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On the Prediction of the Economic Public Opinions in Europe

Maurizio Carpita, Enrico Ciavolino, Mariangela Nitti

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Working Paper

On the Prediction of the Economic Public Opinions in Europe*

Maurizio Carpita†[a], Enrico Ciavolino[b], and Mariangela Nitti[c]

[a]*Department of Economics and Management, University of Brescia, Italy*
[b]*Department of History, Society and Human Studies, University of Salento, Italy*
[c]*Department of Engineering for Innovation, University of Salento, Italy*

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To study the *citizens' perception of the European economics health state*, the Multiple Indicators Multiple Causes (MIMIC) Model with multiple indicators obtained using the Combination of Uniform and shifted Binomial (CUB) Model is proposed. The MIMIC-CUB Model, estimated with the PLS algorithm, measures of the influence of the forecast news about the national macro-economic indicators on the Eurobarometer Public Opinions Survey about the economic situation are obtained, at both national and EU level, for the period 2005-2014.

keywords: MIMIC Model, CUB Model, macro-economic indicators, Eurobarometer Public Opinion Survey, Economic crisis.

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†Corresponding author: maurizio.carpita@unibs.it.

1 Introduction

Is there an effect of the forecast news about the European macro-economic conditions on the citizens' opinion about this economy? This study aims at measuring the extent to which public opinions about the current economic situation of the Europe as Eurobarometer survey (European Commission 2014; Nissen 2014), could be caused by the forecast news about the main macro-economic indicators referred to the 27 European Union (EU27) countries, as periodically detected by the National Statistics Offices.

From the statistical point of view, our purpose is to develop a multivariate statistical model for the description, at the EU27 country-level, of the relationship between directly observable variables such as macro-economic and public opinion indicators, moderated by a 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), with the *feelings* of the public opinion about the European economy for each of the EU27 country used as multiple indicators (i.e. dependent variables) obtained preliminarily using the Combination of Uniform and shifted Binomial (CUB) Model for ordinal response (D'Elia and Piccolo, 2005).

The MIMIC Model has been used by many years and in many research fields: political analysis with structural equation modelling (Stapleton, 1978), social risk factors detection with extension 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) for modelling 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 use their forecast (that are bad/good news for the citizens). From the theoretical point of view, the dependence of the ratings from the macro-economic indicators is expected (the international agencies should use these data to fix their rates), whereas in our study the dependence of the citizen opinions from the forecast of 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 said previously, we used the CUB Model to obtain estimates 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* (Oberski and Satorra, 2013): in the first step, the *feeling* latent variables for the EU27 countries are estimated with the CUB Model; in the second step, the parameters of the MIMIC Model are estimated considering the measurement error variances. 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 between reliability studies and more substantive research (Oberski and Satorra 2013; Ciavolino et al. 2015).

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 realize an ensemble of suggestions and prescriptions on 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 section 2 the MIMIC Model with the PLS-PM estimation algorithm and the CUB Model used to estimate the multiple indicators are presented. The collected datasets for our analysis are described in section 3, and in sections 4 and 5 the results obtained respectively with the CUB Model and MIMIC Model are presented. In section 6 final considerations and suggestions for future research are reported.

2 The MIMIC-CUB Model

In this section the statistical approach used to study the dependence of the public opinions about the European economic situation from the forecast of national macro-economic indicators is described. In subsections 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 are on the ordinal (Likert) scale, in subsection 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: at 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.

2.1 The MIMIC modelling approach

The Multiple Indicators Multiple Causes (MIMIC) Model has been introduced in econometrics by Goldberger (Goldberger, 1972) and subsequently formalized by many methodologists and implemented by researchers in various field of business, mainly in marketing and management (among others, Jöreskog and Goldberger 1975; Bagozzi 2011; Jarvis et al. 2003). The model represents the relations between some observed indicators or *manifest variables* (MVs) and some unobserved costructs or *latent variables* (LVs), and consists of two sets of equations:

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

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

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 Equation (2) in (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, Equation (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 (subsection 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 Figure 1.

Some misconception that often leads to the MIMIC Model comes from its "formative" part in Equation (2), represented by the left side of Figure 1. As a matter of

