A counterfactual analysis of the impact of the 2008 and 2020 crises on Spanish employment

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Abstract

Purpose – The purpose of this paper is to estimate the impact of the 2008 and 2020 economic crises on employment in Spain.

Design/methodology/approach – The authors perform a counterfactual analysis, combining intervention (interrupted time series) analysis and conditional forecasting to estimate a "crisis-free" scenario. These counterfactual estimates are used as a synthetic control, to be compared with the observed values of the main variables of the Spanish Labor Force Survey (EPA).

Findings – The authors measure the effect on Spanish employment of the 2008 recession and the ongoing COVID/Ukraine crisis and the speed of recovery, which yields a rigorous dating for the beginning and end of the crises studied. Finally, the authors provide estimates about which part of the employed and unemployed people was in furlough (ERTE) based on microdata provided by the Spanish Institute of Statistics.

Originality/value – To the best of the authors' knowledge, there are no counterfactual studies covering all the basic variables in EPA and no estimates for the effect of ERTEs on the basic employment variables. Finally, the authors combine well-known intervention and forecasting techniques into an integrated framework to assess the effects of both, past and ongoing crises.

Keywords Employment, 2008 crisis, COVID-19, Ukraine war, Counterfactual analysis

Paper type Research paper

JEL classification – C32, E44, E47

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1. Introduction

The global spread of COVID-19 from 2020 Q1 onwards and the generalized adoption of lockdowns to mitigate its effects on public health had a severe impact on gross domestic product (GDP) and employment worldwide. Therefore, the global health crisis triggered a global economic crisis. This downturn was further aggravated by the invasion of Ukraine by the Russian Federation in 2022 Q1.

To make the matter worse, in 2020 the Spanish economy was recovering from the 2008 crisis. Therefore, it faced these subsequent crises in less favorable economic conditions than those previous to the 2008 crisis.

In this line, this work addresses the following questions: What has been the impact of the 2008 and 2020 crises on employment in Spain? For how long did they affect employment figures? Which part of the employed and unemployed people was actually in furlough (ERTE [1])? To this end, we build on a univariate and intervention analysis (Box *et al.*, 2015) for the basic variables from the Spanish Labor Force Population Survey (EPA [2]). The econometric models resulting from this analysis are used to estimate how the employment would have behaved if the crises starting in 2008 and 2020 did not happen.

Since the 2008 crisis occurs within the sample period, we measured its effect using intervention analysis [3] (Box and Tiao, 1975) which are appropriate when pre- and post-event observations are available. The crisis initiated in 2020 is still unfolding. For this reason, we modeled the sub-sample of EPA ending in 2019 Q4 and used these models to extrapolate the corresponding variables for 2021 and 2022. These out-of-sample forecasts provide, therefore, a "COVID/Ukraine War-free" scenario.

Note that this approach not only allows one to measure the impact of past or present shocks, but it is also useful to monitor in real time the EPA variables and to assess, therefore, when they recover the levels that would have been expected in absence of a crisis. Therefore, it provides the technical basis required for an objective dating of the crises analyzed.

The structure of the work is as follows. Chapter 2 reviews the most relevant literature. Chapter 3 shows the results of the econometric modelling exercise and the resulting counterfactual analysis. Finally, Chapter 4 summarizes the main conclusions and suggests some extensions of this work.

2. Basic concepts and literature review

Traditionally, it is considered that one of the main differences between natural sciences and economics is that, in the former, it is possible to validate universal laws through experiments that compare the results observed in a "treatment group" with those of a counterfactual "control group" which can be determined in different ways. In social sciences, the key challenge in applying this approach is to separate the effects of the treatment from other factors that may influence the observed results.

Despite these difficulties, the experimental approach is gaining weight in economics. Clear examples are the Nobel Prizes in Economics awarded in 2002 to Daniel Kahneman and Vernon Smith and in 2017 to Richard Thaler. The recognition continued in 2019, when the laureates were Abhijit Banerjee, Esther Duflo and Michael Kremer, for their applied work with randomized controlled experiments, and in 2021, when the Prize rewarded the work of David Card, Joshua Angrist and Guido Imbens on natural experiments.

2.1 Experiments with synthetic control

Sometimes, there is no suitable control group to conduct an experiment. In other cases, you may want to combine different control groups, to diversify the risk of choosing the wrong one. Both situations can be addressed through the "synthetic control" approach, based on the seminal work of Abadie and Gardeazábal (2003). This approach builds on the idea that a combination of donor pool units can approximate the characteristics of the affected unit better than any unaffected unit alone. A synthetic control is therefore a weighted average of the units of the donor set. On this basis, Abadie and Gardeazábal (2003) studied the economic impact of terrorism in the Basque Country, comparing the real performance of this region with a counterfactual estimate of the growth it would have experienced in the absence of terrorism. This counterfactual "synthetic control" was estimated by combining data from two closely related Spanish regions, not affected by terrorism problems and with relevant economic characteristics like those of the Basque Country in the 1960s. On this basis, the economic evolution of the counterfactual ("terrorism-free") Basque Country was compared with the actual figures, concluding that the terrorist conflict caused a substantial and significant negative impact on Basque GDP per capita. Other good examples of this approach are Abadie *et al.* (2010, 2015) who estimated, respectively, the effects of a tobacco control program in California and the impact of the 1990 German reunification on the GDP per capita of West Germany.

All these studies used panel data samples, combining a spatial dimension, where some units are exposed to the treatment while others are not, with a temporal dimension. In this context, one has time series belonging to the treatment and control groups, being both correlated. Therefore, a model can be fitted to capture the relationship between all groups for pretreatment observations and, finally, extrapolating this model to the treatment period yields synthetic counterfactual estimates for the treatment group, to be compared with those observed.

2.2 Synthetic control in time series

For the goals of this work – to assess the impact on Spanish employment of the 2008 and 2020 crises – a synthetic control cannot be estimated by means of panel methods because both crises are global and, therefore, there are no unaffected countries that can be used to build synthetic controls. Consequently, the only source of information about the events of interest is in the pre- and post-crisis values of the time series themselves.

