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Poverty and the business cycle: A regional panel data analysis for Spain using alternative measures of unemployment

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Abstract Conventional wisdom predicts that changes in the aggregate unemployment rate may significantly affect a country's income distribution and, consequently, have a relevant impact on the evolution of its poverty rate. However, the relationship between labour macroeconomic indicators and poverty seems to have become weaker recently. Using panel data on unemployment and poverty for Spanish regions, we estimate a system GMM model to model this relationship using alternative measures of the unemployment rate. We also test the hypothesis of asymmetric effects of the business cycle on the share of poor individuals in the population. Our results show that unemployment has a positive impact on severe

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poverty, while inflation has a negative effect. We also highlight the extent to which results differ when alternative intra-household unemployment distribution-sensitive measures are considered. Regarding the existence of asymmetric business cycle effects on severe poverty, our results show that despite the fact that the Great Recession has had a strong and positive effect on severe poverty, the effects of expansions and recessions on poverty are not significantly different.

Keywords Poverty · Unemployment · System GMM model · Spain

1 Introduction

Changes in macroeconomic conditions can have a substantial effect on the economic circumstances of low-income households. Conventional wisdom predicts that changes in unemployment, inflation and, in more general terms, economic growth can produce significant changes in a country's income distribution. Economic downturns are associated with increases in inequality and poverty, while periods of strong aggregate growth are expected to contribute to the reduction of the share of poor individuals in the total population. However, in the years before the Great Recession (i.e., from the late nineties until 2008), many OECD countries experienced strong, rapid economic expansions (only briefly interrupted by mild recessions), while their poverty and income inequality indicators were rather stable or, in some cases, even followed a rising trend.

The idea that economic growth does not always help the poor has generated substantial debate in the academic literature. The assumption that economic growth is unlikely to be an effective antipoverty tool has affected policies and divided analysts and policymakers. As a result, a large number of research papers have examined the extent to which alternative indicators of the business cycle, different from aggregate economic growth, have a significant impact on the income distribution. Since the ground-breaking research of Blank and Blinder (1986) and Cutler and Katz (1991), a substantial number of empirical studies have addressed the issue of the relationship between macroeconomic indicators and the poverty rate. For many years, these models worked reasonably well in predicting poverty based on the unemployment rate and inflation.

Since the mid-eighties, however, these models became less accurate in predicting changes in the economic security of low-income households (Meyer and Sullivan 2011). A major criticism of these methods has been that they do not adequately address the effects of relevant issues on the relationship between the business cycle and poverty. In some countries, the decline in real wages among less skilled workers may have had a relevant impact on this relationship. In other countries, the predicting capacity of these models has been questioned due to the limits of the aggregate unemployment rate as an indicator of the most relevant employment conditions for low-income households. The proportion of workless households or the intra-household distribution of unemployment – e.g., concentrated mostly among spouses and other members different from the household head – can be key factors in explaining changes in the poverty rate.

A further limitation of these models is their implicit assumption of a symmetrical response of poverty indicators to both expansions and recessions. In a similar way as the hysteresis hypothesis is usually considered in unemployment analyses, poverty could be less sensitive to employment growth than to increasing unemployment rates. Empirical studies of the impact of unemployment and inflation on the income distribution have not thoroughly addressed this issue, and relatively little is known about possible asymmetries in their relationship.[1]

This paper aims to analyse how the intra-household distribution of unemployment can be more relevant than aggregate unemployment in explaining poverty changes. We also test the hypothesis of asymmetric effects of the business cycle on the share of poor individuals in the population. We use quarterly data from the Spanish Labour Force Survey that provides us with a rather long period of data – from 1987 to 2015 – and a panel of regional poverty and unemployment rates.

There are several reasons why the Spanish case should be of interest for policy makers and analysts. On the one hand, Spain is one of the OECD countries in which business cycle fluctuations are large while expansions or recessions tend to last longer than in other developed countries. In the aftermath of the global economic crisis that started in late 2007, unemployment grew from 8.6 % to 26.0 % in only five years, and the proportion of households where all active members were unemployed boosted from 2.6 % to 10.5 %. On the other hand, the concentration of unemployment in spouses and other members of the household supports the idea of a somewhat less relevant effect of aggregate unemployment on poverty changes compared to other alternative measures of unemployment that are strongly related to its intra-household distribution. Additionally, the variety of regional experiences – with remarkable differences in demographic structures and employment levels across regions – makes the use of panel data on regional poverty and macroeconomic conditions most interesting.

We use a measure of poverty that is rather similar to what one could identify as severe poverty and that implies an absolute notion of the poverty phenomenon, thus making it independent from the mean or the median value of the income or expenditure distribution at each moment in time. This last characteristic helps us to avoid some of the intrinsic limitations of relative poverty measures when analysing poverty over a long period. Poverty rates are calculated as the proportion of households in the population of a particular region at a given moment in time who do not earn any income from labour, benefit from any Social Security transfers (i.e., pensions or other benefits) or receive unemployment insurance or assistance payments.

We analyse the effects of the business cycle on this measure of severe poverty by estimating a dynamic panel data model using a variety of unemployment rates as covariates – aggregate unemployment, the unemployment rate of household heads and the proportion of households where all active member are unemployed over the total number of households in the population. Dynamic panel data models are shown to have important advantages with respect to time series or traditional static techniques given the high persistence of poverty. We use the one-step system generalized method of moments' estimator (Arellano and Bover, 1995, and Blundell and Bond 1998), which allows for the existence of omitted variables, endogeneity and measurement error problems. We test the robustness of the model by comparing the system GMM estimates with the alternative first-differenced GMM method.

Our results show that both unemployment and inflation are significant in explaining the evolution of poverty rates along the business cycle in Spain in the last two decades. In particular, unemployment is found to have a positive impact on severe poverty, while inflation

[1] A notable exception here is Hines et al. (2001).

has a negative one. Among the three different measures of unemployment specified in the model, the aggregate individual rate of unemployment has the lowest effect on poverty. Interestingly, we find that alternative estimation procedures exhibit important differences in estimates, which underlines the importance of using a suitable estimation method. Despite the fact that the Great Recession had a strong and positive effect on severe poverty, our results on the possible asymmetric effects of the business cycle on poverty during this long period appear to suggest that there were no statistically significant differences between recessions and expansions.

The organization of the paper is as follows. In Section 2, we review the literature on macroeconomic conditions and poverty. Section 3 describes the data used in the analysis. Section 4 presents the dynamic panel data (DPD henceforth) poverty model and briefly comments on the system GMM approach. Section 5 estimates the effects of business cycle on poverty and discusses the main results. Finally, Section 6 concludes.

2 Background

The question of the effects of macroeconomic conditions on poverty has been thoroughly discussed in the literature. The idea that poverty will not disappear with unemployment reductions – the backwash thesis – was already tested in the late sixties [Galloway (1965), Aaron (1967), Metcalf (1969), Thurow (1970), Mirer (1973)]. While some estimates were imprecise, the optimistic view about the role of economic growth on poverty reduction was found to be not particularly straightforward. Despite a number of limitations, e.g., aggregate data or sensitivity to the particular functional form chosen for the relationship, these analyses provided a set of new analytical tools and some insights into the potential relationship between unemployment and poverty

The prototypical model of the relationship between the poverty rate and macroeconomic conditions was developed by Blinder and Esaki (1978) using a very basic regression approach. They used OLS to estimate the relationship between the income of different quintiles, unemployment and inflation. These authors did not impose any particular functional form or measure of well-being to explore the effects of inflation as well as unemployment on the income distribution. From their results, a very clear pattern of the incidence of unemployment by income class emerged – the lowest 40 % of families lost the most when unemployment rose – while the picture for inflation, in contrast, was much gloomier.

Blank and Blinder (1986) extended the work of Blinder and Esaki by adding new years of data and some new wrinkles to their specification. They separated inflation into anticipated and unanticipated components using a simple autoregressive model. They also used a simple geometric distribution lag to test for autocorrelation. Their results showed that high unemployment had significant and systematically regressive effects on the distribution of income. Few significant effects were found for inflation. Blank and Blinder (1986) also estimated the effects on poverty, but instead of including a linear time trend – because poverty data display a pronounced time pattern – they considered different economic variables that were meant to explain the reason why this time pattern exists (government transfers divided by GNP and the poverty line divided by mean household income). Cutler and Katz (1991) developed a second extension of the basic model. They forecasted poverty rates using consumption instead of income and a variety of contemporaneous macroeconomic indicators to find striking differences across demographic groups. These methods became increasingly popular. A number of studies have considered the effects of unemployment to forecast poverty. Despite the fact that the bulk of this literature has focused mainly on the US, a number of authors have also addressed the analysis of the relationship between macroeconomic conditions and income inequality in other countries [Nolan (1987), Burgess et al. (2001), Jäntti and Jenkins (2010) using UK data, Björklund (1991) using Swedish data, Farré and Vella (2008) using Spanish data, and Buse (1982) using Canadian data].

