4. CONCLUSIONS

The financial crisis has clearly proven the importance of the link between macro and finance, and has emphasized the importance of recognizing a role for uncertainty. AGOPP present an interesting summary of the forecasting methods adopted by two of the major central banks, and give applied forecasters useful suggestions for further work that can help improve central banks' forecasts.

DISCLAIMER

The views expressed here are solely the responsibility of the author and should not be interpreted as reflecting the view of the Board of Governors of the Federal Reserve System or of any other person associated with the Federal Reserve System.

[Received May 2014. Accepted August 2014.]

REFERENCES

Baker, S. R., Bloom, N., and Davis, S. J. (2013), "Measuring Economic Policy Uncertainty," Working Paper. [505]

Bloom, N. (2009), "The Impact of Uncertainty Shocks," *Econometrica*, 77, 623–685. [505]

Carlson, M. A., King, T. B., and Lewis, K. F. (2008), "Distress in the Financial Sector and Economic Activity," *B.E. Journal of Economic Analysis and Policy*, 11, 35. [504]

Mitchell, W. C., and Burns, A. F. (1938), *Business Cycle Indicators*, Princeton: Princeton University Press, pp. 162–183. [504]

Pruitt, S. (2012), "Financial Stress Indexes for the Euro Area," working paper. [504]

Scotti, C. (2013), "Surprise and Uncertainty Indexes: Real-Time Aggregation of Real-Activity Macro Surprises," International Finance Discussion Papers 1093, Board of Governors of the Federal Reserve System (U.S.). [505]

Stock, J. H., and Watson, M. W. (2003), "Forecasting Output and Inflation: The Role of Asset Prices," *Journal of Economic Literature*, 41, 788–829. [504]

Van Roye, (2011), "Financial Stress and Economic Activity in Germany and the Euro Area," Kiel Discussion Paper 1743, Kiel Institute for the World Economy (ifW). [505]

Comment

Kirstin Hubrich and Simone Manganelli
Research Department, European Central Bank, 60311 Frankfurt am Main, Germany
(*kirstin.hubrich@ecb.europa.eu; simone.manganelli@ecb.europa.eu*)

According to a famous saying, one "should never ask what's inside a sausage and an economic forecast." We still do not dare to ask how a bratwurst is made, but the authors are to be commended for having written an article that brings to a wider audience an overview of how the forecasting process is conducted in two major central banks, the European Central Bank (ECB) and the Federal Reserve Bank of New York (FRBNY). The reader can appreciate the many challenges faced by forecasters, who have to address a wide variety of issues, ranging from data aggregation, incorporation of judgment, model combination, mixed frequency data, and structural breaks. Forecasters in central banks, unlike forecasters in academia, do not have the luxury to postpone their analysis if they find major roadblocks on their way: their forecasts are needed at regular frequency as a major input into the monetary policy decision process.

The article starts with an in-depth description of the forecasting process at the ECB and the FRBNY. Readers interested in understanding the institutional background behind the forecasts will find this section particularly useful. It then compares and evaluates point forecasts produced by the ECB and FRBNY for gross domestic product (GDP) and inflation during the global financial crisis. A related section is dedicated to explore how and to what extent the inclusion in the forecasting model of high-frequency financial variables improves the macroeconomic forecasts. The article also has a section discussing the development of a broader conceptual framework for the forecasting process, emphasizing in particular scenario-driven forecasting schemes and distributional features to evaluate macroeconomic risks.

In this commentary, we will first provide some broader comments about the nature and characteristics of forecasting in central banks, followed by more specific suggestions about the analysis and results presented in the article.

1. BROADER COMMENTS

The broader comments are interrelated and call for central bank forecasters to give more insight into how forecasts enter the central banker's decision-making process.

It would be incredibly helpful to the reader to know how forecasts are used in a central bank. The authors are rather silent on this aspect, as a discussion about the purpose of the forecast is missing. From a purely econometric and decision theory perspective, forecasts serve the purpose to help the decision maker to take better decisions. However, since central banks are major players in financial markets and in the macroeconomy in general, one could think that the publication of forecasts may also serve to coordinate market expectations. In other words, there is a strategic element in the production and publication of the forecasts which in our opinion deserves more discussion.

