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A note on the predictive power of survey data in nowcasting euro area GDP

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Non-technical summary

Research Question

Forecasts for the gross domestic product (GDP) in the current quarter provide useful metrics for economic policy decisions. What are known as “nowcasts” are usually based on a range of indicators often grouped into two categories: soft and hard indicators. A typical example of a soft indicator is survey data, whereas, industrial output, for instance, is categorised as a hard indicator. Availability and data quality are the criteria that distinguish soft from hard indicators. Although survey data on the current quarter may be fast to come by, they merely reflect personal assessments. Industrial output, on the other hand, is a quantitative measure of economic activity; however, it is available only with a considerable lag. From a forecaster’s perspective, it is desirable to be able to gauge how important the two types of indicators are in relative terms.

Contribution

This paper examines the question as to what extent soft indicators play a role in ensuring accuracy of GDP nowcasts for the euro area. In terms of empirical application, this paper examines, *inter alia*, whether soft indicators contribute to making nowcasts more accurate other than through their early availability. A distinction is made between times of relative tranquillity and times of crisis.

Results

Looking at the entire sample, we find that the soft indicators have virtually no bearing on the accuracy of nowcasts. This apparently also holds irrespective of whether their early availability is taken into account. However, soft indicators prove to be useful in quieter times. Besides early availability, soft indicators appear to contain valuable information relevant to the nowcasts in those periods.

Nichttechnische Zusammenfassung

Fragestellung

Prognosen für das Bruttoinlandsprodukt (BIP) des laufenden Quartals liefern hilfreiche Kennzahlen für wirtschaftspolitische Entscheidungen. Für diese sogenannten Nowcasts wird üblicherweise eine Vielzahl von Indikatoren verwendet, welche oft in zwei Gruppen eingeteilt werden: weiche und harte Indikatoren. Ein typisches Beispiel für weiche Indikatoren sind Umfragedaten, während die Industrieproduktion zu den harten Indikatoren zählt. Weiche und harte Indikatoren unterscheiden sich voneinander hinsichtlich ihrer Verfügbarkeit und ihrer Datenqualität. Umfragedaten für das aktuelle Quartal sind zwar zeitnah verfügbar, aber sie spiegeln lediglich persönliche Einschätzungen wider. Dagegen ist die Industrieproduktion zwar ein quantitatives Maß für die wirtschaftliche Aktivität, sie ist aber nur mit einer größeren Verzögerung verfügbar. Für Prognostiker ist es wünschenswert, die relative Wichtigkeit der beiden Arten von Indikatoren einschätzen zu können.

Beitrag

In der vorliegenden Arbeit wird der Frage nachgegangen, inwiefern die weichen Indikatoren für die Treffgenauigkeit der Nowcasts des BIP im Euroraum eine Rolle spielen. In der empirischen Anwendung wird dabei unter anderem geprüft, ob die weichen Indikatoren über ihre frühere Verfügbarkeit hinaus einen Beitrag zur Treffgenauigkeit leisten. Dabei wird zwischen ruhigeren Zeiten und Krisenzeiten unterschieden.

Ergebnisse

Wenn die gesamte betrachtete Stichprobe zugrunde gelegt wird, so zeigt sich, dass die weichen Indikatoren praktisch keinen Beitrag zur Treffgenauigkeit der Nowcasts leisten. Dies gilt offenbar sogar unabhängig davon, ob ihre frühere Verfügbarkeit berücksichtigt wird oder nicht. In ruhigeren Zeiten erweisen sich die weichen Indikatoren dagegen als hilfreich. Sie scheinen dann auch über ihre frühere Verfügbarkeit hinaus wertvolle Informationen für die Nowcasts zu beinhalten.

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A note on the predictive power of survey data in nowcasting euro area GDP *

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Abstract

This paper investigates the trade-off between timeliness and quality in nowcasting practices. This trade-off arises when the frequency of the variable to be nowcast, such as GDP, is quarterly, while that of the underlying panel data is monthly; and the latter contains both survey and macroeconomic data. These two categories of data have different properties regarding timeliness and quality: the survey data are timely available (but might possess less predictive power), while the macroeconomic data possess more predictive power (but are not timely available because of their publication lags). In our empirical analysis, we use a modified dynamic factor model which takes three refinements for the standard dynamic factor model of Stock and Watson (2002) into account, namely mixed frequency, pre-selections and co-integration among the economic variables. Our main finding from a historical nowcasting simulation based on euro area GDP is that the predictive power of the survey data depends on the economic circumstances, namely, that survey data are more useful in tranquil times, and less so in times of turmoil.

JEL classification: C22, C38, C53, E37.
Keywords: nowcasting; dynamic factor model; mixed frequency; pre-selections; co-integration; survey data; trade-off between timeliness and quality; turmoil and tranquility.

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1 Introduction

The current-quarter forecasting of GDP (usually called nowcasting) is a useful guide to understanding the current state of economic activity. For this purpose, a raft of indicators are often used. Forecasters usually divide these indicators into two groups, soft and hard indicators. A typical example of soft indicators is survey data, while macroeconomic data are a typical example of hard indicators. The reason for making this division is the trade-off between timeliness and the quality of the indicators: survey data have (almost) no time lag for the corresponding month of the reference quarter, but they are not a part of the GDP calculation. Conversely, macroeconomic data such as industrial production are part of GDP, and, hence, possess a higher quality in prediction for GDP, but they are published with some time lags. Other macroeconomic data such as unemployment rates and/or car registrations are not directly a part of GDP, but they still have a high correlation with GDP. Therefore, for empirical nowcasting practices, it is useful to know how the trade-off between timeliness and quality works.

The empirical consensus on this issue is that survey data have useful indicators for GDP nowcasting, but their relevance weakens when hard data are available. See Giannone et al. (2008), for example. Specifically, Girardi et al. (2015) set a hypothetical scenario (where both groups of data are available without any time lags) in order to investigate whether the value of survey data is rooted in their timeliness or in their genuine information content. One of their findings is that survey data have genuine predictive power beyond their timeliness, as also reported in Banbura and Rünstler (2011).

In this paper, we also empirically investigate the role of survey data in nowcasting euro area GDP. The focus is to empirically examine whether the genuine predictive power of survey data depends on the specific economic circumstances: periods of turmoil and periods of tranquility. Our main finding is that the predictive power of survey data depends on the economic circumstances: survey data are more useful in periods of tranquility, and less so in periods of turmoil. In this respect, our empirical result can be regarded as a supplement for the empirical paper of Banbura and Rünstler (2011) and Girardi et al. (2015).

The remainder of the paper is structured as follows. Section 2 briefly describes our nowcasting model. Section 3 presents our empirical data, the design of the historical evaluation and our empirical results. Section 4 concludes the paper.

2 Nowcasting model

2.1 The dynamic factor model and the three refinements

Ever since the paper of Stock and Watson (2002) was published, the dynamic factor model (DFM) has been widely used to forecast macroeconomic key variables such as GDP. For our nowcasting exercise, however, we employ a modified version of the DFM called factor single equation error correction model[1] (FSEECM) based on mixed frequency, pre-selections and error correction mechanism examined in Kurz-Kim (2016). The FSEECM contains three refinements to the DFM, which have been discussed in the literature. To briefly show the modification steps, we start with the (standard) DFM (Stock and Watson, 2002) given as:

$$y_t^Q = \sum_{i=1}^{p} b_i y_{t-i}^Q + \sum_{k=1}^{r} \sum_{j=0}^{q_k} a_{kj} f_{k,t-j}^Q + u_t^Q, \tag{1}$$

where y^Q are changes (growth rates) in quarterly GDP; p the lag order of the lag endogenous variable; b_i the coefficients of the lag endogenous variable; $f_{k,t-j}^Q$ the j-th lag of the k-th quarterly factor; r the (optimal) number of factors; q_k the lag order of the k-th factor; a_{kj} the coefficients of the lag exogenous variables (factors); and u_t^Q the quarterly model disturbances.

