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Multidimensional Measures of Economic Insecurity in Spain: The Role of Aggregation and Weighting Methods*

OLGA CANTÓ**
Universidad de Alcalá and *EQUALITAS*

CARMELO GARCÍA-PÉREZ***
Universidad de Alcalá

MARINA ROMAGUERA-DE-LA-CRUZ****
Universidad Antonio de Nebrija and *EQUALITAS*

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Abstract

Economic insecurity is a relevant dimension of well-being. The limited availability of subjective expectations' surveys makes multidimensional insecurity indices based on living conditions surveys a valuable alternative. We study differences in synthetic indicators of insecurity for Spain using different methods to aggregate and weigh dimensions. We show that its evolution and distribution is robust to the aggregation procedure, even though levels do differ. All procedures present strengths and weaknesses but the counting approach has a direct economic interpretation and can better capture insecurity in the middle classes. Other aggregation methods are less transparent and give more relevance to extreme situations.

Keywords: Economic insecurity, Objective and subjective measures, Polyserial correlations, Counting approach, EU-SILC.

JEL Classification: D69, I39.

1. Introduction

Economic well-being analyses have typically been focussed on individuals' present financial situation: inequality, poverty and material deprivation are measured in relation to the mo-

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** ORCID ID: 0000-0003-0780-3212.

*** ORCID ID: 0000-0001-9322-7914.

**** ORCID ID: 0000-0001-9531-0391.

ment they are experienced. Nevertheless, individuals also anticipate their future, and these expectations partly determine their level of current well-being (Osberg, 2018). Thus, negative expectations about forthcoming economic problems lower current well-being, making the study of economic insecurity essential.

Economic insecurity might worsen quality of life through many channels, as individuals' decisions could be modified to reduce the exposure to uninsurable risk. Insecurity could decrease consumption and housing investment decisions in the short term (Benito, 2006), while in the medium term it could alter labour market decisions, postpone fertility (Fiori *et al.*, 2013; Mansour, 2018; Modena *et al.*, 2014) or increase the political support for right-wing parties (Bossert *et al.*, 2020). Both physical and mental health could deteriorate (Rohde *et al.*, 2016, 2017; Smith *et al.*, 2009; Staudigel, 2016; Watson, 2018) and future generations could be affected through the current reduction in children's education investment (Stiglitz *et al.*, 2009). Several papers confirm the negative impact of insecurity on health through an increase in tobacco consumption (Barnes and Smith, 2011), a rise in obesity (Rohde *et al.*, 2017; Smith *et al.*, 2009; Watson, 2018) or a worsening of mental health (Rohde *et al.*, 2016). The relevance of economic insecurity is thus clear because of its effects on the individuals' sphere but its possible impact at the macro level is still to a large extent unknown.

We believe that economic insecurity is a multifaceted issue and a unidimensional approach is not able to fully capture the phenomenon. Therefore, the main purpose of this paper is to investigate and compare different methods that allow researchers to best aggregate and weigh various dimensions when measuring economic insecurity in a synthetic index, highlighting each method's advantages and disadvantages. We specifically discuss an equal weighted mean as an example of a normative procedure; a principal component analysis (PCA) and a corrected polyserial correlation PCA as statistical weighting methods; and a counting approach following the Alkire and Foster (2011) technique which considers frequency-based weights and normative thresholds. All four strategies have arguments for and against: a simple mean is a straightforward method but may involve double counting if dimensions are strongly correlated, while PCA and polyserial correlation PCA solve this problem but lack transparency. In addition, none of these three methods produce an economic insecurity index with direct economic interpretation, making the counting approach a particularly interesting option because it can be interpreted as the share of weighted insecurity dimensions in which individuals lack security. This approach allows for the estimation of aggregate measures of insecurity incidence or intensity. Moreover, it is decomposable by dimensions and subgroups which is of great advantage to best understand the drivers of a multidimensional phenomenon and its differential impact on diverse population groups.

To test the robustness of economic insecurity to different aggregation procedures, we compute economic insecurity with these four different methods using Spanish data over the 2009-2017 period. Our results show that the evolution and distribution of economic insecurity is robust whatever the strategy to combine insecurity dimensions, even though methods differ in insecurity levels. In essence, economic insecurity in Spain decreases as individual income grows and is positively correlated with the business cycle. A relevant result, is that a significant proportion of Spanish middle class individuals suffer from economic insecurity, indicating that the phenomenon goes way beyond low-income groups, whatever way we measure it: an intermediate counting approach suggests that 14% of Spaniards are economically insecure, while a 32.3% of them are situated between the third and the seventh equivalent income decile, so clearly out of poverty.

The rest of the paper is organized as follows: Section 2 discusses how the previous literature has approached the measurement of economic insecurity along with the main empirical results of the increasing body of research in this field. Section 3 gathers the proposal on dimensions and describes the different aggregation methods when constructing a synthetic economic insecurity index. Then, Section 4 includes an empirical illustration of these methods for Spain while Section 5 discusses our main conclusions.

2. Background

2.1. Understanding (and measuring) economic insecurity in rich countries

Individual well-being is a multifaceted concept. People are worried about their economic resources as much as other dimensions as health, social inclusion, environment or safety, among others. Thus, associating well-being with poverty and inequality exclusively is a huge mistake. In this framework, the notion of economic insecurity has become more important in recent years, particularly after the Great Recession, revealing itself as a threat to many households' living standards. Even though academics acknowledge its relevance, they have not yet been able to reach an agreement on how to define and, most importantly, how to measure this phenomenon. So far, there have been several attempts in the literature to measure the individual or country-averaged level of economic insecurity but each of them has established an *ad-hoc* definition of the phenomenon, leading to an absence of agreement on how to best measure the important role of insecurity in individual current well-being. However, although existing definitions of this phenomenon are imprecise and defined in rather general terms, they have some clearly common elements.

First, economic insecurity is not strictly related with realised risk but rather to individuals' exposure to certain economic hazards when they lack insurance against possible future shortfalls. This risk exposure must be involuntary, involving uncertainty about a forthcoming financial situation generating a sort of current anxiety (Rohde and Tang, 2018). Secondly, insecurity implies a downward economic loss unlike volatility which also includes the probability of the chance to experience well-being improvements (Osberg, 2018). Economic insecurity thus shows a relevant idiosyncratic component, as observable factors may not fully capture the psychological impact of uninsured future economic distress on individuals' welfare. As Rohde and Tang (2018) note, insecurity involves "an 'anxiety function' of which 'economic risk' is a key input".

The definitions for economic insecurity we find in the literature are rather vague and imprecise, although they always refer to downside future economic hazard and its psychological impact. Insecurity involves an involuntary exposure to uncertainty in future financial distress and the perception of uninsurable downside economic hazards. Observed factors do not fully capture this notion and psychological effects become more relevant (Rohde and Tang, 2018). In other words, economic insecurity implies that individuals feel anxiety or stress arising from the exposure to several hazards which could have not yet materialised, but could lead to future economic losses and the inability to cope with them (Berloffa and Modena, 2014; D'Ambrosio and Rohde, 2014; Hacker *et al.*, 2010; Osberg, 1998; Osberg and Sharpe, 2005; Rohde *et al.*, 2014; Rohde and Tang, 2018). This, unlike poverty or inequality, is a dynamic concept, since risk exposure might cause a deterioration of individual well-being which is not strictly related with income distribution issues (Ranci *et al.*, 2017). Therefore, an ideal index of economic insecurity must try to predict individuals' future economic situation, as expectations about forthcoming events shape the level of current insecurity (Osberg, 2015).

Due to the complexity of the issue, there is still no academic consensus on how one should best measure economic insecurity (see Table 1). The first attempts to measure it were based on an aggregate perspective and used macroeconomic data to compute indices at a national level. The work by Osberg (1998) introduced the notion of economic insecurity for the first time, being further developed by Osberg and Sharpe (2002, 2005, 2014) within the construction of a composite index of well-being which included insecurity as one of its dimensions. Initial efforts were concentrated mainly in comparing the degree of insecurity among countries as well as its evolution over time (Osberg and Sharpe, 2002, 2005; Hacker *et al.*, 2010, 2014). In this context, these authors proposed an aggregate economic security index using macroeconomic data but considering the household as reference unit. Drawing on Article 25 of the Universal Declaration of Human Rights[1], they calculated a multidimensional security index as an average of four economic hazards that individuals may encounter –unemployment, sickness, widowhood and old age–, weighting each dimension by its frequency in a reference population. Berloffa and Modena (2014) improved this index by introducing unemployment risk from a household approximation. As a major drawback, Osberg and Sharpe assumed that economic insecurity is proportional to realised risk and that subjective factors become negligible at an aggregate level (Rohde and Tang, 2018). Thus, their economic security index is based on a retrospective approach as they only used past realised hazards to proxy the phenomenon and did not model individuals' future economic situation.

Economic insecurity was also discussed within the Commission on the Measurement of Economic Performance and Social Progress (Stiglitz *et al.*, 2009), proposing the use of risk of poverty rates to approximate this phenomenon. Despite its simplicity, we believe that this approach ignores relevant aspects of economic insecurity beyond the lack of resources, therefore denying the conception of this phenomenon as a separate dimension of well-being. For that matter, economic insecurity can be present along the entire income distribution and not only in its lower tail.