Pushing deeper along these lines, Clive Granger has nailed into our heads the concept that forecast evaluations cannot be carried out in a vacuum, but rather need to take into account

Journal of Business & Economic Statistics
October 2014, Vol. 32, No. 4
DOI: 10.1080/07350015.2014.956874
Color versions of one or more of the figures in the article can be found online at *www.tandfonline.com/r/jbes*.

how the forecasts are used in the decision process. Optimal decisions maximize expected utility, which combines forecast densities and the utility function of the decision maker. It is therefore not possible to talk about risks, without also taking a stance on the preferences of the decision maker. Under- or over-estimation of GDP and inflation is not necessarily a sign of poor forecasts. It could simply indicate asymmetric preferences of the decision maker. This point has been made for instance by Kilian and Manganelli (2008) or by Elliott, Komunjer, and Timmermann (2008). In particular, Kilian and Manganelli (2008) backed out the estimated preferences of the U.S. Federal Reserve Bank during the Greenspan tenure, showing that it was characterized by asymmetric aversion to deflation and output expansions.

Another general comment is about judgment. Judgment is pervasive in any real world decision-making process. It is actually how most decisions are taken in our daily life. Not surprisingly, judgment and rules of thumb play an important role also in the forecasting process of central banks. The authors tell us many times how forecasts are often modified according to judgment, for instance until the outcome "can be explained and defended to senior management." Yet, the process of how judgment is incorporated into the forecast remains unclear and there is no clear description or discussion about this in the article. To be fair, attempts to formalize this process within the classical framework are still very rare also in the academic literature (see, for instance, Manganelli 2009; Gonzalez, Hubrich, and Tesasvirta 2009). One is often referred to Bayesian techniques, which in theory allows for the possibility of incorporating judgment via the priors. In practice, however, the decision maker is left overburdened with the task to map her judgment about inflation or GDP into a complicated multivariate prior on structural model parameters about which she often knows close to nothing (see the discussion in Manganelli 2009).

2. FORECASTING DURING THE GLOBAL FINANCIAL CRISIS

Turning now to more specific comments, the authors investigate the important issues of forecast accuracy and failure during the global financial crisis across institutions. During the global financial crisis, the dramatic fall of GDP growth and the extraordinary volatility in euro area headline inflation made them extremely difficult to forecast, even in the short term. All institutions engaged in official forecasting had a very poor record, and the ECB/Eurosystem (henceforth ECB) and the FRBNY were no exception. The limited comparability of the projections of the two institutions for inflation notwithstanding, Section 3 of the article shows that the ECB and the FRBNY exhibit similar deteriorations of the 1-year-ahead forecast of GDP growth. During the crisis period, the ECB's inflation forecast, in contrast, clearly worsened more. However, as the authors point out, the ECB's quantitative aim of price stability is defined in terms of the harmonised index of consumer prices (HICP) that includes highly volatile food and energy prices that are excluded from the core consumer price index (CPI) inflation measure relevant for monetary policy of the Federal Reserve in the United States. In this context, it is noteworthy, that Hubrich and Skudelny (2011) found root mean square errors when analyzing forecast accuracy for HICP excluding food and energy for the euro area that were similar in the precrisis period and a period including the global financial crisis as is found by the authors for the United States. For HICP *total* (including food and energy) other institutions made similar forecasting errors as the ECB, as Figure 1 illustrates.

Figure 1 shows the evolution of forecasts for annual inflation from different institutions and private forecasters in 2009, a year in which it was particularly difficult to forecast inflation. The first forecasts represented in the chart have been made in January 2008 and were subsequently revised over time at different time intervals (mostly monthly or quarterly). The last forecast for annual inflation in 2009 was published in October 2009. While the outcome of annual inflation in 2009 was 0.3% (the red dot end-2009), it took until mid-2009 for forecasts of different institutions and private forecasters to come close to this number. Also, the different forecasts appear to be quite diverse.

