Poverty and the business cycle: The role of the intra-household distribution of unemployment

Luis Ayala [(1)], Olga Cantó[(2)] and Juan G. Rodríguez[(3)]

(1) Universidad Rey Juan Carlos and EQUALITAS

(2) Universidad de Alcalá and EQUALITAS

(3) Universidad Complutense de Madrid

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Abstract

Conventional wisdom predicts that changes in the aggregate unemployment rate may significantly affect a country's income distribution and, as a consequence, have a relevant impact on the evolution of the poverty rate. However, the relationship between labour macroeconomic indicators and poverty seems to have become weaker in recent times. Using panel data on unemployment and poverty for Spanish regions we estimate a System GMM model in order to model this relationship taking into account that the intra-household distribution of unemployment can be more relevant than aggregate unemployment in order to explain poverty changes. 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 poverty, while inflation has a negative effect. Among the three unemployment measures considered in order to predict poverty, the aggregate unemployment rate registers the lowest explanatory power. Regarding the existence of asymmetric effects of expansions and recessions on severe poverty our results show that, even if we cannot make a general statement because differences are not statistically significant, some of our point estimates indicate a somewhat larger effect of recessions.

Keywords: poverty, unemployment, system GMM model, Spain
JEL: E3, I3

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. In general terms, economic downturns are associated with increases in inequality and poverty while periods of strong aggregate growth are expected to contribute to reduce the share of poor individuals in the total population. However, in the years before the Great Recession began (i.e. since the late nineties until 2008), many OECD countries were experiencing strong and rapid economic expansions (only shortly 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 effect on policies of the assumption that economic growth is unlikely to be an effective antipoverty tool has 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 studies 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, they became less accurate to foresee 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 affecting the relationship between the business cycle and poverty. In some countries, the decline in real wages among less-skilled workers has deteriorated 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 to explain changes in the poverty rate.

A further limitation of these models refers to the implicit assumption of a symmetric response of poverty indicators to both expansions and recessions. In a similar way as the hysteresis hypothesis usually considered in unemployment analyses, poverty could be less sensitive to employment growth than to increasing unemployment rates. Empirical studies of the incidence 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]

Indeed, there are several ways in which the business cycle could affect poverty rates and there is a need for research providing a more complete picture of the effects of the business cycle on low-income households. This paper aims at analysing how the intra-household distribution of unemployment can be more relevant than aggregate unemployment in order to explain 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 time period of data –from 1987 to 2012– 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 where changes in the business cycle are much more pronounced and usually last more. In the aftermath of the global economic crisis that started in late 2007, unemployment grew from 8.6 to 26.0 per cent in only five years and the proportion of households where all active members were unemployed boosted from 2.6 to 10.5 per cent. 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 that of other alternative measures of unemployment strongly related to its intra-household distribution. Additionally, the variety of regional experiences –with remarkable differences in demographic structures and employment

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

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 which 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 in a long period of time. 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 and neither benefit from any Social Security transfers (i.e. pensions or other benefits) nor from 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 using a variety of unemployment rates as covariates – aggregate unemployment, the unemployment rate of household heads and the proportion over the total number of households in the population where all active members are unemployed. 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 comparing the system GMM estimates with alternative methods.

Our results show that both unemployment and inflation are significant in order to explain 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 and significant impact on severe poverty, while inflation has a negative and significant impact on it. 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. Further, our results on the possible asymmetric effects of the business cycle allow us to conclude that when we use either the individual unemployment rate or one of the measures of unemployment that is sensitive to its intra-household distribution our point estimates indicate that recessions have a larger negative effect on severe poverty in comparison with expansions. However, we cannot make a general statement on the significant difference in the impact of unemployment on poverty because the gap in our betas' point estimates is not statistically significant.

The organization of the paper is as follows. In Section 2 we revise 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 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 about the effects of macroeconomic conditions on poverty has been thoroughly discussed in the literature. The idea that poverty will not disappear with unemployment reductions –backwash thesis– was already tested in the late sixties [Galloway (1965), Aaron (1967), Metcalf (1969), Thurow (1970), Mirer (1973)]. While some estimates were imprecise, a consensus was built on the assessment that the optimistic view of economic growth on poverty advanced by some authors was not so 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:

$$S_i(\mathrm{t}) = \alpha + \beta\, U(\mathrm{t}) + \gamma \pi(\mathrm{t}) + \delta\, T(\mathrm{t}) + \varepsilon(\mathrm{t}) \qquad (1)$$

where S_i(t) is the income share of the i^{th} quintile (i = 1, . . ., 5) of the income distribution in the t^{th} year; U is the overall unemployment rate; π is the rate of inflation; and T is a linear time trend. These authors did not impose any particular functional form or measure of well-being in order to enquire into 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 per cent of families lost most when unemployment raised– while the picture for inflation, in contrast, was much gloomier.

Blank and Blinder (1986) extended the work of Blinder and Esaki 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:

$$S_i(t) = a + \beta_1 U(t) + \beta_2 U^2(t) + \gamma_1 \pi^a(t) + \gamma_2 \pi^{ua}(t) + \varphi S_i(t-1) + \delta T(t) + \varepsilon_i(t) \quad (2)$$

where π^a is anticipated and π^{ua} is unanticipated inflation. 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 why this time pattern actually exists (government transfers divided by GNP and the poverty line divided by mean household income).

A second extension of the basic model was developed by Cutler and Katz (1991). They forecasted poverty rates using consumption instead of income and a variety of contemporaneous macroeconomic indicators to find striking differences across demographic groups:

$$P_t = \beta_0 + \beta_1 (z/\mu)_t + \beta_2 \pi_t + \beta_3 U_t + \beta_4 T + \beta_5 P_{t-1} + \varepsilon_t \quad (3)$$

where $(z/\mu)_t$ is the ratio of the poverty line relative to median income, U is the overall unemployment rate; π is the rate of inflation; and T is a linear time trend.

These methods became increasingly popular. Using equations (1), (2) or (3), a number of studies have considered the effects of unemployment to forecast poverty. Despite 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. In order 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 use estimates of the relationship between the poverty rate and the unemployment rate from Blank (2009):

$$P_t = \beta_0 + \beta_1 U_t + \beta_2 WR_t + \beta_3 X_t + \beta_4 (z/\mu)_t + \beta_5 \pi_t + \beta_6 P_{t-1} + \varepsilon_t \quad (4)$$

where WR_t is the log 50/10 wage ratio, and X_t is federal expenditures on public assistance programs in each year as a share of GDP.

Collecting and interpreting the empirical findings from this literature allows us to predict poverty when unemployment changes. In general terms, results are consistent with the hypothesis that unemployment actually bears most heavily on the poor than other macroeconomic indicators.[2] High inflation has weak, if any, effects on poverty. There are however 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, considering distributional issues or not, using regional or national data, and defining time periods.

[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).

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] Further, the bulk of this literature has generally used the U.S. official poverty line in order to determine poverty incidence and only some authors have tested the sensitivity of 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 bring our focus on a too extreme poverty concept which might result in an under estimation of 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 with the labour market situation of household members. However, during the current great economic recession, one of the main issues that have been raised as being most worrisome in developed countries is the severity of the hit of unemployment on households so as to exclude them from the labour market completely. In fact, over the last two decades, a certain split has been opening up 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) underline that household joblessness is an important factor in the

[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 so that they can identify the effect of macroeconomic conditions on the depth of poverty.

[4] Iceland (2003) compares the official US poverty rate with a relative measure using 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, and 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 a family is poor or not. 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.

