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Keyword:

JEL Cassification:

Is Chronicity Growing? Exploring Intertemporal Poverty in Spain over Three Decades*

Olga Cantó[1] & Miguel Parra[2]

[1,2] Department of Economics, Universidad de Alcalá, Spain & EQUALITAS

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Abstract

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Keywords: intertemporal poverty, chronicity, longitudinal data, Spain

JEL codes: D31, D63, I32, I38

*Corresponding author: Olga Cantó, Departamento de Economía, Facultad de Ciencias Económicas, Empresariales y Turismo, Universidad de Alcalá. Plaza de la Victoria s/n, 28802 Alcalá de Henares, Madrid, Spain (✉ olga.canto@uah.es). ORCID: 0000-0003-0780-3212.

1 Introduction

Poverty is both a static and a dynamic phenomenon, yet conventional studies of advanced economies have often overlooked its intertemporal dimension. Over the past three decades, poverty has evolved substantially in ways that cross-sectional indicators simply cannot capture. While headcount poverty rates in some countries have remained stable or even declined since the Great Recession, this masks a critical dimension of economic disadvantage: its chronicity over time. A society in which many individuals experience temporary income shortfalls is fundamentally different from one in which the poor remain trapped in long-term deprivation. Distinguishing between these scenarios is essential for understanding both the nature of poverty and the effectiveness of policy responses.

The consequences of poverty depend fundamentally on whether it is predominantly chronic or transient. For children, sustained exposure to economic hardship impairs cognitive development (Kiernan and Mensah, 2009), worsens physical and mental health (Fitzsimons et al., 2017), and reduces educational attainment (Lacour and Tissington, 2011). These effects tend to emerge early in life and often become more intense over time, persisting into adulthood and fostering the intergenerational transmission of disadvantage (Heckman, 2006). Among adults, repeated poverty spells deteriorate subjective well-being (Clark et al., 2016) and erode individuals' psychological and financial capacity to cope with shocks (Shah et al., 2012), which eventually generates self-reinforcing poverty trajectories that are difficult to escape and may deepen over time. Moreover, at the aggregate level, persistent poverty reduces human capital accumulation, increases pressure on public finances (Blanden et al., 2010), and weakens civic and political participation (Mood and Jonsson, 2016). Whether poverty is becoming more chronic is therefore not only an individual concern but a central question for the sustainability of inclusive growth in advanced economies.

A general conclusion of the research on poverty dynamics in a variety of rich countries up to 2000 was that, in general, most poverty spells were relatively short. This suggested that the percentage of people who experienced any poverty episode during their lifetime was much higher than the proportion of those who were poor in any given year—almost double between 1994 and 2000. Specifically, the percentage of ever-poor individuals reached around 34%, indicating that roughly a third of the European population suffered some poverty spell in a five-year window (Fouarge and Layte, 2005). Evidence for the United Kingdom and Spain was also consistent with this result (Jenkins et al., 2001; Cantó et al., 2012).

Up to now, the literature is still discussing which may be the best measurement framework to identify intertemporal poverty. The extension of static poverty axioms to a dynamic setting is conceptually and empirically challenging (Porter and Quinn, 2013), and alternative approaches often yield different assessments of chronicity. As a result, we still lack strong evidence on whether individuals in EU countries today face a higher risk of chronic poverty than in the past, and on the potential mechanisms behind this change.

These concerns have gained relevance in the aftermath of the Great Recession. A growing body of evidence suggests that the crisis may have altered poverty trajectories in European Union (EU) countries, increasing both the incidence of long-term poverty and the role of state dependence (Mussida and Sciulli, 2022; Franzen and Bahr, 2024). However, robust evidence on the evolution of chronic poverty in advanced economies remains limited. Existing studies typically focus on the 1990s and early 2000s (Bossert et al., 2019; Gradín et al., 2012; Mendola and Busetta, 2012) or provide more recent evidence that is largely descriptive and restricted to short time spans (Vaalavuo, 2015; Franzen and Bahr, 2024).

In the case of Spain, various studies have found significant levels of income mobility at the bottom of the distribution (Cantó, 2000; Bárcena-Martín and Cowell, 2006; Ayala and Sastre, 2008). Most of them showed that the percentage of population that experienced poverty at least once was significantly higher than in other EU countries during the 1990s and the first decade of the 21st century, with over 40% of individuals suffering a poverty spell between 1994 and 2000, and around 45% between 2008 and 2012 (Cantó et al., 2012; Vaalavuo, 2015). Cantó et al. (2012) analysed poverty profiles in six European countries (Spain, Germany, Denmark, France, Portugal, and the United Kingdom) over an eight-year time window. Their findings revealed that Spain had a high recurrence of poverty compared to other countries, even when poverty incidence rates were similar. During the 1990s, approximately 20% of Spaniards experienced poverty recurrently, accounting for 42% of those who were poor at some point during these years, the highest rate among the countries analysed. Consequently, the incidence of persistent poverty in Spain was relatively low (6.1% of the poor population) compared to that observed in other countries such as France or Portugal (8.4% or 12.7%, respectively). Fouarge and Layte (2005) reach a similar conclusion when comparing chronic poverty levels across welfare regimes and a broader set of countries.

However, after the Great Recession, the results already appear to be somewhat different. In a recent paper, Franzen and Bahr (2024) conclude that after the crisis onset, the percentage of individuals who spend more than two out of four years below the poverty threshold significantly increased both in Spain and Italy. Indeed, regarding the determinants of intertemporal poverty, the concept of genuine state dependence plays a crucial role. Once individuals fall below the poverty threshold, their likelihood of re-experiencing poverty increases significantly, even after accounting for their characteristics. The literature confirms that the degree of this effect has become substantial across Europe, even if there are also significant differences by country (Ayllón and Gábos, 2017; Giarda and Moroni, 2018; Bosco and Poggi, 2020). For Spain, Ayllón (2013) found that over 50% of aggregate state dependence could be attributed to the genuine poverty duration factor, with the remaining percentage influenced by individual and household sociodemographic characteristics. Mussida and Sciulli (2022) suggest that this factor increased following the Great Recession, especially in Spain.

In turn, the improvement of individual sociodemographic characteristics may also play a significant role in reducing chronicity. Higher levels of education and more stable employment contracts may act as protective factors against poverty (Fouarge and Layte, 2005). Evidence suggests that transitions in the labour market heavily influence poverty dynamics in rich countries, while employment quality is also crucial. Individuals in standard employment contracts often benefit from income security, while non-standard contracts, generally less protected by labour laws, lead to higher poverty levels (Daly and Valletta, 2006; Polin and Raitano, 2014).

Even if all the literature reviewed here is key to understanding the drivers of poverty dynamics in developed countries, it is important to note that most studies on intertemporal poverty still rely on data from the 1990s and early 2000s, a period that predates the structural disruptions brought about by the Great Recession. Moreover, recent contributions either cover short time spans that preclude the analysis of long-run trends or focus on poverty transitions without explicitly measuring chronicity. As a result, we still lack robust evidence on whether individuals in EU countries today face a higher risk of chronic poverty than in the past, and on the mechanisms that may determine such a change. This paper aims to fill this gap.

We try to answer the question: has poverty in a large EU country such as Spain become more chronic over the past three decades, and if so, what mechanisms drive this trend? To address it, we analyse the evolution of intertemporal poverty from 1994 up to 2023. Spain is a particularly well-suited setting for this purpose, not only because it has consistently exhibited among the highest static poverty rates in the EU, but also because it was one of the EU countries with the largest share of transient poor and one of the smallest shares of chronic poor within the ever-poor at the beginning of the century (Cantó et al., 2012). Furthermore, its economic context and evolution are defined by three structural features. First, it has historically had a marked labour market duality generating recurrent income instability at the bottom of the distribution and limiting the protective role of standard employment contracts against prolonged deprivation (Amuedo-Dorantes and Serrano-Padial, 2010). Second, the Great Recession took the form of a very severe housing crisis, which impacted low-income households asymmetrically through job destruction and a collapse in household wealth for those with the weakest financial buffers. Third, Spain's welfare architecture, characterised by relatively compressed social transfers and strong reliance on family networks, has documented limitations about its limited capacity to prevent poverty (Esping-Andersen, 1990; Amable, 2003). While single-country analysis might limit the capacity to generalise our results, the structural features that Spain shares with other Southern European and Mediterranean welfare states, such as Italy, Greece or Portugal, imply that the evidence presented could be useful to interpret what is happening in other countries.

Our empirical analysis delivers two main findings that speak directly to these contributions. First, the share of individuals ever experiencing a poverty spell has declined since the mid-1990s, while the incidence of chronic poverty and its severity have risen since the Great Recession. Second, an Oaxaca–Blinder decomposition reveals that intertemporal poverty levels are driven by compositional improvements in individual observable characteristics. Thus, conditional on observable characteristics, both the probability of ever experiencing a poverty spell and of suffering chronic poverty have consistently increased in Spain since the 1990's. These results are driven by a structural weakening of the returns to observable characteristics that used to reduce the risk of falling into poverty and of remaining chronically poor.

The remainder of the paper proceeds as follows. Section 2 reviews the literature on the measurement of intertemporal poverty. Section 3 describes the data. Section 4 outlines thoroughly the alternative measures of chronic poverty and the empirical strategy. Section 5 presents the results on levels, trends, and decomposition, while Section 6 details the main conclusions.

2 Measuring Poverty over Time: A Brief Literature Review

The literature on measuring intertemporal and chronic poverty has largely developed since the 1970s, driven by the growing availability of panel datasets on earnings and household income. These developments have enabled a more robust assessment of how individuals experience poverty over time, either by decomposing poverty into chronic and transient components or by developing methods that summarise longitudinal poverty experiences into interpretable measures.

Seminal studies on intertemporal poverty were generally not grounded in an axiomatic framework, and the pioneering articles using longitudinal data for the United States (US) can be classified into three broad strands: the model-based strand, the tabulation strand, and the poverty-transitions strand. The first strand tries to capture the persistent component of poverty by modelling the error structure of earnings (Lillard and Willis, 1978) or income-to-needs ratios (Duncan and Rodgers, 1991). The second basically tabulates the percentage of individuals who are poor for a given number of years (Coe, 1978), and the poverty-transitions strand is based on estimating poverty-entry and poverty-exit probabilities and identifying their determinants (Stevens, 1999). A key contribution on that is Bane and Ellwood (1986), who underline the importance of the number of uninterrupted periods of poverty as a key determinant of poverty chronicity.

In comparison to cross-sectional measures of poverty, analysing poverty dynamics implies that researchers must adopt additional normative assumptions about well-being over time. A central one concerns the extent to which low-income individuals are assumed to be able to save or dissave in order to smooth well-being when their income or needs fluctuate across periods. This reflects alternative views about whether an individual's status is strictly derived from short-term conditions or not so much. Regarding this normative assumption, the literature has traditionally been divided into two main approaches: the permanent income approach and the spells approach.

The permanent income approach assumes that the poor face no credit constraints and can therefore fully smooth income flows by adjusting their financial behaviour over time—i.e. saving during periods of abundance and drawing on or borrowing these resources during periods of deprivation. This implies that short-term status matters less for individuals' well-being than long-term conditions on the basis that they are forward-looking and can substitute income across periods at no cost. Under this assumption, well-being can be assessed using individuals' average income over the relevant period. A major contribution within this approach was made by Ravallion (1988), with a further empirical application on Chinese data by Jalan and Ravallion (1998). The former shows how fluctuations in individual well-being—captured through income risk—affect expected poverty, decomposing it into a chronic and a transient component. Aligned with the full intertemporal compensation assumption, it identifies as chronically poor those whose average income remains below the poverty threshold. This includes both the persistently poor and those who are poor only part of the time, but whose permanent income level falls below the intertemporal poverty line. Formally, this identification rule can be expressed as $\rho_{\text{chron}}(\bar{y}_i, z) = 1$ if $\bar{y}_i < z$, and $\rho_{\text{chron}}(\bar{y}_i, z) = 0$ otherwise, where $\bar{y}_i = \sum_{t=1}^{T} y_{it}/T$.

