European Commission

ISSN 1725-3187 (online)
ISSN 1016-8060 (print)

EUROPEAN ECONOMY

Economic Papers 538 | December 2014

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Economic and Financial Affairs

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More information on the European Union is available on http://europa.eu.

KC-AI-14-538-EN-N (online)
ISBN 978-92-79-35187-7 (online)
doi:10.2765/71951 (online)

KC-AI-14-538-EN-C (print)
ISBN 978-92-79-36153-1 (print)
doi:10.2765/81373 (print)

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Abstract

This paper evaluates the impact of new releases of financial, real activity and survey data on the nowcasting of euro area GDP growth. We show that financial data are only essential for improving nowcasting in the first two months of a nowcast quarter. This contrasts with survey and real data, which are indispensable components throughout the entire nowcasting exercise. When treating variables as if they were all published at the same time and without any time lag, financial series lose all their significance, while survey data remain important. This evidence suggests that survey data offer more than just timeliness for the purpose of nowcasting GDP growth. The latter holds true for financial data only when restricting the analysis to the 2008-09 financial crisis.

JEL Classification: C22, C53, E37.

Keywords: Qualitative, real and financial data, business and consumer surveys, euro area, macroeconomic forecasting, blocking approach, factor models, financial crisis.

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1. INTRODUCTION

Decision makers in various sectors of the economy (business, government, central banks, financial markets) base their choices on an early understanding of the state of economic activity. Quarterly GDP is generally considered the best variable to capture aggregate economic conditions, but it is released with a considerable delay (in Europe, usually around 45 days). Such a time lag limits its usefulness and motivates the effort to compute (regularly updated) forecasts based on the efficient use of short-term information from indicators, which are promptly available at monthly (or even daily) frequencies.

In general, there exists a trade-off between the precision of the signal delivered by a potential predictor and its timeliness. Real activity indicators, like the Industrial Production Index, which more or less directly enter the GDP calculation, are obviously highly correlated with the target series and thus constitute essential ingredients for GDP nowcasts. However, most real data on the euro zone are released with at least 1 ½ months of delay compared to the reference month (data referring to January, for example, is thus only available by mid of March). Financial variables and (business and consumer) surveys, on the other hand, are usually available within or at the end of the reference month. However, this increased timeliness goes at the expense of a lower degree of precision for the purpose of nowcasting GDP. After all, developments on the financial markets are only indirectly related to the real economy, while surveys are somewhat crude in the sense that they refer to vaguely-defined concepts like "business situation", with survey respondents usually just being inquired about the direction of change (improvement, no change, deterioration). In spite of their limited precision, we argue that both financial and survey data have properties beyond their timeliness, which are potentially nowcast-enhancing and mostly ignored in the forecasting literature: First of all, both data categories offer a high degree of stability, since they are usually subject to no or only minor revisions. Secondly, they offer a broader sectoral coverage than forecast-relevant real data (i.e. real data published before the first flash GDP estimate). The main real series on the services sector (service turnover), for instance, is released more than 3 months after the end of the reference quarter, making any nowcast relying exclusively on real data suffer from an under-representation of the largest economic sector. Survey and financial data can fill this gap. Finally, survey data include respondents' views on future developments (e.g. their production expectations). They can thus be assumed to have some leading properties which might render them beneficial for early stages of the nowcasting exercise (i.e. months 1 and 2). ([1])

Against this backdrop, one of the main tasks for economic forecasters is to disentangle signals from the growing amount of potentially relevant data which become available as the nowcasting quarter unfolds. The aim of this paper is to provide some orientation (to the forecaster) as regards the value-added of the different data-categories for the purpose of nowcasting GDP. Is it useful to include financial and survey data in a nowcast model or do they only introduce noise? If the first is true, is their value-added constant over time, or particularly pronounced at the beginning of the nowcasting quarter (i.e. when little real activity data about the quarter of interest is released)? Finally, provided there is a nowcasting-enhancing effect of financial and survey data, is it only rooted in their timely availability or is it genuine, in the sense that it would continue existing, even in the hypothetical scenario that real activity data was released as early as financial / survey data?

To address these questions, we assess the nowcasting performance of a number of models which differ in respect of the data-categories they are based upon (e.g. a model based on survey and real data only, a model based on financial and real data, etc.). In keeping with the relevant literature (Angelini et al., 2011, Banbura and Rünstler, 2011, Giannone et al., 2009, Barhoumi et al., 2009, Drechsel and Maurin, 2011), the models are run, in pseudo real-time, at different stages of the nowcasting quarter.

In order to derive general conclusions about the merits of the different data categories, which are as little as possible influenced by the specific model used, we opt for a factor model, instead of a classical bridge

([1]) Arguably, the same holds for financial markets data. Stock prices, for example, are supposed to mirror expectations about future earnings of the respective company.

model. Such model runs more or less automatically, imposing a factor structure on the dataset (diffusion index models), rather than being based on the forecaster's skills in selecting meaningful predictors. Furthermore, it has a number of advantages going beyond its agnostic nature, which make it a particular attractive nowcasting tool, such as its ability to compensate for deficiencies in single economic indicators (e.g. measurement errors) through the extraction of information from many, rather than just a few, time-series.

Our analysis enriches the body of existing literature on the relative merits of different variable types for nowcasting GDP in several respects. First of all, the forecast horizon considered in the present article (2007q1 onwards) covers the entire financial and sovereign debt crisis, thus complementing the evidence reported in closely related works (Angelini et al., 2011; Banbura and Rünstler, 2011; Drechsel and Maurin, 2011). This enables us to dedicate an explicit highlight section to the crisis period of 2008/09, which shows that the relative importance of the different variable categories for nowcasting GDP substantially changes, when the economy enters into crisis mode. Following Banbura and Rünstler (2011), a counterfactual exercise shows that survey data have "genuine" predictive power beyond their timeliness. We are able to single out the forward-looking character as well as coverage of the services sector as the main reasons behind this finding.

A further contribution concerns the set-up of the nowcasting exercise as such, which facilitates running ten forecasts over the 4½ months period between the start of the nowcasting quarter and the publication of the first GDP flash. This high frequency allows for a more granular view on the evolvement of the value added of different variable categories for nowcasting GDP compared to previous works like Diron (2008) and Banbura and Rünstler (2011). Moreover, we apply an adaptive modelling approach where both the specification and the coefficients of the model are updated before every nowcast round, making our results a useful complement to those already gathered in the context of non-adaptive models (as in Drechsel and Maurin, 2011). Finally, from a more technical perspective, the present works illustrates the validity of the blocking approach (Chen et al., 2012) so as to overcome the mixed frequency and the ragged edge problem by splitting the high frequency information into multiple low frequency time series.

The structure of the paper is as follows. Section 2 illustrates the empirical setup. The dataset and the design of the pseudo real-time exercise are presented in Section 3. In Section 4 and 5 we assess the relative merits of the different categories of data in nowcasting GDP. Section 6 refines the results for the period of the Great Recession. Conclusions follow.

2. EMPIRICAL SETUP

2.1. THE ECONOMETRIC FRAMEWORK

Our paper aims to compare the quality of nowcasts generated by a number of factor-based models which differ in respect of the data categories they are based upon (real, survey and financial data). The assessment shall be based on the pseudo real-time nowcasting performance at various stages of the reference quarter (first month, second month, etc.), rather than just at a single point in time. To mimic the situation faced by a fictive forecaster and neutralize the advantage of knowing how the data look ex-post (Stark and Croushore, 2002), the nowcasting exercise complies with the following self-imposed constraints: (i) every nowcast is based on a customized dataset reflecting realistic data-availability conditions (e.g. a nowcast of 2013q1, fictively conducted on 30 March 2013, may only resort to the Industrial Production Index until (incl.) January 2013, while survey data for all three months of quarter 1 may be used, etc.) ; (ii) we assume that the forecaster's predictions are generated by a newly specified model before each forecast round. Such a modelling approach is called adaptive ([2]) as opposed to the non-adaptive alternative where the estimation of the parameters is updated without changing the equation specification or the fixed parameter case where the parameters are estimated just once but used in forming predictions over the entire forecast horizon ([3]); (iii) we implement a recursive, rather than a rolling, forecasting scheme. The former uses, at any time, all available data for the in-sample regression, whose parameters are used to generate the forecast. The latter fixes a constant sample size for the in-sample regression, which means that distant observations are discarded, as more recent ones are added to the sample. We argue that the usage of a recursive estimation window represents the most intuitive way to replicate the assumed pseudo real time exercise, since the adoption of a rolling scheme also implies setting a "proper" estimation window.

For every model and for every simulated nowcast, our analytical approach requires implementing four steps. The first one is to conduct a factor analysis on the customized dataset which represents realistic (pseudo real-time) data availability conditions. The factor analysis shrinks the vast amount of information from the various available time-series into a limited set of components which can be used as potential predictors for the nowcast model. Formally, such a diffusion index model expresses a N-dimensional multiple time series $X_t = \{x_{1t}, \ldots, x_{Nt}\}$ as

$$X_t = \Lambda F_t + e_t \qquad (1)$$

where F_t *is a* K-dimensional multiple time series of factors (with $K < N$), Λ is a matrix of loadings, relating the factors to the observed time series, and e_t *a*re idiosyncratic disturbances. The factors are unobservable variables and can be estimated consistently by using the first K principal components of the data, i.e. the first K eigenvectors of the variance-covariance matrix of X_t. The factor model is static in the sense that no parametric structure has been imposed on the dynamics of the factors (as, for instance, in Angelini et al., 2011; Banbura and Rünstler, 2011). ([4])

([2]) Note that using an adaptive modelling approach allows us to complement the existing evidence on the relative contribution of different variable types to nowcasts of euro area GDP as gathered in the context of fixed parameter (Drechsel, and Maurin, 2011) or non-adaptive schemes (Banbura and Rünstler, 2011).

