La versione definitiva è disponibile sul sito dell'editore:
https://link.springer.com/article/10.1007/s11205-018-1885-4

Carpita, M., Ciavolino, E. & Nitti, M. The MIMIC–CUB Model for the Prediction of the Economic Public Opinions in Europe. Soc Indic Res 146, 287–305 (2019). https://doi.org/10.1007/s11205-018-1885-4

The MIMIC–CUB Model for the Prediction of the Economic Public Opinions in Europe

Maurizio Carpita, Enrico Ciavolino & Mariangela Nitti

Abstract

To study the Europeans' perception on the economic conditions, a model that combine Multiple Indicators Multiple Causes (MIMIC) and Combination of Uniform and shifted Binomial (CUB) is proposed. The MIMIC–CUB Model, estimated at country-level using the Partial Least Squares, specifies the influence of the economic forecast news on a latent variable named "Citizens' perception of the European economics health state". The survey is related, at both national and EU level, to the period 2005–2014.

Introduction

Is there an effect of the forecasts news about European macro-economic conditions on the citizens' economic opinion? Based on this idea, this study aims to measure the extent to which public opinions about the current economic situation of the Europe, according to the Eurobarometer survey (European Commission 2014; Nissen 2014; Callens 2017), could be caused by the forecasts for the main macro-economic indicators referred to by 27 European Union (EU27) countries, as periodically observed by the National Statistics Offices. Many international researches have showed that news about the state of the economy affect citizens perception and psychological factors, that in turn have an impact on consumptions, savings and investment choices, retirement planning, and voting decisions (Hester and Gibson 2003; Hetherington 1996; Antonides and Sar 1990; Pruitt and Hoffer 1989). In Europe, citizens perception also affects policy support, that plays an important role within the integration process (Gabel and Palmer 1995; Serricchio et al. 2013; Braun and Tausendpfund 2014).

The statistical units of our study are the EU27 member states, and for each of them we collected data about 4 quantitative variables (the macro-economic forecast news) and 2 ordinal variables (the frequency distributions of citizens' opinions about the National and European economy) from 2005 to 2014.

From a statistical point of view, following Maltritz et al. (2012), our purpose is to develop a multivariate statistical model to describe, at an EU27 country-level, the relationship between directly observable variables such as macro-economic and public opinion indicators, moderated by one variable that is not directly observable (i.e. latent variable) such as the Citizens' perception of the European economics health state. To reach this goal, the Multiple Indicator Multiple Cause (MIMIC) Model is used (Goldberger 1972; Krishnakumar and Nagar 2008), with the feelings of the public opinion about the National and European economies for each of the EU27 country used as multiple indicators (i.e. dependent variables) obtained preliminarily using a Combination of Uniform and shifted Binomial (CUB) Model for the ordinal response items (D'Elia and Piccolo 2005).

The MIMIC Model has been used for many years and in many research fields: political analysis with structural equation modelling (Stapleton 1978), social risk factors detection extended to latent class analysis (MIMIC-LCA; Yang 2005), psychological tests in item response theory context (Woods 2009), educational science in multilevel framework (MIMIC-ML; Finch and French 2011; Kim et al. 2015). In macro-economic analysis, the field of our study, the MIMIC Model has been used by Maltritz et al. (2012) to model the country default risk, but their approach is rather different from ours. From the methodological point of view, they have used, as multiple indicators (dependent observed variables), the ratings provided by international agencies transformed into a numerical linear scale, whereas we have used the citizens' opinion, surveyed on the ordinal scale, transformed into a numerical one using the CUB Model; moreover, as multiple causes they have considered actual macro-economic indicators while we used forecasted indicators (i.e. bad/good news for the citizens). From a theoretical point of view, the dependence of the ratings on the macro-economic indicators is expected (the international agencies should use this data to fix their rates), whereas in our study the dependence of the citizen opinions on the forecasts for these macro-economic indicators is not so obvious; finally, our study considers the period from 2005 to 2014, while the study of Maltritz et al. (2012) refers to the pre-crisis period from 1994 to 2006.

As mentioned above, we used the CUB Model to obtain Maximum Likelihood (ML) estimates at the country-level of the citizens' feelings about the National and European economies. A similar approach applied in another research fields (university students' performance) is used by Bertaccini et al. (2013), that adopt the Item Response Theory (IRT) Model to quantify the multiple indicators of the MIMIC Model. Differently from the work of Bertaccini et al. (2013), that used a simultaneous approach, we adopt a two-step procedure.

The two-step procedure has some advantages: it can reduce the complexity of the model and the number of parameters to be estimated, and allows for the separation of reliability studies and more substantive research (Ciavolino et al. 2015).

In the first step of our procedure, the latent variables which measures the citizens' feelings, i.e. their opinion about both the National and the European economies, for the EU27 countries are estimated using the CUB Model; in the second step, the parameters of the MIMIC Model are estimated using the Partial Least Squares-Path Modelling (PLS-PM) approach.

Estimation of parameters of the MIMIC Model is typically based on the assumption of multivariate normality (Skrondal and Rabe-Hesketh 2004; Hand and Crowder 2005) and on the ML estimation method (Jöreskog and Goldberger 1975; Moustaki and Steele 2005), that has been recently generalized to the case of unobserved causal variables (G-MIMIC; Tekwe et al. 2016).

In our study we have preferred to use the PLS-PM approach since it does not require any distributional assumptions, it has the ability to deal with formative as well as reflective indicators, indicating PLS as appropriate for explorative analysis (Esposito Vinzi et al. 2010).

This study falls within the scope of the European Project SYRTO (Systemic Risk Tomography, syrtoproject.eu), aimed at creating an early warning system to identify potential threats to financial stability and create a combination of suggestions and prescriptions for the appropriate policy measures, governance structure and macro-prudential supervision to prevent, manage and resolve systemic crises in the Eurozone.

The paper is organized as follows. In Sect. 2 the MIMIC Model with the PLS-PM estimation algorithm and the CUB Model used to estimate the multiple indicators at the country level are presented. The collected datasets for the EU27 member states used in our analysis are described in Sect. 3, and, in Sects. 4 and 5, results obtained with the CUB Model and MIMIC Model respectively are presented. In Sect. 6 final considerations and suggestions for future research are reported.

The MIMIC–CUB Model

In this section the statistical approach used to study the dependence of the public opinions about the European economic situation on the forecasts for national macro-economic indicators is described. In Sects. 2.1 and 2.2 we present the MIMIC Model and the algorithm for the estimation of its parameters. Since the public opinions data used as dependent variables in the MIMIC Model is on an ordinal (Likert) scale, in Sect. 2.3 the CUB Model used for their transformation on the quantitative scale is described. As explained in the Introduction, to combine the two modelling approaches, we adopt a two step procedure: in the first step we enriched the mathematical property of the ordinal scale for multiple indicators by using the CUB Model and in the second step we link these enriched subjective variables to the macro-economic variables using the MIMIC Model.

The MIMIC Modelling Approach

The Multiple Indicators Multiple Causes (MIMIC) Model represents the relations between certain observed indicators or manifest variables (MVs) and certain unobserved constructs or latent variables (LVs), and consists of two sets of equations:

$$\boldsymbol{y} = \boldsymbol{\Lambda}\boldsymbol{\xi} + \boldsymbol{\epsilon} \tag{1}$$

$$\boldsymbol{\xi} = \boldsymbol{B}\boldsymbol{x} + \boldsymbol{\tau} \tag{2}$$

where $\boldsymbol{y}$ is a p-vector of the MVs (multiple indicators) of the r LVs in the vector $\boldsymbol{\xi}$; $\boldsymbol{x}$ is a q-vector of the MVs (multiple causes) of the r LVs in the vector $\boldsymbol{\xi}$; $\boldsymbol{\Lambda}$ and $\boldsymbol{B}$ are the matrices of coefficients that must be estimated; $\boldsymbol{\epsilon}$ and $\boldsymbol{\tau}$ are the disturbance terms.

By substituting Eq. (2) into Eq. (1) we obtain a reduced form regression model, where the multiple indicators $\boldsymbol{y}$ of the LVs $\boldsymbol{\xi}$ are the dependent variables and the multiple causes $\boldsymbol{x}$ are the independent variables:

$$\boldsymbol{y} = \boldsymbol{\Pi}\boldsymbol{x} + \boldsymbol{\zeta} \tag{3}$$

with $\boldsymbol{\Pi} = \boldsymbol{\Lambda}\boldsymbol{B}$ a (p, q) matrix and the p-vector $\boldsymbol{\zeta} = \boldsymbol{\Lambda}\boldsymbol{\tau} + \boldsymbol{\epsilon}$.