The first refinement is a necessary one in order to apply the DFM for nowcasting *quarterly* growth rates of GDP based on *monthly* data. To make use of information contained in monthly indicators for nowcasting of quarterly GDP, Marcellino and Schumacher (2010) *inter alia* adopt the mixed-frequency technique.[2] The DFM embedded in mixed-frequency technique is now given as:

$$y_t^Q = \sum_{i=1}^{p} b_i y_{t-i}^Q + \sum_{k=1}^{r^s} \sum_{j=0}^{q_k} \sum_{m=0}^{2} a_{kjm} f_{k,t-j-m/3}^M + u_t^Q, \tag{2}$$

[1] Banerjee et al. (1990) popularized the dynamic single equation error correction model (SEECM) for non-stationary variables by using a linear transformation of the autoregressive-distributed lag model. The SEECM is a widely used model in economic analysis, both in structural analysis and in forecasting practice. This is because the SEECM is capable of capturing both the adjustment towards the economic equilibrium (a stable long-run relationship in level) and the short-run dynamics (in difference) and, hence, can reproduce economic equilibrium hypotheses in a statistical model.

[2] See Ghysels et al. (2007) for more details of the mixed data sampling technique.

where $f^M_{k,t-j-m/3}$ the j-th lag in m-th month of the k-th *monthly* factor with $m = 0, 1, 2$ ($m = 0$, for the last month of each quarter; $m = 1$, for the middle month of each quarter; and $m = 2$, for the first month of each quarter).

The second refinement focuses on a pre-selection of indicators. A large set of indicators is not always determined optimally, because the selection is arbitrary to a degree, but also because of changes in the predictive power of individual indicators from quarter to quarter. In the framework of the DFM, Boivin and Ng (2006) study the relationship between the dimension of the panel data and their forecasting performance, and conclude that the factors extracted from a small number of informative indicators often perform better than those extracted from a huge number. Consequently, Bai and Ng (2008) propose *targeted* indicators using certain pre-selection methods, and report improvements in the framework of the DFM. Girardi et al. (2017) also recently documented that predictions obtained through dimension reduction methods in nowcasting euro area GDP outperform both the benchmark AR and the DFM without any pre-selection. One of the most popular pre-selection methods is the least absolute shrinkage and selection operator (lasso) introduced by Tibshirani (1996), which aims to obtain higher prediction accuracy and economic interpretability for estimation in linear models. The DFM based on the mixed-frequency technique and a pre-selection is given as:

$$y^Q_t = \sum_{i=1}^{p} b_i y^Q_{t-i} + \sum_{k=1}^{r} \sum_{j=0}^{q_k} \sum_{m=0}^{2} a_{kjm} \tilde{f}^M_{k,t-j-m/3} + u^Q_t, \tag{3}$$

where $\tilde{f}$ is now estimated factors from a set of the pre-selected indicators. In our empirical analysis, however, we choose the elastic net (EN) technique[3] considered

[3] The EN estimate is given as:

$$\beta^{en} = \text{argmin}_\beta \left\{ \frac{1}{2N} \sum_{i=1}^{N} \left(y - x_i^T \beta\right)^2 + \theta \left[\sum_{j=1}^{n} \left(\frac{1-\alpha}{2} \beta_j^2 + \alpha |\beta_j| \right) \right] \right\}, \tag{4}$$

where the lasso parameter, θ, governs the penalty term for deciding which set of indicators from our whole panel data provide the highest level of prediction with respect to the key variable to be nowcast. The generalization of the lasso estimate by the EN estimate is carried out by the tuning parameter, $\alpha \in [0, 1]$, which also governs the penalty term. For $\alpha \in (0, 1)$, the penalty term interpolates between the L^1- and L^2-norm of β. The EN estimate is the same estimate as the lasso when $\alpha = 1$ and the ridge regression (Hoerl and Kennard, 1970) when $\alpha = 0$. Consequently, the EM method reduces the cross-section dimension of N depending on θ and α. In our case, y and in Zou and Hastie (2005) as the pre-selection method which can be regarded as a generalized lasso technique. The reason for using the EN instead of the lasso is that macroeconomic panel data are often characterized by the 'N(cross-section dimension)>T(time dimension)-problem', and because of the pairwise high correlations of indicators in a group which can be met more effectively by the EN than by the lasso.

Finally, the third refinement takes into account the non-stationarity of macroeconomic variables and, hence, a possible co-integrating relationship between GDP and the factors. In the framework of the generalized DFM, Bai (2004) analytically considers the existence of a co-integrating relationship between non-stationary factors. Consequently, Banerjee et al. (2014, 2017) extend the DFM by modeling an error correction mechanism. They show that the error correction mechanism generally contributes to higher forecasting precision.

By introducing the new concept of *long-run* and *short-run* factors explained below (in subsection 2.2), the modified version of the DFM with the three refinements, namely our FSEECM, is now written as:

$$y_t^Q = b\left[Y_{t-1}^Q - \sum_{k=1}^{r^l} \beta_k \tilde{F}_{k,t-1}^Q\right] + \sum_{i=1}^{p} b_i y_{t-i}^Q + \sum_{k=1}^{r^s} \sum_{j=0}^{q_k} \sum_{m=0}^{2} a_{kjm} \tilde{f}_{k,t-j-m/3}^M + u_t^Q, \qquad (5)$$

where Y^Q is the level of the quarterly GDP; $\tilde{F}_k^Q$ the k-th (*quarterly*) long-run factor; b the loading parameter for the co-integrating term; r^l the (optimal) number of long-run factors; β_k the k-th co-integrating parameter; r^s the (optimal) number of the short-run factors; and y^Q, p, b_i, q_k, a_{kjm} and $\tilde{f}_{k,t-j-m/3}^M$ are explained in (1), (2) and (3).

The FSEECM in (5) can be regarded as a general modeling which reduces to the standard DFM when the error correction term is insignificant ($b = 0$); the lasso parameter is one; and $\hat{f}_{k,t-j-m/3}^M$ is replaced by a quarterly factor (ie, without the mixed-frequency technique). Kurz-Kim (2016) compares the nowcasting performance of the FSEECM and its sub-models and shows the superiority of the nowcasting performance of the FSEECM.[4]

x_i^T is the key variable to be nowcast and a set of indicators with a time dimension of T is applied, respectively.

[4]Our empirical findings are, however, robust against changes in nowcasting models. Using the factor MIDAS (without ECM), for example, we obtained almost the same results.

2.2 Modeling process for empirical applications

In this subsection, we briefly describe how to apply the FSEECM for GDP nowcasting based on a large set of indicators. Suppose we have a non-stationary quarterly GDP series, Y_t^Q with $t = 1, \ldots, T^Q$ which has to be nowcast for $T^Q + 1$. Moreover, we have non-stationary monthly panel data, denoted as X_{it}^M, with a cross-section dimension $i = 1, \ldots, N$ and a time domain dimension $t = 1, \ldots, T^M$. For nowcasting practice, it is assumed that $T^Q \times 3 + 1 \leq T^M \leq T^Q \times 3 + 3$. In order to build an error correction term between the (non-stationary) quarterly GDP series and the (non-stationary) monthly indicators, we need quarterly indicators corresponding to the quarterly GDP. We take values of every last month in a quarter from X_{it}^M and regard them as quarterly panel data, $X_{it}^Q := X_{i,1:3:T^M}^M$, as usually recommended in the literature. Using the EN method, we select the targeted long-run indicators ($\tilde{X}_{it}^Q$) from the entire long-run indicators (X_{it}^Q). In the next step, the principal component method provides us with a small number of long-run factors ($\tilde{F}_t^Q$) from $\tilde{X}_{it}^Q$. To obtain the targeted short-run indicators, we firstly transform the non-stationary monthly indicators into stationary ones using a difference operator, $\Delta X_{i,t-m/3}^M := X_{i,t-m/3}^M - X_{i,(t-1)-m/3}^M$ with $m = 0, 1, 2$, where $m = 0$ indicates observations for every last month in a quarter (henceforth, type 1st of month); $m = 1$ for every middle month in a quarter (henceforth, type 2nd of month); and $m = 2$ for every first month in a quarter (henceforth, type 3rd of month). The EN method enables us to select the targeted short-run indicators for each type of month ($\tilde{X}_{i,t-m/3}^M$) from the stationary short-run indicators, $\Delta X_{i,t-m/3}^M$. The principal component method again provides us with a small number of short-run factors for each type of month ($\tilde{f}_{i,t-m/3}^Q$) from $\tilde{X}_{i,t-m/3}^M$. Based on the estimated long-run factors and short-run factors as well as the lag endogenous variables we now build the FSEECM in (5).