More recently, the Great Recession has sparked renewed interest in this brand of research. To simulate the poverty rate based on recent and projected unemployment rates, some authors have used these models [Monea and Sawhill (2009), Smeeding et al. (2011), Meyer and Sullivan (2011), Isaacs (2011)]. Most of them have used estimates of the relationship between the poverty rate and the unemployment rate from Blank (2009).

Collecting and interpreting the empirical findings from this literature allows us to predict poverty when there are changes in unemployment. In general terms, the results are consistent with the hypothesis that unemployment weighs more heavily on the poor than other macroeconomic indicators.[2] High inflation has weak, if any, effects on poverty. However, there are several methodological decisions that still are open questions in this line of research. These include choosing poverty measures, defining the time structure of the macroeconomic effects, using regional or national data, and defining time periods.

2.1 Poverty measure

Regarding the poverty indicator, most studies use the poverty headcount index, which implies that the core of the available empirical evidence provides an assessment of the effects of unemployment on the incidence of poverty but avoids taking into account the relevance of the unemployment rate on the depth of poverty (poverty intensity) or the inequality of incomes between the poor.[3] Furthermore, the bulk of this literature has generally used the U.S. official poverty line to determine poverty incidence, and not many authors have tested the sensitivity of the results to alternative poverty thresholds.[4] In this context, we believe that regarding the relationship between unemployment and poverty, the sensitivity of results to different income deprivation indicators is a research question that has not yet been straightforwardly answered.

Clearly, choosing a rather strict definition of poverty may draw our focus to a concept of poverty that is too extreme. This might result in underestimating the impact on poverty of changes in macroeconomic conditions related to employment, most likely due to the expected weaker links of very low levels of household income to the labour market situation of household members. However, during the last economic recession, one of the main issues that have been raised as being most worrisome in developed countries is the severity of the effect of unemployment on households, excluding them from the labour market

[2] In the case of Spain, the scarce evidence available also indicates that unemployment has a significant effect, but inflation does not seem to have any statistically significant distributional effect (Farré and Vella 2008).

[3] An exception to this is the work by Gundersen and Ziliak (2004). These authors use both the headcount ratio and the squared poverty gap to identify the effect of macroeconomic conditions on the depth of poverty.

[4] Iceland (2003) compares the official US poverty rate to a relative measure. He uses a reference family poverty threshold equal to half the median income of a two-adult, two-child family and a quasi-relative measure that uses a threshold represented by a dollar amount for food, clothing, shelter, and utilities, as well as a small amount for other needs for a family of four, which are then adjusted using an equivalence scale. Blank (2009) uses the official poverty rate in the U.S. and an alternative definition, taking into account both in-kind transfers and taxes before calculating whether or not a family is poor. Meyer and Sullivan (2011) also look beyond official poverty, examining alternative consumption and income (pre-tax money income, after-tax money income, and after-tax money income plus non-cash benefits) poverty.

completely. Over the last two decades, a certain divide has been widening between 'work rich' and 'work poor' households, as first noted by Gregg and Wadsworth (1996). Indeed, the OECD (2001) shows that workless household rates are more highly correlated with working-age poverty rates across countries than individually based unemployment rates while Gregg et al. (2010) emphasize that household joblessness is an important factor in the transmission of intergenerational effects of poverty given that parental income has significant effects on the future welfare of children.

In this setting, the *Europe 2020 strategy* for jobs, sustainable and inclusive growth has a headline target of reducing of poverty that is evaluated by an indicator that considers both lack of income and lack of earnings (i.e., household joblessness or low work intensity). Consequently, this indicator aims to become a measure that is somewhat closer to a "vulnerability" concept. In fact, we believe that the individual perception of poverty risk or income deprivation is most likely to be conditioned by both the lack of income from any source and household members' labour market exclusion. Thus, a measure of the proportion of households that do not earn income from labour and do not receive any Social Security transfers reflects the incidence of the most severe poverty or deprivation (in employment and income) in a given population. Further, our proposal to measure severe poverty is strongly linked to the idea of "disconnected households", which, unfortunately, has seldom been explored in the European context. This makes our study innovative and links our results to those of an emerging literature for the US in which similar strategies are used in attempting to measure the proportion of households in the population that are disconnected from the labour market and the general system of cash benefits (Turner et al., 2006, Blank and Kovak, 2008, Edelman and Holzer, 2013).

2.2 Time structure of the macroeconomic effects

Macroeconomic shocks may have a long-lasting effect on poverty rates. A number of researchers have attempted to measure the extent to which short-term effects differ from long-term ones. The standard assumption is that inequality and poverty measures adjust to macroeconomic conditions only with a lag. Blank and Blinder (1986) introduced a lagged dependent variable into the regression, making this the most usual procedure for a crude control for any dynamic features of the poverty rate trend. Additionally, sometimes the dynamics of the model impose a slightly different specification. For example, Gundersen and Ziliak (2004) used regression-based three-year moving averages of all variables and introduced a change to the lag structure ($t-2$). Other authors have introduced variability in the dynamic effects of unemployment by differentiating cyclical and structural dimensions. Mocan (1999), for instance, decomposes unemployment into its short- and long-run components; results show that while cyclical unemployment has almost no effect on income poverty, structural unemployment has a significant effect. In general terms, an advantage of a dynamic specification is its ability to distinguish between the short- and the long-run effects of macroeconomic variables on household poverty.

2.3 Regional or national data

Another methodological issue is related to the national or regional nature of the data. Blank and Card (1993) linked regional information on earnings, incomes, and poverty rates for nine areas of the United States to region-specific data on unemployment rates, as well as to the level and dispersion of hourly wages. Differing regional patterns of unemployment and poverty allow the studying of the relationship with far more degrees of freedom than national-level data can provide. Hines et al. (2001) also use nine census divisions in an attempt to avoid the two usual weaknesses of using an aggregate cycle measure: it may pick up the influences of unmeasured aggregate variables and it suffers from a low explanatory power because the number of aggregate cycles is small. Freeman (2001) undertakes a times series analysis that uses national data and a pooled cross-section time series analysis for individual states. Gundersen and Ziliak (2004) also exploited the substantial heterogeneity in poverty and economic activity across states and over time (20-year panel of states). More recently, Meyer and Sullivan (2011) and Isaacs (2011) also examined the relationship between the business cycle and poverty using national and regional data.

With regional data, we have a wider variation in both the independent and dependent variables over time, which should provide more reliable estimates of the effects of labour market factors on poverty. Regional data also allow for the identification of the differentiated effects of state-level policies and can control for other unmeasured factors that affect outcomes in particular regions or in particular years. Regional effects capture any permanent differences in the outcome variable across regions. Finally, year effects capture any aggregate components of the outcome variable that are common across regions.

2.4 Time period

A crucial issue in the analysis of the effects of the business cycle on poverty is the period chosen for the econometric estimates. As we have already mentioned, there is evidence showing that the effects of unemployment on poverty do not hold for each and every period. Haveman and Schwabish (2000) found that in comparison with just analysing the 1970s, if one extends the data to a twenty-year period considering both the 1970s and the 1980s, the correlation between the unemployment rate and the poverty rate diminishes greatly. However, the expected relationship returned again during the nineties. Jäntti and Jenkins (2010) found that for the UK, while macroeconomic effects on inequality were quite large and significant for the full period 1961–1999, no significant effects were found for the 1961–1976 period.

The differential effects of macroeconomic performance on the poverty rate across periods can be tested in different ways. The standard practice is to consider the inclusion of time dummies. Cutler and Katz (1991) introduced a post-1983 time trend (T) to represent post-1983 macroeconomic expansion. These dummies can also address institutional changes. For instance, Jäntti (1994) included an explanatory variable that took the value one from 1981 onwards to accommodate some relevant changes in tax and transfer policies undertaken that year. A slightly different way of accomplishing this is by including interactions between the unemployment rate and a period-specific dummy variable for the periods of interest (Haveman and Schwabish 2000). Blank (2009) and Meyer and Sullivan (2011) also estimated models that allow the relationship between poverty and unemployment to differ by decade. Given that the 1960s differed substantially from ensuing decades in terms of poverty reduction, Freeman (2001) estimated the equations both for the entire 1969-1999 period and a sample excluding observations from the 1960s.