([3]) On the choice between adaptive and fixed-specification models see, among others, Swanson and White (1997) where the former are shown to perform better than the alternative by limiting the effects of heterogeneity over time and structural breaks.

([4]) While some papers find dynamic factors superior over the static ones (Eickmeier and Ziegler, 2008; Giannone et al., 2011), D'Agostino and Giannone (2012) find that both methods perform similarly and produce highly collinear forecasts. Moreover, in the light of the results in Boivin and Ng (2005), static factors estimated via principal components seem to perform systematically better when more complicated but realistic error structures are considered. In addition, imposing an autoregressive structure may induce some rigidities in the model structure which lead to inaccurate forecasts in the presence of sudden changes in the target series over the forecast horizon (see, e.g., Lombardi and Maier, 2011). Moreover, Alvarez et al. (2012) show that dynamic methods to estimate factors result in similar problems as the static one when the set of predictors is large, corroborating our choice of focusing on the static method alone as the "representative method" of the extraction of factors in order to simplify result reporting.

To determine the amount of factors (K), we follow Caggiano et al. (2011) and take explicitly into account the relationship between target series and predictors by resorting to information criteria. ([5]) Concretely, we: (i) run a number of factor analyses differing in respect of the number of factors extracted (with K ranging from 1 to K_{max}); (ii) regress the target series separately on each of the resulting factor sets and compute the AIC; (iii) derive the optimal $K \leq K_{max}$ as the number of factors contained in the regression displaying the lowest AIC. ([6])

In a second step, the extracted factors are plugged into the below regression equation:

$$y_t = c + \sum_{j=1}^{K} \beta_j f_{jt} + \varepsilon_t \qquad (2)$$

where y_t denotes the log-difference of the quarterly target variable (i.e. euro area GDP), f_{jt} the K factors ($j = 1, 2, \ldots, N$) identified above and ε_t a random error shock. Whether or not a factor is retained in equation (2) depends on its statistical significance (i.e. factors with a p-value beyond a critical threshold are discarded), as in Bulligan et al. (2012). Thus, the resulting number of factors entering the forecasting equation will be $\widetilde{K} \leq K$.

The third step uses the parameters generated by equation (2) to compute a forecast for $t+1$ as follows:

$$\hat{y}_{t+1} = \hat{c} + \sum_{j=1}^{\widetilde{K}} \hat{\beta}_j \hat{f}_{jt+1} \qquad (3)$$

where $\hat{c}$ and $\hat{\beta}$'s are the OLS estimates of the parameters in condition (2) and $\hat{f}$'s are the $\widetilde{K}$ factors extracted from the information set evaluated at $t+1$ (that is X_{t+1}).

Since we ultimately want to compare the nowcasting performance of different models at various points of the reference quarter, the fourth step consists in calculating a forecast accuracy measure for every model and for every nowcasting scenario (i.e. when nowcasts are conducted in month 1 of the reference quarters, in month 2, etc.). We resort to the root mean squared error (RMSE), which is calculated as:

$$RMSE = \left[\frac{\sum_{j=1}^{P}(y_{t+j} - \hat{y}_{t+j})^2}{P}\right]^{0.5} \qquad (4)$$

where P equals the number of quarters of the forecast horizon. ([7]) In order to get a grasp of the "goodness" of model (4) we follow in Barhoumi et al. (2009) and use a first-order autoregressive model as the benchmark specification for quarterly GDP growth:

$$y_t = \tilde{c} + \rho y_{t-1} + \varepsilon_t \qquad (5)$$

where y_t denotes the log-difference of the quarterly target variable (i.e. euro area GDP), $\alpha(L) = 1 - \rho L$ with $|\rho| < 1$, $\tilde{c} = (1 - \rho)c$ and ε_t is a random error shock.

2.2. THE BLOCKING APPROACH

The econometric framework presented in Section 2.1. implicitly assumes that the explanatory variables are of quarterly frequency and can thus easily be put into statistical relation with quarterly GDP. The

([5]) The chosen approach differs from popular alternatives, like optimality criteria (see e.g. Bai and Ng, 2002) or the share of the variance explained, where the estimation of K is obtained without reference to the target variable.
([6]) As discussed in Lütkepohl (2005), we use the AIC criterion since it is designed for minimizing the forecast error variance, and thus for favouring models potentially able to produce superior forecasts in both small and large samples.
([7]) The proposed exercise is based on two minimal assumptions: (i) the starting date is set at 1997q1 to be able to exploit information from the services survey of the harmonised EU BCS programme, which is not available earlier ; (ii) the minimum in-sample length is set at 40 quarters so as to ensure a sufficient number of degrees of freedom.

majority of them, however, have monthly frequency so that the well-known mixed-frequency problem arises. In a pure in-sample exercise conducted on the full dataset, that issue could be swiftly resolved by transforming the monthly explanatory variables into quarterly averages. The focus of our analysis on the forecasting performance in pseudo-real time though, means that we are additionally confronted with the ragged edge problem, which is caused by variables being published with a time-lag. When simulating a nowcast of GDP at the end of March, for example, only January's reading of the industrial production index is available so that the strategy of averaging monthly variables to align their frequency with the dependent variable's frequency is not feasible.

Econometric literature proposes a number of solutions to this problem, ranging from dynamic factor models estimated *via* the Kalman filter to simple univariate models to extrapolate the indicators over horizons that depend on both publication lags and the specific forecast round (McGuckin et al., 2007). ([8]) Here instead, we follow Carriero et al. (2012) and apply an alternative strategy, which is somewhat novel in applied economic analyses – the so-called blocking approach. This technique originates from the engineering literature of signal processing (Chen et al., 2012) and consists in splitting the high frequency information into multiple low frequency time series. In our context, monthly observations of a given time-series are distributed into three quarterly series: the first quarterly series (M1) collects observations from the first months of each quarter (i.e. January, April, July and October); the second one (M2) collects observations from the second months (i.e. February, May, August and November), while the last one (M3) assembles the observations from the third months (i.e. March, June, September and December). This means that the amount of variables which can be used for the factor analysis roughly triples (rather than a single Industrial Production Index (IPI) series, the dataset now contains three IPI series: an M1-IPI, M2-IPI and M3-IPI series).

At each of the nowcasting days for a given quarter t (as detailed in Section 3.2 below), the relevant dataset $X_t = \{x_{1t}, \dots, x_{Nt}\}$ is restricted so as to only include those variables which have an observed value for the reference quarter. ([9]) This implies that our nowcasts are exclusively based on actual monthly observations (in the form of different quarterly variables associated with the different months of the quarter). In this respect, blocking is conceptually different from the standard bridging techniques, since it makes it possible to exploit the partially available data at any time with no need to forecast intra-quarterly missing information.

In order to implement the blocking approach, trending series (e.g. industrial production, employment, retail sales, stock and commodity prices, exchange rates) are expressed as (one third of) the percentage change of a given month $i = 1,2,3$ of quarter t with respect to the average of the previous quarter $t-1$:

$$\dot{x}_t^i = \frac{1}{3}\left[\frac{x_t^i}{\frac{1}{3}(x_{t-1}^1 + x_{t-1}^2 + x_{t-1}^3)} - 1\right] \tag{6}$$

so that the quarterly aggregate of the series ($\dot{x}_t$) *is additive with the respect to its monthly compone*nts and can be expressed as $\dot{x}_t = \sum_{i=1}^{3} \dot{x}_t^i$. ([10]) For non-stationary series without trending behavior (unemployment

([8]) Camacho and Perez-Quiros (2010), Camacho et al. (2012), Ferrara et al. (2010), Giannone et al. (2009), Kuzin et al. (2009) provide other ways of dealing with mixed frequency/ragged edges datasets, notably approximate Kalman filter models, Markov-switching dynamic factors, non parametric methods, mixed-frequency VARs, and MIDAS regressions of Clements and Galvão (2008).

([9]) A nowcast conducted at the end of March, for example, will be based on factors extracted from a dataset which includes the M1-version of the industrial production index, but not the M2 and M3 versions, since the February and March values of the index are not yet available.