In our empirical exercise, we choose two as optimal number for both the short-run and the long-run factors for all three types of month and all quarters using the panel criteria of Bai and Ng (2002) and the integrated panel criteria of Bai (2004), respectively, ie, $r^s = r^l = 2$. Moreover, for the purpose of estimating our nowcasting model, we set $p = q_1 = q_2 = 4$ as usually chosen for quarterly data in empirical works. A small number of short-run factors and an appropriate lag length enable us to use unrestricted mixed-frequency modeling.[5] In order to determine the unknown

[5]To avoid the curse of dimensionality of high-frequency models, the mixed-frequency technique usually achieves parsimonious models by means of a temporal aggregation, such as exponential lag polynomials, see Marcellino and Schumacher (2010).

parameters for the EN estimate, α and θ, we adopt a grid search method by setting $\alpha \in [0.01 : 0.01 : 1]$ and $\theta^l, \theta^s \in [0.01 : 0.01 : 0.5]$, as usually recommended in the literature. The step length 0.01 for α, θ^l and θ^s seems to be appropriate with respect to both searching intensity and time required for computing. Consequently, we obtain 250,000 (100×50^2) nowcasts for each type of month in our historical simulation. We choose the combination of the three parameters (α, θ^l and θ^s) at which the nowcasting mean-squared error (MSE) reaches its minimum value.

3 Empirical application

3.1 Data

For our empirical application, we use the euro area dataset deployed by the Deutsche Bundesbank for macroeconomic analysis as well as now- and forecasting. The euro area GDP is aggregated, incorporating seasonally and calendar-adjusted quarterly data from 2000QI to 2016QIV (68 observations). Figure 1 shows the logarithm of the euro area GDP (upper panel) and its quarterly growth rates (lower panel), where the growth rate for 2000QI is not determined.

Figure 1. Euro area GDP and its quarterly growth rates, 2000QI - 2016QIV

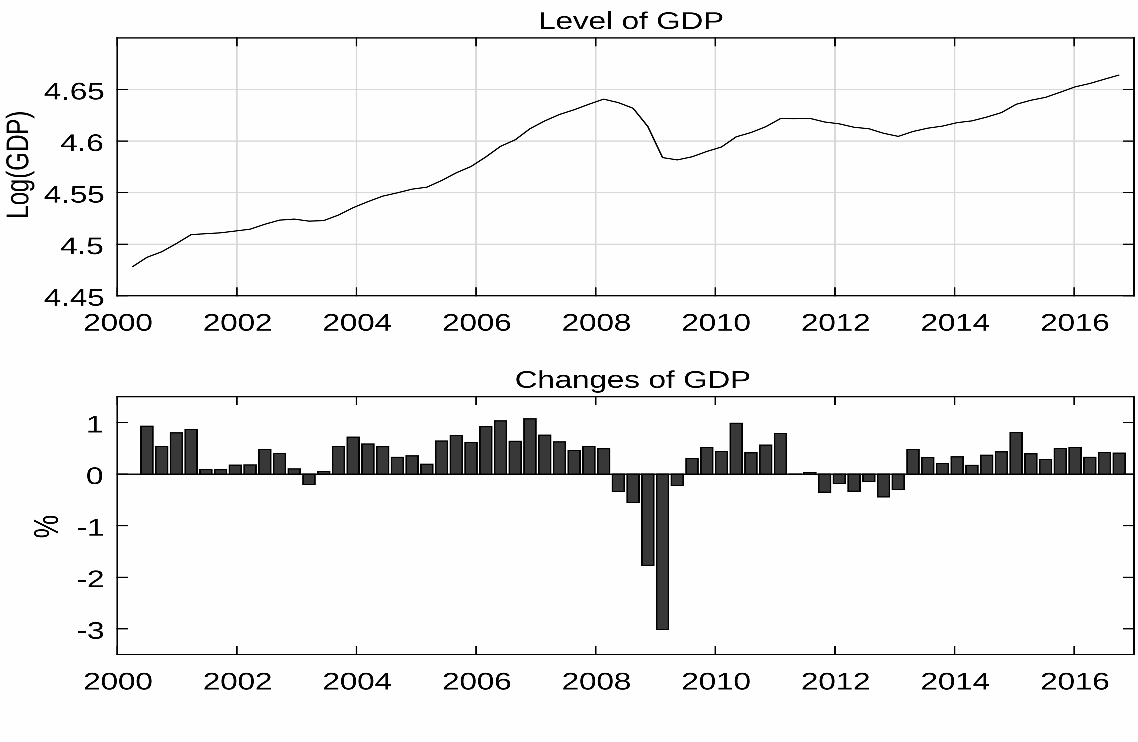


Figure 1 shows two economic recession phases: the recent worldwide economic recession triggered by the financial crisis between 2008QIII and 2009QIII; and the recovery which was, however, disturbed by the so-called euro crisis which began with Greek's sovereign debt crisis in 2010QII. The latter recession period until 2013QII is characterized as a period of turmoil in our paper. Since 2013QIII, growth rates have been smaller than those before the recent worldwide economic recession, but they are positive and stable and, hence, characterized as a period of tranquility.

The panel data serving as a set of high-frequency indicators consist of the 115 monthly time series and span 2000M01 to 2016M12 (204 observations for each series), where 38 series are survey data. A large part of the panel data are euro area aggregated data, some of which are disaggregated national data, such as industrial production in Germany, France, Italy and Spain, for example. The data set was gathered on March 14, 2017, so monthly data until December 2016 are already contained.[6] The whole dataset used in our empirical application is listed in detail in Appendix B.

3.2 Nowcasting exercise

Empirical setting: We first divide our monthly indicators into two sub-samples: the first one covers the period January 2000 to September 2010 (129 observations) and the second one the period October 2010 to December 2016 (75 observations). Each of the two sub-samples is again divided into three sub-samples for the type 1st, 2nd and 3rd of month. The type 1st of month contains all the first months in every quarter, January, April, July and October; the type 2nd of month contains all the middle months in every quarter, February, May, August and November; and the type 3rd of month contains all the last months in every quarter, March, June, September and December. This means that the sample size of each of the three first sub-samples is 43 (=129/3), and the sample size of each of the three second sub-samples is 25 (=75/3). Each of the three first sub-samples serves as the basis for starting our nowcasting models for the type 1st, 2nd, and 3rd of month; and they are extended by one observation recursively in our historical simulation procedure. We consequently gather 25 historical nowcasts for each of the three types of month.

[6] The dataset used for our nowcasting exercise is the latest available and, hence, a finally revised one, not real-time, ie, all revisions made up to the date have already been taken into account. As pointed out by Diebold and Rudebusch (1991), forecasting performance based on the revised data can be substantially better than that based on real-time data. However, a historical simulation aimed at comparing the relative forecasting performance under alternative models should not be greatly affected by using revised data as argued in Girardi (2017). See, Bernanke and Boivin (2003); Schumacher and Breitung (2008).

Empirical nowcasts: For our comparison, we make use of three sets of indicators: the *survey data* alone, the *non-survey data* and the *entire data*.[7] This results in three kinds of nowcasts: the nowcasts based on the survey data ($gdp^{(s)}$), the non-survey data ($gdp^{(\bar{s})}$), and the entire data ($gdp^{(s+\bar{s})}$). Consequently, we obtain three monthly observations in each quarter for each of the nowcasts as follows:

$$\widehat{gdp}_{ij}^{(s)}, \qquad i = 1, 2, 3; \quad j = 2010QIV, \ldots, 2016QIV,$$

$$\widehat{gdp}_{ij}^{(\bar{s})}, \qquad i = 1, 2, 3; \quad j = 2010QIV, \ldots, 2016QIV,$$

$$\widehat{gdp}_{ij}^{(s+\bar{s})}, \quad i = 1, 2, 3; \quad j = 2010QIV, \ldots, 2016QIV,$$

where i signifies types of month and j indicates quarters.[8]

Estimated nowcasting models: Before we present the results of our historical simulation, some features of our nine estimated nowcasting models (three sets of indicators and three types of month) are described. To determine a set of targeted indicators, the parameters in (4) must be known. We choose the combinations given in Table 1 for our nine nowcasting models at which the nowcasting MSE, calculated from the 25 historical nowcasts for each combination of α, θ^l and θ^s, reaches its minimum value.

