Petar Sorić

Blanka Škrabić Perić

Marina Matošec

On the leading properties of Business and Consumer Surveys: new evidence from EU countries

SVEUČILIŠTE U ZAGREBU

On the leading properties of Business and Consumer Surveys: new evidence from EU countries

Petar Sorić
Faculty of Economics and Business, University of Zagreb
psoric@efzg.hr

Blanka Škrabić Perić
University of Split, Faculty of Economics, Department for Quantitative Methods
bskrabic@efst.hr

Marina Matošec
Faculty of Economics and Business, University of Zagreb
mmatosec@efzg.hr

Abstract

Ever since their initiation 60 years ago, the harmonized European Business and Consumer Surveys (BCS) have risen to the challenge of performing as a solid data pillar for quantifying leading indicators of economic activity. However, mainstream research mainly focuses on publicly available composite BCS confidence indicators and inspects their predictive accuracy. We depart from this stance by considering a battery of novel techniques for quantifying BCS-based leading indicators. We build upon the recently established weighted balance method, forecast disagreement, and surprise index. Additionally, we differ from the standpoint of rational expectations by introducing indicators of irrational sentiment and adaptive expectations, which have not previously been used in BCS studies of this sort. Our analysis in industry, consumer, and retail trade sectors of 28 European economies reveals that most of these novel techniques (especially irrational sentiment and adaptive expectations) produce more accurate predictions of economic activity than standard BCS benchmarks. These results are robust to several panel estimation procedures (heterogeneous panel Granger causality test and panel vector autoregressions, in particular).

Key words
Business and Consumer Surveys; Heterogeneous panel Granger causality; disagreement; irrational sentiment; adaptive expectations

JEL classification
C33; E32; E71

1. Introduction

Fourcade, Ollion and Algan (2015) have shown that academics from the field of economics tend to see themselves as dominant over other social scientists. Economists think other disciplines such as e.g. psychology cannot bring any added value to their methodological skills or their overall knowledge. However, the global financial crisis has vividly demonstrated that mainstream economic models are not able to adequately explain (let alone forecast) extreme events such as the abrupt economic downfall in 2008. (Macro)economists have responded by introducing latent psychological variables (such as perceptions and expectations of economic agents) in their analyses. The pivotal role in these efforts has been assigned to Business and Consumer Surveys (BCS).

The aim of BCS is to quantify economic agents' assessments of phenomena such as inflation, unemployment, the general economic climate in the country, as well as of specific variables related to their household or company. BCS are today fully methodologically harmonized on the EU level through The Joint Harmonized EU Programme of Business and Consumer Surveys, and are regularly conducted on a monthly basis in five sectors of each EU economy: the consumer sector, manufacturing industry, construction, services, and retail trade (European Commission, 2020). Since their introduction in 1961, they have "travelled" a long road to become an indispensable tool for macroeconomic analysis.

After 2008, the empirical literature on the role of economic sentiment in governing various forms of economic activity (in the vein of a self-fulfilling prophecy) has literally proliferated (see e.g. Eickmeier and Ng 2011; Bachmann and Sims 2012; Sorić 2018). With that in mind, it is no surprise that BCS data has recently been (mostly successfully) utilized for short-term forecasting of reference macroeconomic variables (Van Arle and Kappler 2012; Sorić et al. 2013; Claveria et al. 2018; 2019a; 2020) and stock market returns (Akhtar et al. 2010; Chen 2011), as well as for elucidating consumer expenditures and political attitudes (Nguyen and Claus 2013), etc. Despite the well-established usefulness of BCS in short-term macroeconomic predictions, quite a few empirical questions still remain unanswered. First of all, several methodological modifications of European BCS sectoral indicators have recently been proposed. The main goal of this paper is to empirically assess these state-of-the-art methods for extracting BCS-based confidence indicators and evaluate their predictive characteristics in comparison to conventional BCS leading indicators.

For instance, a research direction worth pursuing is the concept of *irrational* sentiment, i.e. the component of agents' economic sentiment not accounted for by fundamental economic variables (Baker and Wurgler 2006; Corredor and Santamaria 2015). The predictive accuracy of irrational sentiment may be considerably different than that of conventional BCS indicators, which will be scrutinized within this study.

Another methodological advancement is suggested by Claveria (2010), who introduces the *weighted balance* method, taking into account the percentage of BCS respondents expecting no change in the evolution of the targeted economic variable. Such methodological alternation may lead to a change in the predictive accuracy of BCS indicators, but this topic has not been extensively covered in the literature. As a third methodological twist, we consider a recent geometric indicator of agents' (dis)agreement (Claveria 2019; Claveria et al. 2019b).

We build on these three approaches, but we also construct novel sectoral BCS indicators derived from the idea of a surprise index (Scotti 2016), as well as a novel set of BCS indicators defined through the lens of the adaptive expectations algorithm (Cagan 1956; Nerlove et al. 1979; Pfajfar and Santoro 2010). The latter two concepts have never been empirically quantified, nor has their predictive accuracy ever been assessed, so they constitute one of the contributions of this paper.

Our second important contribution is a wide multisectoral perspective on the predictive accuracy of BCS indicators. We assess both monthly (industrial confidence) and quarterly (confidence in the retail trade and consumer sector) BCS data, covering all individual EU Member States. Relying on such unified methodology enables a straightforward comparison of the obtained results. This is particularly important because previous research efforts of this kind are limited in scope, meaning that they mainly focus on a limited number of countries (Bergström 1995; Hansson et al. 2005; Lemmens et al. 2005; Čižmešija and Sorić 2010), euro area as a whole (Gayer 2005), or only aggregate indicators of total economic activity (Bergström 1995; Hansson et al. 2005), instead of a disaggregated sectoral approach. The results of previous studies are thereby not directly comparable. In this sense, our research strategy resembles the most to Sorić et al. (2013), who apply a panel vector autoregression framework to 27 EU Member States and observe pronounced leading properties of BCS indicators, both in New and Old EU Member States.

Thirdly, we apply a panel version of the heterogeneous Granger causality test that works well for heterogeneous datasets and has good small sample properties even in the case of cross-

sectional dependence. Through such an estimation procedure, we avoid the trap of estimating a panel model and interpreting the obtained "on average" relationships as valid for each individual EU Member State. This is particularly important since previous studies of this kind neglect this issue (with the exception of Lemmens et al. 2005).

The paper is conceptualized as follows. Section 2 briefly reviews the recent research efforts aimed at enhancing the predictive properties of BCS indicators. Section 3 presents the methodological foundations of the utilized panel Granger causality framework. Section 4 pinpoints the main takeaways from the estimated panel models, while the final section concludes the paper and offers some directions for future work.

2. Recent advances in BCS analysis

When the 2008 world financial crisis enlightened the bitter truth about the inability of modern macroeconomic models to predict extreme events, economists were quite taken aback. Macroeconomic thought has consequently experienced a compelling shift based on some *new-old* ideas. The famous mid-crisis work of Akerlof and Shiller (2009), summoning Keynes's (1936) *animal spirits*, restored the notion of human psychology being the crucial driver of economic developments. Realizing that the economic system is not formed of a uniform set of fictional agents, particular importance has lately been attributed to the human factor in the economy. According to some novel trends, the field of economics seems to progressively strive to become an integral part of an interdisciplinary system that encompasses and strongly connects social sciences, such as psychology, sociology and media sciences. Behavioral elements are persuasively becoming the centerpiece of macroeconomic models in a fair amount of new research (e.g. Barsky and Simms 2012; Bachmann et. al 2013; Baker et al. 2016; Benhabib and Spiegel 2019; Shapiro et al. 2020).

An irreplaceable role in an efficient, yet utterly simple way of measuring economic sentiment is attributed to the BCS Programme. Although conceptually not new, BCS is a subject of continuous harmonization and methodological advances, with a particular goal to improve short-term forecasting and timely detection of business cycle turning points (European Commission 2020). To this end, a whole spectrum of BCS indicators has evolved to track economic agents' perceptions, assessments and expectations regarding a wide array of variables from their economic surrounding (e.g. financial situation of the household/firm, propensity to save/consume, general economic outlook in the country, inflation, unemployment, etc.). BCS provide a wide sectoral coverage by calculating individual

confidence indicators for construction, services, manufacturing industry, retail trade and consumers – the latter three being the pivotal sectors for our study.

The quantification procedure within BCS starts with calculating the seasonally adjusted balances of answers (B_t) to monthly/quarterly survey questions:

$$B_t = P_t - M_t \tag{1}$$

$$B_t = (PP_t + 0{,}5P_t) - (0{,}5M_t + MM_t) \tag{2}$$

where P_t is the percentage of respondents expecting a particular economic variable to increase in the future, and M_t is the percentage of those who expect the variable to fall. Equation (1) is commonly used for questions with three answer modalities (expected rise/fall/status quo), while Equation (2) is specifically used within consumer surveys, offering respondents three additional categories – highly optimistic (PP_t), deeply pessimistic (MM_t) and the "don't know" option.

Individual confidence indicators are calculated as unweighted arithmetic means of seasonally adjusted balances of chosen response balances. We consider three sectoral confidence indicators in this paper. Industrial Confidence Indicator (ICI) is calculated as the mean of response balances to questions related to the current order books, current stock of finished products, and the expected production level in the next 3 months (European Commission 2020: 18). Consumer Confidence Indicator (CCI) is conceptualized as the mean of response balances to questions on the financial situation of the household in the last and over the next 12 months, general economic situation in the following year, and the propensity to major purchases over the next 12 months (European Commission 2020: 19). Finally, the Retail Trade Confidence Indicator (RTCI) is designed as the average response balance of questions on sales in the past three months, current stock volume, and the expected sales in the following three months (European Commission 2020: 20). The results of these quantification procedures are usually considered to be (at least) one period ahead forecasts (leading indicators) for their reference macroeconomic series (Claveria 2010).