On one hand, the 2008 crisis has already occurred and, therefore, pre- and post-crisis observations are available. We can address its analysis by a methodology of "interrupted" time series. The events or "interruptions" that are treated by these methods can be of different natures. For example: data errors, changes in measurement criteria, deployment of an advertising campaign or changes in the cost of a service. Logically, a global economic crisis or a pandemic can also be accommodated in this framework.

These methods have a long tradition in the time series literature. For example, the seminal work of Box and Tiao (1975) included applications of their theoretical proposal to the study of changes in pollution in Los Angeles, resulting from a restructuring of traffic and the introduction of a new regulation, and on the effect of a system of controls on the consumer price index in the USA. It is also well known the study of Harvey and Durbin (1986), who estimated the reduction in the number of deaths and serious injuries in traffic accidents in the UK, resulting from the mandatory use of seat belts. For a comprehensive and recent treatment of these techniques, also covering their relationship with Bayesian time series analysis, see McDowall and McCleary (2019).

Interrupted time series analysis is adequate for past events, having a well-defined beginning and end. On the other hand, the COVID/Ukraine crisis is still unfolding, so a different approach is necessary. Our alternative strategy consists in:

- modeling the series using a sample that ends in a pre-event period. In our case we have set the end of the sample in 2019 Q4, since in 2020 Q1 the world economies received disturbing news from China, in first place, and from other countries later;
- calculating out-of-sample forecasts from this date and interpreting them as the most likely evolution path for the series in absence of the COVID/Ukraine crisis. This would be the synthetic control; and
- subtracting the observed values from the forecasts and interpreting this difference as a measure of the deviation between the control and treatment samples.

This approach not only makes it possible to measure the impact of an interruption in real time but is also useful to monitor the variables of interest and to assess whether they recover the expected levels in absence of the event [4].

2.3 Literature on macroeconomic impact of the COVID-19 pandemic

Given the importance and global reach of the pandemic, there are many studies about its impact on the main macroeconomic variables. Here we just mention those closer to our work. On the other hand, the Ukraine crisis is still unfolding and can be viewed as a prolongation of the 2020 COVID crisis, so the literature about it is scarce yet, except for some studies focusing on inflation.

Chudik *et al.* (2020) conducted a counterfactual analysis of COVID-19 using a dynamic multi-country model with thresholds. This model focuses on the growth of the world economy's output and its responses to shocks, either directly or indirectly, through the stock and bond markets. They compare the international monetary fund's GDP forecasts through the end of 2019 with GDP forecasts for 2020, concluding that the pandemic may cause global real GDP to decline for a lasting period and interest rates to fall below their lows.

Cho and Winters (2020) studied the distributional impact of early job loss due to COVID-19 in the US. To estimate a counterfactual scenario, they use the "difference-in-differences" approach, assuming that January 2020 employment rate was not affected by COVID and defining the counterfactual employment rate as the April 2019 rate plus the January 2020 year-on-year difference. The estimates are then computed by subtracting the year-on-year difference of January 2020 from the year-on-year difference of April 2019. They conclude that employment rates fell by 57.3% in March and 47% in April, with a wide-ranging decrease throughout the population.

O'Donoghue *et al.* (2020) studied the distributional implications of the COVID-19 crisis in Ireland. To this end, they use nowcasting methods to simulate a counterfactual income distribution. They conclude that income decreased for all deciles of the distribution but, in absolute terms, the decline was greater at the top than at the bottom of the distribution. The increase in social benefits during the crisis helped to compensate partially the loss of income and, in turn, the fall in market income was followed by a decrease in taxes paid. However, these were not enough to maintain the pre-crisis income level in all but the lowest deciles.

Svabova *et al.* (2021) discuss the impact of COVID-19 on the evolution of unemployment in Slovakia through a before-after comparison for the period 2013–2020. They conclude that there was:

- an average increase of 16.63% in the number of unemployed, compared to the period April 2019–March 2020;
- an average increase of 47.13% in the number of job providers; and
- an increase between 2% and 3% in the Slovakian unemployment rate, when comparing pandemic and pre-pandemic periods.

Lambovska *et al.* (2021) studied the impact of the pandemic on youth unemployment in the EU. They compared the unemployment rate and the number of young unemployed until December 2019, with the evolution of the same variables in the last four months of 2020. The results showed that the highest rates of youth unemployment occurred in Greece, Italy, Spain, Sweden and Lithuania. In other countries, such as Germany, Iceland or Belgium, the number of unemployed young people increased, but to a lesser extent.

Gallant *et al.* (2020) studied temporary unemployment and labor market dynamics in the U.S. during the COVID-19 crisis. They distinguish between temporary and permanent unemployment, understanding that unemployment is temporary if the worker will be called back to the company, and permanent if the worker will not be reinstated. They concluded that:

- the COVID crisis yielded a rapid and unprecedented rise in temporary unemployment; and
- as the pandemic worsened, a significant share of temporary unemployment became permanent.

Focusing on the Spanish economy, Pinilla *et al.* (2021) analyzed the impact of COVID-19 by means of a Bayesian structural model of time series for GDP, production, supply, demand and the unemployment at region level. To estimate the impact of COVID-19, they compare observed and counterfactual time series. Their results show that there has been a sharp fall in GDP in Spain since the beginning of the pandemic, affecting to a greater extent the Autonomous Communities dedicated to the services sector, tourism and industrial activity. They estimate that in 2020, there was an 11.9% increase in the unemployment rate that can be attributed to the COVID crisis.

Perles-Ribes *et al.* (2021) studied the immediate impact on tourism employment in Spain through a Bayesian structural analysis of time series, like Pinilla *et al.* (2021) and sometimes using the univariate methods of Box *et al.* (2015). The impact of COVID is obtained by subtracting the response obtained from a semi-parametric Bayesian estimate and the response observed during the pandemic. They compute two types of counterfactuals: one using the behavior of the rest of the economy and the other using the delayed values of tourist activity. Their main conclusion is that employment in tourism declined less than one might expect in comparison with other activities in the economy.

Our work differs from previous analyses in two fundamental aspects. First, in its *approach*, because it focuses on all the basic employment variables – unemployed, employed, active – in Spain. Second, in its *reach and methodology*, because it provides a conceptual framework that allows one to measure both, the impact of past crises (the one that began in 2008, in our case) and those that are still in progress (that of COVID). This last aspect is important as, according to our results, an econometric model for macroeconomic variables cannot be validated without considering the effect of the previous crisis.