Also, within aggregate measures of insecurity, Hacker *et al.* (2010, 2014) associated economic insecurity with large income drops. These authors also followed a retrospective approach and computed economic insecurity as the percentage of individuals who experience a fall of at least 25% in their household disposable income from one year to the next, provided that they lack enough liquid financial wealth to cope with that loss and taking into consideration medical out-of-pocket spending, which is most relevant in the United States. These authors could not distinguish between large involuntary losses and voluntary declines linked to a desired reduction in individual labour supply, which may be an important issue at the individual level (Osberg, 2018).

Table 1
MAIN ECONOMIC INSECURITY MEASURES

Paper	Index classification				Indicators	Aggregation method	Weighting procedure
	Unit of analysis	Nature of dimensions	Reference period	Number of dimensions			
Anderson (2001)	Individual	Subjective	Forward-looking	1	Perceptions of economic security	—	—
Bossert and D'Ambrosio (2013) D'Ambrosio and Rohde (2014)	Individual	Objective	Forward-looking	1	Wealth dynamics	—	—
Bucks (2011)	Household	Mixed	Mixed	4 (12 indicators)	Economic risks: Not covered by health insurance (O) Poor health (S) Recent unemployment spell (O) High probability of unemployment (O) Income drop (S) Income volatility (S) Income adequacy: Spending > income (O) Poverty level (O) Assets/savings adequacy: Low precautionary savings (S) Credit market experiences and debt burden: Credit constrained (O) Late debt payments (O) High debt payment-to-income ratio (O)	Counting approach	Equal weights Proportional by main dimension Hedonic weights
Espinosa *et al.* (2014)	Individual	Subjective	Forward-looking	1	Expectations about future economic situation	—	—
Hacker *et al.* (2010, 2014)	Aggregate	Objective	Retrospective	1	Large income drops (>25%)	—	—
Osberg and Sharpe (2005, 2014)	Aggregate	Objective	Retrospective	4	Risk from unemployment Financial risk from illness Risk from single-parent poverty Risk from poverty in old age	Weighted mean	Frequency weights
Rohde *et al.* (2014)	Individual	Objective	Retrospective	1	Downward income instability	—	—

(*Continued*)

Paper	**Index classification**				**Indicators**	**Aggregation method**	**Weighting procedure**
	Unit of analysis	**Nature of dimensions**	**Reference period**	**Number of dimensions**			
Rohde *et al*. (2015)	Individual	Mixed	Mixed	6	Job insecurity (S) Overall financial dissatisfaction (S) Inability to raise emergency funds (S) Large income drops (O) Probability of expenditure distress (O) Unemployment risk (O)	PCA	Statistical weights
Rohde *et al*. (2016)	Individual	Mixed	Mixed	8	Job insecurity (S) Overall financial dissatisfaction (S) Inability to raise emergency funds (S) Large income drops (O) Income dynamics (O) Probability of unemployment (O) Probability of large income drop (O) Probability of expenditure related stress (O)	—	—
Rohde *et al*. (2017)	Individual	Mixed	Mixed	4	Job insecurity (S) Overall financial dissatisfaction (S) Inability to raise emergency funds (S) Income volatility (O)	PCA	Statistical weights
Romaguera-de-la-Cruz (2020)	Individual	Mixed	Mixed	6	Inability to face unexpected expenses (S) Financial dissatisfaction (S) Changes in the ability to go on a holiday (S) Large income drops (O) Unemployment risk (O) Probability of extreme expenditure distress (O)	Counting approach	Inverse frequency weights
Stiglitz *et al*. (2009)	Individual	Objective	Retrospective	1	Poverty risk	—	—
Watson (2018)	Individual	Objective	Forward-looking	1	Probability of large income drops	—	—

Note: (S) Subjective indicator, (O) Objective indicator.

Source: Authors' own elaboration.

Given the simplicity of aggregate economic insecurity calculations, they generally involve some assumptions which contradict key economic insecurity components, for instance the relevance of subjective factors is neglected at the aggregated level and exposure to risk is considered proportional to historically realised hazards (Rohde and Tang, 2018). Hence, unidimensional individual insecurity indices have emerged as an interesting alternative to these aggregate measures, allowing researchers to study the distribution of the phenomenon across different subpopulations and to compute an aggregate measure in a second step (Bossert and D'Ambrosio, 2013; Rohde *et al.*, 2014). The main purpose of these indices is to approximate individuals' expectations, but they usually rely on retrospective data so that results are not robust to the selected dimension (Osberg, 2018). In this context, some authors developed multidimensional insecurity measures at the individual level, including perceptions about future financial situation as well as objective exposure to some risks (Rohde *et al.*, 2015, 2016, 2017).

Individual indices are more advantageous as they enable for the analysis of the economic insecurity distribution, its incidence in specific subpopulations and for the identification of key covariables. Moreover, individual measures can be aggregated in a second stage to generate population indices (Bossert and D'Ambrosio, 2013; D'Ambrosio and Rohde, 2014; Osberg, 2015). In this vein, Bossert and D'Ambrosio (2013) associated economic security with the concept of wealth as an emergency buffer stock. Focussing on the psychological component of insecurity and with a forward-looking strategy, they approximated economic insecurity as a weighted sum of current wealth and past changes on wealth stock, giving more weight to past declines and recent events. Current wealth can be turned to an income flow in case of an economic loss in the future, while past changes on this dimension shape individuals' expectations. However, this index is only based on private stocks and does not consider the role of public and private entitlements (Osberg, 2018). On other hand, Rohde *et al.* (2014) measured insecurity as downward income instability. Using panel data, they estimated downward deviations from trend in households' incomes discarding upwards volatility. Even though their purpose is to capture people's perceptions, they also use retrospective data. Inspired by the Hacker *et al.* (2010) aggregate indicator, Watson (2018) used a forward-looking approach to proxy insecurity through the predicted individual probability of experiencing a large income loss.

As we have seen so far, most academics only consider objective dimensions to proxy economic insecurity. Nevertheless, this phenomenon involves an important psychological component as it is related with people's expectations about future economic distress. Some authors have approximated insecurity with individuals' opinion about their future financial situation (Anderson, 2001; Espinosa *et al.*, 2014). Surveys on subjective expectations are the most effective method to measure perceived risk but its production is not widespread, so multidimensional indices of economic insecurity combining objective and subjective dimensions at the individual level have emerged in recent papers. These measures aim to deal with the lack of agreement about which should be the nature of insecurity dimensions and retrieve the idea that economic insecurity is a complex and multifaceted phenomenon which cannot be fully captured in a unidimensional setting. Also, these indices do not give up on the key advantages of constructing an individual measure.

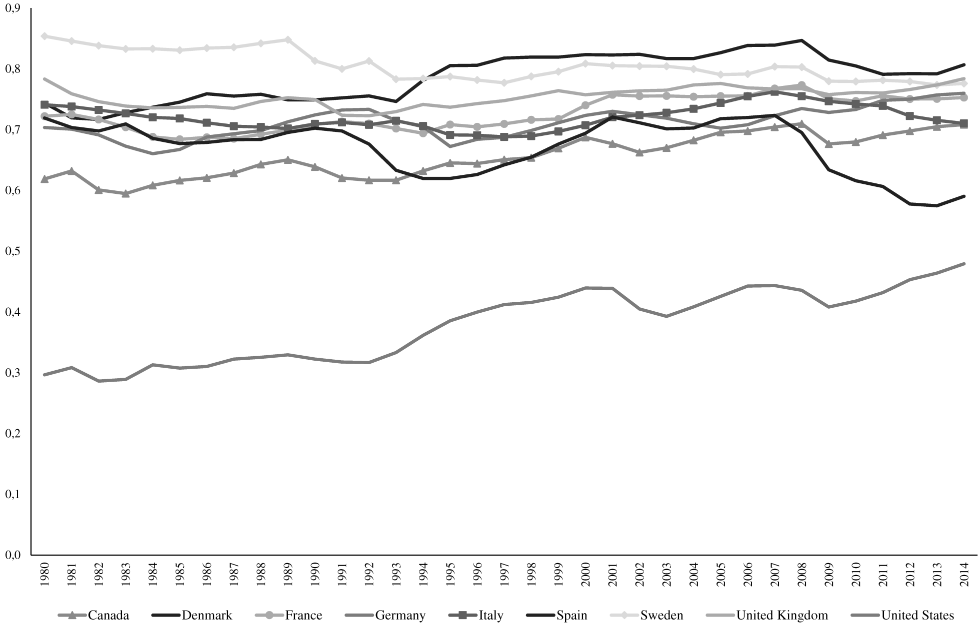
Rohde *et al*. (2015) analysed a variety of economic insecurity indicators in a separate way: perceived job security, financial satisfaction and inability to raise emergency funds as subjective indicators as well as large income drops, a probability of extreme expenditure distress and a probability of unemployment as objective dimensions. Nevertheless, these authors recognised that there can be inconsistent results when using a different range of variables to study insecurity, so they computed the first principal component of all dimensions to investigate the relationship between insecurity and individual socioeconomic characteristics. In this vein, Rohde *et al*. (2017) believe that dimensions of insecurity by themselves represent some undesirable facet of risk but ignore other possible relevant sources. Economic insecurity can be thereby considered as a latent variable which can be inferred from a variety of indicators and a synthetic index to measure it is required.[2] Based on this conception and taking advantage of the broad availability of living conditions surveys in developed countries, the novelty of Romaguera-de-la-Cruz (2020) proposal is that it adapts the approach on insecurity dimensions from Rohde *et al*. (2015) to the European Union Statistics on Income and Living Conditions (EU-SILC), allowing for sound and wide comparisons of individual economic insecurity in the European context.