Although proven particularly useful in nowcasting and forecasting, the information contained in survey driven indicators have still not been used to their full potential. Hence, in the recent past, economic literature yielded several new modifications of the "classic" BCS indicators with characteristics yet to be more thoroughly investigated. Hereby we bring a short review of some new ideas in prediction-oriented BCS analysis.

a) *Weighted Balance Method*

Building on the notion that survey data necessarily entail measurement error due to converting unobservable expectations into quantitative expectation estimates, Claveria (2010) opts for a straightforward alternation of Equations (1) and (2). Presuming as well that the proportion of respondents who are neither optimists nor pessimists is quite high, he corrects the calculation of the BCS balance statistic by considering the proportion of respondents expecting economic variables to stay unchanged in the future. The new, weighted balance statistic (WB_t) is calculated by Equation (3):

$$WB_t = \frac{P_t - M_t}{P_t + M_t} = \frac{B_t}{1 - E_t} \tag{3}$$

where B_t is again determined as the difference of the percentage of respondents choosing an optimistic answer (P_t) and the percentage of pessimists (M_t). E_t is the percentage of respondents anticipating the variable of interest to remain constant.

The use of this novel balance statistic in different settings resulted in overall lower measurement and forecasting errors (Claveria 2010), proving that even the slightest correction of the standard balance statistic might be highly effective when aiming for more accurate predictions. To inspect if this is the case for the industry, consumer, and retail sector, we recalculate ICI, CCI, and RTCI using the weighted balance approach instead of the classic balance statistics presented in Equations (1-2).

b) *Surprise Index*

Another new sentiment-based economic indicator is brought by Scotti (2016). This real-time, real-activity indicator is termed *surprise index,* as its purpose is to point to economic data surprises, assessing how confident were agents about the economy *ex-post* in contrast to the actual data realizations. More specifically, the indicator is constructed to determine the deviation of forecasts (measured via Bloomberg median expectations) from the official releases of selected macroeconomic variables. Negative values of the surprise indexes, which indicate agents were more optimistic about the economy *ex-post*, are associated with the episodes of the Great Recession. On the other hand, positive values are related to post-crisis recovery periods, when actual numbers exceeded lowered expectations due to recession (Scotti 2016).

While proven to be a useful and applicable parsimonious measure of economic data surprises (addressing real agents' sentiment), the index could nevertheless be further modified by linking its background concept to BCS data. Namely, we propose an alternation in the surprise index (*sup$_t$*) quantification to be carried out relying explicitly on the BCS balance statistics:

$$sup_t = B_t^{BL} - B_{t|t-k}^{FL} \tag{4}$$

where B_t^{BL} is the balance of answers to backward-looking survey questions (answered in period *t*), regarding agents' perceptions of current and past economic developments. On the other hand, $B_{t|t-k}^{FL}$ is the balance of answers to forward-looking questions, measuring agents' expectations of future developments (formed in period *t-k* for period *t*).

In that manner, economic data surprises could be calculated only for the sectors with surveys containing both forward- and backward-looking questions concerning the same economic variable (specifically, manufacturing industry, retail trade and consumer sector). However, the gain with this modification is the possibility of its computation and comparison for all the EU countries, as well as getting the needed scope for a comprehensive forecasting exercise.

To be specific, the surprise index for the industry sector is obtained by applying Equation (4) on response balances for questions 1 and 5 in the industrial business survey (questions regarding actual production in the past three months and the expected production level in the next three months, respectively). By analogy, surprise index for the retail sector is calculated using responses from questions 1 and 4 for that sector (assessing the past and expected activity levels in the past/following three months). Finally, the European consumer survey comprises three pairs of backward-/forward-looking questions. The first two questions deal with past/future financial situation of the household, the third and fourth question refer to the past/future general economic situation, and the following two questions relate to aggregate price trends in the country. All stated questions are formulated for the period of last/next year. We apply Equation (4) in all three cases, and then extract the consumer version of surprise index as the arithmetic average of the results obtained in the first step (price trend result having a negative sign, implying a deterioration in economic climate).

c) *Disagreement Index*

A series of extreme and by all means unpredictable events in this millennium, such as terrorist attacks, world financial and debt crisis, Brexit and the recent COVID-19 pandemic has driven

a strand of authors to re-examine the economic uncertainty phenomenon (e.g. Bloom 2009, Baker et al. 2016, Baker et al. 2020). As from 2008, the literature is abundant with evidence of uncertainty negatively affecting developments on financial markets (Arellano et al. 2010), labor markets (Valetta and Bengali 2013), as well as goods and services markets (Knotek and Khan 2011). However, the question of truly reliable and unambiguous economic uncertainty measurement remains.

During the last decade, a quite popular uncertainty proxy stems from survey-driven data, such as BCS, as it is the only direct source of information on economic agent's expectations. This *ex-ante*-type uncertainty was introduced by Bachmann et al. (2013), who created the so-called disagreement measures of uncertainty, putting forward the dispersion (standard deviation) of response balances to forward-looking survey questions as a proxy for uncertainty. It was found that higher disagreement in expectations (of both managers and consumers) leads to larger forecasting errors. Given that uncertainty conditions are seen to inherently harden economic forecasting, the work of Bachmann et al. (2013) was later further upgraded (Rossi et al. 2016; Claveria et al. 2019; Claveria 2020).

Applying the geometric discrepancy indicator from Claveria et al. (2019) to determine the level of managers' and consumers' disagreement about future economic activity, inflation and employment, Claveria (2020) estimates the dynamic response of corresponding macroeconomic variables to innovations in disagreement. The quality of these disagreement-based uncertainty measures in foreseeing the macroeconomic series concerned is also assessed in an out-of-sample forecasting exercise for different time horizons. Although the results are somewhat mixed, they imply that more accurate economic growth predictions could be achieved with business managers' disagreement. This conclusion is also valid for unemployment predictions with consumer unemployment discrepancy and for all examined time horizons.

Our study aims to further scrutinize the predictive properties of disagreement-based indicators, using the discrepancy indicator (D_t) from Claveria et al. (2020) as a starting point:

$$D_t = 1 - \left[\frac{\sqrt{(P_t - 1/3)^2 + (E_t - 1/3)^2 + (M_t - 1/3)^2}}{\sqrt{2/3}} \right] \qquad (5)$$

with P_t, M_t, and E_t denoting the same as in Equation (3).

To ensure comparability of results, we apply Equation (5) to response balances of all forward-looking questions that were utilized in the calculation of surprise indices: expected production

level in the following three months for the industrial sector, expected activity level in the next three months for the retail sector, as well as consumers' expectations on the financial position of the household, general economic situation, and price trends in the following year. Since consumers respond to three forward-looking questions in this setting, we extract consumer disagreement as the arithmetic average of these three discrepancies obtained through Equation (5).

d) *Irrational Sentiment*

Departures of expectations from the official economics statistics evoke another aspect of cognition that orthodox macroeconomic theories are not (entirely) valid. Views on agents' expectation formation and decision-making processes have certainly changed, meaning that economic agents are no longer considered fully informed and perfectly rational utility maximizers (Lagunoff and Schreft 1999; Sorić et al. 2020). Although the term *bounded rationality* was introduced by Simon (1957) long ago, shortcomings of the rationality concept became quite pronounced with the progress of behavioral economics, pointing that people, in essence, are not cognitively limited as much as they are guided by emotions.

In the midst of the Great Recession, Akerlof and Shiller (2009) revive Keynesian ideas about economic agents being led by the so-called *animal spirits* (or pure sentiment), postulating that every serious economic downturn draws its roots from human nature. Although literature is not in consent with sentiment being the main cause of business cycle fluctuations, there is evidence implying economic confidence might affect macroeconomic aggregates in the presence of extraordinary events (Fuhrer 1993; Golinelli and Parigi 2004; Sorić 2018). Unpredicted and unusual events are associated with the culmination of people's emotions, resulting in overreactions to economic stimuli (Katona 1975; Garcia 2013), herding behavior (Chen 2013) and other forms of irrational conduct. In times of economic distress sentiment tends to move independently of macroeconomic fundamentals (Throop 1992).

That being the case, one might benefit from differentiating between rational and irrational economic sentiment. Barsky and Simms (2012) distinguish between *animal spirits* (irrational) and news (rational) shocks in a VAR framework, while a number of authors use similar argumentation to extract irrational sentiment and examine its impact on various forms of financial sector activities (e.g. Baker and Wurgler 2006; Corredor and Santamaria 2015; Das et al. 2020). All of these studies fragment economic sentiment into the rational component, entirely explained by macroeconomic fundamentals (facts), and the irrational component,

measuring agents' excess optimism or pessimism beyond any rationally-sourced reasoning. However, this notion has insofar not been applied to quantify irrational sentiment as the leading indicator of the real economy, so we propose its initial application of that kind based on BCS data. This entails running regressions presented with Equation (6), as adopted from Baker and Wurgler (2006), Corredor and Santamaria (2015), and Das et al. (2020):

$$BCS\_indicator_t = \beta \cdot reference\_series_t + \varepsilon_t \tag{6}$$

where we alternate confidence indicators of interest (ICI, CCI, RTCI) as the dependent variables, and their reference macroeconomic series (industrial production for ICI, and personal consumption for CCI and RTCI) as corresponding independent variables.[1] In this setting, ε_t represents the irrational component of sentiment.

e) *Adaptive Expectations Model*

Pursuant to the above discussion on irrationality, people's behavior and expectations formation are rarely in line with the exact definition of full rationality as set forth by Muth (1961). However, the literature recalls some alternatives to the rational expectations hypothesis, proposing the use of adaptive expectations model (Figlewski and Wachtel 1981; Sorić et al. 2020). It seems fairly logical to assume that agents correct their expectations in subsequent periods according to the difference between their past expectations on relevant economic variables (measured by forward-looking BCS questions) and their respective perceptions of the realizations of these same variables (measured by backward-looking BCS questions).