After completing this first step, Ravallion (1988) adopts the FGT family to estimate the breadth of each component. Let T be the total number of periods, N the population size, z the poverty line, y_{it} the equivalent income of individual i at period t, and $\bar{y}_i$ the permanent income of individual i. Total poverty (R_{tot}), chronic poverty (R_{chron}) and transient poverty

(R_{trans}) are thus defined as follows:

$$R_{\text{tot}}(\alpha) = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{T}\sum_{t=1}^{T}\left(1 - \frac{\min(z, y_{it})}{z}\right)^{\alpha} \tag{1}$$

$$R_{\text{chron}}(\alpha) = \frac{1}{N}\sum_{i=1}^{N}\left(1 - \frac{\min(z, \bar{y}_{i})}{z}\right)^{\alpha} \tag{2}$$

$$R_{\text{trans}}(\alpha) = R_{\text{tot}}(\alpha) - R_{\text{chron}}(\alpha) \tag{3}$$

Intuitively, $R_{\text{chron}}(\alpha)$ captures the share of poverty that persists after full intertemporal income smoothing, while $R_{\text{trans}}(\alpha)$ represents changes in $R_{\text{tot}}(\alpha)$ due to unexpected shocks that cannot be smoothed by individuals' intertemporal financial behaviour. Notably, this strategy for defining chronic poverty requires aggregating individuals' income across periods first, then identifying the chronically poor, and finally assessing population poverty levels using a FGT index (Calvo and Dercon, 2009).

Although this specification prevents considering negligible income drops as transient poverty by satisfying the continuity axiom, a relevant drawback is that its assumption of perfect substitution of resources over time is rather extreme. Since its sequence of analysis makes the indicator insensitive to the duration of poverty, long periods of scarcity can be offset by a single high-income period, ignoring poverty trajectories. Furthermore, as noted by Jappelli (1990) and Azpitarte (2010), low-income households are likely to face significant credit constraints, and the cost of compensating income across time may vary along the economic cycle (Porter and Quinn, 2013). Alternative indicators within the permanent income approach are Hoy and Zheng (2011), which take into account the timing of poverty, and Duclos et al. (2010), who propose a monetary metric to measure how much individuals would be willing to pay (in terms of income reduction) to smooth their income variability. Nevertheless, these indicators still share all the limitations mentioned above.

The second approach, known as the spells approach, takes the opposite view to that of the permanent income approach and defines poverty status on a period-by-period basis, assuming that low-income individuals are fully credit-constrained and therefore unable to transfer resources across time. This approach emphasises that the accumulation of consecutive poverty periods reduces the chances of escaping poverty, linked to a variety of reasons such as asset depletion or reduced well-being (Narayan-Parker and Patel, 2000; Clark et al., 2016) and thus leaving a scar on those who suffer it. Two key contributions in this framework are Bane and Ellwood (1986) and, more recently, Foster (2009). Given that this approach rules out the possibility of intertemporal compensation, income in other periods does not affect the individual's per-period poverty status.

The seminal contribution of Foster (2009) identifies the chronically poor through a dual cut-off strategy and then assesses chronic poverty summing up in society. The first stage of the identification process consists of determining whether individual i is poor in period t. For this purpose, a per-period poverty cut-off z is used, yielding a static identification specification such that $\rho(y_{it}, z) = 1$ if $y_{it} < z$, and $\rho(y_{it}, z) = 0$ otherwise. In a second step, a duration cut-off is set. Denoted as $\tau \in (0, 1]$, it indicates the minimum proportion of time a poor individual must experience poverty to be considered chronically poor. Consequently, individuals are classified as such if they have been in poverty for longer than the duration threshold τ.[1] To reflect the number of periods individual i spends in poverty, per-period values of $\rho(y_{it}, z)$ are summarised in $d_i = \sum_{t=1}^{T} \rho(y_{it}, z)$. Accordingly, the identification rule for chronic poverty is defined as $\rho_{\text{chron}}(d_i, \tau) = 1$ if $d_i > \tau T$, and $\rho_{\text{chron}}(d_i, \tau) = 0$ otherwise.

Subsequently, in the social aggregation stage, it is most common to use the FGT index to evaluate the level of total intertemporal poverty (F_{tot}), chronic poverty (F_{chron}) and transient poverty (F_{trans}). In this case, total poverty is obtained as the level of poverty when $\tau = 0$, which corresponds to the set of individuals who experience poverty at least once in the total time window. Transient poverty can be defined either as the residual between total and chronic poverty, or as the breadth of poverty among individuals who experience at least one poverty spell but whose total duration is below the threshold τ. For chronic poverty, the index is applied to all periods of individuals satisfying the condition $\rho_{\text{chron}}(d_i, \tau) = 1$, denoted by $\mathbf{1}_{\text{chron}}$. Each group is formally defined as follows:

$$F_{\text{tot}}(\alpha) = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{T} \sum_{t=1}^{T} \left(1 - \frac{\min(z, y_{it})}{z}\right)^{\alpha} \tag{4}$$

$$F_{\text{chron}}(\alpha) = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{T} \sum_{t=1}^{T} \left(1 - \frac{\min(z, y_{it})}{z}\right)^{\alpha} \mathbf{1}_{\text{chron}} \tag{5}$$

$$F_{\text{trans}}(\alpha) = F_{\text{tot}}(\alpha) - F_{\text{chron}}(\alpha) \tag{6}$$

The main advantage of Foster (2009)'s method, as well as of all the spell-based contributions, is that it satisfies the intertemporal focus axiom—i.e., a high-well-being period cannot

[1]It is worth noting that the selection of this second threshold is crucial, as it significantly impacts the identification of the chronicity dimension (Israeli and Weber, 2014). A higher cut-off would identify fewer individuals as chronically poor, while a lower one implies including more individuals who experience relatively short spells of poverty.

fully compensate for a period of scarcity. Its sequence of focus–transformation–aggregation is crucial for this purpose (Calvo and Dercon, 2009). In practice, it first identifies chronically poor individuals using the dual cut-off, then applies the FGT family to transform the corresponding poverty experiences, and finally aggregates the results across the population. By placing the focus property first and thus assessing period-by-period poverty, this specification rules out any compensation over time, reflecting the long-lasting effects of each poverty episode and the impossibility of non-poverty periods compensating for them.

Nevertheless, the main limitation of Foster (2009) is that it does not account for individual income trajectories. By considering only the total number of periods spent in poverty, without distinguishing whether these episodes occur consecutively or intermittently, the measure he proposes is insensitive to the pattern of poverty experiences. For instance, over a six-year window, it would treat an individual with alternating poverty spells as equivalent to one with three consecutive episodes, despite the latter being more detrimental to well-being (Clark et al., 2016).

Within the same framework, one of the most robust contributions addressing this issue is that of Gradín et al. (2012), who generalise Foster (2009) and other alternative proposals such as Bossert et al. (2019).[2] These authors propose a flexible intertemporal index that satisfies all the properties they consider desirable. Specifically, the index incorporates three parameters to calibrate the sensitivity to the variability of individual poverty gaps over time, to the duration of poverty spells, and to the degree of aversion to inequality in intertemporal poverty experiences across the population. The key innovation of this measure lies primarily in the second parameter, which introduces the intertemporal poverty spell duration sensitivity axiom. In practice, this formalises the idea that, given two income trajectories with the same number of poverty episodes, the index should assign a higher value when these episodes occur consecutively, *ceteris paribus*.

The empirical strategy in Gradín et al. (2012) is similar to that of Foster (2009): it uses the dual cut-off τ to first identify chronically poor individuals and then constructs an individual-level poverty measure G_i based on a modified FGT index. This metric corresponds to the standard $\text{FGT}(\alpha)_i = \frac{1}{T}\sum_{t=1}^{T}\left(1 - \frac{\min(z, y_{it})}{z}\right)^{\alpha}$ index, but aggregated to the power of γ, which captures sensitivity to inequality in poverty gaps over time: for the same average normalised poverty gap, greater temporal variability results in higher measured chronicity when $\gamma > 1$. In addition, individual poverty experiences are weighted by $w_{it} = (s_{it}/T)^{\beta}$, where s_{it} denotes the length of the consecutive poverty spell that individual i is experiencing at period t, and $\beta > 0$ governs the sensitivity of the measure to spell duration. The higher

[2] The authors build upon the *working paper* that was later published—and cited here.

the value of β, the more weight is assigned to long, uninterrupted spells of poverty relative to intermittent ones. Therefore, G_i can be expressed as:

$$G_i = \frac{1}{T} \sum_{t=1}^{T} \left(1 - \frac{\min(z, y_{it})}{z}\right)^{\gamma} \left(\frac{s_{it}}{T}\right)^{\beta} \tag{7}$$

The aggregation of these individual poverty indexes into total (G_{tot}), chronic (G_{chron}) and transient poverty (G_{trans}) is as follows:

$$G_{\text{tot}}(\gamma, \beta, \alpha) = \frac{1}{N} \sum_{i=1}^{N} \left(\frac{1}{T} \sum_{t=1}^{T} \left(1 - \frac{\min(z, y_{it})}{z}\right)^{\gamma} \left(\frac{s_{it}}{T}\right)^{\beta} \right)^{\alpha} \tag{8}$$

$$G_{\text{chron}}(\gamma, \beta, \alpha) = \frac{1}{N} \sum_{i=1}^{N} \left(\frac{1}{T} \sum_{t=1}^{T} \left(1 - \frac{\min(z, y_{it})}{z}\right)^{\gamma} \left(\frac{s_{it}}{T}\right)^{\beta} \right)^{\alpha} \mathbf{1}_{\text{chron}} \tag{9}$$

$$G_{\text{trans}}(\gamma, \beta, \alpha) = G_{\text{tot}}(\gamma, \beta, \alpha) - G_{\text{chron}}(\gamma, \beta, \alpha) \tag{10}$$

Notably, the indicator nests several existing measures as special cases. When $\beta = 0$ and $\gamma = 1$, it reduces to the chronic and transient poverty measures of Foster (2009) for the same duration cut-off τ; when $\beta = \alpha = 1$, to the measure of Bossert et al. (2019); and when $\alpha = 0$, it yields the proportion of individuals who have ever been poor.

All these spell-based approaches provide valuable insights into poverty over time, satisfying the intertemporal focus and the duration sensitivity properties.[3] However, they all exhibit notable limitations such as censoring issues and measurement errors (Hulme and Shepherd, 2003; Breen and Moisio, 2004). Under this framework, relatively small income fluctuations can produce poverty spells without really reflecting significant changes in individuals' well-being.[4] Furthermore, they all assume that such well-being is strictly determined by individuals' economic situation in each period, without the possibility of drawing on any savings to offset deprivation. When using income, this notion turns rather unrealistic, as income tends to be more easily transferable across periods than consumption (Foster and Santos, 2013).

To reconcile the permanent income and spells approaches, an intermediate perspective on intertemporal substitution is provided by Foster and Santos (2013). This hybrid method avoids adopting extreme positions regarding compensation over time and allows re-

[3]See also the contributions of Mendola and Busetta (2012) or Dutta et al. (2013) within the spells approach framework.