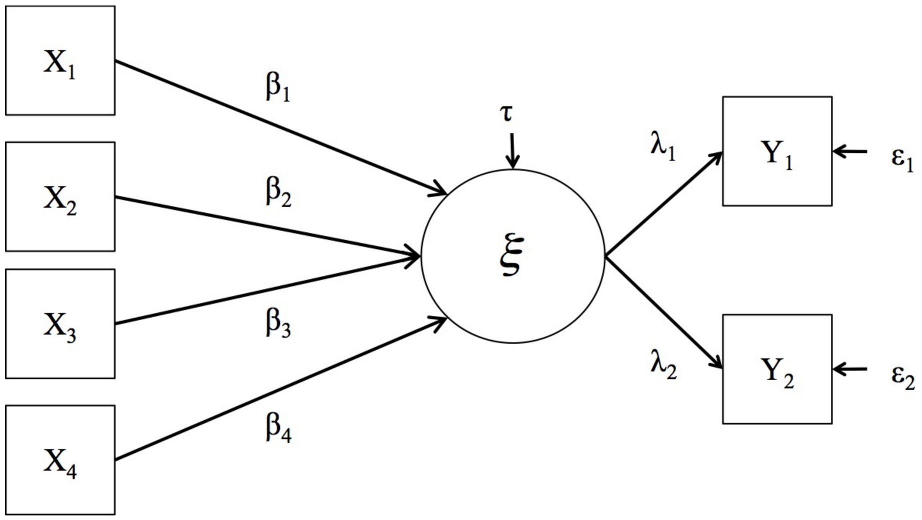

Figure 1: The MIMIC Model with 2 multiple indicators (Y) and 4 multiple causes (X)

fact, this type of model has been proposed, in the frame of 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). 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 and MacKenzie et al. 2005), with the result that this expedient is well established in the applied literature. The main criticisms to 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 interpretational confounding.* The meaning of the formative LV is given by the endogenous (reflective) variables which it predicts rather than by the (formative) items which aim at measuring it. In other words, the MIMIC model would not provide a valid method for measuring a single focal LV by simultaneously using both reflective and formative indicators. It rather models the reflective construct $\boldsymbol{\xi}$ with the exogenous predictors $\boldsymbol{x}$.

2. *The loadings $\boldsymbol{B}$ which connect the formative indicators $\boldsymbol{x}$ to the LV $\boldsymbol{\xi}$ would 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 among a LV that exist independently from its indicators (reflective scheme) and a LV that coincide 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 is not denied if it is not considered as a formative LV model, but rather 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' economic feelings) and multiple causes (forecast of macro-economic indicators).

2.2 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. While the *measurement model* specifies the relationships of the MVs with their LVs, the *structural model* specifies the causal relationships among LVs.

For the sake of the simplicity, the estimation procedure will be described through the theoretical model reported in Figure 2, by using the standard path diagram and formulation of the PLS-PM.

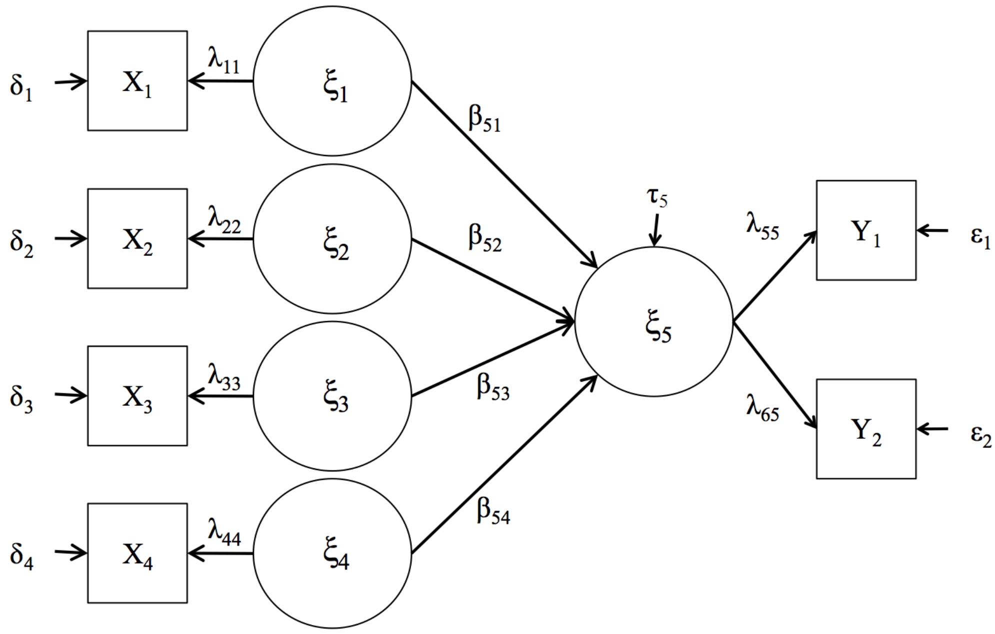

Figure 2: The MIMIC Model in Figure 1 with the PLS-PM notation

The 4 exogenous and 1 endogenous LVs can be formalized in a single vector as follow: $\boldsymbol{\xi} = (\xi_1, \xi_2, \xi_3, \xi_4, \xi_5)'$. 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 formulation for both structural (Equation 4) and measurement (Equation 5) model are reported below:

$$\begin{bmatrix} \xi_1 \\ \xi_2 \\ \xi_3 \\ \xi_4 \\ \xi_5 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ \beta_{51} & \beta_{52} & \beta_{53} & \beta_{54} & 0 \end{bmatrix} \begin{bmatrix} \xi_1 \\ \xi_2 \\ \xi_3 \\ \xi_4 \\ \xi_5 \end{bmatrix} + \begin{bmatrix} \tau_1 \\ \tau_2 \\ \tau_3 \\ \tau_4 \\ \tau_5 \end{bmatrix} \tag{4}$$

