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ORIGINAL RESEARCH

Exploring household economic insecurity in Italy and spain: insights from a trivariate probit regression analysis

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Abstract

Economic insecurity conditions economic behaviour and negatively impacts individuals' quality of life. Previous studies that have examined this issue from a multidimensional perspective present significant methodological shortcomings, ranging from the selection of indicators to the mathematical method used for synthesising data. In this paper, we propose a new methodological framework to analyse the economic insecurity of Italian and Spanish households in the period 2013–2019. Specifically, we compute three components of economic insecurity as dependent variables in a trivariate probit model, allowing us to study the determinants of economic insecurity considering the interdependency of the three outcomes. Our results reveal that while the primary symptom of economic insecurity in Italy is the inability to deal with unexpected expenses, in Spain it is the struggle to make ends meet. In both countries, the main drivers of economic insecurity are the householder's characteristics, although their intensity differs: being unemployed, separated, or divorced; low educational attainment; and being a woman. In Italy, there is a high regional effect, with those living in the South or the Islands significantly more likely to experience economic insecurity. The two main buffers identified as a source of economic insecurity are the tertiary education of the householder and home ownership. Our findings suggest that government policies should prioritise employment promotion, boost access to education and job training, encourage investment in affordable housing, and improve women's working conditions.

Keywords Trivariate probit regression · Risk ratio · Economic insecurity · Household income · Multidimensional perspective · Cross-country comparisons

1 Introduction

Since the 2008 global financial crisis, concerns about economic and financial shocks and their potential effect on individuals have grown (Cantó et al., 2020; D'Ambrosio & Bossert, 2014; Hacker, 2019; Ranci et al., 2021; Romaguera-de-la-Cruz, 2020; Whelan et al., 2017).

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This new scenario has attracted growing interest among researchers and policymakers studying economic insecurity (hereafter EI).

In contemporary literature, EI is widely understood as "the anxiety produced by the possible exposure to adverse economic events and by the anticipation of the difficulty to recover from them" (Bossert & D'Ambrosio, 2024, p. 571). Consequently, a defining characteristic of EI is the presence of uncertainty in enduring an uninsured financial shortfall without adequate protection (Rohde & Tang, 2018). Essentially, EI reflects the apprehension individuals feel about facing possible economic hardships in the future, coupled with the realisation that they may lack the financial resources to mitigate their impact. Such uncertainty triggers anxiety and stress, which negatively impact quality of life, prompting changes in household economic behaviour. These changes include reductions in consumer spending and housing investment (Lepinteur & Rémi, 2022; Linz & Semykina, 2010; Lugilde et al., 2018), shifts in female labour market participation, and declines in fertility rates (Mansour, 2018; Modena et al., 2014) or smaller family sizes (fewer children) (Clark & Lepinteur, 2022), as well as lower investment in education (Lunn & Kornrich, 2018). Moreover, EI is associated with deteriorating health (D'Ambrosio et al., 2023; Watson et al., 2020; Watson & Osberg, 2017) and a range of other factors, including political preferences (Bossert et al., 2023). Ultimately, households suffering economic difficulties may be more likely to have a negative effect on children's development, thus compromising the sustainable development of future generations (Sánchez et al., 2024; Sánchez & Navarro, 2021).

Despite growing interest, our understanding of EI remains incomplete, particularly in terms of its measurement, as no widely accepted empirical method has yet been developed (Gallo et al., 2024; Osberg, 2018; Petrov & Romaguera-de-la-Cruz, 2024; Richiardi & He, 2020). Currently, there are two main methodological approaches for measuring EI: using a single economic variable (i.e., income, wealth, or consumer spending), or treating EI as a multidimensional phenomenon. In the latter case, data from several indicators are combined to construct a composite EI index. Both approaches present shortcomings regarding the choice of variables. The multidimensional approach, in particular, may face additional challenges in determining the appropriate method or mathematical function for aggregating the information into a composite indicator. These issues underscore the need for further research in this area, especially in incorporating statistical advancements to improve the study of EI.

This paper aims to examine EI in Italian and Spanish households from 2013 to 2019, that is, during the period in which the economies of the European Union (EU) had already recovered from the Great Recession and just before the onset of the COVID-19 shock. Italy and Spain were selected as compelling case studies due to their similar statuses. Previous comparative studies on EI have typically chosen countries based on variations in their welfare state coverage. For example, D'Ambrosio and Bossert (2014) compared Italy and the United States (US), while Rohde et al. (2014) analysed the United Kingdom, Germany, and the US, Whelan et al. (2017) examined Iceland, Ireland, and Greece and Romaguera-de-la-Cruz (2020) studied the case of Spain, France, and Sweden. Much of the differences in EI have been attributed to variations in budgetary effort in social spending programmes. In contrast, this study focuses on Italy and Spain, two countries with similar levels of welfare state development (see Bertin et al., 2021; Powell et al., 2020), to better identify and quantify the correlates of EI. In the 2019 ranking of the 27 EU countries based on social government expenditure or welfare state spending, Italy and Spain ranked 11th and 12th, respectively, both falling below the EU average.[1] More importantly, the existing literature indicates that Italy and Spain face similar challenges within their welfare states (see Esping-Andersen, 2016; Esping-Andersen & Billari, 2015; Sánchez, 2023).

This paper pursues three main objectives. First, it aims to propose a new methodological framework for studying EI. Second, it seeks to explore how EI manifests in Italian and Spanish households. Finally, the third objective is to identify the main socioeconomic and spatiotemporal factors associated with EI.

To achieve these objectives, we conduct a critical review of the empirical literature on EI, focusing on the main conceptual and methodological approaches used to measure it. After identifying the primary shortcomings and research gaps, we adopt a multidimensional approach for our empirical strategy to study EI. Specifically, we select three indicators of EI whose analysis will allow addressing the following research questions: (i) Have there been changes in any components of EI among households during the observed period, and do Italy and Spain exhibit similar trends? (ii) On average, was the degree of overlap between the components the same as in Italy and Spain? We also attempt to overcome the methodological issues associated with constructing composite indicators by estimating trivariate probit models (Greene, 2018). These models enable us to identify the drivers and buffers influencing the likelihood of experiencing EI while simultaneously accounting for the three components of EI as dependent variables. Additionally, the trivariate probit models allow us to estimate the correlation between these three components of EI, making this approach particularly suitable for understanding their joint behaviour. By accounting for dependencies among the three indicators, this analysis models the dependence structure of EI and provides a more comprehensive understanding of how different aspects of EI may be interconnected and influenced by various socioeconomic and spatiotemporal factors. We complement this regression analysis with a risk ratio[2] calculation (Mize et al., 2019) to quantify the impact of these factors on the likelihood of a household experiencing EI. Our study uses micro-data from the European Statistics on Income and Living Conditions (EU-SILC) surveys conducted from 2014 to 2020, where respondents reported their experiences from the previous year regarding monetary variables (e.g., income). Therefore, the actual period analysed is 2013–2019. To the best of our knowledge, this is the first study to apply this statistical tool for the analysis of a socioeconomic phenomenon such as EI. Consequently, the study represents a novel and innovative approach to measuring household EI.

The rest of this paper is structured as follows. Section 2 provides a literature review. Section 3 includes a critical review of the empirical studies on multidimensional EI and highlights the methodological contributions of our study. Sections 4 and 5 present the data and the statistical model, respectively. Section 6 describes the main results on EI in Italy and Spain. Finally, Sect. 7 concludes with a discussion on the study's main contributions and results.

[1] Social government expenditure includes expenses on social protection, education, health, and housing. According to Eurostat data (General government expenditure by function COFOG), it is confirmed that in 2019, the last year analysed in this paper, social government expenditure per capita in constant 2015 euros was €9,400 in Italy, €7,080 in Spain, and €9,420 in the EU27.

[2] The risk ratio is a measure primarily used in epidemiological studies. However, it is a well-suited measure for comparing and quantifying the relative increase or decrease in the risk of EI associated with each category of each covariate compared to the baseline category (see Jenkins et al., 2014).

2 Literature review

Research that investigates EI as a target variable, whether at the individual or household level, can be categorised into two main groups. The first group includes studies that examine EI using a single indicator, while the second group consists of empirical investigations that treat EI as a multidimensional concept, incorporating its multiple dimensions. Although our review does not aim to be exhaustive, we examine both types of studies that have notably enhanced our understanding of EI and provided valuable insights into both the conceptual frameworks and empirical methodologies associated with this construct.

2.1 One-dimensional approach to measure economic insecurity

The approach focusing on fluctuations in income over time has significantly influenced the study of EI from a one-dimensional perspective, requiring longitudinal data. The concept of EI as "the degree to which individuals experience and are protected against large economic losses" (Hacker et al., 2014, p. S6) helps to elucidate the central role of changes in income as a proxy for EI. A salient conclusion in this framework is that EI does not refer to levels of resources but rather to changes in these levels, as even a wealthy person could experience EI due to fluctuations in income streams (Bossert et al., 2023). The main hypothesis is that past gains and losses determine an individual's confidence in the present (Bossert & D'Ambrosio, 2024).

The Economic Security Index (ESI), developed by Hacker (2008) in the US, defines EI as the risk of a decline in household disposable income from its previous level. Hacker et al. (2014) adapted the ESI to account for the absence of universal public health coverage in the US, incorporating both sharp increases in out-of-pocket health expenses and income drops of around 25%. Among the studies that consider both losses and gains in household income, Western et al. (2016) analysed the trend in income insecurity among children in the US from 1984 to 2010. They concluded that large income losses have a greater impact on low-income children than large income gains.

Although most studies on EI have primarily examined changes in income over time, a subset has investigated wealth as a key determinant of EI. Bossert and D'Ambrosio (2013) introduced a novel class of EI measures akin to Gini inequality measures. Their framework posits EI as being contingent on current wealth (acting as a buffer against adverse shocks) and past fluctuations in wealth (shaping confidence in future resilience). Applying this methodology, D'Ambrosio and Bossert (2014) contrasted the detrimental effects of the Great Recession in Italy and the US, showing a significant increase in EI, particularly in the US. A notable aspect of these studies is that the results vary depending on whether income or wealth is taken as the EI variable. For the US during the period 2001–2019, Petrov and Romaguera-de-la-Cruz (2024) estimated that the average probability of experiencing well-being losses due to EI was 22% when income was considered and 43% when wealth was taken into account.