Building on a conventional adaptive expectations formation model (as presented in Pfajfar and Santoro 2010 or Sorić et al. 2020), we estimate two slightly different specifications to examine robustness of the obtained results. Monthly specifications are given as:

$$B^{FL}_{t|t-12} - B^{FL}_{t-12|t-24} = \beta_{t,0} + \beta_{t,1}(B^{BL}_t - B^{FL}_{t-12|t-24}) + \varepsilon_t \tag{7}$$

$$B^{FL}_{t|t-12} - B^{FL}_{t-12|t-24} = \beta_{t,0} + \beta_{t,1}(B^{BL}_{t-12} - B^{FL}_{t-12|t-24}) + \varepsilon_t \tag{8}$$

where the dependent variable is the difference of response balances to forward-looking questions formed in periods *t* and *t*-12. Regarding the independent variable, in Equation (7)

---

[1] European Commission (2020: 16) strictly defines the index of industrial production volume as the reference series for ICI and private final consumption expenditure as the reference series for CCI and RTCI. This means that ICI, CCI, and RTCI are specifically designed to track the short-term trajectory of industrial production and private final consumption expenditure; justifying our choice of these variables as macroeconomic fundamentals in the right-hand side of Equation (6).

we assume that agents correct their expectations by looking at the discrepancy between their perceptions at period t (quantified as the balance of answers to backward-looking questions in t) and their expectations formed at period t-12 (obtained as forward-looking response balances from t-12). Since B_t^{BL} in Equation (7) measures agents' perceptions throughout the last 12 months (including the current one), we also assess B_{t-12}^{BL} in Equation (8) as an alternative measure of perception. This way we examine both end periods (t and t-12) scrutinized within the backward looking BCS questions.

Using BCS data, it is possible to estimate Equations (7) and (8) only for the sectors with surveys containing linking backward- and forward-looking questions on the exact same variables, i.e. again the manufacturing industry, retail trade and consumer sector. As the expectation correction component is in the center of our interest, we extract fitted values of Equations (7) and (8) as the adaptive expectations for the three assessed sectors, and we examine their predictive properties.

3. Data and estimation issues

Our empirical analysis is based on survey responses from three BCS sectors: the industrial sector, consumers, and retail trade sector. These three specific areas are chosen because they constitute the appropriate framework for testing the utilitarian value of novel quantification techniques of BCS leading indicators. To be concrete, our version of the surprise index and the suggested adaptive expectations indicator entail a combination of backward- and forward-looking questions on the exact same economic variables. This type of framework is present only in the three assessed BCS sectors, while the other two sectors (services and construction) do not offer such a specific dataset.

We assess BCS data from each of the 27 EU Member States, plus United Kingdom. The dataset is seasonally adjusted using the ARIMA X-12 method.

Let *ICI, ICI_WB, sup_ind, dis_ind,* and *irr_ind* denote the standard confidence indicator, the same indicator obtained via the weighted balance approach, surprise index, disagreement, and the irrational sentiment in the industrial sector (respectively). Let *adapt_ind* and *adapt_ind12* be the adaptive expectations indicators for the industrial sector, obtained via Equations (7) and (8), respectively.

In the same manner, we denote the corresponding indicators for the consumer sector as *CCI, CCI_WB, sup_cons, dis_cons, irr_cons, adapt_cons*, and *adap_cons12*; while the analogous

indicators for the retail sector are denoted as *RTCI, RTCI_WB, sup_ret, dis_ret, irr_ret, adapt_ret,* and *adap_ret12*.

European Commission (2020) strictly defines industrial production (*ind* hereinafter) as the reference series for the industrial sector, while consumer and retail trade confidence indicators are designed to track private consumption (*cons* hereinafter). It is important to notice that private consumption is published on a quarterly basis (as opposed to BCS data and industrial production, which are in monthly frequencies). To circumvent that issue, we calculate quarterly BCS indicators for the consumer and retail sectors as arithmetic averages of three corresponding monthly observations.

All BCS data are obtained from the European Commission, while reference macroeconomic series are published by Eurostat. The examined panel dataset is unbalanced, depending on data availability. The longest observed time span for monthly data is from 2000M01 to 2020M06 and 1996Q1 to 2020 Q2 for quarterly data. Exact time spans for each considered series are given in Table 5 in the Appendix.

To evaluate the predictive characteristics of novel BCS indicators in comparison to conventional BCS confidence measures, we first need to choose the appropriate panel data method for testing Granger (non)causality. Previous research has mostly viewed this issue without examining potential cross-influences between individual countries (e.g. Bergström 1995; Hansson et al. 2005; Gayer 2005; Sorić et al. 2013). However, Lemmens et al. (2005) perform a rigorous El Himdi–Roy testing procedure, concluding that EU countries are rather heterogeneous in terms of output's reactivity to BCS-based economic sentiment. Even more importantly, Lemmens et al. (2005) assess potential spillover effects among these countries in the sense that some countries' output is perhaps responsive not only to its domestic economic sentiment, but also to the expectations of other countries. They find that core EU countries can easily be clustered in clubs of *clout* economies and *receptive* economies. Having this important result in mind, it is necessary to choose the method that allows for both heterogeneity in the influence between cross-sections, and for cross-sectional dependence.

One of the common approaches allowing for cross-sectional heterogeneity is a procedure with time-fixed coefficients, developed by Hurlin and Venet (2001). Unfortunately, this method does not allow for cross-sectional dependence. This procedure is upgraded in several papers (Hurlin 2005; Dumitrescu and Hurlin 2012). Such upgraded version of Granger non-causality

test for heterogeneous panels shows good statistical properties both in small samples and in the presentence of cross-sectional dependence.

It should be mentioned that there are also other methods assuming heterogeneity and cross-sectional dependence. For example, the Seemingly Unrelated Regressions (SUR) methodology (Zellner 1962) is also utilized in a fair amount of empirical research. The main attraction of SUR lies in the fact that it allows for free estimation of contemporaneous error covariances between countries. However, a precondition for utilizing the SUR model is a small number of cross-sections (N<10) and large time dimension T (Pesaran 2006). Since this is obviously not the case in our study (N=28), we opt for applying the non-causality test in heterogeneous panel data in the vein of Dumitrescu and Hurlin (2012).

Dumitrescu and Hurlin (2012) consider the following panel regression to test whether x_{it} Granger-causes y_{it}:

$$y_{it} = \sum_{k=1}^{p} \gamma^{(k)} y_{i,t-k} + \sum_{k=1}^{p} \beta_i^{(k)} x_{i,t-k} + \alpha_i + \varepsilon_{it} \text{, } i = 1,\ldots, \text{N}, t = 1,\ldots, \text{T}, \tag{9}$$

with $p \in N$. The procedure assumes that lag orders p are identical for all cross-sections.

y_{it} and x_{it} are two stationary variables, where $\gamma_i^{(k)}$ is the coefficient of k-th lag of dependent variable y_{it} and $\beta_i^{(k)}$ is the coefficient of k-th lag of independent variable x_{it}. The term α_i is individual-specific, which can be expressed through fixed or random effects for each individual, while ε_{it} are i.i.d. $\left(0, \sigma_{\varepsilon}^2\right)$. Cross-sectional specifics are controlled by introducing α_i in the equation.

From equation (9), it can be seen that coefficients $\beta_i^{(k)}$ are different for each individual, but they are constant over the time. It is possible that, for some cross-sections, the past values of variable x_i cause y_i, while for some other ones there is no causality of that type. Therefore, different $\beta_i^{(k)}$ are essential.

This test assumes two sources of heterogeneity. The first one is heterogeneity in the $\beta_i^{(k)}$ coefficients for different i, and the second one is heterogeneity in the causal relationship from x_i and y_i for different i (implying that some cross-section units exhibit causality, and some do not). It is important to note that a Granger test not considering both possible sources of heterogeneity may lead to wrong conclusions.

The null hypothesis of Homogenous Non-Causality (HNC) test assumes no individual causality from x_i to y_i, which is defined as:

$$H_0 : \beta_i^{(k)} = 0, \forall k \in \{1,...,p\}, \forall i \in \{1,...,N\}. \tag{10}$$

The alternative hypothesis (HEterogenous Non-Causality; HENC) assumes two subgroups of cross-sections. The first one consists of cross-sections with a non-existing causal relationship. The second group comprises cross-sections with a valid causal relationship, allowing for different $\beta_i^{(k)}$ coefficients. It is defined as:

$$\begin{aligned} H_1 : \beta_i^{(k)} &= 0, \forall k \in \{1,...,p\}, \forall i \in \{1,...,N_1\} \\ \exists k &\in \{1,...,p\}, \beta_i^{(k)} \neq 0, \forall i \in \{N_1,...,N\} \end{aligned} \tag{11}$$

where $N_1 \in [0, N-1]$.

To obtain result of Granger test, Dumitrescu and Hurlin (2012) propose the following procedure[2]. In the first step it is necessary to run N separate regression in the form of equation (9) (for each cross-section separately). The second step entails running F tests of p linear hypothesis $\beta_i^{(k)} = 0, \forall k \in \{1,...,p\}$ to retrieve Wald statistics W_i, and finally compute:

$$\overline{W} = \frac{1}{N} \sum_{i=1}^{N} W_i. \tag{12}$$

We assess two different tests statistics for this procedure: $\overline{Z}$ and $\tilde{Z}$.

Under the assumption that Wald statistics W_i are independently and identically distributed across countries, it can be shown that the standardized $\overline{Z}$ follows a standard normal distribution when $T \rightarrow \infty$ and $N \rightarrow \infty$:

$$\overline{Z} = \sqrt{\frac{N}{2K}} \cdot (\overline{W} - p) \xrightarrow{d} \square(0,1). \tag{13}$$

Also, for fixed T dimension with $T > 5 + 3p$, the approximated standardized statistics $\tilde{Z}$ follows normal distribution:

$$\tilde{Z} = \sqrt{\frac{N}{2p}} \cdot \sqrt{\frac{N}{2p} \cdot \frac{T-3p-5}{T-2p-3}} \cdot \left[\frac{T-3p-3}{T-3p-1} \cdot \overline{W} - p \right] \xrightarrow{d} \square(0,1). \tag{14}$$

As a separate robustness check, we asses a bivariate panel VAR model, assuming no heterogeneity of cross-section units:

---

[2] Description of the proposed procedure follows Lopez and Weber (2017).

$$y_{it} = \sum_{k=1}^{p} \gamma_{k1} y_{i,t-k} + \sum_{k=1}^{p} \beta_{k1} x_{i,t-k} + \alpha_{i1} + \varepsilon_{it1}$$
$$, i = 1,\dots, \text{N}, t = 1,\dots, \text{T}, \qquad (15)$$
$$x_{it} = \sum_{k=1}^{p} \gamma_{k2} x_{i,t-k} + \sum_{k=1}^{p} \beta_{k2} y_{i,t-k} + \alpha_{i1} + \varepsilon_{it1}$$

where γ_{k1} and γ_{k2} are coefficients of k-th lag of dependent variable in corresponding equation while β_{k1} and β_{k2} are coefficients of k-th lag of independent variable in corresponding equation. The presented VAR model is estimated for each of the three examined BCS sectors, for each considered BCS indicator separately.