A very relevant issue here is the possibility of testing for the existence of any asymmetric effects of business cycles. As stated by Cutler and Katz (1991), hysteresis effects imply that contractive demand shifts during several years may have long-term effects on the living standards of the poor – outmigration of the middle class, deterioration in social conditions in inner cities or social disintegration in poor neighbourhoods. Hines et al. (2001) tested whether the effect of unemployment differs in expansions and contractions by interacting the variables capturing the cycle with the unemployment rate. Their results show that the effect of a change in the unemployment rate is larger in recessions, also when considering the role of the actual duration of expansions and contractions.

3 Poverty, unemployment and inflation in spain

The data we use to estimate the effects of the business cycle on poverty come from the Spanish Labour Force Survey (1987–2015). This survey is conducted quarterly by the National Institute of Statistics (INE). We take 1987 as the initial date because in that particular year, substantial changes were introduced in the questionnaire. The survey provides homogeneous information for the period considered and covers the resident population in Spain. The sample size of the survey is over 60,000 households, comprising information for a sample of approximately 180,000 individuals. For each survey wave and region, we can calculate a variety of different household-sensitive unemployment rates.

Our measure of poverty, as noted earlier, is an interesting quarterly measure of income deprivation that may be considered a proxy for extreme poverty: the proportion of households who do not earn any income from labour and do not receive any benefit from Social Security transfers (i.e., pensions or other benefits) or from unemployment insurance or assistance payments.[5] Using this measure of poverty implies the assumption of a somewhat restrictive notion of the income deprivation phenomenon given that the poverty threshold is low and, therefore, its evolution might be less sensitive to changes in macroeconomic conditions. However, this more extreme poverty definition helps us to avoid some of the intrinsic limitations of other measures, allowing us to understand the effects of the business cycle, particularly those that fix a poverty threshold relative to the value of mean or median household income.

It is interesting to compare this measure with more traditional relative threshold methodologies in identifying the poor, as it provides information on the ways in which they relate to each other. In Appendix A (online), we provide a detailed discussion about all other possibilities of approaching the measurement of income-based poverty at a regional and national level for Spain. We also highlight the advantages of using our poverty indicator compared to more traditional ones. It is particularly interesting to compare our indicator with the number and characteristics of the households classified as poor using Eurostat's measure of poverty risk in Europe in recent years: any individual living in a household in which equivalent household income is below 60 % of the median equivalent income in a given population is poor.

This methodology has been recurrently used by the European Union in the last decade to compare the risk of poverty in EU countries, and it approaches the idea of an "official" EU poverty measure. It identifies three different groups of households as poor: working poor households (81.7 %), households in which all members are unemployed but are receiving some Social Security transfer (13.5 %) and households that do not earn any income from labour and do not receive any benefit from Social Security transfers or from unemployment insurance or assistance payments (4.8 %). We focus in this last group. Indeed, in terms of poverty incidence, our measure shows very similar results to the method of selecting

[5] These poor households may be receiving benefits from the last safety net in the Spanish social protection system managed by regions and available to some extremely deprived households: Minimum Income Guarantee Benefits. These benefits were effectively received by 190,000 individuals in 2010, and their levels are low.

households in which all members are unemployed and equivalent household income is below a 30 % of median equivalent income in Spain in 2010: 1.5 % of the total households in the population.[6]

Interestingly, our proxy for extreme poverty captures a significantly larger percentage of households that are most vulnerable to changes in household members' labour market conditions (avoiding households without active individuals) and that are found to be, in fact, currently suffering from strong deprivation.[7] In particular, in comparison with other households classified as poor using the Eurostat definition, our measure focuses on households in which the number of active individuals is relatively low (working-age one-member households, lone-parents, etc.) and that have significantly more difficulties in paying their bills or mortgage and in dealing with unexpected expenditures.[8] The percentage of these households that report that they cannot afford to eat meat, chicken or fish three times a week doubles that reported by households classified as poor using the Eurostat definition. Thus, we believe that our measure of poverty is capturing a subgroup of strongly vulnerable households that suffer from severe income deprivation.[9]

Figure 1 illustrates how this poverty rate among Spanish households has changed over the last two and a half decades in the 17 different Spanish regions. Poverty declined particularly rapidly during the economic expansion of the second half of the eighties. Strong economic growth and large increases in social spending have commonly been argued as the determinants of this decreasing trend in poverty. The mild recession that took place between 1992 and 1994 increased poverty rates in many regions after more than a decade of continuous decline.[10] In the following years, when the Spanish economy underwent a long period of expansion, the poverty trend returned to a slight decrease (1995–2007). However, during this second expansion period, it took more than a decade to return to the poverty levels of the early nineties. Furthermore, in recent times, poverty has clearly risen again due to the

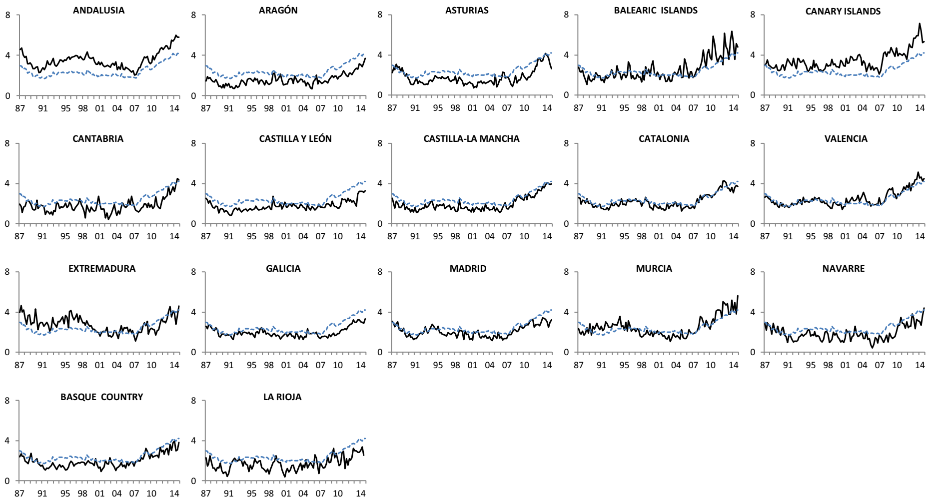
[6] All comparative results with Eurostat poverty measures are calculated by the authors using Spanish EU-SILC microdata (*Encuesta de Condiciones de Vida.* ECV, i.e. the Spanish version of the European Survey of Income and Living Conditions, SILC). The 1.5 % of total households in the population is the equivalent of approximately 265,000 households in 2010. This number is lower than that obtained using the Labour Force Survey data due to the different time span of the information on income in the SILC Survey in comparison with the Labour Force Survey (EPA). The SILC refers to the yearly income, while the EPA refers to quarterly income. The percentage of poor households using a 60 % of median household income poverty threshold is 20.7 % in Spain in 2010. The evolution of our measure in time is quite similar to that of the number of households below a 30 % equivalent income poverty threshold for the years in which both measures can be calculated. A further difference between our measure and that used by Eurostat is that ours is a proportion of households instead of a proportion of individuals.

[7] Households in the other two groups (working poor or all active members unemployed but receiving some Social Security benefits) are also vulnerable to labour market conditions.

[8] Using our measure, up to 30 % of households report a late payment of their mortgage more than twice over the last year, while this percentage falls to approximately 15 % for households with equivalent income below a poverty threshold of 30 % or 60 % of median equivalent income in Spain in 2010. A similar result is obtained when looking at difficulties in "making ends meet": up to 90 % of our households report having difficulties in making ends meet, while for traditionally poor households, this percentage drops to 80 %.

[9] It would be of great interest to contrast our main results with those that could be obtained using a more standard measure of poverty based on a relative income threshold for a long period in a quarterly regional basis. Unfortunately, such a long-term series of regional data on unemployment and income is not available.

[10] Most studies using Family Budget Surveys and standard poverty thresholds – 60 % of median equivalent household income – show a similar pattern (Cantó et al., 2003 and Ayala et al., 2009).



* The continuous line represents the regional LFS poverty measure and the dashed line the national LFS poverty rate.
Source: Authors' calculations using the Spanish Labour Force Survey (*Encuesta de Población Activa*, EPA).