[4]See Porter and Yalonetzky (2019) for a further analysis of measurement error in the measurement of intertemporal poverty.

searchers to explicitly calibrate the degree of income substitutability over time through a single parameter (κ).[5] Their method develops an intertemporal poverty decomposition that is conceptually similar to Ravallion's (1988), although it relies on the Clark et al. (1981) poverty index (CHU) rather than the FGT family. For this purpose, a modified measure of permanent income, $\tilde{y}_{it}$, is estimated using the discount factor κ:

$$\tilde{y}_{it} = \begin{cases} \left(\frac{1}{T} \sum_{t=1}^{T} y_{it}^{\kappa} \right)^{1/\kappa} & \text{if } \kappa \neq 0 \\ \prod_{t=1}^{T} y_{it}^{1/T} & \text{if } \kappa = 0 \end{cases} \tag{11}$$

The interpretation of the generalised average income $\tilde{y}_{it}$ over the analysis period depends on the value of κ. When $\kappa = 1$, it corresponds to the arithmetic mean of income; when $\kappa > 1$, greater weight is assigned to higher income levels; and when $\kappa < 1$, greater weight is placed on lower income levels. The term $1 - \kappa$ captures aversion to intertemporal inequality, while, more importantly, $1/(1-\kappa)$ represents the elasticity of intertemporal compensation. In short, lower values of κ imply a more limited capacity to substitute income across periods, with $\kappa = 1$ reflecting perfect intertemporal substitution—consistent with the permanent income approach—whereas $\kappa \to -\infty$ represents the case of no substitution, as in the spells approach.

The measure $\tilde{y}_{it}$ is used to identify the chronically poor through the comparison of this discounted permanent income and the poverty threshold. Formally, $\rho_{\text{chron}}(\tilde{y}_{it}, z) = 1$ if $\tilde{y}_{it} < z$, and $\rho_{\text{chron}}(\tilde{y}_{it}, z) = 0$ otherwise. The levels of total (FS_{tot}), chronic (FS_{chron}), and transient poverty (FS_{trans}) are then estimated following a similar decomposition strategy as in Ravallion (1988), but in this case adopting the CHU class of poverty measures:

[5] Following Foster and Santos (2013), the original paper uses β to denote this parameter. We adopt κ here to avoid notational conflict with the duration sensitivity parameter β in Gradín et al. (2012).

$$FS_{\text{tot}}(\beta) = \begin{cases} \frac{1}{\kappa}\left[1 - \left(\frac{1}{N}\sum_{i=1}^{N}\frac{1}{T}\sum_{t=1}^{T}\frac{\min(z, y_{it})}{z}\right)^{\kappa}\right] & \text{if } \kappa \neq 0 \\ -\ln\left(\frac{1}{N}\sum_{i=1}^{N}\frac{1}{T}\sum_{t=1}^{T}\frac{\min(z, y_{it})}{z}\right) & \text{if } \kappa = 0 \end{cases} \tag{12}$$

$$FS_{\text{chron}}(\kappa) = \begin{cases} \frac{1}{\kappa}\left[1 - \left(\frac{1}{N}\sum_{i=1}^{N}\frac{\min(z, \tilde{y}_{it})}{z}\right)^{\kappa}\right] & \text{if } \kappa \neq 0 \\ -\ln\left(\frac{1}{N}\sum_{i=1}^{N}\frac{\min(z, \tilde{y}_{it})}{z}\right) & \text{if } \kappa = 0 \end{cases} \tag{13}$$

$$FS_{\text{trans}}(\kappa) = FS_{\text{tot}}(\kappa) - FS_{\text{chron}}(\kappa) \tag{14}$$

In words, and as a particular case, observe that if no individual in the population ever experiences poverty, then $FS_{\text{tot}}(\kappa) = 0$ regardless of the value of κ. The same logic applies to $FS_{\text{chron}}(\kappa)$ when no individual is chronically poor. When this is not the case—as is typically observed—the magnitude of both components varies with the depth of poverty experiences and the degree of penalisation of gaps induced by κ. As usual, transient poverty is defined as a residual component.

Although this hybrid indicator allows for imperfect compensation of resources over time, it still relies on the core principles of the permanent income approach. As a result, it satisfies desirable axioms—such as continuity—but remains insensitive to the duration of poverty and is not path-dependent.[6] The relevant properties that each measure satisfies are summarised in Table 1.

As the table makes clear, no single indicator satisfies all relevant properties simultaneously. While the permanent income and hybrid measures (Ravallion, 1988; Foster and Santos, 2013) satisfy continuity—a marginal income change near the poverty line does not produce an abrupt jump in measured poverty—they are insensitive to the individual poverty profiles, failing the intertemporal focus axiom that the spell-based proposals (Foster, 2009; Gradín et al., 2012) are designed to capture. In other words, the choice of approach therefore involves an explicit normative trade-off: gaining intertemporal focus and duration sensitivity necessarily comes at the cost of continuity, and vice versa. This is precisely why relying on a single indicator would be insufficient, and why the joint use of all four measures constitutes

[6] See Porter and Quinn (2013) for a similar hybrid measure that summarises intertemporal poverty into a single indicator, differing from Foster and Santos (2013) in that it does not decompose poverty into chronic and transient components.

Table 1: Axioms of Intertemporal and Chronic Poverty Indicators

	Ravallion (1988)	Foster (2009)	Gradín et al. (2012)	Foster and Santos (2013)
Weak focus	✓	✓	✓	✓
Time symmetry	✓	✓	✓	✓
Continuity	✓	✗	✗	✓
Intertemporal focus	✗	✓	✓	✓
Duration sensitivity	✗	✗	✓	✗

Note: Only the most important properties for this study are displayed. For further details, see Porter and Quinn (2013).

the central robustness strategy of this paper.

3 Data

Our analysis combines two harmonised longitudinal datasets that provide information on household income and sociodemographic characteristics in the European Union: the European Community Household Panel (ECHP) and the European Union Statistics on Income and Living Conditions (EU-SILC). The ECHP covers the period 1994–2001, while EU-SILC has been conducted annually since 2004 up to now. Both surveys collect comparable information on household income and living conditions and constitute the main sources of panel data for studying income dynamics in Europe.

The two datasets differ in their panel structure. The ECHP follows individuals annually for up to 8 years, whereas EU-SILC uses a rotating panel design, in which respondents are observed for up to 4 consecutive waves. To ensure comparability across datasets and over time, we harmonise the observation window by restricting the ECHP to its first four waves, and to address attrition—an inherent feature of longitudinal surveys (Fusco and Van Kerm, 2023)—we restrict the sample to individuals observed in all four waves of each observation window.[7] This results in a balanced panel of respondents who remain in the survey for four years.[8] Because attrition may be non-random, we use inverse probability weights (IPW) to restore representativeness by assigning greater weight to individuals with a higher probability of dropping out of the panel.[9]

To analyse changes over time, we divide the sample into five sub-periods correspond-

[7]See Fouarge and Layte (2005) for the same strategy in the use of the ECHP.

[8]See Table 6 in the Appendix for detailed information about the sample size in both datasets, along with the time of observation.

[9]See Appendix for more details on our IPW strategy.

ing to distinct macroeconomic phases: the mid-1990s, the pre-Great Recession period, the Great Recession, the post-Great Recession recovery, and the early 2020s. Each four-year observation window is assigned to a given period if at least three of its years fall within that phase. This classification is based on the income reference year (t–1) rather than the survey year (t), ensuring that poverty experiences are attributed to the economic context in which income was generated.[10]

Finally, the relatively short duration of panel windows raises potential concerns about left- and right-censoring. Following the literature on poverty dynamics, we do not explicitly correct for these issues, as previous studies find that censoring has a limited impact on the main estimates of poverty persistence in short panels (McKernan and Ratcliffe, 2005; Arranz and Cantó, 2012).

4 How Will We Measure Intertemporal and Chronic Poverty?

To assess the evolution of intertemporal and, in particular, chronic poverty in Spain, we rely on the four main alternative indicators drawn from the literature reviewed above: the permanent income approach proposed by Ravallion (1988), two spells-based measures developed by Foster (2009) and Gradín et al. (2012), and the hybrid indicator introduced by Foster and Santos (2013).

Within the permanent income approach, Ravallion (1988) classifies individuals as so if their average income over the observation window falls below the poverty line. No additional parameter is required at this stage, as the arithmetic mean serves as the permanent income estimate by construction. Within the spells-based framework, identification proceeds through a dual cut-off. Following Foster (2009) and Gradín et al. (2012), we first determine whether an individual is poor in each period using a per-period poverty line and then apply a duration threshold $\tau = 0.75$ to identify those whose poverty is chronic. This implies classifying individuals as chronically poor when they experience poverty in at least three out of four years, reflecting a high degree of chronicity and capturing situations in which poverty is a prolonged rather than a temporary condition.

For the hybrid indicator of Foster and Santos (2013), identification relies on a modified permanent income measure $\tilde{y}_i$ that incorporates the parameter κ, which reflects the degree of intertemporal income substitutability, with individuals classified as chronically poor if

[10]For instance, in analysing the Great Recession, which spanned approximately from 2008 to 2014, we consider individuals observed for at least three years during this timespan. This implies using those surveyed between the 2008–2011 and the 2013–2016 waves, with their income years 2007–2010 and 2012–2015, respectively. See Table 7 for all cases.

this discounted permanent income falls below the poverty line. Since $\kappa = 1$ corresponds to perfect intertemporal substitution—consistent with the permanent income approach—while $\kappa \to -\infty$ approximates the case of no substitution as in the spells approach, we estimate the measure at $\kappa = 1$, $\kappa = -0.25$, and, more importantly, $\kappa = 0.25$, spanning full, zero, and—as our preferred case—imperfect intertemporal substitution.

Once chronically poor individuals have been identified, population poverty levels are assessed using the relevant index for each approach—the FGT class for Ravallion (1988), Foster (2009), and Gradín et al. (2012), and the CHU index for Foster and Santos (2013). In the main analysis, we focus on a single value of each parameter that best captures the depth and persistence of chronic poverty: $\tau = 0.75$ to restrict chronic status to those with a high degree of chronicity, $\alpha = 1$ to account for both the incidence and intensity of poverty experiences, $\gamma = 2$ and $\beta = 1$ for Gradín et al. (2012) to weight poverty gaps by their intertemporal variability and place maximum emphasis on spell persistence, and $\kappa = 0.25$ for Foster and Santos (2013) to reflect imperfect but meaningful intertemporal income substitution. Results for the full range of alternative parameter values are reported in the Appendix and confirm that the main conclusions are robust to these choices.[11]

For all indicators, poverty is assessed using equivalent disposable household income.[12] The poverty line is defined consistently with the normative assumptions of each approach. For the spells-based measures of Foster (2009) and Gradín et al. (2012), which assess poverty on a period-by-period basis, we apply an annual poverty line set at 60% of the median income in each year. For the permanent income approach of Ravallion (1988) and the hybrid indicator of Foster and Santos (2013), which aggregate income over the observation window before identification, we use a poverty line set at 60% of the median income calculated over the four-year window.[13]

To estimate the drivers of the individual probability of being ever-poor and experiencing a higher level of chronic poverty, we estimate econometric models that assess whether poverty exposure over time and chronic poverty have changed significantly across periods. Specifically, we regress individual-level indicators on a set of demographic and socioeconomic characteristics. This includes individual characteristics (X_{it}), such as age, gender, education, civil status, labour market status, and work experience of the household head,

[11] See Table 8. Specifically, this involves the three dimensions of the FGT index—incidence ($\alpha = 0$), incidence and intensity ($\alpha = 1$), and incidence, intensity, and inequality among the poor ($\alpha = 2$)—alternative values of $\beta \in [0, 1]$ for Gradín et al. (2012) with γ fixed at 2, and $\kappa \in \{-0.25, 0.25, 1\}$ for Foster and Santos (2013).