Given that there is no previous paper that analyses the role of weighting and aggregation procedures in insecurity levels, trends and distribution, the main aim of this paper is to fill this gap in the literature by exploring differences in the results for economic insecurity when using four different methods to aggregate and weigh dimensions. Thus, we test the robustness of multidimensional insecurity indices to the way we combine dimensions, highlighting the main advantages of each procedure as well as its major drawbacks. Our approach includes subjective dimensions which try to capture individuals' negative expectations about future economic distress: household's inability to face unexpected expenses, financial dissatisfaction and changes in the ability to go on a holiday. It also incorporates objective indicators that capture uninsured financial risks: large income drops from one year to another, unemployment risk and a probability of extreme expenditure distress. Insecurity is hence an abstract phenomenon and it is necessary to combine the selected dimensions in a composite index, for which Romaguera-de-la-Cruz (2020) uses a counting approach. This framework can be extrapolated to other living conditions surveys with some minor adjustments.

2.2. Main empirical findings regarding economic insecurity in rich countries

So far, comparative empirical analysis on economic insecurity is still scarce and narrow, as most of the papers focus on insecurity in a small number of countries. Nevertheless, it is worth summarizing the main results of these analyses so far. In their seminal papers on economic insecurity in rich economies and using an aggregate economic security index for 14 OECD countries, Osberg and Sharpe (2005, 2014) found that within most developed economies Nordic countries were the most secure, whereas the United States, Canada and Spain had the largest levels of insecurity (Figure 1). In general, economic security displayed an upward trend everywhere in the period from 1980 to 2005 but slowed down or turned into a downward trend since the Great Recession. Since then there has been a significant rise in the levels of economic insecurity in Mediterranean countries, especially in Spain, where economic security has had persistent falls over the last three decades and experienced a large reduction of more than 15% since 2008.

Figure 1
EVOLUTION OF OSBERG AND SHARPE'S AGGREGATE ECONOMIC SECURITY INDEX 1980-2014



Source: Index of Economic Security, one of the four dimensions of the Index of Economic Well-Being (IEWB), see Osberg and Sharpe (2002, 2005, 2014).

The main factors contributing to the rise of insecurity in Spain were upward trends in unemployment rates and single-parent poverty levels, while public pensions had the opposite role by mitigating old-age poverty. Thus, similarly to what Ayala and Cantó (2018) have concluded for inequality levels, economic insecurity is more strongly correlated with the business cycle in Spain than in other developed countries. Reasons for this are generally related to the functioning of the labour market and the relatively low redistributive capacity of public policies. When analysing the unemployment risk in Osberg and Sharpe's (2005) index taking a household perspective, Berloffa and Modena (2014) also found that Spain is among the most insecure countries together with Italy and the United Kingdom.

Hacker *et al*. (2010, 2014) analysed economic insecurity in the United States approximated by large income drops from one year to the next. Since 1986, insecurity had a steady increase and this trend was more intense during the Great Recession, with more than a fifth of US citizens suffering from large income falls in 2009. Furthermore, these authors note that, although insecurity reduces after an economic recession, it does not return to pre-crisis levels implying a sustained gradual rise. Individuals with dependent children –especially lone-parents– together with those of African American and Hispanic origin are the most insecure groups, while insecurity decreases with age and education.

There are also some empirical comparative studies that make use of individual economic insecurity indices. Using the Bossert and D'Ambrosio (2013) index on wealth, D'Ambrosio and Rohde (2014) found that the US had higher levels of security compared to Italy due to greater accumulation of financial assets. However, the economic crisis had a larger impact on US households because of the fall in assets' prices, with an increase of the percentage of individuals suffering from extreme insecurity while the percentage of those enjoying large levels of security remained constant. On other hand, Rohde *et al*. (2014) reached different conclusions when studying downward income instability: the US is the most insecure country if we consider the role of the government through taxes and benefits, whereas the UK and Germany had greater insecurity considering market income. As we can see, the choice of the insecurity indicator in a unidimensional framework is crucial and can lead us to contradictory results.

Rohde *et al*. (2015) studied economic insecurity in Australia using a multidimensional approach and confirmed its correlation with economic growth as well as to the evolution of the unemployment rate. Insecurity in this country followed a downward trend from 2001 to 2007, increasing very slightly since then. In line with Hacker *et al*. (2010, 2014), young individuals are the most affected by insecurity, since older individuals are more capable to obtain emergency funds due to the accumulation of assets. Moreover, highly educated individuals as well as those with high levels of income benefit from lower levels of this phenomenon.

In the same line of research, Romaguera-de-la-Cruz (2020) found that economic insecurity decreases across the income ladder. She found a significant group of insecure middle-income individuals in Spain and to a lesser extent in France. However, economic insecurity in Sweden is, in contrast, a relevant phenomenon only for poor individuals. In all three countries, a higher educational attainment and a good labour market situation are strongly correlated to a lower probability of suffering insecurity in at least three out of six dimensions. Cantó *et al*. (2020) have extended the analysis to 27 European countries identifying the young, the less educated, the unemployed and those individuals in households with at least one child to be the most insecure subgroups in all regions. Nonetheless, the middle class is only affected by economic insecurity in Mediterranean and Eastern European countries.

3. Measuring economic insecurity using living conditions surveys

3.1. Economic insecurity dimensions

If we agree that economic insecurity is a multidimensional concept which reveals itself in a series of indicators that cannot fully account for the phenomenon when analysed separately, we need a comprehensive insecurity index. Romaguera-de-la-Cruz (2020) develops a broad setting of six insecurity indicators, adjusting the dimensions' proposal developed by Rohde *et al*. (2015) to the information available in EU-SILC[3]. This framework includes some subjective dimensions which try to capture expectations about individuals' future financial situation as well as objective indicators that reflect their exposition to certain economic risks, including probabilities of a series of economic hazards with a forward-looking strategy. In this paper, we explore a variety of methods that allow us to weigh and aggregate various dimensions in order to create a composite index of economic insecurity.

As subjective dimensions, we consider three indicators: (a) *household's incapacity of facing unexpected expenses*, which is a dichotomous variable that takes the value one if the household does not own the resources to afford an unexpected expenditure; (b) *household's financial dissatisfaction*, calculated as the difference between household disposable income and the lowest needed annual income; and (c) *changes in the ability to go on a holiday*, meaning that the household is currently unable to go on a holiday while it was able to afford one week away from home the previous year.[4] In order to capture the exposition to some adverse risks, we consider three objective dimensions: (d) short-term *income drops* over 25%; (e) *unemployment risk* including the risk of losing current employment and the risk of not finding a job[5]; and a (f) *probability of extreme expenditure distress* to capture household's difficulties to meet standard expenses which may exacerbate future economic distress.[6]

3.2. Constructing a composite indicator of economic insecurity: four different methods

To compute a multidimensional index of economic insecurity using the information provided by the aforementioned dimensions, the literature has considered several ways to summarize all the relevant information: Osberg and Sharpe (2005, 2014) use a weighted average, Rohde *et al*. (2015, 2017) use PCA and Bucks (2011) applies a counting approach (Atkinson, 2003; Alkire and Foster, 2011). In this paper, we explore a variety of aggregation procedures discussing their advantages and disadvantages and evaluating if there are substantial differences in the obtained results depending on the procedure chosen to summarize the information within dimensions. In particular, we will compare four different strategies: (i) a normative procedure: mean with equal weights, (ii) two methods with statistical weights: standard PCA and polyserial correlation PCA, and (iii) a mixed scheme which incorporates frequency-based weights and a normative element through the choice of a multidimensional threshold: counting approach.

A natural way to proceed when building a multidimensional economic insecurity index is to use a straightforward method that calculates the average of all normalised insecurity dimensions using equal weights[7]:

$$EI_i^{EW} = \frac{\sum_{j=1}^{D} X_{ij}}{D} \tag{1}$$

where X_{ij} is a specific value for individual i and dimension j and D is the total number of dimensions (in our case, $D = 6$). This method follows a normative approach as weights depend on value judgements which are generally independent from correlations between dimensions. Even though setting weights equal to one implies greater simplicity in calculations, it also involves the consideration of indicators as equally important (Decancq and Lugo, 2013). Of course, this statement might not be valid as dimensions may not actually have the same relevance. In this setting, we would be duplicating the common information in dimensions if they are strongly correlated (double counting problem). However, this does not appear to be an issue in our empirical analysis for the case of Spain as none of the correlation coefficients between dimensions is larger than 0.5 (see Table A3).

A second approach is based on multivariate statistical methods which reduce the dimensionality of simple indicators by using statistical weights to compute a composite indicator. In particular, we apply a standard principal component analysis as we believe that economic insecurity is a latent variable which could be inferred from the dimensions explained above. This method transforms the initial set of dimensions into a set of uncorrelated linear combinations of indicators. In this case, we obtain the first principal component of the data matrix –which explains the greatest data variability– and then predict an individual economic insecurity indicator. We also normalise the achieved results to produce a bounded index between zero and one:

$$EI_i^{PCA} = \sum_{j=1}^{D} \alpha_j X_{ij} \tag{2}$$

where α_j are the coefficients obtained when calculating the first principal component of the data matrix, with a number of rows equal to the number of individuals (N) and a number of columns equal to the number of dimensions ($D = 6$). This aggregation method may solve the double counting problem, as we are capturing the highest possible variation among dimensions using only one factor. Nevertheless, standard PCA has also some relevant drawbacks: first, the correlations do not necessarily represent the actual impact of dimensions on insecurity (Nardo *et al.*, 2008), so we cannot be sure that we are capturing economic insecurity or other underlying phenomena present in the data. Furthermore, the final indicator is typically hard to interpret and does not have a clear economic meaning (Srinivasan, 1994). This procedure also lacks simplicity and transparency while it is not robust to the way one defines dimensions or to outliers and the resulting multidimensional index is not decomposable by dimensions.

