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Detecting economic insecurity in Italy: a latent transition modelling approach

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Abstract

Economic insecurity has increased in importance in the understanding of economic and socio-demographic household behaviour. The present paper aims to analyse patterns of household economic insecurity over the years 2004–2015 by using the longitudinal section of the Italian SILC (Statistics on Income and Living Conditions) survey. In the identification of economic insecurity statuses, we used indicators of economic hardship in a latent transition approach in order to: (i) classify Italian households into homogenous classes characterised by different levels of economic insecurity, (ii) assess whether changes in latent class membership occurred in the selected time span, and (iii) evaluate the effect of employment status and characteristics of individuals on latent status membership. Empirical findings uncovered five latent statuses of economic insecurity from the best situation to the worst. The levels of economic insecurity remained quite stable over the period considered, but a non-negligible worsening can be detected for the unemployed and individuals with part-time jobs.

Keywords Economic insecurity · Latent transition analysis · Longitudinal data

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1 Introduction

The notion of economic insecurity (EI) has attracted growing attention in social, academic, and policy circles. Insecurity is a key aspect of the globalizing world—or our ‘risk society’—which has become a notable factor in explaining socio-economic and demographic behaviour (Scherer 2009). EI has been defined as ‘the anxiety produced by the possible exposure to adverse economic events and by the anticipation of the difficulty to recover from them’ (Bossert and D’Ambrosio 2013, p. 1018), thus affecting the opportunity and future well-being of a person or family. Despite the timely and key relevance of the notion of economic insecurity for contemporary societies, scholars have thus far been insufficiently precise regarding its definition and operationalisation. EI is multifaceted, making any comprehensive formal definition subsuming all possible aspects highly challenging (Ranci et al. 2021; Rohde and Tang 2018). EI should not be understood simply as a data-based designation, but rather as something that combines objective factors, experience, and subjective evaluations.

So far, EI studies are few and far between, with most either based on multidimensional approaches that use aggregate indices for the different insecurity dimensions (Osberg and Sharpe 2005, 2014; Berloffia and Modena 2014), or essentially unidimensional in nature when considering individuals or households (Nichols and Rehm 2014; D’Ambrosio and Rohde 2014; Rohde et al. 2014). Prior studies concur that the employment status and characteristics of individuals are underlying fundamental dimensions of EI. Habitually, approaches to the measurement of insecurity are based only on subjective measures linked to employment or job insecurity (Sverke et al. 2002; Probst et al. 2018). Such an emphasis fails to consider potential heterogeneous levels of EI by actual employment patterns.

This paper seeks to detect EI in Italy, and to assess whether and how changes in employment status and characteristics are associated with EI variation. We have applied the material hardship approach to longitudinal data, considering a household’s goods, its ability to cope with financial obligations, and generally to make ends meet. The analysis is based on data stemming from the Italian section of the European Survey of Living Conditions (EU-SILC), a four-year rotating panel, and covers the period 2004–2015 (nine four-year waves). The state of the national economy and global business is likely to offer an important additional element for justifying the interest in that period. In Italy, GDP per capita has been decreasing since 2008 and, after a partial recovery in 2010 and 2011, we had to wait until 2015 to see a positive sign. The economic downturn was accompanied by a growth in youth unemployment—indeed, the country saw one of the highest peaks in Europe—and a drop in employment (especially for men). The unemployment rate among under-25 s reached 42.7% in 2014, against the European average of 22.2%. Overall, these figures suggest a deterioration in the economic condition of Italian households in the period 2008–2013 (ISTAT 2015). How—and to what extent—these economic trends are coupled with rising or stagnating levels of EI remains to be understood. In the period of the analysis (2004–2014) the emerging class of ‘self-employed employees’ have emerged also in Italy (Borghini and Murgia 2019), where the percentage of self-employed is higher compared with other European countries (only Greece’s numbers are higher), and is stable at just over 20%.

From the statistical point of view, we follow a latent class transition analysis, in turn enabling the identification of increasing levels (i.e., the latent classes or states/statuses) of EI. The underlying assumption held is that the level of anxiety about possible adverse events is positively associated with the level of material hardship experienced by a household. Moreover, two covariates have been employed in the latent transition model: (i) employment status and characteristics, which affect the probability of belonging to a certain EI status (or class); and (ii) year of analysis, chosen to detect the change in EI membership over time. Through the use of a panel perspective, and by emphasising certain interesting features of the latent transition analysis in providing a continuous measure of individual EI, we are thus contributing to the growing body of research concerning EI. As the probability of belonging to the worst EI status (over time) can reveal the extent of anxiety surrounding possible adverse events.

The paper continues as follows: Sect. 2 reviews the literature on EI; Sect. 3 describes the study's analytical strategy and the methodology adopted; Sect. 4 presents the data, as well as certain descriptive statistics; Sect. 5 offers our empirical findings; and Sect. 6 concludes the paper with a summary and final discussion.

2 Literature review

As yet, there has been no general agreement on the conceptual and operational definition of EI. Conceptually, EI arises when individuals perceive a lack of economic safety coupled with the impossibility of receiving protection against unpredictable events or the difficulties in recovering from them (Bossert and D'Ambrosio 2013; Osberg 2015). It originates from economic loss due to unpredictable events (Stiglitz et al. 2009; p. 53; Western et al. 2012). These events can arise from several causes, both economic (e.g., income volatility, unemployment) and non-economic (e.g., long-term unemployment, family dissolution, poor health, etc.). Conceptually, EI differs from risk in that the exposure to risk can often be voluntary (e.g., a risky investment).

The growing attention paid to EI also stems from its strong involvement with institutional, familial and community support in protecting against risks (the so-called 'buffers' against the 'stressors' related to possible adverse events). In reality, individuals can feel secure about their personal status while feeling insecure about, for example, the government's capacity for providing support and security to its citizens (Burns and Gimpel 2000; Costello et al. 2009; UNDESA 2008, among others). Furthermore, individuals can rely on other personal forms of protection, such as parental leave, sick pay, or life insurance.

Recently, Richiardi and He (2020) offered a noteworthy review of the different approaches aimed at defining and measuring EI. Their contribution takes into account several features in the conceptual and operational definition of EI, such as whether the measure is subjective or objective, whether it refers to the micro or macro level, whether it considers levels or changes, and so forth. The present literature review also includes empirical analyses aimed at answering specific research questions in which the EI (and its operationalization) is involved. We

highlight how EI is, in the field of empirical analysis, strictly related to other constructs such as job insecurity and income volatility, among others.

EI has been recognised as affecting health issues such as: suicide and heart diseases (Catalano 1991), smoking habits (Barnes and Smith 2009), obesity (Rohde et al. 2016; Wisman and Capehart 2010), and mental health (Rohde et al. 2016). It also affects issues such as, but not limited to: racial prejudice (Burns and Gimpel 2000); punitive attitudes towards criminals (Costello et al. 2009); violence and the physical abuse of children (Conrad-Hiebner and Paschall 2017); harsh parenting attitudes (Conrad et al. 2019); trust in politicians (Halikiopoulou and Vlandas 2018; Wroe 2016); and fertility intentions (Fiori et al. 2013; Modena et al. 2008).

Two primary aspects best characterise EI: time—due to expectations about future events—and psychological or subjective dimensions—due to anxiety and security being typically determined by the perceptions of individuals. In this respect, Osberg (1998) stated that EI should be better measured through attitudinal surveys, because security can be interpreted as the subjective expectation that the probability of adverse events is approximately zero. Subjective feelings can also account for any heterogeneity in the perception of future situations. However, Osberg argued that it is possible to measure the hazards that produce a sense of insecurity. Osberg found those hazards in objective dimensions such as: unemployment, old age, health, widowhood, family dissolution, according to Article 25 of the UN Universal Declaration of Human Rights. The human rights perspective, called the ‘named risks’ approach, was applied to produce an aggregate measure (i.e., a composite measure) of EI within the Index of Economic Well-Being, or IEWB (Osberg 2009; Osberg and Sharpe 2009, 2014). Indeed, the ‘named risk’ approach underlies, more or less palpably, many contributions, with some of Osberg’s hazards emphasized more than others: job insecurity, in particular, is a common theme.

The idea of considering a set of hazards is common in the subjective approach, as anticipated by Dominick and Manski (1997), who used questions eliciting subjective probabilities of three events in the year ahead: absence of health insurance, victimization by burglary, and job loss. Scheve and Slaughter (2004) conceptualized EI and job insecurity and used survey questions about job satisfaction. In studying the effect of temporary employment on EI, Burgoon and Dekker (2010) focused on the subjective dimension, understood as past experience and worries about future employment and income. Mau et al. (2012) proxied EI with the subjective perception of fear of loss regarding job security, marital security, health care protection, and investigated the association of EI with subjective and objective (institutional) conditions.