([10]) Should the three quarterly series of a certain predictor enter the model with the same estimated coefficient, additivity means that the resulting summation of those variables would be equivalent to the same indicator observed on a quarterly basis and expressed as quarterly percentage changes. In this respect, blocking introduces some flexibility in the specification by considering monthly contribution to observed quarterly growth rates at the cost of extending the dimensionality of the panel of indicators which factors are extracted from.

rates, bond yields and interest rates, stock market volatility), we subtract the average of the previous quarter's values from the figure for a given month of the subsequent quarter as follows:

$$\ddot{x}_t^i = \frac{1}{3}\left[x_t^i - \frac{1}{3}\left(x_{t-1}^1 + x_{t-1}^2 + x_{t-1}^3\right)\right] \qquad (7)$$

As in the case of condition (6), the quarterly aggregate of the series ($\ddot{x}_t^i$) is additive in terms of its monthly components: $\ddot{x}_t = \sum_{i=1}^{3} \ddot{x}_t^i$. ([11])

([11]) Even though month-on-month differences may be preferred as they avoid a moving average structure of the residuals, using transformations based on (6) and (7) yields to better forecasts since it reduces noise in the data by smoothing data irregularities. See also on this Barhoumi et al. (2009).

3. DATA AND DESIGN OF THE SIMULATED OUT-OF-SAMPLE EXERCISE

3.1. THE DATASET

The complete set of indicators consists of more than a hundred time series ranging from January 1997 to March 2014, corresponding to 69 quarterly observations (1997q1-2014q1). Data come from various sources (European Commission, BIS, ECB, Eurostat and National Institutes of Statistics) and are downloaded via DataInsight. All series are seasonally adjusted. The structure of the dataset is similar to (although richer than) those used in other works focussing on nowcasting euro area GDP (see, for instance, Angelini et al., 2011; Banbura and Rünstler, 2011). The indicators are classified according to the following three types of information: financial variables (F); survey indicators (S); quantitative real activity series (Q).

Table 3.1 provides an overview of the composition of the dataset, detailing the number of variables by publication frequency and by transformation type – separately for all three variable types (i.e. F, Q and S). ([12])

Table 3.1:
Composition of the panel of indicators

	F	Q	S	Total
by publication frequency:				
	F	Q	S	Total
daily	14	.	.	14 (13%)
monthly	18	34	45	97 (87%)
by data transformation type:				
	F	Q	S	Total
no transformation	.	.	41	41 (37%)
first differences	15	2	.	17 (15%)
percentage changes	17	32	4	53 (48%)
total:				
	F	Q	S	Total
	32 (29%)	34 (31%)	45 (40%)	111

As the bottom section of Table 3.1 shows, financial indicators make up about 29% of the total information. The financial data set contains several interest rates/bond-yields, stock price and volatility indices, nominal exchange rates of the euro (vis-à-vis the US dollar, the UK Pound and the Japanese Yen), as well as data related to money supply, loan volumes to non-financial corporations and commodity prices.

Real series represent about 31% of the total information. Supply side real activity indicators consist of industrial production indices (IP, both overall and by main sub-sectors), the index of production in construction, the unemployment rate (including the German one due to its prompt availability), as well as core and overall inflation rates. The retail sales index and car registrations are the most relevant demand-side real indicators. Trade variables, as well as real effective exchange rates, are also included.

Qualitative variables account for about 40% of the total information set. All confidence indices for the industry, services, retail trade and construction sectors, as well as the consumer confidence and the overall Economic Sentiment Indicator (ESI) from the European Commission's Joint Harmonised EU Programme of Business and Consumer Surveys (BCS) are included. ([13]) Balance-series from sector-specific survey questions are also used: For the industry sector, firms' assessments of past and future production, the level of overall/export order books, the stock of finished products, as well as their selling

([12]) The complete list of the predictors is given in Appendix 1.
([13]) For more details on the BCS Programme, see: http://ec.europa.eu/economy_finance/db_indicators/surveys/index_en.htm

price and employment expectations are included. Questions from the services sector include managers' appraisal of the past business situation, the level of past and future demand, the past and future evolvement of employment, as well as their selling price expectations. To cover the retail trade sector, series covering managers' views on the past and future business activity, the level of stocks, the expected level of orders placed with suppliers, as well as employment plans and selling price expectations are included in the dataset. Regarding the construction sector, balance series referring to firms' assessments of the past building activity, the overall order books, employment plans and price expectations are used. As for consumer surveys, the information set contains consumers’ evaluation of the current and future economic situation of the general economy, their assessment of the financial situation of their own households (both during the past and the next 12 months), their views on the advisability of saving and of purchasing durable goods, as well as their intentions to save and invest. Questions covering consumers' unemployment expectations and their assessment of the past and future consumer price developments are also considered. To round off the set of qualitative indicators, the economic policy uncertainty index for Europe (Baker et al., 2013), as well as its components, are also included.

As regards the indicators' publication frequencies, the upper part of Table 3.1 illustrates that the largest portion of the series (roughly 87%) is collected at monthly intervals. The remaining portion of the dataset refers to daily (financial) indicators. Focussing on the required data-transformation (see middle part of Table 3.1), it turns out that financial data are expressed either in first differences or as percentage changes to achieve stationarity. By contrast, as in Lombardi and Maier (2011), Giannone et al. (2009) and Bulligan et al. (2012), all qualitative variables are treated as stationary in levels, so that we do not impose transformations on them (except for the uncertainty indicators which have been expressed in percentage changes). Finally, real activity data-series are expressed as percentage changes, apart from the two unemployment rate series which are differenced.

3.2. DETERMINING A SEQUENCE OF NOWCASTS / BACKCASTS PER QUARTER

An important issue that remains to be discussed prior to the presentation of the results is the timing of nowcasts over a given quarter. Obviously, nowcasts could in theory be conducted on every day of the quarter. However, to assess the relative value-added of financial, survey and real data for nowcasting GDP, it suffices to focus on a limited number of carefully-chosen nowcasting dates per quarter.

To guide our selection of nowcasting dates, the following principles are applied: (i) the first nowcast should not be conducted earlier than on the first day of the quarter to which it refers (otherwise it would be a genuine forecast, which is not the focus of this paper). Furthermore, it should only be conducted, when a sufficient number of variables already report observations which concern the reference quarter; (ii) the last nowcast should be conducted not later than one day before the publication of the first flash estimate of GDP of the reference quarter. Since the first GDP flash estimate is usually released some 45 days after the end of the reference quarter, this criterion implies that our "nowcasting" exercise also includes the category of "backcasts" ; (iii) a nowcast should only be conducted when a critical amount of new data relating to the reference quarter has been released, rendering the previous nowcast outdated. As pointed out by Giannone et al. (2008), in the case of the euro area, data releases are relatively clustered at the mid and the end of month when compared to the publication calendar for other advanced economies like the US.

Table 3.2:
Availability of predictors throughout a given calendar quarter

Forecast date	Type of predictor	Available data referring to the predicted quarter...					
		...when Q(t-1) is predicted (**backcast**):			...when Q(t) is predicted (**nowcast**):		
		m1	m2	m3	m1	m2	m3
A.	DP						
(month 1, 12th)	MP 1						
	MP 2						
	MP 3		**VIII**			**I**	
	MP 4						
	MP 5						
	GDP						
B.	DP						
(month 1, 30th)	MP 1						
	MP 2						
	MP 3		**IX**			**II**	
	MP 4						
	MP 5						
	GDP						
C.	DP						
(month 2, 12th)	MP 1						
	MP 2						
	MP 3		**X**			**III**	
	MP 4						
	MP 5						
	GDP						
D.	DP						
(month 2, 15th)	MP 1						
	MP 2						
	MP 3					**IV**	
	MP 4						
	MP 5						
	GDP						
E.	DP						
(month 2, 30th)	MP 1						
	MP 2						
	MP 3					**V**	
	MP 4						
	MP 5						
	GDP						
F.	DP						
(month 3, 12th)	MP 1						
	MP 2						
	MP 3					**VI**	
	MP 4						
	MP 5						
	GDP						
G.	DP						
(month 3, 30th)	MP 1						
	MP 2						
	MP 3					**VII**	
	MP 4						
	MP 5						
	GDP						

Applying the above criteria, we arrive at ten nowcasts per quarter, of which three are conducted after the end of the reference quarter and thus effectively constitute "backcasts". Table 3.2 illustrates the resulting sequence. ([14])

For a quarter Q(t), the first nowcast is conducted on the 12th of month 1 of that quarter (case A in Table 3.2). At that point in time, a first set of variables offers meaningful information directly related to the reference quarter. ([15]) That variable category consists of daily predictors (DP) like stock markets data, nominal exchange rates, etc., whose average over the first twelve days of month 1 can be considered a good proxy of their average reading over the entirety of month 1. ([16]) As illustrated by the dark grey cells of Table 3.2, which represent the availability of data in real-time, on nowcasting date A, all other variable categories (MP1 to MP5) only feature releases related to quarter Q(t-1). Accordingly, they cannot be used to nowcast Q(t). However, they still have an indirect bearing on the nowcast, since they are used to backcast the not yet released Q(t-1). Furthermore, GDP is available neither for Q(t), nor for Q(t-1). The latter implies that, to be able to produce the first nowcast of Q(t), a backcast of Q(t-1) is needed which can be used as a proxy of actual GDP in t-1. Thus, the nowcast of Q(t) in situation A (as well as situations B and C) in fact constitutes a two-step ahead forecast. The second nowcast is conducted on the 30th of month 1 (case B) and differs from the preceding one in so far as it can be based on an additional set of variables (MP1) which feature releases relating to quarter Q(t), notably to month 1 thereof. This set consists of variables which are released at the end of the month to which they refer and mainly covers survey series, in our case from the harmonised EU BCS programme. The third nowcast, implemented on the 12th of month 2 (case C), sees the month-2-version of the daily predictors (DP) added to the set of variables (remember that we apply the "blocking approach" which creates a separate M1-, M2- and M3-version of every variable). Furthermore, the third nowcast can resort to a basket of new indicators (MP2), whose values for month 1 of the quarter have just been released. That basket is rather diverse, spanning from commodity prices to bond yields, as well as the economic policy uncertainty indicator and its components.