In our study, Eq. (1) links the $p = 2$ citizens' *feelings* about the National and European economic situation, the multiple indicators denoted by $\boldsymbol{y}$ obtained using the CUB Model (Sect. 2.3), to the unobservable *Citizens' perception of the European economics health state*, denoted with $r = 1$ LV ξ. Equation (2) models the dependence of $\boldsymbol{\xi}$ as a function of $q = 4$ macro-economic variables, the multiple causes denoted by $\boldsymbol{x}$. The graphical representation of our MIMIC Model is in Fig. 1.

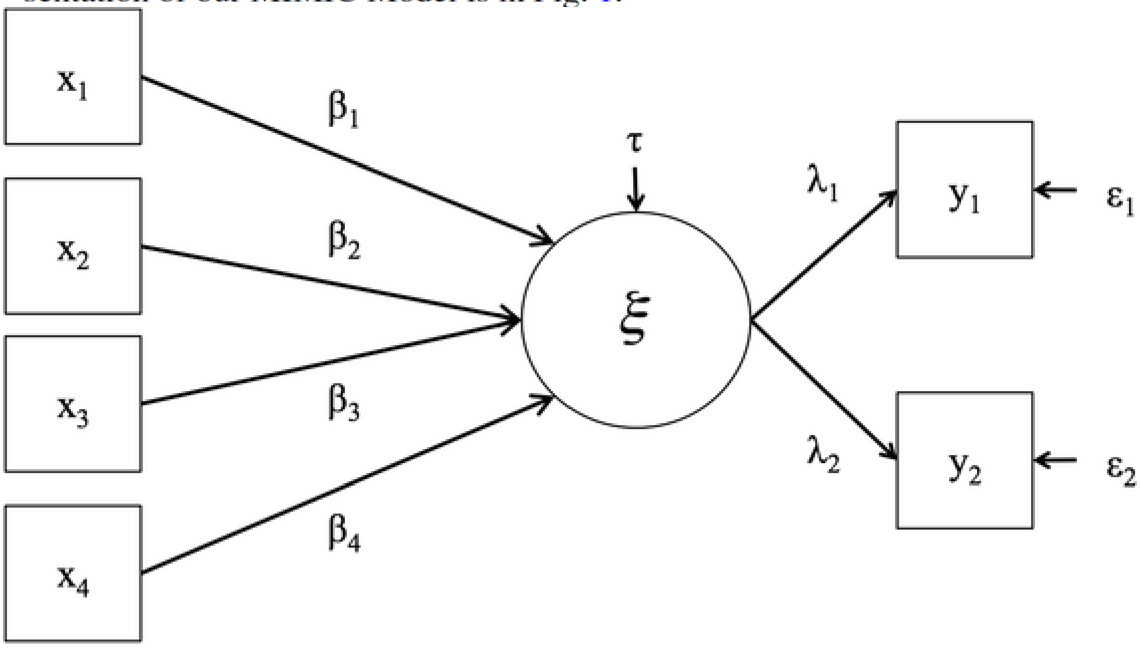

Fig. 1 The MIMIC Model with 2 multiple indicators (Y) and 4 multiple causes (X)

Some misconceptions about the MIMIC Model derive from its "formative" part in Eq. (2), represented by the left side of Fig. 1. As a matter of fact, this type of model has been proposed, as part of a covariance-based Structural Equation Model (SEM), as a tool for overcoming the specification problems arising from the estimation of purely formative constructs (Diamantopoulos and Winklhofer 2001): following this idea, the multiple indicators determine the latent variable; which receives its meaning from the former; some typical examples are socio-economic status, quality of life and career success (Diamantopoulos et al. 2008). Methodological literature recommends the use of the MIMIC Model in order to solve the inherent problems derived from the use of formative variables in empirical work (among others, Jarvis et al. 2003; MacKenzie

et al. 2005), with the result that this expedient is well established in the applied literature. The main criticisms of the use of the MIMIC Model are those pointed out by Lee et al. (2013), that can be summarized as follows:
1. The formative part of the MIMIC Model could provoke confusion of interpretation The meaning of the formative LV is provided by the endogenous (reflective) variables which it is intended to predict, rather than by the (formative) items which aim to measure it. In other words, the MIMIC Model does not provide a valid method for measuring a single focal LV by simultaneously using both reflective and formative indicators. Instead, it models the reflective construct ξ with the exogenous predictors x.
2. The loadings B which connect the formative indicators x to the LV ξ do not represent causal links Instead, they could merely be seen as weights expressing the contribution which, according to the researcher, each indicator provides to the formative construct. This statement is based on an ontological issue, which distinguishes between an LV that exists independently from its indicators (reflective scheme) and an LV that coincides with the indicators used to measure them (formative scheme) and whose meaning changes depending on the indicators used. For this reason, in the formative measurement, talking about causality is a mistake: MVs cannot cause something which does not have an autonomous existence.

In our opinion, the validity of the MIMIC Model stands if, instead of considering it as a formative LV model, is considered as a reflective LV model predicted by a set of causes. This work is based upon such a conceptualization: if, on the one hand, the perception of health of the European economy is not directly observable and the public opinions could constitute the pulse of such economic situation, on the other hand, a set of observable forecast of macro-economic indicators could represent a set of causes of the citizens economic perception. Following this idea, we aim at constructing a LV model with multiple indicators (citizens' feelings about the economy) and multiple causes (forecast of macro-economic indicators).

The PLS-PM Algorithm

In this study we use the Partial Least Squares-Path Modeling (PLS-PM) algorithm to estimate the parameters of the MIMIC Model. In the PLS-PM framework, this model-building procedure can be thought as the analysis of two conceptually different models. Whereas the measurement model indicates the relationships of the MVs with their LVs, the structural model indicates the causal relationships among LVs.

For the sake of simplicity, the estimation procedure will be described by means of the theoretical model represented in Fig. 2, that is a revised version of the model represented in Fig. 1, obtained using the standard path diagram and formulation of the PLS-PM.

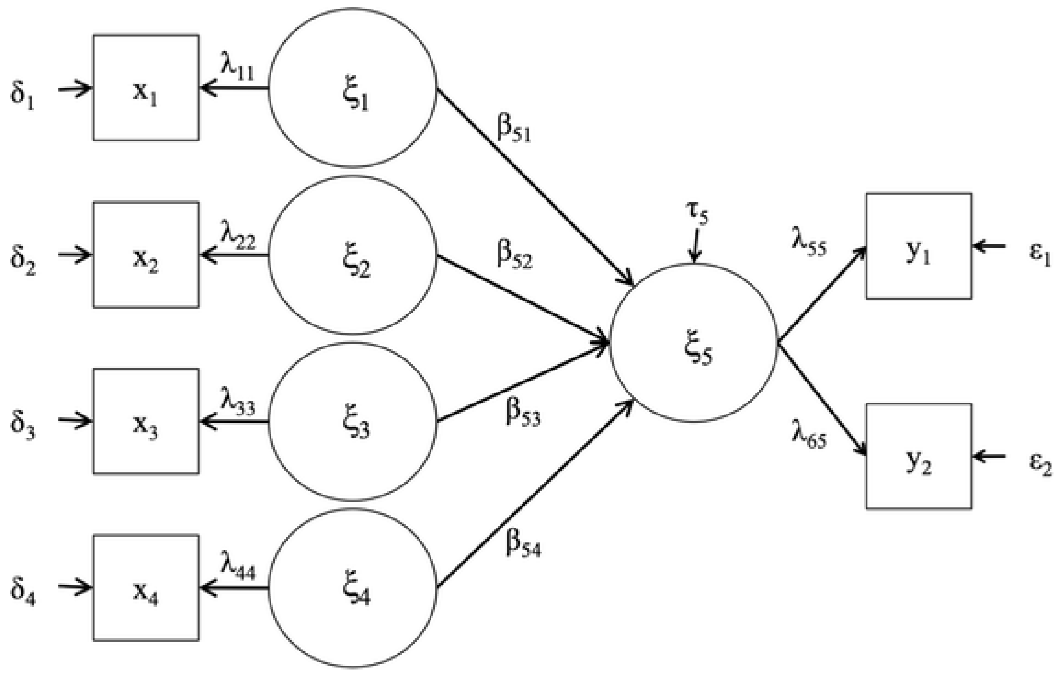

Fig. 2 The MIMIC Model in Fig. 1 with the PLS-PM notation

The 4 exogenous and 1 endogenous LVs can be formalized in a single vector as follows: $\boldsymbol{\xi} = (\xi_1, \xi_2, \xi_3, \xi_4, \xi_5)'$. Finally, the measurement model is defined as a single vector containing both the 4 exogenous and the 2 endogenous MVs $\boldsymbol{v} = (x_1, x_2, x_3, x_4, y_1, y_2)'$. In the end, the measurement error terms are reported in a single vector: $\boldsymbol{\varsigma} = (\delta_1, \delta_2, \delta_3, \delta_4, \varepsilon_1, \varepsilon_2)'$.