Although recognising EI as being multifaceted, reflective of various risks, and involving subjective aspects, several studies have focused on the assumption that the level of anxiety about the possible exposure to adverse events is negatively associated with economic status, wealth status, and financial assets, that is, with objective features of individuals or households.¹ In this respect, we can identify

¹ Across the set of 143 publications retrieved from the Scopus database through the query ‘economic insecurity’ in the title field, we found more than 130 citations of papers with the words ‘income insecurity’ or ‘job insecurity’ in their title.

three strategies, depending on whether EI is fundamentally related to changes in job/work features, income or wealth.

The first strategy is applied in close conjunction with the literature on *job insecurity*, which primarily examines the frequency of job loss and its consequences in terms of wage changes (Gottschalk and Moffit 1999). The emphasis on job/work instead of unemployment is not fortuitous as EI relates to the broad experience of work rather than simply unemployment: e.g., rapid and exponential technological growth can suddenly render skills obsolete (Shafique 2018). Berloffia and Modena (2014) considered the type of contract and used the share of temporary workers as the insecurity dimension of the Italian version of IEWB. Later, the same scholars constructed a macro indicator of insecurity still in line with IEWB (Berloffia and Modena 2014). Without going into detail, because the literature on precarious work and work/job insecurity is huge (Burgoon and Dekker 2010; De Witte et al. 2003; Hacker 2019; Scheve and Slaughter 2004; Sverke et al. 2002), flexible employment (which in current surveys is usually proxied by temporary and part-time employment) is another source of both objective and subjective economic risk. It follows that the job-related features—and in particular the type of contract—of an individual are often considered as proxies of EI. In fertility studies, economic insecurity is customarily operationalized as present and past labour market disadvantages—primarily through unemployment and time-limited employment (Kreyenfeld et al. 2012; Del Bono et al. 2015; for a meta-analysis of European research findings, see Alderotti et al. 2021). For instance, Modena et al. (2008) and Fiori et al. (2013) analysed the effect of EI on fertility intentions where EI was proxied by a couple's employment status and type of contract (besides measures of precarious conditions in term of income and wealth) as an indicator of precariousness. Nonetheless, operationalizations of economic insecurity with objective states of employment tend to downplay its subjective and prospective nature (Comolli 2017; Comolli et al. 2021; Matysiak et al. 2021).

The second strategy is concerned with *income insecurity*. Hacker et al. (2010, 2014) proposed and improved on the Economic Security Index (ESI), which was mainly founded on the experience of large income losses (i.e., greater than 25% between two years) and their frequency, as income has a pervasive impact on economic well-being. Rohde et al. (2014) were interested in providing a micro-based index of EI, and looked at past income volatility, stating that past fluctuations of income can also have forward-looking relevance. Indeed, imagination and the ability to devise different scenarios together play a major role in planning for the future (Beckert and Bronk 2018). In a context in which (bounded) rational calculations of opportunities and constraints concerning family decisions are taken under uncertainty (where the probability distribution of different outcomes is just unknown), recent advances in family demography suggest that actors' choices are influenced by the "shadow of the future" (Huinink and Kohli 2014; Bernardi et al. 2019). The so-called 'Narrative Framework', for instance, views family choices as decisions guided by narratives of the future that can be more or less plausible and normatively oriented (Vignoli et al. 2020a, b). In line with such a framework, recent papers suggest that the subjective side of employment uncertainty may affect

family choices over and above its objective side (Comolli and Vignoli 2021; Bolano and Vignoli 2021; Gatta et al 2021).

The third strategy also uses economic variables to proxy EI. Bossert and D'Ambrosio (2013), while recognising their operationalisation as being perhaps oversimplified, developed a theoretical framework stating that EI depends on the current wealth level and its past changes, with past wealth as a buffer stock for facing adverse events. That approach was applied by D'Ambrosio and Rohde (2014), who operationalized the level of individual wealth by the sum of financial assets (including homeowner equity) minus total liabilities as an individual measure of EI. Recognizing that available data on individual streams of wealth are rare, Bossert and D'Ambrosio (2013) proposed another class of EI indicators more suitable for 'variation in resources', where resources are proxied by household disposable income or consumption.

Other scholars applied more complex approaches by involving both subjective and objective perspectives. Espinosa et al., (2014) analysed how certain objective high-risk situations impact subjective anxiety. Rohde et al. (2016) also considered both the subjective experiences of individuals and their objective aspects reflecting anxiety. That paper stands out because it modelled the probability of downside risk on objective data. Relying on HILDA (Household, Income and Labour Dynamics in Australia) panel data, Rohde et al. (2016) used three subjective variables: job security, financial satisfaction and a household's ability to raise emergency funds. The objective indicators were: (1) a dummy variable indicating whether a household's disposable income had fallen by at least 25% (such as in Hacker et al. 2010) while being below the median value, (2) the inability to meet standard expenses, which is a 0–4 count variable based on four criteria, (3) a dummy variable denoting unemployment. Interestingly, the authors estimated, respectively, an ordered and a bivariate probit model for the last two objective variables, to provide forward-looking measures (p. 4). Finally, they normalized the variables and obtained a composite indicator of EI. A similar approach was recently applied by Romaguera-de-la-Cruz (2020). The author included past experiences and the probability of future events, by adapting the six indicators in Rohde et al. (2014) to EU-SILC panel data.

In several empirical applications, we note a widespread use of multivariate methods on items related to 'economic hardship'. From a theoretical point of view, the concept of 'material hardship' as the 'the inadequate consumption of very basic goods and services such as food, housing, clothing, and medical care' (Beverly 2001a, b, p. 24) is instead included in the measures of poverty, deprivation, and social exclusion (Beverly 2001a; Nelson 2011; Nolan and Whelan 2010). However, the more general concept of 'economic hardship' is recognized as a key component of the 'family stress model': 'mounting economic pressures generally bring budgetary matters to the fore, enhancing preoccupation with financial issues that, in many families, generate frustration, anger, and general demoralization' (Conger et al. 1992, p. 327). Moreover, a high level of economic pressure indicates a family's inability to meet its material needs, delays in debt payments, and a need to cut back expenses. Such circumstances would reflect a family's concern about its economic status which, in turn, influences the emotional status and quality of

interactions between its members. The use of survey items related to economic hardship can be found in Ranci et al. (2021), who conducted a principal component analysis on EU-SILC data, and identified the components of financial strain and over-indebtedness as a multivariate measure of EI. The basic idea was that EI is associated with a ‘high probability of experiencing either a loss of income or a temporary difficult economic situation severe enough to threaten the material independence of individuals/households in the short to medium term’ (p. 4). Nonetheless, the use of EU-SILC items on material deprivation and the capacity to afford unexpected expenses was used in Coli (2018) for studying the effect of social protection benefits on household EI. The author referred to the Eurostat framework of economic security² and constructed a dichotomous variable: economically insecure/economically secure. Overall, an approach based on responses to survey questions related to ‘economic hardship’ has the advantage that both ‘buffers’ and ‘stressors’ would be implicitly incorporated in the response.

We have so far reviewed contemporary research on EI, although some papers are also difficult to categorise because the measurement of EI is not always the aim of the study. Moreover, the operationalization of EI overlaps with those of a number of noteworthy constructs such as, among others, poverty, deprivation, well-being, or income volatility. Compared with such constructs, all authors recognized the forward-looking nature of EI as its peculiarity, as well as the need for a dynamic characterization of EI. Nonetheless, these features were not always accounted for empirically, or theoretically. Subjective data (i.e., the perceived likelihood of future events) should be preferable (Osberg’s view) but it has also been stated that ‘insecurity requires real risks that threaten real hardships’ (Hacker 2019; p. 9). In any event, longitudinal objective data allow the construction of forward-looking indicators such as the probability of a downside risk (as in Rohde et al. 2016), that might be a proxy of anxiety about the future. Table 6 in the Appendix gives a snapshot of the main features of the contributions. In most works, EI is operationalised by the determinants of anxiety (i.e., income or wealth volatility, job insecurity, etc.).