3. Results

The first step to estimate the effects of the crises analyzed on employment consists in modeling the basic EPA series from 2002 Q1 to 2019 Q4.

Note that the first lockdown in Spain began in March 2020, so the analysis could have been done including 2020 Q1 in the sample. We chose not to do so because in this period there were news about the pandemic in other countries, which could have had some impact on the labor market. Therefore, we will test if there was a significant effect in this quarter.

Figure 1 shows the profile of the unemployed and employed workers series from 2002 Q1 to 2022 Q3. The shaded areas correspond to the 2008 crisis (dated according to our results from 2009 Q1 to 2010 Q3) and the post-COVID-19 crisis (dated from 2020Q1 onwards) which includes the Russia/Ukraine war.

First, we fit ARIMA models to these series [5]. The resulting models are later used as an initial specification for the error term of intervention models.

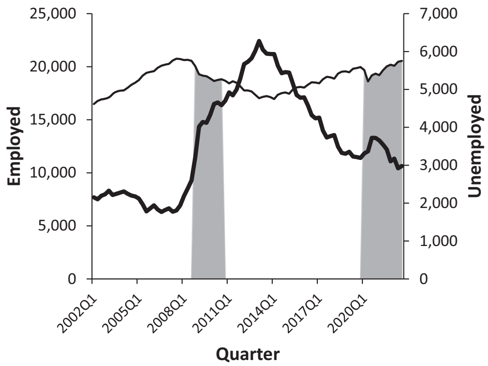
3.1 ARIMA models

After a standard identification analysis (Box *et al.*, 2015) we find that the EPA series of unemployed, employed and active population:

- do not require a Box–Cox transformation (Box and Cox, 1964); and
- display autocorrelation patterns compatible with an ARIMA(1,1,0)x$(0,1,1)_{12}$ process.

Table 1 summarizes the main estimation and diagnostic results for these models. We use the following notation, which is maintained along this work:

- The values in parentheses denote the standard errors of the estimates.
- The values in square brackets are the p-values of the corresponding tests.
- $\hat{\sigma}_a$ denotes the maximum-likelihood estimate for the residual standard deviation.
- HQ denotes the Hannan and Quinn (1979) information criterion.



Source: Authors' own work

Figure 1. Employed (thin line) and unemployed (thick line) workers, in thousands of people, 2002 Q1-2022 Q3

Coefficient/test	Unemployed	Employed	Active
$\hat{\phi}_1$	0.748 (0.085)	0.797 (0.077)	0.263 (0.144)
$\hat{\Theta}_1$	0.722 (0.146)	0.684 (0.099)	0.485 (0.145)
$\hat{\sigma}_a$	110.247	106.368	77.378
HQ information criterion	832.068	827.014	782.624
DH Test (Normality)	24.297 [0.00001]	12.839 [0.0016]	1.759 [0.415]
LM Test (ARCH(4))	17.821 [0.001]	19.975 [0.0005]	3.029 [0.552]
Q(15)	8.526 [0.807]	6.827 [0.910]	40.371 [0.0001]

Notes: All the models conform to an ARIMA(1,1,0) × $(0,1,1)_4$ structure, defined as: $(1-\phi_1 B)\nabla_4\nabla y_t = (1-\Theta_1 B^4)a_t$, where B is the backward shift operator, such that $By_t = y_{t-1}$, $\nabla \equiv 1 - B$, $\nabla_S \equiv 1 - B^S$
Source: Authors' own work

Table 1. Univariate models for EPA series

- The DH statistic (Doornik and Hansen, 2008) tests the null of residual normality.
- The LM [ARCH(4)] statistic denotes the test of joint significance of an autoregression of the square of the residues over their first four delays, in the line proposed by Engle (1982). Accordingly, the null is homoscedasticity of errors against the alternative of, at least, a fourth order ARCH heteroscedasticity.
- Finally, Q(15) denotes the Ljung and Box (1978) portmanteau statistic for the null of no residual autocorrelation, computed for the first 15 lags of the sample autocorrelation function.

The estimation of the corresponding ARIMA models shows that:

- all the coefficients are significant; the residual statistics reject the hypotheses of
- error normality; and
- homoscedasticity.

On the other hand, the null of no autocorrelation is not rejected in the case of unemployed and employed, but rejected for active population.

The rejection of normality and homoscedasticity is due to the presence of outliers in the model residuals from 2008 Q4 onwards, so they could be due to the 2008 financial crisis. On the other hand, residual autocorrelation in the model for active population could either be due to outliers or to a misspecification for the ARIMA model.

The next step, therefore, is to add intervention variables to the models of each series, to assess their statistical adequacy and, after a positive diagnostic checking, start the proposed counterfactual analysis.

3.2 Intervention models

An intervention model (Box and Tiao, 1975) can be seen as the sum of two components. First, a model relating the endogenous variable (number of unemployed, employed and active population in our case) with binary (0–1) exogenous variables designed according to the "signature" of the event of interest. Second, an ARIMA error term, which is usually specified from a univariate analysis such as the one we did in the previous subsection. This error model captures the inertial components of the series which are not described by the exogenous variables.

The intervention models fitted to unemployed, employed and active population are shown in Table 2, where the estimates dated 2008 Q4–2010 Q3 correspond to impulse-type effects (Box and Tiao, 1975) in those dates. These effects can be interpreted as the deviation of the endogenous variable with respect its expected value conditional to the past and future history of the series. The corresponding estimates, therefore, provide a synthetic control for the effects of the 2008 crisis.

The estimates in Table 2 are significant at the usual confidence levels and, thanks to the intervention associated with the 2008 crisis, the residual statistics do not reject the null hypotheses of normality, homoscedasticity and no autocorrelation. Likewise, the HQ information criteria in Table 2 are systematically smaller (i.e. better) than those in Table 1 [6].