Table 1. Parameters for the EN estimate[ab]

	$\widehat{gdp}_i^{(s)}$			$\widehat{gdp}_i^{(\bar{s})}$			$\widehat{gdp}_i^{(s+\bar{s})}$		
i / Parameter	1st	2nd	3rd	1st	2nd	3rd	1st	2nd	3rd
$\hat{\alpha}$	0.99	0.06	1.00	0.90	0.89	0.09	0.80	0.77	0.80
$\hat{\theta}^l$	0.07	0.50	0.50	0.17	0.12	0.17	0.47	0.49	0.13
$\hat{\theta}^s$	0.16	0.37	0.22	0.50	0.48	0.44	0.47	0.47	0.38

[a]The numbers for $\hat{\alpha}$, $\hat{\theta}^l$ and $\hat{\theta}^s$ are determined for the penalty term in (4) by means of a historical simulation. [b]i denotes types of month.

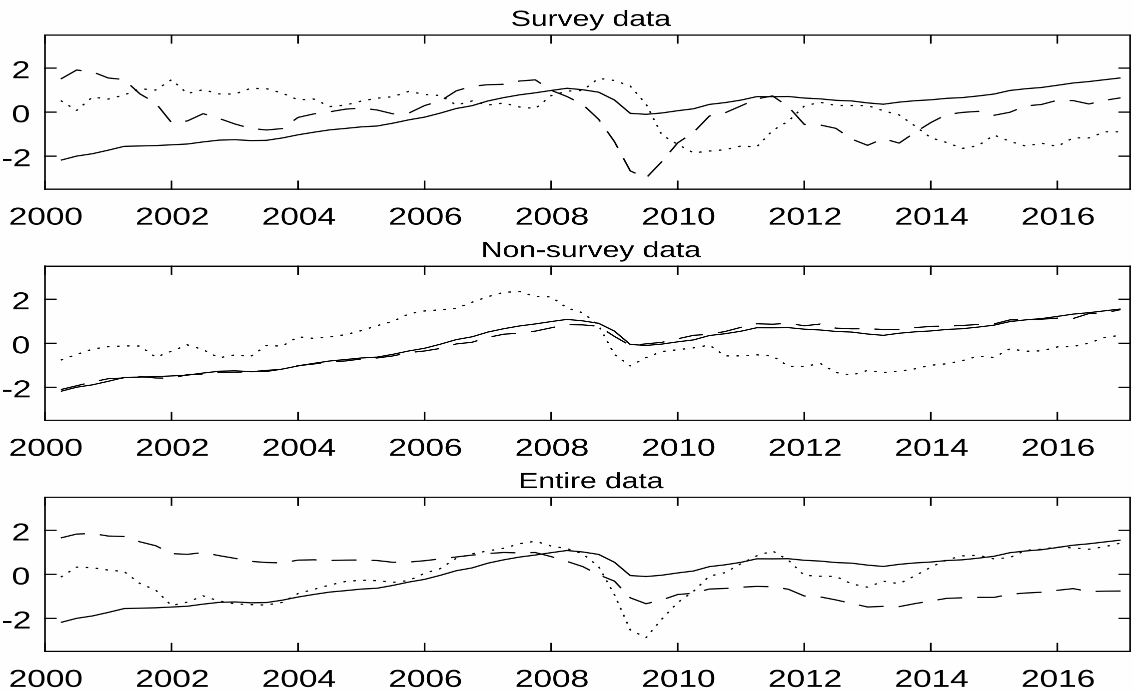
[7]In the literature, financial data are often built as a separate group to evaluate their predictive power. We, however, include them in the non-survey data and concentrate on the survey data. Furthermore, Girardi et al. (2015) found that in the case of no publication lag the financial group usually has (except during the 2008-9 financial crisis) no impact on the accuracy of GDP nowcasts.

[8]The reason for considering the non-survey data separately is that it can provide some useful information on the size of the contribution of the hard data alone, and how the predictive power of the hard data improves through the revision.

Table 1 shows that all models, except $\widehat{gdp}_{3j}^{(s+\bar{s})}$, have an α value of not equal to one. The EN method therefore seems to be a better choice than the lasso for our models.[9] The $\hat{\theta}^l$ and $\hat{\theta}^s$ vary from model to model and month to month, where high(low) θ means a small(large) set of indicators. Again, the estimated values of $\hat{\theta}^l$ and $\hat{\theta}^s$ show that nowcasts based on the targeted indicators usually produce a better nowcasting performance.

Another interesting point regarding the estimated FSEECM models is the behavior of the error correction terms. By definition, a co-integration is given when a linear combination among some non-stationary variables is stationary. We therefore firstly investigate whether the euro area GDP and the first two long-run factors (with the highest loadings) used as explanatory variables are non-stationary. Regarding our three sets of indicators, we obtain three kinds of long-run factors. Each of these three kinds of long-run factors for the whole sample period are illustrated in Figure 2, where the upper, middle and lower panel show the survey, the non-survey and the entire data, respectively. In each panel, the solid, the dashed and the dotted line indicate the standardized GDP, the first long-run factor and the second long-run factor, respectively. All time series are standardized to enable a better comparison.

Figure 2. Level of GDP and estimated long-run factors

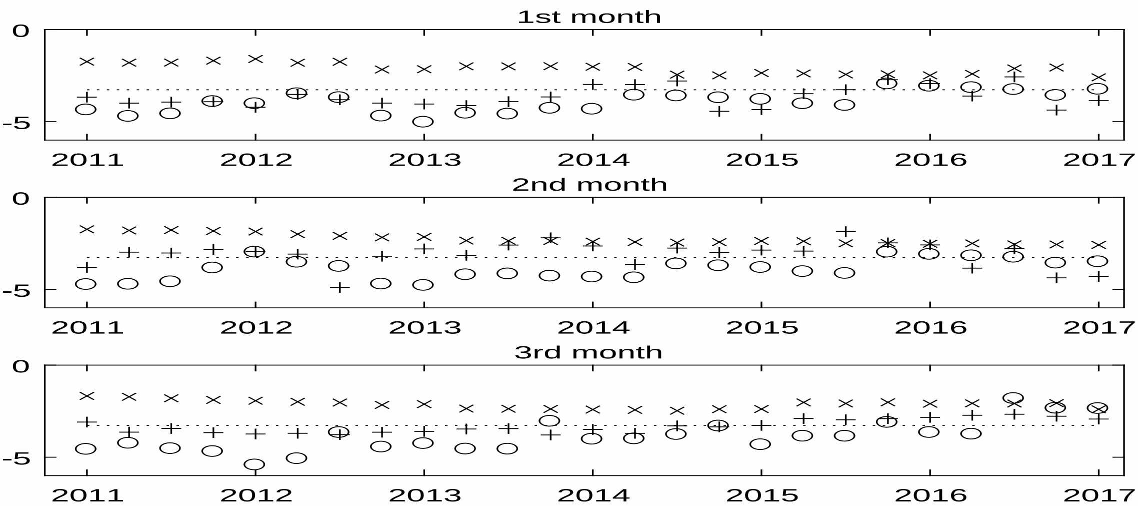


[9] An α value of one means a linear penalty incorporated in the lasso method.

At given critical values of -2.91 and -3.55 at 5 % and 1 % significance level (interpolated for a sample size of 68 observations), respectively, the augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) shows that the GDP is non-stationary with an estimated t statistic of -1.01. The first long-run factor from the survey data is shown to be non-stationary at 1 % significance level (with an estimated t statistic of -2.99) and the second at 5 % significance level (with an estimated t statistic of -2.69). Both of the long-run factors from the non-survey data are non-stationary at 5 % significance level (with an estimated t statistic of -0.90 and -1.50, respectively). Both of the long-run factors from the entire data are also non-stationary at 5 % significance level (with an estimated t statistic of -1.69 and -2.82, respectively). Furthermore, some smooth parallelism between the GDP and the factors is more evident in the non-survey data (middle panel) followed by the entire data (lower panel), at least visually.