[12] We use the modified OECD equivalence scale to make individual well-being comparable across households with different demographic compositions.

[13] Results are robust to applying the four-year poverty line to the spells-based measures as well; conclusions hold regardless of the chosen poverty line.

household-level characteristics (Z_{ht}), such as size, housing tenure, composition, and the share of working, unemployed, and retired members, and region and time fixed effects (λ).[14] For the likelihood of experiencing poverty at any point in time, we estimate a logit model given the binary nature of the dependent variable. For the remaining indicators, which yield continuous individual-level chronic poverty indices, such as G_i, we rely on OLS estimation. In all cases, the mid-1990s serves as the reference period:

$$P_{it} = \mu + \sum_{t=2}^{T} \theta_t \, \text{Period}_t + \phi X_{it} + \delta Z_{ht} + \lambda + \varepsilon \tag{15}$$

where P_{it} denotes each of the two outcomes for individual i in period t and Period_t is a set of binary indicators equal to one if the observation belongs to period t and zero otherwise, with the mid-1990s ($t = 1$) serving as the reference category. The model is estimated with inverse probability weights and standard errors clustered at the household level. The coefficients θ_t capture the change in the poverty measure in period t relative to the mid-1990s baseline, net of all observable characteristics.

Finally, to identify the mechanisms underlying the observed changes, we conduct an Oaxaca–Blinder decomposition of the individual probability of being ever-poor and experiencing a higher level of chronic poverty, which allows us to disentangle the contributions of changes in observable characteristics (endowments), changes in their associated returns (coefficients), and their interaction. This provides insight into whether the evolution of intertemporal and chronic poverty in Spain reflects shifts in population composition or structural changes in the relationship between sociodemographic characteristics and poverty outcomes.[15]

5 Results

5.1 The Evolution of Chronic Poverty in Spain over Three Decades

As noted earlier, previous results on intertemporal poverty in Spain indicate relatively high exposure to poverty in a comparative perspective. For the late 1990s, evidence points to a large proportion of ever-poor individuals and a notably high degree of poverty transience compared with countries displaying similar cross-sectional poverty rates (Cantó et al., 2012). Consistently, studies applying path-dependent intertemporal indicators report relatively low levels of chronicity (Gradín et al., 2012; Bossert et al., 2019).

[14] See Table 8 for the full list of covariates.
[15] See Appendix for more details on the Oaxaca-Blinder decomposition.

Building on this evidence, we draw on the four intertemporal poverty indicators introduced in Section 4 to assess whether chronic poverty has consistently increased following the Great Recession, whatever the approach we choose. Since each approach rests on fundamentally different assumptions regarding intertemporal income substitutability—ranging from full smoothing under Ravallion (1988) to no substitution under Foster (2009) and Gradín et al. (2012), with Foster and Santos (2013) occupying an intermediate position—their joint consistency constitutes the central robustness argument of this section.

Table 2 reflects the identification of each poverty profile according to the three approaches by reporting the share of people classified as intertemporally poor, chronically and transiently poor across the five periods under analysis. Furthermore, to rule out the concern that a change in the ever-poor rate could mechanically drive that in any of the two categories, we relativise these shares and include in parentheses the weight of chronically and transiently poor individuals within the intertemporally poor. Despite differences in the underlying assumptions governing each indicator, all approaches agree on a key conclusion: although the incidence of poverty over time has slightly declined, there has been a substantial rise in chronic poverty during the past three decades, with cumulative increases ranging from approximately 2 to 4 percentage points depending on the approach.

Results indicate that the share of individuals experiencing any poverty spell rose from 34-35% in the mid-1990s to approximately 39% in the pre-crisis period, reflecting rising income volatility and higher poverty exposure among vulnerable groups. Following the Great Recession, however, this figure declined steadily, reaching more than 31% in the early 2020s, which implies that roughly one in three Spaniards experiences poverty at least once over four years today.

Focusing on the chronic poverty rates, the ordering across approaches reflects the respective methodological assumptions. The spells approach, which assumes full credit constraints and identifies as chronically poor only those individuals who spent at least three out of four years below the poverty line, produces the lowest rates by construction, starting from 11.7% in the mid-1990s and reaching 15.7% in the early 2020s. The permanent income approach occupies an intermediate position: by averaging income across periods, it captures individuals for whom the intensity rather than the duration of poverty is what ultimately drives their chronic status. This includes those whose income during non-poverty periods fails to compensate for the depth of their deprivation when it occurred, leaving their permanent income below the poverty line without any duration requirement. Finally, the sub-arithmetic mean specification of the hybrid approach produces the highest rates of chronic poverty throughout, ranging from 16.8% in the mid-1990s to 20.3% at the post-crisis peak.[16]

More importantly, the corresponding shares within the ever-poor reveal a robust pattern: chronic poverty was broadly stable in the decade preceding the Great Recession, rose sharply and simultaneously across all approaches during the crisis, and has since remained well above its pre-crisis levels. Clearly, the Great Recession acted as a structural break. Under the spells approach, the weight of chronically poor among the ever-poor jumped by 10 percentage points during the crisis years alone—by far the largest single-period increase across any approach—while the permanent income and hybrid approaches register increases of 8.1 and 9.5 percentage points, respectively.

Crucially, this deterioration has proved persistent. In the early 2020s, none of the three approaches has returned to pre-crisis levels but remained notably high. The spells approach records a chronicity rate of 16 percentage points above its mid-1990s level and only 0.1 points below its post-crisis peak, indicating continued consolidation rather than recovery. Similarly, the permanent income approach stands at 56.1%, approximately 15 percentage points above its mid-1990s value, while the hybrid indicator registers 59.9%, an increase of nearly 12 percentage points over the same horizon.

Among all these approaches, it is striking how chronic poverty within overall poverty has increased up to more than 50% in recent years, which means that more than half of those who suffer any deprivation experience the issue chronically—either because of duration or low average income. This convergence across methodologically distinct approaches, each resting on different assumptions about intertemporal income substitutability and duration requirements, constitutes strong evidence that the rise in chronic poverty in Spain is a robust empirical finding rather than a consequence of the assumptions underlying any single indicator. What was a predominantly transient phenomenon in the mid-1990s has become, for a substantial and growing fraction of the ever-poor, a prolonged condition.

[16] Unlike Ravallion (1988), the power mean of order $\kappa = 0.25$ lies strictly below the arithmetic mean for any individual with income variability across periods, and the gap widens with volatility. As a result, those whose arithmetic mean income just lies above the poverty line may still be classified as chronically poor under Foster and Santos (2013) if their income trajectory is sufficiently volatile, mechanically generating higher chronicity rates independently of average income and where the two approaches stand on intertemporal substitutability.

Table 2: Incidence of Total Intertemporal Poverty and its Decomposition into Chronic and Transient Components acro

	Permanent Income			Spells		
	Total	Chronic	Transient	Total	Chronic	Transient
Mid-1990s	35.0	14.3 (40.9%)	20.7 (59.1%)	34.1	11.7 (34.3%)	22.4 (65.7%)
Pre-GR	39.5	17.3 (43.8%)	22.2 (56.2%)	38.7	14.0 (36.2%)	24.7 (63.8%)
GR	31.8	16.9 (53.1%)	14.9 (46.9%)	31.9	14.7 (46.1%)	17.2 (53.9%)
Post-GR	33.1	19.2 (58.0%)	13.9 (42.0%)	32.9	16.6 (50.5%)	16.3 (49.5%)
Early 2020s	31.4	17.6 (56.1%)	13.8 (43.9%)	31.1	15.7 (50.5%)	15.4 (49.5%)
Observations		137,125			137,125	

Source: Authors' calculations from ECHP and EU-SILC data.

Note: The permanent income approach follows Ravallion (1988). The spells-based approach follows Foster (2009) and Gradín et a
at $\tau = 0.75$. The hybrid approach follows Foster and Santos (2013), with the degree of intertemporal income substitutability calib

Having established that the proportion of individuals in chronic poverty has risen consistently across all identification approaches, we now analyse to what extent those identified as chronically poor are worse off when different dimensions of poverty—such as depth and persistence—are taken into account. Table 3 reports, for each indicator and period, the assessment of total, chronic and transient poverty following the methodological framework detailed in Section 4.

To recall briefly, under the permanent income approach of Ravallion (1988) and the spells approach shared by Foster (2009) and Gradín et al. (2012), chronic poverty is measured using the standard FGT index with $\alpha = 1$. This captures the poverty incidence and intensity of either those whose average income over the panel falls below the poverty line or those poor for at least three out of four years ($\tau = 0.75$). Gradín et al. (2012) additionally introduces $\gamma = 2$ and, more importantly, $\beta = 1$ to penalise both the intertemporal inequality among the chronic poor and the persistence of their poverty spells. On the other hand, the hybrid indicator of Foster and Santos (2013) applies the CHU decomposition with $\kappa = 0.25$, which, as noted above, uses a sub-arithmetic power mean to restrict income compensation over time.

Regardless of the approach adopted, the picture that emerges corroborates and sharpens the conclusion drawn from the identification stage: chronic poverty has not only become more prevalent but has also grown more severe. Across all indicators, those identified as chronically poor show significantly higher poverty rates after the onset of the Great Recession. This means that in addition to having more people deprived over time, those deprived are now worse off in terms of depth or persistence.

Table 3: Severity of Intertemporal, Chronic and Transient Poverty at the Population Level across Indicators

	Ravallion (1988)			Foster (2009)			Gradín et al. (2012)		
	R_{tot}	R_{chron}	R_{trans}	F_{tot}	F_{chron}	F_{trans}	G_{tot}	G_{chron}	G_{trans}
Mid-1990s	0.057	0.034	0.023	0.057	0.034	0.023	0.019	0.015	0.004
Pre-GR	0.071	0.043	0.028	0.071	0.044	0.027	0.028	0.022	0.006
GR	0.066	0.049	0.017	0.066	0.050	0.016	0.033	0.029	0.004
Post-GR	0.072	0.055	0.017	0.072	0.057	0.015	0.032	0.030	0.002
Early 2020s	0.065	0.049	0.016	0.065	0.051	0.014	0.028	0.026	0.002
Observations		137,125			137,125			137,125	

Source: Authors' calculations from ECHP and EU-SILC data.

Figure 1 relativises the values above and reports the share of chronic poverty within the ever-poor (total poverty). Again, this allows us to address the concern that an increase in the latter could mechanically raise chronic poverty levels. The results reject this, revealing a striking weight of chronicity throughout the entire period. Even in the mid-1990s, chronic poverty accounted for around 60% of intertemporal poverty under both Ravallion (1988) and Foster (2009), approximately 80% under Gradín et al. (2012), and around 68% under Foster and Santos (2013).