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 the reduction 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 nearer to a "vulnerability" concept. We believe that, indeed, both the lack of income from whatever source and household members' labour market exclusion are most likely to condition the individual perception of poverty risk or income deprivation. Thus, a measure of the proportion of households that do not earn income from labour and do not receive any Social Security transfers is reflecting the incidence of a most severe poverty or deprivation (in employment and income) in a given population.

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 in the regression making this the most usual procedure for a crude control for any dynamic features of the poverty rate trend. Also, 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 introduce 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.

Distributional issues

Distributional issues have been a central concern of much of the empirical literature on poverty forecasts. As shown by Freeman (2001), macroeconomic performance does not predict well the magnitude of changes in poverty along time. Others factors, often related to demography, such as the actual shape of the income distribution, the relevance of governmental policies and a variety of labour market factors, also intervene. Indeed, there is enough evidence in the literature showing that technological and institutional factors gave rise to an expansion in inequality across the wage distribution in a variety of countries during the eighties.

While some authors have emphasized the relevance of the shape of the income distribution in order to understand the relationship between macroeconomic performance and poverty, others have decided to include direct measures of earnings inequality as explanatory variables. Blank and Blinder (1986) and Cutler and Katz (1991) proposed the inclusion of the poverty line divided by mean or median income. Since the official U.S. poverty line is a fixed real dollar amount, real economic growth that raises incomes throughout the income distribution naturally lowers the share of the population below the threshold. However, Cutler and Katz (1991) found that median income relative to the poverty line grew rapidly in the eighties while poverty rates fell only slightly. Blank and Card (1993) considered three outcomes from the labour market –the median hourly wage rate, the dispersion in hourly wages, and the unemployment rate– and treat these as determinants of the distribution of family income. Other authors have also included measures of earnings inequality finding that the coefficients are substantially large (Freeman, 2001, Blank, 2009).

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 studying 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; 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 examine 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.

Time period

A crucial issue in the analysis of the effects of the business cycle on poverty is the time 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 held back again during the nineties. Jäntti and Jenkins (2010) found for the UK that 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 deal with institutional changes. For instance, Jäntti (1994) included an explanatory variable that took the value one from 1981 onwards, in order to accommodate some relevant changes in tax and transfer policies undertaken that year. A slightly different way of doing 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 estimate models that allow the relationship between poverty and unemployment to differ by decade. In fact, given that the 1960s differed so much from ensuing decades in poverty reduction, Freeman (2001) estimated the equations both for the entire 1969-1999 period as well as excluding the observations from 1960s from the sample.

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 the social conditions in inner cities or social disintegration in poor neighbourhoods. Hines *et al.* (2001) tested whether or not the effect of unemployment differs in expansions and contractions by interacting 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 primarily from the Spanish Labour Force Survey (1987-2010). 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 time period considered covering the resident population in the whole Spanish territory. The sample size of the survey is 60,000 households comprising information for a sample of approximately 190,000 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 on 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) nor from unemployment insurance or assistance payments.[5] Using this measure of poverty implies assuming 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 in order to understand the effects of the business cycle, in particular, those that fix a poverty threshold relative to the value of mean or median household income.

In order to provide information on how this measure relates to more traditional relative threshold methodologies in identifying the poor, it is interesting to compare it with them. In particular, we compare it with the number and characteristics of the households classified as poor using using EUROSTAT's measure of poverty risk in Europe in recent years: any individual living in a household where equivalent household income is below the 60% of the median equivalent income in a given population is poor.

This methodology has been commonly used by the European Union in the last decade to compare the risk of poverty in EU countries and approaches the idea of an "official" EU poverty measure. It identifies as poor three different groups of households: working poor households (81.7 percent), households where all members are unemployed but are receiving some Social Security transfer (13.5 percent) and households who do not earn any income from labour and do not receive any benefit from Social Security transfers nor from unemployment insurance or assistance payments (4.8 percent). We focus in this last group. Indeed, in terms of poverty incidence, our measure shows very similar results to when selecting households where all members are unemployed and household

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

equivalent income is below a 30% of median equivalent income in Spain in 2010: a 1.5 percent 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 labour market conditions of household members (avoiding households without active individuals) and who 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 where the number of active individuals is relatively low (working-age one-member households, lone-parents, etc.) and who have significantly more difficulties in paying their bills or mortgage and in dealing with unexpected expenditures.[8] In fact, the percentage of these households who report that they cannot afford eating 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]

[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). A 1.5 percent of total households in the population is 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 percent 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. Note that 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] Note, however, that 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] Indeed, using our measure up to a 30 percent of households report a late payment of their mortgage more than twice along the last year while this percentage falls to approximately a 15 percent for households with equivalent income below a poverty threshold of a 30% or a 60% of median equivalent income in Spain in 2010. A similar result is obtained when looking at difficulties in “making ends meet”: up to a 90 percent of our households report to have difficulties in making ends meet while for traditionally poor households this percentage drops to an 80 percent.

[9] Nevertheless, it is important to underline that 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 such a long period of time in a quarterly regional basis. Unfortunately, for now, such a long term series of regional data on unemployment and income is not available.

Figure 1 illustrates how this poverty rate among Spanish households has changed over the last two and a half decades. 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 being the determinants of this decreasing trend in poverty. The mild recession that took place between 1992 and 1994 increased poverty rates after more than a decade of continuous fall.[10] In the following years, when the Spanish economy underwent a long expansion period, the poverty trend turned back to a slight decrease (1995-2007). However, during this second expansion period it took more than a decade to go back to the poverty levels of the early nineties. Further, in recent times poverty has clearly raised again due to the 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 of the last two decades. At the end of 2012, the severe poverty rate is significantly higher than in the mid-eighties and twice as high that 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 hold uniformly 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 to modulate the relationships between economic growth and poverty in their territory. For now, in the comparison of regional differences in Spain a few recent papers show that these differences do not seem to be particularly outstanding within OECD countries [Gorja and Scirankova (2012), Krueger (2012) or Bubbico and Dijkstra (2011)]. However, the currently growing dispersion of unemployment rates, the different demographic structure 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 2]

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

Figure 2 gives general support to the notion that poverty levels drastically differ across the seventeen Spanish regions. The most relevant trait of this picture 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 those other regions with lowest rates. The time profile of poverty changes is also somewhat different. Some regions show some lags in the growth of poverty at the beginning of the great recession while others appear to have more stable trends.[11]

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 2012 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 3]

Figure 3 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 the 1993-98 period unemployment and prices simultaneously fell. The reason was the necessary adjustment of prices to meet the European Monetary Union criteria for inflation. In more recent times, however, inflation has 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 since 2008.

Changes in unemployment rates confirm well-defined trends of macroeconomic conditions in the Spanish economy. After a pronounced reduction of unemployment in the late eighties, the rates grew sharply at the beginning of the nineties –from about 15% in 1991 to about 22% in 1994. However, unemployment declined rapidly along the following years in line with economic recovery. Before the great recession started,

[11] It must be noted that results obtained for the smallest regions –such as Cantabria or La Rioja– should be interpreted with caution due to the reduced sample size in those territories.

Spain was the EU country with the highest employment growth. Aggregate individual unemployment rates reached their lowest value in two decades in 2007: an 8%. These employment gains were eroded again in a very short time. During last economic downturn unemployment rates dramatically increased –moving from rates about 8% in 2007 to 26% in 2012.