2.2 Multidimensional approach to measure economic insecurity

Another line of research focuses on the development of multidimensional indicators for measuring EI. This approach stems from the recognition that EI involves more than just income insecurity. The rationale is that relying only on observable factors or economic resources, such as income or wealth, may overlook the psychological components of EI and present a skewed perspective of the phenomenon (Osberg, 2015; Rohde & Tang, 2018). Additionally, as noted by Rohde et al. (2020), abrupt income declines can contribute to EI if they are unforeseen or occur near the poverty line. However, the adverse effects of such declines may be negligible if they are expected or simply reflect a return to the household's median income for the analysed period. To put it more broadly, two individuals who experience the same income loss in the same period may perceive a different level of EI if they start from different levels of economic resources (Gallo et al., 2024). Therefore, incorporating additional indicators is essential for a more comprehensive analysis of EI.

For purposes of comparison, several studies on EI using a multidimensional approach are summarised in Table 7 of the Appendix. Rohde et al. (2015) assessed EI in Australia using six indicators sourced from the Household Income and Labour Dynamics in Australia (HILDA) Survey. These indicators were normalised to a mean of 100 and a standard deviation of 10, and then aggregated using the arithmetic mean to compute the EI index. Additionally, the authors created a composite index of EI for the most economically insecure decile utilising the first PCA factor calculated from longitudinal averages of the six indicators. Their findings revealed that young, unmarried individuals with lower educational attainment experience higher levels of insecurity compared to the general population.

Whelan et al. (2017) examined the repercussions of the Great Recession on household economic stress in three European countries (Iceland, Ireland, and Greece) that witnessed significant spikes in stress levels. They argued that solely focusing on income changes and material deprivation may not fully capture the impact of the crisis on households. This perspective stems from the notion that the crisis heightened household vulnerability through increased debt and declining asset values, particularly property. To gauge economic stress, the researchers constructed a composite index using five indicators sourced from the EU-SILC. Their primary finding points to the importance of fluctuations in material deprivation in explaining heightened stress levels, but only for the three lowest income classes.

Romaguera-de-la-Cruz (2020) investigated EI in Spain, France, and Sweden from 2008 to 2016 using EU-SILC data. She synthesised six individual indicators into a composite index using the Alkire–Foster counting method. The findings showed that EI tends to decrease as income rises, particularly affecting middle-income households in Spain and France but not in Sweden. Moreover, across all three countries and income levels, higher education and non-fixed-term employment were associated with lower EI. Cantó et al. (2020) extended this analysis to 27 European Union (EU) countries from 2009 to 2016 using the EI index proposed by Romaguera-de-la-Cruz (2020). They found that EI was highest among young, less educated, and unemployed households with dependent children across all countries. However, its impact on the middle class varied by country, with Ireland and the United Kingdom experiencing greater insecurity due to substantial income losses.

Ranci et al. (2021) examined EI across eight EU countries from 2007 to 2012. Utilising 14 dummy variables from EU-SILC and employing PCA, the authors identified three primary dimensions of EI: financial strain, over-indebtedness, and material deprivation. Additionally, they introduced the indicator "Temporary poverty", which calculates fluctuations in household income below the poverty line. Combining these dimensions and the temporary poverty indicator, they constructed an EI index using a modified Alkire–Foster method.

Their findings revealed widespread EI across Europe, even in countries with low-income inequality, and highlighted its impact on middle-class households as well.

3 Research gaps and contributions

Although we recognise the importance of past gains and losses in income and wealth in determining EI, our study of EI employs a multidimensional approach grounded in the idea that EI encompasses more than just one economic indicator, such as income or wealth. For this reason, in this section, we focus on empirical studies on multidimensional EI to first critically review the published studies and then present our proposal.

3.1 A critical review of empirical studies on multidimensional economic insecurity

Our comparative review of studies conducted according to a multidimensional approach identified some methodological gaps that warrant further investigation. The three main shortcomings are related to two interconnected pillars of constructing composite indicators: the choice of individual indicators or observable variables and the mathematical or statistical function to build the composite indicator.

First, it is essential to clarify the conceptual distinction between adverse events that represent financial threats and their subsequent effects or symptoms. This differentiation is visually represented in Fig. 1. On the left side, life course adversities (e.g., retirement, widowhood, orphanhood, divorce, and separation), labour market difficulties (e.g., those arising from economic crises), and health challenges serve as primary contributors to EI, as indicated in the existing literature (D'Ambrosio & Bossert, 2014; Hacker, 2008; Western et al., 2012, 2016). Conversely, the right side illustrates a range of symptoms or outcomes resulting from these adverse events. The presence of these symptoms within a household provides clear indications of EI. When studying concepts like EI, which are abstract and hence not directly measurable, it is crucial to approximate them using the appropriate measurable variables. From our perspective, these observable variables should be selected from the effects (right side of Fig. 1) rather than the potential causes (left side of Fig. 1). This is important because the mere occurrence of adverse events does not necessarily lead to feelings of EI about the future. For instance, a person who is voluntarily unemployed may not perceive financial insecurity. Consequently, we view the inclusion of variables like unemployment in constructing composite EI indicators as a methodological limitation for two reasons. Firstly, from a conceptual standpoint, the construction of composite EI indicators

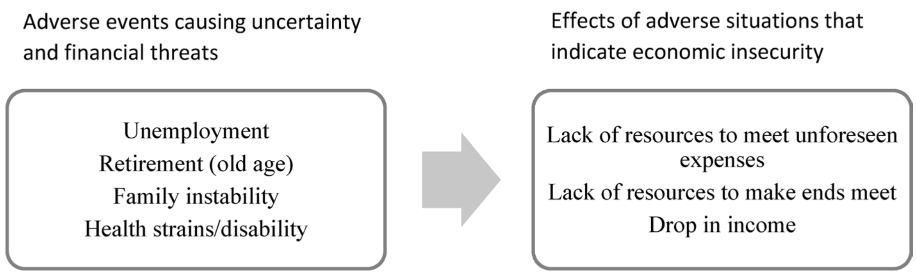

Fig. 1 Differentiation between causes and effects of economic insecurity

that mix cause and effect indicators lacks validity. Secondly, if the objective is to identify the factors most correlated with EI in regression models, it is incorrect to build composite indicators—serving as dependent variables—that include the determining factors identified in the literature. For instance, to build the composite indicator of EI, some studies include the risk of unemployment among their individual indicators and, in the next step, estimate the regression between this composite indicator (dependent variable) and the labour situation of the householder (unemployed/employed) as an explanatory variable (see Cantó et al., 2020; Romaguera-de-la-Cruz, 2020). This practice can lead to endogeneity issues.

Second, when choosing indicators to measure EI, the inclusion of specific indicators or dimensions that measure material deprivation or poverty should be avoided. However, this practice has been observed in very recent studies (e.g., Cantó et al., 2020; Ranci et al., 2021; Romaguera-de-la-Cruz, 2020). While EI and poverty or material deprivation share certain commonalities (see, e.g., Whelan et al., 2017), it is important to recognise that they represent distinct phenomena that require different analytical frameworks (Western et al., 2012). Studies focusing on poverty and material deprivation aim to depict current circumstances (e.g., inability to go on a holiday, eat meat every two days, or keep the house warm; or not having access to a washing machine, car, PC, or colour TV), whereas those addressing EI are concerned with anticipating future events (Richiardi & He, 2020). Unlike poverty or deprivation, EI is not solely tied to one's position in the income distribution or a given social class. As a result, anyone, regardless of their position in the income distribution or social class, can suffer EI (Bossert et al., 2023). As Rohde and Tang argued (2018, pp. 301–303), while both EI and poverty entail a reduction or lack of welfare, exposure to involuntary financial uncertainty is a defining characteristic of EI. For example, individuals with high incomes who face the looming possibility of company closure and subsequent unemployment might suffer from anxiety or stress when thinking about their future. That is, they may experience EI before becoming unemployed, even though their status as non-poor remains unchanged. Even if they were finally fired from their companies, unemployment benefits post-termination can prevent them from falling below the poverty line. However, these individuals might have experienced EI before becoming unemployed and might already have suffered the negative effects on their well-being, leading them to modify their economic behaviour (e.g., reduction in consumption and investments). Thus, it is evident that, unlike poverty, EI manifests itself in the apprehension of future financial stability, profoundly affecting individuals' present and future economic decisions.

Finally, the third source of problems arises from the mathematical or analytical methods used to build composite indicators of EI. Composite indicators constructed using arithmetic means (e.g., Rohde et al., 2015) fail to facilitate benchmarking, as they lack the mathematical structure necessary for comparative analysis. Neither do they avoid the duplication of information provided by the individual indicators; thus, an increase in the number of individual indicators does not necessarily translate into a better composite indicator -they lack exhaustivity (see Jiménez-Fernández et al., 2022a, p. 9; Jiménez-Fernández et al., 2022b). Additionally, they allow for perfect compensability among individual indicators, meaning that a high score in one indicator can completely offset lower scores in other indicators. However, this raises questions about whether such simplicity compromises the reliability and robustness of the EI index given that a non-compensatory aggregation method is generally advisable (Casadio Tarabusi & Guarini, 2013; Terci et al., 2021). Another group of empirical applications for the measurement of EI have relied on the Alkire–Foster method to construct their EI indexes (e.g., Cantó et al., 2020; Romaguera-de-la-Cruz, 2020) or an adaptation of that method (Ranci et al., 2021). The main justification for using this method to measure EI is that "the results have a direct and simple economic interpretation" (Cantó et al., 2020, p. 4). From a methodological perspective, this approach has significant shortcomings that undermine the reliability of its findings. The primary concern lies in the subjective or arbitrary nature of threshold selection, combined with the method's lack of exhaustiveness in addressing redundant information inherent in the individual indicators used to study EI. In this context, Whelan et al. (2017) employed the methodology developed by Desai and Shah (1988) for poverty measurement to assess EI. This method attempts to mitigate the former concern by quantifying the distance between household consumption patterns and the community's normative expectations (defined by the modal frequency of an event within the community). However, it fails to address the issue of redundant information in its approach. In previous methods, the correlation or overlap among individual indicators can skew the outcome of the composite indicator, influenced by the selection and the number of specific indicators employed. Failing to account for these methodological pitfalls has substantial consequences, potentially compromising the validity and interpretation of study results (Becker et al., 2017; Jiménez-Fernández & Ruiz-Martos, 2020; Jiménez-Fernández et al., 2022a).