The present paper relies on the following definition of EI: ‘a state of anxiety produced by a lack of economic safety’ (Osberg 1998), where the lack of economic safety is operationalised by the ‘economic hardship’ approach. The longitudinal structure of data and the methodology of the latent transition analysis allow the estimation of the forward-looking probability of downside risk (similarly with Rohde et al. 2016). Indeed, the transition matrix expresses the probability of passing from one EI status to another between two points in time. More precisely, EI is operationalized through a set of household variables related the ability to face unexpected expenses, material hardship and financial strain included in the longitudinal EU-SILC surveys. Moreover, we have recovered the role of the

² Quality of life indicators: economic security and physical safety: https://ec.europa.eu/eurostat/statistics-explained/index.php/Quality_of_life_indicators_-_economic_security_and_physical_safety.

employment status of the head of the household, which also includes the status of part-time workers. That variable acts as a covariate of the latent transition model. Indeed, job/work features play an important role in the operationalization of EI.

Employment commonly provides the economic basis that enables a person to set up a household, ensures their own and their family's livelihood, and grants economic independence and welfare protection over the course of their life (Neyer et al. 2013). In most countries, this can only be achieved through full-time employment or through such employment as secures an income at the level of full-time employment. Full-time employment may thus be regarded as a proxy for a person's capacity to form and maintain an autonomous household, ensure independent social protection, and maintain bargaining power in a partnership. These elements are what most commonly distinguishes full-time employment from part-time work. Part-time work is often accompanied by lower income, lower social-security benefits, a reduced capacity to sustain a household and, in couples with an unequal amount of paid work, it implies reduced bargaining power in relationships (Bittman et al. 2003). On the other side, self-employed work includes several situations that differ in terms of needs and contributory capacities, ranging from small firms such as artisans and traders, to people pursuing professional activities. They also include individuals who fall into precarious working arrangements—namely, cases of involuntary transition from employee to self-employed, with the consequence of reduced income (Kautonen et al. 2010; Hatfield 2015). Another noteworthy feature is the emerging category of workers with only one or two clients, who face a limitation in work autonomy (the so-called 'self-employed employees'). Hence, on the one hand, the self-employed may be more protected with respect to EI due to their own independent business; on the other, their increased insecurity related to fluctuating income from self-employment has also been emphasized.

3 Methodology

In the present study, we analysed the changing levels of EI over time and by employment patterns through the use of: (i) a latent transition modelling approach to measure EI over time and the classification of households into mutually and exhaustive (ordinal) latent classes (status) on the basis of proxy indicators of the latent variable EI, and (ii) an index to assess the household EI stability over the studied period.

3.1 Classifying households over time

In analysing latent variable models, latent transition analysis (LTA) and latent class analysis (LCA) are related methods. LCA is a statistical method used to group individuals (cases, units) into classes (categories) of an unobserved (or latent) variable. It is a statistical procedure for identifying class membership probabilities among statistical units (e.g., individuals, families, etc.), using the responses provided to a chosen set of observed variables. In LCA, however, both the class

membership probabilities (i.e., the probability of an individual belonging to a certain class) and the item response probabilities conditional upon class membership (i.e., the probability of an individual providing certain responses to a specific item given their classification into a specific latent class) are estimated and—according to the item response probabilities—observations are grouped (clustered) into classes (Collins and Lanza 2010; Magidson and Vermunt 2004; Lazarsfeld 1950).³ LTA analysis allows us to: (i) measure EI by using selected variables (according to suggestions in the literature) as a proxy of this latent concept; (ii) classify Italian households on the basis of the model results, (iii) analyse the latent transition probabilities in order to evaluate the changes in EI latent class membership of Italian households over time.

LTA and LCA have been often called ‘person-centred analyses’, as these models use response patterns of observed variables to assign individuals to unobserved latent groups (Bye and Schechter 1986; Collins and Lanza 2010; Bergman and Magnusson 1997; Masyn 2013) in contrast to a variable-centered analysis such as factor analysis (FA) or latent trait analysis (or IRT), where the focus is on relationships among variables (Bauer and Curran 2004; Molenaar and von Eye 1994). LCA differs from IRT (item response theory), as in the latter the latent variable is assumed to be continuous, whereas in LC models the it is assumed to be categorical and to consist of two or more nominal or ordered classes (Hagenaars and McCutcheon 2002). IRT models use the observed responses (to a number of items) to measure a continuous latent variable, and the strength of the relationship between item scores, that is, the probability of responding into a particular category (De Ayala 2009; Hambleton and Swaminathan 1985; Sijtsma and Molenaar 2002). LCA assumes a parametric statistical model and uses observed data to estimate parameter values for the selected model. Each individual has a certain probability of membership of each latent class. Observations within the same latent class are homogeneous on certain criteria, whereas those in different latent classes are dissimilar from each other. In this way, latent classes are represented by distinct categories of a discrete latent variable. LCA and LTA are also very similar with respect to cluster analysis (CA; Kaufman and Rousseeuw 2005; Tryon 1939) as both of them are procedures that group individuals into homogeneous classes. However, CA is not based on an underlying statistical model and does not provide information about the probability that a given individual belongs to a certain class. The standard CA simply relies on a matrix of distances among the classified objects, and the researcher is left to choose the proper metrics for calculating such distances. Moreover, CA does not provide information about item response behaviour in terms of probabilities (e.g., given that an individual said ‘yes’ to a certain item, what is the probability that she or he belongs to a certain class?).

Typically, when longitudinal data are to be analysed, research questions deal not only with latent class membership, but also with changes over time. In this regard,

³ The number of classes selected can be a questionable issue. Theoretically and conceptually, classes may be identified according to a priori research assumptions, then statistical criteria can be used to confirm theoretical expectations. Criteria for assessing the number of classes suggests the existence of several statistical methods. For instance, Nylund et al. (2007) indicate the Bayesian Information Criteria (BIC) as being the most suitable, so the number of classes is selected by minimizing the BIC value.

LTA is a type of latent class model specified include both latent class membership and transitions to it over time. In LCA, latent classes represent stable sets of characteristics or states of behaviour, whilst in LTA individuals may change their latent class over time. Thus, in this framework, the term latent *status* is used instead of latent class. Moreover, as subgroup membership was not assumed to be stable over time, the model is referred to as a latent *transition* model.

Three sets of parameters were estimated in LTA: (1) the latent status membership probabilities were estimated for each time period; (2) the transition probabilities reflecting the chances of transitioning from one particular latent status at time t to another latent status at time $t + 1$ —typically displayed in a matrix with rows corresponding to the earlier time and columns corresponding to the later time. The transition probabilities express the incidence of transitioning to the latent status column, conditional on earlier membership in the latent status row. The diagonal elements of the transition probability matrix represent the probability of being in a particular latent status at one-time conditional on being in that same latent status at the previous time. The third parameter (3) was a set of item-response probabilities reflecting the correspondence between the observed indicators of the latent variable at each time period and latent status membership, in much the same way that factor loadings link observed indicators to latent variables in factor analysis.

That is, further to the number of classes (and their sizes) being subject to change, we deemed it noteworthy to locate the households classified as ‘stayers’ (in the same class at each time) and those who classified as ‘movers’.

Furthermore, as in LCA, some covariates were necessary to introduce into the model. The purpose of introducing covariates into a latent transition model is to identify characteristics that predict membership in the different latent statuses and/or predict transitions between them.

As such, let L_t represent the categorical latent variable at Time (t) with latent statuses (S), where $s_1 = 1...S$ at Time 1, $s_2 = 1...S$ at Time 2, and so on, up to $s_T = 1...S$ at Time T . Additionally, the covariate, X , was used to predict latent status membership at Time 1 and transitions between latent statuses at any two adjacent times. Accordingly, the latent transition model can be expressed as:

$$P(Y = y|X = x) = \sum_{s_1=1}^S \cdots \sum_{s_T=1}^S \delta_{s_1}(x)\tau_{s_2|s_1}(x) \cdots \tau_{s_T|s_{T-1}}(x) \prod_{t=1}^T \prod_{j=1}^J \prod_{r_{jt}=1}^{R_{jt}} \rho_{j,r_{jt}|s_t}^{I(y_{jt}=r_{jt})} \quad (1)$$

Equation (1) expresses how the probability of observing a particular vector of responses, conditioning to X , is a function of the probabilities of membership in each latent status. At Time 1, δ_{s_1} , the probabilities of transition to a latent status (at a particular time) is conditional on latent status membership at the time immediately prior to it (τ), and the probabilities of observing each response (at each time) are conditional on latent status membership (ρ). As each unit (individual) is in only one class status, these can be considered both exhaustive and mutually exclusive.