Besides these limitations, standard PCA has been used to produce composite indices regardless the type of indicators available, which are often measured by ordinal or dichotomous scales. Due to complexity in modelling these variables, it is often assumed that the distance between points in an ordinal scale is constant. This simplification can generate asymmetric distributions (with high kurtosis) which would violate the normality assumption. In that case, standard PCA would not be a proper technique since it was originally designed for Pearson correlation matrices obtained from multivariate normal continuous variables, thus causing an underestimation of data correlations (Kolenikov and Angeles, 2009). Hence, when having a set of ordinal indicators, it would be more adequate to apply PCA to the polychoric correlations matrix. However, to obtain this polychoric correlations, one must assume that each variable is continuous and follows a normal distribution while both must follow a bivariate normal one. When ordinal and continuous variables are combined, we must use the related concept of polyserial correlation. Given that two of our proposed insecurity dimensions are dichotomous variables while the rest are continuous, we also compute the first principal component from the polyserial correlation matrix. The individual economic insecurity index would be expressed in a similar way to (2), even though coefficients from the linear combination of insecurity dimensions are obtained with this polyserial approach.

An interesting alternative to the three previous methods is to use a counting approach (Atkinson, 2003), commonly adopted in the literature focussed on measuring multidimensional poverty (Alkire and Foster, 2011) and conveniently used in this area by Bucks (2011) and Romaguera-de-la-Cruz (2020). This method involves setting two thresholds to carry out the identification of the economically insecure: first, one must establish a threshold in each of the indicators to locate individuals who lack of security in a given dimension and, subsequently, one must use a further multidimensional threshold to classify individuals as economically insecure or not (*double threshold* strategy). In our particular case, we establish the mean as the most adequate threshold for unemployment risk and for probability of extreme expenditure distress, whereas we consider that an individual lacks security in inability to meet unexpected expenses, financial dissatisfaction, income drops and changes in the ability to go on holidays when the specific indicator is different from zero. The resulting individual economic insecurity index (EI_i) will count the number of weighted dimensions in which the individual lacks security:

$$EI_i = \sum_{j=1}^{D} w_j I_{ij} \tag{3}$$

where I_{ij} takes the value 1 if individual i lacks security in dimension j and 0 otherwise. D is the total number of dimensions ($D = 6$) and w_j is the weight given to each dimension. We also explore the robustness of this counting approach method to different weighting specifications. If all insecurity dimensions have the same relevance, we may consider equal weights ($w_j = 1$). However, it is also reasonable to consider prevalence weights so that we can introduce a relative perspective that allows us to adapt the index to the distribution of dimensions in a specific society. These prevalence weights w_j can be expressed as:

$$w_j = \frac{D * P_j}{\sum_{j=1}^{D} P_j} \tag{4}$$

where P_j is the share of individuals who lack (do not lack) security in dimension j and D is the total number of dimensions. The use of frequency weights allows us to obtain a more absolute perspective of economic insecurity, since we give greater importance to those dimensions in which a larger share of the population lacks security (Osberg, 2002, 2005). On the contrary, by weighting indicators by the share of individuals not lacking security in a certain dimension (inverse frequency weights), we can introduce objective indicators of subjective feelings of insecurity in the way that people feel worse if they observe that a huge proportion of the population has security when they are among those who are insecure (Desai and Shah, 1988; Romaguera-de-la-Cruz, 2020). Furthermore, in order to compare this method with the other aggregation procedures, we present normalised results for the counting approach which are obtained by dividing EI_i by the total number of dimensions D.

In a second stage, we must fix a multidimensional threshold (k) to identify economically insecure individuals. We here explore three possible thresholds: (i) an union approach, which implies that an individual is economically insecure if he/she lacks security in one out of six weighted dimensions ($k \geq 1$); (ii) an intermediate approach, with which an individual is insecure if he/she lacks security at least in half of the sum of weighted dimensions ($k \geq 3$), and (iii) the intersection approach, with which the individual must lack security in all dimensions ($k = 6$).

It is our understanding that a counting approach following the Alkire and Foster (2011) method is the most appropriate technique to analyse multidimensional economic insecurity for several reasons. First, the counting approach individual index has a direct and straightforward economic interpretation: EI_i is the number of weighted dimensions in which individuals lack security. Likewise, this procedure is more transparent and is not influenced by the way dimensions are defined or by outliers, while equal weighting and PCA are more sensitive to these issues. We are also able to adapt the index to a given context by incorporating the distribution of dimensions in a society through frequency weights and the union and intersection approach enable the study of economic insecurity from a broad perspective. Nonetheless, the counting approach has also some drawbacks, as it ignores inequality among those economically insecure and implicitly assumes perfect substitutability among dimensions below the multidimensional threshold, while the same indicators are perfect complements from this threshold onwards (Rippin, 2017; Espinoza-Delgado and Silber, 2018).

3.3. An aggregate social measure of insecurity: the advantages of using a counting approach

Using Alkire and Foster's (2011) multidimensional threshold to identify economically insecure individuals allows us to study aggregate insecurity in any specific population. This method provides us with an adequate social measure of this phenomenon that considers incidence and intensity at the same time and allows for a sound comparison between several countries or subpopulations as well as different periods of time.

Thus, the incidence of economic insecurity (H_{EI}) is the proportion of economically insecure people among all individuals in a given population:

$$H_{EI} = \frac{\sum_{i=1}^{N} I(EI_i \geq k)}{N} = \frac{q_{EI}}{N} \tag{5}$$

where $I(EI_i \geq k)$ takes the value 1 if the individual is considered economically insecure, q_{EI} is the number of people classified as insecure when being above the multidimensional threshold k and N corresponds to the total population. Furthermore, we can measure the intensity of economic insecurity:

$$\mu_{EI}^{q_{EI}} = \frac{\sum_{i=1}^{N} EI_i I(EI_i \geq k)}{\sum_{i=1}^{N} I(EI_i \geq k)} \rightarrow A = \frac{\mu_{EI}^{q_{EI}}}{D} \tag{6}$$

where $\mu_{EI}^{q_{EI}}$ is the mean of the variable EI_i within the group of economically insecure. A is standardised intensity, namely the share of possible insecurity dimensions D in which average economically insecure individual lacks security. Therefore, we can calculate the economic insecurity adjusted rate (M_{EI}), which is the total weighted sum of those dimensions in which economically insecure individuals lack security divided by the maximum insecurity dimensions that the entire population could experience. This indicator can be expressed as the product of incidence and normalized intensity:

$$M_{EI} = \frac{\sum_{i=1}^{N} EI_i I(EI_i \geq k)}{ND} = \frac{q_{EI}}{N}\frac{\mu_{EI}^{q_{EI}}}{D} = H_{EI}A \tag{7}$$

Additionally, the economic insecurity adjusted rate can be decomposed by dimensions to obtain the contribution of each element to overall insecurity within our study population:

$$M_{EI} = \sum_{j=1}^{D} \frac{w_j \cdot H_{EIj}}{D} \tag{8}$$

where H_{EIj} is the share of economically insecure people who lack security in the j dimension and w_j is its correspondent weight. Similarly, M_{EI} can be decomposed by specific subgroups of the population and can be expressed as a weighted sum of each subpopulations' insecurity adjusted rates:

$$M_{EI} = \sum_{x=1}^{S} \frac{N_x}{N} \cdot M_{EIx} \tag{9}$$

where N_x is the size of subgroup x and M_{EIx} is its corresponding economic insecurity adjusted rate.

4. An empirical application of different aggregation and weighting methods to the measurement of economic insecurity in Spain

As previously stated, economic insecurity is a dynamic phenomenon which involves expectations about individuals' future economic situation. This complexity leads us to believe that economic insecurity is a latent variable that shows up in a variety of indicators, none of which captures this phenomenon to its full extent. In this context, we use different weighting and aggregation procedures described in detail in Section 3 to provide a variety of measures of economic insecurity over the 2009-2017 period in Spain, a country with relatively high levels of insecurity and an upward trend[8]. This analysis will allow us to compare the results on economic insecurity when using different methods to construct a composite economic insecurity index and will additionally provide us with interesting new empirical evidence on insecurity levels, evolution and distribution in a large developed country in recent years.

4.1. Data

To calculate all our different indices of economic insecurity, we use the Survey of Living Conditions (*Encuesta de Condiciones de Vida*, *ECV*). This data set is the Spanish version of EU-SILC, a standardized source of income and socioeconomic data in the European Union which allows for sound comparisons on European countries' well-being. It contains annual individual and household data on multiple variables such as income, employment, education, material deprivation or health. As economic insecurity is a dynamic phenomenon, we are using the longitudinal version of the survey which is a four-year rotating panel that follows individuals for a maximum of four waves. However, we must be aware that income variables are referred to the prior year of interview, while demographic and socioeconomic information are related to the interview year. Since 2008, administrative records of Social Security and tax databases are combined with survey information to construct better-quality income variables and avoid the use of imputation procedures. Our income variable is real household equivalized disposable income, deflated by Consumer Price Index at constant 2015 prices and adjusted for household size and composition by using the OECD modified scale.