Principal Component Analysis (PCA) is another method used for computing EI composite indicators (Ranci et al., 2021; Rohde et al., 2015). PCA can eliminate overlapping information, but only linear redundant information. Nevertheless, its application in constructing composite indices for EI raises critical questions regarding the underlying conceptual framework. Specifically, it invites examination of whether the model being analysed is formative or reflective. In the context of EI, the construct aligns with a formative model, where causality flows from individual indicators to the composite measure. For instance, when assessing changes in EI over time within a household, an increase in insecurity does not necessarily entail deterioration across all economic insecurity indicators. A household might experience a reduction in income and struggle to handle unexpected financial burdens, but it has sufficient resources to cover its monthly expenses. Conversely, PCA is better suited for reflective models, where improvements or declines in the construct correspond directly to similar shifts in all individual indicators, much like measuring children's intelligence (see Diamantopoulos et al., 2008; Mazziotta & Pareto, 2019). Hence, the compatibility of PCA with the theoretical underpinnings of EI warrants careful consideration to ensure robust and meaningful interpretations.

3.2 Contributions of this study

Building on the main guidelines established in the literature on EI, we aim to provide a methodological framework for measuring EI from a multidimensional perspective that addresses the research gaps identified in the previous section. Our empirical strategy consists of two main steps: (i) the selection of three indicators or components of EI, and (ii) the computation of an innovative statistical model to study its correlates.

In the first step, we propose a comprehensive analysis focusing on three components of EI (explained in detail in Sect. 4.1) that meet the following criteria:

- The three components are selected from the effects or symptoms of EI rather than from the potential causes of EI.

- The selected indicators are not specific indicators used to measure poverty or material deprivation.
- There are both kinds of indicators, subjective and objective. As an advantage, subjective indicators reflect individuals' perceptions of their financial situation and encompass the psychological components of EI (Rohde & Tang, 2018). Additionally, subjective and self-reported indicators capture information on a household's financial and real estate wealth, savings capacity, and personal skills of its members. Since a household's current economic situation and its ability to bounce back depend not only on a flow variable such as income but also on the above factors (OECD, 2021; Verbunt & Guio, 2019), incorporating these elements is essential for a comprehensive study of EI.
- To obtain a comprehensive view of EI over time, we selected three proxy components: one representing the household's current financial situation, another reflecting forward-looking expectations, and a third component providing insights from historical (backward-looking) data.
- The EI indicators have been combined at the level and in changes to provide a complete picture, as recommended in the literature (Bossert et al., 2023; Gallo et al., 2024; D'Ambrosio & Bossert, 2014).

To overcome problems that may arise when constructing the EI composite indicators, in the second step we attempt to introduce a statistical method that is rarely used in the social sciences to perform regression analysis. More specifically, we rely on a trivariate probit model (Greene, 2018) that allows simultaneously estimating the socioeconomic drivers/buffers of the likelihood of experiencing EI in each of its three components. That is, in a model we simultaneously estimate three equations, where the dependent variables are the three identified EI components or symptoms. Additionally, the trivariate probit model estimates the correlation between the three symptoms of EI, so it is a suitable approach for understanding the joint behaviour of the three components of EI. We complete this regression analysis by calculating the predicted probabilities and the risk ratios (Mize et al., 2019) to quantify the impact of various socioeconomic factors on the probability of a household experiencing EI. For this purpose, we have developed a programme in Stata that allows us to quantify the relationship between the three types of EI symptoms and the set of spatiotemporal and socioeconomic variables analysed.

4 Data and variables

To perform our analysis, we use micro-level data from the EU-SILC dataset obtained from the surveys carried out in Italy and Spain from 2014 until 2020. Considering that all the income questions in the surveys refer to the previous year and the interviews were conducted before March 2020, our studied period is 2013–2019, just before the COVID-19 shock. The EU-SILC is an international, standardised household survey launched annually in the EU, thus allowing for comparisons between Italy and Spain. The survey collects individual and household-level data on income, living conditions, socio-economic and demographic characteristics, poverty, and social exclusion.

Specifically, in this paper, we work with seven successive cross-sectional datasets, covering the period from 2013 to 2019 (i.e., surveys conducted from 2014 to 2020). The total

Table 1 Indicators of economic insecurity

Indicator	Description	Definition	Characteristics
I1	Inability to cope with unexpected expenses	Households unable to cope with unexpected expenses	Subjective evaluation Forward-looking
I2	Difficulty in affording the standard expenses	Households perceive their disposable income as lower than the self-assessed minimum income to make ends meet	Subjective evaluation Measure of the current situation
I3	Drop in income	Households experiencing a decline in income of more than 25% from one year to the next and falling below their average income level over the period studied	Objective measure Longitudinal indicator Backward-looking

number of observations is 30,391 for Italy and 20,233 for Spain. Likewise, the longitudinal version of the EU-SILC enables analysing changes in income over time to study EI with a dynamic perspective. Our selection sample method is explained in the Appendix (Table 8).

4.1 Dependent variables: components of economic insecurity

As explained in Sect. 3.2, we identify three components of EI (Table 1). These components are operationalised through three binary indicators (I1, I2, and I3) that are the dependent variables in our regression models.

The first component, I1, is the *inability to cope with unexpected expenses*. The information to build this indicator proceeds from the EU-SILC question HS060 - Capacity to face unexpected financial expenses; the answer takes the value of 1 “yes” and 2 “no”. Like Rohde et al. (2015), Whelan et al. (2017), Cantó et al. (2020), and Romaguera-de-la-Cruz (2020), we build the binary indicator I1, which takes the value of 1 if the household lacks the financial resources to afford an unexpected, required expenditure (i.e., the answer was 2).

The second component is *difficulty in affording the standard expenses.* In line with the measure of financial dissatisfaction built by Romaguera-de-la-Cruz (2020), we construct a binary indicator I2 by comparing the lowest monthly income to make ends meet[3] multiplied by 12 (w_{it} at year t) and the annual equivalised household disposable income (g_{it} at time t). Thus, an individual *i* experiences insecurity in this component at year *t* if the equivalised household disposable income does not cover the minimum annual income perceived as necessary to make ends meet, and zero otherwise, as follows:

[3] The information is provided by the minimum income question HS130 de EU-SILC:” In your opinion, what is the very lowest net monthly income that your household would have to have in order to make ends meet, that is to pay its usual necessary expenses? Here the respondents provide a monthly income figure.

$$I2_{it} = \begin{cases} 1\, if\ w_{it} > g_{it} \\ 0\, otherwise \end{cases}$$

The third component of EI is *drop in income*, which is inspired by the proposal to measure EI using a single indicator as developed by Hacker (2008) and Hacker et al. (2014). More specifically, as in Rohde et al. (2015), we build the binary indicator I3 using the longitudinal information of our dataset. We define a household as experiencing a large drop in income if its annual equivalised disposable income decreases by at least 25% from the previous year and falls below its average income; that is, the drop is not due to mean reversion following a transitory increase:

$$I3_{it} = \begin{cases} 1\, if\ g_{it} < 0.75 g_{it-1}\ and\ g_{it} < \bar{g}_i \\ 0\, otherwise \end{cases}$$

where g_{it} is the annual equivalised household disposable income, $g_{it-1}$is the same income from the previous year, and $\bar{g}_i$ is the average equivalent household disposable income for each household and for the period available in the EU-SILC data in surveys conducted from 2014 to 2020.[4]

In summary, the selected indicators allow us to focus on the effects or symptoms of EI (right side of Fig. 1) rather than selecting proxies for adverse events that may or may not lead to EI (left side of Fig. 2). We work with two subjective indicators (I1 and I2) that reflect individuals' perceptions of their financial situation (how the respondents themselves are experiencing/feeling about their economic-financial situation), and one objective indicator (component I3) that is built with longitudinal observations. Specifically, indicator I1 (inability to cope with unexpected expenses) reflects forward-looking anticipation, indicat-

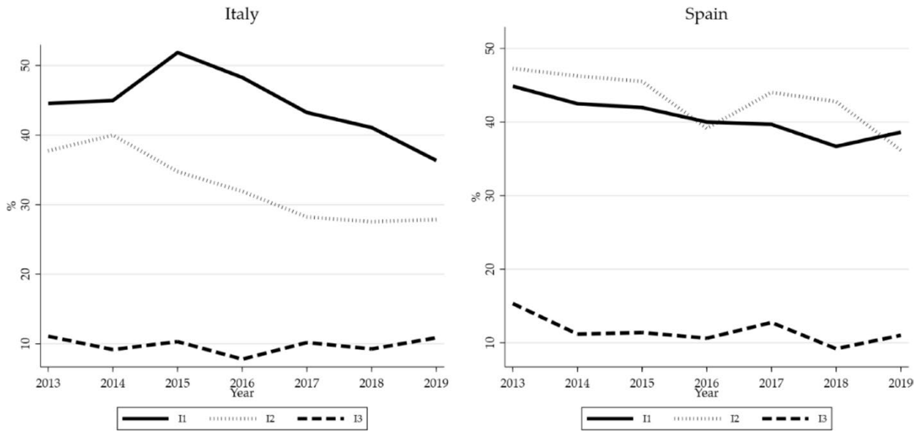

Fig. 2 Trend of the three components of economic insecurity in Italy and Spain, 2013–2019 (% of households)

[4] All income measures used in the different indicators are deflated by the Consumer Price Index provided by Eurostat for each region in the analysis (base 2015).

ing whether households have private reserves, such as liquid financial assets, to mitigate drops in income or significant, unavoidable expenses. Indicator I2 (difficulty to afford standard expenses) is a proxy measure for the household's current financial situation. The objective indicator I3 captures income insecurity or changes over time, providing insights from historical data (backward-looking). Additionally, with the choice of these three indicators of EI, we are combining measures at the level (I1 and I2) and in changes (I3).