System (15) is estimated via the Least Squared Dummy Variables (LSDV) estimator. Since our dataset is characterized by a large T dimension, endogeneity bias induced by the correlation between $y_{i,t-k}$ and α_{i1} is tolerably small (Kiviet 1995). We used Stata code provided by Cagala and Glogowsky (2014) for estimation purposes.

4. Empirical results

Before conducting the Granger causality test, cross-sectionally augmented ADF (CADF) unit root test (Pesaran 2007) was performed. The test showed that variables *ind* and *cons* are I(1), i.e. stationary in first differences. All other variables are stationary in levels. Hence, to avoid spurious regression issues, all further econometric modelling is done with first differences of I(1) variables (*dind* and *dcons*, respectively).

Table 1 summarizes the heterogeneous Granger causality test results for the industrial sector, while Tables 2 and 3 provide the same information for the consumer and retail sector (respectively). The optimal lag order for all considered Granger causality tests is chosen via the *Bayesian Information Criterion (BIC)*. The obtained p-values for $\bar{Z}$ and $\tilde{Z}$ test statistics reveal that in the vast majority of specifications (in all three tables) the null hypothesis of homogeneous non-causality is firmly rejected, leading to the conclusion that $\beta_i^{(k)}$ in Equation (9) are not equal to zero for all examined countries. Therefore, for each particular bivariate case, we should be able to extract a subgroup of economies exhibiting causality in the observed variables, as well as a subgroup of economies with no evidence of causality. The p-values presented in the body of the tables indicate possible rejection of the heterogeneous non-causality hypothesis at conventional significance levels.

Table 1. Results of Granger non-causality test for heterogeneous panel (industrial sector)

	ICI	ICI_WB	ind_sup	ind_dis	ind_irr	ind_adapt	ind_adapt12
Homogenous Non-Causality (HNC) vs HEterogeneous Non-Causality (HENC) hypothesis							
$\overline{Z}$ (p-value)	0.0000	0.0000	0.0001	0.3823	0.0000	0.0000	0.0000
$\tilde{Z}$ (p-value)	0.0000	0.0001	0.4150	0.0000	0.0000	0.0000	0.0000
lags	2	2	2	2	2	1	2
Austria	0.0553*	0.0251**	0.0142**	0.7268	0.0221**	0.0023**	0.0055**
Belgium	0.0417**	0.0327**	0.0386**	0.7908	0.0169**	0.3204	0.0179**
Bulgaria	0.0001**	0.0009**	0.0485**	0.3270	0.0000**	0.0000**	0.3130
Croatia	0.0508*	0.0544*	0.8890	0.4467	0.0195**	0.6389	0.7685
Cyprus	0.0262**	0.1194	0.504	0.0098**	0.0029**	0.0383**	0.3256
Czechia	0.0524*	0.026**	0.0863*	0.6580	0.075*	0.0006**	0.0326**
Denmark	0.0006**	0.1342	0.4033	0.9703	0.0003**	0.1147	0.1074
Estonia	0.0011**	0.0082**	0.0023**	0.2837	0.0019**	0.0002**	0.0000**
Finland	0.0001**	0.0004**	0.2985	0.4511	0.0000**	0.1816	0.0447**
France	0.1844	0.0591*	0.2356	0.2611	0.0949*	0.0028**	0.3799
Germany	0.0000**	0.0005**	0.1742	0.0294**	0.0000**	0.0015**	0.0036**
Greece	0.2709	0.4252	0.5105	0.3015	0.1182	0.1438	0.4108
Hungary	0.2513	0.2434	0.2675	0.2696	0.0243**	0.0054**	0.0659*
Ireland	0.5895	0.4255	0.6811	0.0386**	0.3339	0.6201	0.7208
Italy	0.0005**	0.0097**	0.4741	0.7000	0.0003**	0.0000**	0.083*
Latvia	0.0387**	0.4891	0.0582*	0.5931	0.0259**	0.0001**	0.0003**
Lithuania	0.4244	0.3134	0.2395	0.9363	0.2984	0.3092	0.1372
Luxembourg	0.0599*	0.6437	0.2081	0.9624	0.0513*	0.0832*	0.4500
Malta	0.6915	0.6351	0.3587	0.6615	0.5831	0.9311	0.4566
Netherlands	0.0378**	0.1774	0.0235**	0.7864	0.0182**	0.3384	0.3580
Poland	0.3935	0.7511	0.5892	0.2796	0.6842	0.0010**	0.5795
Portugal	0.0002**	0.0003**	0.4458	0.2140	0.0016**	0.1594	0.8369
Romania	0.0448**	0.5702	0.9365	0.2682	0.0482**	0.0073**	0.8307
Slovakia	0.1627	0.3895	0.6471	0.6162	0.1629	0.6721	0.8691
Slovenia	0.0000**	0.0009**	0.0203**	0.8622	0.0000**	0.1858	0.0551*
Spain	0.4132	0.2935	0.3938	0.3774	0.2698	0.0000**	0.3466
Sweden	0.0002**	0.0012**	0.1106	0.2152	0.0000**	0.1247	0.0012**
United Kingdom	0.0163**	0.0396**	0.3758	0.0564*	0.0158**	0.0306**	0.0582*

Note: Table entries are p-values. *(**) denote significance at the 10%(5%) level.

A mere glance at Table 1 reveals that ICI (as the corresponding sectoral BCS indicator) predicts industrial production with a two months lead in as many as 19 (out of 28) analyzed countries. Therefore, quantifying a better leading indicator than ICI seems to be a rather hard task. However, *ind_irr* provides even better results, revealing 21 significant cases of Granger causality. Apart from *ind_irr* as the relative winner of this empirical comparison, another noteworthy result is generated by *ind_adapt*, Granger-causing industrial production in

respectable 15 countries. Calculating ICI according to the weighted balance approach (Claveria 2010) results in respectable 14 cases of significant Granger causality. The other three approaches (*ind_sup*, *ind_dis*, and *ind_adapt12*) do not produce noteworthy results.

Table 2. Results of Granger non-causality test for heterogeneous panel (consumer sector)

	CCI	CCI_WB	cons_sup	cons_dis	cons_irr	cons_adapt	cons_adapt12
Homogenous Non-Causality (HNC) vs HEterogeneous Non-Causality (HENC) hypothesis							
$\overline{Z}$ (p-value)	0.0006	0.0000	0.7127	0.0006	0.0000	0.0000	0.0120
$\tilde{Z}$ (p-value)	0.0014	0.0000	0.8053	0.0014	0.0000	0.0000	0.0192
lags	2	1	2	1	1	1	1
Austria	0.384	0.2106	0.3494	0.384	0.6449	0.411	0.233
Belgium	0.7219	0.3997	0.9776	0.7219	0.5926	0.3911	0.1624
Bulgaria	0.604	0.1853	0.9022	0.604	0.5431	0.6534	0.8996
Croatia	0.4094	0.5927	0.9397	0.4094	0.2752	0.2184	0.7131
Cyprus	-	-	-	-	-	-	-
Czechia	0.5796	0.83	0.5431	0.5796	0.2076	0.1701	0.4196
Denmark	0.0185**	0.013**	0.0659*	0.0185**	0.0074**	0.0837*	0.1425
Estonia	0.3867	0.2656	0.4991	0.3867	0.0403**	0.0351**	0.1119
Finland	0.0166**	0.0001**	0.6772	0.0166**	0.0087**	0.023**	0.3394
France	0.1882	0.4113	0.1925	0.1882	0.0346**	0.1254	0.0322**
Germany	0.3879	0.8103	0.9257	0.3879	0.0902*	0.0165**	0.7599
Greece	0.0659*	0.1812	0.1376	0.0659*	0.515	0.221	0.4487
Hungary	0.2599	0.1367	0.3278	0.2599	0.0014**	0.1232	0.1589
Ireland	0.7337	0.3698	0.243	0.7337	0.85	0.0909*	0.4256
Italy	0.0837*	0.7561	0.5147	0.0837*	0.5508	0.0385**	0.3944
Latvia	0.7615	0.3912	0.9966	0.7615	0.4329	0.5037	0.8896
Lithuania	0.0103**	0.1235	0.3584	0.0103**	0.0158**	0.0033**	0.0612*
Luxembourg	0.2086	0.8664	0.2782	0.2086	0.9056	0.9901	0.4074
Malta	0.6381	0.6539	0.9834	0.6381	0.3122	0.1966	0.8813
Netherlands	0.6718	0.5411	0.2864	0.6718	0.9494	0.0168**	0.4724
Poland	0.0491**	0.1726	0.4079	0.0491**	0.947	0.655	0.7102
Portugal	0.2281	0.4329	0.6735	0.2281	0.1042	0.0655*	0.4264
Romania	0.5275	0.001**	0.9369	0.5275	0.3229	0.0192**	0.0094**
Slovakia	-	-	-	-	-	-	-
Slovenia	0.7074	0.1798	0.4289	0.7074	0.6869	0.3016	0.9852
Spain	0.0053**	0.0767*	0.0258**	0.0053**	0.0051**	0.0266**	0.0572*
Sweden	0.4772	0.4438	0.8681	0.4772	0.2046	0.3668	0.8765
United Kingdom	0.1881	0.0684*	0.0066**	0.1881	0.0295**	0.0009**	0.0037**

Note: Table entries are p-values. *(**) denote significance at the 10%(5%) level. Private consumption data for Cyprus and Slovakia is unavailable.

Table 2 reveals that *cons_adapt* and *cons_irr* dominate over all other considered indicators, even the standard CCI. As opposed to the industrial sector (Table 1), this time the adaptive expectations indicator (*cons_adapt*) performs the best.