The parameters (ρ) express the relationship between each manifest variable (or indicator) and each latent class—which is to say that *item response probabilities* indicate how individuals can be classified into the specified latent classes, given

their manifest variable values. Item response probabilities are occasionally termed measurement parameters due to their utility in measuring the latent variable and interpreting latent classes. Each individual provides only one response to the observed variable and, consequently, the vector of item response probabilities for a particular observed variable is conditional on a particular latent class adding to 1. LC parameters were estimated to characterise each class; the response patterns being in relation to the latent classes and each of their size.

Item response probabilities and latent class membership can help accurately categorise households into a specific class (or status). Using the LTA also allowed us to observe *stability* and *change* in the latent classes, which was useful for identifying stayer households (those in the same class at each wave) and the number of movers. We also sought the possibility to distinguish between households that moved to a lower or higher class. The latent transition matrix reported in (2) provided us with this information. At each latent state (in LTA the latent class is called latent state or latent status), membership was mutually exclusive and exhaustive; that is, individuals belonged to one (and only one) latent state at each time. Among the individuals in a latent state S_t at time t , each individual was in one (and only one) latent state at time $t + 1$. S_{t+1} could well have represented the same latent state as S_t , though this may not necessarily be the case.

$$\begin{bmatrix} \tau_{1_{t+1}|1_t} & \tau_{2_{t+1}|1_t} & \dots & \tau_{S_{t+1}|1_t} \\ \tau_{1_{t+1}|2_t} & \tau_{2_{t+1}|2_t} & \dots & \tau_{S_{t+1}|2_t} \\ \dots & \dots & \dots & \dots \\ \tau_{1_{t+1}|S_t} & \tau_{2_{t+1}|S_t} & \dots & \tau_{S_{t+1}|S_t} \end{bmatrix} \tag{2}$$

Finally, the probability of class membership was dependent on the values (or levels) of the covariates through a multinomial logistic regression—where the dependent variable is latent rather than observed (Agresti 2002). Information on transitions were synthesised using a single measure of stability, as explained in the following Sect. 3.2.

3.2 Measuring changes over time

As the latent statuses are ordered categories, we considered the directional index in Ferretti and Ganugi (2013), which takes into account both the extent to which units change their status and the prevalent direction that changes take. More specifically, the index shows the predominant direction by comparing the transition probabilities below and above the main diagonal. If the direction of latent statuses is towards worse situations, the mean of the upwards probabilities (i.e., probabilities below the main diagonal) is: $\frac{2}{k(k-1)} \left(\sum_{j < i} P_{ij} \right)$ and the mean of the downwards probability (i.e., probabilities above the main diagonal) is: $\frac{2}{k(k-1)} \left(\sum_{j > i} P_{ij} \right)$ where j is column (current status), i is row (past status), and k is the number of statuses. This index is the difference between the mean upwards and downwards probabilities. If the index is negative, the downwards direction is prevalent. The accounted probabilities, therefore, clearly concern future states given past events, under the assumption that

‘current experiences and past events plausibly influence the estimation of future hazards’ (Osberg 2015; p. 8).

4 Data and descriptive analysis

EI was measured using the Italian version of the EU-SILC. This is a standardised survey on income and socio-economic data in the European Union, allowing comparisons to be made between EU countries. It contains annual data on individual and household income, employment, education, material deprivations, or health issues, among other factors. We used the longitudinal version of the survey, which is a four-year rotating panel—first conducted by Eurostat in 2004—that follows individuals for a maximum of four waves. The first available wave covers 2004–2007, with the last covering 2012–2015. Thus far, we have used nine waves from 2004–2007 to 2012–2015, thus covering the whole period 2004–2015. For each household, we selected items related to economic insecurity, as per a set of indicators listed by the EU-SILC questionnaire related to the following three dimensions^{4,5}:

1. *Possession of durables.*

Items that ask respondents whether they (1) cannot afford a car, (2) cannot afford a PC, (3) cannot afford a washing machine, and (4) cannot afford a colour TV. These items were summarized as a single variable so as to better measure a household’s ability to afford durable goods (**goods possession**)

2. *Housing conditions.*

Items that ask respondents about the

(1) house tenure status (**tenure status**), and

⁴ We considered a wider set of variables but, on the basis of the entropy index, only the most heterogeneous variables measured have been selected. Shannon’s (1948) entropy H index is often used to measure the heterogeneity of a categorical variable’s distribution, where f_i is the relative frequency of category i and K is the number of categories.

$$H = -\sum_{i=1}^K f_i \ln f_i$$

Since its maximum value depends on the number of categories, the normalized (0,1) entropy index is defined where:

$$\text{normalized } H = \frac{H}{H_{\max}} = -\frac{\sum_{i=1}^n f_i \ln f_i}{\ln K}$$

⁵ The analysis has been carried out considering the answers provided by the so-called reference person (the household head) by considering both personal (with reference to individual characteristics) and household (considering the answers provided to the questionnaire regarding the household) characteristics. The ‘economic hardship’ items are referred to the household (which is the unit of analysis) and the information about the employment status is referred to the household head. This approximation is sometimes used, see for example Cracolici et al. (2013) or Latner (2019) although, in the latter paper the author also included variables on household compositions.

(2) leaking roof, damp walls/floors/foundation, or cases of rot found in window frames or floors (**problems with dwelling/accommodation**)

3. *Financial strain*. Items that ask respondents about

- (1) the household's ability to make ends meet (**ability to make ends meet**),
- (2) the financial burden of debt repayment from hire purchases or loans (**financial burden of the repayment of debts from hire purchases or loans**),
- (3) the capacity to face unexpected financial expenses (**capacity to afford unexpected financial expenses**),
- (4) the capacity to afford meals with meat or fish (or a vegetarian equivalent) every second day, (**capacity to afford a meal with meat, chicken, fish (or vegetarian equivalent) every second day**) and
- (5) the ability to adequately heat the home (**ability to keep home adequately warm**)

Furthermore, we included *employment status* and the *wave* (year of survey) in the model as covariates. So that, we consider nine wave (from 2004–2007 up to 2012–2015) and seven employment status: employee working full-time; employee working part-time; self-employed working full-time; self-employed working part-time; unemployed;

Inactive (student, further training, unpaid work experience, permanently disabled and/or unfit to work, in compulsory military community or service, fulfilling domestic tasks and care responsibilities, etc.); retired (in retirement or has given up business).

For the variable related to the employment status, the EU-SILC survey asks the respondents for their self-defined current employment status. The self-declared main activity status is, in principle, determined on the basis of how most time is spent, but no criteria have been specified explicitly. *Self-employed* persons are defined as persons who work in their own business, professional practice or farm for the purpose of earning a profit. *Employees* are defined as persons who work for a public or private employer and who receive compensation in the form of wages, salaries, fees, gratuities, payment by results or payment in kind; non-conscripted members of the armed forces are also included. A key role is played by the distinction between full-time and part-time work that should be made on the basis of a spontaneous answer provided by the respondent. It is impossible to establish a more exact distinction between part-time and full-time work, due to variations in working hours between European countries, and also between branches of industry. By checking the answer with the number of hours usually worked, it should be possible to detect and even to correct implausible answers, since part-time work will hardly ever exceed 35 h, while full-time work will usually start at about 30 h.

The overall sample contains 131,964 observations from 32,991 households that were followed for four years between 2004 and 2015. A description of, as well as statistical information on, the indicators used are displayed in Table 1.