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. Plotting unemployment changes in some selected regions one can conclude that both their levels and, even if more partially, trends appear to be different. For example, Balearic and Canary Islands show a largely marked pro-cyclical pattern compared to other regions. Indeed, unemployment rates in other regions rose slower than the average. In particular, at the beginning of the great recession aggregate individual unemployment rose only modestly in regions like the Basque Country. These regional differences reinforce the relevance of panel data analysis to estimate more precisely the relationship between unemployment and poverty.[12] 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 80s, despite the outsized growth of unemployment, inequality and poverty rates fell in Spain. The main factor commonly adduced to explain this apparent contradiction is the crucial protective function that the Spanish family provided, mainly because unemployment affected most intensely other

[12] To complement this analysis we have decomposed the dispersion (measured by the general entropy index for α=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 since its share on total dispersion is greater than 30%. Hence, we can state that the regional dimension is relevant to understand to better understand the evolution of poverty throughout the business cycle. These results are not shown, but they can be obtained from the authors on request.

members of the family different from 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 where 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 or not these indicators provide stronger effects on poverty than standard measures of unemployment.

[FIGURE 4]

Figure 4 illustrates the changes in various unemployment measures in the long-term. Two things are notable. One is that, traditionally, 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 as compared to what happened in previous periods of economic downturns.

Focusing on the results for household heads' unemployment rate first, and in contrast to what happened in the short contraction of the early 1990s, this rate has been growing even more sharply than aggregate individual unemployment in recent times. As mentioned earlier on, in previous recessions massive youth unemployment was partially offset by the employment of household heads. In the economic downturn of the late 00s, this rate has been growing at a higher pace than in any other period reaching its historical maximum in 2012. While in 1994 – when the aggregate unemployment rate reached its highest value – household heads' unemployment rate was about half of aggregate overall unemployment, during the great recession that proportion increased up to an 85%. A similar behaviour can also be observed for the proportion of workless households in the population. While this type of households were a 2.5% of total population in 2007, by the end of 2012 this group is 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 a reference to the main unemployment benefit reforms undertaken in Spain during the 1987-2012 period. Since our definition of poverty comprises households not receiving 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 either the requirements for receiving an unemployment subsidy or the level of benefits.[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 are classified as long-term unemployed. In 1992, in contrast, eligibility was significantly restricted by rising the required minimum period of social security contributions from six months to one year. In 2002, unemployment subsidies were reformed further making them more strongly related to previous worker's 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 to reduce poverty, while the 2002 reform worsened its incidence.

4. A DYNAMIC PANEL DATA MODEL FOR POVERTY CHANGES

Among 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 in particular regions or years.

The standard regression approach to the relationship between the business cycle and poverty has been Ordinary Least Squares (OLS). Blinder and Esaki (1978) in their

[13] The main Spanish Unemployment Benefit (UB) scheme is a compulsory social insurance scheme for employees able and available for work who have lost their job. In order to be entitled to the benefits workers must have contributed to social insurance covering unemployment. In order 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 once 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 dependants.

pioneering work stated that more sophisticated techniques did not seem to be called for. One motive was that there is no reason to expect any important reverse causation from the income distribution to unemployment or inflation. Second, they argued that heteroskedasticity would not normally be expected in a regression where none of the variables (apart from time itself) show much of a time trend. Some authors have challenged this view using alternative estimation strategies. Jäntti (1994), for instance, applies 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 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 dependent variable use standard OLS or weighted OLS (Gundersen and Ziliak, 2004).

The growing availability of regional data has allowed a certain 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 particular 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. We know that variables that are bounded in the unit interval do not possess a unit root since they cannot have an infinite variance (see Jäntti and Jenkins, 2010). Accordingly, neither the poverty variable nor the unemployment rates can have a unit root because they are bounded by the unit interval. To show this and study the stationarity of the inflation time series, we run the Im-Pesaran-Shin panel-data unit-root test (Im *et al.*, 2003). The null hypothesis is that each individual time series contains a unit root against the alternative that at least one time series is stationary.[14] We include a linear trend, the lag structure is such that the

[14] An advantage of this test with respect to the Levin-Lin-Chu test (Levin *et al.*, 2002) is that it does not impose the alternative hypothesis that each time series is stationary.

Bayesian Information Criterion (BIC) for the regression is minimized and in order to mitigate potential cross-sectional dependence, cross-sectional means are removed. 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. In addition to this, we have also implemented the four panel cointegration tests developed by Westerlund (2007) for one lag with and without a constant and a trend. The hypothesis of cointegration for the panel as a whole is rejected in all cases.[15]

[TABLE 1]

To analyse the effects of unemployment and inflation upon severe poverty, we propose then 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, so 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 or not there is conditional convergence among regions.

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

$$P_{it} = \alpha_i + \beta_1 P_{it-1} + \beta_2 U_{it} + \beta_3 \pi_{it} + \varepsilon_{it} \tag{5}$$

where P_{it} is severe poverty in region i at time t; α_i represents those fixed factors which are time-invariant and inherent to each region, and are not directly observed or included in the model, such as regional social, geographical and policy characteristics; U_{it} is an unemployment measure in region i at time t; π_{it} is inflation in region i at time t; finally, ε_{it} encompasses any effects of a random nature which are not considered in the model.[16] In addition, we also consider three stationary dummies to control for quarterly variations and three dummies to control for the unemployment benefit reforms in 1989,

[15] In comparison with the tests proposed by Pedroni (2004), these tests have small size distortions and good power against highly autoregressive alternatives (see Baltagi, 2008). The Westerlund panel cointegration tests are not shown, but they can be obtained from the authors on request.

[16] 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 $s \neq t$.

1992 and 2002.[17] 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 2012.

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 (5) as follows:

$$\Delta P_{it} = \alpha_i + (\beta_1 - 1) P_{it-1} + \beta_2 U_{it} + \beta_3 \pi_{it} + \varepsilon_{it} \tag{6}$$

The interpretation of equation (6) 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 to the steady-state the poverty of region *i* is converging to. 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 –β_2 in equation (6)– and the long-run effects –$\beta_2/(1 - \beta_1)$ in equation (6)– 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 explicative variable what introduces long-term effects into the model (see Gundersen and Ziliak, 2004).

The easiest way to estimate a panel data model like (5) is to ignore any unobserved regional specific heterogeneity – i.e., set $\alpha_i = \alpha$ for all *i* – and then apply OLS to pooled data. However, this strategy may result in biased and inconsistent estimates when region

[17] In the next section, we present the results only for severe poverty, inflation, unemployment and the labor reforms in 1989 and 2002 because the 1992 labor reform is never significant. We have tested for non-linear effects, in particular, we have included a quadratic term for inflation, unemployment, and both, but none of them were statistically significant. Also, we have omitted the stationary dummies and, alternatively, we have seasonally adjusted (according to the *X-12 procedure* and the *additive difference from moving average method*) the dependent and explanatory variables. In none of these cases did results change significantly. Note that earnings inequality measures and regional public transfers are not included in our analysis because, unfortunately, they are not available in our dataset.

heterogeneity exists (Nickell, 1981, Anderson and Hsiao, 1982, and Hsiao, 2002). When applying OLS in expression (5) the total error component is given by the disturbance ε_{it} plus the unobservable individual specific effect α_i. Since P_{it} is a function of α_i, it follows that P_{it-1} is correlated with α_i and, consequently, with the total error component. This implies that the OLS coefficient for the lagged poverty variable is biased upwards.