Table 3. Results of Granger non-causality test for heterogeneous panel (retail sector)

	RTCI	RTCI_WB	ret_sup	ret_dis	ret_irr	ret_adapt	ret_adapt12
Homogenous Non-Causality (HNC) vs HEterogeneous Non-Causality (HENC) hypothesis							
$\overline{Z}$ (p-value)	0.2274	0.0000	0.2975	0.0004	0.0000	0.0000	0.9002
$\tilde{Z}$ (p-value)	0.3294	0.0000	0.3511	0.0008	0.0000	0.0000	0.8472
lags	1	1	1	1	1	1	1
Austria	0.6042	0.5249	0.4019	0.0584*	0.3708	0.1837	0.614
Belgium	0.8996	0.3389	0.6344	0.2365	0.5403	0.5915	0.7316
Bulgaria	0.8462	0.3037	0.0173**	0.6524	0.7368	0.8975	0.3439
Croatia	0.3683	0.9155	0.9074	0.7017	0.3615	0.3114	0.9704
Cyprus	-	-	-	-	-	-	-
Czechia	0.5838	0.0442**	0.4548	0.4753	0.3339	0.0008**	0.4669
Denmark	0.2265	0.0712*	0.3351	0.6535	0.0629*	0.9672	0.9690
Estonia	0.0236**	0.0268**	0.3830	0.0537*	0.0019**	0.0012**	0.3031
Finland	0.9089	0.7439	0.554	0.3074	0.6454	0.0007**	0.4952
France	0.1686	0.6736	0.1574	0.7309	0.2398	0.0266**	0.1572
Germany	0.9119	0.5828	0.0642*	0.0622*	0.1266	0.0114**	0.4472
Greece	0.5943	0.0308**	0.2703	0.6409	0.3706	0.8036	0.1642
Hungary	0.0993*	0.2180	0.7757	0.0010**	0.0502*	0.7401	0.5246
Ireland	0.5961	0.1282	0.7070	0.7340	0.8885	0.0583*	0.5259
Italy	0.0470**	0.0590*	0.2130	0.2764	0.0910*	0.0233**	0.1411
Latvia	0.6347	0.4534	0.8106	0.7885	0.6175	0.0002**	0.6522
Lithuania	0.0949*	0.0041**	0.0675*	0.7760	0.0022**	0.0063**	0.0112**
Luxembourg	-	-	-	-	-	-	-
Malta	0.0682*	0.0149**	0.1708	0.4098	0.0035**	0.2486	0.2747
Netherlands	0.9039	0.0994*	0.6708	0.1038	0.4271	0.0000**	0.6826
Poland	0.6092	0.8959	0.9508	0.1639	0.3936	0.0351**	0.5939
Portugal	0.1147	0.7372	0.1562	0.0334**	0.0422**	0.002**	0.0863*
Romania	0.5684	0.9468	0.1009	0.1279	0.8039	0.1372	0.6302
Slovakia	-	-	-	-	-	-	-
Slovenia	0.9389	0.9416	0.3650	0.5064	0.9254	0.0932*	0.3859
Spain	0.0302**	0.0014**	0.1748	0.0042**	0.0300**	0.6927	0.5780
Sweden	0.5812	0.5247	0.2929	0.7252	0.8149	0.0004**	0.7588
United Kingdom	0.6899	0.5693	0.7310	0.8754	0.6571	0.3632	0.6916

Note: Table entries are p-values. *(**) denote significance at the 10%(5%) level. Private consumption data for Cyprus and Slovakia is unavailable, just as the BCS retail sector data for Luxembourg.

Table 3 paints a very similar picture. The adaptive expectations indicator (*ret_adapt*) has 14 significant cases of Granger causality, while RTCI as the standard sectoral BCS indicator has only seven of them. Indicator *ret_irr* also works rather well, just as the weighted balance approach (*RTCI_WB*).

Comparing the results of Tables 1-3, it becomes evident that psychological factors are far more relevant in the industrial sector than in the consumer and retail trade sectors. Indicators *ind_irr*, ICI, and *ind_adapt* Granger-cause industrial production in a vast majority of countries, while none of the examined indicators in the consumer and retail trade sector are found to be significant drivers of economic activity in more than half of the analyzed countries. Private consumption is obviously substantially less psychologically driven than the industrial production, where expectations and uncertainty play a pivotal role in planning and executing future business endeavors. This brings us back to the premise of Katona (1960), who made a clear distinction between the *ability* to consume and *willingness* to consume.[3] Our results implicitly confirm the dominance of the former factor in comparison to the latter one.

Tables 1-3 vigorously demonstrate that the irrational component of economic sentiment (*ind_irr, cons_irr,* and *ret_irr*) is mostly a more important driver of economic activity than respective confidence indicators (ICI, CCI, and RTCI). One would usually compare the hereby obtained results to the ones of previous studies. However, although the irrational component of economic sentiment is a well-established driver of financial markets (Lagunoff and Schreft 1999; Baker and Wurgler 2006; Verma et al. 2008; Schmeling 2009; Das et al. 2020) and housing markets (Das et al. 2020), to the best of our knowledge, the literature is completely silent on the role of irrational sentiment in governing aggregate economic activity in particular areas such as the manufacturing industry, consumer, or retail sector. Our results clearly highlight this as a very promising direction for future research.

Some additional insights could be drawn here from a cross-country comparison of the results obtained in Tables 1-3. Looking at the significant cases of Granger causality with respect only to the irrational sentiment indicators, one might notice the repeating list of countries across the observed sectors. Namely, economic activity in Estonia and Denmark is driven by irrational sentiment in all three sectors, whereas a fair share of countries records significant irrational sentiment indicators in two out of three sectors (Finland, France, Germany,

---

[3] See e.g. Roos (2008) for an empirical re-appraisal of Katonian consumption theory on BCS data.

Hungary, Italy, Lithuania, Portugal, Spain, UK). It is to assume that economic agents' decision making in the referred countries is in general guided by different forms of non-rational reasoning.

The foundation behind this irrational conduct might be found in the traumatic experience of the Great Recession. According to Eurostat data, Estonia, Lithuania, Finland, and Italy were among the six EU countries with the sharpest initial (2008-2009) general economic downfall, while many peripheral EU countries generally experienced severe economic struggle (e.g. Portugal and Spain). Dealing with the most acute economic distress in 2009, Estonia and Lithuania experienced nearly a 15% GDP decline.

Furthermore, Estonian public debt to GDP ratio almost doubled between 2007 and 2009, while other EU countries also started to face high public debt growth rates as the financial crisis began to turn into a debt crisis. Between 2008 and 2013 public debt grew at an average annual rate higher than 17% in Estonia and Spain, 16% in Lithuania[4] and 13% in the UK. On the other hand, a serious cause for concern stemmed from the high *levels* of public indebtedness. Not just during the crisis, but even in the whole observed period (2000-2019), the average public debt to GDP ratio accounted for almost 120% in Italy, 100% in Portugal and 80% in France, pointing to unsustainable debt accumulation.

Extreme GDP declines, followed by a sovereign debt crisis, called for an unconventional crisis management based on harsh austerity measures. Taking again Estonia for example, Peters et al. (2011) described their hard austerity process which included internal devaluation, VAT increase and dismissal and retraining of public employees. Although Estonia succeeded in gaining greater efficiency and public savings quite fast, a question arises was it worth the price in terms of effects on people's lives, attitudes and general welfare. As the most severe and unpredicted event in the past two decades (which is the used time span for most of our variables), the Great Recession generated not solely economic, but also psychological consequences long-rooted in people's minds.

A similar conclusion can be drawn for the adaptive expectations algorithm. Indicators *ind_adapt, cons_adapt*, and *ret_adapt* seem to successfully predict their corresponding reference macro series. Although the concept of adaptive expectations has been thoroughly examined and proven credible e.g. in the case of inflation expectations (Pfajfar and Santoro

---

[4] In Lithuania, public debt to GDP ratio was higher by as much as 145% in 2013 compared to 2007.

2010; Sorić, et al. 2020), no serious attempt has been made to scrutinize its relevance in governing the real economy.

The results presented in Tables 1-3 do not tell the full story behind the functioning mechanisms of economic sentiment and the way it influences aggregate activity. Namely, one should certainly scrutinize the sign and magnitude of its effect, along with the intertemporal dynamics between BCS indicators and the chosen reference series. To provide an insight into the stated phenomena, we continue by estimating a standard panel VAR model with the same number of lags as in the corresponding Granger causality test for heterogeneous panels (chosen according to the BIC criterion). The obtained impulse response functions (IRFs) to one standard deviation shocks are presented in Figures 1-3. We treat this model as a robustness check.

IRFs for the manufacturing industry sector (Fig. 1) follow an unsurprising and relatively similar pattern for most of the observed sentiment indicators. As expected, a unit shock in all BCS indicators except *ind_dis* increases industrial production in the initial period. The increase is rather sharp, after which it declines and fades away to zero relatively fast. The only exception is the insignificant disagreement indicator, which is in line with the results from Table 1. *ICI* and *ind_irr* have the greatest magnitude of the initial effect on the industrial production, unsurprisingly, as they turned out to be the relative winners according to the heterogeneous Granger causality test results.

The story behind the consumer and retail trade sectors (Fig. 2-3) is somewhat different. A standard deviation shock in consumer and retail trade sentiment indicators results in a personal consumption increase, except for the case of disagreement, surprise and adaptive (*adapt_cons12* and *adap_ret12*) expectations indicators in both sectors. Impulse response function patterns for other BCS indicators resemble each other but are not similar to the ones observed in the manufacturing industry sector. In fact, the positive effect of higher consumer and retail trade managers' sentiment stays positive much longer and diminishes into the steady-state very slowly. This might be on a trace of one of Katona's (1975) key principles underlining the slow nature of agents' learning process, which in turn could make the here observed effects more permanent. Namely, newly gained beliefs and subsequent people's reactions require mutual boost and information exchange among peers, meaning that a mass response could happen even after several periods (Garner 1981).