Fig. 1 Poverty rates by regions, 1987–2015*

deep economic downturn that began in the late months of 2007. Indeed, the Great Recession pushed severe poverty back to mid-eighties rates, reaching, in a short recession period of only two years, its historic maximum for the last two decades. At the beginning of 2015, the severe poverty rate was significantly higher than that of the mid-eighties and more than twice as high as the rate registered just before the outbreak of the crisis.

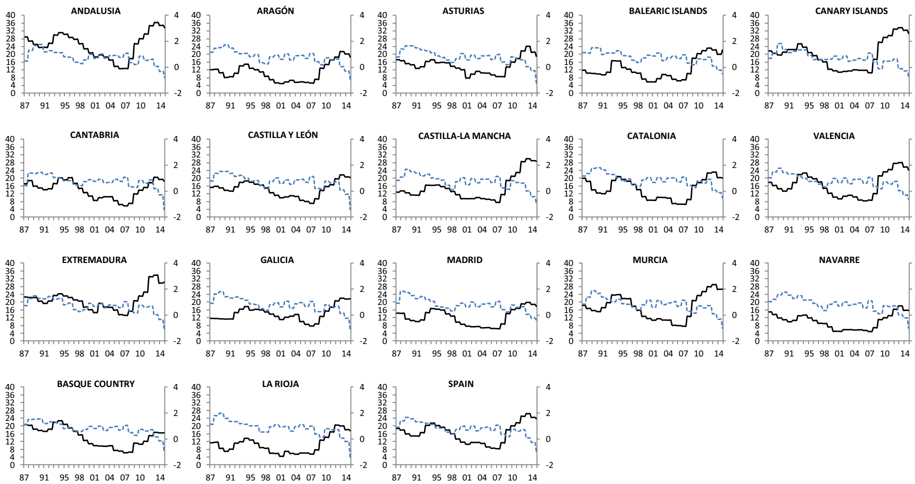
The potential effects of the business cycle on the observed poverty trend raise numerous interesting questions. Surely, given that we use a regional panel dataset, one of the questions we can pose is to what extent these trends are uniformly held across Spanish regions. Although, in the long run, a moderate convergence process has been registered, differences still persist among Spanish regions in terms of inequality and poverty (Ayala et al. 2011) given that an accelerated process of territorial decentralization has given Spanish regions a certain margin in which to modulate the relationships between economic growth and poverty in their territory. When comparing regional differences in Spain, a few recent papers show that these differences do not seem to be particularly outstanding within OECD countries [Bartsch 2012, Krueger (2012) or Bubbico and Dijkstra (2011)]. However, the currently growing dispersion of unemployment rates, the different demographic structures of the regions or the growing disparity in social policies since the beginning of the crisis could give rise to very different relationships between the business cycle and poverty.

Figure 1 gives general support to the notion that poverty levels drastically differ across the seventeen Spanish regions. The most relevant pattern is the existence of a significant territorial dispersion of the proposed poverty measure. The incidence of poverty in some regions – Extremadura, Andalusia or Canary Islands – is twice that of other regions with the lowest rates. The time profile of poverty changes is also somewhat different across regions, although poverty presents two different trends before and after 2007 in almost all regions. For this reason, we will check for the existence of a structural break due to the Great Recession in Section 5.

The key question in our analysis is how these changes are related to the business cycle. Macroeconomic conditions are represented by the evolution of unemployment and prices between 1987 and 2015 at a regional level. The Labour Force Survey provides us with quarterly information on regional unemployment rates while inflation data are taken from monthly variation of the Consumer Price Index (CPI) by regions.

Figure 2 presents long-term trends of both macroeconomic indicators. As expected, both variables show the opposite trend in time, with inflation increasing (falling) when unemployment falls (increases). However, this behaviour does not hold during the whole period in most regions. In the 1993–98 period, unemployment and prices simultaneously fell. This was due to the necessary adjustment of prices to meet the European Monetary Union criteria for inflation. In the first stage of the economic crisis, however, inflation followed a growing trend together with the rise of unemployment, suggesting a period of some stagflation that could be linked to the low interest rates in the Eurozone and the pop of the speculative housing market bubble in 2008. In the current decade, inflation has decreased while unemployment has increased by a further 4 percentage points.

Changes in unemployment rates confirm well-defined trends of macroeconomic conditions in the Spanish economy. After a pronounced reduction in unemployment in the late eighties, rates grew sharply at the beginning of the nineties – from approximately 15 % in 1991 to approximately 22 % in 1994 throughout the whole country. However, unemployment declined rapidly over the following years in line with economic recovery. Before the Great Recession started, Spain had the highest employment growth in the EU. Aggregate individual unemployment rates reached their lowest value in two decades in 2007 at 8 %. These employment gains were eroded again very quickly. During the last economic downturn, unemployment rates dramatically increased – moving from rates of approximately 8 % in 2007 to 26 % in 2012 and 24 % in 2015. Plotting unemployment changes in all regions, one can conclude that both their levels and, even if partially, their trends appear to be different. For example, Balearic and Canary Islands show a much more marked pro-cyclical pattern than other regions. Indeed, unemployment rates in other regions rose slower than the



* The continuous line represents the unemployment rate (left scale) and the dashed line the inflation rate (right scale).
Source: Authors' calculations using the Spanish Labour Force Survey (*Encuesta de Población Activa*, EPA).

Fig. 2 Unemployment and Inflation by regions, 1987–2015, annual data* average. In particular, at the beginning of the recession, aggregate individual unemployment rose only slightly in some regions, such as the Basque Country.

Two different questions arise regarding the interpretation of our estimates on the effects of unemployment on poverty. First, the impact of unemployment on poverty could be dramatically different across regions given the large regional differences in income growth and unemployment during our sample period. These regional differences reinforce the relevance of panel data analysis in estimating more precisely the relationship between unemployment and poverty.[11] Further, our modelling strategy allows for unobserved fixed effects to be specified in the model.

A second important issue in the analysis is the validity of the aggregate unemployment rate as the key variable for the relationship between macroeconomic conditions and poverty. In countries where unemployment is unevenly distributed among the members of the household, alternative specifications of family unemployment rates can yield more precise estimates. Throughout the 1980s, despite the outsized growth of unemployment, inequality and poverty rates fell in Spain. The main factor commonly noted to explain this apparent contradiction is the crucial protective function that the Spanish family provided, mainly because unemployment most intensely affected other members of the family rather than the household head, mostly spouses and siblings. Therefore, other measures of unemployment taking into account this singular intra-household unemployment distribution might have a more direct effect on the poverty rate. For instance, household heads' unemployment rates or the proportion of households in which all active members are unemployed are measures that incorporate intra-household unemployment distribution. In practice, one of the main contributions of this paper is testing whether these indicators have stronger effects on poverty than standard measures of unemployment.

Figure 3 illustrates the changes in various unemployment measures over the long term. Two things are notable. One is that, in general, these stricter definitions of unemployment have a much lower incidence among Spanish households than the overall unemployment rate. Second, the three indicators present remarkable differences in the Great Recession compared to events in previous periods of economic downturn.

Focusing on the results for the household heads' unemployment rate and in contrast to what happened in the short contraction of the early 1990s, we can easily see that this rate has been growing even more sharply than aggregate individual unemployment recently. As mentioned earlier, in previous recessions, massive youth unemployment was partially offset by the employment of household heads. In the economic downturn of the late 2000s, this rate grew at a higher pace than in any other period, reaching its historical maximum in 2013. While in 1994 – when the aggregate unemployment rate reached its highest value – household heads' unemployment rate was about half of the aggregate overall unemployment, during the Great Recession, that proportion increased up to 85 %. A similar behaviour can also be observed for the proportion of workless households in the population. While

[11] To complement the analysis, we have decomposed the dispersion (measured by the general entropy index for $\alpha = 2$) of poverty, unemployment and inflation into the between-groups and within-groups components. If the regional dimension is important for these variables, the magnitude of the between-groups component should be significant. We find that the between-groups component for all variables other than inflation is important because its share on total dispersion is greater than 30 %. Hence, we can state that the regional dimension is relevant to understanding the evolution of poverty throughout the business cycle. These results can be obtained from the authors on request.