4.2 Independent variables: socioeconomic characteristics and regional dimension

We examine socioeconomic variables that may be associated with the EI of households and categorise them into two groups: characteristics of the householder (i.e., the breadwinner), and characteristics of the household (see Table 2). For the householder's socioeconomic characteristics, we consider gender, age, educational attainment, employment status, and marital status. Female is a dummy variable which takes the value of 1 if the householder is a woman. The age of the head of household is classified into five groups: under 45 years old, 45–55, 56–65, 66–75, and over 75, with the first group serving as the reference category. Educational attainment is captured using three dummy variables: one for householders with lower secondary or basic education (up to ISCED 2), another for those with upper secondary to post-secondary non-tertiary education (between ISCED 3 and 4), and a third one for those with tertiary education (ISCED 5 or higher), with ISCED 3 and 4 as the reference category. For employment status, we define four dummy variables: self-employed or employee (reference category), retired or with a disability, unemployed, and student or other. For marital status, we define the dummy variables as never married, married or consensual union (our reference category), separated or divorced, and widowed.

As explanatory variables at the household level, the variable housing tenure status takes the value of 1 if the household owns its dwelling. Following the Eurostat DEGURBA classification, the variable degree of urbanisation takes the value of 1 if the household is in a densely populated area (cities or large urban areas), and zero if it is in an intermediate density area (towns and suburbs or small urban areas) or a thinly populated area (rural areas). The variable housing typology indicates the type of dwelling and takes the value of 1 if the household resides in a flat in a building. To study the association with the household composition, we include variables for household size and the presence of children, seniors, and individuals with chronic illnesses. Household size is divided into four categories: 1 member, 2 members, 3 members, and 4 or more members, with the 3-member category as the reference. Two dummy variables, children and seniors, are used to indicate the presence of members less than 16 years old and more than 65 years old, respectively, in the household. Additionally, a dummy variable for the presence of chronic illness takes the value of 1 if at least one household member has a chronic condition. We analyse the regional effects by considering observations distributed across five macro-regions of 20 Italian regions and seven macro-regions of 17 Spanish regions.[5] The reference categories

[5] The five Italian macro-regions are North-West, labelled as ITC (Piemonte, Valle d'Aosta, Liguria, and Lombardia), South as ITF (Abruzzo, Molise, Campania, Puglia, Basilicata, and Calabria), Insular as ITG (Sicilia and Sardegna), North-East as ITH (Bolzano, Trento, Veneto, Friuli-Venezia Giulia, and Emilia-Romagna) and Central as ITI (Toscana, Umbria, Marche, and Lazio). The seven Spanish macro-regions are Northwest labelled as ES1 (Galicia, Asturias, and Cantabria), Northeast as ES2 (País Vasco, Navarra, La Rioja, and Aragón), Comunidad de Madrid as ES3, Central as ES4 (Castilla y León, Castilla-La Mancha, and Extremadura), East as ES5 (Cataluña, Comunidad Valenciana, and Islas Baleares), South as ES6 (Andalucía and Región de Murcia) and Islas Canarias as ES7.

Table 2 Variables description and summary statistics

Variable	Description	Variable levels	Percentage (Italy)	Percentage (Spain)
Gender[a]	Gender	0 = **male**	62.73	62.69
		1 = female	37.27	37.31
Age[a]	Age (in classes)	1 = **age ≤ 45**	27.96	33.57
		2 = 45 < age ≤ 55	21.26	21.34
		3 = 55 < age ≤ 65	15.93	15.29
		4 = 65 < age ≤ 75	15.05	14.31
		5 = age > 75	19.79	15.49
Education[a]	Education level (ISCED framework)	1 = up to ISCED 2	20.65	25.29
		2 = **ISCED 3 or 4**	62.44	41.19
		3 = ISCED 5 or more	16.91	33.52
Employment status[a]	Employment status	1 = **self-employed or employee**	56.35	55.50
		2 = retired or with disability	33.45	30.44
		3 = unemployed	3.59	6.95
		4 = student or other	6.61	7.11
Marital status[a]	Marital status	1 = never married	23.94	22.77
		2 = married or consensual union	51.50	53.24
		3 = separated or divorced	8.27	9.88
		4 = widowed	16.29	14.11
Housing tenure status	Housing tenure status	0 = **other**	40.51	49.66
		1 = own it outright	59.49	50.34
Degree of urbanisation	Degree of urbanisation of the area in which the household lives	0 = **other**	63.76	48.92%
		1 = living in a city	36.24	51.08%
Housing typology	Housing typology where the household lives	0 = **other**	45.64	31.86%
		1 = flat in building	54.36	68.14%
Household size	Household size	1 = 1 member	32.36	23.85
		2 = 2 members	29.95	33.37
		3 = **3 members**	18.17	20.50
		4 = 4 members or more	19.52	22.27
Children	Presence of children < 16 years in the household	0 = **other**	76.60	71.68
		1 = presence of children < 16 years	23.40	28.32
Senior person	Presence of senior person (> 65-year-old) in the household	0 = **other**	59.34	64.39
		1 = presence of person > 65 years old	40.66	35.61
Chronic illness	Presence of at least a person suffering from any chronic illness	0 = **other**	78.43	63.59
		1 = presence of any person affected by chronic illness	21.57	36.41

Table 2 (continued)

Variable	Description	Variable levels		Percentage (Italy)	Percentage (Spain)
Year	Year of the survey	**2013**		11.27	19.47
		2014		11.27	19.99
		2015		11.16	20.24
		2016		11.35	6.76
		2017		11.21	6.78
		2018		11.20	6.77
		2019		32.54	20.00
Macro-region	Macro-region in which the household lives	**ITC**	ES1	28.23	9.47
		ITF	ES2	21.11	9.95
		ITG	**ES3**	10.46	13.65
		ITH	ES4	19.91	12.25
		ITI	ES5	20.29	29.61
			ES6		20.72
			ES7		4.34

In bold the reference category used in the statistical models. [a]Variable refers to the householder. ISCED 2 is lower secondary education, ISCED 3 is upper secondary education, ISCED 4 is post-secondary non-tertiary education, and ISCED 5 is short-cycle tertiary education. In Italy, ITC = North-West Regions, ITF = Southern regions, ITG = Islands, ITH = North-East regions, and ITI = Central regions. In Spain, ES1 = Northwest, ES2 = Northeast, ES3 = Central regions, ES4 = Madrid Province, ES5 = East, ES6 = South, and ES7 = Canary Islands. $n_{Italy} = 30{,}391$, $n_{Spain} = 20{,}233$

are the North-West (ITC) region in Italy and the Comunidad de Madrid (ES3) in Spain. Finally, regarding the year variable, the reference category is set to 2013.

Concluding, the rationale behind the choice of the reference categories (i.e., the zero level of the dummy variables) is twofold. First, we select the most frequent category within each variable to ensure statistical robustness. Second, we opt for categories that do not imply the exclusion of other relevant characteristics considered in the analysis. The objective is to define a reference profile — referred to as the baseline household in Sect. 6.3 — that is well-represented in the data and can serve as a realistic and interpretable benchmark for comparisons across different households or situations.

5 Statistical model

We employ a trivariate probit model to estimate the key drivers and buffers of the likelihood of experiencing EI and the correlation between its three components (see Greene, 2018). This model simultaneously estimates the three distinct components of EI, denoted as I1, I2, and I3. Our analysis is based on a pool of seven successive cross-sectional datasets covering the period from 2013 to 2019.

Let y_{1i}^*, y_{2i}^*, and y_{3i}^* represent three continuous latent variables corresponding to the risk of experiencing EI concerning the first component (*inability to cope with unexpected expenses*), the second component (*difficulty in affording standard expenses*), and the third component *(drop in income*), respectively. These latent variables determine the observed binary outcomes $I1_i$, $I2_i$, and $I3_i$, respectively, through the rule $y_{vi} = 1_{\{y_{vi}^*>0\}}$ for v = 1,2,3.

The general specification of the trivariate probit model is as follows:

$$y_{1i}^{*} = \boldsymbol{x}'_{1i}\boldsymbol{\beta}_{1} + \epsilon_{i1}$$

$$y_{2i}^{*} = \boldsymbol{x}'_{2i}\boldsymbol{\beta}_{2} + \epsilon_{i2}$$

$$y_{3i}^{*} = \boldsymbol{x}'_{3i}\boldsymbol{\beta}_{3} + \epsilon_{i3}$$

$$i = 1 \ldots n_j$$

where n_j denotes the sample size in country *j* (*j*=1,2) and, $\boldsymbol{x}'_{\mathrm{v}\boldsymbol{i}} = (1, \boldsymbol{x}_{\mathrm{v}2\boldsymbol{i}}, \ldots \boldsymbol{x}_{\mathrm{v}\boldsymbol{Ki}})$ for v=1, 2,3 is the i^{th} row vector of the $n_j \times K$ model matrix **X**, that includes time, regional, and socioeconomic characteristics of each household *i* (see Table 2), and $\boldsymbol{\beta}_1$, $\boldsymbol{\beta}_2$ and $\boldsymbol{\beta}_3$ are parameter vectors to be estimated. In this context, the three equations are assumed to be correlated, with their joint estimation based on the assumption that the three error terms $(\epsilon_{i1}, \epsilon_{i2}, \epsilon_{i3})$ follow a trivariate standard normal distribution.

$$\begin{pmatrix} \varepsilon_{i1} \\ \varepsilon_{i2} \\ \varepsilon_{i3} \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho_{12} & \rho_{13} \\ \rho_{21} & 1 & \rho_{23} \\ \rho_{31} & \rho_{23} & 1 \end{pmatrix}\right)$$

This assumption enables a comprehensive analysis of the interrelated nature of the errors across the three equations in the model with cumulative distribution function $\Phi_3(\epsilon_{i1}, \epsilon_{i2}, \epsilon_{i3}, \Sigma)$ where Σ is the variance-covariance matrix. The coefficients $\rho_{..}$ are of interest as they measure the covariance in the errors between each pair of equations. These coefficients offer insights into the degree and direction of correlation among the disturbances in the three equations, highlighting how changes in one equation may be associated with changes in another.