In the context of the two stage estimation procedure for error correction models proposed in Engle and Granger (1987), a test for co-integration is usually performed by the ADF test on the residuals from the estimated (hypothetical) co-integrating relationships.[10] Figure 3 shows the recursively estimated ADF t statistics for the three types of month for 25 quarters (1st month in top panel, 2nd month in middle panel and 3rd month in bottom panel), where '$\times$', '+' and 'o' stands for the survey, the non-survey and the entire data, respectively; and the dotted line marks the critical value of -3.27 at 5 % significance level[11].

Figure 3. Estimated ADF-statistic for 25 quarters



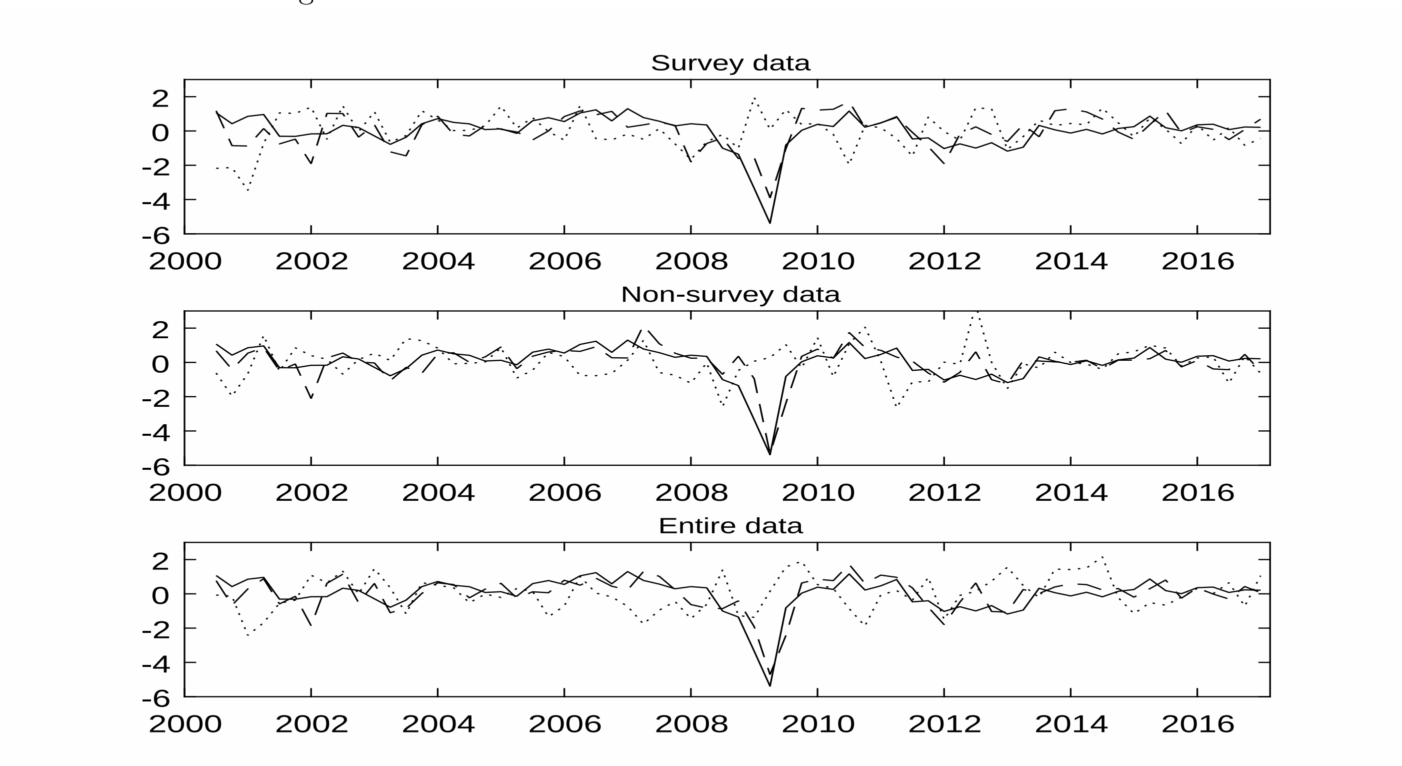
[10] Götz et al. (2014), for example, use the ADF test for co-integration in the framework of their error correction mixed-frequency models.

[11] The critical values are tabulated in Phillips and Ouliaris (1990).

Figure 3 clearly shows that the estimated t statistics for the error correction term based on the entire data are more significant than those based on the survey data. The mean values of the ADF t statistics for the entire data are -3.94, -3.92 and -3.90 for the 1st, 2nd and 3rd type of month, respectively, and highly significant.[12] Conversely, the mean values of the ADF t statistics for the survey data alone are -2.11, -2.27 and -2.13 for the 1st, 2nd and 3rd type of month, respectively, and not significant. Interestingly, the mean values of the ADF t statistics for the non-survey data are -3.65, -3.10 and -3.31 for the 1st, 2nd and 3rd type of month, respectively, and they are more significant than those for the survey data, but less significant than those for the entire data. This means that the hard indicators play a more important role for building a stable long-run relationship to the GDP. On the other hand, this implies that the survey data are more related to the short-run dynamics of the GDP if they make a 'genuine' contribution to predicting GDP.

Figure 4 shows growth rates of the euro area GDP and the two estimated short-run factors, where the solid, dashed and dotted line indicate growth rates of the GDP, the first and the second short-run factor, respectively. All time series are standardized to enable a better comparison.

Figure 4. Growth rates of GDP and estimated short-run factors



The ADF-test shows that growth rates of the euro area GDP are stationary with an estimated t statistic of -3.70. All of the short-run factors from the survey data,

[12]The critical value at 1 % significance level is -3.84.

the non-survey data and the entire data are also stationary (with a t-statistic of -4.88 and -6.74 for the survey data; -5.23 and -7.23 for the non-survey data; -3.88 and -5.15 for the entire data, respectively). The largest economic contractions seem to be better predicted by the hard data as shown in middle and lower panel.

3.3 Evaluation of nowcasting performance

We compare the nowcasting performance of the three groups of data sets in the hypothetical scenario that the non-survey data were released as early as the survey data. For the sake of simplicity, we merely present the average value of the three types of month.[13] Figure 5 shows the results of this comparison for each of the 25 quarters, where the solid line signifies the realizations of GDP, '×', '+' and 'o' signifies $\sum_{i=1}^{3}\widehat{gdp}_{ij}^{(s)}/3$, $\sum_{i=1}^{3}\widehat{gdp}_{ij}^{(\bar{s})}/3$ and $\sum_{i=1}^{3}\widehat{gdp}_{ij}^{(s+\bar{s})}/3$, respectively, in the upper panel; and the lower panel shows the nowcast errors for a better comparison.

Figure 5. Empirical results for 25 quarters (in %) (2010QIV - 2016QIV)