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

The model can be formalized by the two following equations:

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

Since 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:

$$\mathbf{w}_j = \mathbf{V}_j{}'\mathbf{z}_j$$

for Mode A (reflective relationship), and:

$$\mathbf{w}_j = (\mathbf{V}_j{}'\mathbf{V}_j)^{-1}\mathbf{V}_j{}'\mathbf{z}_j$$

for Mode B (formative relationship).

The PLS algorithm starts by initializing the first outer weight to one and zero the other per 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 $\boldsymbol{B}$ matrix) may be obtained through the Ordinary Least Squares (OLS) method[1].

To evaluate the quality of the model, some indexes are proposed in literature (Esposito Vinzi et al. 2010), like the communality index, the R^2 and the Goodness-of-Fit (GoF) index. The *communality index* measures how much of the MVs variability in the j^{th}

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

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 follow:

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

with Cor the linear correlation coefficient and $\hat{\xi}_5$ the estimated score of the 5^{th} 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 $(\xi_1, ..., \xi_4)$.

2.3 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 2011, 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 are modelled by a mixture of a Shifted Binomial and a discrete Uniform random variables. In practice, the observed rating $r = 1, \ldots, m$ is a realization of the discrete random variable R with probability distribution:

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

that is

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

with $\pi \in (0, 1]$, $\theta \in [0, 1]$. For a given m, $V(m, \theta)$ is a Shifted Binomial random variable, with trial parameter m and success probability $y = (1 - \theta)$, modelling the *feeling* component of a decision process, and $U(m)$ is a discrete Uniform random variable defined over the support $\{1, \ldots, m\}$, aimed to model the *uncertainty* component. The CUB Model is identifiable for $m > 3$ (Iannario, 2010). In terms of interpretability, $y = (1 - \theta)$ is the *feeling* parameter and measures the agreement with the object being evaluated, while $(1 - \pi)$ is the *uncertainty* parameter and measures the intrinsic uncertainty in choosing the ordinal response.

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, fitting measures and computational strategies have been published (see Iannario and Piccolo 2012, and the references therein)[2]. In addition, the CUB models have been extended in several directions, for

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

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 2014b). Many applications of CUB models in different fields have also been proposed in the literature (Iannario et al. 2012). A recently proposed generalization of the CUB models is the so-called Nonlinear CUB (Manisera and Zuccolotto 2014a). 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 $y = (1 - \theta)$ of the CUB Model for each of the EU27 countries of the Eurobarometer survey data for each period from 2005 to 2014 (section 3) to quantify two citizen opinions, about the National and European economies respectively (section 4); these *feelings* are then used as multiple indicators in the MIMIC Model (section 5). In the next section more information about the dataset used in this study is presented.

3 Data

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 $\boldsymbol{x}$ on the right hand side of Equation (2) of the MIMIC Model have been extracted from the Economic Forecast reports spread by the Directorate General for Economic and Financial Affairs (DG ECFIN) on behalf of the Commission[3]. The forecasts are usually released in Winter (February), Spring (May) and Autumn (November). The chosen economic indicators are the following:

- X_1 Gross domestic product per capita (GDP);

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

- X_2 Unemployment rate (UNEMP);
- X_3 Harmonised Index of Consumer Prices (HICP);
- X_4 Gross Debt, general government as % of GDP (DEBT).