Fig. 1. Impulse response functions of *dind* to a shock in BCS indicator

a)

b)

c)

d)

e)

f)

g)
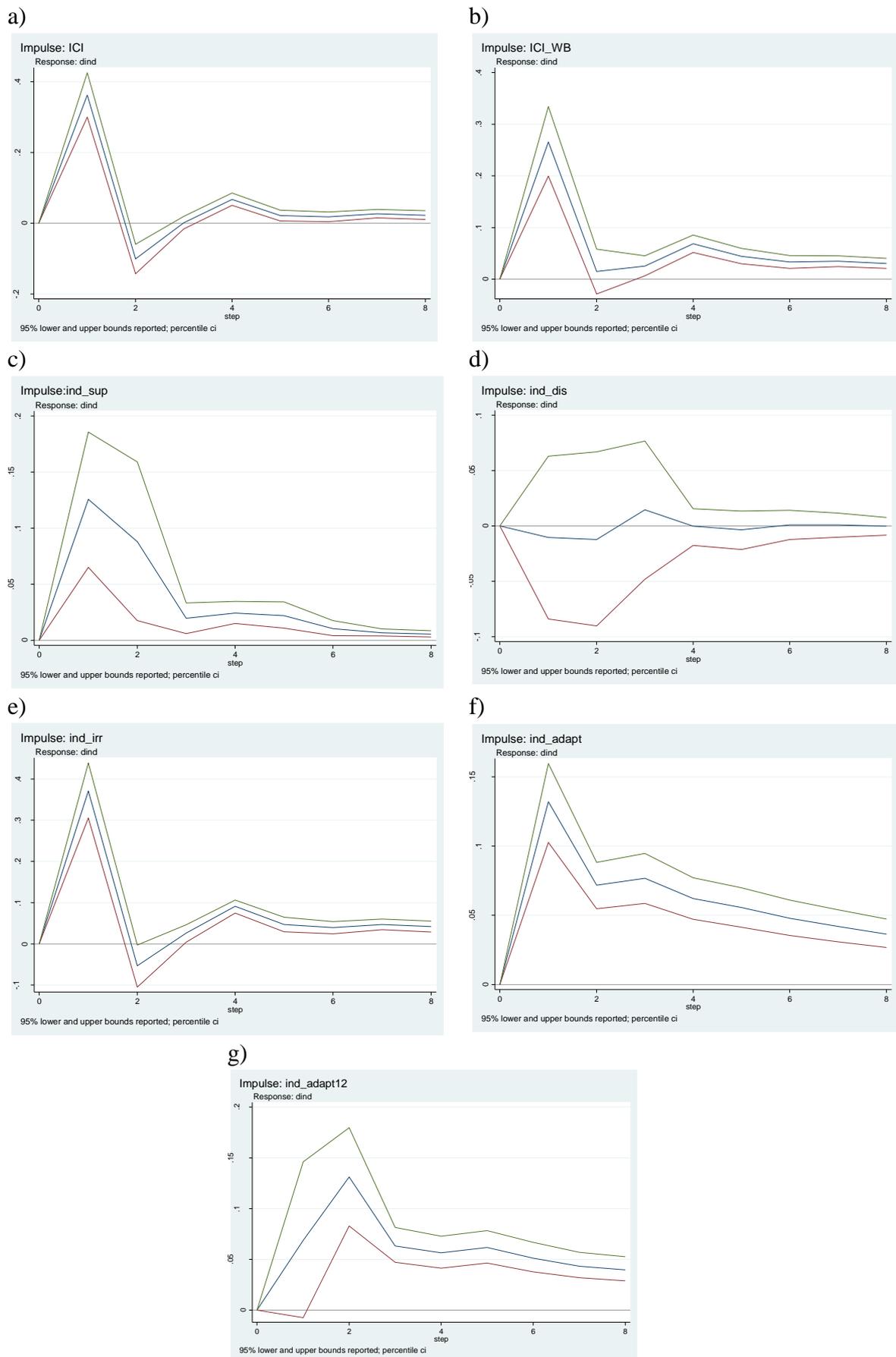
Fig. 2. Impulse response functions of *dcons* to a shock in BCS indicator (consumer sector)

a)

b)

c)

d)

e)

f)

g)
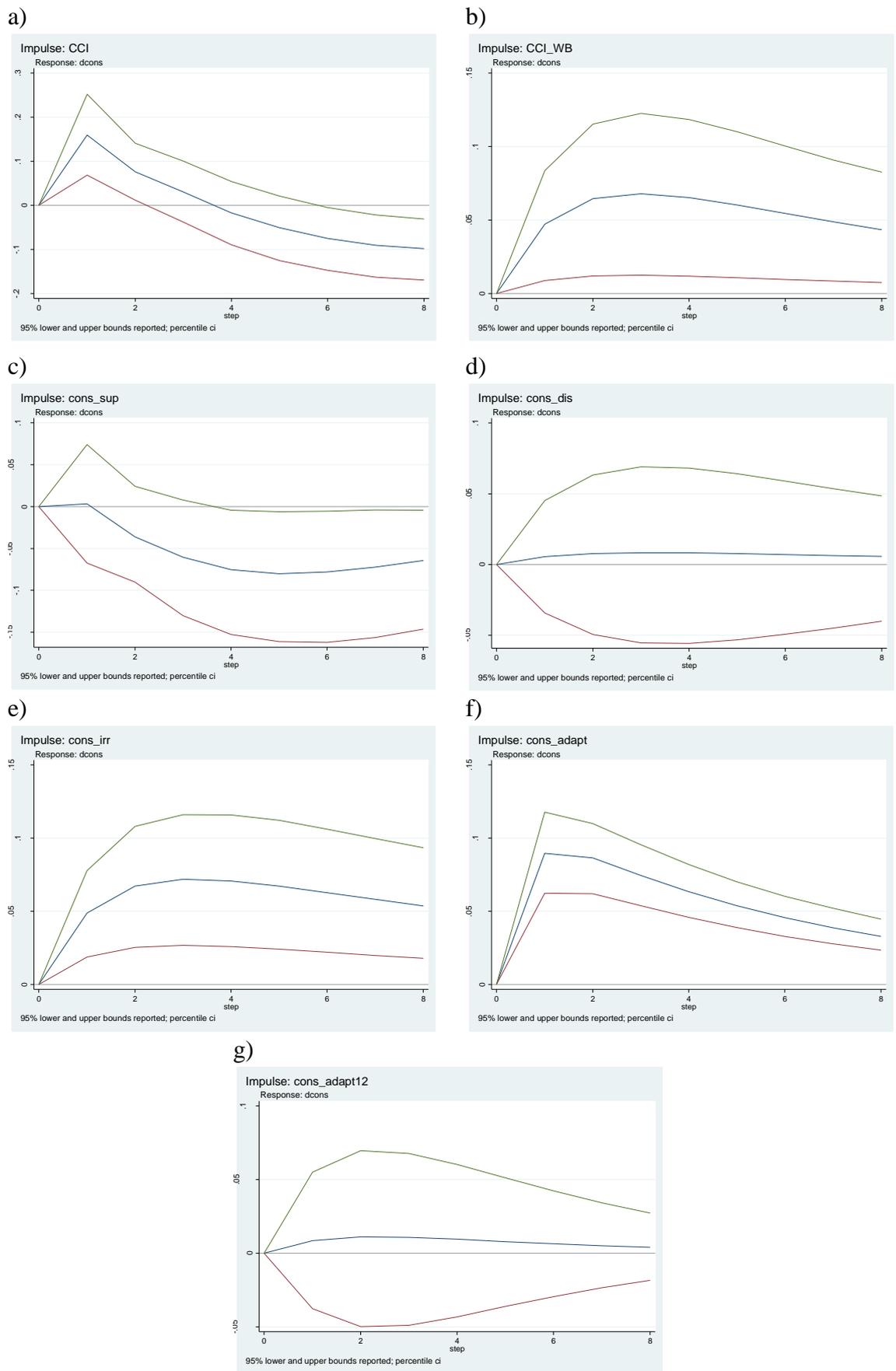
Fig. 3. Impulse response functions of *dcons* to a shock in BCS indicator (retail sector)

a)

b)

c)

d)

e)

f)

g)
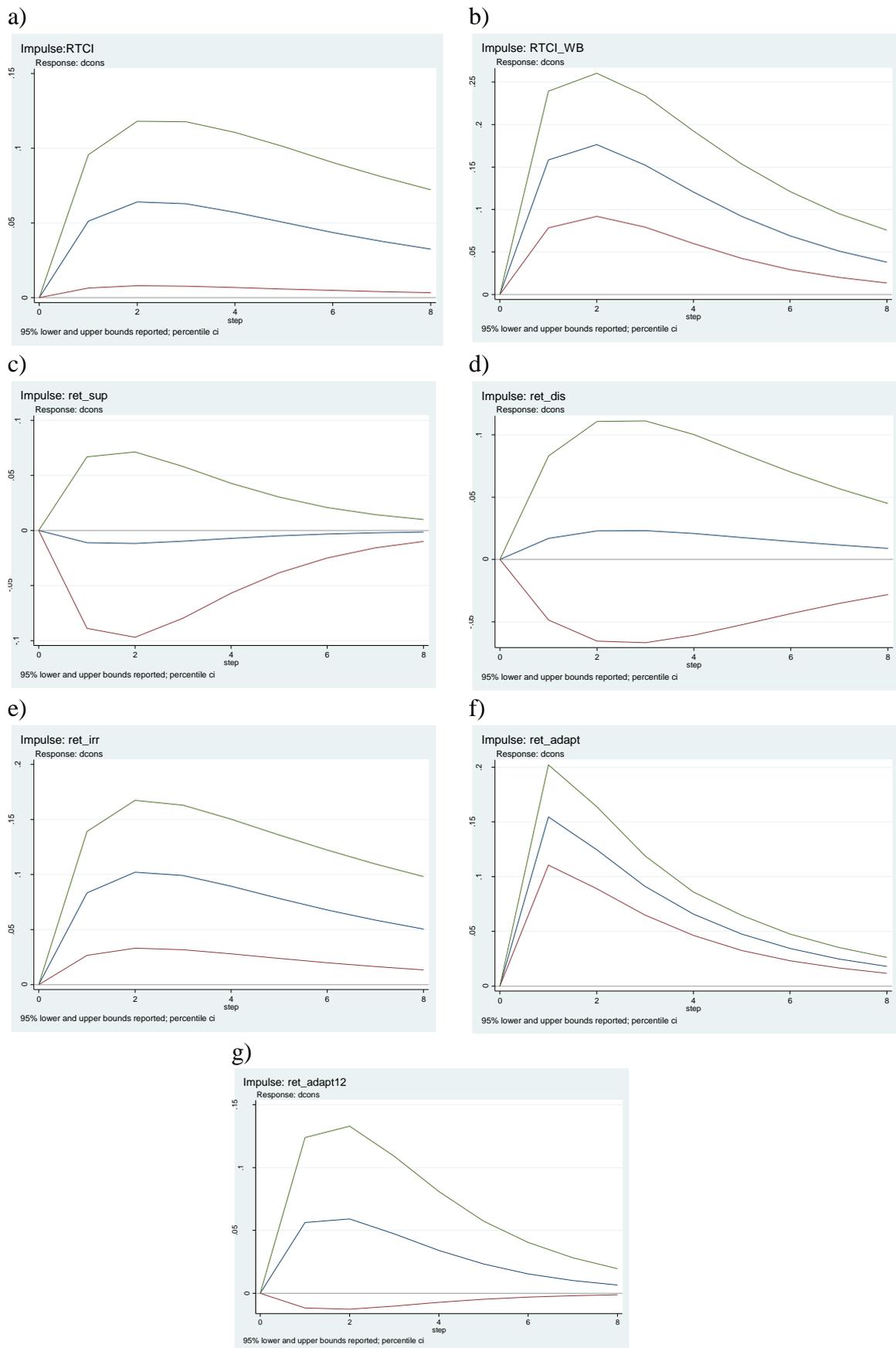
Finally, as the last robustness check, we perform a conventional Granger causality test in the panel VAR model of form (15). The results are presented in Table 4. Again, for all three considered sectors, the results firmly disapprove of the leading characteristics of agents' disagreement. Surprise index and the adaptive expectations with a 12-month lag also do not work well in most cases, while the other examined variables seem to have pronounced leading characteristics.