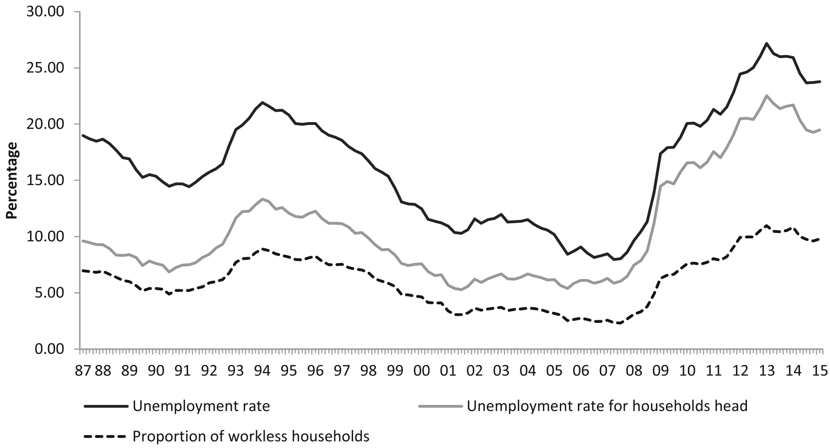


Fig. 3 Alternative unemployment rates, 1987–2015

this type of household constituted 2.5 % of the total population in 2007, at the beginning of 2015, this group was more than four times larger. To the extent that these alternative unemployment measures may have a more direct impact on extreme forms of poverty, it seems reasonable to consider them adequate explanatory variables in the specification of our models.

Finally, we should make reference to the main unemployment benefit reforms undertaken in Spain during the 1987–2015 period.[12] Because our definition of poverty comprises households that do not receive income from unemployment benefits, any significant change in unemployment protection legislation might produce shifts in poverty trends. Among the numerous labour market reforms implemented in Spain during the last decades, only a few have modified the requirements for receiving an unemployment subsidy or the benefit level.[13] Regarding these, we find the following relevant reforms. In 1989, unemployment assistance benefit eligibility was extended to all the unemployed older than 55 years who were classified as long-term unemployed. In 1992, in contrast, eligibility was significantly restricted by raising the required minimum period of social security contributions from six months to one year. In 2002, unemployment subsidies were reformed, making them more strongly related to previous workers' contributions. In the next section, we show that only the first and the third of these labour market reforms had significant effects on poverty. The 1989 reform helped in reducing poverty, while the 2002 reform worsened its incidence.

[12] Benefit rules do not differ between regions.

[13] The main Spanish Unemployment Benefit (UB) plan is a compulsory social insurance scheme for employees able and available for work but have lost their job. To be entitled to receive the benefits, the worker must have paid the required period of contributions. A non-contributory scheme, Unemployment Assistance (UA), is also in place in case the worker exhausts UB or is not entitled to receive contributory benefits. This is a means-tested benefit that is conditional on family unit income being below an income test, being over 45 years of age or having dependents.

4 A dynamic panel data model for poverty changes

Based on the different methodological decisions reviewed in previous sections, in this paper we have chosen to use a measure of severe poverty and a variety of alternative definitions of unemployment to test the relationship between the business cycle and poverty. The availability of regional data allows us to consider panel data analysis in our estimation strategy. Regional data allows for a wider variation in both the independent and dependent variables over time, which should provide more reliable estimates of the effects of unemployment on poverty. Regional data can also control for other unmeasured factors that affect outcomes and that are particular features of some regions or years.

The standard regression approach to the relationship between the business cycle and poverty has been Ordinary Least Squares (OLS). In their pioneering work, Blinder and Esaki (1978) stated that more sophisticated techniques did not seem to be called for. First, they believed that there was no reason to expect any important reverse causation from the income distribution on unemployment or inflation. Second, they argued that heteroskedasticity would not normally be expected in a regression in which none of the variables (apart from time itself) shows much of a time trend. Some authors have challenged this view using alternative estimation strategies. Jäntti (1994), for instance, applied a Generalized Least Squares (GLS) estimation to analyse the effects of unemployment and inflation on quintile shares of family income in the U.S. According to him, joint cross-equation tests are more appropriate because quintile group shares are jointly determined. GLS is generally more efficient for gauging the validity of the model specification because coherent inference can only be drawn using the full variance-covariance matrix. Nevertheless, most studies taking a poverty headcount measure as a dependent variable use standard OLS or weighted OLS (Gundersen and Ziliak 2004).

The growing availability of regional data has allowed development of panel data analysis in this field. These panel data models have allowed for a better control of unmeasured factors that affect outcomes in particular regions or years. However, there still are many open questions that could be addressed using regional panels. The high persistence of poverty, for instance, raises some doubts about the most convenient panel data method.

Given the importance of non-stationarity in generating spurious regressions (Parker 2000) and recent developments in panel data cointegration analysis, we should provide a discussion on the most convenient method of estimation by studying the stationarity and cointegration of the time series in our database. In principle, variables that are bounded in the unit interval do not possess a unit root because they cannot have an infinite variance (see Jäntti and Jenkins, 2010). However, it is possible that the distribution has a stochastic trend at other moments such as at the mean or kurtosis (White and Granger 2010). Thus, a variable that is a function of some income distribution may exhibit such high levels of persistence that it is better approximated by an I(1) nonstationary process (Malinen 2013a). For this reason, despite the fact that the poverty variable and the unemployment rates are bounded by the unit interval, we test for possible unit roots. To study the stationarity of all the time series, we run the traditional Im-Pesaran-Shin (IPS) panel unit-root test (Im et al. 2003), which assumes cross-section independence, and the second-generation test by Pesaran (2007), which controls for the possible bias of cross-sectional correlation. The null hypothesis is that each individual time series contains a unit root against the alternative

Table 1 The Im-Pesaran-Shin and Pesaran panel-data unit-root tests

	Im-pesaran-shin test				Pesaran Test			
	without trend		with trend		without trend		with trend	
Variable	Statistic	p-value	Statistic	p-value	Statistic	p-value	Statistic	p-value
Poverty	−12.943	0.000	−16.359	0.000	−15.907	0.000	−16.511	0.000
Aggregate unemployment rate	−2.847	0.002	−2.449	0.007	−4.815	0.000	−5.939	0.000
Household head's unemployment rate	−4.461	0.000	−4.381	0.000	−10.351	0.000	−10.559	0.000
Households with all active members unempl.	−2.767	0.003	−4.087	0.000	−7.212	0.000	−10.302	0.000
Inflation	−19.608	0.000	−18.977	0.000	−13.204	0.000	−12.462	0.000

Ho: All panels contain unit roots Number of panels = 17 Ha: Some panels are stationary Number of periods = 112 Cross-sectional means removed Lags average chosen by BIC

that at least one time series is stationary.[14] For the IPS test, cross-sectional means are removed to mitigate potential cross-sectional dependence. For both tests, we consider the equation with and without a linear trend, and the lag structure is such that the Bayesian Information Criterion for the regression is minimized. The results for each variable in the model are shown in Table 1. We clearly observe that the unit-root hypothesis is rejected for all variables regardless of the unit-root test under consideration.

To analyse the effects of unemployment and inflation upon severe poverty, we then propose a dynamic panel data (DPD henceforth) model. A DPD approach is shown to have important advantages with respect to time series or traditional static techniques. First, a DPD approach allows us to work with the entire data panel, which ensures that unobserved or omitted fixed effects can be specified to estimate the relevant parameters in the model (Hsiao 2002). Second, the high persistence of poverty requires a dynamic model specification. Third, a dynamic specification highlights the short-term dynamics and whether there is conditional convergence among regions.

Accordingly, severe poverty is explained in our basic model by four-period lagged levels of poverty, unemployment and inflation as follows:

$$P_{it} = \alpha_i + \beta_1 P_{it-4} + \beta_2 U_{it-4} + \beta_3 \pi_{it-4} + \varepsilon_{it} \tag{1}$$

where P_{it} is severe poverty in region i at time t; α_i represents those fixed factors that are time-invariant, inherent to each region and not directly observed or included in the model, such as regional social, geographical and policy characteristics; U_{it} is an unemployment

[14] An advantage of these tests with respect to the traditional Levin-Lin-Chu test (Levin et al. 2002) is that they do not impose the alternative hypothesis that each time series is stationary.

measure in region i at time t; π_{it} is inflation in region i at time t; and finally, ε_{it} encompasses any effects of a random nature that are not considered in the model.[15] We lag not only the dependent variable but also the other explanatory variables (unemployment and inflation) to reduce the potential problem of reverse causation. We take four-period lags for three main reasons. First, there is a necessary period of adjustment to the loss of employment given that other alternative income sources surely accrue to the household during a limited period. After that, if unemployment persists, an entry into poverty is likely to occur. Despite the unclear assumption that this period is precisely a year, we here follow the literature on time series that usually considers 4 lags when dealing with quarterly data. Second, unemployment and, above all, inflation are characterized by important seasonal variations (trading day's effect, Easter holiday effect, Christmas effect, etc.). To eliminate the influence of these intra-year effects in our model we have considered four-period lags. Third, we reduce reverse causation by taking a greater lag (in our case, 4 periods instead of 1).