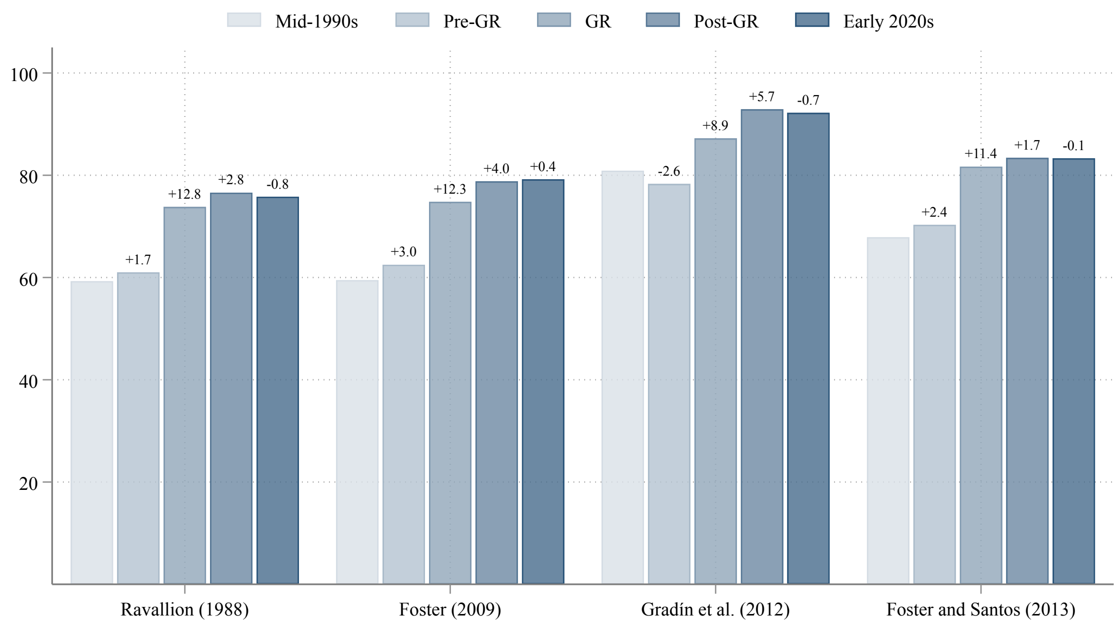
The ordering across indicators is again consistent with what the identification and assessment stages would lead us to expect. Foster (2009) and Gradín et al. (2012) yield higher chronic shares than Ravallion (1988) because they capture a smaller but more severely deprived group. This means a smaller set of individuals deemed chronically poor at the identification stage (incidence) but assessed with deeper poverty experiences at the aggregation stage (incidence and intensity). The even higher levels produced by Gradín et al. (2012) relative to Foster (2009) stem from the additional weight placed on the consecutiveness of spells.[17]

Finally, Foster and Santos (2013) presents an interesting pattern that differs across the two stages of analysis. At the identification stage, it produces the highest chronicity rates among all approaches, as the sub-arithmetic power mean of order $\kappa = 0.25$ classifies more individuals as chronically poor than either the arithmetic mean of Ravallion (1988) or the duration cut-off of Foster (2009). However, once we assess the level of chronic poverty through the CHU index, its chronic share of intertemporal poverty falls back to levels similar to those of the two baseline indicators and well below Gradín et al. (2012). This reflects the fact that the CHU index applies a power transformation to income ratios that compresses measured poverty depth relative to the FGT family, particularly among the most severely deprived. By contrast, Gradín et al. (2012) amplifies the contribution of extreme and consecutive poverty spells through the parameters β and γ, pushing the chronic share considerably higher. The result is that Foster and Santos (2013) identifies more individuals as chronically poor but assigns them a lower assessed poverty level, while Gradín et al. (2012) identifies fewer but weights their experiences more heavily.

More importantly for our purposes, all four indicators display a marked upward trend

[17] Figure 4 in the Appendix explores this further by reporting, for each value of β, the chronic poverty index of Gradín et al. (2012) relative to the period average. A value above one indicates that chronic poverty in a given period exceeds the average across all periods, and vice versa. Two patterns emerge clearly. First, the upward shift after the Great Recession is present regardless of how heavily persistence is penalised. Second, and more importantly, higher values of β amplify the post-crisis levels relative to the period average while simultaneously compressing the mid-1990s values below it. This confirms that the Great Recession did not merely increase the duration of poverty spells but fundamentally altered their structure, making them more consecutive than before.

Figure 1: Chronic Poverty as a Share of Total Poverty: Evidence Across Indicators



Source: Authors' calculations from ECHP and EU-SILC data.

Note: Bars report the weight of chronic poverty relative to total poverty (%) for each indicator and period. Annotations indicate the change in percentage points relative to the previous period. For Ravallion (1988), Foster (2009), and Gradín et al. (2012), chronic and total poverty are computed following the FGT family, with the relevant parameters being $\alpha = 1$ in all of them, $\tau = 0.75$ in Foster (2009) and Gradín et al. (2012), and $\gamma = 2$ and $\beta = 1$ in Gradín et al. (2012). For Foster and Santos (2013), the CHU decomposition is applied with $\kappa = 0.25$.

over the period, with the bulk of the increase concentrated around the Great Recession. The crisis triggered a sharp and broadly simultaneous jump across all approaches: the chronic share of total poverty rose by 12.8 percentage points under Ravallion (1988), 12.3 under Foster (2009), 8.9 under Gradín et al. (2012), and 11.4 under Foster and Santos (2013). Clearly, the pre-crisis period shows no notable divergence across indicators, with all four series remaining broadly stable between the mid-1990s and the onset of the crisis—changes of no more than 3 percentage points in any direction. Following the Great Recession, the chronic share stabilised at its new elevated level under most approaches, with only marginal changes in the post-crisis and early 2020s periods. Taken together, these results confirm that the Great Recession left a lasting scar on the structure of poverty in Spain, shifting it towards a more chronic form of deprivation.[18]

[18] Table 9 depicts a robustness check through different values of the parameter α for Ravallion (1988), Foster (2009), and Gradín et al. (2012), and κ for Foster and Santos (2013).

5.2 Mechanisms Underlying the Evolution of Poverty over Time

The descriptive evidence presented so far points to a sustained process of increasing poverty chronicity in Spain, with the Great Recession acting as a structural turning point whose effects have proved difficult to reverse. However, these patterns may partly reflect shifts in the sociodemographic composition of the population over this long period rather than a genuine change in the relationship between individual circumstances and chronic poverty.

To assess this, we proceed in two steps. We first estimate a series of regression models in which the status of ever-poor and the severity of chronic poverty at the individual level, using different approaches, are regressed on a rich set of demographic and socioeconomic characteristics, allowing us to test whether the observed decrease in the incidence of intertemporal poverty and the increase in chronicity remain significant once compositional differences across periods are held constant. We then conduct an Oaxaca–Blinder decomposition to go further and disentangle the extent to which each trend reflects changes in the sociodemographic characteristics of the population—such as shifts in household structure or educational attainment—from changes in the returns associated with those characteristics.

Table 4 presents a series of logit estimates of the probability of experiencing poverty at least once over the four-year window, sequentially incorporating different sets of controls. Given the similarity of results shown in Table 2, we illustrate the estimates only using the spells approach. Column (a) includes no controls and thus reproduces the descriptive picture: relative to the mid-1990s, the likelihood of experiencing any poverty spell declined in all subsequent periods, consistent with the falling rates documented in Section 5.1. However, this picture changes markedly once individual and household characteristics are accounted for. As controls are progressively added in columns (b) through (d)—covering individual and household characteristics, household demographic composition, and labour market variables respectively—the period coefficients not only increase in magnitude but reverse in sign, turning positive and statistically significant across all periods.

This reversal indicates that the decline in the probability of being ever-poor is largely a compositional effect: it is driven by improvements in individuals' observable characteristics—including rising educational attainment, shifting household structures, and stronger labour market attachment—rather than by a reduction in the underlying risk of poverty conditional on those characteristics. Once these structural changes are held constant, individuals are shown to face a higher probability of experiencing intertemporal poverty today than thirty years ago, suggesting that the prevalence of favourable sociodemographic characteristics that protect against poverty have grown considerably over this period.

Table 4: Probability of Being Ever-Poor Across Periods using a Spells Approach

	(a)	(b)	(c)	(d)
Mid-1990s	–	–	–	–
Pre-GR	0.199^{***}	0.640^{***}	0.851^{***}	0.865^{***}
GR	-0.099^{***}	0.164^{***}	0.437^{***}	0.439^{***}
Post-GR	-0.055	0.219^{***}	0.560^{***}	0.550^{***}
Early 2020s	-0.136^{***}	0.232^{***}	0.696^{***}	0.683^{***}
Constant	-0.658^{***}	-0.122	1.001^{***}	0.981^{***}
Observations	105,061	105,061	105,061	105,061
Region & Time FE		✓	✓	✓
Indiv. & Household Charact.		✓	✓	✓
HH Demographic Charact.			✓	✓
HH Labour Charact.				✓

Source: Authors' calculations from ECHP and EU-SILC data.

Note: Estimates are obtained from a logit model weighted by inverse probability weights. The mid-1990s period serves as the reference period. Standard errors clustered at the household level. (*) $p < 0.10$, (**) $p < 0.05$, (***) $p < 0.01$

We also estimate the statistical power of the change in the chronic poverty levels using the different measurement approaches discussed above—i.e., the individual chronic poverty indices, such as FGT_i or G_i. Table 5 reports, for each indicator, the baseline specification without controls and the full model, having verified that the conclusions are consistent across all intermediate specifications. The results confirm the research hypothesis across all approaches: whereas the unconditional estimates already point to a higher likelihood of chronic poverty in the post-crisis periods relative to the mid-1990s, the positive gradient becomes substantially more pronounced once individual, household, and labour market characteristics are held constant. This pattern mirrors the finding for poverty over time more broadly—controlling for observable characteristics reveals that the structural risk of chronic poverty has increased by more than the raw trends suggest. Taken together, these results provide robust econometric support for the conclusion that poverty in Spain has become genuinely more chronic over the past three decades.

Table 5: Determinants of the Severity of Chronic Poverty

	Ravallion (1988)		Foster (2009)		Gradín et al. (201	
	(a)	(d)	(a)	(d)	(a)	
Mid-1990s	–	–	–	–	–	
Pre-GR	0.009***	0.034***	0.010***	0.035***	0.007***	0.021
GR	0.015***	0.035***	0.016***	0.036***	0.014***	0.025
Post-GR	0.021***	0.043***	0.024***	0.045***	0.015***	0.025
Early 2020s	0.015***	0.045***	0.017***	0.047***	0.011***	0.027
Constant	0.034***	0.057***	0.034***	0.051***	0.014***	0.026
Observations	105,061	105,061	105,061	105,061	105,061	105,(
Region & Time FE		✓		✓		
Indiv. & Household Charact.		✓		✓		
HH Demographic Charact.		✓		✓		
HH Labour Charact.		✓		✓		

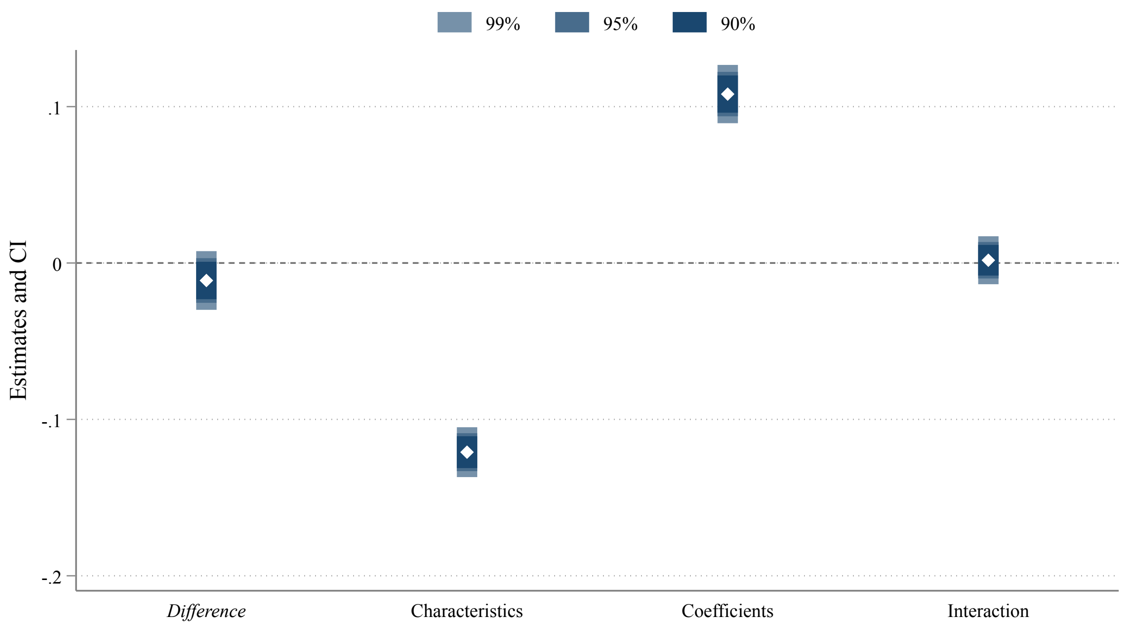
Source: Authors' calculations from ECHP and EU-SILC data.