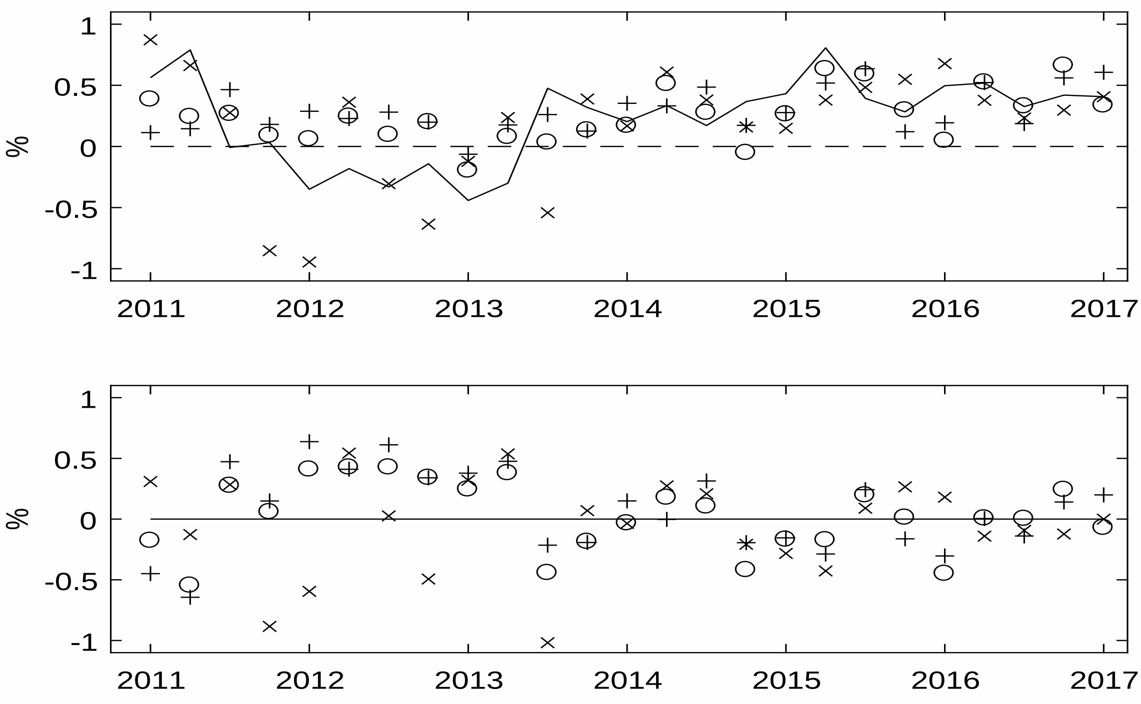


Figure 5 shows that the nowcasting errors based on the entire sample are smaller than those based on the survey data. A smaller nowcasting error of $\sum_{i=1}^{3}\widehat{gdp}_{ij}^{(s+\bar{s})}/3$ than that of $\sum_{i=1}^{3}\widehat{gdp}_{ij}^{(s)}/3$ can be observed 16 times during the 25 quarters. We also test the significance of the difference by the Diebold/Mariano-test (Diebold

[13]See Figure A1 in Appendix A for the results of each type of month.

and Mariano, 1995). Furthermore, due to the small number of nowcasts, we use the Student's t distribution proposed in Harvey et al. (1997). The null hypothesis of equality of forecast accuracy with an estimated statistic of 1.46 cannot be accepted at a significance level of 7.87% according to the Student's t-distribution with 24 degrees of freedom. Interestingly, the better nowcasting performance based on the entire data is, at least visually, clearer in the first half of the nowcasting exercise period up to 2013QIII, and it seems to be not considerable in the second half of the nowcasting exercise period. This is the main empirical evidence highlighted in this paper. We will come back to this issue later. Table 2 summarizes the results for all types of month separately by means of the MSE and the mean absolute deviation (MAD).

Table 2. Nowcasting performance of three data sets (2010QIV – 2016QIV)[ab]

Nowcasts i	MSE $\widehat{gdp}_i^{(s)}$	MSE $\widehat{gdp}_i^{(\bar{s})}$	MSE $\widehat{gdp}_i^{(s+\bar{s})}$	MAD $\widehat{gdp}_i^{(\bar{s})}$	MAD $\widehat{gdp}_i^{(\bar{s})}$	MAD $\widehat{gdp}_i^{(s+\bar{s})}$
1	0.56	0.29	**0.30**	0.33	0.22	**0.21**
2	0.52	0.26	0.27	0.31	0.22	0.19
3	**0.51**	0.26	0.21	**0.26**	0.18	0.18

[a]The numbers are average of the growth rates (in percentage) from 25 realizations for each type of month. [b]The numbers in bold indicate a realistic comparison taking the publication lags into account.

Table 2 confirms the visual impression provided by Figure 5 that the MSE and the MAD of $\widehat{gdp}_j^{(s+\bar{s})}$ are smaller than those of $\widehat{gdp}_j^{(s)}$ not only on average, but also for every type of month. Additionally, Table 2 also shows that the nowcasting errors for all three sets of indicators decrease from month to month (even though some of the improvements are very small). This indicates not only the predictive power of the three sets of indicators, but also the convergence property of our nowcasting model. Using MSE or MAD as the loss function of forecasters, our tentative summary would be that, for the whole sample period, the entire data have more predictive power than the survey data. However, these results are of little empirical relevance for nowcasting practices as they are obtained from the hypothetical scenario that the non-survey data were released as early as the survey data.

For this reason, an appropriate evaluation regarding the trade-off between timeliness and quality in practical nowcasting would be a comparison between the nowcasting performance of $\widehat{gdp}_{3j}^{(s)}$ (nowcasts in the third month, based on the survey data) and that of $\widehat{gdp}_{1j}^{(s+\bar{s})}$ (nowcasts in the first month, based on the entire data). This is a realistic scenario because the time lag between publishing the survey and the hard data is usually two months. In this regard, Table 2 again shows that the nowcasting performance, based on the entire data in the first month (0.30 and 0.21 measured by MSE and MAD, respectively), is even better than that based on the survey data in the third month (0.51 and 0.26). In the same setting as presented in Figure 5, Figure 6 shows this result by presenting nowcasts for all the quarters, where, again, '×' signifies nowcasts based on the survey data in the *third* month ($\widehat{gdp}_{\mathbf{3}j}^{(s)}$); '+' signifies nowcasts based on the non-survey data in the *first* month ($\widehat{gdp}_{\mathbf{1}j}^{(\bar{s})}$); and 'o' signifies nowcasts based on the entire data in the *first* month ($\widehat{gdp}_{\mathbf{1}j}^{(s+\bar{s})}$).

Figure 6. Trade-off between timeliness and quality (in %)

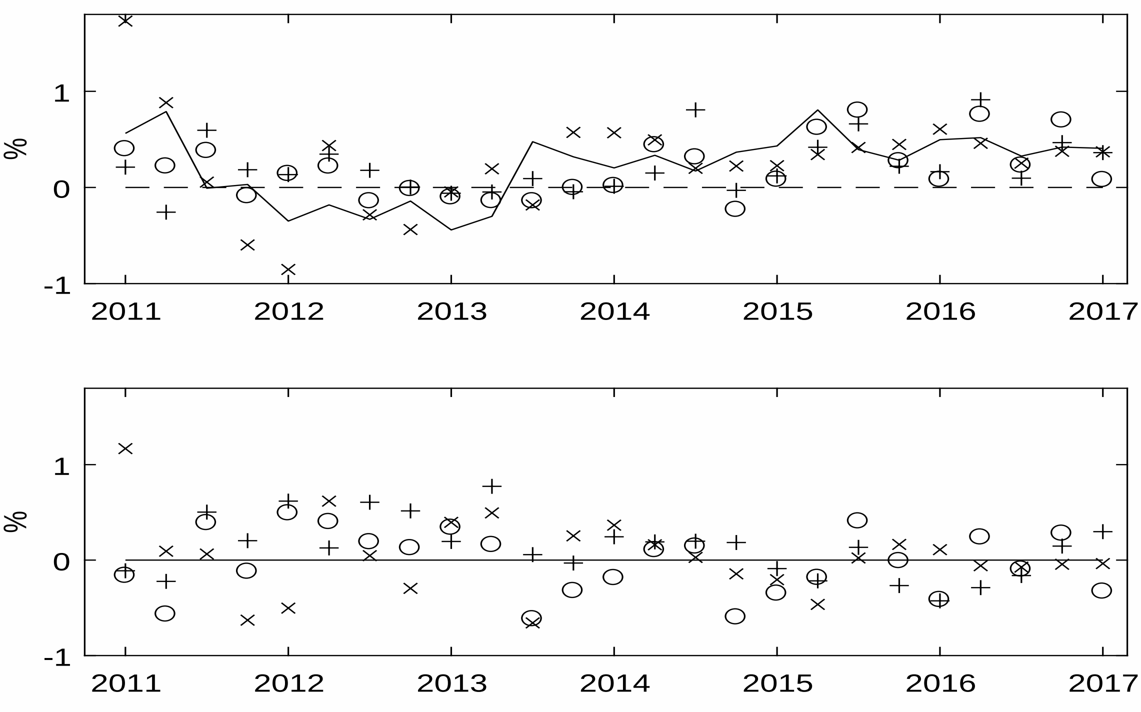


Figure 6 shows that the deviation of $\widehat{gdp}_{1j}^{(s+\bar{s})}$ from the GDP is generally smaller that that of $\widehat{gdp}_{3j}^{(s)}$. This would mean that nowcasting based on the entire data (despite their delayed availability) generally provides a better performance than based on the survey data. However, similar to Figure 5, the better nowcasting performance of $\widehat{gdp}_{1j}^{(s+\bar{s})}$ is clearer in the first half sample period up to 2013QIII, and the difference is not considerable (or rather, almost equal) in the second half of the sample period. To this end, we divide our sample into two sub-samples, namely 2010QIV-2013QII (11 observations) and 2013QIII-2016QIV (14 observations). This division corresponds to the different economic circumstances in the two sub-samples, namely periods of turmoil and tranquility as discussed in Figure 1. Tables 3a and 3b summarize the results for periods of turmoil and tranquility, respectively.