Table 1 Statistical description of indicators

Variable description	<i>Freq</i>	<i>Cum Freq</i>	<i>%</i>	<i>Cum. %</i>
Tenure status				
1 = outright owner	104,208	104,208	0.79	0.79
2 = owner paying mortgage or tenant or subtenant paying rent at prevailing or market price	13,978	118,186	0.11	0.90
3 = accommodation is rented at a reduced rate (lower price than market price) or free	13,778	131,964	0.10	1.00
Goods possession				
1 = yes	67,179	67,179	0.51	0.51
2 = no cannot afford	5630	72,809	0.04	0.55
3 = other reason (not financial reasons)	59,155	131,964	0.45	1.00
Problems with dwelling/accommodation				
1 = yes	28,189	28,189	0.21	0.21
2 = no	103,775	131,964	0.79	1.00
Ability to keep home adequately warm				
1 = yes	115,866	115,866	0.878	0.878
2 = no	16,098	131,964	0.122	1.00
Ability to make ends meet				
1 = with great difficulty	18,614	18,614	0.14	0.14
2 = with difficulty	26,188	44,802	0.20	0.34
3 = with some difficulty	51,423	96,225	0.39	0.73
4 = easily/very easily	35,739	131,964	0.27	1.00
Financial burden of the repayment of debts from hire purchases or loans				
1 = none	110,730	110,730	0.84	0.84
2 = repayment is a heavy burden	10,399	121,129	0.08	0.92
3 = repayment is somewhat/not a burden	10,835	131,964	0.08	1.00
Capacity to afford a meal with meat, chicken, fish (or vegetarian equivalent) every second day				
1 = yes	115,866	115,866	0.88	0.88
2 = no	16,098	131,964	0.12	1.00
Capacity to afford unexpected financial expenses				
1 = yes	90,827	90,827	0.69	0.69
2 = no	41,137	131,964	0.31	1.00
Total sample (number of households)				32,991
Number of observations (number of households followed for 4 years)				131,964

This table reports the description of the indicators used to measure economic insecurity and some descriptive statistical measures useful for data analysis

Table 2 Percentage of households classified in each state for the first time

	State				
	1	2	3	4	5
Size	20.80%	33.14%	28.19%	14.11%	3.75%

This table shows the percentage of households classified for each latent state for the total of the sample

5 Results

5.1 Model choice and interpretation of states

In the process of model specification, a major concern in LTA (as in LCA) is choosing the number of latent states to retain. This is done by considering the parsimony and interpretability of the possible solutions, while seeking to give substantial meaning to the identified latent status (Magidson and Vermunt 2004; Nylund et al. 2007). In order to determine the optimal number of latent states, we estimated different models while specifying a different number of states for each. Specifically, we imposed a constraint of ‘order restricted states’, which required the restriction of the cluster-specific item probabilities in order to be monotonically increasing. As such, the parameter corresponding to cluster $i + 1$ should have at least been as large as the parameter corresponding to states i . This means that on a scale of positive values, ordered from the lowest to the highest value, the first latent state collects the lowest ratings, and the last latent state collects the highest ratings; in our case, with its ordinal item responses, this was deemed a reasonable constraint. Among all the models considered eligible (with their different number of states), we selected the model with the lowest Bayesian information criterion (BIC) value (Collins and Lanza 2010). EI was specified as a proxy of the eight indicators described in Sect. 3. The most apt model had five latent states with the lowest BIC value, and a good classification error (approximately 17%). Table 2 displays the percentage of households stratified in each state for the first time.⁶ Naturally, some households have a well-determined latent class membership with high probability in one cluster, whereas other households show probabilities distributed on more contiguous clusters. Nevertheless, we found the most likely classification among all the clusters for each household, which in turn allowed us to cross this information with other characteristics of the households. Figure 1 provides evidence with which to support the assignment probability. This was very high for the two extreme classes (1 and 5), while the remainder were found to have suitable values (> 0.5 out of five alternatives).

⁶ Although latent status 5 includes a very small number of households we preferred the model with 5 classes rather than with 3 classes because in terms of model fit the one with 5 classes is the best and also as we have preferred to “isolate” the households with heavier level of economic insecurity.

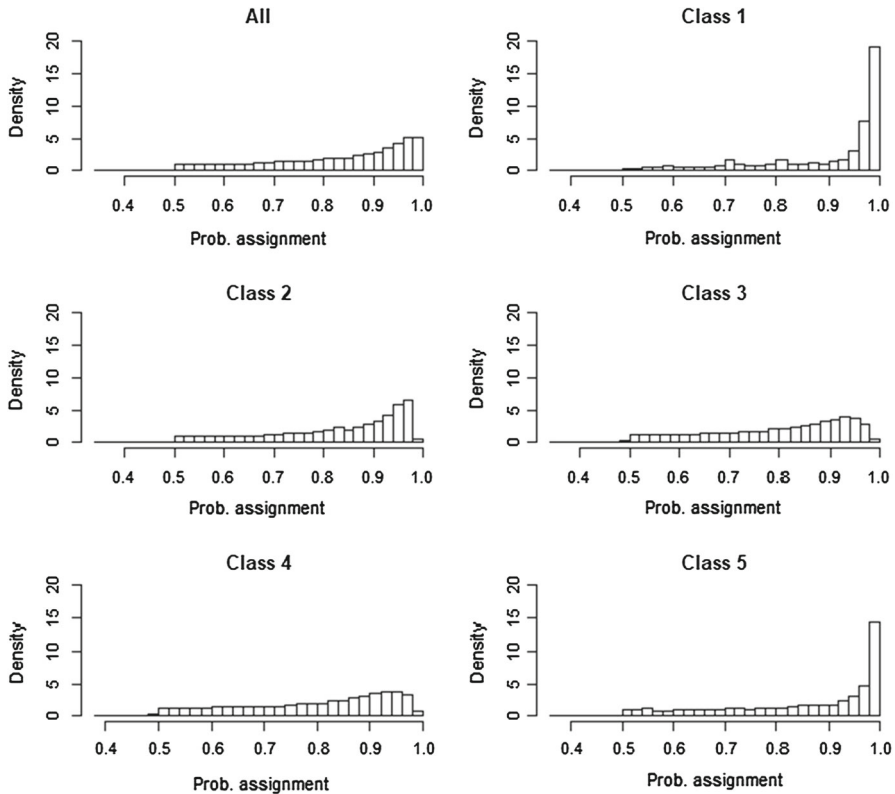


Fig. 1 Probability of assignment into the class. The figure shows the probability of belonging to each class. It is very clear (and expected) that this probability is very high for the two extreme classes i.e., the first and the last

5.2 Interpretation of states and covariates

The item-response probabilities in both the LTA and LCA represented the basis for assigning labels to latent statuses. The item response probabilities highlighted the differences among the response patterns, which helped us to distinguish and interpret the statuses (see Table 3). Therefore, looking at the pattern of responses provided us with an overall picture of the meaning of the states, which in turn allowed us to label them appropriately and meaningfully.

Table 3 contains the item-response probabilities corresponding to each item's endorsement. The latent variable was specified as being ordinal, thus status 1, S_1 , groups households with lower values of economic insecurity (the most desirable state) up to status 5, S_5 , which groups households with the highest level of economic insecurity (the least desirable state).

In S_1 , households own their homes, have durable goods, are without arrears in utility bills or in mortgage or rental payments, can easily make ends meet, and are

Table 3 Item response probabilities

	State				
	1	2	3	4	5
Tenure status					
1 = outright owner	0.922	0.860	0.756	0.601	0.412
2 = owner paying mortgage or tenant or subtenant paying rent at prevailing or market price	0.024	0.055	0.120	0.236	0.402
3 = accomodation is rented at a reduced rate (lower price than market price) or free	0.055	0.085	0.124	0.163	0.186
Goods possession					
1 = yes	0.694	0.577	0.444	0.300	0.157
2 = no cannot afford	0.002	0.008	0.032	0.120	0.344
3 = other reason	0.304	0.415	0.524	0.581	0.499
Problems with dwelling/accomodation					
1 = yes	0.094	0.156	0.249	0.372	0.515
2 = no	0.906	0.844	0.751	0.628	0.485
Ability to keep home adequately warm					
1 = yes	0.996	0.980	0.898	0.611	0.219
2 = no	0.004	0.020	0.102	0.389	0.781
Ability to make ends meet					
1 = with great difficulty	0.000	0.009	0.125	0.497	0.820
2 = with difficulty	0.006	0.104	0.367	0.386	0.169
3 = with some difficulty	0.161	0.617	0.490	0.117	0.012
4 = easily/very easily	0.833	0.269	0.018	0.000	0.000
Financial burden of the repayment of debts from hire purchases or loans					
1 = none	0.858	0.866	0.846	0.783	0.665
2 = repayment is a heavy burden	0.020	0.042	0.087	0.171	0.306
3 = repayment is somewhat/not a burden	0.122	0.092	0.067	0.046	0.029
Capacity to afford a meal with meat chicken. fish (or vegetarian equivalent) every second day					
1 = yes	0.997	0.987	0.937	0.748	0.373
2 = no	0.003	0.013	0.063	0.252	0.627
Capacity to afford unexpected financial expenses					
1 = yes	0.993	0.930	0.561	0.110	0.012
2 = no	0.007	0.071	0.439	0.890	0.988

This table reports the item response probabilities by showing how individuals (households in this case) can be classified into the specified latent classes, given the responses provided to each item (the manifest variable)

able to afford a meal with meat or fish (or vegetarian equivalent) every second day. Conversely, S₅ refers to households who rent their homes, do not have durable goods due to economic difficulties, are in arrears regarding utility bills, or mortgage or rental payments, make ends meet with difficulty, and are not able to afford a meal

with meat or fish (or vegetarian equivalent) every second day. Employment status and wave were here selected as covariates to estimate the probability of membership. The inclusion of the wave allowed us to consider the impact of economic crises on EI. Table 4 shows the mean probabilities for wave, year and