The standard alternatives are the Fixed Effects (FE) and Random Effects (RE) estimators, which wipe out the α_i term by transformation. However, the FE and RE models do not allow us to handle other problems such as endogeneity, measurement errors and omitted variables. For instance, the within transformation wipes out the individual effect α_i, but $(P_{it-1} - \overline{P}_{i.-1})$ where $\overline{P}_{i.-1} = \frac{1}{T-1}\sum_{t=2}^{T} P_{it-1}$ is correlated with $(\varepsilon_{it} - \overline{\varepsilon}_{i.})$ where $\overline{\varepsilon}_{i.} = \frac{1}{T}\sum_{t=1}^{T} \varepsilon_{it}$ because P_{it-1} is correlated with $\overline{\varepsilon}_{i.}$ by construction ($\overline{\varepsilon}_{i.}$ contains ε_{it-1}). As a result, the Within Groups estimator gives a downwards-biased estimate of the coefficient for the dynamic term (see Nickell, 1981). Therefore, a consistent estimate of β_1 can be expected to lie in between the OLS and Within Groups estimates (Sevestre and Trognon, 1996 and Bond *et al.*, 2001).[18]

In the absence of suitable external instruments, to address all these potential problems we could apply the first-differenced generalized method of moments (GMM henceforth) estimator proposed by Arellano and Bond (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 the Appendix). 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. 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.

[18] Nerlove (1999, 2000) has made this observation in the context of empirical growth models.

For all these reasons in this paper we use 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).[19] Accordingly, we choose to use the one-step system-GMM estimator.[20] In addition, errors in panel models like (5) 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.

In order to discuss the importance of considering this approach, we follow Blundell *et al.* (2000), and compare the system-GMM estimates with respect to the OLS pooling estimation, the within groups estimation and the first-difference GMM estimation. In principle, a finding that the first-differenced GMM estimate of the coefficient on the lagged dependent variable lies close or below to the corresponding within groups parameter estimate can be regarded as a signal that biases due to weak instruments may be important. The assumptions underlying these econometric methods are validated by using the Hausman, $m1$, $m2$ and Hansen tests. The null of the Hausman test (Hausman, 1978) is the existence of random effects. 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. And the Hansen test of over-identifying restrictions is the most commonly used test to assess the joint validity of the proposed instruments set. This test basically examines the correlation between the instruments and the regression residuals, where the null hypothesis is the absence of such correlation. The Hansen test should not

[19] There may be computational problems in calculating the two-step estimates and serious estimation errors may arise for the case where 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 works 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.

[20] We use the algorithm *xtabond2* programmed in Roodman (2009) for Stata.

be relied upon too faithfully, however, as it is prone to weakness. In particular, the test grows weaker the more conditions there are.

We assume that the main explanatory variables (inflation and unemployment) and disturbances are correlated so regressors are endogenous. This is more general than assuming exogenous or predetermined regressors which 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). Besides, the omission of other regressors might cause their correlation with disturbances (Baltagi, 2008).[21]

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, for the set of level equations, only one lag is ordinarily used for each period and instrumental variable. We follow in this paper 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, for example, it can weaken the Hansen test. Unfortunately, there is little guidance from the literature on how many instruments is too many (Ruud, 2000). To limit this problem in our case, we only use two lagged levels as instruments for the set of transformed equations.

5. RESULTS

The results of the model summarized in the previous section using the one-step system-GMM estimator are presented in Tables 2, 3, and 4. We estimate this basic model using the three possible unemployment measures. As stated earlier, we compare the results with those of alternative methods: the OLS pooling estimates (OLS-POOL), the Within Group estimates (WG), and 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 are presented.

[21] However, the results are similar when inflation and unemployment are considered as strictly exogenous regressors. These results are available from the authors upon request.

According to the estimated results, the Hausman test rejects the null hypothesis of random effects at any standard level of significance. Second, the *m*1 and *m*2 tests find first-order but not second-order serial correlation for any GMM-based estimates. Hence, there is not autocorrelation. Third, the Hansen test does not reject the adequacy of moment conditions. Hence, we conclude that moment conditions underlying GMM estimates are robustly supported. In accordance to our results, OLS-POOL seems to give an upward-biased estimate of the β_1 coefficient, while WG appears to give a downwards-biased estimate of this coefficient. The β_1 coefficient for the GMM estimation is clearly below the corresponding WG estimate, suggesting the presence of important finite sample bias due to weak instruments. In this respect is important to note that the estimated coefficients of the remaining regressors differ among the alternative procedures. Consequently, using a method resulting in biased estimates – as in our case the OLS-POOL, WG or the GMM – might lead us to mistaken conclusions.

[TABLES 2, 3 and 4]

We can focus our attention on the one-step system-GMM estimator computed with heteroskedasticity-consistent asymptotic standard errors. The parameter estimated for the endogenous variables are significant, positive and smaller than one. Hence, evidence for conditional convergence is found.

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

The results for the two indicators representing macroeconomic conditions –inflation and 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 for the Spanish economy has substantial and significant effects on our measure of poverty. Focusing our attention on the system-GMM estimates, the coefficient is 0.0299 in the short-term and 0.1044 in the long-term. We know from above that the larger the coefficient of persistence β_1 is, the longer the influence of unemployment on poverty, so the difference between the short- and long-term effects is significant because the coefficient for the lag of poverty is closer to 1 than to 0.

In contrast to the results in other countries, the impact of 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 fattens 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.

The key issue in our estimates is the extent to which results differ when alternative intra-household unemployment distribution sensitive measures are considered instead of the aggregate unemployment rate. Table 3 presents the results corresponding to the unemployment rates for households' heads. Two things are most notable. One is that the impact of inflation is similar to the previous case. Second, the coefficient on the household heads' unemployment rate has the expected sign and is significant. In all specifications coefficients are larger than those resulting from using the overall unemployment rate instead. In fact, focusing our attention on the system-GMM estimates, the 95% confidence interval for the coefficient of the household heads' unemployment rate is [0.0283 0.0538] while the 95% confidence interval for the coefficient of the aggregate unemployment rate is [0.0226 0.0372].

Similar findings result from the model that considers the proportion of households where all active members are unemployed as unemployment measure (Table 4). This proxy of workless households shows again a strong and significant effect of the business cycle on poverty. The coefficient of inflation is negative and similar to the one found for the specification with the overall unemployment rate. The results for unemployment are also stronger than in the first model. Thus, the 95% confidence interval for the coefficient of the proportion of households where all active members are unemployed is [0.0519 0.0902] when focusing on the system-GMM estimates.

To adequately predict poverty changes it seems, therefore, more reasonable to introduce these alternative family unemployment rates as explanatory variables. For assessing the validity of this statement, we compare the three non-nested models developed above by computing the Akaike Information Criterion (AIC) and the Schwarz or Bayesian

Information Criterion (BIC). Choosing a model based on the lowest information criterion, we observe that the first model where the aggregate unemployment rate is used is the worst model according to both prediction criteria (see Tables 2, 3 and 4). Therefore, it is most plausible that the intra-household distribution of unemployment matters in the relationship between the business cycle and poverty. Despite the fact that the aggregate overall unemployment rate shows strong and significant effects on severe poverty, the compensating role played by the intra-household distribution of unemployment might reduce the estimated impact.

As previously stated, some specific legislative changes in unemployment protection may have had 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, two dummies were added to the model trying to catch the effects caused by the implementation of new rules in 1989 and 2002. We find that, to a high degree of statistical confidence, these variables have relevant effects on the severe poverty trend. While the 1989 reform helped in reducing severe poverty, the 2002 reform worsened its incidence.[22]

5.2. Asymmetric effects of the business cycle

So 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.