The matrix formulations for both structural (Eq. 4) and measurement (Eq. 5) model are reported below:

$$\begin{bmatrix} \xi_1 \\ \xi_2 \\ \xi_3 \\ \xi_4 \\ \xi_5 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ \beta_{51} & \beta_{52} & \beta_{53} & \beta_{54} & 0 \end{bmatrix} \begin{bmatrix} \xi_1 \\ \xi_2 \\ \xi_3 \\ \xi_4 \\ \xi_5 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ \tau_5 \end{bmatrix} \tag{4}$$

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} \lambda_{11} & 0 & 0 & 0 & 0 \\ 0 & \lambda_{22} & 0 & 0 & 0 \\ 0 & 0 & \lambda_{33} & 0 & 0 \\ 0 & 0 & 0 & \lambda_{44} & 0 \\ 0 & 0 & 0 & 0 & \lambda_{55} \\ 0 & 0 & 0 & 0 & \lambda_{65} \end{bmatrix} \begin{bmatrix} \xi_1 \\ \xi_2 \\ \xi_3 \\ \xi_4 \\ \xi_5 \end{bmatrix} + \begin{bmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \\ \delta_4 \\ \varepsilon_1 \\ \varepsilon_2 \end{bmatrix} \tag{5}$$

The model can be formalized using the following two equations:

$$\boldsymbol{\xi}_{(5,1)} = \boldsymbol{B}_{(5,5)}\boldsymbol{\xi}_{(5,1)} + \boldsymbol{\tau}_{(5,1)}$$
$$\boldsymbol{v}_{(6,1)} = \boldsymbol{\Lambda}_{(6,5)}\boldsymbol{\xi}_{(5,1)} + \boldsymbol{\varsigma}_{(6,1)}$$

Given that, in the MIMIC Model, the multiple causes are formalized by fixing $\xi_j = x_j$ with $j = 1, \ldots, 4$, and the consequences are that $\lambda_{jj} = 1$ and $\delta_j = 0$ with $j = 1, \ldots, 4$.

The parameters estimation (Ciavolino and Al-Nasser 2009; Ciavolino 2012; Esposito Vinzi et al. 2010; Wold 1975; Jöreskog and Goldberger 1975) follows a double approximation between the measurement and structural model, related to the $(4 + 2)$ MVs (multiple causes and indicators) of the $(4 + 1)$ LVs.

Using data, the external *measurement* estimate of $\boldsymbol{\xi}_j$, named $\mathbf{s}_j$, is obtained as the product of the block of MVs $\mathbf{V}_j$ (considered as the matrix units for variables) by the outer weights $\mathbf{w}_j$ (which represent the estimates of measurement coefficients, $\boldsymbol{\Lambda}$). The internal *structural* estimate, $\mathbf{z}_j$, is obtained as the product of the external estimate $\mathbf{s}_j$ and the inner weights $\mathbf{e}_{ji}$. The inner weights $\mathbf{e}_{ji}$ are defined through the correlations between $\mathbf{s}_j$ and the connected $\mathbf{s}_i$, with $i \neq j$. According to the hypothesized relationship between MVs and LVs, outer weights are computed as:

The PLS algorithm starts by initializing the first outer weight to one and zero the other for each LV; then, the parameters estimation is performed, until convergence, by iteratively computing:

1. *external estimation*, $\mathbf{s}_j = \mathbf{V}_j\mathbf{w}_j$;
2. *internal estimation*, $\mathbf{z}_j = \sum_{j\neq i} \mathbf{e}_{ji}\mathbf{s}_j$;
3. *outer weights estimation*, with Mode A or B.

The causal paths among LVs (the coefficients in the B matrix) may be obtained through the Ordinary Least Squares (OLS) method1

To evaluate the quality of the model, some indices are proposed in literature (Esposito Vinzi et al. 2010), as the communality index, the R2 and the goodness of fit (GoF) index. The communality index measures how much of the MVs variability in the jth block is explained by their own LV scores. In our MIMIC Model we have just one endogenous LV with two MVs, so the communality index for ξ_5 is defined as follows:

$$Com_{\xi_5} = \frac{1}{2}\sum_{i=1}^{2} Cor^2\left(y_i, \hat{\xi}_5\right) \tag{6}$$

with Cor being the linear correlation coefficient and $\hat{\xi}_5$ being the estimated score of the 5th LV.

The *GoF index* is defined as the geometric mean of the average communality and the average R^2 for endogenous LVs, ranging from 0 to 1.

$$GoF = \sqrt{\overline{Com} \cdot \overline{R^2}} \tag{7}$$

where $\overline{Com}$ is the average of the communalities (that measures the quality of the external model) and $\overline{R^2}$ is the average of the multiple coefficients of determination calculated for each endogenous LV, according to the exogenous LVs which explain it (that measures the quality of the inner model). In our MIMIC Model both $\overline{Com}$ and $\overline{R^2}$ are just Com_{ξ_5} and $R^2_{\xi_5}$, since we have just one endogenous LV ξ_5 and four exogenous LVs $(\xi_1, \ldots, \xi_4)$.

Recent studies have extended the application of the PLS-PM to the estimation of high-order LV models, to the resolution of formative second-order model identification issues as well as to the provision of qualitative external information (Ciavolino and Nitti 2013a, b; Nitti and Ciavolino 2014; Ciavolino et al. 2015).

The CUB Modelling Approach

Quantification of ordinal variables has a long history in methodological research, related to the nonlinear multivariate analysis (Gifi 1990; Carpita and Manisera 2012), and the CUB Model has been introduced in the statistical literature by D'Elia and Piccolo (2005) to analyse ordinal (rating or ranking) data.

With the CUB Model, data is modelled by a mixture of a Shifted Binomial and a discrete Uniform random variables. In practice, the observed rating r=1,…,m is a realization of the discrete random variable R with probability distribution:

$$Pr\{R = r|\pi, \theta\} = \pi \cdot Pr\{V(m,\theta) = r\} + (1-\pi) \cdot P\{U(m) = r\}$$

that is

$$Pr\{R = r|\pi, \theta\} = \pi \cdot \binom{m-1}{r-1}\theta^{m-r}(1-\theta)^{r-1} + (1-\pi)\cdot\frac{1}{m} \qquad r = 1, \ldots, m \tag{8}$$

To assess the goodness of fit of the CUB Model, a normalized in [0,1] *dissimilarity index* which compares *observed* f_r and *expected* $\hat{f}_r$ relative frequencies is used:

$$Diss = 1 - \frac{1}{2}\sum_{r=1}^{m} |f_r - \hat{f}_r|. \tag{9}$$

Obviously, lower values of the Diss index in equation (7) are preferable.

Several papers concerning CUB inferential issues, measures of fit and computational strategies have been published (see Iannario and Piccolo 2012, and the references therein)2. In addition, the CUB Models have been extended for use in several directions, for example to consider subjects' and objects' covariates, shelter effect (resulting in a very high frequency on a given response category), overdispersion, don't know responses in rating scales, and the possible presence of multimodal response distributions (Iannario 2012, 2014; Grilli et al. 2014; Manisera and Zuccolotto 2015). Many applications of CUB Models in different fields have also been proposed in the literature (Iannario 2012). Recent proposals of generalization of the CUB Models are the bivariate and multivariate extensions (Corduas 2014; Colombi and Giordano 2016), and the Nonlinear CUB (Manisera and Zuccolotto 2014). Recently, Oberski and Vermunt (2015) showed that the CUB Model can be represented as a restricted loglinear Latent Class Model.
In this study we estimate the feeling parameter y=(1−θ) of the CUB Model for each of the EU27 countries of the Eurobarometer survey data for each period from 2005 to 2014 (Sect. 3) to quantify two citizen opinions, about the National and European economies respectively (Sect. 4); these feelings are then used as multiple indicators in the MIMIC Model (Sect. 5). In the next section more information about the dataset used in this study is presented.

The European Economic Forecasts and the Eurobarometer Surveys

The data of the multiple causes of the MIMIC Model are referred to the 27 European Union (EU27) countries in the time-span from 2005 to 2014.
The four causal indicators xxxx on the right hand side of Eq. (2) of the MIMIC Model have been extracted from the Economic Forecast reports broadcasted by the Directorate General for Economic and Financial Affairs (DG ECFIN) on behalf of the European Commission3. The forecasts are usually released in winter (February), spring (May) and autumn (November). The chosen economic indicators are the following:

- x1 Gross domestic product per capita (GDP);
- x2 Unemployment rate (UNEMP);
- x3Harmonised Index of Consumer Prices (HICP);
- x4 Gross Debt, general government as % of GDP (DEBT).