Table 4 Mean probabilities for year, wave, and employment

	State 1	State 2	State 3	State 4	State 5
Wave					
2004–2007	0.211	0.349	0.289	0.119	0.032
2005–2008	0.201	0.353	0.286	0.125	0.035
2006–2009	0.203	0.349	0.286	0.131	0.031
2007–2010	0.214	0.336	0.273	0.140	0.036
2008–2011	0.210	0.336	0.267	0.140	0.047
2009–2012	0.239	0.298	0.269	0.153	0.042
2010–2013	0.221	0.314	0.258	0.159	0.048
2011–2014	0.213	0.295	0.279	0.160	0.053
2012–2015	0.214	0.308	0.274	0.156	0.048
Employment status					
Employee working full-time	0.251	0.354	0.260	0.110	0.025
Employee working part-time	0.208	0.285	0.265	0.184	0.059
Self-employed working full-time	0.320	0.377	0.218	0.071	0.015
Self-employed working part-time	0.298	0.297	0.207	0.141	0.057
Unemployed	0.044	0.165	0.275	0.321	0.194
Inactive	0.109	0.269	0.330	0.219	0.074
Retired	0.222	0.350	0.285	0.121	0.023
Year					
2004	0.211	0.357	0.288	0.114	0.030
2005	0.206	0.357	0.290	0.115	0.031
2006	0.205	0.355	0.285	0.124	0.030
2007	0.206	0.352	0.285	0.127	0.030
2008	0.202	0.348	0.278	0.137	0.035
2009	0.211	0.333	0.279	0.140	0.037
2010	0.220	0.321	0.270	0.149	0.040
2011	0.223	0.321	0.270	0.144	0.042
2012	0.224	0.314	0.270	0.151	0.041
2013	0.214	0.319	0.272	0.153	0.043
2014	0.212	0.300	0.283	0.157	0.048
2015	0.209	0.305	0.283	0.158	0.045
Total	0.208	0.331	0.282	0.141	0.037

This table shows the mean probabilities of households' belonging to each of the five statuses by classifying households with respect to wave, year and employment status.

employment status. Households belonging to the most recent waves were more likely to be included in S_4 and S_5 (the least desirable states).

Those households in which the reference person is unemployed (especially) or a part-time employee also had a higher probability of belonging to S_4 (mostly) and S_5 . On the contrary, full-time employees, the self-employed, or people retired were more likely to be classified as being in the most desirable states (S_1 , S_2). Overall, considering the employment status, we conclude that the self-employed are those who are better off in terms of economic insecurity (they are the least economically insecure), but for a better understanding it is necessary to take into account the type of contract, whether part-time or full-time. In fact, for the self-employed working full-time we note that the probability of belonging to the worst status is very low, while for self-employed working part-time it is higher and comparable with that of part-time employees (with the exception of some years such as 2005, 2010, 2014). The reason for this probably lies in the fact that part-time workers (whether employed or self-employed) working fewer hours also have a lower salary in economic terms and, therefore, fewer financial resources to use, but also that a 'part-time' job is conceived nowadays more as a form of labour market instability than an opportunity. Working part-time is often accompanied by lower income, lower social-security benefits, a reduced capacity to sustain a household and, in couples with an unequal amount of paid work, it implies a reduced bargaining power in relationships (Bittman et al. 2003).

Descriptive analysis of household features was beneficial in assessing the partition into EI statuses derived through the latent transition analysis (Table 7). In this regard, the analysis of EI with respect to the geographical area of residence confirms the well-known North–South divide. Indeed, families in northern Italy exhibited lower (or, better) levels of EI: approximately 25% of northern families were classified as being in the first state, compared with only 17% of southern families. Northern Italian regions, which are more integrated with the global economy, were more strongly affected by the recession in the short term than their southern counterparts, where the recession was initially milder, but was more protracted and its impact intensified with time (Crescenzi et al. 2016).

Considering other variables, such as gender, age, level of education of the reference person and type of household (single, or couples with or without children and so on), we found that younger people, or those with lower levels of education, or households with children (under 18 years old) appeared slowly to make up the population segments most exposed to low levels of EI.

Even membership probabilities could also be used to express a household's level of EI. Indeed, assuming that individuals feel economically insecure when they perceive a significant economic risk, the probability of belonging to the worst latent class(es) may quantify the extent of that perception. In this regard, the left panel of Fig. 2 reports the distribution of an individual's probability of belonging to class 5 over time, classified by employment status. The bimodal distribution was determined by the effectiveness of the latent class analysis, which was able to find a lower number of units with intermediate values of the probabilities of belonging to class 5. Moreover, the small peak around 1 illustrates the fact that comparatively few households belong to the least desirable class. Figure 2 allows us

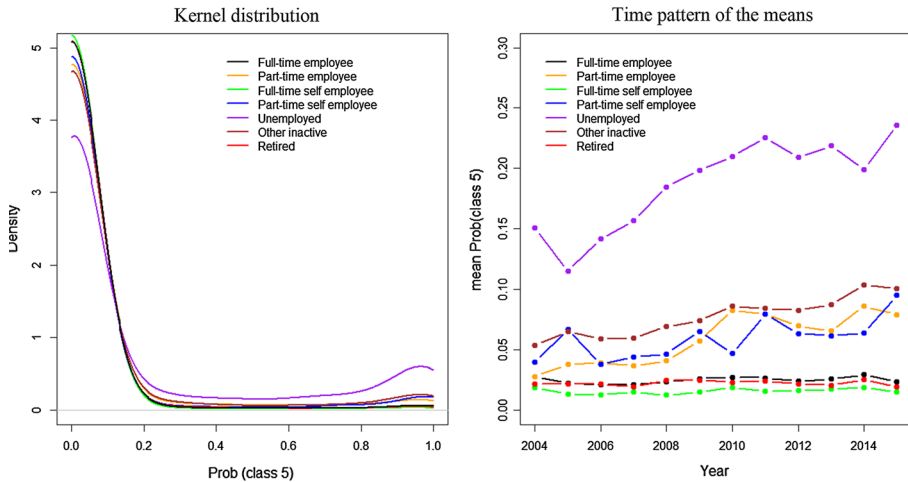


Fig. 2 Probability to belong to the least desirable class (i.e. class 5). The figure reports the Kernel distribution and the distribution of an individual's probability of belonging to class 5 over time, classified by employment status

to appreciate the weakest position of the unemployed as compared with other groups. This situation is further confirmed by the right panel, which reports the average of those probabilities by employment status. The probability of belonging to the least desirable class is considerably higher for the unemployed, with a significant growth before the onset of the global economic recession (i.e., from 2005). Even inactive people, part-time employees, and the part-time self-employed exhibit a growth pattern, though it should be noted that the probability remained at lower levels. The most desirable and stable situation was found to occur for full-time employees, the self-employed, and retired persons.

5.3 Latent transition probabilities

Transition probabilities are often of primary interest because they express how change occurs between latent statuses over time. Table 5 presents the transition probabilities, which is to say the probability of transition to a certain class at time point $t + 1$, given class membership at time point t .

Values that describe the probabilities of status stability are presented along the diagonal axis, with values describing the probabilities of movement between statuses being presented on the off-diagonal. The diagonal elements of the transition probability matrix represent the probability of being in a particular latent status at a specific time, conditional on being in that same latent status at the previous time. Taken as a whole, the information on change represented by the transition probabilities matrix presents a parsimonious, yet detailed, picture of how households move into and out of insecurity latent statuses during the studied time span (from the 2004–2007 wave to the 2012–2015 wave). Several important patterns emerge from the transition matrices. First, all households were found to be

Table 5 Latent transition probabilities

	State				
	1	2	3	4	5
State[– 1]					
1	<i>0.961</i>	0.027	0.010	0.003	0.000
2	0.010	<i>0.912</i>	0.068	0.009	0.001
3	0.010	0.080	<i>0.819</i>	0.086	0.005
4	0.006	0.036	0.178	<i>0.758</i>	0.022
5	0.001	0.006	0.073	0.136	<i>0.784</i>