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

$$P_{it} = \alpha_i + \beta_1 P_{it-1} + \beta_2 (U_{it} \times Exp) + \beta_3 (U_{it} \times \mathrm{Re}c) + \beta_4 \pi_{it} + \varepsilon_{it} \tag{7}$$

[22] The effects of the 1992 reform that imposed more severe restrictions on the access to unemployment subsidies are not well defined. This might explain why a new reform was put into action some years later.

where the dummies *Exp* and *Rec* are constructed from the unemployment rate series at a regional basis. 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 where all active members are unemployed). We have also used a national-business-cycle dating, though the results did not change significantly. Results are presented in Table 5. We observe that a given change in unemployment has a larger effect in a recession than in an expansion for the aggregate unemployment rate and the percentage of households where all active members are unemployed, while the opposite is true for the households' head unemployment rate. In any of the three cases, these differences are statistically significant (see the *p*-values for the tests of equal coefficients in Table 5). Thus, even if we cannot make a general statement on the significant difference between the different impact of unemployment on poverty during recessions and expansions, we find some evidence on a larger effect of recessions in comparison to expansions when using either the individual unemployment rate or when the measure of unemployment chosen is sensitive to the intra-household distribution of unemployment in a particular way: the percentage of households where all active members are unemployed.

[TABLE 5]

There may be different reasons that can justify the difference found in non-asymmetric effects between individual unemployment rate and the head of household unemployment rate. Indeed, one would expect that if the individual unemployment rate shows asymmetric effects during the business cycle, the head of household unemployment rate would also show them. However this does not appear to be the case. First, recession periods in Spain in our twenty-five-year time span are relatively short and thus the number of observations during economic downturns might be too small in comparison to the number during expansion periods. Second, it may be the case that the high persistence of the dependent variable makes it rather difficult to find significant differences in the observed changes in the business cycle. Thirdly, expansions and recessions results might be sensitive to different specifications including temporal effects for unemployment protection reforms. In Table 5 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 pattern.

We extend our analysis by also considering the 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 length 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 expression to be estimated is the following:

$$P_{it} = \alpha_i + \beta_1 P_{it-1} + \beta_2 U_{it} + \beta_3 DExp + \beta_4 D\mathrm{Re}c + \beta_5 (U_{it} \times DExp) + \beta_6 (U_{it} \times D\mathrm{Re}c) + \beta_7 \pi_{it} + \varepsilon_{it} \quad (8)$$

where the dummies *DExp* and *DRec* represent the duration of expansions and recessions, respectively. This specification allows the effect of unemployment to differ as quarters accumulate in periods of expansion or recession. Results show that length dummies have a non-significant effect on poverty (see Table 6). In the same manner, results are not significant when the covariates capturing the potential effects of reforms of the unemployment protection system are dropped from the basic specification. For all the three unemployment variables, the coefficients estimated for the length of recessions are not statistically different from those estimated for the duration of expansions (see the *p*-values for the tests of equal coefficients in Table 6). Nevertheless, the effects of the length of expansions seem more modest than those of recessions.

[TABLE 6]

6. CONCLUDING REMARKS

The question of whether or not 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. While for many decades these models worked reasonably well in predicting poverty, since the mid-eighties they became less accurate to foresee 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 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 plausibly 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 2012 considering inflation and unemployment as our main explanatory variables–as it 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 significant in order 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 some of the enacted reforms of the unemployment protection system produced relevant effects on severe poverty: while the 1989 reform helped to reduce severe poverty, the 2002 reform worsened its incidence.

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 where 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 compensating role played by the intra-household distribution of unemployment might reduce its estimated impact. In order 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 our results show that even if we cannot make a general statement on the significant difference between the impact of unemployment on poverty during recessions and expansions, we find evidence on a larger effect of recessions in comparison to expansions when using either the individual unemployment rate or the percentage of households where all active members are unemployed. A similar result was found for the length of the different changes in the business cycle with more relevant (but non-significant) effects for the duration of recessions.

On the methodological side, a remarkable issue we should mention is that alternative estimation strategies exhibit largely biased estimates, which should call researchers' attention to the importance of considering a suitable estimation method. The procedure used here has been shown to solve many of the problems that arise in traditional panel data procedures. In fact, our results suggest that it may be of interest to review the results obtained with traditional procedures for the cyclical determinants of poverty, and show the relevance of considering a suitable panel data estimation method.

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Appendix: Estimating a DPD Poverty Model by System GMM

To estimate our dynamic model, we use the one-step System GMM estimator (Arellano and Bover, 1995, and Blundell and Bond, 1998), which allows for omitted variables, endogeneity and measurement error problems, and avoids using weak instruments with persistent series like poverty. We should first differentiate equation (5) and remove the fixed effect term,[23]

$$\Delta P_{it} = \beta_1 \Delta P_{it-1} + \beta_2 \Delta U_{it} + \beta_3 \Delta \pi_{it} + \Delta \varepsilon_{it}, \qquad \text{(A1)}$$

and then assume a standard structure for the error component and that the initial condition P_{i1} is predetermined, that is, $E\,[P_{i1}\varepsilon_{it}] = 0$ for $i = 1,..., N$ and $t = 2,..., T$. As a result, the following orthogonally moment conditions are valid:

$$E\,[P_{it-s}\Delta\varepsilon_{it}] = 0 \qquad \text{(A2)}$$

$t = 3,...,T$ and $2 \le s \le t$-1, for $i = 1,.., N$. These conditions can be written more compactly as $E\,[Z_i^{'}\Delta\varepsilon_i] = 0$ for $i = 1,..,N$ where Z_i is the (T-2) x0.5(T-1)(T-2) matrix given by:

$$Z_i = \begin{bmatrix} [P_{i1}] & & & 0 \\ & [P_{i1}, P_{i2}] & & \\ & & \ddots & \\ 0 & & & [P_{i1},..., P_{iT-2}] \end{bmatrix} \qquad \text{(A3)}$$

and$\Delta\varepsilon_i$ is the (T-2) vector ($\Delta\varepsilon_{i3}$, $\Delta\varepsilon_{i4}$, …, $\Delta\varepsilon_{iT}$).

We assume that the main explanatory variables in the model, inflation and unemployment, are endogenous. Consequently, assuming that $E\,[U_{i1}\varepsilon_{it}] = E\,[\pi_{i1}\varepsilon_{it}] = 0$ for $i = 1,...,N$ and $t = 2,..., T$ we have the following additional 0.5(T-1)(T-2) moment conditions for each endogenous regressor:

$$E\,[U_{it-s}\Delta\varepsilon_{it}] = 0$$

[23] To simplify the exposition of this section, we do not include stationary or labor reform dummies.

$$E\,[\pi_{it-s}\Delta\varepsilon_{it}] = 0 \tag{A4}$$

$t = 3,...,T$ and $2 \leq s \leq t\text{-}1$, for $i = 1,.., N$. By adding these new conditions to each diagonal element of Z_i in (A3) we obtain the following (T-2) x1.5(T-1)(T-2) matrix:

$$Z_i^{\,D} = \begin{bmatrix} [P_{i1}, U_{i1}, \pi_{i1}] & & & 0 \\ & [P_{i1}, P_{i2}, U_{i1}, U_{i2}, \pi_{i1}, \pi_{i2}] & & \\ & & \ddots & \\ 0 & & & [P_{i1},.., P_{iT-2}, U_{i1},.., U_{iT-2}, \pi_{i1},.., \pi_{iT-2}] \end{bmatrix} \tag{A5}$$

Then, the matrix of instruments $Z^D = \left[Z_1^D\ Z_2^D\ ...\ Z_N^D\right]'$ is exploited by the first-difference GMM estimator.[24]

As mentioned in the main text, this approach allows us to tackle the endogeneity, measurement errors and omitted variables problems. However, the first-differenced GMM estimator has poor finite sample properties when the time series are persistent (our case). In this case, we should use the System GMM approach proposed by Blundell and Bond (1998), which might overcome the weak instruments problem.