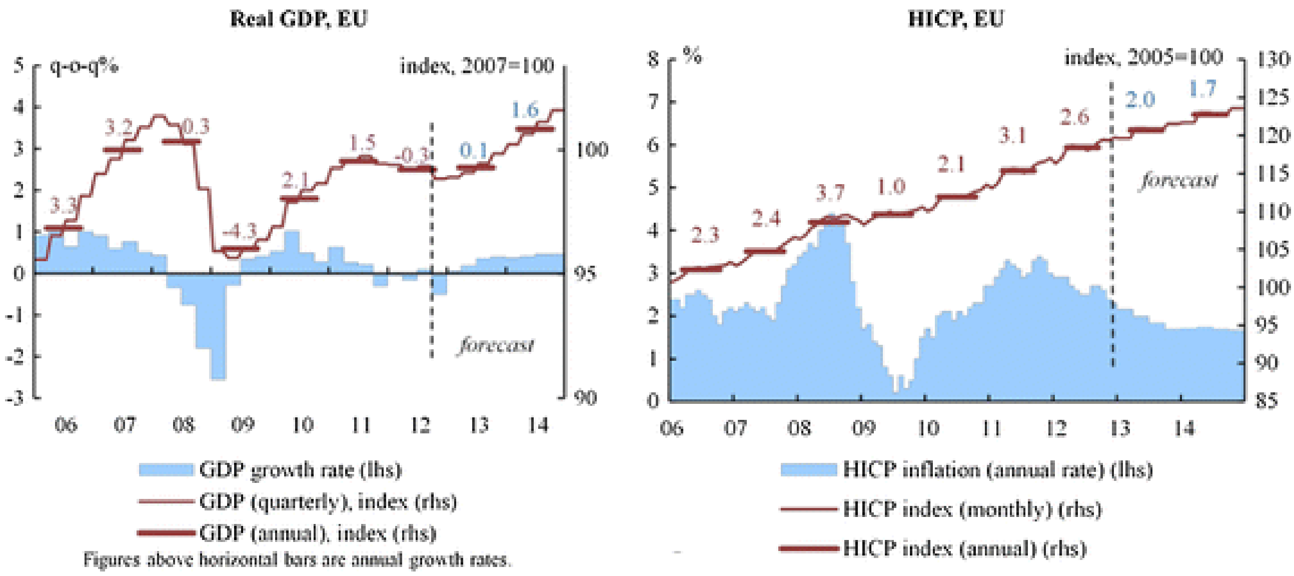

Fig. 3 Real GDP and HICP trends (2006–2012, actual data) and forecasts (2013–2014).
Source: European Commission—European Economic Forecast Report, Winter 2013

Each seasonal release reports forecasts extended for a time horizon of at least 2 years, in addition to the time-series of actual indicators of the previous years. Figure 3 has been taken from the Winter 2013 Forecast; it shows the GDP and HICP trends from 2006 to 2012 (actual data) and the forecasts for the period 2013–2014. On the left are displayed the real GDP quarter-on-quarter percentage change, while, on the right, there

are the harmonized index of consumer prices. For example, in 2014, consumer prices are forecast to increase by 1.7% in the EU.
The data of the multiple indicators y on the left hand side of Eq. (1) of the MIMIC Model are from the Standard Eurobarometer Project. The Eurobarometer survey was started in 1973 by the European Commission, consists of random multi-stage samples of approximately 1000 face-to-face interviews per member state (exceptions are Germany, UK and Luxembourg with 1500, 1300 and 500 interviews respectively) and reports are published twice yearly. History, methodological foundations and weaknesses of the largest European survey are well described by Nissen (2014), and many applications can be found in the research letterature (see for example the latest: Bottazzi et al. 2016; Djankov et al. 2016; Hobolt and Vries 2016; Hovi and Laamanen 2016; Dickes et al. 2010; Havasi 2013). The citizen opinions about the European economy have been measured by means of the following two questions from the Standard Eurobarometer survey, published in spring (usually in May) and autumn (November):
How would you judge the current situation in each of the following?

- y1 The situation of the (NATIONALITY) economy (NAT);

- y2 The situation of the European economy (EUR).

The data at the country-level was extracted using the Eurobarometer Interactive Search System from the website on public opinion surveys of the European Commission,4 choosing the sub-questions y1 and y2 in Step-1 for the question 54 and selecting all the regions and period with starting date 2005.06 and end date 2014.06.

Table 1 Standard Eurobarometer survey—spring 2014 (EB81) and autumn 2013 (EB80) Waves

"How would you judge the current situation of your national economy?"				
	EU28		Italy	
	EB81 Spring 2014	EB80 Autumn 2013	EB81 Spring 2014	EB80 Autumn 2013
Total good	34%	+ 3	5%	− 2
Total bad	63%	− 5	94%	+ 1
Don't know	3%	+ 2	1%	+ 1

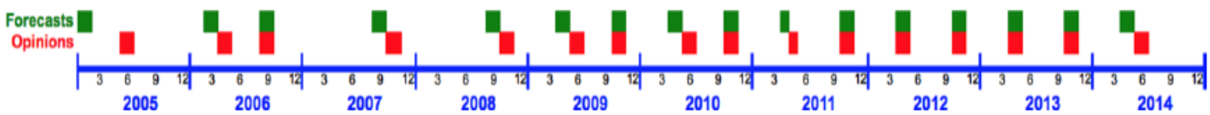

Fig. 4 Timing of *Forecasts* (European Commission) and *Opinions* (Eurobarometer)

Table 1 shows an example of this data: a comparison between EU28 citizens' and Italian citizens' answers to the question "How would you judge the current situation of your national economy?". The survey was conducted from the 31st of April to the 14th of June 2014; the answers are grouped as Total "good" and Total "bad".
The table shows the stark difference between Europeans and Italians perceptions: while only the 5% of Italians considers the national economic situation good, a much more positive perception is displayed by the EU28 citizens (34% of Total "good"). Furthermore, the EU28 citizens' judgement improved (++ 3%) with respect to the autumn 2013 survey, while the Italian perception get worse (− 2%).
Note that, in our study—which covers the period 2005–2014—we considered the EU27 country list: we excluded Croatia, which joined the EU as its 28th member state on 1st July 2013, and became part of the Standard Eurobarometer survey with the second wave of 2013.

For the MIMIC Model in Fig. 1 we assume that the economic forecasts (the measures or multiple indicators x's) are the causes of the effect defined as the citizens perception of the European Economic Health State (the construct or latent variable $\xi 5$), that in turn is the cause of the citizens opinion expressed in the Eurobarometer survey (y's). Following Edwards and Bagozzi (2000), causal relationship between constructs and measures requires that: (1) cause and effect are distinct entities; (2) cause occurs before effect; (3) association between cause and effect; (4) elimination of rival explanations.
For our Model condition (1) is satisfied, because x's are the observed macro-economic variables that are not the unobserved perception about the European economic health state and the observed citizens opinion. Condition (2) is also satisfied, as shows Fig. 4, that is the temporal synchronization of x's and x's: the economic forecast news are broadcast by media before or in the same period of the Eurobarometer survey results. In other terms, citizens perception and opinion of a period cannot influence the economic forecasts in the same period, but it can be that the latter can have effects on the first, as assumed by our MIMIC Model. As the construct $\xi 5$ is not observable, it's association with the multiple causes x'sx's required by condition (3) can be only inferred by using methods that do not rely on a direct observation: as suggested in general by Edwards and Bagozzi (2000), at the end of the next section we use the correlations among the x's and the multiple measures (feeling parameters) y's of the construct obtained using the CUB Model as indirect evidence of the association between the causes x's and the effect $\xi 5$. The (4) and last condition for causality in Edwards and Bagozzi (2000) is the most difficult to satisfy, because it implies the elimination of rival explanations for the presumed causal relationship of the construct from the economic forecasts: in our study rival explanations can be incorporated into the MIMIC Model, for example if it's assumed that the forecast news are proxies of the macro-economic and social conditions of the European member states.

Note that data is available for 16 periods, not for 2005-2, 2007-1 and 2008-1, because in these three periods the Eurobarometer survey was not performed. Furthermore, the analysis for 2005-1 is based on only 25 countries because, for this period, the Eurobarometer data for Bulgaria and Romania is missing.

Results of the CUB Model

In this section we present the results obtained by applying the CUB Model described in Sect. 2.3 to the data of the standard Eurobarometer Public Opinion survey carried out for each of the EU27 countries from June 2005 to June 2014.

