 3a. Results for SPAIN

Predictor variables	Actual Spain	Synthetic Spain		
		[1]	[4]	[7]
Gini index	31.88	28.50	27.16	27.27
Work intensity (%)	59.73	61.80	60.33	60.80
Ln (GDP per capita)	10.02	10.51	10.08	10.03
Social protection benefits (% GDP)	19.98	23.36	20.48	20.04
Standard material deprivation rate 2008	10.79	10.85	11.05	—
Standard material deprivation rate 2007	11.08	10.95	—	—
Standard material deprivation rate 2005	10.74	10.81	10.81	10.79

Table 3b. Results for GREECE

Predictor variables	Actual Greece	Synthetic Greece		
		[1]	[4]	[7]
Gini index	33.64	32.44	33.67	31.93
Work intensity (%)	58.60	62.89	58.66	59.19
Ln (GDP per capita)	9.88	9.88	9.85	9.88
Social protection benefits (% GDP)	23.55	19.28	22.52	23.57
Standard material deprivation rate 2008	21.81	21.82	20.72	—
Standard material deprivation rate 2007	21.99	21.99	—	—
Standard material deprivation rate 2005	26.33	25.83	25.63	25.58

Source: Own elaboration from the Eurostat database.

Table 4. Impact results (estimated gap) (%)

Year	Treatment unit: SPAIN			Treatment unit: GREECE		
	[1]	[4]	[7]	[1]	[4]	[7]
2009	2.903	1.823	1.596	0.404	3.306	3.225
2010	4.671	3.498	3.144	1.808	2.310	2.881
2011	2.218	0.396	0.003	3.774	6.960	7.383
2012	5.579	2.459	1.940	7.058	9.905	10.743
2013	5.231	2.935	2.299	10.921	13.382	14.971
2014	7.011	3.775	2.966	15.553	18.379	19.944
Average	4.602	2.898	2.389	7.823	9.040	9.858

Source: Own elaboration.

APPENDIX

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.
	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 approach (%)*	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 deviates 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[13]. These include disability, sickness/healthcare, old age, survivor, family/child, unemployment, housing and social exclusion provisions not covered elsewhere.

Source: Eurostat and own elaboration.

Notes: (1) The asterisk (*) is denoting variables used in sensitivity tests; (2) *Temporary employment* has been used instead of *Work intensity* when extending the preunemployment shock time period.

[13] 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]	[4]	[7]	[1]	[4]	[7]
Austria	0	0	0	0	0	0
Belgium	0	0	0	0	0	0
Bulgaria	0.032	0	0	0	0.118	0.133
Cyprus*	—	—	—	—	—	—
Czech Republic	0	0	0	0	0	0
Denmark	0	0	0	0	0	0
Estonia	0	0	0	0	0	0
Finland	0	0.110	0	0	0	0
France	0	0	0	0	0.062	0.291
Germany	0.314	0.203	0.190	0	0	0
Greece**	—	—	—	—	—	—
Hungary	0	0	0	0.116	0	0
Ireland	0	0	0	0.400	0	0
Italy	0	0	0	0	0	0
Latvia	0	0	0	0	0	0
Lithuania	0	0	0	0	0	0
Luxembourg	0.396	0.195	0.192	0	0	0
Malta	0	0.492	0.555	0	0	0
Netherlands	0	0	0.063	0	0	0
Poland	0	0	0	0.255	0.133	0.131
Portugal	0.132	0	0	0.106	0.117	0
Romania	0	0	0	0	0	0
Slovakia	0	0	0	0	0	0
Slovenia	0	0	0	0	0	0
Spain**	—	—	—	—	—	—
Sweden	0.126	0	0	0	0	0
United Kingdom	0	0	0.175	0.123	0.571	0.446

Note: (*) Conflicting country excluded; (**) Countries of treatment