Table 4. VAR Granger causality test

BCS indicator Granger causes *dind*		BCS indicator Granger causes *dcons*		BCS indicator Granger causes *dcons*	
BCS indicator	p-value	BCS indicator	p-value	BCS indicator	p-value
ICI	0.0000	CCI	0.0000	RTCI	0.0226
ICI_WB	0.0000	CCI_WB	0.0186	RTCI_WB	0.0002
ind_sup	0.0000	cons_sup	0.227	ret_sup	0.7634
ind_dis	0.9844	cons_dis	0.7809	ret_dis	0.6293
ind_irr	0.0000	cons_irr	0.0029	ret_irr	0.0005
ind_adapt	0.0000	cons_adapt	0.0000	ret_adapt	0.0000
ind_adapt12	0.0000	cons_adapt12	0.7531	ret_adapt12	0.1274

Reflecting on these results, one should certainly avoid the misperception that the generating process of economic agents' sentiment can be boiled down to strictly one of the assessed theoretical models (rational expectations vs. adaptive expectations, or e.g. complete irrationality). The human nature is inherently a mixture of all examined concepts. On occasion, economic agents are firmly irrational (e.g. when faced with the circumstances of uncertainty and high economic volatility). Sometimes they are strictly rational in the sense of incorporating all relevant information in the decision-making process and producing unbiased predictions of targeted economic variables. This is perhaps possible in the case of consistent formal policy announcements (Bernoth and von Hagen 2004) and in stable economic surroundings (Sorić et al. 2020). Our argumentation on the interchangeable expectation generation processes (depending on the prevailing economic conditions) should certainly be brought in relation to Pfajfar and Santoro (2010), who identify specific regions of underlying formation mechanisms in the case of inflation expectations. To be specific, they identify a nearly rational region around the median of the distribution, a highly irrational region with systematic forecasting errors in the left tail of the distribution, and an adaptive learning region in its right tail.

5. Conclusion

BCS indicators have become an indispensable tool for short-term macroeconomic forecasting, providing *soft* information complemental to *hard* economic data. These kinds of psychological indicators are proven to be of particular importance in times of economic crisis and turmoil (Sorić 2018). Given the recent global financial crisis, followed by high uncertainty episodes of the European sovereign debt crisis, Brexit, USA-China trade war, and the COVID-19 pandemic, it comes as no surprise that the prognostic performance of BCS measures has recently been thoroughly examined by several studies. Even more important, some attempts of methodological improvements of standard BCS indicators have recently been introduced in the literature. We add to this specific literature branch by examining a wide variety of tendency survey indicators, as well as by suggesting six methodological alternations and novel concepts of measuring economic expectations. The leading properties of all six examined indicators are then tested in the framework of a heterogeneous panel Granger causality test, which has good finite sample properties even in the case of cross-sectional dependence. Additionally, we also estimate panel VAR models to scrutinize the robustness of our results.

We build upon the literature strand on the *irrational sentiment*, i.e. the component of economic sentiment that is not derived from economic fundamentals. In that sense, we follow the approach of Baker and Wurgler (2006) and Corredor and Santamaria (2015), finding that this type of indicator considerably outperforms classical BCS barometers. Irrational sentiment Granger-causes economic activity in the huge majority of analyzed countries in the industrial sector, and it also produces promising results in the consumer and retail trade sectors. Further on, we add to the literature by examining an expectations indicator derived on the premise of adaptive expectations, which have insofar been almost completely neglected in BCS research. The obtained results again seem quite promising. As opposed to irrational sentiment, this type of indicator has the most pronounced predictive properties in the consumer and retail trade sector. Additionally, we build upon the surprise index approach (Scotti 2016) and apply it to BCS data for the first time. This method does not bring any added value in comparison to standard BCS indicators. Similar conclusions are also drawn for the measure of agents' disagreement (Claveria, Monte and Torra 2019b), while the weighted balance approach (Claveria 2010) performs rather well, especially in the retail trade sector.

To summarize, irrational sentiment and adaptive expectations provide the widest scope of significant Granger causality amongst European countries. As they seem to capture the erratic human nature rather well, we strongly encourage further research efforts focused on these two classes of BCS indicators.

References

Akerlof, G. A., Shiller, R. J.: Animal Spirits: How Human Psychology Drives the Economy and Why It Matters for Global Capitalism. Princeton University Press (2009)

Akhtar, S., Faff, R., Oliver, B., Subrahmanyam, A.: The power of bad: The negativity bias in Australian consumer sentiment announcements on stock returns. J. Bank. Finance, 35, 1239-1249 (2010)

Arellano, C., Bai, Y., Kehoe, P.: Financial markets and fluctuations in uncertainty. Federal Reserve Bank of Minneapolis Working Paper. http://www2.nber.org/conferences/2011/EFGf11/arellano.pdf (2010). Accessed January 19 2021.

Bachmann, R., Sims, E.R.: Confidence and the transmission of government spending shocks, J. Monet. Econ. 59, 235-249 (2012)

Bachmann, R., Elstner, S., Sims, E. R.: Uncertainty and Economic Activity: Evidence from Business Survey Data. Am. Econ. J.: Macroecon. 5, 217–249 (2013)

Baker, S. R., Bloom, N., Davis, S. J.: Measuring economic policy uncertainty. Q. J. Econ. 131, 1593–1636 (2016)

Baker, S. R., Bloom, N., Davis, S. J., Terry, S. J.: COVID-Induced Economic Uncertainty. NBER Working Paper No. 26983. (2020)

Barsky, R.B., Sims, E.R.: Information, animal spirits, and the meaning of innovations in consumer confidence. Am. Econ. Rev. 102, 1343–1377. (2012)

Benhabib, J., Spiegel, M. M.: Sentiments and Economic Activity: Evidence from US States. *Econ. J.* 129, 715–733. (2019)

Bergström, R.: The relationship between manufacturing production and different business survey series in Sweden 1968–1992, Int. J. Forecast. 11, 379– 393. (1995)

Bernoth, K., von Hagen, J.: The Euribor market: Efficiency and the impact of ECB policy announcements. Int. Finance. 7, 1-24. (2004)

Bloom, N.: The impact of uncertainty shocks. Econometrica. 77, 623–685. (2009)

Cagala, T., Glogowsky, U.: XTVAR: Stata module to compute panel vector autoregression. Stat. Softw. Compon. S457944, Boston College Department of Economics, revised 02 Apr 2015.

Cagan, P.: The monetary dynamics of hyperinflation. In: M. Friedman (ed.) Studies in the quantity theory of money, pp. 25–117. University of Chicago Press, Chicago (1956)

Chen, S.: Lack of consumer confidence and stock returns, J. Empir. Finance. 18, 225-236. (2011)

Chen, T.: Do investors herd in global stock markets? J. Behav. Finance. 14, 230-239. (2013)

Claveria, O.: Qualitative survey data on expectations. Is there an alternative to the balance statistic? In: Molnar, A. T. (ed.) *Economic Forecasting*, pp. 181-189. Nova Science Publishers, New York (2010)

Claveria, O.: Forecasting the unemployment rate using the degree of agreement in consumer unemployment expectations. J. Labour. Mark. Res. 53, 1-10. (2019)

Claveria, O.: Uncertainty indicators based on expectations of business and consumer surveys. *Empirica* (2020). https://doi.org/10.1007/s10663-020-09479-1.