Therefore, in our analysis, the special case $\rho_{12} = \rho_{13} = \rho_{23} = 0$ implies the lack of dependence between the three components of EI. Accordingly, a likelihood ratio test for

H_0: $\rho_{12} = \rho_{13} = \rho_{23} = 0$ against H_1: at least one different from zero.

can be used to test the statistical significance of the correlation between the errors of each pair of equations. The null hypothesis typically tests that the correlation coefficients are equal to zero (no correlation between the error terms). If the statistical tests indicate that these coefficients are significantly different from zero, the null hypothesis may be rejected. This rejection suggests that the three dependent variables are jointly determined, indicating evidence of interdependence or correlation among the underlying factors influencing the outcomes. This type of analysis is valuable for understanding the complex relationships between the variables and providing insights into the joint determination of the three dichotomous outcomes. That is, using the estimated trivariate probit model, we compute the predicted probabilities of experiencing only one symptom of EI as well as the joint probability of experiencing all three symptoms at the same time. The trivariate probit model is estimated using *mvprobit package* (Cappellari & Jenkins, 2006) in Stata software (StataCorp, 2015).

Additionally, the risk ratio serves as a useful measure for assessing the impact of different factors on the outcome of interest (Mize et al., 2019). It is computed as the ratio between two predicted probabilities based on the fitted model: one is the predicted probability when the variable of interest equals 1, fixed all other covariates; the other is the predicted probability when the variable of interest equals 0, fixed all other covariates. These predicted probabilities are then averaged over the entire dataset. The risk ratio is, therefore, the ratio of the mean predicted over the whole set of observations. This ratio is a relative measure of the effect of a specific characteristic on the outcome. A risk ratio greater than 1 indicates a positive association (i.e., the presence of the characteristic increases the likelihood of the outcome), and a risk ratio less than 1 suggests a negative association (i.e., the presence of the characteristic decreases the likelihood of the outcome).

Specifically, in our empirical analysis, we establish a clear standard for assessing the effects of different covariates. We define a baseline household as one with all covariates set to zero, ensuring that the risk ratio reflects the impact of a single characteristic relative to this baseline. This approach allows us to systematically compare how changes in specific covariates (e.g., education, geographic location) influence the outcome while controlling for other variables specified in the model.

6 Results of economic insecurity in Italy and Spain

6.1 Descriptive analysis

In this section, we present the percentage of households experiencing the three EI symptoms in Italy and Spain from 2013 to 2019 (Fig. 2) and estimate the extent of overlap among the three components and their pairs (Table 3). An analysis of the distribution and overlaps offers a more comprehensive understanding of the nature and severity of household EI in Italy and Spain. More importantly, this descriptive analysis allows us to address two of our research questions, which entail the second objective of this paper: (i) Have there been changes in any components of EI among households during the observed period and do Italy and Spain exhibit similar trends? (ii) On average, was the degree of overlap between the three components the same in Italy and Spain during this period?

Figure 2 displays the percentage of households in Italy and Spain affected from 2013 to 2019 by each of the three components of EI, either in isolation or in conjunction with the other two symptoms.

At first glance, the drop in income (I3) is the type of EI with the lowest incidence in households in both countries. In Italy, the inability to cope with unexpected expenses (I1) is the type of EI that most affects households, while Spanish households have difficulties in

Table 3 Distribution of households according to the symptoms of economic insecurity they experience in Italy and spain, 2013–2019 (% of households)

Combinations of (I1,I2,I3)	Italy	Spain
(000)	45.5	41.1
(100)	18	12.6
(010)	11	15.8
(001)	3.3	2.7
(110)	14	17.7
(101)	1.4	1
(011)	2.8	3.8
(111)	3.7	5.3

I1 (inability to cope with unexpected expenses), I2 (difficulty in affording standard expenses), I3 (drop in income). $n_{Italy} = 30{,}391$, $n_{Spain} = 20{,}233$

affording standard expenses (I2). Focusing on I1 and I2, a downward trend is observed in Italy since 2015, while these indicators show a more volatile evolution in Spain. In 2019, a smaller percentage of households in Italy were affected by symptoms I1 and I2 compared to Spain, while the percentage of households affected by drops in income was similar in both countries.

We pool the data from the seven years for each country to aggregate households and count the number of symptoms of insecurity they have experienced. The overlap analysis for each component reveals the percentage of households experiencing EI in a single dimension, in two dimensions, or in all three components. Table 3 illustrates the results. Specifically, (000) indicates the percentage of households not experiencing EI based on any indicator, while (111) represents the percentage of households suffering from EI according to all indicators. This breakdown provides a clearer understanding of the distribution of households with different levels of insecurity based on the combination of symptoms they exhibit.

The results show that the components with the highest degree of overlap in both countries are I1 (inability to cope with unexpected expenses) and I2 (difficulty in affording standard expenses), indicating symptoms of insecurity concerning both future and current situations. Notably, the overlap between I1 and I2 (110) is quite high at 14% for Italy and 17.7% for Spain. More specifically, 42.6% of Spanish households reported experiencing EI related to difficulty in affording standard expenses (I2), either in isolation or in conjunction with the other two symptoms (010, 011, 110, and 111 in Table 3). Similarly, 37.1% of Italian households reported an inability to cope with unexpected expenses (I1) (100, 110, 101, and 111 in Table 3). This suggests that, in general, the degree of EI in Spain is higher than in Italy during the period studied.

In contrast, only 11.2% of Italian households and 12.8% of Spanish households experienced EI related to drops in income (I3)—both in isolation and in conjunction with the other two symptoms (001, 101, 011, and 111 in Table 3). Finally, it is important to highlight the most vulnerable households, namely those experiencing the three EI symptoms. More specifically, the overlap among all three components is relatively moderate at 3.7% for Italy and 5.3% for Spain, respectively.

6.2 The correlates of economic insecurity

The results of the trivariate probit model, which includes the three dependent variables (I1, I2, and I3) for Italy and Spain are presented in Table 4[6]. The first model addresses the inability to cope with unexpected expenses (column EP1), the second model focuses on the difficulty in affording standard expenses (column EP2), and the third model captures the drop in income (column EP3). The results indicate correlations (coefficients ρ) between the three models, highlighting the need for their joint estimation. Hence, using the trivariate probit model for the analysis is appropriate. Notably, the correlations between the various dimensions are generally higher in Spain than in Italy, with the strongest correlation observed between indicator I2 (difficulty in affording standard expenses) and indicator I3 (drop in income).

[6] To assess the validity and stability of the results, tests in two directions were carried out: the definition of the explanatory variables and the estimation of the models with alternative estimators. In all cases, we have achieved similar results. The results of these tests will be provided upon request.

Table 4 Estimates of the trivariate probit model for the three components of economic insecurity in Italy and spain, 2013–2019

	Italy			Spain		
Variables	EP1	EP2	EP3	EP1	EP2	EP3
Year						
2014	0.0294	-0.000719	-0.0848*	-0.119**	-0.0518	-0.105*
	(0.0398)	(0.0400)	(0.0488)	(0.0533)	(0.0514)	(0.0632)
2015	0.117***	-0.0388	-0.0349	-0.0134	-0.0567	-0.221***
	(0.0399)	(0.0406)	(0.0498)	(0.0552)	(0.0516)	(0.0671)
2016	0.0600	-0.0852**	-0.0932*	-0.0438	-0.148***	-0.216***
	(0.0391)	(0.0399)	(0.0491)	(0.0548)	(0.0521)	(0.0658)
2017	-0.0508	-0.0892**	-0.211***	-0.112**	-0.0885*	-0.190***
	(0.0431)	(0.0432)	(0.0542)	(0.0562)	(0.0527)	(0.0639)
2018	-0.0393	-0.218***	-0.0182	-0.145**	-0.102*	-0.207***
	(0.0380)	(0.0389)	(0.0467)	(0.0573)	(0.0541)	(0.0672)
2019	-0.0990***	-0.171***	-0.0645	-0.107**	-0.314***	-0.243***
	(0.0351)	(0.0351)	(0.0426)	(0.0471)	(0.0454)	(0.0544)
Macro regions						
REG1				-0.230***	-0.0893	-0.134*
				(0.0591)	(0.0557)	(0.0724)
REG2	0.482***	0.353***	-0.0336	-0.327***	-0.541***	-0.0563
	(0.0304)	(0.0306)	(0.0377)	(0.0577)	(0.0542)	(0.0689)
REG3	0.632***	0.528***	-0.0683			
	(0.0400)	(0.0400)	(0.0520)			
REG4	-0.0620**	-0.176***	-0.127***	-0.156***	-0.101*	-0.114
	(0.0288)	(0.0290)	(0.0355)	(0.0584)	(0.0542)	(0.0694)
REG5	0.110***	0.124***	0.0303	0.0279	-0.101**	-0.0561
	(0.0279)	(0.0277)	(0.0338)	(0.0509)	(0.0492)	(0.0622)
REG6				0.282***	0.0777	-0.0414
				(0.0537)	(0.0530)	(0.0685)
REG7				0.725***	0.127	0.165
				(0.0968)	(0.0897)	(0.112)
Gender (male)						
Female	0.160***	0.128***	0.109***	0.158***	0.202***	0.113***
	(0.0237)	(0.0238)	(0.0299)	(0.0353)	(0.0341)	(0.0432)
Age (age≤45)						
(45–55]	-0.0421	-0.0938***	-0.0460	0.0106	0.00771	-0.00594
	(0.0320)	(0.0321)	(0.0380)	(0.0460)	(0.0432)	(0.0557)
(55–65]	-0.142***	-0.125***	0.00426	-0.143**	-0.159***	-0.128*
	(0.0394)	(0.0395)	(0.0476)	(0.0587)	(0.0548)	(0.0693)
(65–75]	-0.230***	-0.0523	-0.150*	-0.261***	0.0361	-0.218**
	(0.0664)	(0.0675)	(0.0812)	(0.0927)	(0.0893)	(0.108)
75 or more	-0.136*	-0.118*	-0.425***	-0.269***	0.106	-0.334***
	(0.0696)	(0.0710)	(0.0857)	(0.0968)	(0.0935)	(0.113)
Education (SCED 3 or 4)						
Up to ISCED 2	0.336***	0.283***	0.0235	0.527***	0.200***	-0.0683
	(0.0302)	(0.0311)	(0.0435)	(0.0404)	(0.0398)	(0.0501)
ISCED 5 or more	-0.523***	-0.479***	-0.0806**	-0.708***	-0.577***	-0.107**
	(0.0304)	(0.0304)	(0.0342)	(0.0391)	(0.0356)	(0.0461)
Employment status (self-employed or employee)						

Table 4 (continued)