Table 3a. Predictive power in periods of turmoil (2010QIV – 2013QII)^{ab}

Nowcasts i	MSE $\widehat{gdp}_i^{(s)}$	$\widehat{gdp}_i^{(\bar{s})}$	$\widehat{gdp}_i^{(s+\bar{s})}$	MAD $\widehat{gdp}_i^{(\bar{s})}$	$\widehat{gdp}_i^{(\bar{s})}$	$\widehat{gdp}_i^{(s+\bar{s})}$
1	0.74	0.19	**0.21**	0.53	0.17	**0.21**
2	0.59	0.27	0.26	0.43	0.21	0.23
3	**0.70**	0.33	0.13	**0.40**	0.19	0.20

[a]The numbers are average of the growth rates (in percentage) from 11 realizations for each type of month. [b]The numbers in bold indicate a realistic comparison taking the publication lags into account.

Table 3a shows a clear trade-off between timeliness and quality in favor of the hard data. The nowcasting performance based on the entire data in the *first* month of a quarter ($\sum_j \widehat{gdp}_{1j}^{(s+\bar{s})}/11 = 0.21, 0.21$ by means of the MSE and MAD, respectively), is far superior to that based on the survey data in the *third* month of a quarter ($\sum_j \widehat{gdp}_{3j}^{(s)}/11 = 0.70, 0.40$). This means that nowcasts based on the survey data should be more cautiously interpreted in periods of turmoil.

Table 3b. Predictive power in periods of tranquility (2013QIII – 2016QIV)^{ab}

Nowcasts i	MSE $\widehat{gdp}_i^{(s)}$	$\widehat{gdp}_i^{(\bar{s})}$	$\widehat{gdp}_i^{(s+\bar{s})}$	MAD $\widehat{gdp}_i^{(\bar{s})}$	$\widehat{gdp}_i^{(\bar{s})}$	$\widehat{gdp}_i^{(s+\bar{s})}$
1	0.19	0.18	**0.15**	0.16	0.13	**0.14**
2	0.17	0.18	0.15	0.18	0.13	0.09
3	**0.11**	0.17	0.11	**0.11**	0.10	0.09

[a]The numbers are average of the growth rates (in percentage) from 14 realizations for each type of month. [b]The numbers in bold indicate a realistic comparison taking the publication lags into account.

Table 3b shows two remarkable points: firstly, the nowcasting performance of $\widehat{gdp}_{\mathbf{3}}^{(s)}$ is just better than that of $\widehat{gdp}_{\mathbf{1}}^{(s+\bar{s})}$.[14] And, secondly, the nowcasting performance

[14]According to the viewpoint of Armstrong (2007), the preferred model should minimize just the loss functions, regardless of whether the difference in forecasting performance is significant.

of $\widehat{gdp}_{\mathbf{3}}^{(s)}$ is, even in a hypothetical scenario, as good as that of $\widehat{gdp}_{\mathbf{3}}^{(s+\bar{s})}$ according to the MSE (and almost equally good according to the MAD). These empirical findings would mean that nowcasts based on the survey data are quite reliable in periods of tranquility. The equal nowcasting performance measured by the MSE can be regarded as empirical evidence that the survey data have genuine predictive power beyond their timeliness, as reported in Banbura and Rünstler (2011) and Girardi et al. (2015). The nowcasting performance of $\widehat{gdp}_i^{(\bar{s})}$ lies somewhere between those of $\widehat{gdp}_i^{(s)}$ and $\widehat{gdp}_i^{(s+\bar{s})}$ for all types of month. This can be again regarded as empirical evidence that the survey data have genuine predictive power beyond their timeliness. In this case, the genuine predictive power of the survey data is measured by the improvement from $\widehat{gdp}_i^{(\bar{s})}$ to $\widehat{gdp}_i^{(s+\bar{s})}$.

To sum up, our empirical analysis indicates that the survey data have quite considerable predictive power (almost as strong as that of the hard data) in periods of tranquility, but less so in periods of turmoil. This could be one possible explanation for the mixed empirical results regarding the predictive power of survey data. Our results therefore suggest that practitioners should take greater account of the economic environment for interpretations when engaging in nowcasts. The implication of the results is limited, however, because it is driven by a single dataset.

4 Summary

We performed a pseudo nowcasting exercise for the euro area GDP based on the panel data deployed by the Deutsche Bundesbank. The focus of our historical simulation was to investigate the trade-off between timeliness and quality regarding the survey data and the macroeconomic data. Our findings show that the survey data seem to have significant predictive power in periods of tranquility, but less so in periods of turmoil.

This empirical evidence is consistent with findings in Banbura and Rünstler (2011) and Girardi et al. (2015) that qualitative surveys are not only (timely) proxies for hard data, but contain complementary information for understanding business cycle developments, especially in periods of tranquility. Leduc and Sill (2013) also document that *a perception that good times are ahead typically leads to a significant rise in current measures of economic activity.*

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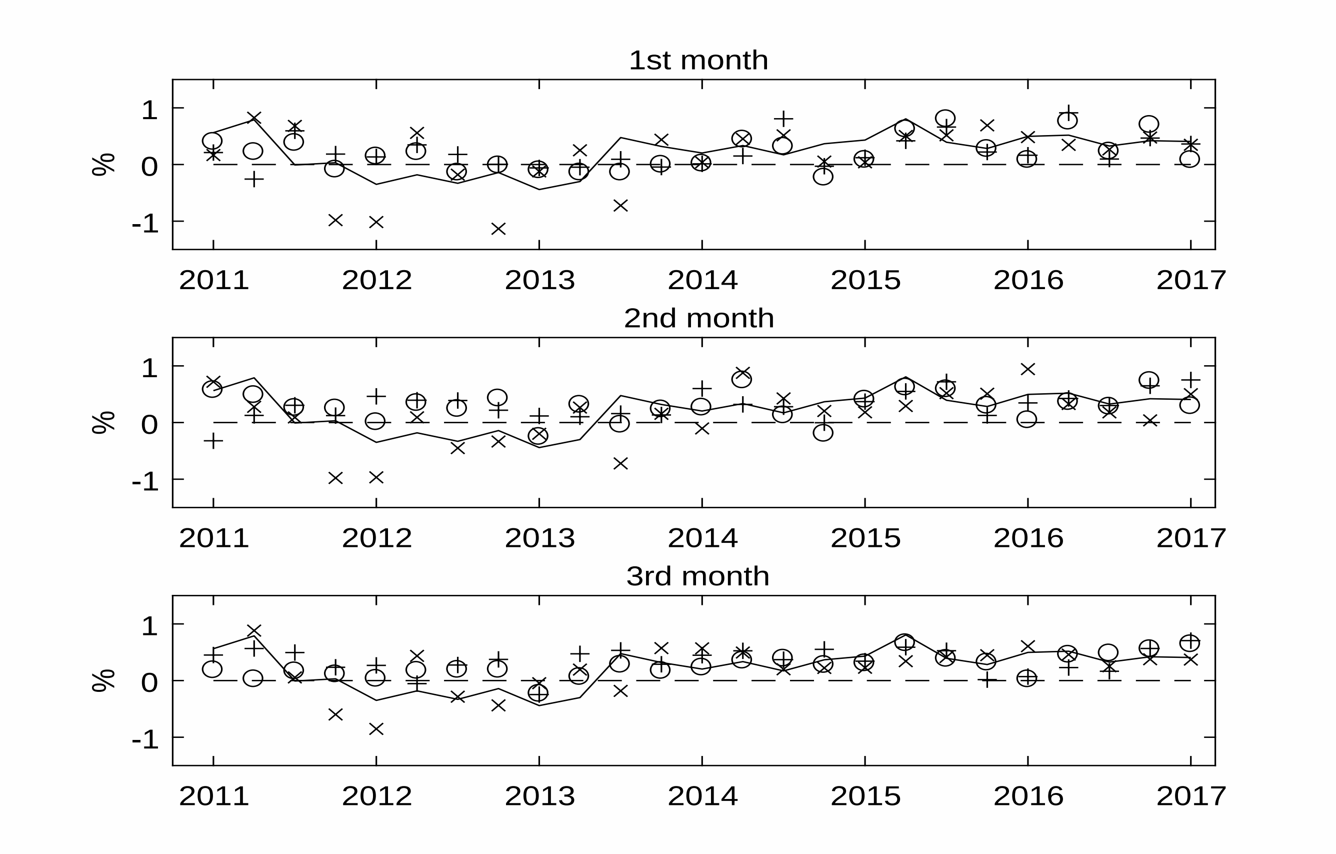
Appendix A