Note: For Ravallion (1988), Foster (2009), and Gradín et al. (2012), the individual-level chronic poverty index is computed follow
parameters being $\alpha = 1$ in all of them, $\tau = 0.75$ in Foster (2009) and Gradín et al. (2012), and $\gamma = 2$ and $\beta = 1$ in Gradín et al. (
CHU index is applied with $\kappa = 0.25$. Coefficients are expressed as the estimates of an OLS model. Standard errors are clustered a
weighted using IPW weights. (*) $p < 0.10$, (**) $p < 0.05$, (***) $p < 0.01$.

Having established that the rise in chronic poverty is robust to compositional change, we now turn to the Oaxaca–Blinder decomposition to shed further light on the mechanisms underlying both findings. Recall that the regression analysis revealed two distinct patterns: for the likelihood of experiencing any poverty spell, the observed decline over time is largely a compositional effect driven by improvements in observable characteristics; for chronic poverty, by contrast, the increase persists and intensifies once those characteristics are held constant, pointing to a genuine structural change in the risk of prolonged deprivation.

Figure 2 reports the decomposition of the change in the probability of being ever-poor. Although the difference between the mid-1990s and subsequent periods is negative, consistent with the descriptive evidence showing a decline in the proportion of individuals exposed to poverty during the observation window, the analysis reveals that this decline is almost entirely accounted for by improvements in observable characteristics.

Figure 2: Oaxaca-Blinder Decomposition using a Spells Approach: Ever-Poor



Source: Authors' calculations from ECHP and EU-SILC data.

Specifically, the characteristics component is negative and sizeable, indicating that changes in sociodemographic composition—such as higher educational attainment or improved labour market attachment—have mechanically reduced the risk of experiencing poverty at some point in time.[19] In contrast, the coefficients component is positive and statistically significant across all confidence levels, implying that, conditional on a given set of charac-

[19]See Table 10 for all Oaxaca-Blinder estimates.

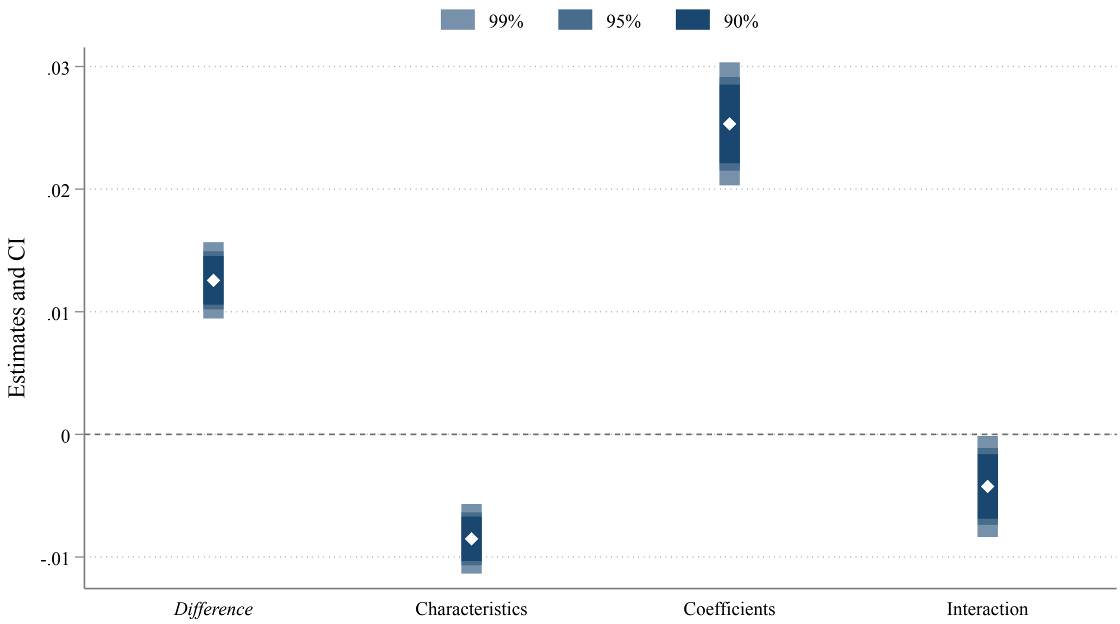
teristics, individuals today face a higher probability of entering poverty at some point than comparable individuals in earlier periods. In other words, the protective power of observed characteristics against poverty has weakened. The interaction term plays a comparatively minor role. Clearly, these results reconcile the apparent contradiction between the descriptive and econometric findings: while population endowments have improved sufficiently to reduce raw poverty incidence, the underlying relationship between characteristics and poverty risk has deteriorated, and it is this structural change that the regression coefficients are capturing.

Figure 3 reports the equivalent decomposition for chronic poverty using Gradín et al. (2012) chronic poverty measure. Given that all indicators lead to the same conclusions, and again for the sake of brevity, we show only this measure in the main body of the paper.[20] The picture that emerges contrasts sharply with the previous one and confirms that, unlike the ever-poor case, the overall difference is now positive and statistically significant, indicating that chronic poverty has genuinely increased over the period. Crucially, the characteristics component is negative—consistent with the improvement in population endowments documented above—yet insufficient to offset the strong positive coefficients component, which is the dominant driver of the increase. This implies that, if the sociodemographic composition of the population had remained unchanged, the rise in chronic poverty would have been even larger. The structural change in the returns to observable characteristics—that is, the weakening of their protective power against prolonged deprivation—is therefore the primary mechanism behind the increase in poverty chronicity in Spain over the past three decades. The interaction term is negative and modest in magnitude, playing a secondary role in the overall decomposition.

These results suggest a consistent mechanism operating across all dimensions of poverty over time. Improvements in population characteristics have played an important role in containing poverty risks, particularly at the extensive margin. However, the effectiveness of these characteristics in shielding individuals from poverty over time has declined markedly. For the ever-poor, this decline is masked by strong compositional gains, leading to falling raw rates despite rising conditional risks. For the varied chronic poverty indicators, by contrast, endowment improvements are insufficient, resulting in a substantial increase. All these points point to a structural weakening of the socioeconomic mechanisms that traditionally protected individuals from poverty.

[20] The remaining results are reported in Figure 5

Figure 3: Oaxaca-Blinder Decomposition: Chronic Poverty



Source: Authors' calculations from ECHP and EU-SILC data.

Note: Estimates are computed using $\gamma = 2$, $\beta = 1$, $\alpha = 1$, $\tau = 0.75$.

6 Conclusion

This paper has examined whether poverty in Spain has become more chronic over the past three decades, providing what is, to the best of our knowledge, the first long-run study of intertemporal poverty for a large European Union country. Exploiting harmonised longitudinal data from the ECHP and EU-SILC over the period 1994–2023, and drawing on four methodologically distinct approaches to the measurement of chronic poverty, we have tried to answer a question with direct implications for both individuals' well-being and the country's economic growth: has the nature of poverty in Spain shifted from a predominantly transient to a predominantly chronic phenomenon, and if so, what mechanisms underlie this transformation?

The evidence presented provides a clear and robust answer: Poverty in Spain has become substantially more chronic over the past three decades. This finding holds regardless of the normative assumptions one is willing to make about individuals' capacity to transfer income across time. While the share of individuals experiencing at least one poverty spell has declined modestly since the mid-1990s—falling from 34.1% to 31.1%—this reduction masks a sharp increase in the persistence of poverty among them. The share of always-poor individuals nearly doubled between the mid-1990s and the post-crisis years, rising from 6%

to 9.9%, and the average duration of poverty spells increased from just over two to two and a half years.

Between the mid-1990s and the early 2020s, the share of chronically poor among the ever-poor rose by approximately 17 percentage points under the spells approach, 15 under the permanent income approach, and 12 under the hybrid indicator. The bulk of this increase was concentrated in the Great Recession years, when all four series registered their largest single-period jumps, and none has since returned to pre-crisis levels. Notably, the pre-crisis decade was one of near-stability across all approaches, indicating that the structural shift in poverty chronicity was triggered by the crisis rather than being a continuation of a pre-existing long-run trend. This asymmetry—rapid deterioration during the crisis, persistent elevation thereafter—points to a scarring effect of the Great Recession on the structure of poverty in Spain that standard cross-sectional indicators have been unable to capture.

The most policy-relevant finding concerns the mechanisms underlying this shift. The regression analysis reveals an important asymmetry: whereas the observed decline in poverty exposure over time is largely a compositional effect—driven by improvements in educational attainment, household structure, and labour market attachment—the rise in chronic poverty is not. Even after controlling fully for observable characteristics, the probability of being chronically poor has increased significantly across all periods and all indicators, pointing to a genuine structural deterioration. The Oaxaca–Blinder decomposition sharpens this interpretation further. For both the ever-poor and the chronically poor, the endowments component is negative and sizeable, confirming that sociodemographic improvements have played a real and meaningful role in containing poverty risks. But the coefficients component is positive and dominant, indicating that the returns these characteristics command against poverty have deteriorated markedly over the period. If the composition of the population had remained unchanged since the mid-1990s, the increase in chronic poverty would have been even larger. What has changed, fundamentally, is not who people are but what their circumstances can protect them from.

These findings carry policy implications. The results suggest that strategies aimed at improving the sociodemographic composition of the population at risk—through educational expansion, active labour market policies, or support for household formation—are necessary but no longer sufficient to contain chronic poverty in Spain. The structural weakening of returns means that the same observable characteristics now provide less protection against prolonged deprivation than they did thirty years ago, and this gap cannot be closed through endowment improvements alone. Effective policy will need to address the returns side of the equation: strengthening the income-stabilising function of employment by reducing labour market duality, extending the coverage and generosity of social transfers to households that fall through the gaps of the existing system, and designing income-support mechanisms that are sensitive not just to the incidence but also to the persistence of poverty spells.

Several limitations of the present analysis point to avenues for future research. The income-based framework adopted here, while standard in the intertemporal poverty literature, cannot capture non-monetary dimensions of deprivation—housing quality, health, or access to services—which may have evolved differently from income and whose dynamics are also relevant for understanding poverty chronicity. The restriction to balanced panels, while necessary for the consistent estimation of intertemporal poverty measures, introduces attrition-related concerns that our inverse probability weighting strategy partially but not fully addresses. Finally, the single-country design, while providing the depth of institutional context needed to interpret the decomposition results, necessarily limits the generalisability of the findings. Spain shares its core structural features—labour market duality, reliance on family networks, limited universalism in social protection—with other Southern European and Mediterranean welfare states. Extending this framework to Italy, Greece, and Portugal, and assessing whether the structural weakening of protective returns is a common feature of this welfare regime or a distinctively Spanish phenomenon, would constitute a natural and valuable step for future comparative research.