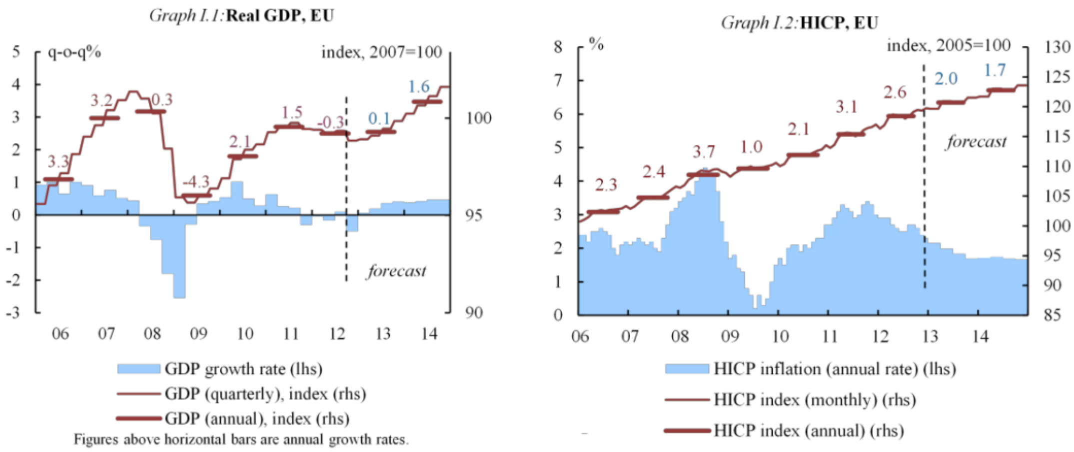

Figure 3: European Economic Forecast Report, Winter 2013 - GDP and HICP

Each seasonal release reports forecasts extended over a time horizon of at least two 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, the real GDP quarter-on-quarter percentage change while on the right the harmonized index of consumer prices, are drawn. As an example, in 2014 consumer prices are forecast to increase by 1.7% in the EU.

The data of the multiple indicators $\boldsymbol{y}$ on the left hand side of Equation (1) of the MIMIC Model are from the Standard Eurobarometer Project. It was established in 1973, each survey consists of approximately 1,000 face-to-face interviews per country, and reports are published twice yearly. The citizen opinions about the European economy have been measured through the following two questions from the Eurobarometer

Standard survey, published in Spring (usually in May) and Autumn (November):

How would you judge the current situation in each of the following?

- Y_1 The situation of the (NATIONALITY) economy;

- Y_2 The situation of the European economy.

The data were extracted with the Eurobarometer Interactive Search System from the website on public opinion surveys of the European Commission[4], choosing the sub-questions Y_1 and Y_2 in Step-1 for the question 54 and selecting all the regions and period with starting 2005.06 and final 2014.06.

Figure 4 shows an example of these data, a comparison between EU28 citizens' (outer pie) and Italian citizens' (inner pie) answers to the question "*How would you judge the current situation of your national economy?*". The survey was conducted from the 31^{th} of April to the 14^{th} of June 2014; the answers are clustered into the groups Total "*Good*" (in blue) and Total "*Bad*" (in red).
The graph underlines the stark difference between Europeans and Italians perception: while only the 5% of Italians considers the national economic situation good, a better perception emerges from 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, that joined the EU as its 28th member state on 1^{th} July 2013, and entered in the Standard Eurobarometer Survey with the second wave of 2013.

The following Figure 5 shows the temporal synchronization of the data, in way to use the macro-economic forecasts to predict the economic opinion: most of the times, the

[4]Available at the url: ec.europa.eu/public_opinion/cf/index_en.cfm.

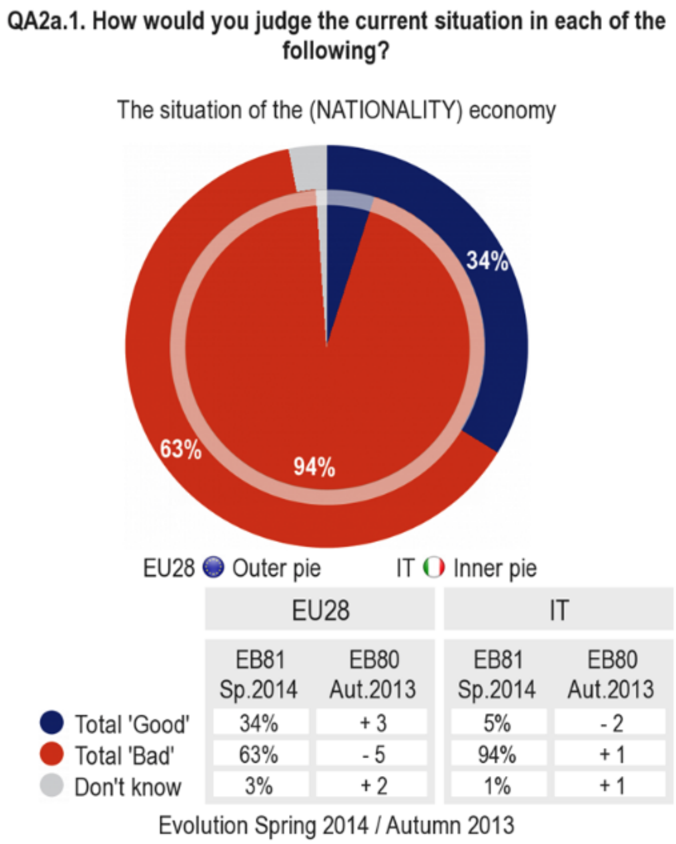

Figure 4: Standard Eurobarometer Survey - Spring and Autumn Waves

economic forecasts are spread immediately before the Eurobarometer survey. For some of the periods there is an overlap, as the Eurobarometer survey is conducted in the same days in which the economic forecasts are released.