Figure A1. Empirical results for 25 quarters (in %) (2010QIV - 2016QIV)



Appendix B: Data description

GDP : euro area 19, quarterly, working day and seasonally adjusted, index

Industrial production (total 13)

1. Euro area 19 (fixed composition) - IP index, total industry
2. Euro area 19 (fixed composition) - IP index, total industry (excluding construction)
3. Euro area 19 (fixed composition) - IP index, manufacturing
4. Euro area 19 (fixed composition) - IP index, construction
5. Euro area 19 (fixed composition) - IP index, all buildings
6. Euro area 19 (fixed composition) - IP index, all civil engineering works
7. Euro area 19 (fixed composition) - IP index, total industry excluding construction and MIG Energy
8. Euro area 19 (fixed composition) - IP index, electricity, gas, steam and air conditioning supply
9. Euro area 19 (fixed composition) - IP index, MIG capital goods industry
10. Euro area 19 (fixed composition) - IP index, MIG durable consumer goods industry
11. Euro area 19 (fixed composition) - IP index, MIG energy
12. Euro area 19 (fixed composition) - IP index, MIG intermediate goods industry
13. Euro area 19 (fixed composition) - IP index, MIG non-durable consumer goods industry

Retail (total 4)

14. Euro area 19 (fixed composition) - total turnover index, retail trade including fuel, except of motor vehicles and motorcycles
15. Euro area 19 (fixed composition) - total turnover index, manufacture of food products; manufacture of beverages
16. Euro area 19 (fixed composition) - total turnover index, retail sale of non-food products including fuel
17. Euro area 19 (fixed composition) - car registration, new passenger cars, absolute value

Labor market (total 1)

18. Euro area 19 (fixed composition) - standardized unemployment rate, total (all ages), Eurostat

Industry survey (total 8)

19. Industrial confidence Indicator (Q2 + Q4 + Q5) / 3
20. Production trend observed in recent months
21. Assessment of order-book levels
22. Assessment of export order-book levels
23. Assessment of stocks of finished products
24. Production expectations for the months ahead
25. Selling price expectations for the months ahead
26. Employment expectations for the months ahead

Consumer survey (total 8)

27. Confidence indicator (Q2 + Q4 + Q7 +Q11) / 4
28. General economic situation over last 12 months
29. General economic situation over next 12 months
30. Price trends over last 12 months
31. Price trends over next 12 months

32. Unemployment expectations over next 12 months
33. Major purchases at present
34. Major purchases over next 12 months

Construction survey (total 5)

35. Confidence indicator (Q3 + Q4) / 2
36. Building activity development over the past 3 months
37. Evolution of current overall order books
38. Employment expectations over the next 3 months
39. Prices expectations over the next 3 months

Retail trade survey (total 5)

40. Confidence indicator (Q1 - Q2 + Q4) / 3
41. Business activity (sales) development over the past 3 months
42. Volume of stock currently
43. Business activity expectations over the next 3 months
44. Employment expectations over the next 3 months

Services survey (total 12)

45. Confidence indicator (Q1 + Q2 + Q3) / 3
46. Business situation development over the past 3 months
47. Evolution of demand over the past 3 months
48. Expectation of demand over the next 3 months
49. Evolution of employment over the past 3 months
50. Expectations of employment over the next 3 months
51. Market Surveys, euro area manufacturing PMI headline adjusted
52. Market Surveys, euro area services PMI headline adjusted
53. Market Surveys, euro area composite (M+S) PMI headline adjusted
54. Market Surveys, euro area composite (M+S) PMI output index adjusted
55. Market Surveys, euro area composite (M+S) PMI new orders index adjusted
56. Market Surveys, euro area composite (M+S) PMI employment index adjusted

Prices (total 6)

57. Euro area 19 (fixed composition) - producer price index, domestic sales, total industry (excluding construction)
58. Euro area 19 (fixed composition) - producer price index, domestic sales, MIG energy
59. Euro area 19 (fixed composition) - producer price index, domestic sales, MIG intermediate Goods industry
60. Euro area 19 (fixed composition) - producer price index, domestic sales, MIG non-durable consumer goods industry
61. Euro area 19 (fixed composition) - HICP - overall index, monthly index
62. Euro area 19 (fixed composition) - HICP - all-items excluding energy and unprocessed food, monthly index, Eurostat

International trade (total 4)

63. Total trade - intra euro area 19 (fixed composition) trade, export ECU/Euro, Eurostat
64. Total trade - extra euro area 19 (fixed composition) trade, export ECU/Euro, Eurostat
65. Total trade - intra euro area 19 (fixed composition) trade, import ECU/Euro, Eurostat
66. Total trade - extra euro area 19 (fixed composition) trade, import ECU/Euro, Eurostat

Foreign countries (USA) (total 5)

67. US, PMI manufacturing index
68. US, unemployment rate
69. US, industrial output, industrial production index
70. US, employment, civilian
71. US, total retail trade

Commodities (total 7)

72. World price index (2010) - raw materials - total (euro based)
73. World price index (2010) - raw materials - excl. energy-based products (euro based)
74. HWWA comodity price index - raw materials - crude oil (USD based)
75. Gold price, US Dollar, fine ounce (fixing in London)
76. Crude oil future price - 1 month ahead
77. World price index (2010) - raw materials - coal (USD based)
78. World price index (2010) - raw materials - copper (USD based)

Financial market (total 3)

79. ECB nominal effective exchange rate
80. ECB real effective exchange rate, CPI deflated
81. ECB nominal effective exchange rate, producer price deflated

Exchange rate (total 3)

82. Euro/USD exchange rate
83. Euro/British pound exchange rate
84. Euro/Yen exchange rate

Stock markets (total 4)

85. Euro Stoxx 50 index
86. Euro Stoxx 50 volatility index
87. Standard & Poors 500 Index
88. Dow Jones Index (price-weighted average of 30 blue chips)

Bonds, treasury notes, interest rates (total 13)

89. Government bond rate 10-year, GDP-weighted composition
90. Interest rate, loans
91. Interest rate, housing loans
92. Spread corporate AA and government bond maturities 7-10 years
93. Spread corporate BBB and government bond maturities 7-10 years
94. Eonia
95. 1-month interest rate, Euribor
96. 3-month interest rate, Euribor
97. 6-month interest rate, Euribor
98. 1-year interest rate, Euribor
99. 10-year government bond yield
100. Spread Euribor 1 year 1 month
101. Spread 10 year 3 month

Money (total 3)

102. Money M1

103. Money M2
104. Money M3

Euro countries (total 11)

105. Germany - IP index, total industry (excluding construction)
106. Germany - IP index, construction
107. France - IP index, total industry (excluding construction)
108. France - IP index, construction
109. Italy - IP index, total industry (excluding construction)
110. Italy - IP index, construction
111. Spain - IP index, total industry (excluding construction)
112. Spain - IP index, construction
113. Spain - total turnover index, accommodation and food service activities
114. Spain - total turnover index, information and communication
115. Spain - total turnover index, total of other services and retail trade as covered by the STS Regulation