Three days later, on the 15th of month 2, another nowcast is conducted (case D). While the range of predictors remains the same, the GDP figure of the preceding quarter (Q(t-1)) has just been published so that nowcast D is the first one to constitute just a one-step ahead forecast. The ensuing nowcast on the 30th of month 2 (case E) sees the month-2-version of all MP1 variables added, as well as a new variable category (MP3), whose values for month 1 have just been made available. The new variables comprise, inter alia, the unemployment rate and car registrations, as well as a number of monetary variables (inflation rates and money supply). The 12th of month 3 (case F) is a crucial nowcast, since it is based, for the first time in the nowcasting sequence, on (the month-1-versions of) euro area industrial production data and retail sales (MP4). Especially the former display high correlations with GDP, making them particularly effective predictors. To complete the picture, also the month-2-versions of variable category MP2, as well as the month-3-versions of category DP become available. The sequence of nowcasts conducted during the reference quarter is rounded off with nowcast G, which is implemented on the 30th of month 3 and differs from the previous one only in that the month-3-version of MP1 variables (i.e. surveys) has become available.

([14]) In the absence of a "genuine" real-time dataset for the entire set of predictors used in the analysis, we proceed via a pseudo real-time exercise by mimicking as closely as possible the real time pattern of data availability using the latest available (revised) series. Most soft indicators, such as financial and survey data, are not subject to revision, while GDP and some of the real activity variables (such as industrial production indices) are revised after the first release. A large part of the existent literature is based on the latest available data because of the dearth of data vintages, although, since Diebold and Rudebush (1991), it is well known that the use of the latest available data can significantly overstate the forecasting performance of models based on preliminary and unrevised data. Exceptions are few and always conducted in data parsimonious environments (Diron, 2008; Camacho and Perez-Quiros, 2010). However, if the aim of the pseudo real time exercise is to compare the relative forecasting ability of alternative approaches (rather than to measure absolute forecasting ability), then their ranking should not be greatly affected by neglecting data revisions (Bernanke and Boivin, 2003; Schumacher and Breitung, 2008).

([15]) While choosing the 15th of month 1 would be more intuitive on first glance, the reason for picking the 12th is that it coincides with the release of the industrial production index of month 2 of the preceding quarter.

([16]) For the sake of computational simplicity, we considered as value for a given financial variable in month t the average readings of that variable over the entire month, even if the scenario refers to the 12th/15th of the month.

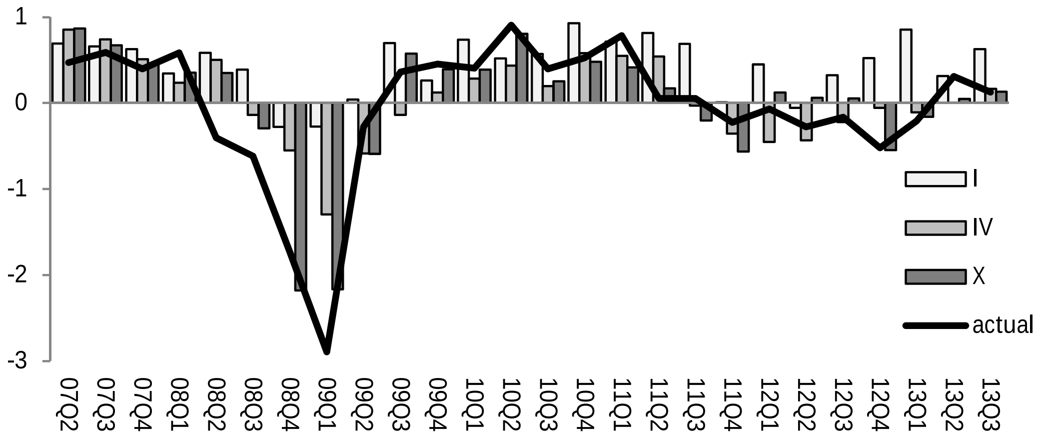
The last three exercises are, by definition, backcasts, since they are made when the nowcast quarter has already passed, but the relevant Flash GDP estimate has not yet been released. Concretely, they are conducted on the 12th and 30th of the first month, as well as the 12th of the second month of the quarter following the actual nowcast quarter. The third column of rows A, B and C in Table 3.2 presents the data-availability for these backcasts. As the dark grey cells show, the backcasts are characterised by a relative abundance of data. On the 12th of month 1 (case A), three out of six variable cateogories provide full information on all three months of the backcast quarter. In the last backcast on the 12th of month 2 (case c), this is even the case for five out of six categories. While the practical value added of a backcast is debatable, since it is by definition a very late prediction of GDP, whose official (flash) release is immediately impending, it should be understood that in our framework the backcast of a quarter Q(t-1) serves as an ingredient for the nowcast of the following quarter Q(t), which is conducted on the same day.

4. ASSESSING THE INFORMATION CONTENT OF FINANCIAL, SURVEY AND REAL ACTIVITY DATA

4.1. THE BASELINE MODEL

In the baseline specification the set of predictors X_t *in condition (1)* contains all variable categories, i.e. financial (F), survey (S) and quantitative real (Q) data (FSQ model). As for the determination of the RHS of the regression equation (2), we set K_{max} *equal to* 10. ([17]) Statistically redundant factors (with a p-value larger than 0.10) in each estimated equation are then deleted. ([18]) The out-of-sample period goes from 2007q2 to 2013q3, so that the forecast accuracy measures we report are computed over a relatively wide forecast horizon which comprises 26 observations. ([19])

Graph 4.1: **Out-of-sample forecasts from selected forecast rounds**



Source: European Commission, DataInsight

To have a first idea of how our modelling approach nowcasts, Figure 4.1 presents the (ex-post) realization of the target series (solid line) plotted against the predictions obtained from the FSQ model in selected forecasts rounds (namely I, IV and X which are reported in white, light grey and dark grey bars, respectively). It clearly emerges that moving from the first nowcast to the last backcast the sequence of forecasts overlaps to a greater extent with the target series (the correlation rises from 0.68 to 0.92), indicating that the econometric setup makes good use of the new monthly releases.

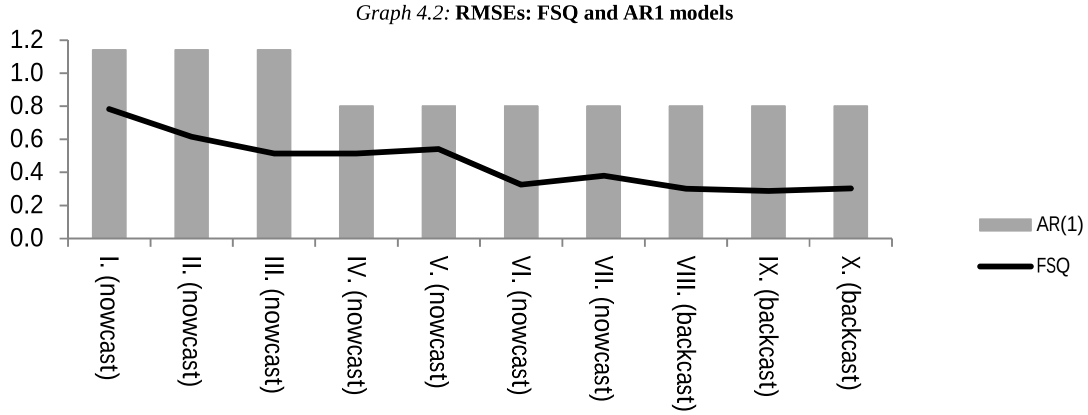
([17]) Before extracting factors from the monthly indicators, the series are standardized so as to have mean zero and variance one. The applied standardisation parameters (mean and standard deviation) are not fixed, but are regularly updated in the course of the nowcasting exercise, as more observations become available.

([18]) Annex 2 reports some diagnostic checks for the entire forecast exercise, based on 260 individual forecasts. In Tables A2.1 and A2.2, rows indicate the calendar quarter for which the forecast is conducted, while columns indicate the forecast round in a way consistent with the timing reported in Table 3.2. As for the number of factors entering the forecast equations, the AIC indicates an average of about 7, while the parsimonious specifications use on average around five factors. The results from the main diagnostics checks are comforting: I) the estimated residuals do not suffer from severe autocorrelation problems, since only in 3 (15) entities of references the LM test indicate rejections of the null at the 1 (5) per cent significance level; II) although somewhat more frequent (in 35 and 40 cases at the 1 and 5 per cent significance level, respectively), departures from the normality assumption characterise less than 15 per cent of the entire set of regression considered in the exercise; III) finally, the goodness of fit (as measured by the adjusted R^2) tends to improve when moving from early nowcasts (around 45-60%) to late backcasts (75-80%) and from 2009 onwards (around 75% or even better).