Let us consider the additional assumptions that are required to apply the system GMM approach. Following Blundell and Bond (1998), we additionally assume that $E\,[\alpha_i\Delta P_{i2}] = E\,[\alpha_i\Delta U_{i2}] = E\,[\alpha_i\Delta\pi_{i2}] = 0$ for $i = 1,..,N$. These assumptions combined with the model set out above yield 3·(T-2) further linear moment conditions:

$$E\,[v_{it}\Delta P_{it-1}] = 0 \quad \text{for } i = 1,..,N \text{ and } t = 3,..., T,$$

$$E\,[v_{it}\Delta U_{it-1}] = 0 \quad \text{for } i = 1,..,N \text{ and } t = 3,..., T,$$

$$E\,[v_{it}\Delta\pi_{it-1}] = 0 \quad \text{for } i = 1,..,N \text{ and } t = 3,..., T \tag{A6}$$

[24]Note that additional instruments are available if regressors are predetermined or strictly exogenous variables (Bond *et al.*, 2001, and Bond, 2002).

where $v_{it} = \alpha_i + \varepsilon_{it}$. These allow the use of lagged first-differences of the series as instruments for equations in levels, as suggested by Arellano and Bover (1995).

Given all the above conditions, we obtain, for every cross-section i, the following 2(T-2) x[1.5(T-1)(T-2) + 3(T-2)] matrix:

$$Z_i^S = \begin{bmatrix} [Z_i^D] & & & 0 \\ & [\Delta P_{i2}\ \Delta U_{i2}\ \Delta\pi_{i2}] & & \\ & & \ddots & \\ 0 & & & [\Delta P_{iT-1}\ \Delta U_{iT-1}\ \Delta\pi_{iT-1}] \end{bmatrix} \tag{A7}$$

where Z_i^D is given in (A5). The new matrix of instruments is therefore $Z = [Z_1^S\ Z_2^S\ ...\ Z_N^S]'$ and the system GMM estimator is

$$\hat{\beta} = \left(\tilde{X}'ZG_N Z'\tilde{X}\right)^{-1}\left(\tilde{X}'ZG_N Z'\tilde{Y}\right) \tag{A8}$$

where

$$\hat{\beta} = \begin{bmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \\ \hat{\beta}_3 \end{bmatrix},\ \tilde{Y} = \begin{bmatrix} \Delta P_1 \\ ... \\ \Delta P_N \\ P_1 \\ ... \\ P_N \end{bmatrix},\ \tilde{X} = \begin{bmatrix} \Delta P_{1-1} & \Delta U_1 & \Delta\pi_1 \\ ... & ... & ... \\ \Delta P_{N-1} & \Delta U_N & \Delta\pi_N \\ P_{1-1} & U_1 & \pi_1 \\ ... & ... & ... \\ P_{N-1} & U_N & \pi_N \end{bmatrix} \tag{A9}$$

and $\Delta P_i = [\Delta P_{i3}\ ...\ \Delta P_{iT}]'$, $P_i = [P_{i3}\ ...\ P_{iT}]'$, $\Delta P_{i-1} = [\Delta P_{i2}\ ...\ \Delta P_{iT-1}]'$, $P_{i-1} = [P_{i2}\ ...\ P_{iT-1}]'$, $\Delta U_i = [\Delta U_{i3}\ ...\ \Delta U_{iT}]'$, $U_i = [U_{i3}\ ...\ U_{iT}]'$, $\Delta\pi_i = [\Delta\pi_{i3}\ ...\ \Delta\pi_{iT}]'$, $\pi_i = [\pi_{i3}\ ...\ \pi_{iT}]'$ for i = 1,.., N.

Two possible choices for the matrix G_N result in two different system GMM estimators. The one-step system GMM estimator sets:

$$G_{N,1} = \left(\sum_{i=1}^{N} Z_i^{S'} G Z_i^S\right)^{-1} \tag{A10}$$

where the G matrix is a 2(T-2) square matrix with 2's on the main diagonal, -1 on the first off-diagonals and zero elsewhere. The two-step system GMM estimator sets:

$$G_{N,2} = \left(\sum_{i=1}^{N} Z_i^{S'} \Delta\hat{v}_i \Delta\hat{v}_i' Z_i^S \right)^{-1} \tag{A11}$$

where estimated residuals are computed from the one-step System GMM estimator.

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). Consequently, we apply this estimator in our empirical exercise.

Table 1. The Im-Pesaran-Shin panel-data unit-root test

Ho: All panels contain unit roots	Number of panels =	17
Ha: Some panels are stationary	Number of periods =	103
Time trend included	Cross-sectional means removed	
Lags average chosen by BIC		

Variable	**Statistic**	**p-value**
Poverty	-15.9723	0.0000
Aggregate unemployment rate	-4.3313	0.0000
Household head's unemployment rate	-5.1466	0.0000
Households with all active members unempl.	-5.7746	0.0000
Inflation	-60.4297	0.0000

Table 2. Estimates of the poverty dynamic model.
(Unemployment: aggregate unemployment rate)

	OLS-POOL		**WG** (Fixed Effects)		**GMM**		**System GMM**	
Regressors	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*
Lag of poverty	0.7477**	47.55	0.6229**	33.06	0.4094**	9.28	0.7135**	19.64
Inflation	-0.0341**	-3.38	-0.0361**	-3.69	-0.0407**	-4.05	-0.0347**	-3.38
Unemployment	0.0257**	12.53	0.0300**	13.43	0.0453**	7.16	0.0299**	8.70
Unem. benefit reform 1989	-0.0174	-0.47	-0.0722*	-1.97	-0.1663**	-2.96	-0.0270	-0.81
Unem. benefit reform 2002	0.1313**	6.56	0.1670**	8.51	0.2090**	3.69	0.1444**	4.95

Tests	*Estimates*	*p-value*	*Estimates*	*p-value*	*Estimates*	*p-value*	*Estimates*	*p-value*
R^2	0.783	--	0.780	--	--	--	--	--
Hausman test	--	--	157.51	0.00	--	--	--	--
*m*1 test	--	--	--	--	-3.93	0.00	-3.81	0.00
*m*2 test	--	--	--	--	0.19	0.85	0.82	0.41
Hansen test	--	--	--	--	12.46	1.00	13.30	1.00
AIC	--	--	--	--	--	--	-1.883	--
BIC	--	--	--	--	--	--	-1.855	--

Note: OLS-POOL is OLS applied to the entire pool of data and WG is the Within Groups estimator. For GMM estimates, we take as instruments the lagged levels of *P* and the endogenous regressors dated *t*-2 and earlier. For System GMM estimates, we use the lagged difference of *P* and all regressors dated *t*-1 as additional instruments. For the GMM and System GMM, we report their one-step estimations. R^2 is the coefficient of determination. The null of the Hausman test is the existence of random effects. The null of the *m*l and *m*2 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: 8 (stationary dummies are not shown); number of cross sections: 17; number of time periods: 103 (1987IIQ-2012IVQ).
* significant at 5%; ** significant at 1%.