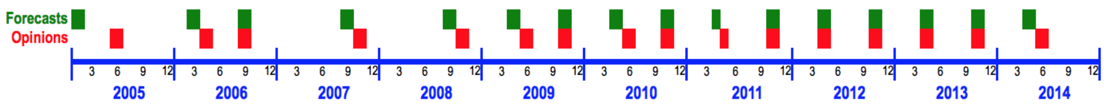

Figure 5: Timing of *Forecasts* (European Commission) and *Opinions* (Eurobarometer)

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

4 Results of the CUB Model

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

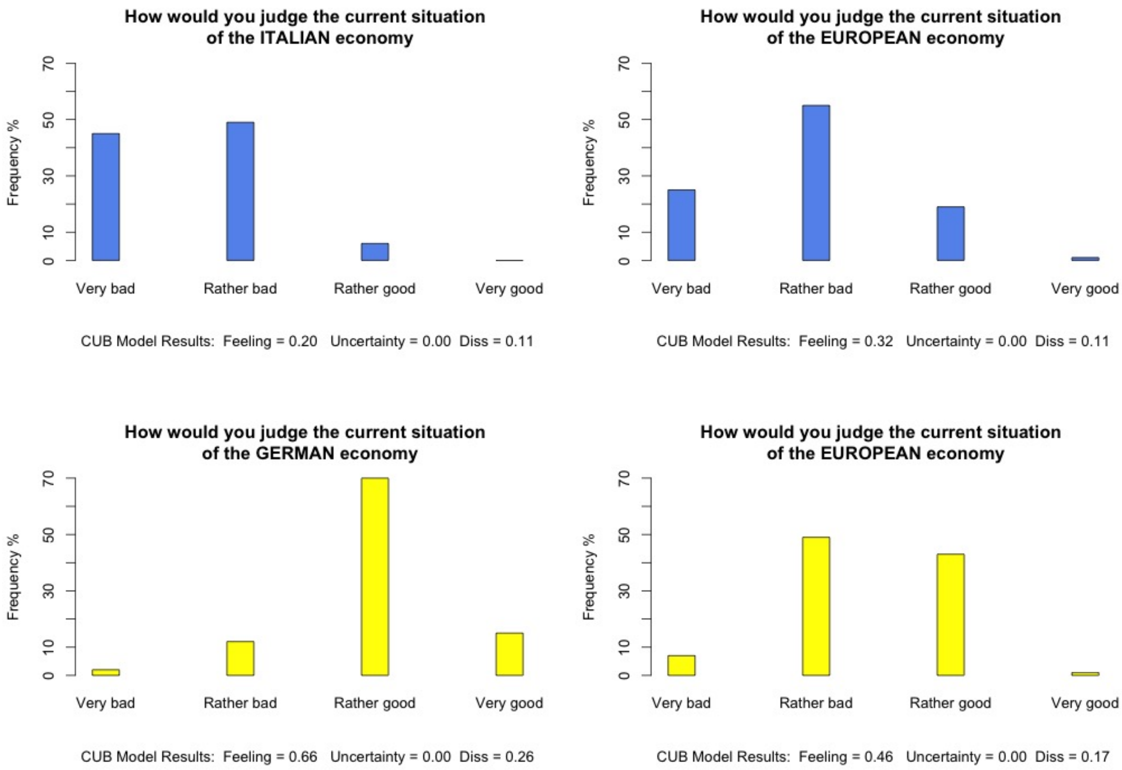

Figure 6: Results of the CUB Model for Italy and Germany (Eurobarometer, June 2014)

Figure 6 shows two examples referred to the National and European economic situation perceived by Italian (upper graphs) and Germans (lower graphs) citizens in June 2014 (the last period considered in this study). Under each frequency distribution of responses related to the four ordered categories (from Very "*bad*" to Very "*good*") the estimates of the *feeling* $y = (1 - \theta)$ and the *uncertainty* $(1 - \pi)$ parameters of the CUB Model, together with the goodness-of-fit statistic $Diss$ in Equation (9) are showed.

It is possible to notice that the estimate of the *uncertainty* parameter $(1 - \pi)$ is equal to zero in all four cases, indicating the absence of intrinsic uncertainty in choosing the ordinal response. These parameter estimates were not significant and close to zero for both questions, for all countries and for all the periods considered. Obviously, in this study we are interested in the *feeling* parameter $y = (1 - \theta)$, that 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 bad, while, estimates close to 1 indicate that the citizens' opinion of the economic situation tends to be good.