		Italy			Spain		
Retired or with disability		0.131***	0.112***	0.164***	0.258***	0.0579	0.142**
		(0.0427)	(0.0430)	(0.0529)	(0.0601)	(0.0583)	(0.0651)
Unemployed		0.739***	0.532***	0.574***	0.925***	0.547***	0.524***
		(0.0618)	(0.0596)	(0.0620)	(0.0683)	(0.0623)	(0.0762)
Student or other		0.391***	0.430***	0.332***	0.522***	0.228***	0.0265
		(0.0537)	(0.0540)	(0.0683)	(0.0794)	(0.0779)	(0.0930)
Marital Status (married or consensual union)							
Never married		0.120***	0.0172	0.226***	0.325***	-0.0675	0.234***
		(0.0336)	(0.0344)	(0.0413)	(0.0500)	(0.0465)	(0.0609)
Separated or divorced		0.209***	0.186***	0.310***	0.555***	0.207***	0.385***
		(0.0405)	(0.0395)	(0.0465)	(0.0560)	(0.0542)	(0.0675)
Widowed		0.0791**	-0.0882**	0.186***	0.186***	-0.236***	0.322***
		(0.0383)	(0.0400)	(0.0524)	(0.0608)	(0.0596)	(0.0721)
Housing tenure status (other)							
Own it outright		-0.542***	-0.271***	-0.101***	-0.504***	-0.287***	-0.0965**
		(0.0233)	(0.0231)	(0.0286)	(0.0351)	(0.0328)	(0.0407)
Degree of urbanisation (other)							
Living in a city		-0.0266	0.0659***	-0.00622	-0.0359	-0.0713**	-0.0673
		(0.0231)	(0.0233)	(0.0279)	(0.0346)	(0.0331)	(0.0447)
Housing typology (other)							
Flat in building		0.0781***	-0.0577***	-0.0188	0.114***	-0.0256	0.00554
		(0.0220)	(0.0222)	(0.0274)	(0.0366)	(0.0342)	(0.0449)
Household size (3 members)							
1 member		-0.0157	0.510***	-0.426***	-0.297***	0.564***	-0.431***
		(0.0409)	(0.0417)	(0.0483)	(0.0582)	(0.0554)	(0.0731)
2 members		-0.0700**	0.131***	-0.125***	-0.141***	0.128***	-0.0612
		(0.0350)	(0.0360)	(0.0406)	(0.0458)	(0.0445)	(0.0533)
4 members or more		0.0866**	0.00135	0.0689	0.119**	-0.0137	0.0832
		(0.0387)	(0.0392)	(0.0441)	(0.0473)	(0.0447)	(0.0528)
Presence of children (other)							
Yes		-0.0700*	0.123***	-0.177***	-0.0359	0.186***	-0.168***
		(0.0397)	(0.0406)	(0.0457)	(0.0509)	(0.0484)	(0.0587)
Presence of senior (other)							
Yes		0.0612	-0.183***	-0.116**	-0.00947	-0.204***	0.0420
		(0.0476)	(0.0485)	(0.0557)	(0.0620)	(0.0604)	(0.0683)
Presence of chronic illness (other)							
Yes		0.164***	0.0215	0.0144	0.202***	0.0390	0.000545
		(0.0256)	(0.0258)	(0.0333)	(0.0333)	(0.0321)	(0.0440)
Observations		30,391	30,391	30,391	20,233	20,233	20,233
Correlation coefficients							
ρ_{12}	0.2949	***		0.3569	***		
	(0.0125)			(0.0172)			
ρ_{31}	0.0854	***		0.1274	***		
	(0.0165)			(0.0242)			
ρ_{32}	0.4123	***		0.4388	***		
	(0.0145)			(0.0202)			

Table 4 (continued)

	Italy	Spain
Likelihood ratio test		
H_0:	Prob > chi2	Prob > chi2
$\rho_{12} = \rho_{31} = \rho_{32} = 0$	0.0000	0.0000

In Italy, REG1 = ITC North-West Regions, REG2 = ITF Southern regions, REG3 = ITG Islands, REG4 = ITH North-East regions, and REG5 = ITI Central regions. In Spain, REG1 = ES1 Northwest, REG2 = ES2 Northeast, REG3 = ES3 Central regions, REG4 = ES4 Madrid Province, REG5 = ES5 East, REG6 = ES6 South, and REG7 = ES7 Canary Islands. For more details see Note 2. Robust standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

The effects of the covariates related to the year dummies and geographical location are similar in both countries. In general, the results do not indicate a strong effect of the time component; many parameters of the time dummies are not significantly different from zero. However, the statistically significant coefficients are negative (except for I1 in Italy in 2015), indicating that, compared to 2013, the probability of experiencing EI decreased over the years, particularly for symptom I2 (difficulty in affording standard expenses) in both countries and I3 (drop in income) in Spain.

As regards the effects of geographical location, both countries exhibit a notable regional effect. In Italy, households in the south and the islands have a higher probability of experiencing EI related to I1 (inability to cope with unexpected expenses) and I2 (difficulty in affording standard expenses) compared to those in the northwestern regions. In Spain, a north-south symmetric effect in EI is observed, but only for I1. Specifically, households located in the southern part of the Peninsula and in the Canary Islands report a greater likelihood of experiencing EI than those in the Comunidad de Madrid (which includes the capital). In contrast, the probability decreases for households living in regions in the northern and central regions of the country. Notably, we found no statistically significant spatial effect for indicator I3.

Focusing on the characteristics of householders, the direction of the relationships between these characteristics and the probability of experiencing any of the symptoms of EI are similar in both countries. Households with a female householder are more likely to experience the three symptoms of EI than households with a male householder. Younger people (45 years old or younger) appear to be more disadvantaged. Conversely, being 65 years or older strongly reduces the probability of experiencing insecurity such as a drop in income (I3), and the likelihood of reporting insecurities due to unexpected expenses (I1). Moreover, householders with primary or lower secondary education compared to those with upper secondary or post-secondary non-tertiary education increase the probability of EI in the two self-reported symptoms (I1 and I2). However, the probability of experiencing EI in its three components decreases for householders with tertiary education. Employment status also has a significant influence on EI. Specifically, being unemployed, retired, disabled, or a student, as opposed to being self-employed or employed, increases the probability of experiencing all three dimensions of EI. Marital status has a significant effect as well. The results indicate that individuals who are separated or divorced experience greater financial insecurity across all components of EI than those who are married or living with a partner. Similarly, those who have never married or are widowed are particularly vulnerable to the inability to cope with unexpected expenses (I1) and experiencing a drop in income (I3). Notably, being widowed, compared to living with a partner, reduces the probability of reporting difficulties in affording standard expenses (I2).

As for the characteristics of the households, the results are quite similar for both countries, with some exceptions. Household owners were less likely to experience all three symptoms of EI. Compared to the other variables in the model, the effects of living in a city and type of housing are relatively low. Small households with one or two members, compared to those with three members, are associated with a higher likelihood of experiencing EI due to the inability to afford standard expenses (I2), but with a lower likelihood of experiencing insecurity due to unexpected expenses (I1) and drops in income (I3). In contrast, larger households with four or more members are more likely to report insecurity due to unexpected expenses (I1). The presence of children in the household is associated with a higher probability of reporting difficulties in affording standard expenses (I2) but a lower likelihood of reporting the other two types of EI (I1 and I3). Additionally, the presence of a senior member (65 years or older) in the household is linked to less difficulty in affording standard expenses (I2) and, specifically in Italy, to a lower probability of experiencing drops in income in the past (I3). Finally, in households where one or more members suffer a chronic illness, the probability of EI significantly increases, but only for the first indicator (unexpected expenses).

6.3 Predicted probabilities and risk ratios of economic insecurity

In the estimated probit models, the signs of the estimated parameters provide insight into the directions of the relationships between the probability of occurrence of the EI symptoms and the explanatory variables. To fully understand these relationships, however, it is of utmost importance to complete the analysis by computing the predicted probabilities and risk ratios. This requires, as a first step, defining a baseline household which serves as a standard for assessing the effects of each covariate. Specifically, the baseline household corresponds to the combination of reference categories (see Sect. 4.2) for all explanatory variables included in the statistical models. We then predict the probability that the reference household experiences EI, both for the three symptoms together (I1, I2, and I3) and for each symptom separately, in Italy (Table 5) and Spain (Table 6). Next, we compute the predicted probabilities for each specific household configuration by varying one covariate at a time. Finally, the risk ratio is calculated as the quotient between the predicted probability for each specific household and the predicted probability of the baseline household.

It is important to note that estimating predicted probabilities and risk ratios allows us to focus on the correlates of EI in the most vulnerable households, particularly those experiencing all three symptoms of EI simultaneously. Starting with the predicted probabilities for the reference household, we observe that the predicted probability of joint EI is nearly twice as high in Spain as in Italy (0.07 vs. 0.04). As for the main drivers of joint EI, the estimated model indicates that households with an unemployed householder in comparison with being employed have a probability of 0.16 in Italy and 0.26 in Spain of experiencing all three symptoms of EI (I1, I2, and I3). Based on the risk ratio values, we can infer that the probability of experiencing joint EI when the householder is unemployed is 3.84 times higher in Italy and 3.69 times higher in Spain than in the reference household. The second most important driver of joint EI is when the householder is separated or divorced compared to being married or living in a consensual union. The probability that these households will

Table 5 Predicted probability (PP) and risk ratio (RR) of economic insecurity in italy, 2013–2019