We decided to trim the data eliminating the 1% tails of the household disposable income distribution (Cowell and Victoria-Feser, 2006) and to discard those individuals remaining in the survey only for a single wave, due to the dynamic nature of certain dimensions. Our final dataset includes 254,723 observations corresponding to individuals observed from two to four times during the 2008-2017 period (Table A2).[9]

4.2. Results on economic insecurity levels, trends and distribution

In this section, we study the joint distribution of insecurity dimensions by exploring different ways to weigh and aggregate our proposed simple indicators into a composite index (Table 2). Within the counting approach, we find that, on average, the Spanish population is insecure in 30% of insecurity dimensions when we use the share of population lacking security to weight dimensions (frequency weights). In other words, the average number of weighted dimensions in which individuals lack security is approximately 1.8 out of 6 dimensions. On the contrary, individual insecurity is lower when considering inverse frequency weights: on average, Spaniards are insecure in 23.7% of insecurity dimensions, this is 1.4 out of 6 dimensions. All three versions of this method show a larger standard deviation than the simple mean or the statistical aggregation methods.

The evolution of economic insecurity is robust to the aggregation method we use (Figure 2). All six methods indicate a similar pattern: insecurity increased in 2010 while GDP was dropping, with a brief recovery the following year, and rising again for three consecutive periods. From 2014 onwards, the economic insecurity index had a steep downward trend achieving pre-crisis levels just before the pandemic crisis in 2020. Certainly, economic insecurity appears to be correlated with the economic cycle despite the aggregation procedure used: negative GDP growth rates as well as the failure of labour market institutions, the loss of unemployment benefits for long-term unemployed and austerity measures during the Great Recession have been related with the large increase in economic insecurity through subjective and objective indicators. The return to positive growth rates and the reduction of unemployment brought about by the economic recovery also resulted in a decrease of this phenomenon. Thus, it seems that our economic insecurity indices capture reductions in economic activity relatively quickly, but the subsequent recovery is reflected in economic insecurity indicators with some delay. This is probably because it is more difficult to recover individuals' positive expectations after an economic crisis than to push them into negative ones at the beginning of a strong recession.

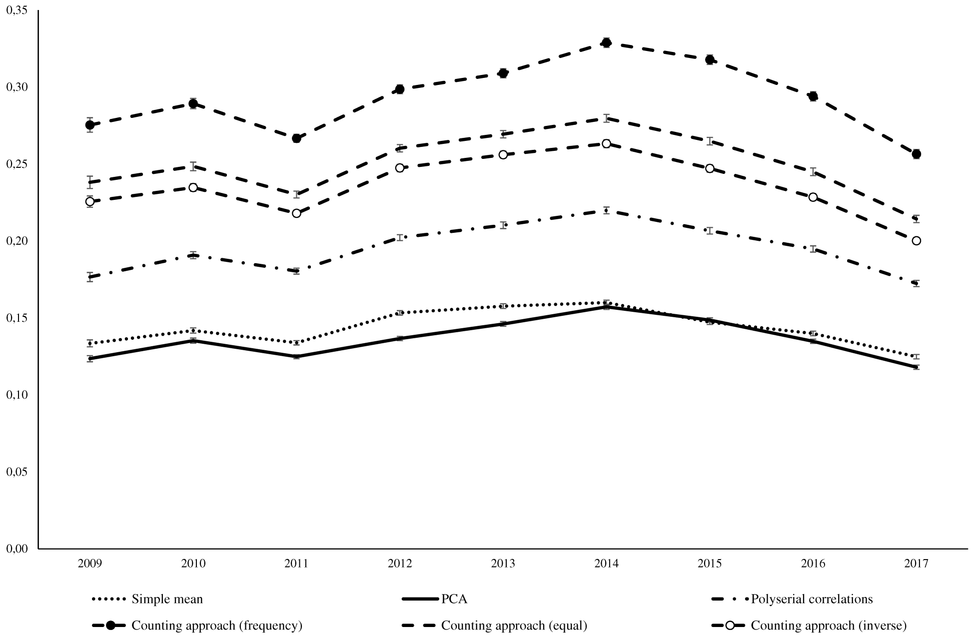
Table 2
INDIVIDUAL ECONOMIC INSECURITY INDEX - DESCRIPTIVE STATISTICS

		Mean	Median	Standard deviation	Min	Max
Simple mean		0.144 (0.001)	0.090	0.147	0	0.802
PCA		0.137 (0.001)	0.100	0.143	0	1
Polyserial correlations		0.197 (0.001)	0.100	0.202	0	1
Counting approach (EI_i)	Frequency weights	0.295 (0.001)	0.239	0.289	0	1
	Equal weights	0.251 (0.001)	0.167	0.244	0	1
	Inverse frequency weights	0.237 (0.001)	0.171	0.231	0	1

Notes: (1) Results correspond to the nine-year period and should be interpreted as a mean for the whole time-window. (2) Bootstrap standard errors (1000 replications) for the means are shown in brackets.

Source: Author's calculations based on longitudinal EU-SILC data set.

Figure 2
EVOLUTION OF ECONOMIC INSECURITY INDEX (2009-2017)

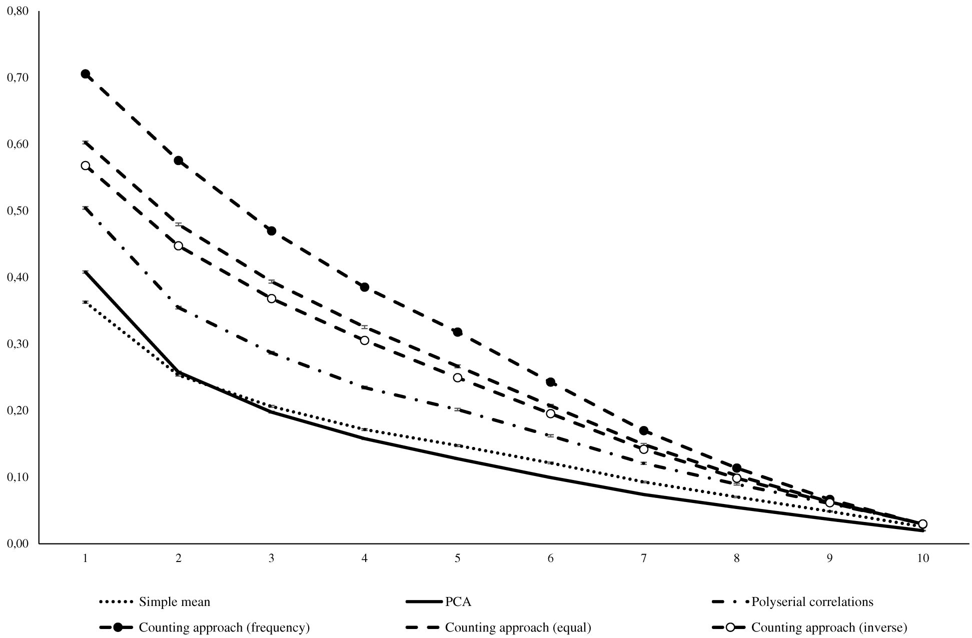


Notes: Confidence intervals are presented in vertical lines.

Source: Author's calculations based on longitudinal EU-SILC data set.

Figure 3 displays the distribution of the economic insecurity index by income decile. Regardless of the aggregation procedure used, economic insecurity decreases with income: poorer individuals are suffering from anxiety about future financial distress in addition to other threats to well-being. We must highlight that individuals situated in middle-income deciles (from the third to the seventh decile) register significant levels of economic insecurity. Thus, not only poor individuals suffer from this phenomenon in Spain and, unfortunately, only those situated in the highest deciles (from the eighth decile onwards) are able to avoid economic insecurity. Between the counting approach indices, the one with frequency weights dominates the rest all across the income distribution. The equal weighting index is closer to the one using inverse frequency weights.

Figure 3
ECONOMIC INSECURITY INDEX BY DISPOSABLE INCOME DECILE



Notes: Confidence intervals are presented in vertical lines.

Source: Author's calculations based on longitudinal EU-SILC data set.

Table 3 displays individual economic insecurity indices by socioeconomic characteristics with respect to overall insecurity[10]. We find no differences between aggregation procedures in the characterisation of individuals most at risk of insecurity regarding gender and basic activity status, but we do find some other differences regarding age, level of education, employment situation, household type or income decile.

In general, we observe that young individuals (those between 16 and 30) are the most insecure whatever approach we use to measure economic insecurity: their insecurity level is between 14 and 16% above that of the whole population, while those above 30 show less insecurity probably due to a sounder and less precarious labour market situation. Older individuals are the most secure which is surely related to their access to lifetime savings and public pension benefits. This age pattern is observable regardless of the weighting and aggregation procedure, even though we do observe that the differential insecurity risk between young and old individuals is somewhat larger using a standard PCA approach. Interestingly, other methods such as the simple mean strategy and polyserial PCA smooth insecurity across the age distribution more than PCA or the counting approach. The results on insecurity of different methods show a larger variation when we focus on older individuals: while they are approximately 23% less insecure than the average population with a standard PCA and a frequency-weighted counting approach, they are only 10.4% less insecure when computing the index with a simple mean. In turn, we find that children are more likely to be insecure with respect to the overall population when using a counting approach with frequency weights compared to other methods.