([19]) Since every nowcasting exercise starts with a two-step ahead forecast (cases I, II, III of the nowcasting sequence in Section 3.2.) and ends with a one-step ahead prediction (cases IV to X), calculating comparable RMSEs for the different scenarios is only possible when discarding the first forecasting error (2007q1) in cases I to III and the last one (2013q4) for cases IV to X.

A more complete picture can be gathered from an analysis of the RMSEs generated by the FSQ and the AR(1) benchmark model across the different nowcast dates. We use the RMSEs as the criterion for distinguishing between model performances in line with the viewpoint by Armstrong (2007) and Beechey and Österholm (2010). That is, in choosing among a set of plausible competing models, the preferred model is that which minimises the loss functions of the forecaster, regardless of whether the difference in forecasting performance is significant. However, we also report test statistics from the Diebold and Mariano (1995) test assuming both absolute and quadratic loss functions in Appendix 3. Generally, we expect that the richness of information contained in the FSQ dataset will facilitate the production of models persistently outperforming the naïve benchmark model, with the RMSEs following a decreasing pattern as the nowcast quarter unfolds and a growing amount of data becomes available. Figure 4.2 plots the RMSEs of the full model combining financial, survey and real data (solid line) compared to the one of the benchmark model (bars).

Graph 4.2: **RMSEs: FSQ and AR1 models**



Source: European Commission, DataInsight

The FSQ model, indeed, displays a lower RMSE at any point of the nowcast quarter (with gains in the range between 0.25 and 0.5 percentage points), providing support to the adequacy of the set of regressors used in tracking future GDP growth developments. By the same token, the RMSEs of the full model follow a broad downward path as the nowcast quarter unfolds (i.e. when a growing amount of data becomes available).

4.2. EVIDENCE FROM MODELS BASED ON SUBSETS OF PREDICTORS

The value-added of the different classes of indicators (namely financial, qualitative and real variables) is assessed by re-conducting the entire nowcasting exercise described in Section 4.1. on three different versions of the underlying dataset: the FQ model is based on financial and real data only, the SQ model is limited to survey, as well as real data, while the FS model includes everything but real data. Our interest is to compare the nowcasting performance of the models generated on the basis of these different datasets.

In order to gauge how much better or worse a given partial model (FQ, SQ or FS) performs when compared to the full specification containing all three data categories, the RMSEs by model and across the different points of the nowcasting exercise are listed in Table 4.1. The RMSEs of the full and AR model are reported in levels, while the RMSEs of the other models are expressed as fractions of the RMSE generated by the FSQ model. A value of 1.20, for example, indicates that the RMSE is inflated by 20 per cent, while a value of 0.80 signals a decrease by 20 per cent. The best-performing model is flagged with an asterisk, while the worst forecasting performance is reported in boldface.

Table 4.1:
Forecast accuracy (entire forecast horizon: 2007q2–2013q3): RMSEs by model

			AR	FSQ	FQ	SQ	FS
Q(t)	m1	d12	1.14	0.78*	1.02	**1.20**	1.07
		d30	1.14	0.62*	**1.31**	1.29	1.03
	m2	d12	1.14	0.51*	**1.72**	1.54	1.18
		d15	0.8	0.51	**1.69**	1.56	0.94*
		d30	0.8	0.54*	**1.47**	1.35	1.01
	m3	d12	0.8	0.33*	1.80	1.12	**1.85**
		d30	0.8	0.38	1.44	0.79*	**1.59**
Q(t+1)	m1	d12	0.8	0.30	1.27	0.88*	**2.08**
		d30	0.8	0.29	1.25	0.96*	**2.17**
	m2	d12	0.8	0.30	1.09	0.74*	**2.05**

Note:
>> * flags the best-performing model among FSQ, FQ, SQ, FS.
>> Figures in bold highlight the worst-performing models among FQ, SQ, FS.
>> RMSEs for AR and FSQ in levels.
>> RMSEs of FSQ and AR models reported in levels.
>> RMSEs of FQ, SQ and FS models expressed as fractions of the RMSEs of the FSQ model.

As regards financial data, the Table suggests that they are relevant for nowcasting/backcasting GDP (model FSQ performing best), but only at the earlier stages of the nowcasting exercise: If financial data are excluded from the model in the first of the nowcasts (on the 12th of month 1), the RMSE increases by some 20% (see model SQ). Dropping survey data (see model FQ) or real data (see model FS) from the full model inflates the RMSE by only 2-7 percentage points. ([20]) Also on the 30th of month 1 financial data prove to be pivotal, being practically as important as survey data (with RMSE-ratios of 1.29 and 1.31, respectively). In month 2, both data sets are important, but dropping survey data leads to a stronger worsening of forecast performance. From the 30th of month 3 of the respective quarter onwards, the best specification (model SQ) does not contain financial data, suggesting that they have a detrimental effect on the model's performance in the last (four) forecast rounds, as evidenced by RMSE ratios between 0.96 and 0.74 for the SQ specification.

The concentration of the relative value added of financial data at the beginning of the nowcasting exercise contrasts with the role of survey data which proves the most important data category during the second half of month 1 and the entire month 2. As the bold figures in column FQ show, dropping survey data from the full model results in RMSE increases of 31 to 72%. Neither the removal of financial nor of real data would mean a comparable blow to the model's nowcasting performance.

The picture changes from month 3 onwards, where real activity series take over as the most relevant data category: omitting real variables would drive up the RMSE by up to 117%. Considering that the EA industrial production index, which is one of the variables most correlated with GDP, features the first release related to the reference quarter on the 12th of month 3, the observation that real data dominate the nowcast from that point onwards appears plausible.

([20]) On first glance, one would suspect that the RMSEs of the FQ and FS models for the first stage of the nowcasting exercise (on the 12th of month 1) should be identical. After all, the only variable category featuring releases related to the reference quarter at this early stage of the nowcasting exercise are financial data. However, it should be borne in mind that the first three nowcasts are 2-step ahead forecasts: While the exclusion of survey or real activity data has no impact on the data available for the nowcast (2nd step), it affects the structure of the dataset available for the backcast (1st step) and, potentially, its quality.

5. A COUNTERFACTUAL EXPERIMENT

5.1. NEGLECTING THE PUBLICATION LAG: A RE-ASSESSMENT

The decreasing relative importance of survey data over the nowcasting quarter might be interpreted as an indication that the main value added of survey data over real series is their timely availability. Drechsel and Maurin (2011) find that surveys are especially relevant in the months previous to the publication of hard data. Since qualitative data refer to vaguely-defined concepts like "business situation" and the survey respondents are usually just inquired about the direction of change (improvement, no change, deterioration), there is no point in refuting that they are of a less precise nature than real activity variables. The same is true for financial data, which have arguably only an indirect link to real activity.

To investigate whether the value-added of survey and financial data for nowcasting is only rooted in their timeliness, we follow Banbura and Rünstler (2011) and re-run the nowcasting exercise by resorting to a dataset which is re-arranged so as to simulate that all data were available at the beginning (i.e. at the 12th) of the reference month. Under this scenario, January's industrial production, for instance, is considered to be available on 12 January, while, under realistic circumstances, it would only be available by 12 March. ([21]) This set-up allows distilling the possible intrinsic information content of the three data categories, controlling for their different release dates.

Table 5.1 reports the RMSEs for the FSQ specification, as well as, for each of the partial models, the ratio of their RMSEs over the FSQ model's RMSE.

Table 5.1:
Counterfactual exercise (entire forecast horizon: 2007q2–2013q3): RMSEs by model

			FSQ	FQ	SQ	FS
Q(t)	m1	d12 d30	0.38*	1.35	1.02	**1.81**
	m2	d12	0.33	1.29	0.97*	**2.03**
		d15 d30	0.32	1.31	0.95*	**1.86**
	m3	d12 d30	0.30	1.09	0.74*	**2.05**

Note:
>> * flags the best-performing model among FSQ, FQ, SQ, FS.
>> Figures in bold highlight the worst-performing models among FQ, SQ, FS.
>> RMSEs of FSQ model reported in levels.
>> RMSEs of FQ, SQ and FS models expressed as fractions of the RMSEs of the FSQ model.

As was to be expected, the RMSEs of the full model are significantly reduced compared to the ones produced by the nowcasting exercise under realistic data-availability conditions (see Table 4.1). Furthermore, real series are shown to be the most important ingredient for a good nowcast. Dropping them from the full model would increase the RMSE by 81 to 105%, as the column for model FS shows.

Figures for model SQ indicate that financial data lose all their significance: the RMSE is practically invariant to the inclusion or exclusion of financial data in months 1 and 2 and even decreases markedly when financial data are excluded in month 3 (the RMSE ratios drop to 0.74). This is a clear indication that the benefits of financial data at the beginning of the nowcast quarter can be mainly attributed to their timeliness. These results are in line with Forni et al. (2003), Stock and Watson (2003), where all variables

([21]) According to this artificial scenario, forecasts produced on day 12 or day 30 are identical, since all indicators are assumed to be available right from the start. The only difference in month 2 is the release of GDP for Q(t-1) on day 15. Backcasts, i.e. projections carried out in Q(t+1) are not reported in this counterfactual scenario, since it would imply using monthly information which relates to the first months of Q(t+1), while projections shall refer to Q(t).

are treated as if they were available without publication lags, as well as the counterfactual exercise in Banbura and Rünstler (2011).