Comparison items	PP(I1,I2,I3)	RR(I1,I2,I3)	PP(I1)	RR(I1)	PP(I2)	RR(I2)	PP(I3)	RR(I3)
Reference	*0.04*	*1.00*	*0.35*	*1.00*	*0.28*	*1.00*	*0.17*	*1.00*
Year 2019	0.03	*0.76*	0.32	0.90	0.23	*0.81*	0.15	0.91
Southern regions	0.08	*1.80*	0.54	*1.53*	0.41	*1.46*	0.16	0.95
Islands regions	0.08	*1.89*	0.60	*1.70*	0.48	*1.70*	0.15	0.90
Female[a]	0.06	*1.37*	0.41	*1.17*	0.33	*1.16*	0.20	*1.17*
Age (45–55][a]	0.04	*0.87*	0.34	0.96	0.25	*0.89*	0.16	0.93
ISCED2[a]	0.07	*1.62*	0.48	*1.37*	0.39	*1.36*	0.18	1.04
ISCED5[a]	0.02	*0.36*	0.18	*0.52*	0.15	*0.52*	0.15	*0.88*
Unemployed[a]	0.16	*3.84*	0.64	*1.82*	0.48	*1.71*	0.35	*2.07*
Retired or with a disability[a]	0.06	*1.36*	0.40	*1.14*	0.32	*1.14*	0.21	*1.26*
Separated /divorced[a]	0.08	*1.89*	0.43	*1.23*	0.35	*1.23*	0.26	*1.53*
Housing own	0.02	*0.42*	0.18	*0.51*	0.20	*0.70*	0.15	*0.86*
Living in a city	0.05	1.06	0.34	0.97	0.31	1.08	0.17	0.99
Living in a flat	0.04	0.91	0.38	1.08	0.26	0.93	0.16	0.97
2-member household	0.04	0.91	0.33	0.93	0.33	*1.16*	0.14	*0.83*
Presence of children	0.03	*0.78*	0.33	0.93	0.33	*1.15*	0.13	*0.76*
Presence of senior	0.04	*0.83*	0.38	1.07	0.22	*0.79*	0.14	*0.84*
Presence of chronic illness	0.05	*1.12*	0.42	*1.18*	0.29	1.03	0.17	1.02

[a]Denotes the householder's characteristics. I1 is the inability to cope with unexpected expenses, I2 is the difficulty in affording the standard expenses, and I3 is the drop in income. Figures in italics greater than 1 denote a statistically significant positive relationship with economic insecurity, and figures in italics less than 1 a statistically significant negative relationship. $n = 30{,}391$

experience joint EI is 1.89 times higher in Italy and 2.56 times higher in Spain than the reference category (i.e., where the householder is either married or in a consensual union). We also observe that territorial factors play a significantly larger role in Italy than in Spain. In Italy, the probability of joint EI is 1.89 times higher for those living in the island regions and 1.80 times higher for those living in the southern regions, compared to other areas. Although less pronounced, the territorial effect of the southern regions is also significant in Spain where the joint probability of EI is 1.22 times higher. Other factors contribute to joint EI in both countries. For example, female householders have 1.37 times the probability in Italy and 1.43 times the probability in Spain of experiencing EI compared to male householders. A low education level (ISCED 2) is also associated with an increased joint risk of EI, with the probability being 1.62 times higher in Italy and 1.48 times higher in Spain compared to the reference household where the householder has at least an upper secondary education. Householders who are retired or have a disability face a probability of experiencing joint EI 1.36 times higher in Italy and 1.54 times higher in Spain compared to those who are self-employed or employed.

As for the factors that mitigate the probability of joint EI, the householder's educational attainment stands out for its beneficial impact. If the householder has a tertiary education

Table 6 Predicted probability (PP) and risk ratio (RR) of economic insecurity in spain, 2013–2019

Comparison items	PP(I1,I2,I3)	RR(I1,I2,I3)	PP(I1)	RR(I1)	PP(I2)	RR(I2)	PP(I3)	RR(I3)
Reference	0.07	*1.00*	*0.37*	*1.00*	*0.51*	*1.00*	*0.19*	*1.00*
Year 2019	0.04	*0.58*	0.33	*0.89*	0.39	*0.76*	0.13	*0.69*
Northwest regions	0.05	*0.69*	0.29	*0.78*	0.48	0.93	0.16	*0.82*
Southern regions	0.08	*1.22*	0.48	*1.30*	0.54	1.06	0.18	0.94
Female[a]	0.10	*1.43*	0.43	*1.17*	0.59	*1.16*	0.23	*1.17*
Age (45–55][a]	0.07	1.08	0.37	1.01	0.52	1.01	0.19	0.99
ISCED2[a]	0.10	*1.48*	0.58	*1.56*	0.59	*1.15*	0.18	0.91
ISCED5[a]	0.02	*0.36*	0.15	*0.40*	0.29	*0.57*	0.17	*0.86*
Unemployed[a]	0.26	*3.69*	0.72	*1.96*	0.72	*1.40*	0.37	*1.89*
Retired or with a disability[a]	0.11	*1.54*	0.47	*1.27*	0.54	1.04	0.24	*1.21*
Separated/divorced[a]	0.18	*2.56*	0.59	*1.59*	0.59	*1.16*	0.32	*1.63*
Housing own	0.04	*0.52*	0.20	*0.54*	0.40	*0.78*	0.17	*0.87*
Living in a city	0.07	0.97	0.36	0.96	0.48	0.94	0.18	0.91
Living in a flat	0.07	1.08	0.41	*1.12*	0.50	0.98	0.20	1.01
2-member household	0.06	0.91	0.32	*0.86*	0.56	1.10	0.18	0.92
Presence of children	0.06	*0.85*	0.36	0.96	0.59	*1.14*	0.15	*0.78*
Presence of senior	0.07	1.01	0.36	0.99	0.43	*0.84*	0.21	1.06
Presence of chronic illness	0.08	*1.22*	0.45	*1.21*	0.53	1.03	0.19	1.00

[a]Denotes the householder's characteristics. I1 is the inability to cope with unexpected expenses, I2 is the difficulty in affording the standard expenses, and I3 is the drop in income. Figures in italics greater than 1 denote a statistically significant positive relationship with economic insecurity, and figures in italics less than 1 a statistically significant negative relationship. $n = 20{,}233$

(ISCED 5) compared to upper secondary education (ISCED 3 or 4), the risk ratio in both countries is 0.36, indicating that the risk ratio of joint EI is reduced by 64%. Likewise, home ownership (versus not owning a home) acts as a buffer, reducing the risk ratio of joint EI by 58% in Italy and 48% in Spain.

Overall, the percentage of vulnerable households experiencing the three types of EI during the period 2013–2019 was estimated at 3.7% in Italy and 5.3% in Spain (Table 3). Therefore, it is worth reviewing some results from Tables 5 and 6, which highlight the probabilities and risk ratios for reporting symptoms I1 (inability to cope with unexpected expenses) and I2 (difficulty in affording standard expenses), as these are the most prevalent forms of EI in households in both countries (see Table 3). As noted, being an unemployed householder is the main driver of financial insecurity in Italy. More specifically, unemployed householders are 1.82 times more likely to experience the inability to cope with unexpected expenses (I1) and 1.71 times more likely to have trouble affording standard expenses (I2) compared to employed householders, highlighting the significant impact of unemployment on financial insecurity. The territory matters in Italy since the location of households in island regions increases the risk ratio of reporting I1 and I2 by 70%. The third risk factor in Italy is the low educational attainment of the householder. In households where the householder has attained ISCED level 2 or less, the risk ratio of reporting I1 and I2 is approximately 1.37 compared to households in which the householder has attained ISCED level 3 or 4. This indicates that households with lower educational attainment are 1.37 times more likely to report I1 and I2, highlighting the impact of lower education levels on EI. The fourth risk factor that increases the probability of reporting these two types of EI in Italy is the householder's separated or divorced status, with a risk ratio of 1.23. This means that separated or divorced householders are 1.23 times more likely to report these forms of economic insecurity compared to those who are married or single. In Spain, the main drivers of EI types I1 and I2, in order of importance, are the householder's unemployment status, low educational attainment, and being separated or divorced. This is followed by living in the southern regions, which is less relevant and has a significant impact only on I1.

As concerns factors that help mitigate EI, including the inability to cope with unexpected expenses (I1) and difficulty in affording standard expenses (I2), an educational level equal to ISCED 5 of the householder is the main buffer. Specifically, it reduces the risk ratio of reporting I1 by 48% in Italy and by 60% in Spain as well as the risk ratio of experiencing I2 by 48% in Italy and 43% in Spain. Being the owner of the dwelling is the second buffer of financial insecurity identified by our results.

7 Conclusions

The first aim of this paper is to propose a new methodological framework to study EI. We have critically reviewed the empirical literature concerning EI, to elucidate the strengths and limitations of existing methodologies and frameworks used to measure EI. Highlighting the complexity of the phenomenon, we aimed to explore and quantify manifestations of this phenomenon in Italian and Spanish households from 2013 to 2019 (the second aim of this paper). Likewise, we have identified the drivers and buffers of the likelihood of experiencing EI in both countries (the third aim of this paper). Below, we present the main conclusions.

First, rather than working with a composite EI indicator, we proposed a set of three indicators that identify if a household is affected or suffering from EI (I1, the inability to cope with unexpected expenses; I2, the difficulty in affording standard expenses; and I3, a drop in income). The choice of these three indicators has been guided to more accurately capture the probability that a household is experiencing EI. Unlike previous studies, we focus on the effects or symptoms of EI because they offer clear indications of the existence of EI in the household. The three indicators capture the perception of individuals (I1 and I2); provide an objective measurement that reflects changes in a household's disposable income (I3); and supply information about the past (I3), the present (I2), and future expectations (I1).

Second, our results indicate that, over the period 2013–2019, Spanish households were slightly more affected by EI than Italian ones. Specifically, 58.9% of Spanish households experienced one or more of the three EI symptoms compared to 54.5% of households in Italy.

Additionally, from 2013 to 2019, the drop in income (I3) was the least prevalent symptom of EI in Italian and Spanish households, with 11.2% of Italian households and 12.8% of Spanish households reporting this type of EI, either alone or in conjunction with the other two symptoms. In contrast, the inability to cope with unexpected expenses (I1) is the EI that most affects Italian households (around 37.1%), while the greatest financial difficulty facing Spanish households is being able to afford standard expenses (I2), affecting around 42.6% of households. This indicates that studies on EI which focus solely on changes in income (e.g., Hacker, 2008; Hacker et al., 2014; Petrov & Romaguera-de-la-Cruz, 2024; Rohde et al., 2014; Western et al., 2016) underestimate the extent of the phenomenon. People may feel financial insecurity in the present or when thinking about their future, even if their income does not change; for example, in the face of the looming possibility of company closure and subsequent unemployment. This experience of insecurity will condition their quality of life and economic behaviour. Therefore, this result supports our proposal to study EI from a multidimensional perspective.