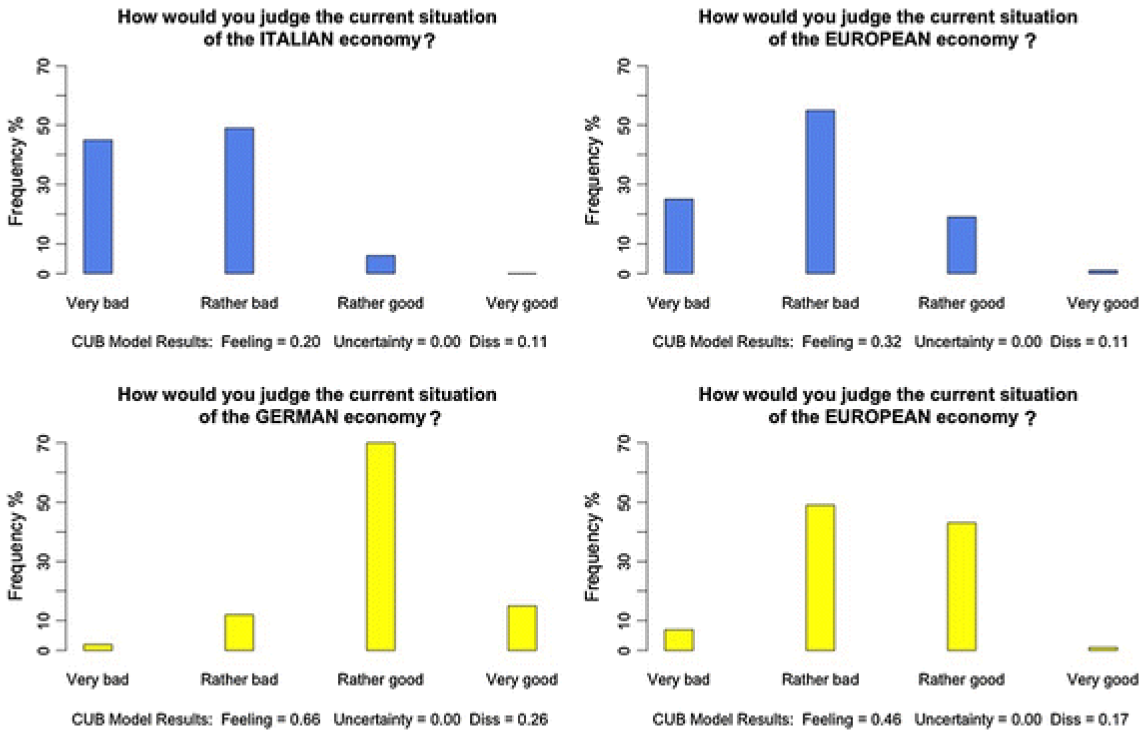

Fig. 5 Results of the CUB Model for Italy and Germany (Eurobarometer, June 2014)

Figure 5 shows two examples referring to the National and European economic situation as perceived by Italian (graphs above) and Germans (graphs below) citizens in June 2014 (the last period considered in this study). Under each frequency distribution of responses of each country relating to the four ordered categories (from Very "bad" to Very "good") there are estimates of the country feeling γ=(1−θ) and the country uncertainty (1−π) parameters of the CUB Model, together with the goodness of fit statistic Diss in Eq. (9) are showed.
It can be noted that the estimate of the country uncertainty parameter (1−π) is equal to zero in all four cases, indicating the absence of intrinsic uncertainty in choosing the ordinal response. These parameter estimates were insignificant and close to zero for both questions, for all countries and for all the periods considered: this is a good result, as the interpretation of a significative uncertainty parameter can be difficult to interpret Golia (2015).
Obviously, in this study we are interested in the feeling parameter γ=(1−θ), which is a measure of the citizen opinion about the economy: feeling estimates close to 0, indicate that citizens' opinion about the economic situation tends to be negative, while, estimates close to 1 indicate that the citizens' opinion of the economic situation tends to be positive.

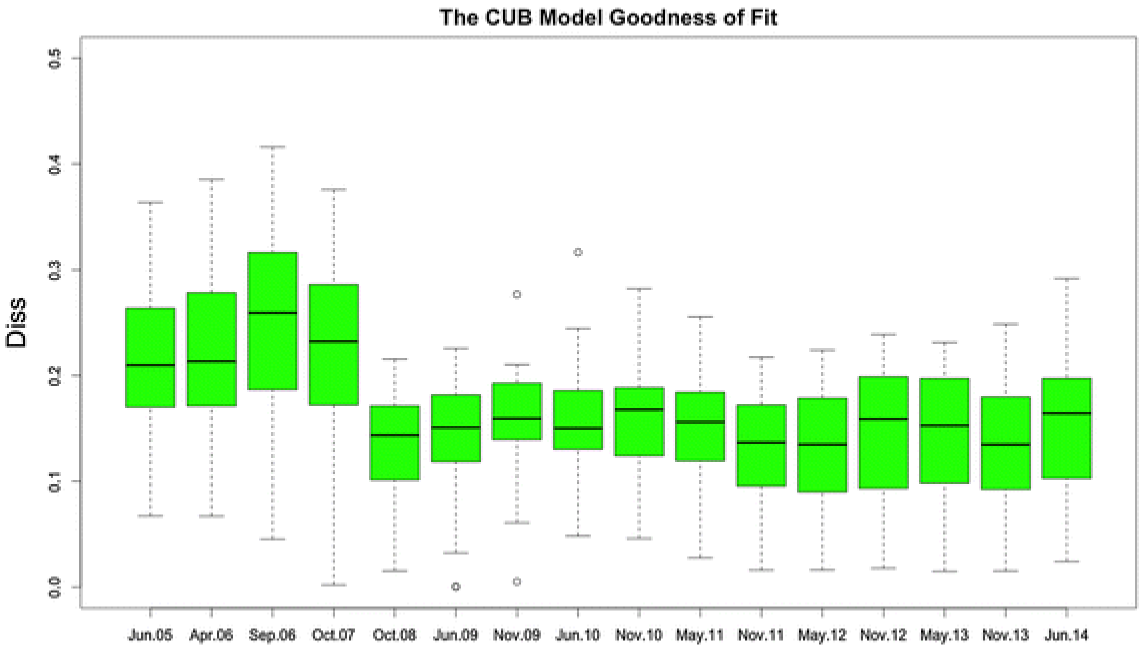

Fig. 6 Results of the CUB Model for the Diss index (Eurobarometer EU27 countries, June 2005–June 2014)
For the sample of Italian citizens, low values (0.20 and 0.32) of the feeling parameter indicate a negative opinion about the economic situation for their country and for Europe. Instead, for the sample of German citizens, high values of the feeling parameter (0.66 and 0.46 respectively) indicate a positive opinion about the economic situation for their country and for Europe.
To assess the goodness of fit of the CUB Model, we used the Diss index in Eq. (9): its values are low (0.11) for the sample of Italian citizens and slightly higher for the sample of German citizens (0.17) in the question for their country and 0.26 for Europe).
Figure 6 shows the distributions of the Diss index for the EU27 countries from June 2005 to June 2014: the goodness of fit of the CUB Model is lower until the beginning of the economic crisis (from June 2005 to October 2008, the median of the Diss index varies between 0.2 and 0.25, the third quartile is slightly above 0.3 and the maximum slightly greater than 0.4), while in recent years the model fit significantly improves (the median of the Diss index varies between 0.15 and 0.25, the third quartile does not exceed 0.2 and the maximum does not exceed 0.3).
As explained at the end of the previous section, with the two feeling parameters of the CUB Model estimated from the NAT and EUR frequency distributions for each European country we can indirectly assess the causal condition (3) of Edwards and Bagozzi (2000), i.e. the association between causes (the economic forecasts)

and effect (the citizens perception of the European Economic Health State) assumed by our MIMIC Model. In particular, we compute at the European country-level and for the two periods 2005–2008 and 2009–2014 the correlations, t statistics and p values between the 4 economic forecasts and the 2 estimated feelings of the CUB Models (Table 2): significance of these correlations gives evidence of statistical association between the multiple causes and the latent variable of the MIMIC Model.

Table 2 Correlations (with *t* stats and *p* values) between economic forecasts and estimated feeling parameters of the CUB Model at the European country-level for the periods 2005–2008 and 2009–2014

	GDP	UNEMP	HICP	DEBT
2005–2008				
NAT	− 0.041	− 0.493	− 0.386	− 0.314
t stat	− 0.601	− 8.205	− 6.073	− 4.790
p value	0.274	0.000	0.000	0.000
EUR	0.615	− 0.019	0.096	− 0.487
t stat	11.311	− 0.274	1.401	− 8.077
p value	0.000	0.392	0.081	0.000
2009–2014				
NAT	0.278	− 0.658	− 0.030	− 0.371
t stat	4.968	− 15.025	− 0.511	− 6.852
p value	0.000	0.000	0.305	0.000
EUR	0.212	− 0.240	0.082	− 0.605
t stat	3.724	− 4.253	1.411	− 13.042
p value	0.000	0.000	0.080	0.000

Note that this statistical evidence of correlation provides necessary but not sufficient support for the hypothesized causal relationship of the unobserved construct from the observed measures (Edwards and Bagozzi 2000), but with the fulfilment of the other three conditions discussed in the previous section, we are confident about the soundness of our MIMIC Model.

Results of the MIMIC Model

This section presents the results obtained with the MIMIC Model in Fig. 1 using the four macro-economic indicators described in Sect. 3 such as multiple causes x and the feeling of the CUB Model described in Sect. 4 as multiple indicators y for the EU27 countries from June 2005 to June 2014.