As Figure 1 illustrates, it is an important question for policy institutions as well as academia how to improve forecasting models and, in particular, how to address the deterioration of forecast accuracy in crisis episodes. There are a number of different ways to address this issue: (1) to use mixed frequency methods to incorporate more detailed and timely information on financial variables; (2) to employ forecast combination methods to hedge against bad forecast performance of single models

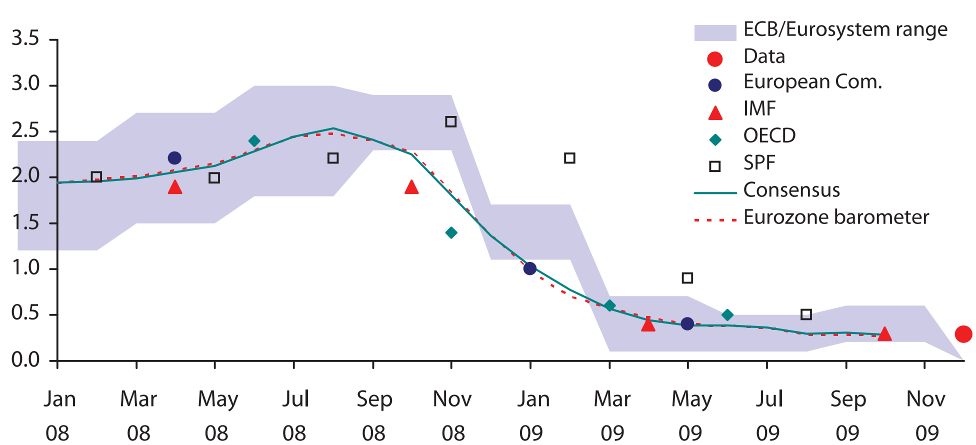

Figure 1. Forecasts for annual inflation (the y-axis) in 2009; forecasts made at different points in time (the x-axis) by a number of institutions (see legend); published ranges are shown for (Broad) Macroeconomic Projections of the ECB/Eurosystem. Source: Hubrich and Skudelny (2011).

during such periods and provide more robust forecasts; and (3) to consider risk scenarios.

The study by Alessi et al. (2014) in particular considers (1) and (3). In Section 4, they ask whether the financial market signals were fully accounted for. To address this question, they employ a simple average of mixed-data sampling (MIDAS) regressions involving one of the financial series considered at a time and Bayesian model averaging (BMA). In Section 5, they consider scenario-driven risk profiles.

3. THE ROLE OF FINANCIAL INFORMATION IN THE FORECAST

Financial market information has of course always been part of the input into forecasts of Central Banks. However, the global financial crisis has triggered an intense discussion of how financial market information should be incorporated in macroeconomic models in general. More weight is now assigned to the role of financial markets, in particular, in the amplification of the macroeconomic effects of financial crises and the feedback effects between the financial sector and the macroeconomy.

The authors present results from a simple average across MIDAS regressions of the forecast errors of the ECB/Eurosystem and the FRBNY, respectively. The authors argue that their finding suggests that MIDAS regressions with financial variables could have improved the forecast accuracy of GDP growth forecast. They support this conclusion by showing improvements in terms of average R^2 of MIDAS regressions over a simple autoregressive model of the forecast errors not including any financial information. The MIDAS regressions contain forecast errors of the respective central bank regressed on different single financial variables on a daily basis. This is indeed a noteworthy finding. The literature has so far presented mixed results on the role of financial variables in improving forecast accuracy. It would therefore be interesting to investigate more in-depth what is driving the results presented in this article. The current set of results raises three potential reasons: (1) MIDAS models are more effective than other approaches at incorporating mixed frequency information; (2) the information contained in higher frequency financial variables is "per se" helpful in improving forecast accuracy; and (3) the use of model averaging drives the improvement in the results.

To better understand points (1) and (2), it would be useful to discuss the results in the light of the findings of the literature. For instance, Banbura et al. (2013) found that daily financial variables do not help improving precision of GDP nowcasts of mixed frequency dynamic factor models for U.S. GDP. On the other hand, with MIDAS models a role for financial variables in predicting economic activity has been found by Andreou, Ghysels, and Kourtellos (2013). On point (3), Hubrich and Skudelny (2011) found that forecast combination does hedge against bad forecast performance in crisis times for euro area inflation. To address point (3), the authors discuss the results underlying the summary statistics that they present in Table 5 for the euro area (the single MIDAS regressions are not shown for space constraints). They find that commodity prices, fixed income indicators, the change in stock market volatility, and corporate bond spreads sometimes improve the forecast over the autoregressive model of order one. However, the improvement in forecast accuracy is only evident for certain horizons and those horizons vary across variables. Therefore, the improvement of MIDAS regressions with financial variables across all horizons displayed by the authors in Table 5 is at least partly coming from the averaging of the different MIDAS models.