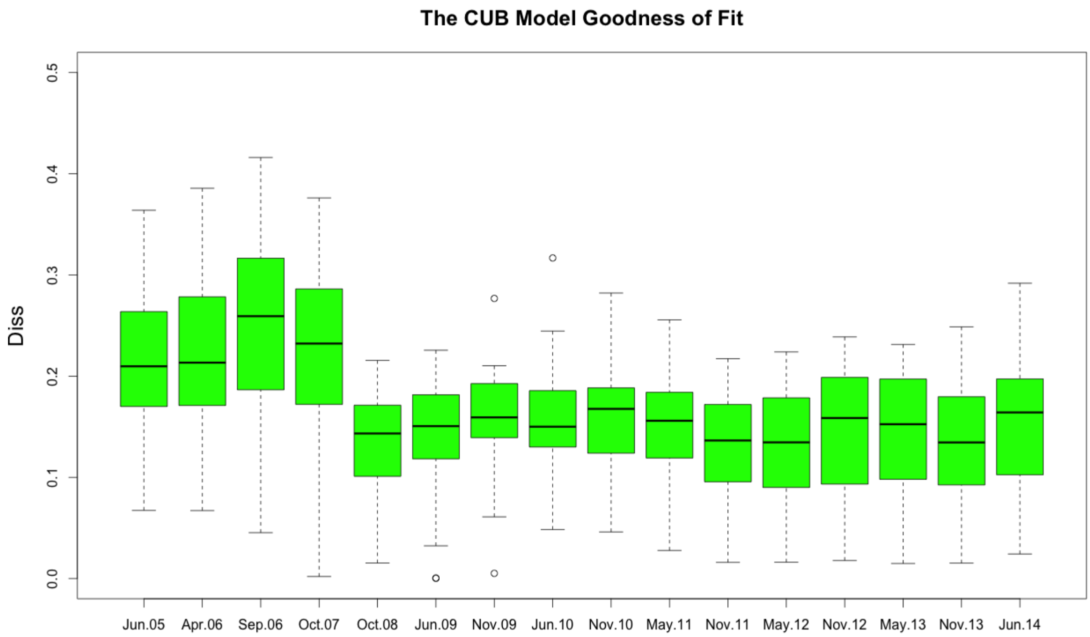

Figure 7: Results of the CUB Model for the $Diss$ index of goodness of fit (Eurobarometer EU27 countries, June 2005 - June 2014)

For the sample of Italian citizens, low values (0.20 and 0.32) of the feeling parameter indicate a bad 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 Equation (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 7 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).

5 Results of the MIMIC Model

This Section presents the results obtained with the MIMIC Model in Figure 1 using the four macro-economic indicators described in section 3 such as multiple causes $\boldsymbol{x}$ and the *feeling* of the CUB Model described in section 4 as multiple indicators $\boldsymbol{y}$ for the EU27 countries from June 2005 to June 2014.

Figure 8 shows the goodness-of-fit statistics R^2 and GoF (Equation 7) for the MIMIC Model in the period considered. Since until 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 last 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.

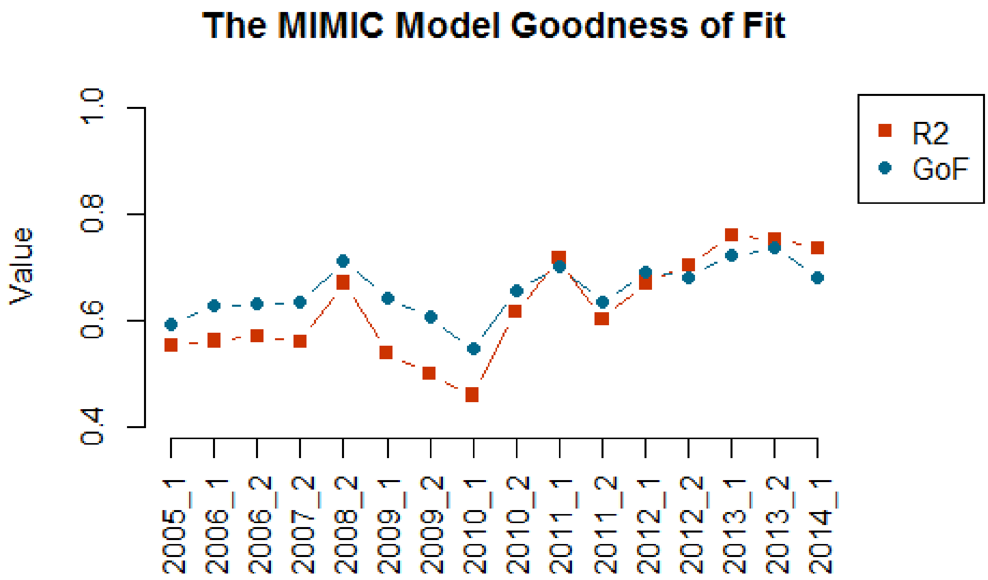

Figure 8: Results of the MIMIC Model for the R^2 and GoF goodness of fit indices

Figure 9 shows the intervals at the 95% confidence level for the four parameters $\beta_{51},...,\beta_{54}$ in Equation (4) of the formative part of the MIMIC Model related 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 (just in correspondence of 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.