Claveria, O., Monte, E., Torra, S.: A data-driven approach to construct survey-based indicators by means of evolutionary algorithms. Soc. Indic. Res. 135, 1-14. (2018)

Claveria, O., Monte, E., Torra, S.: Using survey data to forecast real activity with evolutionary algorithms: A cross-country analysis. J. Appl. Econ. 20, 329-349. (2019a)

Claveria, O., Monte, E., Torra, S.: Economic uncertainty: A geometric indicator of discrepancy among experts' expectations. Soc. Indic. Res. 143, 95-114. (2019b)

Claveria, O., Monte, E., Torra, S.: Economic forecasting with evolved confidence indicators. Econ. Model. 93, 576-585. (2020)

Corredor, P., Santamaria, R. The impact of investor sentiment on stock returns in emerging markets: The case of Central European Markets. East. Eur. Econ. 53, 328-355. (2015)

Čižmešija, M., Sorić, P.: Assessing Croatian GDP components via economic sentiment indicator. *Econ. Res.* 23, 1-10. (2010)

Das, P., Füss, R., Hanle, B., Russ, I.N.: The cross-over effect of irrational sentiments in housing, commercial property, and stock markets. J. Bank. Finance. 114, 05799. (2020)

Dumitrescu, E.-I., Hurlin, C.: Testing for Granger non-causality in heterogeneous panels. Econ. Model. 29, 1450–1460. (2012)

Eickmeier, S., Ng, T.: Forecasting national activity using lots of international predictors: An application to New Zealand. Int. J. Forecast. 27, 496-511. (2011)

European Commission: The Joint Harmonised EU programme of business and consumer surveys. Brussels, Belgium: User Guide. (2020)

Figlewski, S., Wachtel, P.: The formation of inflationary expectations. Rev. Econ. Stat. 63, 1–10. (1981)

Fourcade, M., Ollion, E., Algan, Y.: The Superiority of Economists. J. Econ. Perspect. 29, 89-114. (2015)

Fuhrer, J. C.: What Role Does Consumer Sentiment Play in the U.S. Macroeconomy? Federal Reserve Bank of Boston. N. Engl. Econ. Rev. 32-44. (1993)

Garcia, M. J. R.: Financial Education and Behavioral Finance: New Insights into the Role of Information in Financial Decisions. J. Econ. Surv. 27, 297-315. (2013)

Garner, C. A.: Economic determinants of consumer sentiment. J. Bus. Res. 9, 205-220. (1981)

Golinelli, R., Parigi, G.: Consumer sentiment and economic activity: A cross country comparison. J. Bus. Cycle Meas. Anal. 1, 147-170. (2004)

Hansson, J., Jansson, P., Löff, M.: Business survey data: Do they help in forecasting GDP growth? Int. J. Forecast. 21, 377–389. (2005)

Hurlin, C.: Testing Granger Causality in Heterogeneous Panel Data Models with Fixed Coefficients. Rev. écon. 56, 799-809. (2005)

Hurlin, C., Venet, B.: Granger Causality Tests in Panel Data Models with Fixed Coefficients Working Paper Eurisco. No. 2001– 09, University of Paris Dauphine. (2001)

Katona, G.: The Powerful Consumer. McGraw-Hill, New York. (1960)

Katona, G.: Psychological Economics. Elsevier, New York. (1975)

Keynes, J. M.: The General Theory of Employment, Interest and Money. Palgrave Macmillan, London. (1936)

Knotek II, E. S., Khan, S.: How do households respond to uncertainty shocks?. Econ. Rev. Federal Reserve Bank of Kansas City, No. 63 (2011)

Lagunoff, R., Schreft, S.L.: Financial fragility with rational and irrational exuberance. J. Money Credit Bank. 31, 531-560. (1999)

Lemmens, A., Croux, C., Dekimpe, M.G.: On the predictive content of production surveys: A pan-European study. Int. J. Forecast. 21, 363–375. (2005)

Lopez, L., Weber, S.: Testing for Granger Causality in Panel Data. Stata J. 17, 972–984. (2017) https://doi.org/10.1177/1536867X1801700412.

Muth, J.: Rational expectations and the theory of price movements. Econometrica. 29, 315–335. (1961)

Nerlove, M. L., Grether, D. M., Carvalho, J. L.: Analysis of economic time series: A synthesis. Revised edition, 1995. Academic Press, Inc., New York. (1979)

Nguyen, V.H., Claus, E. Good news, bad news, consumer sentiment and consumption behavior. J. Econ. Psychol. 39, 426-438. (2013)

Pesaran, M.H.: A simple panel unit root test in the presence of cross-section dependence. J. Appl. Econom. 22, 265–312. (2007)

Pesaran, M.H.: Estimation and Inference in Large Heterogeneous Panels with a Multifactor Error Structure. Econometrica. 74, 967–1012. (2006)

Peters, B. G., Pierre, J., Randma-Liiv, T.: Global Financial Crisis, Public Administration and Governance: Do New Problems Require New Solutions?. Public Organ. Rev. 11, 13-27. (2011)

Pfajfar, D., Santoro, E.: Heterogeneity, learning and information stickiness in inflation expectations. J. Econ. Behav. Organ. 75, 426–444. (2010)

Room, M.W.M.: Willingness to consume and ability to consume. J. Econ. Behav. Organ, 66: 387-402. (2008)

Rossi, B., Sekhposyan, T., Soupre, M.: Understanding the Sources of Macroeconomic Uncertainty. Universitat Pompeu Fabra. Economics Working Paper Series. Working Paper No. 1531. (2016)

Schmeling, M.: Investor sentiment and stock returns: Some international evidence. J. Empir. Finance. 16, 394-408. (2009)

Scotti, C.: Surprise and uncertainty indexes: Real-time aggregation of real-activity macro-surprises. J. Monet. Econ. 82, 1-19. (2016)

Shapiro, A. H., Sudhof, M., Wilson, D. J.: Measuring news sentiment. J. Econom. https://doi.org/10.1016/j.jeconom.2020.07.053. (2020)

Simon, H. A.: Models of Man: Social and Rational – Mathematical Essays on Rational Human Behavior in a Social Setting. Wiley, New York. (1957)

Sorić, P.: Consumer confidence as a GDP determinant in New EU Member States: A view from a time-varying perspective. Empirica. 45, 261-282. (2018)

Sorić, P., Lolić, L., Matošec, M.: Some properties of inflation expectations in the euro area. Metroeconomica. 71, 176-203. (2020)

Sorić, P., Škrabić, B., Čižmešija, M.: European Integration in the Light of Business and Consumer Surveys. East. Eur. Econ. 51, 5-21. (2013)

Throop, A. W.: Consumer sentiment: its causes and effects. Econ. Rev. Federal Reserve Bank of San Francisco, 35-39. (1992)

Van Aarle, B., Kappler, M.: Economic sentiment shocks and fluctuations in economic activity in the euro area and the USA. Intereconomics. 47, 44-51. (2012)

Verma, R., Baklaci, H., Soydemir, G.: The impact of rational and irrational sentiments of individual and institutional investors on DJIA and S&P500 index returns. Appl. Financ. Econ. 18, 1303-1317. (2008)

Zellner, A.: An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias. J. Am. Stat. Assoc. 57, 348–368. (1962)

Appendix

Table 5. Time spans of the observed dataset

Country	Macroeconomic data		BCS data		
	ind	cons	Industry	Consumers	Retail trade
Austria	2000M01-2020M06	1996Q1-2020Q2	2000M01-2020M06	1995Q4-2020Q2	1996Q1-2020Q2
Belgium	2000M01-2020M06	1995Q1-2020Q2	2000M01-2020M06	1995Q1-2020Q2	1995Q1-2020Q2
Bulgaria	2000M01-2020M06	1995Q1-2020Q2	2000M01-2020M06	2001Q2-2020Q2	1995Q1-2020Q2
Croatia	2000M01-2020M06	1995Q1-2020Q2	2008M05-2020M06	2005Q2-2020Q2	2008Q4-2020Q2
Cyprus	2000M01-2020M06	-	2001M01-2020M06	2001Q2-2020Q2	2002Q2-2020Q2
Czechia	2000M01-2020M06	1996Q1-2020Q2	2000M01-2020M06	1995Q1-2020Q2	1995Q1-2020Q2
Denmark	2000M01-2020M06	1995Q1-2020Q2	2000M01-2020M06	1995Q1-2020Q2	2010Q2-2020Q2
Estonia	2000M01-2020M06	1995Q1-2020Q2	2000M01-2020M06	1995Q1-2020Q2	1995Q1-2020Q2
Finland	2000M01-2020M06	1995Q1-2020Q2	2000M01-2020M06	1995Q4-2020Q2	1997Q1-2020Q2
France	2000M01-2020M06	1995Q1-2020Q2	2000M01-2020M06	1995Q1-2020Q2	1995Q1-2020Q2
Germany	2000M01-2020M06	1995Q1-2020Q2	2000M01-2020M06	1995Q1-2020Q2	1995Q1-2020Q2
Greece	2000M01-2020M06	1995Q1-2020Q2	2000M01-2020M06	1995Q1-2020Q2	1995Q1-2020Q2
Hungary	2000M01-2020M06	1995Q1-2020Q2	2000M01-2020M06	1995Q1-2020Q2	1996Q1-2020Q2
Ireland	2000M01-2020M06	1995Q1-2020Q2	2000M01-2020M06	1995Q1-2020Q2	1997Q4-2020Q2
Italy	2000M01-2020M06	1996Q1-2020Q2	2000M01-2020M06	1995Q1-2020Q2	1995Q1-2020Q2
Latvia	2000M01-2020M06	1995Q1-2020Q2	2000M01-2020M06	2001Q2-2020Q2	1996Q1-2020Q2
Lithuania	2000M01-2020M06	1995Q1-2020Q2	2000M01-2020M06	2001Q2-2020Q2	1995Q2-2020Q2
Luxembourg	2000M01-2020M06	1995Q1-2020Q2	2000M01-2020M06	2002Q1-2020Q2	-
Malta	2000M01-2020M06	2000Q1-2020Q2	2002M11-2020M06	2002Q4-2020Q2	2011Q2-2020Q2
Netherlands	2000M01-2020M06	1996Q1-2020Q2	2000M01-2020M06	1995Q1-2020Q2	1995Q1-2020Q2
Poland	2000M01-2020M06	1995Q1-2020Q2	2000M01-2020M06	2001Q2-2020Q2	1995Q1-2020Q2
Portugal	2000M01-2020M06	1995Q1-2020Q2	2000M01-2020M06	1995Q1-2020Q2	1995Q1-2020Q2
Romania	2000M01-2020M06	1995Q1-2020Q2	2000M01-2020M06	2001Q2-2020Q2	1995Q1-2020Q2
Slovakia	2000M01-2020M06	-	2000M01-2020M06	1999Q2-2020Q2	1995Q1-2020Q2
Slovenia	2000M01-2020M06	1995Q1-2020Q2	2000M01-2020M06	1996Q1-2020Q2	1999Q1-2020Q2
Spain	2000M01-2020M06	1995Q1-2020Q2	2000M01-2020M06	1995Q1-2020Q2	1995Q1-2020Q2
Sweden	2000M01-	1995Q1-	2000M01-	1995Q4-	1996Q3-

	2020M06	2020Q2	2020M06	2020Q2	2020Q2
United Kingdom	2000M01-2020M06	1995Q1-2020Q2	2000M01-2020M06	1995Q1-2020Q2	1995Q1-2020Q2