In addition, we consider three stationary dummies to control for quarterly variations, three dummies to control for the unemployment benefit reforms in 1989, 1992 and 2002 and one dummy that takes the value one from the last quarter of 2007 onwards to address the Great Recession.[16] The identification of the parameters comes from differences in the severity and timing of cycles across regions. All variables are taken for each Spanish region between 1987 and 2015.

The lagged level of severe poverty controls for short-term dynamics and conditional convergence, which is of special interest because regions share common targets and policies. To show this, we rewrite the model in Eq. 1 as follows:

$$\Delta_4 P_{it} = \alpha_i + (\beta_1 - 1)\, P_{it-4} + \beta_2\, U_{it-4} + \beta_3\, \pi_{it-4} + \varepsilon_{it} \tag{2}$$

where $\Delta_4 P_{it} = P_{it} - P_{it-4}$. The interpretation of Eq. 2 depends on the level of β_1. A β_1 smaller than one is consistent with conditional convergence, which means that regions relatively close to their steady-state per capita poverty levels will experience a slowdown in their poverty growth. In this case, fixed effects, unemployment and inflation affect the steady-state poverty level to which region $i$converges. On the other hand, if β_1 is greater than one, there is no convergence effect and all regressors would measure differences in steady-state poverty growth rates. Our results show that β_1 is lower than one in all cases, so there is conditional convergence (see Section 5). A second interpretation of the coefficient on the lagged poverty rate is the ability to distinguish between the short-run – β_2 in Eq. 2 – and long-run effects –β_2/(1 – β_1) in Eq. 2 – of unemployment on poverty. Thus, the larger the parameter of persistence, β_1, is, the longer the influence of unemployment upon the poverty time series. It is the inclusion of the lag of poverty as an explanatory variable that introduces long-term effects into the model (see Gundersen and Ziliak, 2004).

In the absence of suitable external instruments, we could apply the first-differenced generalized method of moments (GMM henceforth) estimator proposed by Arellano and Bond

15 We assume a standard structure for the error component: $E\ [\varepsilon_{it}] = 0$; $E\ [\alpha_i] = 0$; $E\ [\alpha_i \varepsilon_{it}] = 0$; and, $E\ [\varepsilon_{it}\varepsilon_{is}] = 0$, for $i = 1, ..., N$, t =1,..., T and s ? t.

16 We have also checked that our main conclusions do not change if we consider a dummy equal to one (start of the recession) for a later quarter, such as the first quarter of 2008 onwards. In the next section, we present the results only for severe poverty; inflation; unemployment; the labour reforms in 1989, 1992 and 2002; and the structural break due to the Great Recession. Earnings inequality measures and regional public transfers are not included in our analysis because, unfortunately, they are not available in our dataset.

(1991). First differences in the regression equation are taken to remove unobserved time-invariant effects, and then, the levels of the series lagged two or more periods are used as instruments (see Online Appendix C). However, using the model only in first-differences may lead to important finite sample bias problems when variables are highly persistent, which is expected to be the case for variables such as poverty. Moreover, the removal of unobserved time-invariant effects may lead to a spuriously better fit for the data and to a change in the inference drawn from the estimation (Bond et al. 2001; Malinen 2013b). Under these conditions, lagged levels of the variables are only *weak* instruments for subsequent first-differences. To overcome this problem, the system-GMM procedure (Arellano and Bover 1995; Blundell and Bond 1998) adds a set of equations in levels to the first-difference model, where the instruments of the levels are suitable lags of their own first differences.

For all these reasons, we focus on the system-GMM estimator, which allows for omitted variables, endogeneity and measurement error problems. In contrast with the two-step version, the one-step system-GMM estimator has standard errors that are asymptotically robust to heteroskedasticity and have been found to be more reliable for finite sample inference (Blundell and Bond, 1998; Blundell et al., 2000, Bond, 2002, and Windmeijer, 2005).[17] Accordingly, we choose to use the one-step system-GMM estimator.[18] In addition, errors in panel models such as (1) are generally heteroskedastic and, most likely, serially correlated, as some unobservable variables correlated with poverty might persist over time. We correct for these problems by considering panel-robust standard errors.

To discuss the importance of considering this approach, we compare the system-GMM estimates with respect to the first-difference GMM estimation. The assumptions underlying these econometric methods are validated by using the $m1$, $m2$ and Hansen tests. The null of the $m1$ and $m2$ tests is the absence of first- and second-order serial correlation in the disturbances, respectively (Arellano and Bond 1991). Absence of autocorrelation requires that the $m1$ test rejects the null, while the $m2$ does not. Additionally, the Hansen test of over-identifying restrictions is the most commonly used test in assessing the joint validity of the proposed instruments set. This test examines the correlation between the instruments and the regression residuals, where the null hypothesis is the absence of such a correlation.

We assume that the main explanatory variables (inflation and unemployment) and disturbances are correlated so that regressors are endogenous. This is more general than assuming exogenous or predetermined regressors that satisfy more restrictive assumptions. In particular, strictly exogenous ones cannot be correlated with disturbances at any date, while predetermined ones cannot be contemporaneously correlated with disturbances (Bond et al., 2001 and Bond, 2002). Moreover, the omission of other regressors might cause their correlation with disturbances (Baltagi 2008).

[17] There may be computational problems in calculating the two-step estimates and serious estimation errors may arise for the case in which the total number of instruments is large relative to the cross-section dimension of the panel (Arellano and Bond, 1991, and Doran and Schmidt, 2006). Correspondingly, most empirical studies with a relatively small cross-section dimension report results of the one-step GMM estimator. Moreover, Monte Carlo studies have shown that the efficiency gains of the two-step estimator are generally small. It also has the problem of converging to its asymptotic distribution relatively slowly. Hence, in finite samples, its variance-covariance matrix can be seriously biased.

[18] We use the programme *xtabond2* by Roodman (2009b) for Stata.

For the set of level equations, most of the associated moment conditions are mathematically redundant with the instruments of the first-differenced equations. As a result, only one lag is used for each period and instrumental variable. In this paper, we follow this standard treatment for endogenous variables. On the other hand, it is well-known that the first-differenced and system-GMM estimators can generate moment conditions prolifically, with the instrument count quadratic in the time dimension of the panel. This can cause several problems in finite samples, e.g., weakening the Hansen test. Unfortunately, there is little guidance from the literature on how many instruments is too many given that more moment conditions introduce a bias while increasing efficiency (Ruud 2000). The literature suggests that a subset of these moment conditions should be used to take advantage of the trade-off between the reduction in bias and the loss in efficiency. In addition, Roodman's (2009b) suggests that one should keep the number of instruments lower than the number of cross-sectional units (regions). To this end, we collapse the matrix of instruments and restrict the use of lags. The advantage of collapsing the matrix of instruments is that only one instrument for each variable and lag distance is created, rather than one for each time period, variable and lag distance.

5 Results

The results of the model summarized in the previous section using the one-step system-GMM estimator are presented in Table 2. We estimate this basic model using the three possible unemployment measures. As stated earlier, we compare the results with those of the first-difference GMM approach (GMM). Associated with each parameter, the t significance test statistic is also shown. Moreover, standard specification tests for each model and the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) are presented.

According to the estimated results, the parameter estimated for the endogenous variables is always significant, positive and smaller than one. Hence, evidence for conditional convergence is found. Second, the $m1$ and $m2$ tests find first-order but not second-order serial correlation; therefore, there is no autocorrelation. Third, the Hansen test does not reject the adequacy of moment conditions for the system-GMM estimates, but it does for the GMM estimates. As mentioned above, lagged levels of the variables may be only weak instruments when variables are persistent. Here, we find an example of this. Despite the fact that we are using two instruments more with GMM than with system-GMM, the p-value on the Hansen test for the GMM-based estimates is too low. In addition, we observe that regardless of the unemployment variable under consideration, GMM estimations are worse than system-GMM estimations according to both the AIC and the BIC criteria. For these reasons, we focus from this point onwards on the one-step system-GMM estimator computed with heteroskedasticity-consistent asymptotic standard errors.