Despite the aggregation strategy, we find that insecurity decreases as the level of education grows and its reduction is large when individuals hold tertiary education. Individuals who reached tertiary education are between 40% and 43% more secure than the whole population. However, relative insecurity for those with the lowest educational attainment is smaller when using a counting approach strategy than any other. Moreover, differences between the weighting procedures within the counting approach are somewhat larger than those for other levels of education.

Regarding individual labour market situation, the unemployed are the most insecure whatever method we use. However, relative insecurity for employed people is somewhat lower when using a counting approach than other aggregation methods. Furthermore, the level of insecurity of the unemployed is more than double that of the whole population when applying a simple mean of dimensions as well as both standard and polyserial PCA, while relative indicators are slightly smaller for the counting approach. Interestingly, individuals with a medium level occupation display a slightly higher index of individual insecurity when computed with a counting approach (especially when using frequency weights) than using a PCA approach.

With respect to household typology, we find that single-parent families suffer from the highest levels of insecurity, followed by other households with more than two adults and at least one dependent child. Clearly, many of these individuals had to turn to their families to combat the effects of the economic crisis. Nevertheless, individuals living alone also show large economic insecurity levels, as their insecurity cannot be mitigated by the safety of any other household member and they cannot benefit from the economies of scale of a larger household. For these three household types, the standard PCA approach seems to report larger insecurity levels than for the whole population in comparison to other procedures. Also, the weighting procedure we choose within the counting approach method appears to have higher relevance in this case: while single-parent households display 43.7% more insecurity than the population when considering frequency weights, this percentage is only 35.9% when applying inverse frequency weights. Homeowners are more secure than tenants, especially when considering PCA.

Table 3
RELATIVE ECONOMIC INSECURITY INDEX BY SOCIOECONOMIC CHARACTERISTICS

	Simple mean	PCA	Polyserial correlation	Counting approach		
				Frequency weights	Equal weights	Inverse frequency weights
Age						
< 16	1.014	1.066	1.030	1.081	1.060	1.046
16 – 30	1.139	1.161	1.142	1.136	1.147	1.148
31 – 45	1.007	1.022	0.995	1.017	1.020	1.017
46 – 65	0.931	0.891	0.919	0.885	0.892	0.890
> 65	0.896	0.774	0.868	0.769	0.805	0.819
Gender						
Female	1.000	1.000	0.995	1.000	1.000	0.996
Male	1.007	1.007	1.000	0.997	1.000	1.000
Level of education						
Primary or less	1.354	1.336	1.371	1.305	1.303	1.300
Secondary	1.146	1.168	1.147	1.169	1.163	1.160
Tertiary	0.597	0.577	0.574	0.573	0.586	0.591
Basic activity status						
Inactive	1.014	0.985	1.010	0.990	0.996	0.996
Employed	0.806	0.796	0.797	0.827	0.825	0.819
Unemployed	2.042	2.182	2.066	1.942	1.976	1.983
Level of occupation						
Without occupation	1.208	1.204	1.203	1.163	1.179	1.181
High	0.507	0.496	0.487	0.498	0.510	0.511
Medium	1.035	1.022	1.025	1.041	1.036	1.030
Low	1.500	1.555	1.533	1.525	1.510	1.502
Type of household						
One adult, no children	1.056	1.080	1.051	1.075	1.044	1.025
Two adults, no children	0.951	0.912	0.939	0.922	0.924	0.920
Other HH, no children	0.958	0.912	0.939	0.898	0.920	0.928
One adult, children	1.417	1.504	1.457	1.437	1.382	1.359
Two adults, children	0.903	0.934	0.904	0.966	0.952	0.941
Other HH, children	1.285	1.350	1.299	1.315	1.307	1.295
Homeowner						
No	1.521	1.664	1.563	1.563	1.538	1.523
Yes	0.875	0.839	0.858	0.861	0.869	0.869
Income decile						
1	2.521	2.978	2.558	2.393	2.402	2.397
2	1.757	1.883	1.802	1.949	1.912	1.890
3	1.431	1.445	1.457	1.593	1.570	1.553
4	1.194	1.153	1.193	1.305	1.295	1.287
5	1.028	0.934	1.025	1.078	1.064	1.051
6	0.840	0.723	0.822	0.824	0.825	0.823
7	0.646	0.540	0.614	0.576	0.594	0.599
8	0.486	0.401	0.452	0.386	0.406	0.418
9	0.340	0.270	0.310	0.224	0.251	0.262
10	0.181	0.146	0.152	0.098	0.120	0.127

Notes: (1) We present the ratio between the individual economic insecurity index for a given subgroup and the one for the whole Spanish population. (2) *Level of occupation* includes the following categories: Without occupation (none), High (1 = Managers; 2 = Professionals; 3 = Technicians and Associate Professionals; 10 = Armed Forces Occupations), Medium (4 = Clerical Support Workers; 5 = Services and Sales Workers; 7 = Craft and Related Trades Workers; 8 = Plant and Machine Operators and Assemblers) and Low (6 = Skilled Agricultural, Forestry and Fishery Workers; 9 = Elementary Occupations).

Source: Author's calculations based on longitudinal EU-SILC data set.

When analysing economic insecurity by income decile, we find that whatever the method we use, it decreases as income grows in line with Figure 3. Spaniards situated in the first income decile have always a larger insecurity index than the whole population. However, it is interesting to note that the magnitude of this ratio differs depending on the aggregation method: those in the first decile show almost three times more insecurity than total population with a standard PCA strategy, while this ratio decreases to 2.4 when using a counting approach. From the second to fifth decile, the counting approach displays more economic insecurity than the rest of methods. On the contrary, simple mean and polyserial correlations PCA give more relevance to higher-income groups (from the seventh decile onwards) in comparison to other procedures. Thus, the counting approach method seems to be able to best capture insecurity levels in middle classes in comparison with other aggregation procedures that give more relevance to extreme situations.[11]

To determine whether a given individual characteristic contributes similarly to economic insecurity irrespective of the aggregation and weighting method we have also estimated multivariate regressions. Results show that our previous conclusions generally hold: the young, the unemployed and the low educated have a higher level of economic insecurity, whatever the method we use. However, these estimations suggest that the counting approach discriminates more by occupation, so that individuals in higher occupations have significantly lower levels of economic insecurity compared to those in middle ones, probably because this method detects more insecure individuals in middle-income deciles. Whatever the aggregation or weighting method we find that a higher household disposable income is inversely related to the probability of suffering from economic insecurity, coefficients are nevertheless larger for the counting approach than for other methods.

Table 4
ECONOMIC INSECURITY DETERMINANTS (OLS regressions)

	Simple mean	PCA	Polyserial correlation	Individual economic insecurity		
				Frequency weights	Equal weights	Inverse weights
Male	0.001	0.001	0.002	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Age						
< 16	-0.008***	-0.008***	-0.009***	-0.014***	-0.013***	-0.011***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
31 – 45	-0.003*	-0.001	-0.005**	0.000	0.001	0.001
	(0.002)	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)
46 – 65	-0.003***	-0.005***	-0.003**	-0.011***	-0.011***	-0.012***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
> 65	-0.002	-0.005***	-0.006**	-0.006*	-0.009***	-0.019***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)
Level of education						
Secondary	-0.010***	-0.004***	-0.018***	-0.004**	-0.006***	-0.009***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
Tertiary	-0.023***	-0.013***	-0.039***	-0.030***	-0.035***	-0.049***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
Basic activity status						
Inactive	-0.012***	-0.014***	-0.019***	-0.025***	-0.026***	-0.032***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)

(*Continued*)

	Simple mean	PCA	Polyserial correlation	Individual economic insecurity		
				Frequency weights	Equal weights	Inverse weights
Unemployed	0.071***	0.070***	0.097***	0.098***	0.099***	0.104***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
Married	-0.013***	-0.008***	-0.020***	-0.011***	-0.011***	-0.013***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Bad health status	0.029***	0.022***	0.044***	0.036***	0.040***	0.052***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)
Status in employment						
Never worked	0.002	0.005***	0.003	0.018***	0.019***	0.023***
	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)
Temporary employee	0.033***	0.039***	0.047***	0.076***	0.078***	0.086***
or without contract	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Employer	-0.009***	-0.005***	-0.021***	-0.007**	-0.011***	-0.021***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)
Independent worker	-0.005***	-0.004***	-0.012***	-0.001	-0.002	-0.007**
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
Level of occupation						
High	-0.012***	-0.004**	-0.017***	-0.013***	-0.015***	-0.019***
	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)
Medium	-0.005**	-0.008***	-0.008***	-0.003	-0.003	-0.003
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)
Low	0.006**	0.002	0.011***	0.015***	0.017***	0.024***
	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.005)
Homeowner	-0.024***	-0.033***	-0.040***	-0.039***	-0.044***	-0.059***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
HH disposable income	-0.126***	-0.149***	-0.174***	-0.208***	-0.222***	-0.262***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Type of household						
Two adults, no children	0.003	-0.002	0.004	0.000	-0.003	-0.013**
	(0.003)	(0.002)	(0.004)	(0.004)	(0.004)	(0.005)
Other HH, no children	-0.007**	-0.014***	-0.010***	-0.020***	-0.028***	-0.051***
	(0.003)	(0.002)	(0.004)	(0.004)	(0.004)	(0.005)
One adult, children	0.008**	0.005	0.020***	0.009	0.012*	0.019**
	(0.004)	(0.003)	(0.006)	(0.006)	(0.006)	(0.008)
Two adults, children	-0.009***	-0.011***	-0.009**	-0.011**	-0.013***	-0.021***
	(0.003)	(0.002)	(0.004)	(0.004)	(0.004)	(0.005)
Other HH, children	-0.005*	-0.009***	-0.003	-0.008*	-0.013***	-0.026***
	(0.003)	(0.002)	(0.004)	(0.004)	(0.005)	(0.005)
Constant	1.378***	1.592***	1.903***	2.266***	2.416***	2.863***
	(0.009)	(0.008)	(0.012)	(0.014)	(0.015)	(0.019)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	123550	123550	123550	123550	123550	123550
R-squared	0.527	0.705	0.562	0.584	0.599	0.604

Notes: (1) Results correspond to the nine-year period and should be interpreted as a mean for the whole time-window. (2) References of categorical variables are the following: between 16 and 30 years (age), primary (education), working (basic activity status) as a permanent employee (employment status), with no information on occupation (level of occupation), not married (marital status), in good health, living in a rented housing in a one adult without children (type of household).