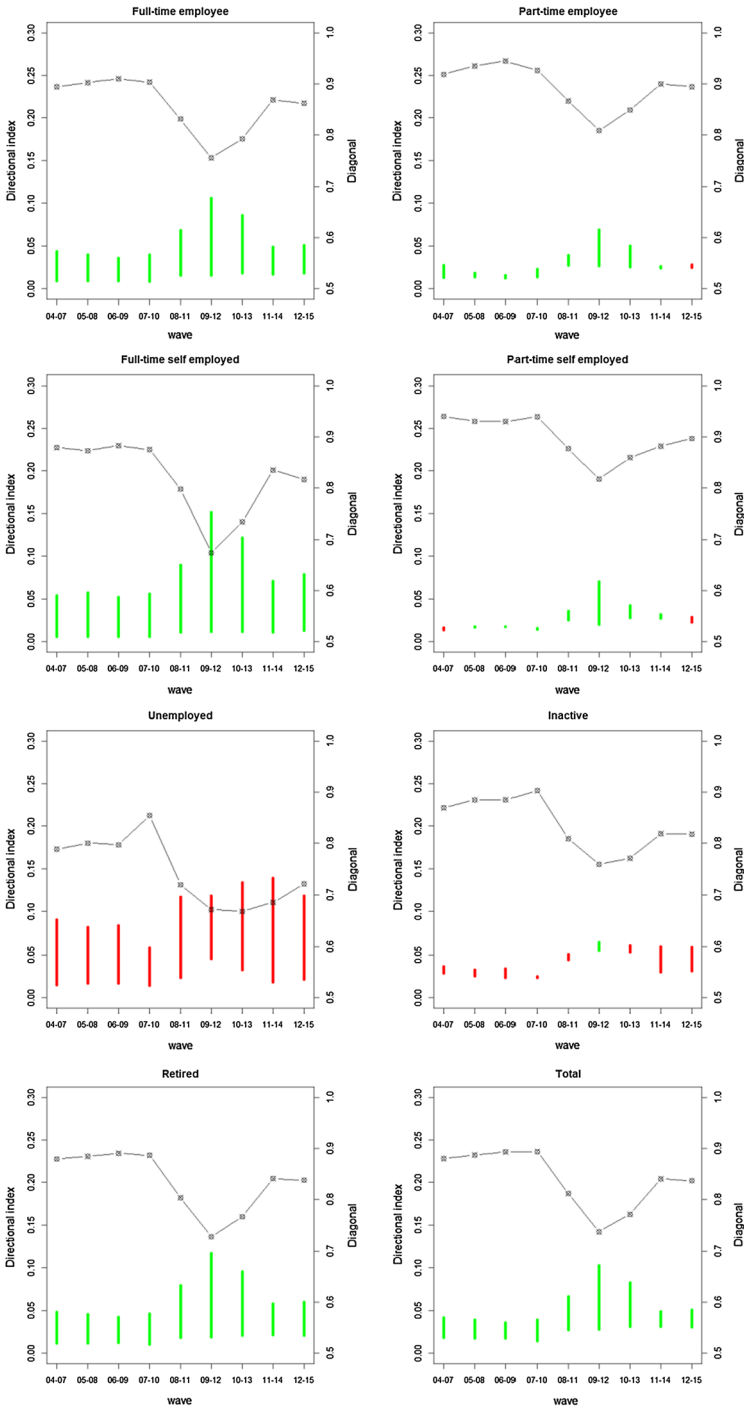
This table presents the transition probabilities, which is to say the probability of transition to a certain class at time point $t + 1$, given class membership at time point t .

more likely to remain in the same latent status—especially those in the low–medium insecurity state. Households in the more desirable states (1, 2) typically tended to be more stable; whilst households in less desirable states (4, 5) strove to improve their position—leading to less stability.

A more methodical and comprehensive reading can be obtained by analysing the transition matrices by wave and employment status. For each employment status, Fig. 3 illustrates the patterns of the two components of the transition matrix: the mean of the probabilities below and above the main diagonal (see Sect. 3.2, above). The use of green or red represents cases when the mean of the upwards probabilities is greater or lower than the mean of the downward probabilities. The graphs also visualise the time pattern of the average diagonal probabilities, expressing stability in the same status between the two periods (the first and last years of the wave). Generally speaking, the waves immediately after 2008 experienced lower levels of stability, with an almost 10% decrease in the main diagonal probabilities (graph titled ‘Total’) with a recovery beginning in 2013. Such an occurrence is accompanied by larger movements across statuses (see bar height), with some exceptions. For part-time employees and inactive persons, upward and downward probability are almost balanced—although the latter pattern slightly prevails (shown in red) across inactive persons. On the whole, part-time jobs were not found to facilitate improvements, in stark contrast to full-time jobs. The most impressive results were obtained for the unemployed, who exhibited a significant and sizeable (bar height) persistent downward movement (red).

6 Conclusions

EI is of growing interest to policy makers and academics alike. For the Commission on the Measurement of Economic Performance and Social Progress, EI contributes to the overall well-being of individuals by generating stress and anxiety, and making it more challenging for families to invest in education and housing (Stiglitz et al. 2009). There is now a broad consensus that EI has a considerable impact on individuals and their choices, especially those concerning the family (Scherer 2009).



◀ **Fig. 3** Stability and mobility by wave and employment status. The figure illustrates, for each wave and for each employment status, the patterns of the two components of the transition matrix: the mean of the probabilities below and above the main diagonal (see Sect. 3.2, above). The use of green or red represents cases when the mean of the upwards probabilities is greater or lower than the mean of the downwards probabilities. The graphs also visualise the time pattern of the average diagonal probabilities, expressing stability in the same status between the two periods (the first and last years of the wave)

EI is a multifaceted and multidimensional concept and, consequently, a global and formal definition of it cannot be reached straightforwardly simply. The existing literature has explored alternate ways to proxy insecurity, resulting in a variety of indices, from aggregate *versus* individual indices, to subjective *versus* objective indices, or unidimensional *versus* multidimensional indicators (Rohde and Tang 2018).

This paper proposes an empirical analysis of the level and evolution of EI in Italy from 2004 to 2015 by synthesising several EI indicators into a single measure of EI through a latent class transition approach. This methodology allowed us to identify the most economically insecure subgroups in the population, as well as the main sources of insecurity. We followed Italian households for four-year periods from 2004–2007 to 2012–2015. These households were first classified into five latent ordinal statuses (from the most to the least desirable condition, respectively). Once this was done, and through the transition probabilities matrix and the directional index, EI household stability across ordinal EI statuses was assessed. S_1 households had the most desirable conditions relating to home ownership, ease of debt repayments, and affordability of goods. S_5 households, conversely, are lacking these desirable conditions and the security they can offer. Households belonging to the most recent waves (from 2010 onwards), part-time employees, and the unemployed were found to have a higher probability of being included in the least favourable latent states. In contrast, employees working full-time, the self-employed, or people retired were significantly more likely to be categorised into the most desirable states. In terms of stability, the most impressive results were obtained for the unemployed, who exhibited a significant, and persistent, downward movement. For part-time workers, the recovery of stability was also difficult, though not as difficult as for the unemployed. Other than the unemployed and the inactive, all groups were almost able to reach pre-crisis conditions of stability in terms of membership of the same latent status over time.

This paper is not without its limitations. First, although we emphasised the importance of distinguishing between full- and part-time employment, we cannot state the voluntary nature of the part-time working conditions. Distinguishing between voluntary and involuntary employment conditions is crucial for a better understanding of the consequences of EI on private lives, as it encompasses various (often unobserved) job-related amenities (Vignoli et al. 2020a, b, c). Second, the present study uses just one reference person to assess the effect of household characteristics on EI. To address this limitation, future research would do well to include additional covariates related to family members.

Despite these limitations, our study reveals that—aside from the most detrimental situation of being unemployed—part-time workers have the weakest position.

Indeed, social assistance for families and the unemployed is less generous in Southern Europe than in Central and Northern Europe (Esping-Andersen 1999; Javornik 2014). In addition, Southern Europe is known for high levels of employment protection (particularly among more senior workers) and, as a result, high youth unemployment, high temporary employment and high involuntary self-employment are commonplace (Barbieri and Scherer 2009). Further to this, our results mark the younger generations as those with the highest risk of experiencing EI. This finding reiterates the particularly weak position of young adult individuals in times of economic uncertainty. They are often viewed as the ‘losers of globalization’ (Mills and Blossfeld 2013), with reduced chances of intergenerational upward mobility (Barone 2019; Hacker 2019).