5.1 The effects of the intra-household distribution of unemployment on poverty

The results for the two indicators representing macroeconomic conditions – lagged inflation and lagged unemployment – are presented in rows 3 and 4 in Table 2. Several points are worth mentioning. In general terms, our results support the contention that cyclical fluctuations have a profound effect on poverty. The overall unemployment rate in the Spanish economy has substantial and significant effects on our measure of poverty. Focusing our attention on the system-GMM estimates, the coefficient is 0.076 in the short-term and 0.093

Table 2 Estimates of the poverty dynamic model

	Unemployment Rate				Household Heads Unemployment Rate				All Active Members Unemployment Rate			
	GMM		System GMM		GMM		System GMM		GMM		System GMM	
Regressors	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*
Poverty lag_4	0.3025***	4.14	0.1794**	2.31	0.3247***	5.40	0.1979**	2.61	0.3207***	4.03	0.2009**	2.84
Inflation lag_4	−0.0288***	−4.94	−0.0258**	−2.64	−0.0243***	−3.99	−0.0264**	−2.72	−0.0261***	−3.84	−0.0258**	−2.78
Unemployment lag_4	0.1019***	3.35	0.0763***	5.07	0.1060***	4.06	0.0827***	6.07	0.2018***	4.08	0.1371***	5.13
Unem. benefit reform 1989	0.1250	1.04	−0.0768	−0.77	−0.0141	−0.15	−0.1625	−1.65	0.1379	1.20	−0.1082	−1.14
Unem. benefit reform 1992	0.1111*	1.76	0.1049*	1.81	−0.0157	−0.17	0.0035	0.05	0.0819	1.16	0.0419	0.69
Unem. benefit reform 2002	0.0496	0.49	0.2634***	3.08	0.0273	0.32	0.1212**	2.48	0.0669	0.70	0.2488***	4.03
Post 2007	0.0123	0.13	0.3980***	4.59	−0.0801	−0.77	0.2376**	2.67	−0.0040	−0.04	0.4506***	6.69
Num. Instruments	16		14		16		14		16		14	
Tests	*Estimates*	*p-value*	*Estimates*	*p-value*	*Estimates*	*p-value*	*Estimates*	*p-value*	*Estimates*	*p-value*	*Estimates*	*p-value*
$m1$ test	−3.23	0.00	−3.27	0.00	−3.14	0.00	−3.19	0.00	−3.30	0.00	−3.31	0.00
$m2$ test	−1.52	0.13	−1.92	0.06	−0.52	0.60	−1.32	0.19	−0.60	0.55	−1.55	0.12
Hansen test	15.16	0.02	4.09	0.25	14.62	0.02	4.67	0.20	12.39	0.05	4.14	0.25
AIC	−2.35	–	−2.40	–	−2.31	–	−2.38	–	−2.29	–	−2.38	–
BIC	−2.32	–	−2.37	–	−2.28	–	−2.35	–	−2.26	–	−2.34	–

Note: We report the GMM and system GMM one-step estimations. To keep the number of instruments lower than the number of cross-sectional units, we collapse the matrix of instruments combined with lag restriction. The null of the ml and m2 test is the absence of first- and second-order serial correlation in the disturbances, respectively. The null of the Hansen test is the adequacy of moment conditions. AIC: Akaike Information Criterion. BIC: Bayesian Information Criterion. Number of regressors: 10 (stationary dummies are not shown); number of cross sections (regions): 17; number of time periods: 112 (1987IIQ-2015IQ). * Significant at 10 %; ** significant at 5 %; *** significant at 1 %.

in the long term. We know from the above analysis that the larger the coefficient of persistence β_1, the longer the influence of unemployment on poverty; therefore, the difference between the short- and long-term effects is not large because the coefficient for the lag of poverty is closer to 0 than to 1.

In contrast to results in other countries, the impact of lagged inflation on poverty is well defined and negative. Previous empirical evidence for Spain shows a more mixed picture. Using counterfactual income distributions, Farré and Vella (2008) found that unemployment increases the lower part of the income distribution but did not find any statistically significant distributional effect for inflation. However, this divergence should be taken cautiously due to differences in methodological approaches, the poverty measure, datasets, and time periods.

One key contribution is to highlight the extent to which results differ when alternative intra-household unemployment distribution-sensitive measures are considered instead of the aggregate unemployment rate. Three issues arise. First, the impact of lagged inflation is negative and similar for the three cases. Second, the coefficients on the household heads' unemployment rate and the proportion of households in which all active members are unemployed are significant and larger than that which results from using the overall unemployment rate instead. Despite the fact that the aggregate overall unemployment rate shows strong and significant effects on severe poverty, the role played by the intra-household distribution of unemployment might modify the estimated impact. Third, the Great Recession has had a strong and positive effect on severe poverty, and its greatest impact is observable when explaining poverty through the proportion of households in which all active members are unemployed. This result implies that the recent economic crisis has not affected all households in the same way. To adequately understand the relationship between the business cycle and poverty it seems, therefore, convenient to introduce these alternative family unemployment rates as explanatory variables.[19]

As previously stated, some specific legislative changes in unemployment protection may have had a significant effect on the poverty indicator. The use of time dummies may help to capture the specific effects of some of the reforms made to unemployment benefits during the period under study. More specifically, three dummies were added to the model to try to catch the effects caused by the implementation of new rules in 1989, 1992 and 2002. We find that only the 2002 reform has a robust effect on the poverty trend; in particular, this reform contributed to an increase severe poverty.

5.2 Asymmetric effects of the business cycle

Thus far, we have estimated the global effect of the business cycle on poverty. As we have already mentioned, the business cycle might have asymmetric effects on poverty given that the effect of unemployment could differ in expansions (*Exp*) and contractions (*Rec*). Hines et al. (2001), for instance, found asymmetrical effects of unemployment in expansions and contractions in the U.S. economy. For employment, working hours, and earnings, the effects of changes in unemployment rates were larger in recessions.

[19] In Figure B.1. in the Online Appendix B, we compare our observed poverty rates with the fitted poverty rates from model I (unemployment rate), model II (households' head unemployment rate) and model III (all active members' unemployment rate). It is easy to see that predictions track the poverty rates at the regional level quite well. Among the three models, predictions based on the model, including "all active members' unemployment rate" as explanatory variable, are the best fit of the actual regional poverty rate.

One common approach to address this issue is to include new temporal variables identifying periods of economic expansions and contractions within the basic model:

$$P_{it} = \alpha_i + \beta_1 P_{it-4} + \beta_2 (U_{it-4} \times Exp_{t-4}) + \beta_3 (U_{it-4} \times Rec_{t-4}) + \beta_4 \pi_{it-4} + \varepsilon_{it} \quad (3)$$

where the dummies *Exp* and *Rec* are constructed from the unemployment rate series on a regional basis.[20] Focusing only on the system-GMM method, we have estimated the above expression for the three measures of unemployment: the aggregate unemployment rate, the household heads' unemployment rate and the proportion of households in which all active members are unemployed. To better capture the asymmetric effects of the business cycle on poverty, we have not included the *Post2007* variable as a regressor because, given that it essentially refers to a recession period, it would reduce the explanatory power of the decomposition of our periods into expansions and recessions. The results are presented in Table 3. In none of the three cases are differences statistically significant (see the p-values for the tests of equal coefficients in Table 3). Thus, we cannot make a general statement on the difference between the impact of unemployment on poverty during recessions and expansions.

Because the results of expansions and recessions might be sensitive to different specifications including temporal effects for unemployment protection reforms, in Table 3, we also present results for alternative specifications excluding the covariates representing these reforms. Although there are more marked differences in the effects of unemployment changes in recessions and expansions, when reform dummies are excluded, coefficients do not change their basic pattern.

We further extend our analysis by considering the potential role of the duration of recessions and expansions on the impact of unemployment on poverty. Long-term changes in poverty can be due not only to the transition from a period of long-lasting growth to an economic downturn but also to the different lengths of both processes. The duration of expansions may be measured as the number of quarters since the most recent trough (0 if in a recession), while the duration of recessions is measured as the number of quarters since the most recent peak (0 if in an expansion). In this case, the expressions to be estimated are the following:

$$P_{it} = \alpha_i + \beta_1 P_{it-4} + \beta_2 U_{it-4} + \beta_3 DExp_{t-4} + \beta_4 DRec_{t-4} + \beta_5 \pi_{it-4} + \varepsilon_{it} \quad (4)$$

$$P_{it} = \alpha_i + \beta_1 P_{it-4} + \beta_2 U_{it-4} + \beta_3 (U_{it-4} \times DExp_{t-4}) + \beta_4 (U_{it-4} \times DRec_{t-4}) + \beta_5 \pi_{it-4} + \varepsilon_{it} \quad (5)$$

where the dummies *DExp* and *DRec* represent the duration of expansions and recessions, respectively. The first specification adds the duration variables to the base-case in Eq. 1, while the second specification allows the effect of unemployment to differ as quarters accumulate in periods of expansion or recession. Again, we exclude the variable *Post2007* from the regressions to better capture the asymmetric effects of the business cycle on severe poverty.