Figure 10 shows the intervals at the confidence level of 95% for the two parameters λ_{55} and λ_{65} in Equation (5) of the reflective part of the MIMIC Model, which represents the

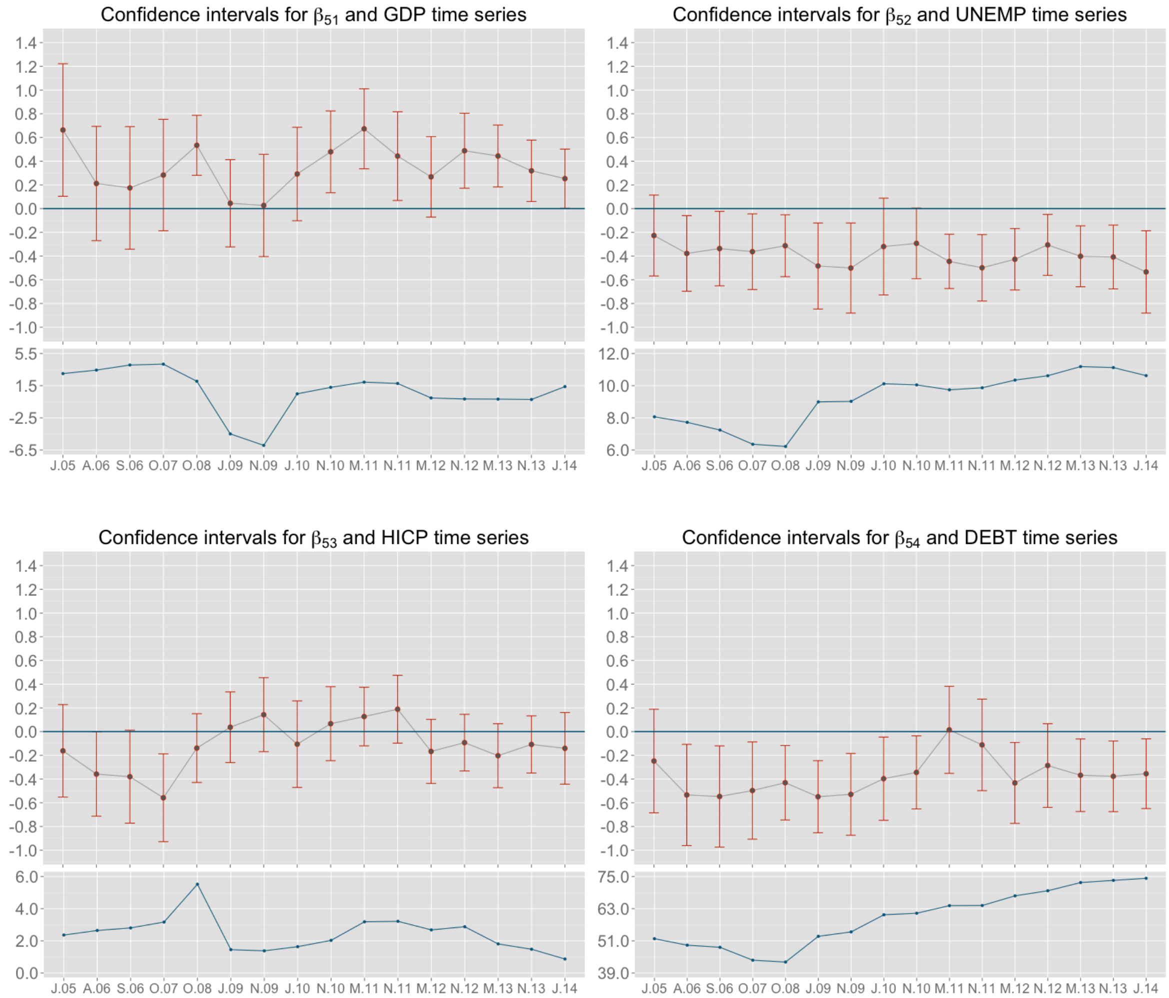

Figure 9: Path coefficient estimates (95% confidence intervals) for the forecast macroeconomic indicators (multiple causes) of the MIMIC Model (Eurostat, June 2005 - June 2014)

dependence from the LV ξ_5 - the *citizens' perception of the European economics health state* - of the *feelings* of European citizens about National and European economic situation respectively, as obtained with the CUB Model using the Eurobarometer data of 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 Euro-