Survey data, by contrast, turn out to be a relevant ingredient throughout the entire nowcasting exercise, which is evidenced by the ratios larger than 1 in column FQ. This means, survey data enhance the nowcasting performance through more than just their timely availability. They seem to carry information which is not contained in available real data and makes them an indispensable complement to real data when nowcasting GDP.

5.2. ON THE SOURCES OF SURVEY DATA PREDICTIVE POWER – BEYOND TIMELINESS

There are two potential sources of the above diagnosed extra-information contained in qualitative data: First of all, survey data have a broader sectoral coverage than forecast-relevant real series (i.e. data published before the first flash GDP estimate). The main real series on the services sector (service turnover), for instance, is released more than 3 months after the end of the reference quarter, making any nowcast relying exclusively on real data suffer from an under-representation of the largest economic sector. Survey data can fill this gap. Secondly, survey data include respondents' views on future developments (e.g. their production expectations). They can thus be assumed to have some leading properties which might render them beneficial for early stages of the nowcasting exercise (i.e. months 1 and 2). As reported in Table 5.1, survey data prove most relevant in month 1 of the nowcast quarter (their omission causing an RMSE increase by 35%), while least so in month 3. In months 1 and 2, both the forward-looking character of (some) survey data, as well as their broad sectoral coverage can potentially provide added value. In month 3, however, the forward-looking character of survey data is irrelevant, since all real data related to the quarter is available, so that only the broader sectoral coverage of survey data adds to the model.

To shed more light on the likely causes of the genuine forecasting power of survey data, we repeat the counterfactual exercise for three different model set-ups: i) the FQ model which is based exclusively on financial and real data, ii) a model which is identical to the FQ model except in that forward-looking and services related survey data are added (FSQ1) and iii) a model which is like the FQ model, but all survey data other than forward-looking ones and those related to the services sector are added (FSQ2). Our assumption is that the FSQ1 model achieves to drive down the RMSE considerably in comparison to the basic FQ model. In line with our above argumentation, the beneficial impact is supposed to be particularly pronounced in the first two months of the quarter. The FSQ2 model, by contrast, should provide little value added compared to the FQ model, perhaps even perform weaker than the latter.

Table 5.2 reports the results of the exercise, displaying the RMSEs of the FQ model in levels, while the RMSEs of the FSQ1 and FSQ2 models are presented as fractions of the FQ model's RMSEs.

Table 5.2:
Counterfactual exercise (entire forecast horizon: 2007q2–2013q3):
RMSEs by model (surveys)

			FQ	FSQ1	FSQ2
Q(t)	m1	d12 d30	0.51	0.83	0.96
	m2	d12	0.42	0.91	0.97
		d15 d30	0.42	0.90	0.88
	m3	d12 d30	0.33	0.92	1.06

Note:
>> RMSEs of FQ model reported in levels.
>> RMSEs of FSQ1 and FSQ2 models expressed as fractions of the RMSEs of the FS model.

As the ratios smaller 1 in column FSQ1 indicate, adding forward-looking and service sector related survey questions to the FQ model drives down the RMSE substantially at any point of the nowcast quarter. The added value of this subset of survey data is particularly pronounced at the beginning of the nowcasting exercise, notably in month 1, where the RMSE is driven down by 17% compared to the FQ model. Later in the quarter, the effect shrinks to improvements of 8%. In contrast, the FSQ2 model shows a significantly poorer performance, with ratios around 1 or even larger in all forecast rounds except for month 2, when both the FSQ1 and FSQ2 exhibit a similar performance in terms of forecast accuracy. Taken together, these results provide a strong case that the finding of survey data having genuine forecasting power (i.e. beyond their timeliness) is mainly due to their forward-looking nature and the coverage of the services sector. In this respect, our results are consistent with the recent literature showing that qualitative surveys are not only (timely) proxies for hard data, but contain complementary information for understanding business cycle developments (Leduc and Liu, 2012; Leduc and Sill, 2013).

6. A FOCUS ON THE GREAT RECESSION PERIOD

Since models differ in how well they can forecast when the volatility of underlying economic data changes (Stock and Watson, 2004; D'Agostino and Giannone, 2012; Lombardi and Maier, 2011), all conclusions reached so far might be influenced by the period looked at. It is thus conceivable that variable types proving irrelevant in economically calm times, for example, might turn out to be essential in times of economic turmoil.

Compared to the relevant literature (Angelini et al., 2011, Banbura and Rünstler, 2011, Barhoumi et al., 2009, Drechsel and Maurin, 2011, Caggiano et al., 2011), our forecast evaluation exercise covers a much more recent period, which includes not only the period before the Great Recession (2008-2009) but also the global crisis and the subsequent developments over the last few quarters. The crisis of 2008-2009 lends itself to an analysis of whether certain variable types gain or lose importance for nowcasting GDP when the economy is in crisis mode. In this respect, we argue that the role of financial data, which includes variables closely linked to the crisis (e.g. money supply, loan volume to non-financial corporations), might become more prominent in the financial crisis. Likewise, the forward-looking nature of most of the survey variables might be helpful when forecasts are run in periods of high volatility.

Table 6.1 presents the RMSEs of the FSQ specification as well as the three models based on sub-samples of variables (expressed as fractions of the full model's RMSEs) for the crisis period, which is set from 2008q1 to 2009q4 as in Lombardi and Maier (2011).

Table 6.1:

Forecast accuracy (crisis period: 2008q1–2009q4): RMSEs by model

			FSQ	FQ	SQ	FS
Q(t)	m1	d12	1.19*	1.03	**1.32**	1.11
		d30	1.06*	1.17	**1.27**	1.04
	m2	d12	0.83*	1.56	**1.60**	1.22
		d15	0.84	1.49	**1.61**	0.92*
		d30	0.90*	**1.39**	1.38	1.03
	m3	d12	0.52*	1.71	1.06	**1.96**
		d30	0.60	1.35	0.75*	**1.68**
Q(t+1)	m1	d12	0.44	1.11	0.88*	**2.35**
		d30	0.41	1.09	0.94*	**2.44**
	m2	d12	0.45	1.02	0.68*	**2.27**

Note:

>> * flags the best-performing model among FSQ, FQ, SQ, FS.

>> Figures in bold highlight the worst-performing models among FQ, SQ, FS.

>> RMSEs of FQ, SQ and FS models expressed as fractions of the RMSEs of the FSQ model.

Compared to the RMSEs achieved over the entire forecast horizon (2007-2013), the full model's RMSEs (see column FSQ) have considerably increased, owing to the difficult to predict events of the financial crisis. Looking at the partial models, it turns out that the major conclusions reported above remain valid: For virtually all stages of the nowcasting exercise, the best model (flagged with an asterisk) contains both survey data and real data. They are thus also in times of economic turmoil an essential ingredient to generate relatively more accurate nowcasts. Also financial data continues being ir-relevant at the end of the nowcasting exercise (see ratios smaller 1 in column SQ). However, it is now the most relevant variable category throughout the first 1 ½ months of the nowcasting quarter (see figures in bold in column SQ). Moreover, in the second half of month 2, it shares the rank of most important variable type with the category of survey variables. This is in sharp opposition with the analysis over the entire forecast horizon, where financial data was shown to be the most important category only in the first forecast round.

To check whether the importance of financial data remains a mere artifact of their timeliness or whether it has genuine predictive power complementing the one of survey and real data, the counterfactual analysis is re-conducted. Contrary to the findings in Section 5.1., the results in Table 6.2 indeed show that the exclusion of financial data in the first month of the nowcasting exercise leads to an increase of the RMSE by 11%. Survey and real data turn out to be essential variables both in calm and turbulent times, whereby real data continue being the most important variables also in times of crisis. All in all, the beneficial effect of financial data during the financial crisis is thus due to both their timeliness and their thematic relevance during the financial crisis, reinforcing previous findings.

Table 6.2:
Counterfactual exercise (crisis period: 2008q1–2009q4): RMSEs by model

			FSQ	FQ	SQ	FS
Q(t)	m1	d12 d30	0.55*	1.35	1.11	**2.13**
	m2	d12	0.48	1.19	0.97*	**2.35**
		d15 d30	0.48	1.17	0.90*	**2.07**
	m3	d12 d30	0.45	1.02	0.68*	**2.27**

Note:
>> * flags the best-performing model among FSQ, FQ, SQ, FS.
>> Figures in bold highlight the worst-performing models among FQ, SQ, FS.
>> RMSEs of FQ, SQ and FS models expressed as fractions of the RMSEs of the FSQ model.

7. CONCLUSIONS

This papers evaluates the impact of new releases of financial, real and survey data on nowcasting (or backcasting) euro-area wide GDP throughout the quarter. We present a framework which allows us to analyse ten nowcasts/backcasts per quarter. We find that survey and real data are essential to improve forecast accuracy throughout the entire sequence of nowcasts, while the information content of financial data is mainly limited to the first two months of the quarter (when real series are scarcer).

While the existent literature considers timeliness as the main/only "quality" of survey data, our findings document that there is informational content even when timeliness is controlled for, suggesting that surveys are beneficial in GDP nowcasting also because of their broad sectoral coverage and (sometimes) forward-looking nature. This is in opposition to what we found for financial data, which turn out to be irrelevant predictors once timeliness has been controlled for. On the other hand, a sub-sample analysis focused on the years of the Great Recession highlights the usefulness of financial data as relevant predictors in times of financial turmoil.