Table 3.Estimates of the poverty dynamic model.
(Unemployment: unemployment rates for households' heads)

	OLS-POOL		**WG** (Fixed Effects)		**GMM**		**System GMM**	
Regressors	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*
Lag of poverty	0.7000**	42.30	0.5668**	29.12	0.3322**	7.56	0.6658**	13.30
Inflation	-0.0293**	-2.96	-0.0309**	-3.23	-0.0318**	-3.06	-0.0291**	-2.76
Unemployment	0.0388**	15.10	0.0436**	16.38	0.0616**	7.96	0.0420**	6.86
Unem. benefit reform 1989	-0.1051**	-2.82	-0.1740**	-4.77	-0.3204**	-4.87	-0.1236**	-2.93
Unem. benefit reform 2002	0.0340	1.77	0.0571**	3.05	0.0394	0.78	0.0356	1.49

Tests	*Estimates*	*p-value*	*Estimates*	*p-value*	*Estimates*	*p-value*	*Estimates*	*p-value*
R^2	0.790	--	0.788	--	--	--	--	--
Hausman test	--	--	204.29	0.00	--	--	--	--
*m*1 test	--	--	--	--	-3.85	0.00	-3.80	0.00
*m*2 test	--	--	--	--	-0.02	0.984	0.90	0.40
Hansen test	--	--	--	--	13.83	1.00	9.44	1.00
AIC	--	--	--	--	--	--	-1.946	--
BIC	--	--	--	--	--	--	-1.917	--

Note: see Note on Table 1.

Table 4.Estimates of the poverty dynamic model.
(Unemployment: percentage of households where all active members are unemployed)

	OLS-POOL		**WG** (Fixed Effects)		**GMM**		**System GMM**	
Regressors	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*
Lag of poverty	0.7085**	43.36	0.5603**	28.90	0.3632**	7.50	0.6788**	15.82
Inflation	-0.0321**	-3.23	-0.0338**	-3.56	-0.0369**	-3.57	-0.0329**	-3.15
Unemployment	0.0642**	14.74	0.0821**	16.97	0.1080**	6.89	0.0711**	7.86
Unem. benefit reform 1989	-0.0634	-1.71	-0.1319**	-3.68	-0.2493**	-4.39	-0.0765*	-2.23
Unem. benefit reform 2002	0.1565**	7.84	0.2054**	10.55	0.2285**	5.60	0.1681**	7.02

Tests	*Estimates*	*p-value*	*Estimates*	*p-value*	*Estimates*	*p-value*	*Estimates*	*p-value*
R^2	0.789	--	0.784	--	--	--	--	--
Hausman test	--	--	224.50	0.00	--	--	--	--
*m*1 test	--	--	--	--	-3.94	0.00	-3.80	0.00
*m*2 test	--	--	--	--	0.00	0.99	0.82	0.41
Hansen test	--	--	--	--	15.90	1.00	6.84	1.00
AIC	--	--	--	--	--	--	-1.942	--
BIC	--	--	--	--	--	--	-1.914	--

Note: See Note in Table 1

Table 5.The role of expansions and recessions.
(System-GMM estimates)

	Unemployment Rate				Households' Heads Unemployment Rate				All Active Members Unemployment Rate			
Regressors	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*
Lag of poverty	0.7212**	19.11	0.7518**	20.71	0.6621**	13.18	0.6804**	14.84	0.6847**	15.46	0.7276**	17.77
Inflation	-0.0352**	-3.50	-0.0457**	-4.57	-0.0279**	-2.72	-0.0273**	-2.68	-0.0335**	-3.33	-0.0445**	-4.37
U_{it} x expansion	0.0265**	7.07	0.0198**	5.03	0.0475**	6.69	0.0437**	6.55	0.0652**	7.32	0.0474**	5.74
U_{it} x recession	0.0281**	7.93	0.0249**	6.85	0.0429**	7.20	0.0414**	7.12	0.0697**	7.94	0.0617**	7.08
Unem. benefit reform 1989	-0.0269	-0.84			-0.1311**	-2.91			-0.0728*	-2.23		
Unem. benefit reform 2002	0.1298**	5.11			0.0506*	2.28			0.1536**	7.23		
p-value for test of equal coefficients	0.8205		0.4966		0.7183		0.8476		0.7964		0.3834	
Tests	*Estimates*	*p-value*	*Estimates*	*p-value*	*Estimates*	*p-value*	*Estimates*	*p-value*	*Estimates*	*p-value*	*Estimates*	*p-value*
*m*1 test	-3.81	0.00	-3.83	0.00	-3.80	0.00	-3.83	0.00	-3.81	0.00	-3.84	0.00
*m*2 test	0.81	0.42	0.88	0.38	0.91	0.36	0.88	0.38	0.82	0.41	0.91	0.36
Hansen test	12.17	1.00	12.12	1.00	10.81	1.00	14.44	1.00	2.25	1.00	3.74	1.00

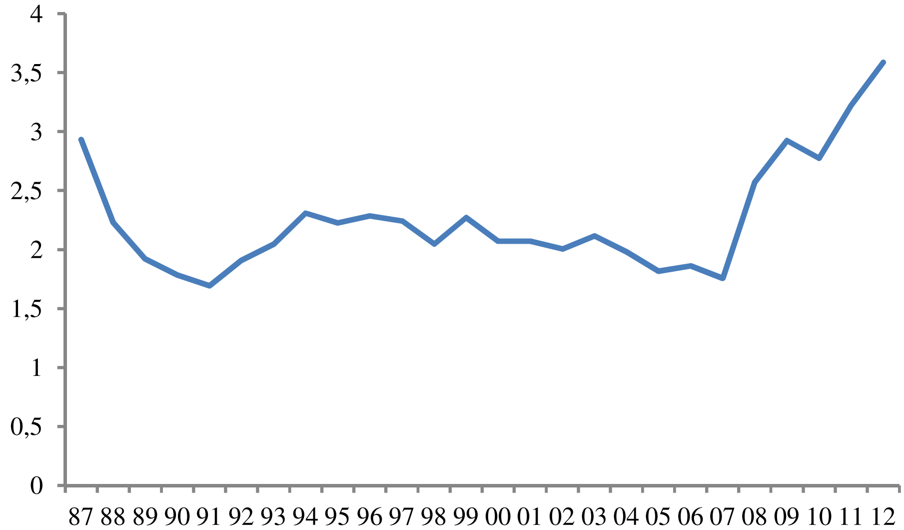
Note: see Note on Table 1.