The models for the unemployed and employed series have the same dynamic structure as those in Table 1 while the model for active population, after removing the outliers, is different. To understand this result, bear in mind that this variable is the sum of the series of unemployed and occupied. For this reason, first, the coefficients of the intervention variables are in general, smaller than those corresponding to unemployed and employed, and sometimes, they are even nonsignificant [7]. This is because an impulse of a given sign in the

Table 2.
Intervention models for EPA series

Coefficient*/test	Unemployed	p-value	Employed	p-value	Active	p-value
2008 Q4	281.107	6.79E-06	−228.711	0.001	74.708	0.078
2009 Q1	738.085	2.05E-11	−686.885	1.06E-08	20.644	0.711
2009 Q2	712.330	3.94E-07	−788.308	3.11E-07	−82.662	0.114
2009 Q3	482.666	0.001	−665.194	6.09E-05	−173.107	0.001
2009 Q4	384.785	0.011	−534.620	0.001	−146.033	0.009
2010 Q1	338.765	0.016	−420.068	0.007	−92.235	0.031
2010 Q2	308.557	0.005	−328.215	0.007	–	–
2010 Q3	103.359	0.091	−124.560	0.070	–	–
$\hat{\phi}_1$	0.804	5.85E-21	0.801	3.41E-20	0.447	0.001
$\hat{\Phi}_1$	–	–	–	–	−0.163	0.111
$\hat{\Phi}_2$	–	–	–	–	−0.669	5.96E-11
$\hat{\Theta}_1$	0.547	0.001	0.524	0.001	–	–
$\hat{\sigma}_a$	78.292	–	87.007	–	60.281	–
HQ information criterion	726.483	–	739.031	–	717.592	–
DH Test (Normality)	0.627	0.731	4.092	0.129	4.120	0.127
LM Test (ARCH(4))	3.389	0.494	2.792	0.593	7.892	0.095
Q(15)	10.857	0.622	28.209	0.008	20.434	0.059

Notes: *The entries 2008:4–2010:3 represent impulse-type interventions in the corresponding dates. An impulse is a type of intervention which affects the series at a specific time point and never again. It can be captured by an artificial variable with zeros in all positions except a unit value at the specified date. The corresponding coefficient is an estimate of the difference between the observed and expected values of the series. The error model is an ARIMA(1,1,2) × (0,1,1)$_4$: $(1-\phi_1 B)\,(1-\phi_1 B-\phi_2 B^2)\,\nabla_4\nabla y_t=(1-\Theta_1 B^4)\,a_t$
Source: Authors' own work

unemployed series would be compensated, at least partially, with another one of opposite sign in the series of occupied, which therefore dampens the effect of the outlier-generating event on active population. Second, the aggregation of the ARIMA models of unemployed and employed does not necessarily yields the same dynamic structure in the aggregated series; see Casals *et al.*'s (2012) Chapter 10 for a discussion of the effects of aggregation.

3.3 Counterfactual analysis for unemployed, employed and active population

The intervention coefficients of the models in Table 2 provide counterfactual estimates for the 2008 crisis, as they can be interpreted as changes in the expected value of the series in the corresponding dates. These models can also be used to predict the number of unemployed, employed and active from 2020 Q1 onwards, being these forecasts the counterfactual values required to assess the impact of the 2020 crisis.

To properly interpret the results, we should note that, according to the EPA methodology, people are considered on furlough only when the suspension of employment lasts for more than three months. Otherwise, they are classified as employed. When the layoff exceeds three months and the worker continues to receive at least 50% of the salary, she/he is still classified as employed. Additionally, if on furlough, she/he will be considered unemployed or inactive, depending on whether she/he has been seeking a job or not in that period.

As the EPA does not provide data on workers in ERTE, we analyzed the microdata collected by the surveys from 2019 Q1 to 2022 Q3 [8]. As far as we know, this study is unprecedented in the literature. The result of our analysis is presented in Figure 2, which displays the share of working age population who was in ERTE, and the distribution among employed, unemployed and inactive people. The main conclusion drawn is that ERTEs peaked in 2020 Q2 and came back to 2019 Q3 levels only from 2022 Q2 onwards. Most workers affected by this layoff were considered employed (around 85% in 2020 Q1 and Q2 and 65% approximately in 2020 Q3 and Q4). Only a nonsignificant amount was labeled as unemployed, particularly in 2020 Q2 and 2021 Q1. We will use these results later, to improve the interpretation of our counterfactual results.

3.3.1 Unemployed. Figure 3 shows the evolution of the number of unemployed compared with the counterfactual estimates and their 95% confidence interval. As could be expected, the uncertainty associated with the counterfactual estimate grows as we move away from the available sample values. For this reason, tracking an event in real time is more inaccurate than a past one.

Table 3 shows the numerical results corresponding to the 2008 crisis. It points out that the crisis produced significant effects from 2008 Q4 onwards, reaching an excess of almost 739 thousand unemployed people in 2009 Q1, which represents an increase of 22.3% with

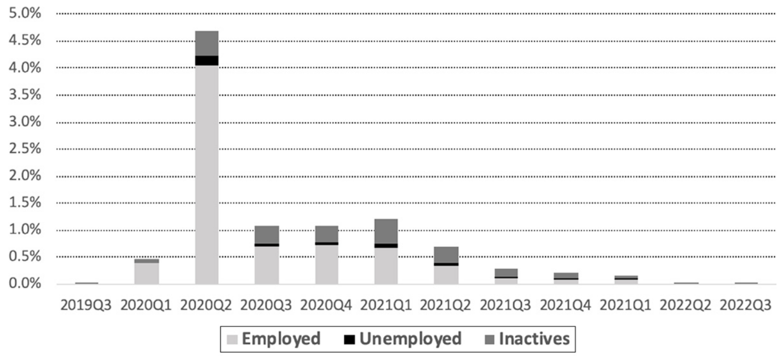


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Figure 2. Percentage of working age population on furlough (ERTE) and its distribution by categories, from 2019Q3 to 2022Q3

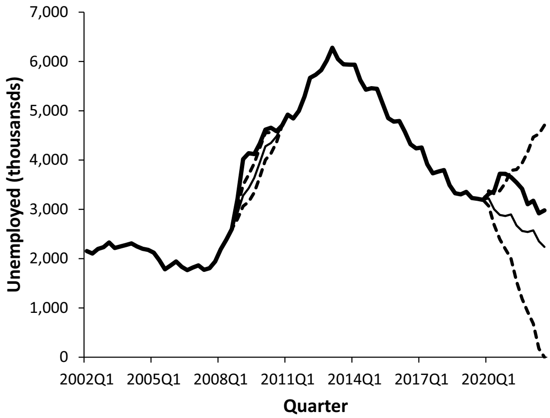

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Figure 3. Time series of unemployed workers (thick line) and counterfactual estimation (thin line)

respect to the counterfactual value. This impact decreased in subsequent quarters until 2010 Q3. In the following quarters, the observed values do not differ significantly from the counterfactual path.