Source: Authors' calculations based on longitudinal EU-SILC data set.

Even though our main empirical results on economic insecurity are robust to different aggregation procedures, we believe that the counting approach is the most advantageous of them all. This is because, first, this method is not influenced by the way we define the dimensions or by the presence of outliers and by weighting the simple indicators by the population affected (not affected) by the specific phenomenon we are introducing varying degrees of relativity of the insecurity concept, capturing the social and economic context in which the index is calculated. Secondly, the counting approach strategy helps to better capture economic insecurity in middle-income groups, those individuals with secondary education and those employed with a medium-level occupation in contrast with other aggregation methods which only locate insecure individuals within the lowest income deciles and the most vulnerable subgroups (for instance, the unemployed or the less educated). And finally, and most importantly, the individual index obtained with this method is not only a way of summarizing the insecurity dimensions in a composite indicator but has a clear economic interpretation: the number of weighted dimensions in which individuals lack security with respect to the total number of dimensions considered.

Using a counting approach, we can study both the incidence and intensity of economic insecurity (Table 5). More than half of the population in Spain is considered economically insecure when we apply a multidimensional threshold of one dimension (union approach) and inverse frequency weights, whereas the incidence of this phenomenon is 58.2% with frequency weights and 61.5% when all dimensions are considered equally important. This pattern is very similar when we use an intermediate strategy, meaning that to be considered insecure the individual must lack security at least in three dimensions. Notwithstanding, even though incidence is larger when using an equal weighting strategy, intensity is lower than that when applying frequency weights. Only when dimensions are weighted by the population not affected by each simple indicator –inverse frequency weights–, the normalised intensity is higher in the union approach than the intermediate strategy (0.64 *vs*. 0.42). These results show how useful the analysis of the economic insecurity adjusted rate (M_{EI}) is, as this indicator combines incidence and intensity and enables us to conduct more sound comparisons. The M_{EI} is higher when using a union approach regardless the weighting scheme used. On the other hand, when comparing different weighting strategies, the frequency-based adjusted rate is larger both in the union and in the intermediate approach. Finally, incidence is close to zero with an intersection strategy, which indicates that considering only individuals who lack security in all six dimensions is a remarkably restrictive criterion.

Table 5
AGGREGATE INDICATORS OF ECONOMIC INSECURITY - COUNTING APPROACH

			Union approach	**Intermediate approach**	**Intersection approach**
Frequency weights	Incidence	H_{EI}	0.582 (0.002)	0.243 (0.002)	0.001 (0.000)
	Normalised intensity	A	0.492 (0.001)	0.718 (0.001)	1.000 (0.000)
	Economic insecurity adjusted rate	M_{EI}	0.286 (0.001)	0.174 (0.001)	0.001 (0.000)

(*Continued*)

			Union approach	**Intermediate approach**	**Intersection approach**
Equal weights	Incidence	H_{EI}	0.615 (0.002)	0.256 (0.002)	0.001 (0.000)
	Normalised intensity	A	0.397 (0.001)	0.600 (0.001)	1.000 (0.000)
	Economic insecurity adjusted rate	M_{EI}	0.244 (0.001)	0.153 (0.001)	0.001 (0.000)
Inverse frequency weights	Incidence	H_{EI}	0.510 (0.002)	0.139 (0.001)	0.001 (0.000)
	Normalised intensity	A	0.654 (0.001)	0.423 (0.001)	1.000 (0.000)
	Economic insecurity adjusted rate	M_{EI}	0.216 (0.001)	0.091 (0.001)	0.001 (0.000)

Notes: (1) Results correspond to the nine-year period and should be interpreted as a mean for the whole time-window. (2) Standard errors are shown in brackets.

Source: Author's calculations based on longitudinal EU-SILC data set.

5. Concluding remarks

Economic insecurity is a key dimension of individual well-being. Nevertheless, academics have not yet reached an agreement on its definition or on the best procedure to measure it. In this paper, we have thoroughly reviewed the existing literature in this field, analysing different insecurity measures and the main empirical results for developing countries. Even though current definitions of insecurity are vague and imprecise, we can find two common elements: (i) insecurity implies uninsured downside economic risks and (ii) involves anxiety steaming from people's financial perceptions. The focus on expectations about the future and how these expectations affect individuals' well-being makes the measurement of this phenomenon a challenging task.

All current measurement approaches to insecurity have advantages and drawbacks: aggregate indicators stand out for simplicity in its calculations and may be useful if our focus is to measure insecurity at a national level but rely on historical realised risks rather than modelling future distress, while unidimensional individual indices allow for the analysis of subpopulations and key covariates, but choosing different variables can lead to non-robust results. Due to the idiosyncratic nature of this notion, information from subjective expectations' surveys seems to be the best approach, but the lack of availability of this information makes other measurement strategies necessary. A good alternative could be the computation of multidimensional indices of economic insecurity which include some subjective indicators along with the objective exposure to several economic hazards.

In this paper, we sustain that economic insecurity is a multifaceted phenomenon and cannot be fully captured with a single variable. Rather, insecurity can be understood as a latent variable present in the joint distribution of a variety of indicators. In this context, we consider both subjective and objective dimensions within a household perspective with the individual as the unit measure and it could be easily implemented for other living conditions surveys with minor adjustments. In this paper, we have explored different aggregation and weighting procedures when computing a composite index of insecurity to try to understand the differences between them. We have compared an equal weighted average of insecurity dimensions, a standard PCA, a polyserial correlation PCA and a counting approach.

Comparing the results on economic insecurity using data for Spain over the 2009-2017 period, we show that the evolution and distribution of the phenomenon is robust to the aggregation procedure, even though the relative relevance of some sociodemographic characteristics in increasing the risk of insecurity are different depending on the method. First, the differential insecurity risk between young and old individuals is somewhat larger using a standard PCA approach. Second, relative insecurity for those with the lowest educational attainment is smaller when using a counting approach strategy than any other while differences between the weighting procedures within the counting approach are somewhat larger than those for other levels of education. The insecurity of the unemployed is more than double that of the whole population when applying a simple mean of dimensions as well as both standard and polyserial PCA, while results are smaller for the counting approach. Interestingly, individuals with a medium-level occupation display a slightly higher individual insecurity when computed with a counting approach (especially when using frequency weights) than using a PCA approach. Finally, it is interesting to note that when analysing the incidence of insecurity by income decile there are relevant differences by aggregation method: those in the first decile show almost three times more insecurity than total population with a standard PCA strategy, while this ratio decreases when using a counting approach. From the second to fifth decile, the counting approach displays more economic insecurity than the rest of methods. On the contrary, simple mean and polyserial correlations PCA give more relevance to higher-income groups in comparison to other procedures. Thus, the counting approach method seems to be able to best capture insecurity levels in middle classes in comparison with other aggregation procedures that give more relevance to extreme situations.

All methods present strengths and weaknesses but a counting approach seems to be the most useful because it has a direct and straightforward economic interpretation and is not influenced by the way dimensions are defined or by outliers. In fact, we can conclude that both the simple mean and the PCA have some major drawbacks: both resulting indices do not have a direct economic interpretation and are very sensitive to the definition of insecurity dimensions. On the contrary, the individual index constructed using a counting approach can be interpreted as the number of weighted dimensions in which individuals lack security. Moreover, by weighting the dimensions by the share of individuals who lack (or do not lack) security allows for the introduction of a relative notion and captures the influence of the social context. The counting method also enables us to compute aggregate indicators such as the economic insecurity adjusted rate, which combines incidence and intensity and is decomposable by dimensions and by subpopulations.