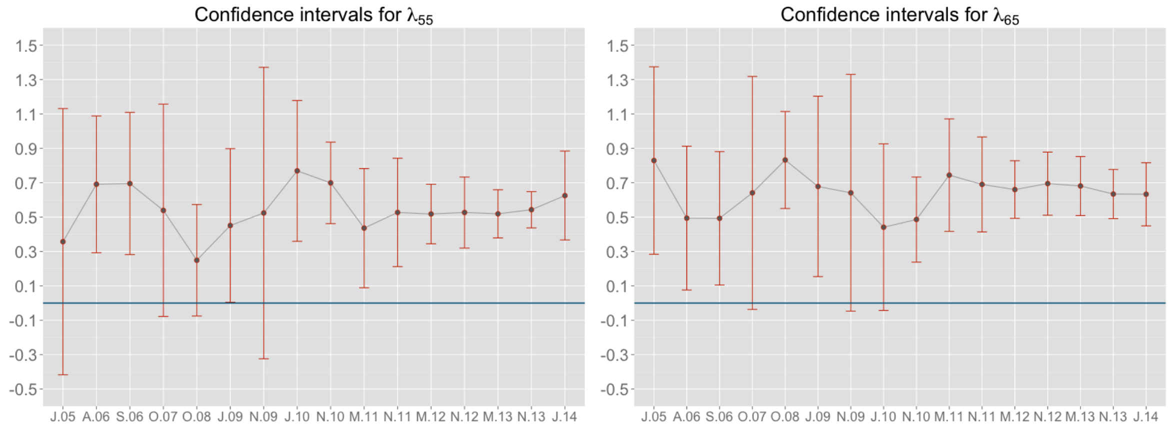

Figure 10: Path coefficient estimates (95% confidence intervals) for the citizen economic opinions (multiple indicators) of the MIMIC Model (Eurobarometer, June 2005 - June 2014)

pean 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 ξ_5.

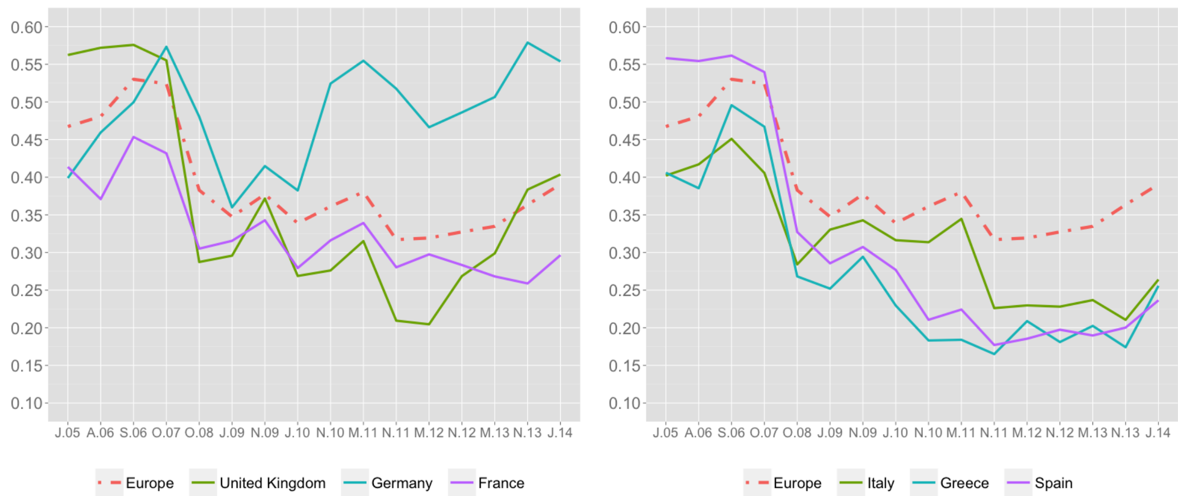

Figure 11: *Citizens' perception of the European economics health state* by country estimated with the MIMIC-CUB Model (June 2005 - June 2014)

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 ξ_5 for each country is the average of the two multiple indicators y_1 and y_2, weighted with the PLS estimates of λ_1 and λ_2 respectively, and can be used with others macro-economic indicators for economic analysis: increasing (decreasing) values of this estimate is a statistical evidence of more positive (negative) perception of the citizens about the European economics health state.

In Figure 11 the estimate of ξ_5 is represented 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) 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 last years (0.40 in June 2014). The graph on the left highlights the more positive perceptions about the European economics health state of the German citizens, and the less positive perceptions of the citizens of France and United Kingdom (but for this country the positive perception increased from 0.20 in 2012 to 0.4 in 2014). The graph on the right shows the decline of positive perceptions (from more than 0.40 in 2006-2007 to less than 0.20 in 2011-2012) about the European economics health state of the citizens of Italy, Greece and Spain (for this country the indicator was greater 0.55 before 2008 and goes down to 0.15 in March 2011). For these three countries we observe a weak trend-inversion in June 2014.

6 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 to measure the influence of the forecast news about 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 in the period;
- The MIMIC Model is an effective representation of the causal relation between the forecast news (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 of the macro-economic indicators and the citizens' opinion;
- The MIMIC-CUB Model allows 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 to 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).

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