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IPW Strategy

We use a logit model to estimate the likelihood of remaining in the survey (Ps_i), conditioned on a set of characteristics of the individuals and the household. These demographic and socioeconomic covariates are observed in the first wave. The longitudinal weight of each observation i, calculated as the inverse of such probabilities, is defined as follows:

$$\phi_{i,t} = \frac{1/Ps_i}{\frac{\sum\left(\frac{1}{Ps_i}\right)}{N_{t-1}}} = \frac{1}{Ps_i} \cdot \frac{N_{t-1}}{\sum(1/Ps_i)} \tag{16}$$

where $N_{t=1}$ denotes the initial sample size, and from which we can deduce that $\sum_i \phi_{i,t} = 1$.

It should be noted that the resulting weights are sensitive to the choice and specification of variables. Therefore, all variables that might significantly influence attrition probability should be included in the estimation. Additionally, regression models present the limitation that they exclude observations with missing values in any explanatory variable, preventing weight estimation for these individuals. This is particularly problematic, as the inclusion of variables with a high non-response rate could lead to serious sample size problems. To address these concerns, we perform robustness checks to assess the sensitivity of the results and ultimately select a set of relevant variables.

Oaxaca-Blinder decomposition

The Oaxaca-Blinder decomposition is used to determine how much of the difference in average outcomes between two groups can be attributed to variations in explanatory variables, and how much is due to differences in the impact (or coefficients) of those variables (Blinder, 1973; Oaxaca, 1973).

The difference in mean outcomes to be explained, denoted as $\Delta\bar{Y}$, is simply the difference between the average outcomes of two groups ($\bar{Y}_A$ and $\bar{Y}_B$):

$$\Delta\bar{Y} = \bar{Y}_A - \bar{Y}_B \tag{17}$$

In our case, Y refers to the level of chronic poverty among the ever-poor, B to the mid-1990s, and A to the rest of the periods. The mean outcomes are obtained through linear models such that $\bar{Y}_P = \bar{X}'_P\hat{\beta}_P$, where $P \in (A, B)$. Hence, if $\Delta\bar{Y}$ can be written as $\bar{X}'_A\hat{\beta}_A - \bar{X}'_B\hat{\beta}_B$, the decomposition formula is as follows:

$$\Delta\bar{Y} = \underbrace{(\bar{X}_A - \bar{X}_B)\hat{\beta}_B}_{\text{endowments}} + \underbrace{\bar{X}'_B(\hat{\beta}_A - \hat{\beta}_B)}_{\text{coefficients}} + \underbrace{(\bar{X}_A - \bar{X}_B)'(\hat{\beta}_A - \hat{\beta}_B)}_{\text{interaction}} \tag{18}$$

In a nutshell, the endowments term captures the portion of the difference explained by group differences in the level of explanatory variables; the coefficient term reflects differences in the returns to those characteristics; and the interaction term captures the simultaneous effect of both.

Note that for the intertemporal poverty outcome, which is binary, the standard Oaxaca-Blinder framework is not directly applicable. We therefore follow Fairlie (2005), who extends the decomposition to non-linear models such as logit and probit by computing the contribution of each variable using predicted probabilities rather than linear projections. The decomposition structure remains the same, but the endowments component is evaluated at the non-linear prediction of the logit model, ensuring consistency with the discrete nature of the dependent variable.

Table 6: Sample Sizes across Periods

	Initial	No Attrition	Four Waves
Mid-1990s	24,816 (100.0%)	18,167 (73.2%)	16,050 (64.7%)
Pre-GR	44,175 (100.0%)	28,029 (63.4%)	26,266 (59.5%)
GR	87,599 (100.0%)	40,227 (45.9%)	37,873 (43.2%)
Post-GR	68,363 (100.0%)	27,940 (40.9%)	25,462 (37.2%)
Early 2020s	56,494 (100.0%)	34,415 (60.9%)	31,474 (55.7%)
Overall	281,447 (100.0%)	148,778 (52.9%)	137,125 (48.7%)

Source: Authors' calculations from ECHP and EU-SILC data.

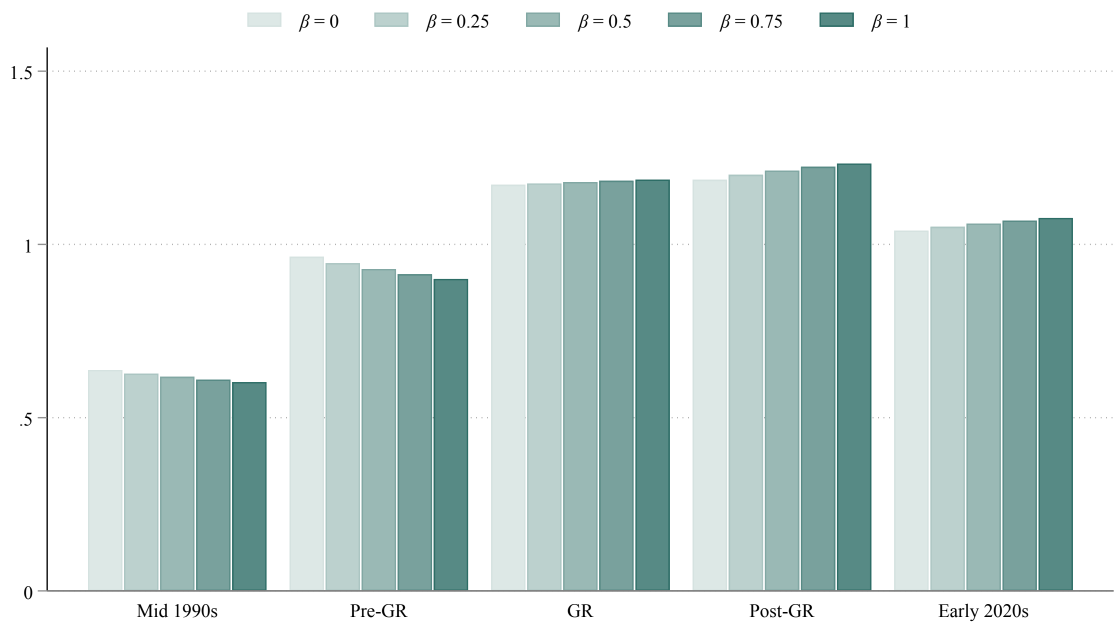
Note: The first column reports the number of individuals in the initial sample before any restrictions are applied. The second sho present at least one intermediate missing value in the variables used in the analysis. The third presents the number of individuals therefore constitute our estimation sample. The fourth indicates the number of individuals for whom complete information is avai estimations, including those required for the inverse probability weighting (IPW) procedure. The percentages in parentheses indic relative to the initial sample.

Table 7: Sample Classification

	Years of obser
Mid 1990s	1994 –
Pre-GR	2004 – 2007 | 2005 – 2008 | 2006 – 2009 | 2007 –
GR	2008 – 2011 | 2009 – 2012 | 2010 – 2013 | 2011 – 2014 | 2012 – 2015 | 2013 –
Post-GR	2014 – 2017 | 2015 – 2018 | 2016 – 2019 | 2017 – 2020 | 2018 –
Early 2020s	2019 – 2022 | 2020 – 2023 | 2021 –
Overall	

Source: Authors' calculations from EU-SILC and ECHP data.

Figure 4: Sensitivity of Chronic Poverty to Persistence following Gradín et al. (2012)



Source: Authors' calculations from ECHP and EU-SILC data.

Note: Values are expressed relative to the period-average of the index. Fixed parameters are set as $\tau = 0.75$, $\gamma = 2$, and $\alpha = 1$.

Table 8: Variable Specification

Variable	Description
Period indicators (ref.: Mid-1990s)	
Pre-GR	Binary indicator for the pre-Great Recession period
GR	Binary indicator for the Great Recession period
Post-GR	Binary indicator for the post-Great Recession period
Early 2020s	Binary indicator for the early 2020s period
Individual characteristics of household head	
Age group	18–39 | 40–64 | >64 (ref.: under 18)
Gender	Binary indicator for female household head
Education level	Medium | High (ref.: primary)
Marital status	Married | Separated/widowed/divorced (ref.: single)
Health-related limitation	Binary indicator for health-related limitation
Labour market experience	Years of labour market experience
Labour market status	Self-employed | Unemployed | Retired | Other inactive (ref.: employee)
Household characteristics	
Household size	2–4 members | >4 members (ref.: 1 member)
Housing tenure	Binary indicator for renting (ref.: ownership)
Single-parent household	Binary indicator for single-parent household
Children aged 0–2	Share of household members aged 0–2
Children aged 3–5	Share of household members aged 3–5
Children aged 6–11	Share of household members aged 6–11
Children aged 12–15	Share of household members aged 12–15
Children aged 16–17	Share of household members aged 16–17
Youth aged 18–25	Share of household members aged 18–25
Adults aged 65–74	Share of household members aged 65–74
Adults aged 75 and over	Share of household members aged 75 and over
Share employed	Share of employed household members
Share unemployed	Share of unemployed household members
Share retired	Share of retired household members
Fixed effects	
Region	Set of regional dummies at the NUTS level
Year	Set of year dummies

Table 9: Total and Chronic Poverty by Indicator and Different Values of α and κ

		Ravallion (1988)			Foster (2009)		
		R_{tot}	R_{chron}	%	F_{tot}	F_{chron}	%
$\alpha = 0$	Mid-1990s	0.183	0.143	78.3	0.182	0.104	57.2
	Pre-GR	0.210	0.173	82.3	0.208	0.122	58.9
	GR	0.191	0.170	88.7	0.192	0.132	68.6
	Post-GR	0.207	0.192	92.7	0.207	0.150	72.3
	Early 2020s	0.197	0.176	89.6	0.195	0.142	72.8
$\alpha = 1$	Mid-1990s	0.057	0.034	59.2	0.057	0.034	59.5
	Pre-GR	0.071	0.043	61.1	0.071	0.044	62.5
	GR	0.066	0.049	73.7	0.066	0.050	74.8
	Post-GR	0.072	0.055	76.6	0.072	0.057	78.8
	Early 2020s	0.065	0.049	75.8	0.065	0.051	79.2
$\alpha = 2$	Mid-1990s	0.030	0.013	43.0	0.030	0.018	59.3
	Pre-GR	0.045	0.018	39.9	0.045	0.028	61.2
	GR	0.047	0.025	52.7	0.047	0.032	69.7
	Post-GR	0.040	0.025	62.6	0.040	0.033	80.9
	Early 2020s	0.036	0.022	62.3	0.036	0.029	81.4

Table 9 (cont.): Total and Chronic Poverty by Indicator and Different Values of α and κ

		Foster and Santos (2013)		
		FS_{tot}	FS_{chron}	%
$\kappa = 1$	Mid-1990s	0.057	0.034	59.2
	Pre-GR	0.071	0.043	61.1
	GR	0.066	0.049	73.7
	Post-GR	0.072	0.055	76.6
	Early 2020s	0.065	0.049	75.8
$\kappa = 0.25$	Mid-1990s	0.083	0.056	67.9
	Pre-GR	0.095	0.067	70.3
	GR	0.087	0.071	81.7
	Post-GR	0.103	0.086	83.4
	Early 2020s	0.091	0.075	83.2
$\kappa = -0.25$	Mid-1990s	0.134	0.107	79.8
	Pre-GR	0.125	0.100	80.2
	GR	0.113	0.101	88.8
	Post-GR	0.141	0.127	90.1
	Early 2020s	0.119	0.109	92.1

Source: Authors' calculations from ECHP and EU-SILC data.