Table 6.The role of the length of expansions and recessions.
(System-GMM estimates)

	Unemployment Rate				Households' Heads Unemployment Rate				All Active Members Unemployment Rate			
Regressors	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*	*Estimates*	*t*
Lag of poverty	0.7466**	20.57	0.7632**	21.64	0.6789**	15.20	0.6953**	16.47	0.7039**	17.24	0.7328**	19.02
Inflation	-0.0347**	-3.53	-0.0412**	-3.86	-0.0259**	-2.60	-0.0245*	-2.36	-0.0322**	-3.33	-0.0391**	-3.70
Unemployment	0.0236**	4.31	0.0211**	3.82	0.0484**	6.44	0.0457**	6.69	0.0557**	5.43	0.0490**	5.19
Length exp.	-0.0005	-0.21	0.0018	1.01	0.0008	0.33	0.0009	0.46	-0.0017	-1.03	0.0011	0.79
Length rec	-0.0070	-0.91	0.0033	0.47	-0.0023	-0.40	-0.0021	-0.38	-0.0078	-1.51	0.0029	0.55
U_{it} x length exp.	0.0001	0.19	-0.0001	-0.03	0.0001	0.31	0.0001	0.23	0.0006	1.06	0.0003	0.60
U_{it} x length rec.	0.0004	0.88	0.0003	0.60	-0.0002	-0.46	-0.0002	-0.34	0.0012	1.64	0.0009	1.18
Unem. benefit reform 1989	-0.0226	-0.73			-0.1312**	-3.25			-0.0761**	-2.71		
Unem. benefit reform 2002	0.1265**	5.32			0.0383	1.60			0.1559**	6.32		
p-value for test of equal coefficients	0.5600		0.6434		0.6792		0.7568		0.5630		0.5732	
Tests	*Estimates*	*p-value*	*Estimates*	*p-value*	*Estimates*	*p-value*	*Estimates*	*p-value*	*Estimates*	*p-value*	*Estimates*	*p-value*
*m*1 test	-3.79	0.00	-3.80	0.00	-3.80	0.00	-3.81	0.00	-3.79	0.00	-3.81	0.00
*m*2 test	0.82	0.41	0.85	0.40	0.95	0.34	0.90	0.40	0.86	0.39	0.87	0.38
Hansen test	3.81	1.00	2.30	1.00	3.12	1.00	2.01	1.00	3.07	1.00	3.02	1.00

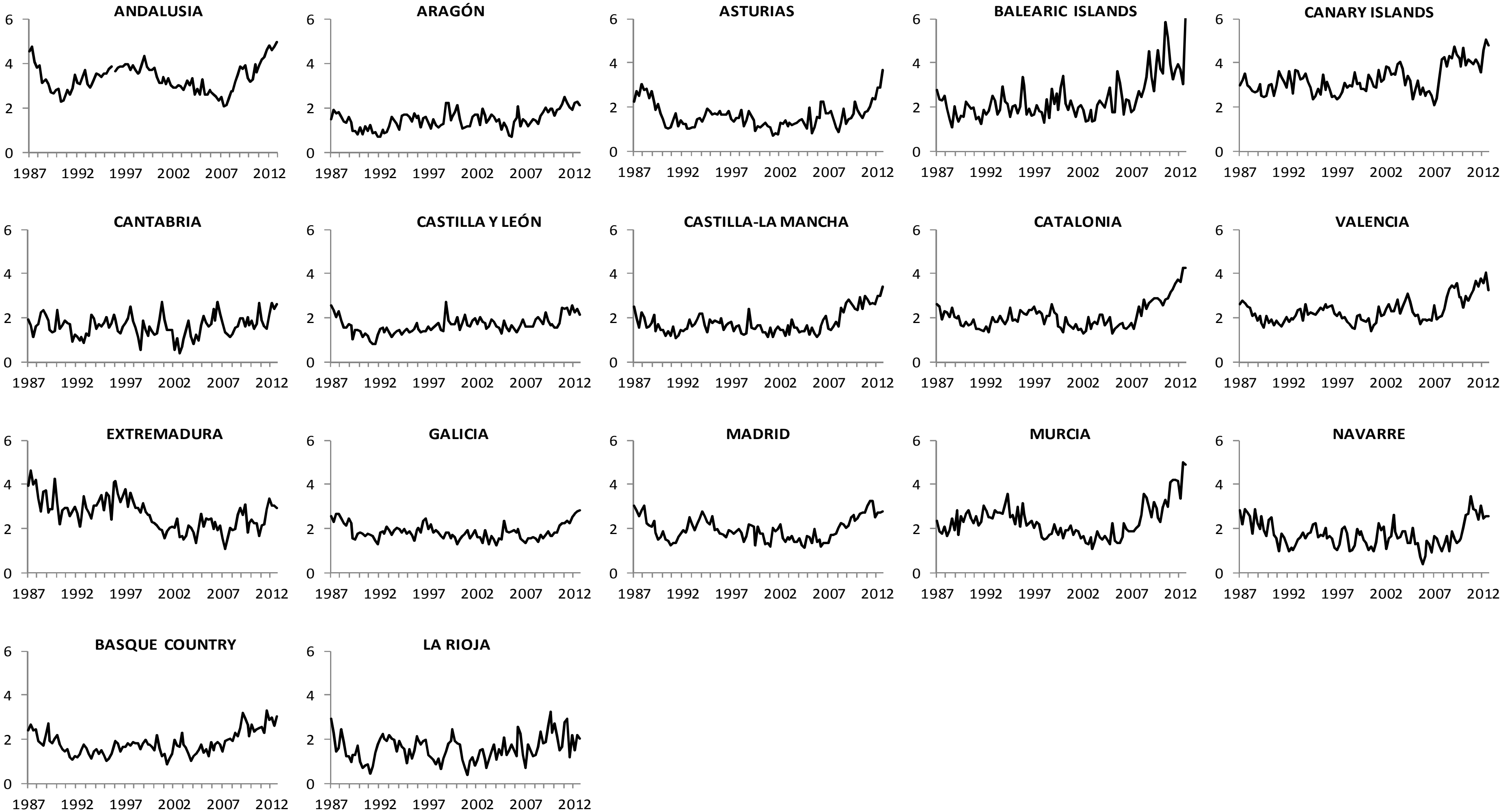
Note: see Note on Table 1.

FIGURE 1. Poverty rate, 1987-2012



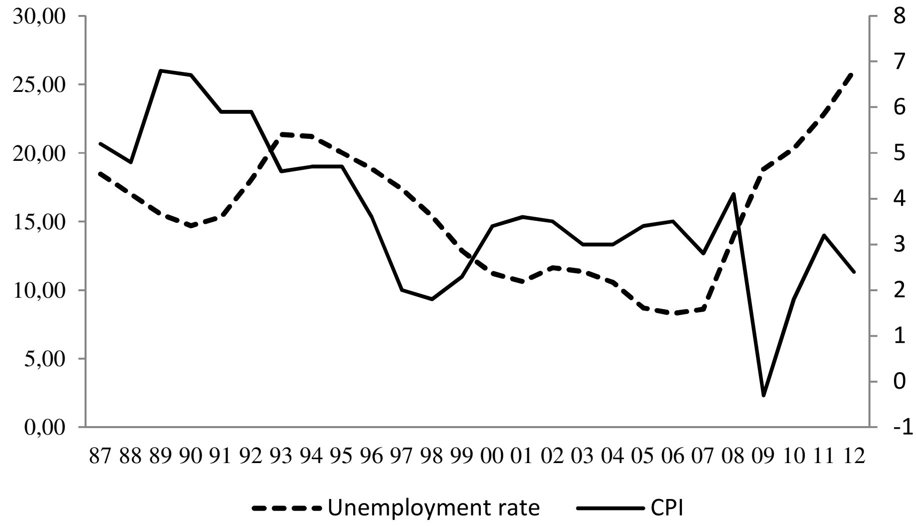
Source: Author's calculations using the Spanish Labour Force Survey, 2nd quarter, (*Encuesta de Población Activa*, EPA)

FIGURE 2. Poverty rates by regions, 1987-2012



Source: Author's calculations using the Spanish Labour Force Survey, 2nd quarter, (*Encuesta de Población Activa*, EPA)

FIGURE 3. Unemployment and Inflation, 1987-2012



Source: Author's calculations using the Spanish Labour Force Survey, 2nd quarter, (*Encuesta de Población Activa*, EPA)

FIGURE 4. Alternative unemployment rates, 1987-2012

Source: Author's calculations using the Spanish Labour Force Survey, 2nd quarter, (*Encuesta de Población Activa*, EPA)