On the other hand, Table 4 shows the estimated excess unemployment corresponding to the COVID-19/Ukraine crisis. Interestingly, we find that:

- in 2020 Q1, which we retained as predictive quality control, the deviation between the two series was not statistically significant;
- in the following quarters, the excess unemployment becomes significant, reaching a maximum of 870 thousand people in 2021 Q2; and
- in 2021 Q4, both series seemed to initiate a convergence, but
- in 2022, this timid improvement stalled, probably due to the Ukraine War.

Therefore, unemployment has not yet recovered levels like those in the counterfactual scenario and its recent evolution does not suggest that this will happen soon.

3.3.2 Employed. Table 5 shows the main results for the series of employed in the 2008 crisis. Note that the peak value occurs in the 2009 Q2, when the number of employed fell by

Quarter	Unemployed	Counterfactual*	Difference	Difference/Counterfactual (%)
2008 Q4	3,206.8	2,925.7 (62.5)	281.1 (62.5)	9.6
2009 Q1	4,018.2	3,280.1 (110.1)	738.1 (110.1)	22.5
2009 Q2	4,139.6	3,427.3 (140.4)	712.3 (140.4)	20.8
2009 Q3	4,124.4	3,638.7 (151.2)	482.7 (151.2)	13.3
2009 Q4	4,335.0	3,950.2 (151.4)	384.8 (151.4)	9.7
2010 Q1	4,617.7	4,278.9 (140.1)	338.8 (140.1)	7.9
2010 Q2	4,655.3	4,346.7 (109.0)	308.6 (109.0)	7.1
2010 Q3	4,585.4	4,482.0 (61.1)	103.4 (61.1)	2.3

Notes: *The control is computed by subtracting from the observed unemployed figure the corresponding coefficients of the intervention model, which are shown in the "Difference" column. The standard errors of both estimates, indicated in parentheses, are the same
Source: Authors' own work

Table 3. Counterfactual analysis of the 2008 crisis effect on unemployed

Quarter	Unemployed	Counterfactual*	Difference	Difference/Counterfactual (%)
2020 Q1	3,313.0	3,222.4 (78.3)	90.6 (78.3)	2.8
2020 Q2	3,368.0	2,999.3 (161.5)	368.7 (161.5)	12.3
2020 Q3	3,722.9	2,885.5 (161.5)	837.4 (161.5)	29.0
2020 Q4	3,719.8	2,864.5 (342.1)	855.3 (342.1)	29.9
2021 Q1	3,653.9	2,896.3 (455.5)	757.6 (455.5)	26.2
2021 Q2	3,543.8	2,674.2 (577.9)	869.6 (577.9)	32.5
2021 Q3	3,416.7	2,561.2 (702.7)	855.5 (702.7)	33.4
2021 Q4	3,103.8	2,540.9 (826.6)	562.9 (826.6)	22.2
2022 Q1	3,174.7	2,573.2 (965.5)	601.5 (965.5)	23.4
2022 Q2	2,919.4	2,351.6 (1,111.5)	567.8 (1,111.5)	24.2
2022 Q3	2,980.2	2,238.9 (1,259.3)	741.3 (1,259.3)	33.1

Notes: *The counterfactual figures are out-of-sample forecasts computed using the intervention model. The figures in parentheses are the standard errors of the corresponding forecasts
Source: Authors' own work

Table 4. Counterfactual analysis of the 2020 crisis effect on unemployed

about 789 thousand people with respect to the control, which represents a difference of −2.2%. From this moment onwards, it began to decrease, reaching a deviation of −0.7% in relation to the control value in 2010 Q3, so the impact of the crisis was no longer substantial.

Figure 4 and Table 6 show the main results of the analysis for the COVID-19/Ukraine crisis. In Table 6, we see that the forecast for 2020 Q1 is significantly larger than the observed value, so there was a deficit of employed people even before the lockdown.

The largest drop in employed occurred in 2020 Q2, with almost 1.8 million employed people less that in the counterfactual scenario [9].

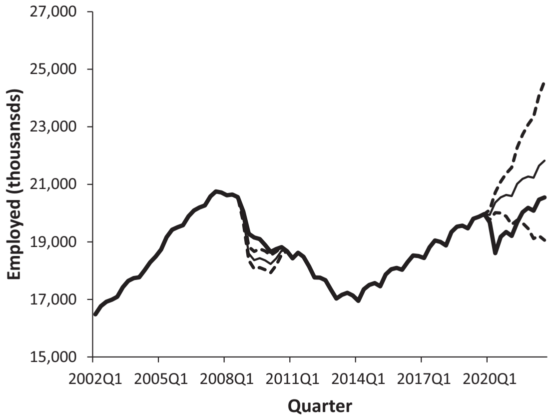
Finally, from 2021 Q4 onward, employment shows a stable deficit of 1.1–1.2 million people, without any indication of a recovery.

3.3.3 Active population. Table 7 shows the estimates of the 2008 crisis effect on active population. Note that the effect of the crisis is smaller and less significant than the one observed for unemployed and employed. This is a sensible result because active population is, by definition, the sum of employed and unemployed people. Therefore, under an approximately constant participation rate if the number of unemployed rises, the number of employed will decrease accordingly, so the final change in active population would be compensated, at least partially.