4. THE ROLE OF NONLINEARITIES

One more general question is to what extent the forecast improvement due to financial variables might differ between normal times and crisis times. The split-sample analysis presented for the United States goes some way to address this question. Two recent attempts from the literature to incorporate financial market information into empirical macroeconomic models and at the same time allowing for nonlinearities to distinguish between different stress episodes are Hubrich and Tetlow (2012) and Hartmann et al. (2014). Both articles incorporate measures of financial instability into an empirical macroeconomic model.

As an illustration, we first present impulse responses from Hartmann et al. (2014), focusing on the systemic dimension of financial stress and its potential implications for the euro area. They find striking differences in terms of output and inflation reaction to a financial stress shock between the systemic fragility regime and the tranquil regime (see Figure 2). In

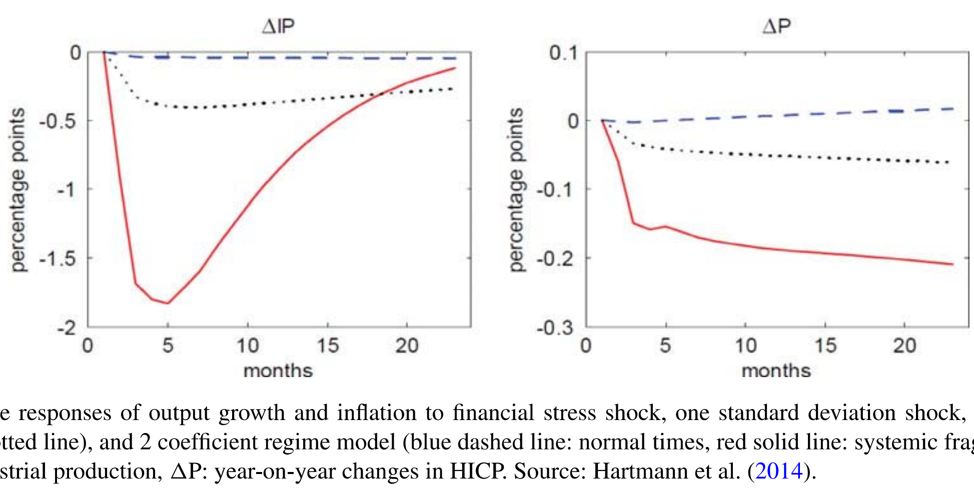

Figure 2. Impulse responses of output growth and inflation to financial stress shock, one standard deviation shock, comparison constant parameter model (dotted line), and 2 coefficient regime model (blue dashed line: normal times, red solid line: systemic fragility). ΔIP: year-on-year changes in industrial production, ΔP: year-on-year changes in HICP. Source: Hartmann et al. (2014).

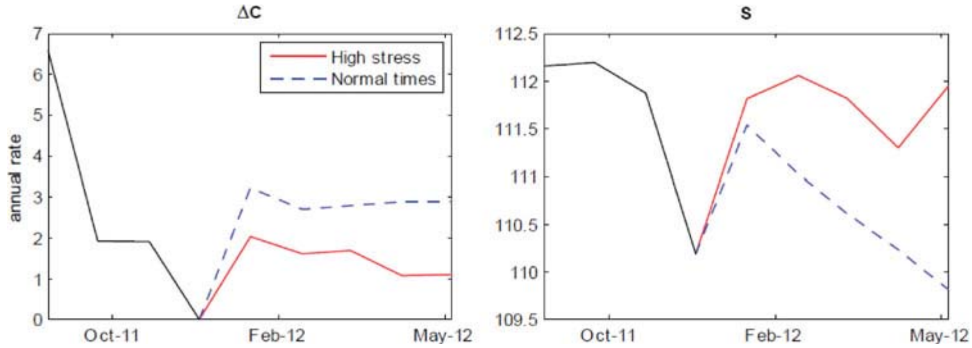

Figure 3. Forecast conditional on regime (high-stress coefficients vs. low). ΔC: annualized changes in consumption; S: indicator of financial stress. Source: Hubrich and Tetlow (2012).