The proposed framework is general enough to be applied for other economies. Furthermore an in-depth assessment of the role of foreign/global variables on the euro-area GDP is conceivable as well as an analysis of the relative merits of the different data categories for the purpose of nowcasting, when they are aggregated into composite indicators rather than factors. These issues are left for further research.

ANNEX 1

Annex 1

Table A1.1:
Overview of selected indicators

Variable	Avail.	Trsf.	Type	Variable	Avail.	Trsf.	Type
bond 10y	MP2	1	F	ip (vehi.)	MP4	2	Q
bond 10y, us	MP2	1	F	ip (wear.)	MP4	2	Q
bond 2y	MP2	1	F	ip c	MP4	2	Q
bond 3m, us	MP2	1	F	ip d	MP4	2	Q
bond 3y	MP2	1	F	ip d-d	MP4	2	Q
bond 5y	MP2	1	F	real exr broad	MP3	2	Q
bond 7y	MP2	1	F	real exr narr.	MP3	2	Q
dow30, us	DP	2	F	ret. sal.	MP4	2	Q
dow65, us	DP	2	F	ur	MP3	1	Q
ecb rate	DP	1	F	ur, de	MP1	1	Q
estoxx	DP	2	F	bud. bal. idx.	MP2	2	S
eurib. 3m	DP	1	F	buil. cof	MP1	0	S
exr. dollar	DP	2	F	buil. q1	MP1	0	S
exr. pound	DP	2	F	buil. q2 (weath.)	MP1	0	S
exr. yen	DP	2	F	buil. q3	MP1	0	S
gold pr.	MP2	2	F	buil. q4	MP1	0	S
int. loan nfc.	MP4	1	F	buil. q5	MP1	0	S
libor 3m, us	MP3	1	F	cons. cof	MP1	0	S
loan nfc.	MP3	2	F	cons. q1	MP1	0	S
M1	MP3	2	F	cons. q11	MP1	0	S
M2	MP3	2	F	cons. q12	MP1	0	S
M2, us	MP3	2	F	cons. q2	MP1	0	S
M3	MP3	2	F	cons. q3	MP1	0	S
oil idx.	MP2	2	F	cons. q4	MP1	0	S
oil pr.	DP	2	F	cons. q5	MP1	0	S
raw enrg. idx.	MP2	2	F	cons. q6	MP1	0	S
raw mat. idx.	MP2	2	F	cons. q7	MP1	0	S
sp500, us	DP	2	F	cons. q8	MP1	0	S
tbill 3m, us	MP3	1	F	cons. q9	MP1	0	S
vdax, de	DP	0	F	cpi idx.	MP2	2	S
vix, us	DP	0	F	esi	MP1	0	S
vstoxx	DP	0	F	indu. cof	MP1	0	S
cars	MP3	2	Q	indu. q1	MP1	0	S
exp. ext.-ea	MP5	2	Q	indu. q2	MP1	0	S
exp. int.-ea	MP5	2	Q	indu. q3	MP1	0	S
exp. int.-eu	MP5	2	Q	indu. q4	MP1	0	S
hicp	MP3	2	Q	indu. q5	MP1	0	S
hicp core	MP1	2	Q	indu. q6	MP1	0	S
imp. ext.-ea	MP5	2	Q	indu. q7	MP1	0	S
imp. int.-ea	MP5	2	Q	news idx.	MP2	2	S
imp. int.-eu	MP5	2	Q	pol. unc. idx.	MP2	2	S
ip (bas m.)	MP4	2	Q	reta. cof	MP1	0	S
ip (buil.)	MP4	2	Q	reta. q1	MP1	0	S
ip (cap. g.)	MP4	2	Q	reta. q2	MP1	0	S
ip (chem.)	MP4	2	Q	reta. q3	MP1	0	S
ip (cons. g.)	MP4	2	Q	reta. q4	MP1	0	S
ip (dur g.)	MP4	2	Q	reta. q5	MP1	0	S
ip (ener.)	MP4	2	Q	reta. q6	MP1	0	S
ip (food)	MP4	2	Q	serv. cof	MP1	0	S
ip (int g.)	MP4	2	Q	serv. q1	MP1	0	S
ip (leat.)	MP4	2	Q	serv. q2	MP1	0	S
ip (mach.)	MP4	2	Q	serv. q3	MP1	0	S
ip (ndur. g.)	MP4	2	Q	serv. q4	MP1	0	S
ip (ot. tr.)	MP4	2	Q	serv. q5	MP1	0	S
ip (rubb.)	MP4	2	Q	serv. q6	MP1	0	S
ip (text.)	MP4	2	Q				

Table A2.1:
Overview of specifications (by forecast equation)

Panel A. Optimal number of factors determined by the AIC

	07Q2	07Q3	07Q4	08Q1	08Q2	08Q3	08Q4	09Q1	09Q2	09Q3	09Q4	10Q1	10Q2	10Q3	10Q4	11Q1	11Q2	11Q3	11Q4	12Q1	12Q2	12Q3	12Q4	13Q1	13Q2	13Q3
I	1	1	1	1	1	1	4	1	6	7	7	7	7	7	7	7	7	7	10	10	10	10	10	10	10	10
II	3	3	3	3	7	5	3	9	9	10	10	10	10	10	10	10	10	10	10	7	8	8	8	10	10	8
III	3	3	3	3	3	10	10	10	10	3	3	3	3	3	3	10	10	10	10	10	10	10	10	10	3	3
IV	3	3	3	3	3	10	10	10	10	3	3	3	3	3	3	10	10	10	10	10	10	10	10	10	3	3
V	3	3	3	3	3	3	3	3	10	10	10	10	10	10	10	10	10	10	10	9	9	9	9	9	9	9
VI	3	3	3	3	3	9	10	9	7	7	7	8	8	8	8	8	8	8	9	10	10	10	10	9	10	10
VII	3	3	3	3	3	9	10	8	10	10	8	8	8	8	8	9	9	9	9	10	10	10	10	10	10	10
VIII	3	3	3	3	4	6	7	7	8	8	8	8	8	8	8	8	9	8	9	10	7	9	9	9	9	9
IX	3	3	3	4	4	6	7	7	7	7	8	8	8	8	8	9	9	9	9	10	9	9	9	9	9	9
X	3	3	3	3	4	6	6	6	8	9	9	9	9	7	7	7	7	7	10	10	7	9	9	9	9	9

Panel B. Number of retained factors

	07Q2	07Q3	07Q4	08Q1	08Q2	08Q3	08Q4	09Q1	09Q2	09Q3	09Q4	10Q1	10Q2	10Q3	10Q4	11Q1	11Q2	11Q3	11Q4	12Q1	12Q2	12Q3	12Q4	13Q1	13Q2	13Q3
I	1	1	1	1	1	1	1	1	3	3	4	4	4	4	3	3	3	3	3	3	4	4	4	4	4	4
II	2	2	2	2	2	3	3	5	6	6	5	5	5	5	4	5	5	5	5	3	3	3	4	6	6	5
III	3	3	2	2	2	3	4	4	4	3	3	3	3	3	3	4	5	5	5	6	4	5	5	5	3	3
IV	3	3	2	2	2	4	3	3	5	3	3	3	3	3	3	4	5	5	5	6	4	5	5	5	3	3
V	2	2	2	2	2	2	2	2	4	3	4	5	5	5	5	6	6	6	7	4	4	5	5	4	4	4
VI	3	3	3	3	3	5	5	7	6	6	6	7	6	7	7	6	6	7	7	9	7	7	8	7	8	8
VII	3	3	2	2	2	6	5	5	7	7	7	7	6	6	5	5	6	5	6	6	7	7	7	8	7	7
VIII	3	3	3	3	2	5	6	6	6	7	7	7	6	8	6	8	7	8	8	8	7	8	8	8	8	8
IX	3	3	3	3	2	5	6	6	6	5	6	6	6	8	7	8	9	7	7	7	7	7	7	7	7	7
X	2	3	3	3	3	6	6	5	6	6	6	6	6	7	6	7	6	5	6	6	5	6	7	7	6	5