Note: For Ravallion (1988), Foster (2009), and Gradín et al. (2012), the indicator follows the FGT family, with α taking values of
and intensity, and incidence, intensity, and inequality among the chronically poor, respectively. For Foster (2009) and Gradín et a
$\tau = 0.75$. For Gradín et al. (2012), we additionally set $\gamma = 2$ and $\beta = 1$. For Foster and Santos (2013), the CHU index is applied

Table 10: Oaxaca–Blinder Decomposition following a Spells Approach: Estimates

	Ever-Poor			
	Endowments	Coefficients	Interaction	Endowments
Indiv. & Household Characteristics				
Age				
0–17	–	–	–	–
18–39	-0.003	-0.008	0.000	-0.001*
40–64	0.002	-0.006	-0.000	0.001*
65+	-0.001	0.002	0.000	0.000
Female	-0.000	-0.009	0.000	-0.000
Household Size				
1–2	–	–	–	–
3–4	-0.001**	0.002	0.000	-0.000*
4+	0.004	-0.003	0.000	0.001
Renting	0.000	0.153***	0.000	0.000
Household Type (presence of)				
Children 0–2	-0.000	-0.001	0.000	-0.000***
Children 3–5	-0.001***	-0.005***	0.000	-0.000***
Children 6–11	-0.003***	-0.008***	0.000	-0.001***
Children 12–15	-0.003***	0.001	-0.000	-0.001***
Children 16–17	-0.004***	-0.000	0.000	-0.001***
Youth 18–24	-0.011***	-0.008	0.000	-0.001***
Elderly 65–74	0.001*	0.000	-0.000	0.000**
Elderly 75+	-0.003***	0.009***	0.000	-0.000***
Single-parent	0.001***	-0.001***	-0.000	0.000

Table 10 (cont.): Oaxaca–Blinder Decomposition following a Spells Approach: Estimates

	Ever-Poor			C
	Endowments	Coefficients	Interaction	Endowments
% Working	-0.015***	-0.050***	-0.001	-0.000
% Unemployed	0.001***	-0.006*	-0.000	0.000***
% Pensioners	-0.015***	0.003	0.000	-0.000
HH Demographic Characteristics				
Age				
< 30	–	–	–	–
30–44	0.004***	0.016**	-0.000	-0.000
45–64	-0.011***	0.051***	0.001	-0.000
65+	-0.004***	0.019**	0.000	-0.000
Female	0.002	0.006*	0.000	0.001***
Education Level				
Low	–	–	–	–
Middle	-0.019***	0.009**	0.000	-0.002***
High	-0.033***	0.000	0.000	-0.002***
Civil Status				
Single	–	–	–	–
Married	0.000	-0.033**	0.000	0.001***
Other	-0.001	-0.000	-0.000	-0.001***

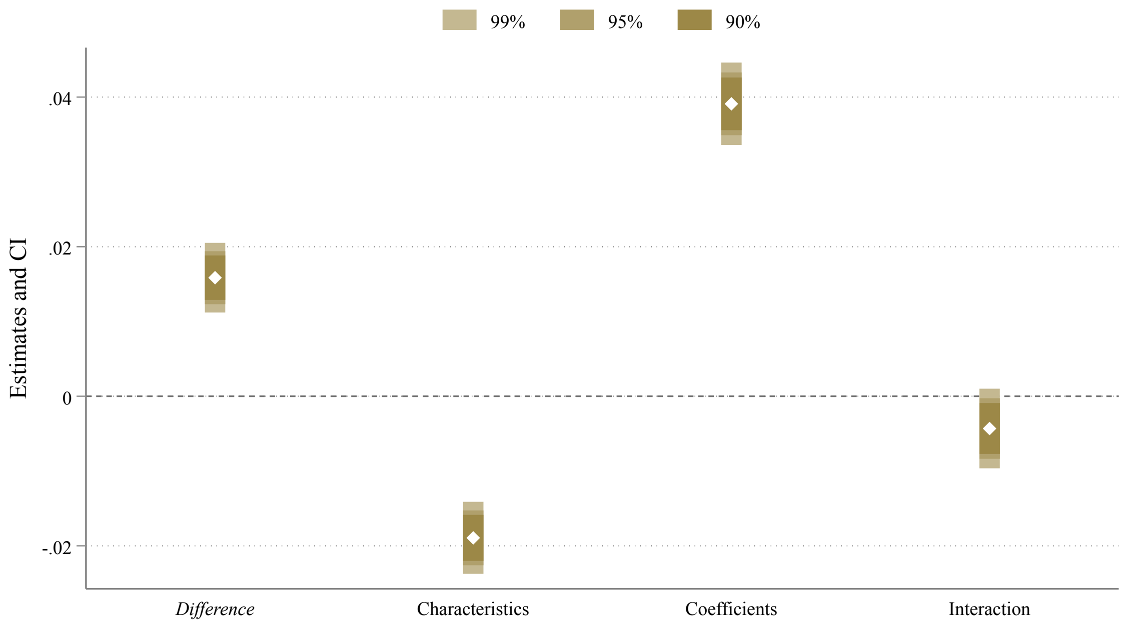
Table 10 (cont.): Oaxaca–Blinder Decomposition following a Spells Approach: Estimates

	Ever-Poor			
	Endowments	Coefficients	Interaction	Endowments
HH Labour Characteristics				
Health Related Limitations	0.003***	-0.002	-0.000	0.000
Work Experience				
< 11	–	–	–	–
11–20	-0.002***	-0.001	-0.000	-0.000***
21–30	-0.002***	-0.005	-0.000	-0.000
31+	0.000	-0.058***	0.001	0.000
Employment Status				
Employed	–	–	–	–
Self-employed	-0.008***	0.001	-0.000	-0.001***
Unemployed	0.000	-0.003*	-0.000	0.000
Pensioner	0.010***	-0.027***	-0.001	0.001***
Other	-0.005***	-0.014***	0.001	-0.001***
Δ	-0.121***	0.108***	0.005	-0.008***
Constant		0.084		
Observations		420,242		
Region & Time FE		✓		

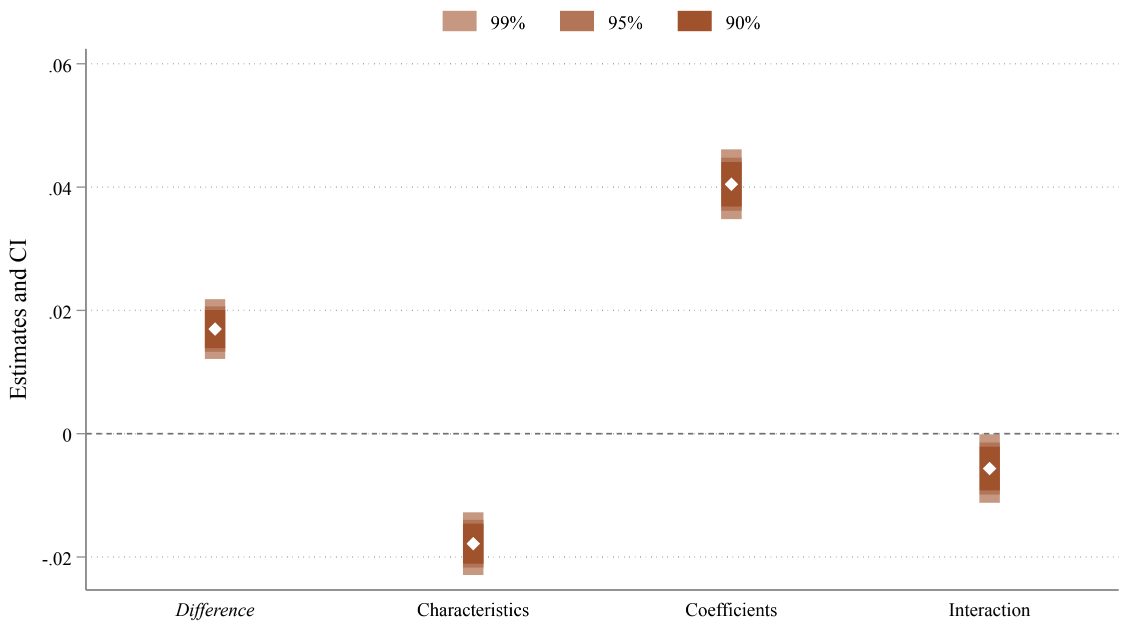
Source: Authors' calculations from ECHP and EU-SILC data.

Note: Estimates following Gradín et al. (2012) are computed using $\gamma = 2$, $\beta = 1$, $\alpha = 1$, $\tau = 0.75$. Standard errors are clustered a
weighted using IPW weights. (*) $p < 0.10$, (**) $p < 0.05$, (***) $p < 0.01$

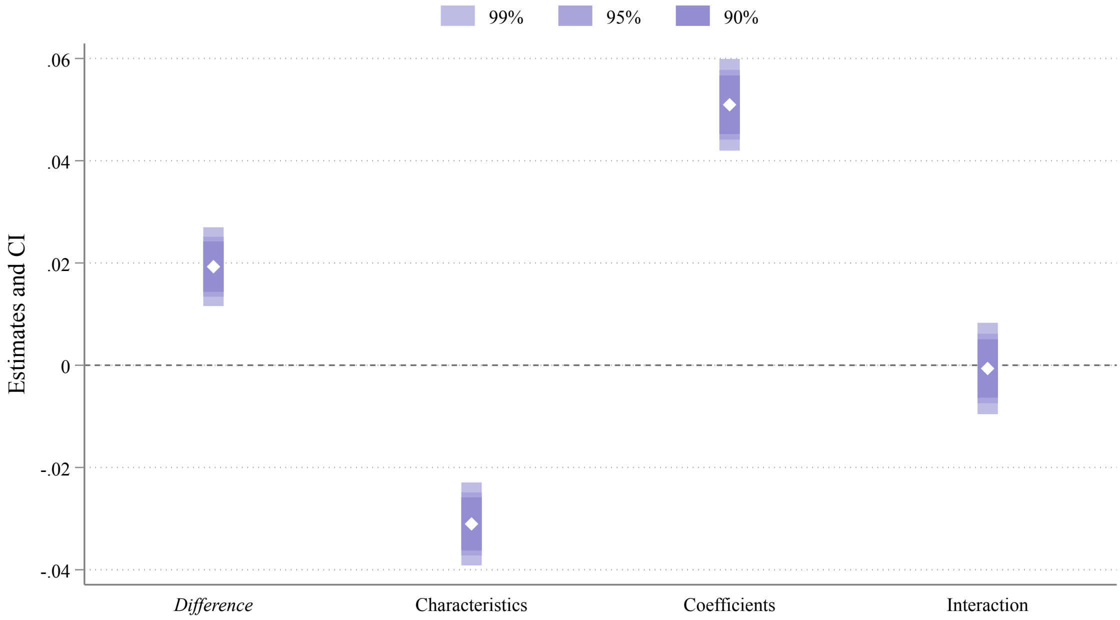
Figure 5: Oaxaca–Blinder Decomposition: Chronic Poverty



a. Ravallion (1988)



b. Foster (2009)



c. Foster and Santos (2013)

Note: We set $\alpha = 1$ in Ravallion (1988) and Foster (2009), $\tau = 0.75$ in Foster (2009), and $\kappa = 0.25$ in Foster and Santos (2013).