Third, to overcome the shortcomings inherent in the mathematical methods used to construct composite indicators in the reviewed literature, we computed the three EI indicators as dependent variables in a trivariate probit model. This approach demonstrated the existence of a correlation between the indicators. Thus, our proposal for joint estimation is deemed appropriate. To the best of our knowledge, the application of this econometric estimator to a socioeconomic phenomenon such as EI represents an innovative aspect of our paper. In both countries, we found the highest correlation between indicator I2 (difficulty in affording standard expenses) and indicator I3 (drop in income). This finding statistically demonstrates that past experiences are highly correlated with current financial insecurity. This is a key hypothesis in other studies (see, e.g., Bossert & D'Ambrosio, 2024) which, from our point of view, had not been empirically tested before.

Fourth, regarding the socioeconomic factors associated with EI, a remarkable finding is that the main driver of the three components of EI is the unemployed status of the householder. Thus, our approach of not mixing causes with symptoms of EI by constructing an EI composite index prevents endogeneity issues. We refer to studies that construct composite indicators of EI by incorporating factors such as the risk of unemployment. In their inferential analyses, these studies often include the householder's labour market status—such as "unemployed"—as an explanatory variable of EI (see, e.g., Cantó et al., 2020; Romaguera de la Cruz, 2020).

Fifth, as concerns the spatio-temporal effect, we found that the likelihood of experiencing EI decreased over the years compared to 2013, especially for symptom I3 (drop in income). This result can be explained by the fact that Italy and Spain had already emerged from the economic recession during the period of analysis (2013–2019) and had entered into a phase of economic recovery prior to the onset of the COVID-19 shock. Both countries exhibit a strong regional effect, especially Italy. Notably, households in a region in southern or island regions of Italy and Spain are more vulnerable to EI symptoms I1 and I2, but not to drops in income (I3). It is plausible that public policies, including the European Union's Cohesion Policy, whose fundamental objective is to reduce territorial disparities, have succeeded in eliminating the regional effect in terms of income declines but have not adequately addressed the other symptoms of EI.

Sixth, it is worth highlighting that our methodological approach has allowed us to successfully combine multidimensional aspects of EI with a regression analysis that addresses the shortcomings present in previous studies. Specifically, we refer to cases in where the direction of the associations (i.e., the signs of the parameters) between certain socioeconomic characteristics and the three types of EI (I1, I2, and I3) studied differ depending on the specific component of EI analysed. For instance, in both Italy and Spain, being "widowed" is associated with a higher probability of experiencing I1 and I3 but a lower probability of self-reporting I2; and the presence of children in the household increases the probability of I2 but decreases the probability of I3. These findings highlight some shortcomings of approaches that study EI with composite indicators that synthesise information from several EI indicators. As a result, the subsequent inference analysis intended to study the socioeconomic correlates of the composite EI indicator may obscure the specific and different effects of each socioeconomic characteristic and component of EI. In such cases, this could lead to a distorted or biased understanding of reality.

Seventh, to complement the results of the trivariate probit models, we calculated the predicted probabilities and risk ratios, allowing us to quantify the relationship between the three types of EI symptoms and the set of spatiotemporal and socioeconomic variables analysed. Additionally, to focus on *the most vulnerable households* in Italy and Spain, we computed the predicted probabilities and the risk ratios for households that experienced all three symptoms of EI (I1, I2, and I3).

8 Public policy implications

Focusing on the most vulnerable households (i.e., those exhibiting all three symptoms of EI), our results for both countries point out three characteristics of the householder as main drivers of the financial insecurity: being unemployed, separated or divorced, and being a woman. In the EU, labour income is the main source of household market income, accounting for 92.2% in Spain and 79.8% in Italy in 2019 (Eurostat, Household statistics on income, saving, and investment). Therefore, in Spain and Italy, which recorded an unemployment rate of 14.1% and 9.9% in 2019, respectively (Eurostat, EU Labour Force Survey), employment promotion policies may need to be reformulated to become more effective and reduce household EI. Regarding the second characteristic, several studies have shown that being married or living with a partner is powerful insurance against the risks that workers face in the labour market, such as being fired, or against exogenous income shocks (Clark et al., 2023; Shore, 2010). Finally, being a female householder is identified as a driver of EI for the most vulnerable households because in both Italy and Spain there is a persistent gender gap in salaries (4.7% and 9.4%, respectively) and employment rates in 2019 (19.4% and 11.9%, respectively) (Eurostat, EU Labour Force Survey). Thus, female-headed households, which are often single-parent families, face significant economic disadvantages.

On the other hand, we also identify two buffers or protective factors that reduce the likelihood of experiencing the three components of EI: the householder has a tertiary education, and the family owns the dwelling. As regards educational attainment, the literature on human capital predicts a positive correlation between human capital and wages. Furthermore, ceteris paribus, households in which the householder has attained a high level of education are predictably more able to bounce back and move forward (OECD, 2021). The purchase of a house is probably the most important investment towards which households channel their savings. This type of wealth provides them with financial security and savings on rental housing costs.

In summary, the main findings of our study align with the core principles for promoting fair and well-functioning labour markets and social protection systems, as set out in the European Pillar of Social Rights Action Plan endorsed by all Member States in 2021 (European Commission, 2021). To help reduce EI and prevent its negative economic and social impacts, it is essential to strengthen government programmes in at least three key areas. First, policies to promote employment should be developed or reformulated. Such measures must go hand in hand with schemes to improve the educational attainment and job training of the population, particularly in Italy, which currently ranks lowest in the EU.[7] Second, increased government investment in housing should be prioritised, recognising it as a preferred good of the welfare state and considering its role as a buffer of the EI. Data on public expenditure show significant room for improvement in terms of access to housing in both Spain and Italy, as well as across the EU.[8] Third, interventions to improve women's working conditions must be strengthened in both countries to reduce the gender gap in wages and employment rates, ensuring that being a female head of household is no longer a driver of EI. Likewise, public programmes to protect families and children should receive greater budgetary attention to reduce families' EI, since Italy and Spain have the lowest fertility rates in the EU,[9] putting the sustainability of their welfare states at risk (see Esping-Andersen, 2016; Esping-Andersen & Billari, 2015).

These interventions could be aligned with the objectives of the EU Cohesion Policy to help reduce territorial differences, as we have identified a strong regional component of EI in Italy and Spain. It is essential to account for territorial diversity and recognise that economic challenges and opportunities can differ significantly across regions even within the same country (European Commission, 2020; Sánchez & Jiménez-Fernández, 2023).

[7] The indicator "young people neither in employment nor in education and training by sex" (NEET) recorded the following values in Italy (22.3%), Spain (14.9%), and the EU (12.8%) in 2019 (Eurostat, Labour Force Survey). Italy registered the highest value of the 27 member states and Spain ranked in the fifth worst place.

[8] Public spending on housing programmes in 2019 compared to other preferred goods (i.e., education and healthcare) is very low in both Italy (1% of total public spending vs. 8.1% for education and 14% for healthcare in 2019) and Spain (1% of total public spending vs. 9.5% for education and 14.4% for healthcare) and is somewhat lower than in the EU as a whole (1.2%, 10.1%, and 15% respectively) (Eurostat, General government expenditure by function COFOG).

[9] In 2019, Italy registered 1.27 live births per woman and Spain registered 1.23. Together with Malta (1.13), these are the lowest fertility rates of the entire EU (1.53) (Eurostat, Population and migration statistics).

Appendix

See Tables 7 and 8.

Table 7 Indicators and methods to measure economic insecurity according to the multidimensional approach

Authors	Subjective and objective individual indicators	Method to synthesise
Rohde et al. (2015)	Objective (3): income drops, inability to pay from one to four concepts (rent, the pawning of a household item, inability to pay utilities, and skipping of meals) and the unemployment risk. Subjective (3): inability to cope with unexpected expenses, job insecurity, financial dissatisfaction.	Arithmetic mean and principal component analysis
Whelan et al. (2017)	Objective (2): households having a structural problem with arrears relating to mortgage or rent; households that had to go into debt within the last 12 months to meet ordinary living expenses such as mortgage repayments, rent, or back-to-school expenses. Subjective (3): inability to cope with unexpected expenses, difficulty to make ends meet, perception that household costs are a heavy burden.	Weighted arithmetic mean
Romaguera-de-la-Cruz (2020); Cantó et al. (2020)	Objective (3): income drops, the probability of future unemployment and the probability of extreme expenditure distress. Subjective (3): inability to cope with unexpected financial expenses, a measure of financial dissatisfaction, and changes in the ability to go on a holiday.	Alkire–Foster counting method
Ranci et al. (2021)	Objective-Dimension 1 (financial strain): unexpected expenses, make ends meet, holidays, meat, keep house warm, housing burden. Objective-Dimension 2 (over-indebtedness): arrears rent, arrears bill, arrears loan, debt burden. Objective-Dimension 3 (material deprivation): washing machine, car, PC, colour TV. Objective-Temporary poverty.	Principal component analysis and counting method

Table 8 Annual releases and rotational structure of EU-SILC: selection of households by year

	Rotational group			
Release	RG1	RG2	RG3	RG4
2014			2011	
			2012	2012
	2013		2013	2013
	2014		2014	2014
2015				2012
	2013			2013
	2014	2014		2014
	2015	2015		2015
2016	2013			
	2014	2014		
	2015	2015	2015	
	2016	2016	2016	
2017		2014		
		2015	2015	
		2016	2016	2016
		2017	2017	2017
2018			2015	
			2016	2016
	2017		2017	2017
	2018		2018	2018
2019				2016
	2017			2017
	2018	2018		2018
	2019	2019		2019
2020	2017			
	2018	2018		
	2019	2019	2019	
	2020	2020	2020	

Explanation of the sample selection method. In the EU-SILC, each household remains part of the sample for four years and is interviewed on four annual occasions. Each year, all households in one of the rotational groups (the group that has just been interviewed for the fourth time) leave the sample, while a new set of households is interviewed for the first time. Thus, one-quarter of the sample is replaced each year. As can be observed, some households have been included in the sample in more than one release. For instance, households in 2014 of rotational group 2 are also available in 2015, 2016, and 2017, whereas households surveyed in 2013 and 2014 of rotational group 3 appear in only one year. Consequently, an exhaustive sample selection is required to prevent several households from becoming duplicated in the resulting dataset. To this end, our sample selection method includes, from each release of longitudinal data, households for which both criteria hold: (i) they formed part of the sample for the latest wave of data collection before being replaced (this is identified with the largest wave of data available for each rotational group), and (ii) they were also in the sample the previous year. Thus, for each year, we select the households of the rotational group in grey in the Appendix

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