Panel C. Adjusted R^2

	07Q2	07Q3	07Q4	08Q1	08Q2	08Q3	08Q4	09Q1	09Q2	09Q3	09Q4	10Q1	10Q2	10Q3	10Q4	11Q1	11Q2	11Q3	11Q4	12Q1	12Q2	12Q3	12Q4	13Q1	13Q2	13Q3
I	0.18	0.18	0.17	0.17	0.18	0.16	0.12	0.41	0.55	0.57	0.57	0.57	0.57	0.57	0.54	0.54	0.54	0.54	0.51	0.53	0.56	0.56	0.56	0.52	0.49	0.48
II	0.32	0.33	0.31	0.31	0.31	0.35	0.33	0.61	0.73	0.74	0.72	0.72	0.72	0.72	0.72	0.69	0.72	0.71	0.72	0.71	0.69	0.7	0.7	0.72	0.72	0.72
III	0.39	0.39	0.34	0.34	0.36	0.43	0.49	0.68	0.76	0.64	0.61	0.62	0.61	0.61	0.61	0.64	0.68	0.67	0.69	0.71	0.69	0.71	0.7	0.71	0.62	0.62
IV	0.38	0.36	0.34	0.34	0.33	0.46	0.49	0.64	0.76	0.63	0.62	0.62	0.61	0.61	0.61	0.65	0.67	0.67	0.68	0.69	0.69	0.71	0.7	0.71	0.62	0.62
V	0.42	0.41	0.42	0.42	0.4	0.35	0.37	0.6	0.76	0.73	0.75	0.75	0.75	0.75	0.75	0.75	0.75	0.74	0.75	0.72	0.74	0.75	0.75	0.74	0.74	0.73
VI	0.49	0.47	0.47	0.47	0.46	0.55	0.62	0.72	0.83	0.83	0.83	0.83	0.83	0.83	0.84	0.83	0.82	0.82	0.81	0.83	0.82	0.83	0.82	0.83	0.84	0.83
VII	0.5	0.49	0.49	0.49	0.48	0.59	0.64	0.74	0.85	0.84	0.84	0.84	0.85	0.84	0.84	0.84	0.84	0.83	0.84	0.83	0.84	0.84	0.84	0.85	0.85	0.84
VIII	0.5	0.49	0.49	0.48	0.46	0.56	0.64	0.76	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.86	0.85	0.85	0.85	0.86	0.85	0.86	0.85	0.86	0.86	0.86
IX	0.5	0.48	0.48	0.47	0.47	0.58	0.64	0.76	0.87	0.86	0.86	0.87	0.86	0.86	0.86	0.86	0.86	0.85	0.86	0.86	0.85	0.86	0.86	0.86	0.86	0.86
X	0.52	0.52	0.53	0.53	0.53	0.61	0.68	0.79	0.89	0.88	0.88	0.88	0.87	0.88	0.88	0.88	0.87	0.87	0.87	0.88	0.87	0.87	0.87	0.88	0.87	0.87

Table A2.2:

Serial correlation and normality tests (by forecast equation)

Panel A. LM serial correlation test

	07Q2	07Q3	07Q4	08Q1	08Q2	08Q3	08Q4	09Q1	09Q2	09Q3	09Q4	10Q1	10Q2	10Q3	10Q4	11Q1	11Q2	11Q3	11Q4	12Q1	12Q2	12Q3	12Q4	13Q1	13Q2	13Q3
I	0.28	0.29	0.29	0.25	0.23	0.24	0.13	0.17	0.05	0.04	0.06	0.08	0.06	0.05	0.02	0.02	0.02	0.02	0.01	0.01	0.02	0.02	0.01	0.00	0.00	0.00
II	0.28	0.30	0.27	0.24	0.21	0.73	0.65	0.45	0.92	0.80	0.55	0.63	0.88	0.90	0.88	0.91	0.86	0.88	0.76	0.95	0.93	0.91	0.91	0.83	0.84	0.97
III	0.73	0.77	0.61	0.57	0.60	0.75	0.98	0.96	0.89	0.11	0.09	0.31	0.38	0.33	0.30	0.29	0.67	0.57	0.74	0.73	0.46	0.80	0.62	0.76	0.21	0.21
IV	0.75	0.60	0.62	0.55	0.60	0.83	0.96	0.55	0.93	0.14	0.11	0.34	0.37	0.32	0.29	0.29	0.53	0.59	0.74	0.65	0.41	0.79	0.65	0.76	0.21	0.24
V	0.79	0.68	0.63	0.52	0.52	0.92	0.73	0.83	0.82	0.79	0.78	0.63	0.60	0.65	0.62	0.73	0.64	0.81	0.78	0.83	0.81	0.74	0.81	0.82	0.85	0.77
VI	0.56	0.41	0.46	0.41	0.44	0.71	0.72	0.98	0.97	0.89	0.87	0.98	0.97	1.00	1.00	1.00	0.99	0.97	0.96	0.96	0.86	0.83	0.88	0.82	0.88	0.90
VII	0.62	0.46	0.78	0.47	0.44	0.96	0.88	0.93	0.95	0.86	0.61	0.62	0.71	0.87	0.96	0.95	0.89	0.80	0.77	0.92	0.85	0.87	0.86	0.93	0.90	0.92
VIII	0.39	0.26	0.30	0.30	0.84	0.23	0.30	0.29	0.32	0.26	0.29	0.25	0.44	0.30	0.59	0.38	0.55	0.37	0.44	0.69	0.40	0.24	0.24	0.26	0.29	0.27
IX	0.46	0.32	0.36	0.36	0.73	0.22	0.44	0.32	0.27	0.27	0.20	0.22	0.38	0.25	0.30	0.34	0.24	0.52	0.36	0.73	0.39	0.30	0.29	0.33	0.37	0.30
X	0.83	0.19	0.21	0.19	0.21	0.19	0.27	0.10	0.18	0.20	0.26	0.17	0.22	0.20	0.14	0.25	0.48	0.43	0.40	0.55	0.40	0.37	0.33	0.35	0.36	0.36

Panel B. JB normality test

	07Q2	07Q3	07Q4	08Q1	08Q2	08Q3	08Q4	09Q1	09Q2	09Q3	09Q4	10Q1	10Q2	10Q3	10Q4	11Q1	11Q2	11Q3	11Q4	12Q1	12Q2	12Q3	12Q4	13Q1	13Q2	13Q3
I	0.47	0.50	0.45	0.40	0.39	0.39	0.88	0.72	0.70	0.70	0.74	0.76	0.83	0.74	0.23	0.20	0.33	0.29	0.30	0.67	0.41	0.37	0.42	0.31	0.24	0.23
II	0.52	0.58	0.50	0.45	0.43	0.58	0.85	0.77	0.32	0.25	0.44	0.42	0.85	0.57	0.74	0.15	0.55	0.31	0.42	0.83	0.01	0.01	0.13	0.06	0.17	0.51
III	0.95	0.95	0.85	0.88	0.88	0.73	0.70	0.83	0.81	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.17	0.05	0.00	0.00	0.00	0.01	0.00	0.00
IV	0.93	0.80	0.82	0.86	0.84	0.88	0.77	0.56	0.66	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.10	0.02	0.00	0.00	0.00	0.01	0.00	0.00
V	0.52	0.47	0.49	0.50	0.49	0.31	0.28	0.71	0.11	0.74	0.49	0.09	0.04	0.06	0.13	0.50	0.45	0.69	0.95	0.00	0.00	0.06	0.05	0.02	0.01	0.01
VI	0.72	0.62	0.61	0.66	0.65	0.65	0.55	0.47	0.27	0.37	0.43	0.31	0.59	0.40	0.44	0.31	0.43	0.44	0.54	0.52	0.56	0.62	0.60	0.33	0.24	0.24
VII	0.63	0.55	0.57	0.53	0.55	0.65	0.20	0.29	0.20	0.39	0.39	0.27	0.25	0.25	0.29	0.31	0.36	0.47	0.35	0.39	0.38	0.35	0.32	0.36	0.52	0.49
VIII	0.88	0.78	0.77	0.80	0.81	0.44	0.61	0.33	0.61	0.33	0.32	0.24	0.41	0.39	0.61	0.42	0.56	0.53	0.37	0.53	0.48	0.48	0.55	0.54	0.53	0.60
IX	0.89	0.79	0.77	0.80	0.84	0.45	0.62	0.19	0.28	0.76	0.49	0.20	0.34	0.30	0.32	0.36	0.35	0.34	0.34	0.44	0.47	0.44	0.44	0.42	0.38	0.45
X	0.91	0.83	0.83	0.86	0.86	0.67	0.73	0.37	0.13	0.35	0.28	0.22	0.34	0.24	0.32	0.28	0.42	0.36	0.38	0.43	0.47	0.57	0.48	0.44	0.45	0.47

ANNEX 3

Annex 3

Table A3.1:

Diebold-Mariano test (factor-based specifications vs. naïve benchmark)

			Quadratic loss function				Absolute loss function			
			FSQ	FQ	SQ	FS	FSQ	FQ	SQ	FS
Q(t)	m1	d12	-1.096	-1.058	-0.72	-0.98	-0.802	-0.74	-0.735	-0.795
		d30	-1.425	-1.05	-1.106	-1.382	-1.996	-0.757	-0.958	-1.996
	m2	d12	-1.545	-0.864	-1.149	-1.449	-2.054	-0.359	-1.032	-1.925
		d15	-1.04	0.236	-0.047	-1.105	-1.051	1.251	0.744	-1.194
		d30	-0.954	-0.062	-0.342	-0.952	-1.057	0.753	0.03	-1.221
	m3	d12	-1.477	-0.79	-1.481	-0.792	-2.353	-0.431	-1.968	-0.963
		d30	-1.386	-0.913	-1.55	-0.765	-2.151	-0.594	-2.205	-0.838
Q(t+1)	m1	d12	-1.48	-1.318	-1.537	-0.71	-2.092	-1.378	-2.268	-0.45
		d30	-1.504	-1.362	-1.516	-0.716	-2.214	-1.537	-2.154	-0.454
	m2	d12	-1.489	-1.421	-1.572	-0.716	-2.173	-1.691	-2.356	-0.454

Note:

Test conducted using both quadratic and absolute loss functions. Negative values indicate better forecasting performance of the factor-based model compared to the naïve benchmark.

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