tranquil regimes, industrial production growth and inflation display hardly any reaction to a shock in the level of financial distress. By contrast, in the systemic fragility regime a positive shock in financial stress leads to a quick, severe, and protracted contraction in economic activity and a decline in inflation. For example, a positive one standard deviation shock by 0.1 leads to a sharp decline in output growth by about 2 percentage points over the first 5 months.

For the U.S. economy, Hubrich and Tetlow (2012) presented different forecasts conditional on high stress and normal regime from a Markov switching model.

Figure 3 shows two forecast paths from the end of the sample in December 2011, one (the red solid line) conditional on a high-stress regime in both coefficients and variances, the other (the blue dashed line) conditional on a low-stress regime. The stress forecast (Figure 3, right panel) is much lower in normal times than in high-stress episodes. Personal consumption growth (Figure 3, left panel) is much weaker in the high-stress regime and is accompanied by elevated levels of financial stress. The results in Hubrich and Tetlow (2012) for the United States and Hartmann et al. (2014) for the euro area suggest important nonlinearities in the relation between financial instabilities and the macroeconomy.

Overall, some broad lessons can be drawn from recent studies, including the present one, for economic forecasting from the global financial crises: first, a greater variety of tools is needed to better cope with similar crisis episodes in the future, in particular to account for financial factors, nonlinearities, and exploit new data sources. Second, there is a need to employ and develop further methods to handle the complexity arising from a large number of tools, in particular forecast combination methods. Third, further development of risk assessment and scenario analysis is important, for instance the use of scenarios to consider low-probability, high-impact events.

[Received May 2014. Accepted August 2014.]

REFERENCES

Andreou, E., Ghysels, E., and Kourtellos, A. (2013), "Should Macroeconomic Forecasters Look at Daily Financial Data?," *Journal of Business and Economic Statistics*, 31, 240–251. [508]

Banbura, M., Giannone, D., Modugno, M., and Reichlin, L. (2013), "Now-Casting and the Real-Time Data Flow," in *Handbook of Economic Forecasting* (Vol. 2), eds. G. Elliott and A. Timmermann, pp. 195–236, North Holland: Elsevier. [508]

Elliott, G., Komunjer, I., and Timmermann, A. (2008), "Biases in Macroeconomic Forecasts: Irrationality or Asymmetric Loss?," *Journal of the European Economic Association*, 6, 122–157. [507]

Gonzáles, A., Hubrich, K., and Teräsvirta, T. (2009), "Forecasting Inflation With Gradual Regime Shifts and Exogenous Information," CREATES Research Paper 2009-3 (also ECB Working Paper No. 1363, July 2011). [507]

Hartmann, P., Hubrich, K., Kremer, M., and Tetlow, R. J. (2014), "Melting Down: Systemic Financial Instabilities and the Macroeconomy," Manuscript, European Central Bank. Available at *http://ssrn.com/abstract=2462567*. [508,509]

Hubrich, K. and Skudelny, F. (2011), "Forecast Combination for Euro Area Inflation—A Cure in Times of Crisis?," presented to the Working Group of Forecasting of the ESCB. [507,508]

Hubrich, K., and Tetlow, R. J. (2012), "Financial Stress and Economic Dynamics: The Transmission of Crises," in *Finance and Economics Discussion Series*, Federal Reserve Board, 2012–82 (also ECB Working Paper No. 1728, 2014). [509]

Kilian, L., and Manganelli, S. (2008), "The Central Banker as a Risk Manager: Estimating the Federal Reserve's Preferences Under Greenspan," *Journal of Money, Credit, and Banking*, 40, 1103–1129. [507]

Manganelli, S. (2009), "Forecasting With Judgement," *Journal of Business & Economic Statistics*, 27, 553–563. [507]