Table 5. Counterfactual analysis of the 2008 crisis effect on employed

Quarter	Employed	Counterfactual	Difference	Difference/Counterfactual (%)
2008 Q4	20,055.3	20,284.0 (67.5)	−228.7 (67.5)	−1.1
2009 Q1	19,284.4	19,971.3 (120.1)	−686.9 (120.1)	−3.4
2009 Q2	19,154.2	19,942.5 (154.1)	−788.3 (154.1)	−3.9
2009 Q3	19,098.4	19,763.6 (165.9)	−665.2 (165.9)	−3.4
2009 Q4	18,890.4	19,425.0 (165.8)	−534.6 (165.8)	−2.6
2010 Q1	18,652.9	19,073.0 (154.4)	−420.1 (154.4)	−2.2
2010 Q2	18,751.1	19,079.3 (121.5)	−328.2 (121.5)	−1.7
2010 Q3	18,819.0	18,943.6 (68.7)	−124.6 (68.7)	−0.7

Source: Authors' own work



Source: Authors' own work

Figure 4. Time series of employed workers (thick line) and counterfactual estimation (thin line)

The largest deviation of the series in relation to the counterfactual scenario occurs in 2009 Q3, with an estimated deficit in active population of 174 thousand people, which implies a 0.8% reduction with respect to the counterfactual estimate.

Figure 5 and Table 8 show the main results obtained for the COVID/Ukraine crisis. Figure 5 shows that the active population fell significantly below the forecast even in 2020 Q1, reaching an estimated deficit of 1.4 million people in 2020 Q2. As seen in Figure 2, this drop is partly due to a statistical effect, because many people in ERTE were classified as inactive because they did not meet the condition of active job search that the EPA methodology requires. According to Figure 2, this amounted to 0.5% of working age population, roughly 200 thousand people.

From mid-2020 onwards, active population recovers but did not reach the counterfactual value in the sample period, so the estimate for current deficit is 256 thousand people.

4. Conclusions

In the last 20 years, the world suffered two major economic drawbacks: the 2008 crisis and the COVID/Ukraine recession. This paper quantifies the impact of both crises on employment in Spain. To this end, we estimate counterfactual scenarios for the fundamental quarterly series of unemployed, employed and active population.

We estimate the impact of the 2008 crisis by incorporating qualitative 0–1 variables designed for this purpose into an intervention model (Box and Tiao, 1975). The coefficients associated with these variables can be interpreted as changes in the level of the endogenous

Table 6.
Counterfactual analysis of the 2020 crisis effect on employed

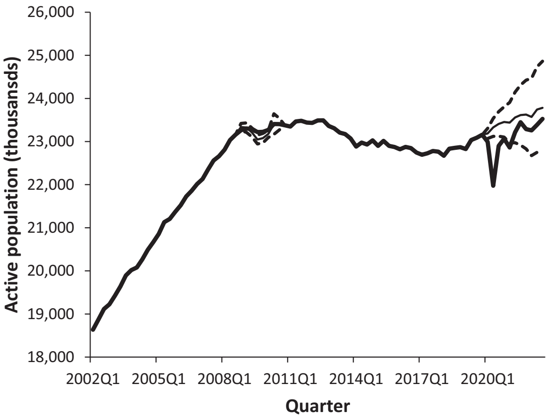
Quarter	Employed	Counterfactual	Difference	Difference/Counterfactual (%)
2020 Q1	19,681.3	19,938.5 (87.0)	−257.2 (87.0)	−1.3
2020 Q2	18,607.2	20,366.3 (179.3)	−1759.1 (179.3)	−8.6
2020 Q3	19,176.9	20,548.5 (278.2)	−1371.6 (278.2)	−6.7
2020 Q4	19,344.3	20,630.8 (379.2)	−1286.5 (379.2)	−6.2
2021 Q1	19,206,8	20,594.1 (505.9)	−1387.3 (505.9)	−6.7
2021 Q2	19,671.7	21,015.2 (643.1)	−1343.5 (643.1)	−6.4
2021 Q3	20,031.0	21,192.1 (783.0)	−1161.1 (783.0)	5.5
2021 Q4	20,184.9	21,270.1 (921.9)	−1085.2 (921.9)	−5.0
2022 Q1	20,084.7	21,230.0 (1,078.7)	−1145.3 (1,078.7)	−5.4
2022 Q2	20,468.0	21,648.4 (1,243.6)	−1180.4 (1,243.6)	−5.5
2022 Q3	20,545.7	21,823.2 (1,410.7)	−1277.5 (1,410.7)	−5.9

Source: Authors' own work

Table 7.
Counterfactual analysis of the 2008 crisis effect on active population

Quarter	Active population	Counterfactual	Difference	Difference/Counterfactual (%)
2008 Q4	23,262.1	23,187.4 (42.5)	74.7 (42.5)	0.3
2009 Q1	23,303.6	23,283.0 (55.7)	20.6 (55.7)	0.1
2009 Q2	23,293.8	23,376.5 (52.3)	−82.7 (52.3)	−0.4
2009 Q3	23,219.8	23,392.9 (52.3)	−173.1 (52.3)	−0.8
2009 Q4	23,225.4	23,371.4 (55.8)	−146.0 (55.8)	−0.6
2010 Q1	23,270.5	23,362.7 (42.9)	−92.2 (42.9)	−0.4

Source: Authors' own work



Source: Authors' own work

Figure 5. Time series of active population (thick line) and counterfactual estimation (thin line)

Quarter	Active population	Counterfactual	Difference	Difference/Counterfactual (%)
2020 Q1	22,994.2	23,188.1 (60.3)	−193.9 (60.3)	−0.9
2020 Q2	21,975.2	23,327.5 (106.1)	−1352.3 (106.1)	−5.8
2020 Q3	22,899.8	23,408.3 (145.3)	−508.5 (145.3)	−2.2
2020 Q4	23,064.1	23,453.5 (179.1)	−389.4 (179.1)	−1.7
2021 Q1	22,860.7	23,438.7 (238.6)	−578.0 (238.6)	−3.1
2021 Q2	23,215.5	23,559.7 (299.6)	−344.2 (299.6)	−1.5
2021 Q3	23,447.7	23,614.0 (355.7)	−166.3 (355.7)	−0.8
2021 Q4	23,288.8	23,626.5 (406.4)	−337.7 (406.4)	−1.5
2022 Q1	23,259.4	23,570.2 (457.6)	−310.8 (457.6)	−1.3
2022 Q2	23,387.4	23,741.6 (506.2)	−354.2 (506.2)	−1.5
2022 Q3	23,525.9	23,781.8 (551.6)	−255.9 (551.6)	−1.1

Source: Authors' own work

Table 8. Counterfactual analysis of the 2020 crisis effect on active population

variable associated with the modeled event and allow, therefore, to estimate in-sample counterfactual values for the series of interest.