The effects of the unemployment variables remain significant when the duration variables are included in the model (see Table 4). The point estimates on the variables of duration are not statistically significant, although they indicate that increasing the length of the recession might worsen severe poverty and that increasing the length of the expansion

[20] We have also used a national-business-cycle dating, though the results did not change significantly.

Table 3 The role of expansions and recessions. (System-GMM estimates)

	Unemployment Rate				Household Heads Unemployment Rate				All Active Members Unemployment Rate			
Regressors	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*
Poverty lag_4	0.2032**	2.42	0.2449**	2.81	0.2036**	2.52	0.2179**	2.88	0.2232***	2.93	0.2644***	3.39
Inflation lag_4	−0.0314***	−3.24	−0.0314***	−3.40	−0.0307***	−3.23	−0.0281***	−3.10	−0.0324***	−3.53	−0.0316***	−3.72
U_{it-4} x $expansion_{t-4}$	0.0794***	7.32	0.0845***	6.98	0.0857***	7.25	0.0926***	9.91	0.1466***	7.04	0.1591***	7.05
U_{it-4} x $recession_{t-4}$	0.0831***	8.55	0.0973***	8.50	0.0821***	7.20	0.0959***	9.47	0.1502***	7.41	0.1833***	8.20
Unem. benefit reform 1989	−0.0110	−0.09			−0.1686	−1.47			−0.0660*	−0.55		
Unem. benefit reform 1992	0.0936	1.60			0.0024	0.04			0.0313	0.57		
Unem. benefit reform 2002	0.4809***	6.95			0.2750***	5.84			0.5124***	9.89		
p-value for test of equal coefficients	0.8543		0.5804		0.8672		0.8540		0.9259		0.5768	
Num. Instruments	15		12		15		12		15		12	
Tests	*Estimates*	*p-value*	*Estimates*	*p-value*	*Estimates*	*p-value*	*Estimates*	*p-value*	*Estimates*	*p-value*	*Estimates*	*p-value*
$m1$ test	−3.25	0.00	−3.30	0.00	−3.17	0.00	−3.18	0.00	−3.31	0.00	−3.36	0.00
$m2$ test	−1.96	0.05	−1.83	0.07	−1.30	0.19	−1.16	0.25	−1.48	0.14	−1.07	0.29
Hansen test	6.49	0.17	8.48	0.08	5.98	0.20	6.06	0.20	6.87	0.14	8.59	0.07

Note: see Note on Table 2.

Table 4 The role of the length of expansions and recessions. (System-GMM estimates)

	Unemployment Rate				Household Heads Unemployment Rate				All Active Members Unemployment Rate			
Regressors	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*
Poverty lag_4	0.1768*	2.05	0.1792**	2.30	0.1876**	2.34	0.1910**	2.49	0.2028**	2.77	0.2045**	2.80
Inflation lag_4	−0.0308***	−3.10	−0.0305***	−3.17	−0.0279***	−3.04	−0.0282***	−3.08	−0.0298***	−3.34	−0.0294***	−3.27
Unemployment lag_4	0.0904***	3.01	0.0871***	5.39	0.0972***	5.85	0.0931***	6.96	0.1585***	4.11	0.1549***	5.55
Length exp_{t-4}	−0.0002	−0.05			−0.0005	−0.22			−0.0021	−0.81		
Length rec_{t-4}	0.0041	0.42			0.0026	0.48			0.0104	1.50		
U_{it-4} x length exp_{t-4}			−0.0001	−0.41			−0.0001	−0.13			−0.0010	−1.05
U_{it-4} x length rec_{t-4}			0.0002	0.50			0.0003	0.89			0.0012	1.37
Unem. benefit reform 1989	−0.0445	−0.46	−0.0427	−0.43	−0.1516	−1.54	−0.1529	−1.55	−0.0631	−0.70	−0.0586	−0.63
Unem. benefit reform 1992	0.0970	1.54	0.1047*	1.97	−0.0181	−0.26	−0.0142	−0.24	0.0249	0.37	0.0414	0.83
Unem. benefit reform 2002	0.4974***	5.41	0.4961***	5.07	0.2294***	4.14	0.2180***	3.73	0.5021***	7.47	0.4866***	6.84
p-value for test of equal coefficients	0.6042		0.5936		0.6069		0.6104		0.0754		0.1630	
Num. Instruments	15		15		15		15		15		15	
Tests	*Estimates*	*p-value*	*Estimates*	*p-value*	*Estimates*	*p-value*	*Estimates*	*p-value*	*Estimates*	*p-value*	*Estimates*	*p-value*
$m1$ test	−3.26	0.00	−3.27	0.00	−3.17	0.00	−3.20	0.00	−3.35	0.00	−3.38	0.00
$m2$ test	−1.84	0.07	−1.93	0.05	−1.16	0.25	−1.26	0.21	−1.56	0.12	−1.64	0.10
Hansen test	4.37	0.23	4.30	0.23	5.40	0.15	5.02	0.17	4.70	0.20	4.80	0.19

Note: see Note on Table 2.

might lead to an improvement in poverty. For the proportion of households in which all active members are unemployed, the coefficient estimated for the length of recessions is significantly different from that estimated for the duration of expansions at 10 per cent of confidence (see the p-values for the tests of equal coefficients in Table 4). With respect to the second specification, the results show that the effect of unemployment on poverty might differ with the length of expansion and recession, although the test statistics reported in the table are not significant.

6 Concluding remarks

The question of whether poverty depends on changes in macroeconomic conditions has attracted a great deal of attention from economists and policymakers. For many years now, the most popular way of testing this relationship has been by means of models that were able to track poverty based on the unemployment rate and inflation. Although these models worked reasonably well for many decades in predicting poverty, since the mid-eighties they became less accurate in foreseeing changes in this variable. Due to the continuous increase in unemployment rates since the very beginning of the Great Recession, these models have gained renewed interest. The key question is the extent to which a substantial increase in unemployment has resulted in increasing poverty rates.

The possibilities of these models to provide a clear picture of these effects is largely constrained by the way macroeconomic conditions – and especially unemployment – are captured. The usual procedure of selecting the aggregate unemployment rate as an indicator of the most relevant employment conditions for low-income households might diminish the predicting capacity of these models. The unemployment rates for households' heads or the proportion of workless households might be better alternatives to foresee changes in the incidence of poverty. Additionally, most of these models have not addressed the key question of other plausible, though different, responses of poverty rates to periods of expansion and recession. Poverty could be less sensitive to employment growth than to increasing unemployment rates.

This paper has tried to extend the traditional models to forecast poverty using a dynamic panel data model for severe poverty in Spain. We have used a panel data for seventeen Spanish Regions from 1987 to 2015 considering inflation and unemployment as our main explanatory variables – as is most common in the related literature. More precisely, we have used the one-step system GMM approach of Blundell and Bond (1998), finding that both covariates are relevant to explain the evolution of poverty in Spain. Unemployment has a positive and significant impact on severe poverty, while inflation has a negative and significant impact on it. We also find that the enacted 2002 reform of the unemployment protection system produced relevant effects on severe poverty; in particular, it worsened its incidence. More importantly, the Great Recession has had a strong and positive effect on severe poverty, and its greatest impact is best identified when using the proportion of households in which all active members are unemployed. It seems that the recent economic crisis has not affected all households in the same way.

A key issue in our results is that among the three unemployment variables considered, the aggregate rate of unemployment has the lowest coefficient, while the percentage of households in which all active members are unemployed has the highest one. Therefore, despite the fact that the aggregate overall unemployment rate shows strong and significant effects on severe poverty, the role played by the intra-household distribution of unemployment might modify its estimated impact. To adequately predict poverty changes, it seems more reasonable to introduce as covariates these alternative rates that are sensitive to the intra-household distribution of unemployment.

Regarding the possibility of asymmetric effects of expansions and recessions, we do not find evidence of a larger effect of recessions in comparison to expansions when using either the individual unemployment rate, the percentage of households in which all active members are unemployed or the households' head unemployment rate. Similarly, the length of the business cycle waves are not found to have a clear effect on poverty trends. On the methodological side, our results suggest that it may be of interest to review the results obtained by traditional procedures for the cyclical determinants of poverty and show the relevance of considering a suitable panel data estimation method.

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