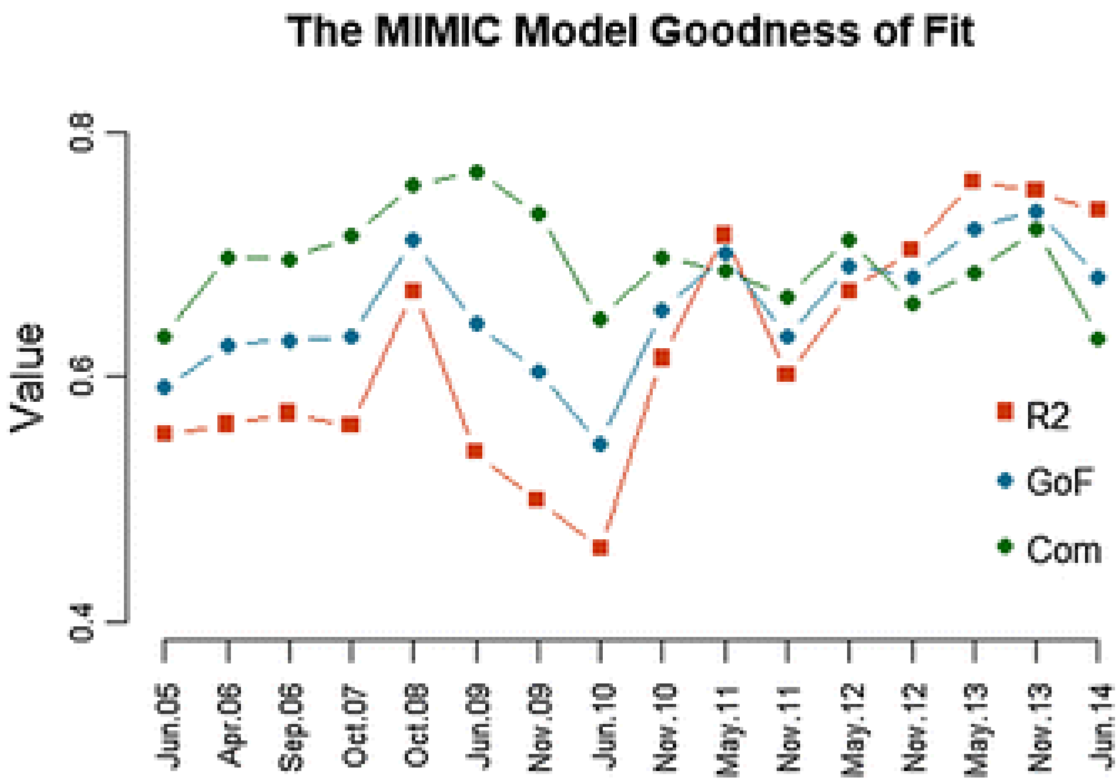

Fig. 7 *Results of the MIMIC Model for the R2R2, Com and GoF indices*

Figure 7 shows the goodness of fit statistics R2R2, Com and GoF (Eqs. 6, 7) for the MIMIC Model in the period considered. Whereas, up to 2008, the goodness of fit of the model is approximately 60%, from 2009 to 2010 (the year of the beginning of the global economic crisis), the goodness of fit decreases to about 40%; instead, in the subsequent years the MIMIC Model shows a significant improvement in its explanatory power so that, for the final year considered, the two indices are close to 80%. These statistical results support the idea that global crisis has made European citizens more sensitive to the macro-economic news.

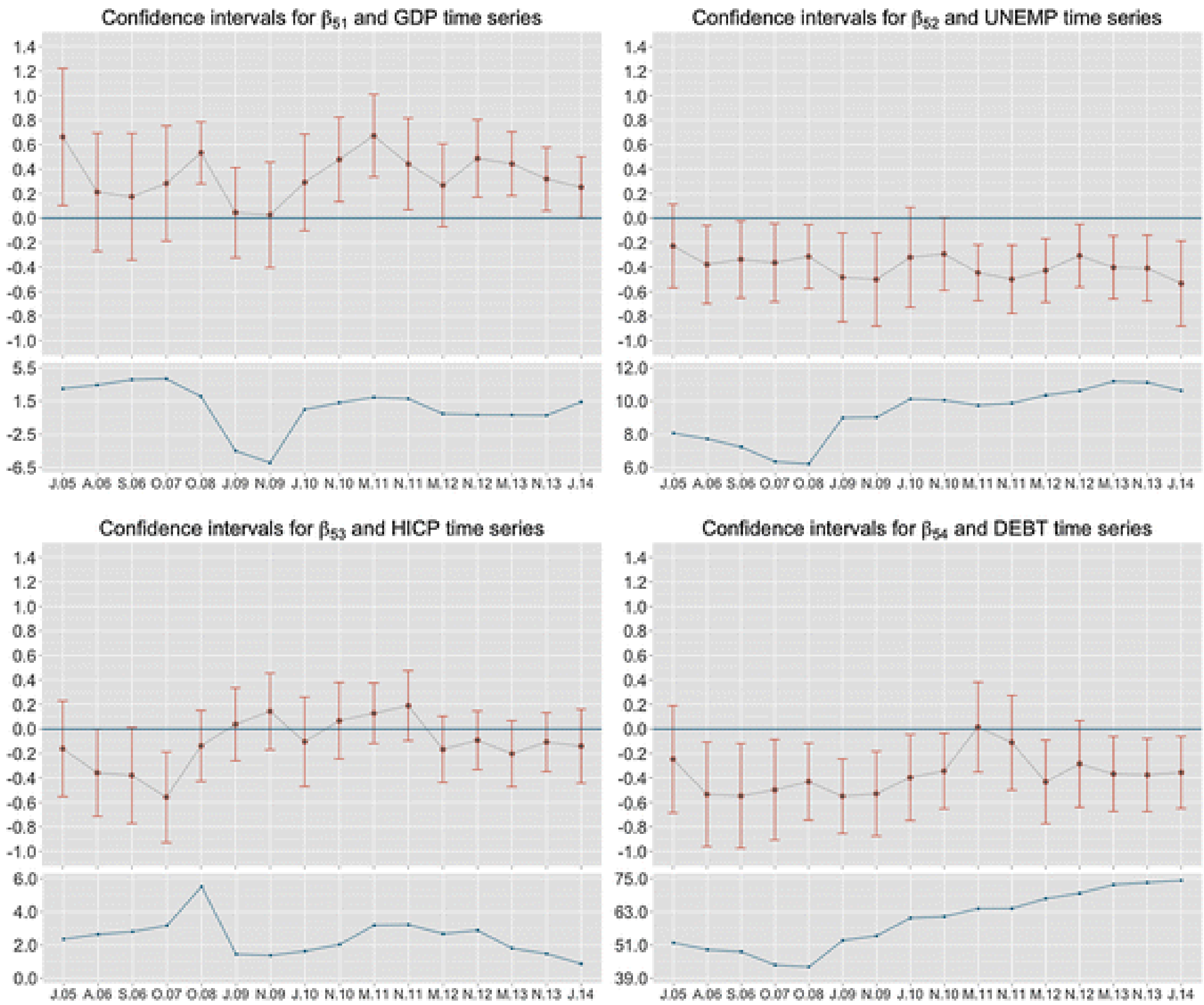

Fig. 8 *Path coefficient estimates (95% confidence intervals) for the forecast macro-economic indicators (multiple causes) of the MIMIC Model (Eurostat, June 2005–June 2014)*

Figure 8 shows the intervals at the 95% confidence level for the four parameters β51,…,β54 in Eq. (4) of the formative part of the MIMIC Model relative to forecast news of macro-economic indicators GDP, Unemp, HICP and Debt (multiple causes indicators) in the period from June 2005 to June 2014. Below the confidence intervals, the time series of the four indicators at the European level are reported. The estimates are generally significant, with the exception of some periods: 2009 for the GDP (only in correspondence with its lowest value) and 2011 for the other indicators. As expected, the estimated effect of GDP on the perception of the European economy health is positive, while the estimated effects on this latent variable for the other three macro economic indicators are negative. Clearly, during the last three years the dependency of the perception of the European economic health on the GDP seems to be reduced, while substantially stable for the three other macro-economic indicators.