Since the COVID/Ukraine crisis is still unfolding, in this case we:

- truncated the modeled sample up to 2019 Q4; and
- calculated out-of-sample forecasts from 2020 to 2022.

The results from both strategies are comparable. In each case we estimate counterfactual series under a "no crisis" scenario, with the corresponding standard errors. Comparing these estimates with the observed values provides clear and rigorous metrics on the impact of both recessions on Spanish employment.

From the methodological point of view, the originality of this work in comparison with its precedents (see subsection 2.3) is precisely the joint, rigorous and efficient treatment of past and present crises in a single econometric and conceptual framework.

The results obtained for the 2008 crisis indicate that:

- In the case of the unemployed and employed, it generated significant deviations between the observed values and the counterfactual path, from 2008 Q4 to 2010 Q3.
- The significant effects on active population were moderate, as they are limited to the period from the 2009 Q2 to 2010 Q1.
- The largest impact on unemployed and employed took place in the first two quarters of 2009, with an estimated excess unemployment of 738 and 712 thousand people, respectively; and employment deficit of 687 and 788 thousand people, respectively.

On the other hand, the estimated impact for the post-2020 crisis was more abrupt and severe. Consequently:

- There are significant effects on employed and active population already in 2020 Q1, while the effect on unemployment was not formally significant. Therefore, the first effects of the crisis were already felt before the lockdown.
- The estimated excess in unemployed escalated until a peak value of 870 thousand people in 2021 Q2. On the other hand, the employment deficit has been above one million people, from 2020 Q2 until the end of the sample. The largest deviation occurred in the 2021 Q1, with an employment deficit close to 1.4 million people.
- To understand these estimates, one should consider that, at the beginning of the crisis, a large part of the employed population entered in ERTE. This eventually led to layoffs or longer than expected ERTE extensions, accompanied by a decrease in wages. The employed people in ERTE, became unemployed when the suspension of employment lasted more than three months and received less than 50% of the salary. Our analysis, based in the microdata collected during the original surveys, indicates that people in ERTE peaked in 2020 Q2 (4.7% of working age population, around 1.9 million) and that most of them (around 85%) were classified as employed. An interesting point here is that, as these people was working less hours and receiving a lower salary, the relationship between employment and output or consumer spending was distorted by ERTEs.
- Compared to the 2008 crisis, the pandemic had a greater impact on active population. This happens partially because, during lockdown, people could not be actively looking for employment, so they were classified as inactive. Accordingly, in 2020 Q2, when lockdown is decreed, there was a deficit in active population around 1.4 million people.
- Finally, two years after the beginning of the pandemic, the convergence between the observed paths and their corresponding counterfactual values was progressing very slowly and the Ukraine war ended this timid recovery.

The methodology used here can be applied to other macroeconomic variables, such as inflation, GDP or production indicators, for example. It also suggests different methodological extensions. The ones that look more promising to us are the following.

First, in this work we used univariate methods to model the analyzed series, but the same analysis could have been done by modeling simultaneously the three variables (unemployed, employed and active population). This would result in a more complex, but potentially more accurate model.

Second, the EPA series are linked by a static restriction, as the active population at time t is equal to the sum of employed and unemployed people in the same period. It would be interesting to investigate how to implement this restriction in the analysis. This problem has already been discussed and solved by Guerrero and Peña (2000) for out-of-sample forecasts, such as those we have used to analyze the 2020 crisis. However, we are not aware that it has been addressed for in-sample estimates, such as those that we calculated for the 2008 crisis.

Third, estimation of counterfactual series could be addressed by missing value techniques (Gómez *et al.*, 1999) using state space methods, see Casals *et al.* (2016). The analytic strategy would consist of:

- recoding the series by marking the observations corresponding to crisis periods as missing values;
- estimating the corresponding models by maximum likelihood using the Kalman (1960) filter; and
- interpolating the absent values using an algorithm known as fixed interval *smoother* (Casals *et al.*, 2016, Chapter 4).

These interpolated values and their corresponding standard errors would be comparable to the counterfactual estimates that we have shown in this paper.

The fundamental advantages of this strategy are that:

- it is computationally more efficient, because it does not require estimating the parameters associated with the intervention variables;
- it is easier to implement in software, because it does not distinguish between the calculation of interpolations and out-of-sample forecasts, so that
- the treatment of past and present crises is unified. On the other hand, this procedure is more complex and requires specialized software or programming skills.

Notes

1. ERTE is an acronym for: "Expediente de Regulación Temporal de Empleo," meaning a temporary suspension of employment, where the worker receives a subsidy proportional to the wage.
2. EPA is an acronym for the Spanish "Encuesta de Población Activa," meaning "Labor Force Survey."
3. In the quantitative literature, this type of analysis is also known as "interrupted time series." We will use both terms interchangeably.
4. An equivalent method would consist in fitting an intervention model for all the sample, with an impulse-type dummy variable for the eight post-crisis quarters. This approach, however, is not efficient since it adds eight parameters to the econometric model. As is known, the maximum likelihood estimation methods are fragile and expensive when applied to models with too many parameters, so we chose to address the analysis as an out-of-sample forecasting problem.
5. In comparison with their alternatives, ARIMA models are adequate for our analysis because they can capture the seasonality and accommodate intervention variables to capture the exogenous shocks affecting the EPA series. On the other hand, they are implemented by many econometric software packages, so our results can be easily replicated or applied to other time series.
6. This result is consistent with the corresponding Akaike (1974) and Schwarz (1978) criteria which, for brevity, were omitted in Tables 1 and 2.
7. We maintained in the active population model the nonsignificant coefficients corresponding to 2008 Q4, 2009 Q1 and 2009 Q2 to show the transition that occurs since an initial insignificant

increase in the active population in the first two quarters, perhaps due to the initial entry into the labor market of people who previously did not need to work, until the beginning of the fall in the number of assets, which began timidly in 2009 Q2.