A final note about the method adopted is worth making. We are aware that relying on a single indicator of EI might be limited in terms of scope, but a multifaceted indicator will unavoidably have to comply with partial ordering or dominance criteria due to the difficulty of finding a trade-off between variations in the single indicators (let us say: employment status and financial assets). Therefore, including such an indicator as a covariate in a model explaining the effect of EI on household or individual behaviour could well be fraught with challenges. We believe that one promising contribution for the operationalisation of EI offered by our LTCA approach is the estimation of the individual probability of belonging to the least favourable classes, which could be used as a continuous proxy of the sense of ‘anxiety’, ‘worry’, or ‘insecurity’ about exposure to adverse economic events. For this reason, our approach can be usefully replicated with the aim of assessing the effects of different levels of EI on family-related behaviours.

Appendix

See Tables 6 and 7.

Table 6 Operationalisations of EI

Author	EI conceptualisation	Operationalisation	Data/target unit	Aim
Berloffo and Modena (2014)	EI as employment and job insecurity	Employment insecurity: risk of unemployment and risk associated with being a temporary worker (i.i. share of temporary worker in an economy)—Objective	Macro data/country	Aggregate analysis of EI (EI as a part of IEWB)
Berloffo and Modena (2014)	EI arises from the exposure of individuals, communities and countries to adverse events, and from their inability to cope with and recover from the costly consequences of those events (UNDESA 2008; p. iv)	Employment insecurity: risk of unemployment of household's members—Objective	Cross-section micro data/household	Aggregate analysis of EI (EI as a part of IEWB)
Bossert and D'Ambrosio (2013)	EI is the anxiety produced by a possible exposure to adverse economic events and by the anticipation of the difficulty to recover from them	Current level of wealth and a weighted sum of the past level of gains/losses where losses are given higher weights—Objective	Micro	Axiomatic definition of EI
Bossert and D'Ambrosio (2013)	A gain in resources is associated with lower level of EI	Household disposable income or consumption—Objective	Micro	Axiomatic definition of EI
Burgoon and Dekker (2010)	Subjective; past experience and worries about job and income insecurity	Questions such as: "whether you worry about..."—Subjective	Macro and micro data/individual	Research question: whether flexible employment (temporary and part-time) affects subjective EI
Coli (2018)	EI as a state of anxiety produced by a lack of economic safety (Osberg)	Financial situation and material deprivation of household—Objective	Micro and macro data/household	Research question: how social protection benefits impact EI
D'Ambrosio and Rohde (2014)	Bossert and D'Ambrosio (2013) approach	sum of financial assets (including homeowner's equity) minus total liabilities—Objective	Longitudinal micro data/individual	Measure of EI:

Table 6 continued

Author	EI conceptualisation	Operationalisation	Data/target unit	Aim
Dominitz and Manski (1997)	Subjective: perception of risk about health insurance, job loss, bulgarily	Eliciting probabilities: "What do you think is the percent chance ... next 12 months."—Subjective	Longitudinal micro data/individual	Individual measure of EI
Espinosa et al. (2014)	Insecurity is a concept related either to the exposure to adverse events or to the risk of exposure to adverse events	Survey question on How is well being in the next future (1 or 3 years)—Subjective	Longitudinal micro data/household head	Research question: investigating variables influencing EI
Fiori et al. (2013)	EI is linked to adverse events, such as unemployment, family dissolution, or poor health, and depends on the context of insurance relationships surrounding the households	Employment status and job contract of the couple, and household's difficulties in income and wealth—Objective/subjective	Cross sectional microdata/household	Research question: effect of EI on fertility intentions
Hacker et al. (2010, 2014)	Economic security is the degree to which individuals are protected against hardship causing economic losses	Frequency over time of large (> 25%) income losses (except when entering retirement) including household out-of-pocket medical spending—Objective	Several datasets including longitudinal microdata/households	Aggregate measure of EI (ESI index)
Mau et al. (2012)	Perception of risk and fear of loss regarding job security, marital security, health care protection	Questions such as: "How likely is it that during the next 12 months..."—Subjective	Macro and micro data (European Social Survey)	Research question: how objective socio-economic and institutional conditions affect subjective EI
Osberg (1998, 2009) Osberg and Sharpe (2009, 2014)	US Declaration of the Human Rights art. 25	Named risk approach—Objective	Macro data/country	Aggregate index of EI as a dimension of IEWB; revised version of IEWB (2014)

Table 6 continued

Author	EI conceptualisation	Operationalisation	Data/target unit	Aim
Ostberg (2015)	Review and discussion of several definitions and measurement approaches of EI	items related to material over-indebtedness, financial strain—Objective	Longitudinal household microdata/country	cross country analysis of EI
Ranci et al. (2021)	a high probability of experiencing either a loss of income or a temporary difficult economic situation severe enough to threaten the material independence of individuals/households in the short to medium term	Objective		
Rohde et al. (2014)	threats to future income and wealth	EI as income volatility—Objective	Matched cross sections micro data/household	Answer research question: distributional characteristics of EI (as income insecurity)
Rohde et al. (2016)	EI is a combination of forward-looking perception and objective hazards	Questions eliciting subjective feeling (from HILDA survey). Objective indicators: 25% income drop; inability of household to meet given expenses, future unemployment. A probit model was estimated for providing a forward looking variable.—Objective/subjective	Longitudinal micro data/individual	Individual measure of EI and modelling EI vs. individual covariates
Romaguera-de-la-Cruz (2020)	EI is a combination of forward-looking perception and objective hazards	Rohde et al. (2015) indicators adapted to EU-SILC data—Objective/subjective	Longitudinal micro data/household	Individual (composite) and aggregate measure of EI
Scheve and Slaughter (2004)	EI as work and income insecurity	Satisfaction/dissatisfaction about job and job security—Subjective	Longitudinal microdata and macro data / individual	Research question: international economic integration increases wage's volatility and thus EI

This table gives a snapshot of the main features of the contributions

Table 7 Mean probabilities for some household characteristics

	STATUS (absolute values)					STATUS (row percentage)				
	1	2	3	4	5	1	2	3	4	5
Gender										
Male	15,129	23,759	19,650	9839	2684	0.213	0.334	0.277	0.138	0.038
Female	12,849	20,229	17,054	8491	2206	0.211	0.333	0.280	0.140	0.036
Age										
16–34	2123	3371	2780	1512	385	0.209	0.331	0.273	0.149	0.038
35–44	1755	2485	2260	1136	325	0.220	0.312	0.284	0.143	0.041
45–54	4378	7269	5933	2978	828	0.205	0.340	0.277	0.139	0.039
55–64	5285	8268	6879	3264	941	0.215	0.336	0.279	0.132	0.038
65–74	5017	7866	6505	3270	870	0.213	0.334	0.276	0.139	0.037
75 +	9441	14,756	12,362	6178	1544	0.213	0.333	0.279	0.140	0.035
Education										
Pre-primary education	1335	2199	1964	944	279	0.199	0.327	0.292	0.140	0.042
Primary education	6633	10,536	8808	4364	1081	0.211	0.335	0.280	0.139	0.034
Lower secondary education	7090	11,277	9379	4842	1321	0.209	0.333	0.277	0.143	0.039
(Upper) secondary education	8756	13,687	11,213	5599	1549	0.215	0.335	0.275	0.137	0.038
Post-secondary non tertiary education	1043	1567	1286	576	132	0.227	0.340	0.279	0.125	0.029
First stage of tertiary education (Not leading directly to an advanced research qualifications)	3142	4749	4069	2013	531	0.217	0.327	0.281	0.139	0.037
Household type										
Singles	5219	8066	6658	3686	938	0.212	0.328	0.271	0.150	0.038
Couples without children	4947	7436	6277	3346	865	0.216	0.325	0.274	0.146	0.038
Couples with children under the age of 18	5010	7619	6548	3330	954	0.214	0.325	0.279	0.142	0.041
Couples with children over the age of 18	3287	5100	4193	2327	618	0.212	0.329	0.270	0.150	0.040
Single parents	2099	2924	2585	1319	326	0.227	0.316	0.279	0.143	0.035
two or more families and other	656	1081	907	418	185	0.202	0.333	0.279	0.129	0.057

Table 7 continued

	STATUS (absolute values)					STATUS (row percentage)				
	1	2	3	4	5	1	2	3	4	5
Geographical area										
North	15,466	21,151	16,180	7776	1940	0.247	0.338	0.259	0.124	0.031
Centre	5729	10,606	8761	3784	903	0.192	0.356	0.294	0.127	0.030
South	4927	8833	8924	4873	1422	0.170	0.305	0.308	0.168	0.049
Islands	1877	3425	2854	1905	628	0.176	0.320	0.267	0.178	0.059

This table provides some additional information by considering other household variables, such as gender, age, type of household, level of education and territorial area (of the reference person).

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