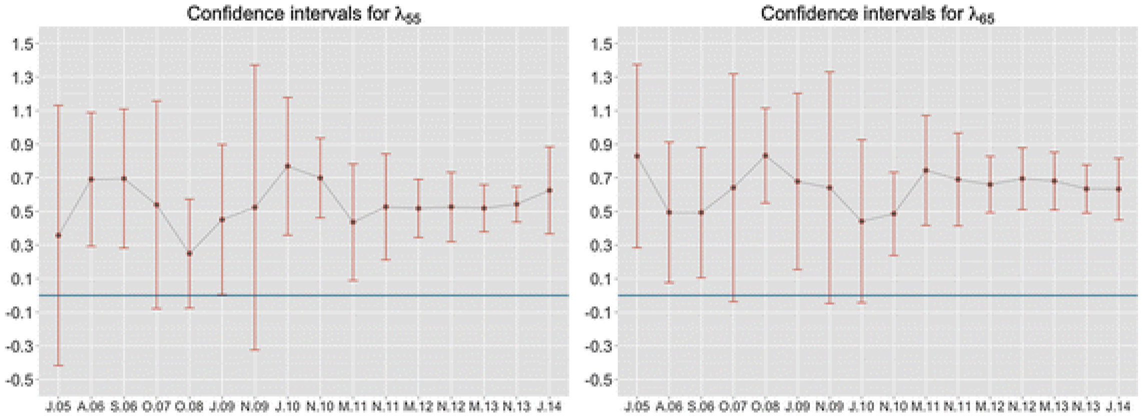

Fig. 9 *Path coefficient estimates (95% confidence intervals) for the citizen economic opinions (multiple indicators) of the MIMIC Model (Eurobarometer, June 2005–June 2014)*

Figure 9 shows the intervals at the confidence level of 95% for the two parameters λ55 and λ65 in Eq. (5) of the reflective part of the MIMIC Model, which represents the dependence of the LV ξ5—the Citizens' perception of the European economics health state—on the feelings of European citizens about National and European economic situation respectively, as obtained with the CUB Model using the Eurobarometer for the period 2005–2014. Almost all the estimates are significant, with the exception of June 2005 and November 2009, for the opinion about the National economy.

As expected, both estimates are positive: the improvement (worsening) of the European economic health perceptions have positive (negative) effect on the feelings of the European citizens. Finally, it is very clear the reduction in the amplitude of the confidence intervals occurred in recent years: in other words, with the protracted crisis, the opinions of the European citizens are increasingly sensitive to the LV ξ5.

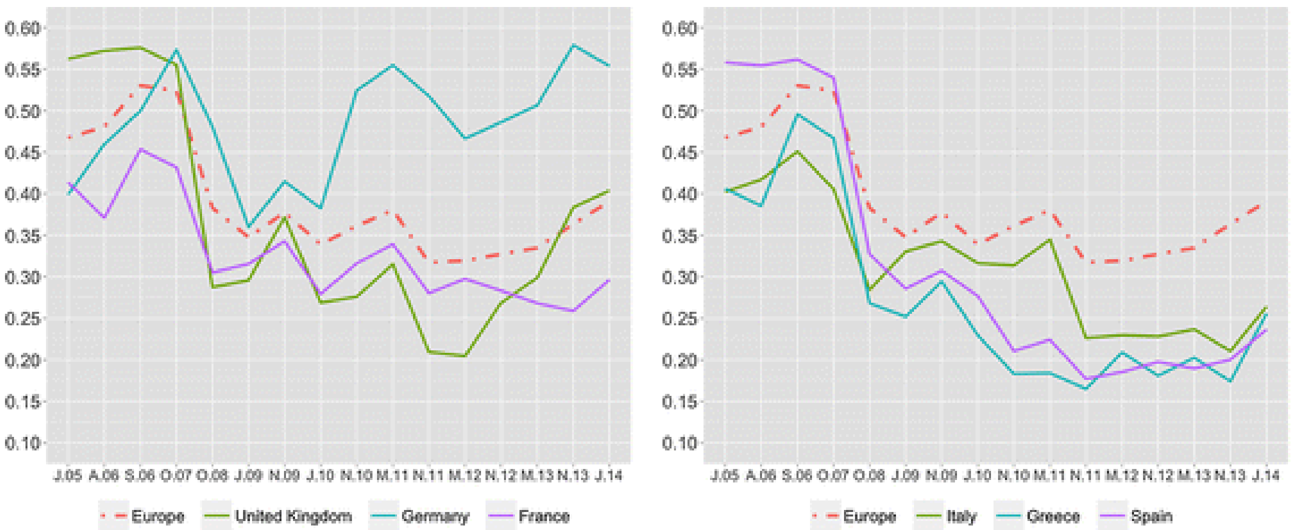

Fig. 10 *Citizens' perception of the European economics health state by country estimated with the MIMIC–CUB Model (June 2005–June 2014)*

Finally, with the estimate of the parameters λ, we can easily obtain an estimate of the LV Citizens' perception of the European economics health state. The PLS estimate of ξ5 for each country is the average of the two multiple indicators y1 and y2, weighted with the PLS estimates of λ1 and λ2 respectively, and can be used with others macro-economic indicators for economic analysis: increasing (decreasing) values of this estimate is a statistical evidence of a more positive (negative) perception of the citizens about the state of the health of European economics.

In Fig. 10, the estimate of ξ5 is recorded for six countries (on the left: United Kingdom, Germany and France; on the right: Italy, Greece and Spain) and for Europe (the average of the UE27 country estimates, weighted with the annual population size) for the period June 2005–June 2014). The European citizens' perception (dot-dash line) which was high (greater than 0.50) before the start of the economic crisis in 2008, decreases over time until 2012 (the minimum was 0.32), and increases in the final years (0.40 in June 2014). The graph on the left highlights the more positive perceptions about the state of the health of European economics among the German citizens, and the less positive perceptions of the citizens of France and United Kingdom (but for the second of these, the positive perception increased from 0.20 in 2012 to 0.4 in 2014). The graph on the right shows the reduction in positive perceptions (from more than 0.40 in 2006–2007 to less than 0.20 in 2011–2012) of the state of the health of European economics among the citizens of Italy, Greece and Spain (for this last country the indicator was greater than 0.55 before 2008 and drop to 0.15 in March 2011). For these three countries, we observe a weak trend-inversion in June 2014.

Conclusions and Future Research

In order to study the Citizens' perception of the European economics health state, we used the MIMIC Model with multiple indicators obtained using the CUB Model. This model allows us to measure the influence of the forecasts for the national macro-economic indicators on the Eurobaromenter Public Opinions survey for the economic situation, at both National and European EU27 country-level, for the period 2005–2014.
Our main results are the following:

- The CUB Model is a good way to quantify the feelings about the economic situation, as it gives easily interpretable results and its goodness of fit increases over the course of the period of study;
- The MIMIC Model is an effective representation of the causal relation between the forecasts (multiple causes) and the economic opinions (multiple indicators), via the latent variable Citizens' perception of the European economics health state;
- The goodness of fit and the parameter estimates of the MIMIC–CUB Model over the period 2005–2014 show the model's improvement in explaining the relationship between the forecasts for the macro-economic indicators and the citizens' opinion;
- The MIMIC–CUB Model allows us to obtain an estimate of the latent variable Citizens' perception of the European economics health state that can be used with the others macro-economic indicators for economic analyses.

Considered the interesting results of this analysis, we can evaluate two future advancements of our study:

- The extension of the study to include a dynamic MIMIC Model, with the specification of the time-dependent parametrization;
- The consideration of other macro-economic and public opinion simple or composite indicators.

Finally, we believe that this model is useful to monitor the European systemic risk and will hopefully be integrated into the main framework of the SYRTO Project (syrtoproject.eu).

Notes

We used the R package PLS-PM ver. 0.4.1 by Sanchez, Trinchera and Russolillo, available online at the url: https://cran.r-project.org/web/packages/plspm/index.html.

In our study we use the R functions CUB Models INFERENCE ver. 3.0 by Iannario and Piccolo, available online at the url: www.labstat.it/home/research/resourses/cub-data-sets-2/.

The full index of European Economic Forecasts is available at: http://ec.europa.eu/economy_finance/publications/european_economy/forecasts_en.htm.

Available at the url: http://ec.europa.eu/public_opinion/cf/index_en.cfm.

References

- Antonides, G., & Van Der Sar, N. L. (1990). Individual expectations, risk perception and preferences in relation to investment decision making. Journal of Economic Psychology, 11(2), 227–245.
- Bertaccini, B., Grilli, L., & Rampichini, C. (2013). An IRT-MIMIC Model for the analysis of university student careers. Journal of Methodological and Applied Statistics, 15, 95–110.