8. www.ine.es/dyngs/INEbase/es/operacion.htm?c=Estadistica_C&cid=1254736176918&menu=resultados&idp=1254735976595#!tabs-1254736030639
9. According to the calculations in Figure 2, 1.6 million people were in ERTE (furlough), from which 1.4 million were working fewer hours because of technical or economic reasons, while still recorded as employed. Note that in 2020 Q2 the EPA registered a reduction of around one million employed but only an increase of 55 thousand unemployed, meaning that many workers who lost their jobs were classified as out of the labor force. Certainly, this was their only possibility as they could not seek for a job during the lockdown. Figures show that it is in 2020 Q3 when the labor force recovers almost fully, and only half of those who had lost their jobs returned to participate in the labor force as employees. We thank a referee for drawing attention to this point.

References

Abadie, A. and Gardeazábal, J. (2003), "The economic costs of conflict: a case study of the Basque Country", *American Economic Review*, Vol. 93 No. 1, pp. 112-132.

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*, Vol. 105 No. 490, pp. 493-505.

Abadie, A.A., Diamond. and J., Hainmueller. (2015), "Comparative politics and the synthetic control method", *American Journal of Political Science*, Vol. 59 No. 2, pp. 495-510.

Akaike, H. (1974), "A new look at the statistical model identification", *IEEE Transactions on Automatic Control*, Vol. AC-19 No. 6, pp. 716-723.

Box, G.G., Jenkins, G., Reinsel, C. and Ljung, G.M. (2015), "Time series analysis: forecasting and control", Wiley Series in Probability and Statistics.

Box, G.E.P. and Cox, D. (1964), "An analysis of transformations", *Journal of the Royal Statistical Society, Series B*, Vol. 26 No. 2, pp. 211-243.

Box, G.E.P. and Tiao, G.C. (1975), "Intervention analysis with applications to economic and environmental problems", *Journal of the American Statistical Association*, Vol. 70 No. 349, pp. 70-79.

Casals, J., Garcia-Hiernaux, A. and Jerez, M. (2012), "From general state-space to VARMAX models", *Mathematics and Computers in Simulation*, Vol. 82 No. 5, pp. 924-936.

Casals, J., García-Hiernaux, A., Jerez, M., Sotoca, S. and Trindade, A. (2016), "State-space methods for time series analysis: theory, applications and software", Chapman-Hall/CRC Press.

Cho, S.J. and Winters, J.V. (2020), "The distributional impacts of early employment losses from COVID-19", IZA DP Working papers. No. 13266.

Chudik, A.K., Mohaddes, K., Mohaddes, H., Pesaran, M., Raissi, M. and Rebucci, A. (2020), "A counterfactual economic analysis of Covid-19 using a threshold augmented multi-country model", *Journal of International Money and Finance*, Vol. 119, p. 102477.

Doornik, J.A. and Hansen, H. (2008), "An omnibus test for univariate and multivariate normality", *Oxford Bulletin of Economics and Statistics*, Vol. 70 No. 6, pp. 927-939.

Engle, R.F. (1982), "Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation", *Econometrica*, Vol. 50 No. 4, pp. 987-1007.

Gallant, J., Kroft, K., Lange, F. and Notowidigdo, M.J. (2020), "Temporary unemployment and labor market dynamics during the COVID-19 recession", National Bureau of Economic Research, No. w27924.

Gómez, V., Maravall, A. and Peña, D. (1999), "Missing observations in ARIMA models: skipping approach versus additive outlier approach", *Journal of Econometrics*, Vol. 88 No. 2, pp. 341-363.

Guerrero, V.M. and Peña, D. (2000), "Linear combination of restrictions and forecasts in time series analysis", *Journal of Forecasting*, Vol. 19 No. 2, pp. 103-122.

Hannan, E. and Quinn, B. (1979), "The determination of the order of an autoregression", *Journal of the Royal Statistical Society, Series B*, Vol. 41 No. 2, pp. 713-723.

Harvey, A.C. and Durbin, J. (1986), "The effects of seat belt legislation on British road casualties: a case study in structural time series modelling", *Journal of the Royal Statistical Society, Series A*, Vol. 149 No. 3, pp. 187-227.

Kalman, R.E. (1960), "A new approach to linear filtering and prediction problems", *Journal of Basic Engineering*, Vol. 82 No. 1, pp. 35-45.

Lambovska, M., Sardinha, B. and, Belas, J. Jr (2021), "Impact of the COVID-19 pandemic on youth unemployment in the European union", *Ekonomicko-Manazerske Spektrum*, Vol. 15 No. 1, pp. 55-63.

Ljung, G.M. and Box, G.E.P. (1978), "On a measure of lack of fit in time series models", *Biometrika*, Vol. 65 No. 2, pp. 297-303.

McDowall, D. and McCleary, R. (2019), *Interrupted Time Series Analysis*, Oxford University press, Oxford.

O'Donoghue, C.D., Sologon, I., Kyzyma, I. and McHale, J. (2020), "Modelling the distributional impact of the COVID-19 crisis", *Fiscal Studies*, Vol. 41 No. 2, pp. 321-336.

Perles-Ribes, J.A., Ramón-Rodríguez, A.B., Jesús-Such-Devesa, M. and Aranda-Cuéllar, P. (2021), "The immediate impact of Covid19 on tourism employment in Spain: debunking the myth of job precariousness?", *Tourism Planning and Development*, Vol. 20, pp. 1-11, doi: 10.1080/21568316.2021.1886163.

Pinilla, J.O., Barber, L., Vallejo-Torres, S., Rodríguez-Mireles, B., López-Valcárcel, L. and Serra-Majem, L. (2021), "The economic impact of the SARS-COV-2 (COVID-19) pandemic in Spain", *International Journal of Environmental Research and Public Health*, Vol. 18 No. 9, p. 4708.

Schwarz, G. (1978), "Estimating the dimension of a model", *Annals of Statistics*, Vol. 6 No. 2, pp. 461-464.

Svabova, L.E., Tesarova, M., Durica, M. and Strakova, L. (2021), "Evaluation of the impacts of the COVID-19 pandemic on the development of the unemployment rate in Slovakia: counterfactual before-after comparison", *Equilibrium. Quarterly Journal of Economics and Economic Policy*, Vol. 16 No. 2, pp. 261-284.

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