Appendix

Table A1
DEFINITION OF INSECURITY DIMENSIONS

	Indicator	Variable	Description	Threshold
Subjective	D1	Incapacity to face unexpected expenses	Household cannot afford an unexpected required expense and pay through its own resources, meaning not asking for financial help, the account must be debited within the required period and the situation regarding potential debts is not deteriorated.	Household cannot face unexpected expenses (=1).
	D2	Financial dissatisfaction	Difference between lowest annual income necessary to make ends meet (to pay usual necessary expenses) and current household disposable income in relation to necessary income. This indicator has a value of zero when the difference is negative (disposable income is larger than needed income).	Household is financially dissatisfied (>0). Disposable income is smaller than necessary income.
	D3	Changes in ability to go on a holiday	Household's incapacity to afford one week away from home in the current period (t), while the household could afford this vacation the previous period (t-1).	Household cannot afford holidays in t while it was able in t-1 (=1).
Objective	D4	Income drops	Fall in household equivalised disposable income from one year (t-1) to another (t). This indicator takes a value of zero if this fall is smaller than 25% and current income is not below permanent income.	Household has a large income drop (<0).
	D5	Unemployment risk	Probability of unemployment (not finding a job or losing the current one).	Individual has a probability of unemployment above the society mean.
	D6	Probability of extreme expenditure distress	Probability of having at least two arrears in the following household payments: (1) mortgage or rent, (2) utility bills, (3) hire purchase instalments or other loans.	Individual has a probability of extreme expenditure distress above the society mean.

Source: Author's own elaboration based on longitudinal EU-SILC data set.

Table A2
SAMPLE OBSERVATIONS

Year	Interview 1	2	3	4	Total Frequency	Total Percentage
2008	9,279	0	0	0	9,279	3.64%
2009	8,802	9,692	0	0	18,494	7.26%
2010	8,159	9,191	8,892	0	26,242	10.30%
2011	7,165	8,566	8,241	7,914	31,886	12.52%
2012	6,773	8,192	7,904	7,645	30,513	11.98%
2013	6,410	7,960	7,423	7,208	29,002	11.39%
2014	6,732	7,881	7,447	7,040	29,100	11.42%
2015	6,995	7,966	7,760	7,340	30,062	11.80%
2016	6,356	7,817	7,754	7,409	29,336	11.52%
2017	0	7,119	6,933	6,757	20,809	8.17%
Total	66,672	74,383	62,354	51,314	254,723	

Source: Author's own elaboration based on longitudinal EU-SILC data set.

Table A3
CORRELATION BETWEEN INSECURITY DIMENSIONS

	D1	**D2**	**D3**	**D4**	**D5**	**D6**
D1	1					
D2	0.282	1				
D3	0.149	0.029	1			
D4	-0.118	-0.441	-0.040	1		
D5	0.295	0.206	-0.002	-0.110	1	
D6	0.441	0.394	0.002	-0.107	0.406	1

Notes: (1) We display Pearson correlation coefficients between insecurity dimensions. (2) D1 = Incapacity to face unexpected expenses; D2 = Financial dissatisfaction; D3 = Changes in the ability to go on a holiday; D4 = Income drops; D5 = Unemployment risk; D6 = Probability of extreme expenditure distress.

Source: Author's own elaboration based on longitudinal EU-SILC data set.

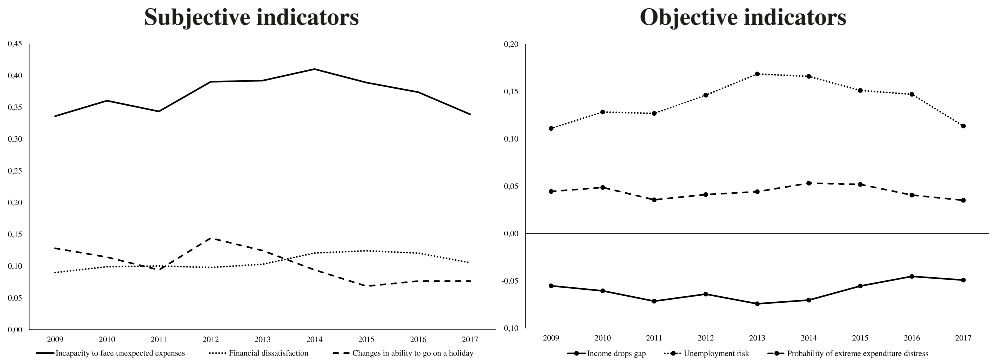
Table A4
INDIVIDUAL ECONOMIC INSECURITY DIMENSIONS - DESCRIPTIVE STATISTICS.

	Overall					Individuals affected	
	Mean	**Median**	**Standard deviation**	**Min**	**Max**	**Incidence**	**Mean**
Incapacity to face unexpected expenses	0.386 (0.001)	0	0.487	0	1	38.56%	—
Financial dissatisfaction	0.116 (0.001)	0	0.201	0	0.992	36.20%	0.303 (0.001)
Changes in ability to go on a holiday	0.078 (0.001)	0	0.269	0	1	7.82%	—
Income drops gap	-0.060 (0.001)	0	0.162	-0.985	0	12.96%	-0.441 (0.001)
Unemployment risk	0.143 (0.001)	0.053	0.212	0	0.936	—	—
Probability of extreme expenditure distress	0.039 (0.000)	0.015	0.060	0	0.610	—	—

Notes: (1) We present descriptive statistics of the dimensions of economic insecurity. The overall mean includes indicator values equal to zero. (2) Affected individuals are defined as those who do not have a value of zero in a certain insecurity dimension, and the incidence is calculated by dividing the observations of affected individuals by the total for each indicator. (3) We do not display statistics for affected individuals with regards to unemployment risk and extreme expenditure distress, as these dimensions are probabilities (we do not observe zero values), neither do we display the means of affected individuals for binary variables (incapacity to face unexpected expenses and inability to go on a holiday). (4) Bootstrap standard errors for the means are shown in brackets.

Source: Author's calculations based on longitudinal EU-SILC data set.

Figure A1
EVOLUTION OF SUBJECTIVE AND OBJECTIVE ECONOMIC INSECURITY DIMENSIONS



Source: Author's calculations based on longitudinal EU-SILC data set.

Notes

1. Article 25.1 of the Universal Declaration of Human Rights provides: "Everyone has the right (...) to security in the event of unemployment, sickness, disability, widowhood, old age or other lack of livelihood in circumstances beyond his control."

2. They measured the phenomenon using the same dimensions as in Rohde *et al*. (2015), although they used income volatility as an objective indicator instead of large income drops. To compute income volatility, Rohde *et al*. (2017) estimate a fixed effects model from which they extract the error component and use its square as an indicator of income risk. Rohde *et al*. (2016) added a level-and-change index of income dynamics, in line with the Bossert and D'Ambrosio (2013) measure.

3. For a detailed description of insecurity dimensions see Table A1 in the Appendix.

4. Changes in this indicator will reflect the perception of a strain in the household and individuals will save money allocated to holidays to cope with the uncertainty of a future economic loss (Deutsch *et al*., 2014).

5. This unemployment risk is calculated through a probit estimation with lagged explanatory variables for active individuals in the household. Then a household's unemployment probability computed as a weighted average of previous predicted probabilities is imputed to inactive individuals.

6. The probability of extreme expenditure distress is calculated with an ordered probit model at the household level. The dependent variable is an indicator from 0 to 3 counting a series of arrears. Subsequently, the probability of experiencing two or three of these overdue payments is computed and imputed to each member.

7. We normalise economic insecurity dimensions between zero and one by using the max-min transformation: $z_{ij} = \frac{x_{ij} - min(x_j)}{max(x_j) - min(x_j)}$, where z_i and x_i are normalised and actual outcomes for individual *i* and dimension *j*, respectively.

8. Economic security in Spain, as measured by the *IEWB Economic Security Index* (Osberg and Sharpe, 2005, 2014), dropped 17.9% between 1980 and 2014. This is a significantly different result to what has happened in other European countries, in which economic security either barely changed in that period or even increased.

9. All our income variables are referred to the previous calendar year, while other information is related to the year of the interview. We pool all waves from the longitudinal EU-SILC data set containing information from 2008 to 2017 and discard duplicated observations. Our sample is the Spanish version of the EU-SILC survey, the *Encuesta de Condiciones de Vida* (ECV) provided by the Spanish Statistical Office (INE). An individual can only be observed for a maximum of four consecutive waves due to the rotational design of the panel. Our nine-year window sample consists of an accumulation of waves from various years constructed with the four-wave panel of different individuals corresponding to different interview years.

10. Absolute economic insecurity indices by subpopulations are available upon request.

11. In order to check the external validity of our results for Spain we have also used information from another two big EU countries (UK and France). The main conclusions of our analysis hold: even though economic insecurity levels differ by country and method, the evolution and distribution of the phenomenon is robust to the aggregation and weighting procedure. Economic insecurity in France seems to be a structural phenomenon with little variation, even though we can observe a slight increase in 2013 and a subsequent decrease linked to economic recovery. The correlation of economic insecurity with the business cycle is stronger in the UK, where the increase in insecurity due to the Great Recession is larger. If we analyze results by income decile, insecurity decreases as we move to higher income deciles in both countries too whatever the aggregation method used.

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Resumen

La inseguridad económica es una dimensión relevante del bienestar. La escasez de encuestas sobre expectativas subjetivas hace a los índices multidimensionales basados en encuestas de condiciones de vida una alternativa valiosa. En este trabajo estudiamos las diferencias entre los indicadores sintéticos de inseguridad en España según el método de agregación y ponderación de las dimensiones. Los resultados indican que ni su evolución ni su distribución cambia, pero sí su nivel. El enfoque del conteo con una interpretación económica sencilla y capacidad para captar mejor la inseguridad en clases medias parece preferible a otros que dan más relevancia a situaciones extremas.

Palabras clave: inseguridad económica, medidas objetivas y subjetivas, correlaciones policóricas, enfoque del conteo, EU-SILC.

Clasificación JEL: D69, I39.