• Bottazzi, L., Da Rin, M., & Hellmann, T. (2016). The importance of trust for investment: Evidence from venture capital. Review of Financial Studies, 29, 2283–2318.
• Braun, D., & Tausendpfund, M. (2014). The impact of the euro crisis on citizens support for the european union. Journal of European Integration, 36(3), 231–245.
• Callens, M. (2017). Long term trends in life satisfaction, 1973–2012: Flanders in europe. Social Indicators Research, 130(1), 107–127.
• Carpita, M., & Manisera, M. (2012). Constructing indicators of unobservable variables from parallel measurements. Electronic Journal of Applied Statistical Analysis, 5(3), 320–326.
Ciavolino, E. (2012). General distress as second-order latent variable estimated through PLS-PM approach. Electronic Journal of Applied Statistical Analysis, 5(3), 458–464.
• Ciavolino, E., & Al-Nasser, A. D. (2009). Comparing generalised maximum entropy and partial least squares methods for structural equation models. Journal of Nonparametric Statistics, 21(8), 1017–1036.
• Ciavolino, E., Carpita, M., & Al-Nasser, A. (2015a). Modelling the quality of work in the Italian social co-operatives combining NPCA-RSM and SEM-GME approaches. Journal of Applied Statistics, 42(1), 161–179.
• Ciavolino, E., Carpita, M., & Nitti, M. (2015b). High-order PLS path model with qualitative external information. Quality & Quantity, 49(4), 1609–1620.
• Ciavolino, E., & Nitti, M. (2013a). Simulation study for PLS path modelling with high-order construct: A job satisfaction model evidence. In A. N. Proto, M. Squillante, & J. Kacprzyk (Eds.), Advanced dynamic modeling of economic and social systems (pp. 185–207). Berlin: Springer.
• Ciavolino, E., & Nitti, M. (2013b). Using the hybrid two-step estimation approach for the identification of second-order latent variable models. Journal of Applied Statistics, 40(3), 508–526.
• Colombi, R., & Giordano, S. (2016). A class of mixture models for multidimensional ordinal data. Statistical Modelling, 16(4), 322–340.
• Corduas, M. (2014). Analyzing bivariate ordinal data with cub margins. Statistical Modelling,. https://doi.org/10.1177/1471082X14558770.
• D'Elia, A., & Piccolo, D. (2005). A mixture model for preference data analysis. Computational Statistics and Data Analysis, 49, 917–934.
• Diamantopoulos, A., Riefler, P., & Roth, K. P. (2008). Advancing formative measurement models. Journal of Business Research, 61(12), 1203–1218.
• Diamantopoulos, A., & Winklhofer, H. M. (2001). Index construction with formative indicators: An alternative to scale development. Journal of Marketing Research, 38(2), 269–277.
• Dickes, P., Fusco, A., & Marlier, E. (2010). Structure of national perceptions of social needs across EU countries. Social Indicators Research, 95(1), 143.
• Djankov, S., Nikolova, E., & Zilinsky, J. (2016). The happiness gap in eastern europe. Journal of Comparative Economics, 44(1), 108–124.
• Edwards, J. R., & Bagozzi, R. P. (2000). On the nature and direction of relationships between constructs and measures. Psychological Methods, 5(2), 155.
• Esposito Vinzi, V., Chin, W. W., Henseler, J., & Wang, H. (2010). Handbook of partial least squares. Berlin: Springer.
• European Commission. (2014). Public opinion in the European Union. Standard Eurobarometer 81, Spring. European Commission. http://ec.europa.eu/public_opinion/cf/index_en.cfm. Accessed Oct 2015.
• Finch, W. H., & French, B. F. (2011). Estimation of MIMIC Model parameters with multilevel data. Structural Equation Modeling, 18(2), 229–252.
• Gabel, M., & Palmer, H. D. (1995). Understanding variation in public support for european integration. European Journal of Political Research, 27(1), 3–19.
• Gifi, A. (1990). Nonlinear multivariate analysis. Chichester: Wiley.
• Goldberger, A. S. (1972). Structural equation methods in the social sciences. Econometrica: Journal of the Econometric Society, 40(6), 979–1001.
• Golia, S. (2015). On the interpretation of the uncertainty parameter in CUB Models. Electronic Journal of Applied Statistical Analysis, 8(3), 312–328.
• Grilli, L., Iannario, M., Piccolo, D., & Rampichini, C. (2014). Latent class CUB Models. Advances in Data Analysis and Classification, 8(1), 105–119.

• Hand, D. J., & Crowder, M. J. (2005). Measuring customer quality in retail banking. Statistical Modelling, 5(2), 145–158.
• Havasi, V. (2013). Financial situation and its consequences on the quality of life in the EU countries. Social Indicators Research, 113(1), 17–35.
• Hester, J. B., & Gibson, R. (2003). The economy and second-level agenda setting: A time-series analysis of economic news and public opinion about the economy. Journalism & Mass Communication Quarterly, 80(1), 73–90.
• Hetherington, M. J. (1996). The media's role in forming voters' national economic evaluations in 1992. American Journal of Political Science, 40, 372–395.
• Hobolt, S. B., & de Vries, C. E. (2016). Public support for european integration. Annual Review of Political Science, 19, 413–432.
• Hovi, M., & Laamanen, J.-P. (2016). Mind the gap? Business cycles and subjective well-being. Applied Economics Letters,23, 1206–1209.
• Iannario, M. (2012). Modelling shelter choices in a class of mixture models for ordinal responses. Statistical Methods and Applications, 20, 1–22.
• Iannario, M. (2014). Modelling uncertainty and overdispersion in ordinal data. Communications in Statistics-Theory and Methods, 43(4), 771–786.
• Iannario, M., & Piccolo, D. (2012). CUB Models: Statistical methods and empirical evidence. In R. S. Kenett & S. Salini (Eds.), Modern analysis of customer surveys (pp. 231–258). New York: Wiley.
• Jarvis, C. B., MacKenzie, S. B., & Podsakoff, P. M. (2003). A critical review of construct indicators and measurement model misspecification in marketing and consumer research. Journal of Consumer Research, 30(2), 199–218.
• Jöreskog, K. G., & Goldberger, A. S. (1975). Estimation of a model with multiple indicators and multiple causes of a single latent variable. Journal of the American Statistical Association, 70(351a), 631–639.
• Kim, E. S., Yoon, M., Wen, Y., Luo, W., & Kwok, O.-M. (2015). Within-level group factorial invariance with multilevel data: Multilevel factor mixture and multilevel MIMIC Models. Structural Equation Modeling: A Multidisciplinary Journal, 22(4), 603–616.
Krishnakumar, J., & Nagar, A. L. (2008). On exact statistical properties of multidimensional indices based on principal components, factor analysis, mimic and structural equation models. Social Indicators Research, 86(3), 481–496.
• Lee, N., Cadogan, J. W., & Chamberlain, L. (2013). The MIMIC Model and formative variables: Problems and solutions. AMS Review, 3(1), 3–17.
• MacKenzie, S. B., Podsakoff, P. M., & Jarvis, C. B. (2005). The problem of measurement model misspecification in behavioral and organizational research and some recommended solutions. Journal of Applied Psychology, 90(4), 710.
• Maltritz, D., Buehn, A., & Eichler, S. (2012). Modelling country default risk as a latent variable: A multiple indicators multiple causes approach. Applied Economics, 44(36), 4679–4688.
• Manisera, M., & Zuccolotto, P. (2014). Modeling rating data with Nonlinear CUB Models. Computational Statistics & Data Analysis, 78, 100–118.
• Manisera, M., & Zuccolotto, P. (2015). Visualizing multiple results from nonlinear CUB Models with r grid viewports. Electronic Journal of Applied Statistical Analysis, 8(3), 360–373.
• Moustaki, I., & Steele, F. (2005). Latent variable models for mixed categorical and survival responses, with an application to fertility preferences and family planning in Bangladesh. Statistical Modelling, 5(4), 327–342.
• Nissen, S. (2014). The eurobarometer and the process of European integration. Quality & Quantity, 48(2), 713–727.
• Nitti, M., & Ciavolino, E. (2014). A deflated indicators approach for estimating second-order reflective models through PLS-PM: An empirical illustration. Journal of Applied Statistics, 41(10), 2222–2239.
• Oberski, D., & Vermunt, J. (2015). The CUB Model and its variations are restricted loglinear latent class models. Electronic Journal of Applied Statistical Analysis, 8(6), 374–383.
• Pruitt, S. W., & Hoffer, G. E. (1989). Economic news as a consumer product: An analysis of the effects of alternative media sources on the formation of consumer economic expectations. Journal of Consumer Policy, 12(1), 59–69.

- Serricchio, F., Tsakatika, M., & Quaglia, L. (2013). Euroscepticism and the global financial crisis. JCMS: Journal of Common Market Studies, 51(1), 51–64.
- Skrondal, A., & Rabe-Hesketh, S. (2004). Generalized latent variable modeling: Multilevel, longitudinal, and structural equation models. Boca Raton: CRC Press.
- Stapleton, D. C. (1978). Analyzing political participation data with a MIMIC Model. Sociological Methodology, 9, 52–74.
- Tekwe, C. D., Carter, R. L., & Cullings, H. M. (2016). Generalized multiple indicators, multiple causes measurement error models. Statistical Modelling, 16(2), 140–159.
- Wold, H. (1975). Path models with latent variables: The NIPALS approach. In Blalock, H. M. (Ed.), Quantitative Sociology (pp. 307–357). New York: Academic Press, INC.
- Woods, C. M. (2009). Evaluation of MIMIC-Model methods for DIF testing with comparison to two-group analysis. Multivariate Behavioral Research, 44(1), 1–27.
- Yang, C.-C. (2005). MIMIC latent class analysis model for alcoholic diagnosis. Structural Equation Modeling, 12(1), 130–147.