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Abstract

This paper documents macroeconomic forecasting during the global financial crisis by two key central banks: the European Central Bank and the Federal Reserve Bank of New York. The paper is the result of a collaborative effort between the two institutions, allowing us to study the time-stamped forecasts as they were made throughout the crisis. The analysis does not focus exclusively on point forecast performance. It also examines density forecasts, as well as methodological contributions, including how financial market data could have been incorporated into the forecasting process.

Key words: macro forecasting, financial crisis

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1 Introduction

The purpose of this paper is to document macroeconomic forecasting during the global financial crisis (henceforth referred to as *the crisis*) by two of the key central banks: the European Central Bank and the Federal Reserve Bank of New York (hereafter respectively ECB and FRBNY). The paper is the result of a collaborative effort between the two institutions, allowing us to study the time-stamped forecasts during the global financial crisis . These forecasts of key macroeconomic variables were the inputs of the extraordinary measures taken by central banks both in terms of conventional interest rate policy as well as in terms of the creation of many crisis-driven special purpose facilities which provided much needed support to a financial sector on the brink of collapse.

A number of assessments have been made about the forecast performance of central banks during the Great Recession, including Potter (2012a) and Stockton (2012). It is well known and well articulated notably by Stockton (2012), that the forecasting tools and monetary policy processes have been put through a severe stress test by the events of the past five years. Both Potter (2012a) and Stockton (2012) observe that the forecast performance during the Great Recession has been noticeably worse than prior to the crisis.

The analysis in this paper builds on this literature and benefits from a unique access to the time-stamped, real-time forecast records of the European Central Bank and the Federal Reserve Bank of New York. In this respect our analysis is similar and complementary to Stockton (2012) who provides a thorough review of the Bank of England forecasting performance during the crisis. However, our analysis also goes beyond the traditional forecast evaluation exercises and discusses methodological advances which most likely will shape the future of the macroeconomic forecasting process at central banks.

The paper is organized as follows. In section 2 we start with a brief summary of the institutional backgrounds of the forecasting process at the FRBNY and ECB and we discuss the data used in the study. Section 3 examines the point forecast performance. Since the main trigger of the crisis was a meltdown of the US subprime mortgage market, we pay special attention in section 4 to whether financial market signals were fully accounted for in the central banks forecasting process. Section 5 presents a new conceptual and methodological framework for prediction and policy guidance which grew out of the challenges faced in particular at the FRBNY. The framework has two key ingredients: (1) the emphasis on what might be called scenario-driven forecasting schemes, and (2) the recognition that one should pay attention to distributional features beyond point forecasts, in line with general notions of macroeconomic risk. This analysis naturally links into section 6 which covers model and density forecast evaluations.

2 The Forecasting Process: Institutional Backgrounds and Data Description

Before discussing the specific cases, it is worth recalling some of the literature on the general topic of Central Bank forecasting *prior* to the Great Recession.[1] Christoffel, Coenen, and Warne (2010) compare the forecast accuracy of the New Area-Wide Model (NAWM), designed and used by the European Central Bank for macroeconomic forecasts, with Bayesian DSGE-VARs, BVARs and reduced-form models. They find that the DSGE-VAR model outperforms DSGE, NAWM, VAR, and BVAR models in forecasting output. Similarly, Edge, Kiley, and Laforte (2010) compare the performance of Estimated Dynamic Optimization-based model (EDO) from the Board of Governors of the Federal Reserve Board (FRB) with VAR, BVAR, univariate autoregressive model, and the Greenbook and FRB forecasts. They find that the out-of-sample real time forecasts of the EDO are comparable to the autoregressive model but generally not statistically different from it and to other models.

Another important literature focuses on the forecast of macroeconomic variables using factor models, which are a parsimonious way of extracting large information on overall economic conditions. Stock and Watson (2002), Marcellino, Stock, and Watson (2003) and Forni, Hallin, Lippi, and Reichlin (2000) survey applications of these models in forecasting macroeconomic and financial variables. The majority of these studies find that factor models consistently outperform univariate and multivariate autoregressive models and, often, judgmental forecasts both during expansions and recessions. Moreover, Wang (2009) compares the out-of-sample forecast performance for US output growth of DSGE models with VARs and factor models and finds that factor models generally outperform any other model in the short run.

A growing literature focuses on nowcasting and short term forecasting GDP growth using mixed frequency models.[2] These models are based on the idea that it is possible to use information contained in more timely indicators (available at a higher frequency) to improve the forecast of quarterly output growth. This literature is gaining prominence in particular against the background of the failure of standard models during the global financial crisis, and it will be one of the topics highlighted later in the paper. Early contributions include the use of so-called bridge equations, see e.g. Baffigi, Golinelli, and Parigi (2004) and Diron (2008), a traditional modeling strategy for obtaining an early estimate of quarterly GDP growth by exploiting information in monthly variables. Using mixed frequency data, Evans (2005), Nunes (2005) and Giannone, Reichlin, and Small (2008), among others, have formalized the process of updating forecasts as new releases of data become available. More specifically, they use state-space models and the Kalman filter as a representation of the joint dynamics of real GDP and the monthly data releases. This allows to nowcast in presence of staggered data releases, a common feature of high frequency indicators, often showing missing observations at the end of the sample due to

[1] Excellent recent surveys on the topic appear in Chauvet and Potter (2013), Del Negro and Schorfheide (2013) and Wieland and Wolters (2013).

[2] See in particular the recent surveys of Andreou, Ghysels, and Kourtellos (2011) and Banbura, Giannone, Modugno, and Reichlin (2013).

non-synchronized publication lags (the so called jagged/ragged edge problem). An alternative reduced form strategy put forward in recent work by Ghysels, Santa-Clara, and Valkanov (2002), Ghysels, Santa-Clara, and Valkanov (2006) and Andreou, Ghysels, and Kourtellos (2010) uses so-called MIDAS regressions. There are some conceptual differences between the two approaches. The former involves latent variable state-space models, while the latter is purely regression-based.

Applications of mixed frequency models to nowcast GDP growth in the U.S. or euro area include Clements and Galvão (2008), Clements and Galvão (2009), Marcellino and Schumacher (2010), Kuzin, Marcellino, and Schumacher (2011), Angelini, Camba-Mendez, Giannone, Reichlin, and Rünstler (2011), Andreou, Ghysels, and Kourtellos (2013), Kuzin, Marcellino, and Schumacher (2013) among others. The general finding is that these nowcasting models generally outperform models using quarterly frequency only, and are comparable to judgmental forecasts. In particular, Kuzin, Marcellino, and Schumacher (2011) find that the nowcasting and forecasting ability of the MIDAS and mixed-frequency VAR (MF-VAR) for quarterly GDP growth in the euro area are complements as the MIDAS does better for short horizons (up to 5 months), whereas MF-VARs are better for longer horizons (up to 9 months).

The following subsections highlight the salient features of the forecast conducted at the Federal Reserve Bank of New York and at the European Central Bank. First, in the US the FOMC meeting calendar determines the frequency and occurrence of the forecasting process, while at the ECB the forecasting process follows the Governing Council fixed meeting calendar.[3] Second, the US Federal Reserve focuses on so called core inflation - excluding energy prices, whereas the ECB targets the HICP, which includes such prices. Finally, the ECB is assisted by national central banks that are members of the Eurosystem. As a result, the ECB forecasting process requires a coordination effort between the ECB and the national central banks. In contrast, the FRBNY is a member of the Federal Reserve System but exclusively relies on its own research staff.

Before discussing the differences between the ECB and FRBNY, it is important to stress many common features of the forecasting process at both institutions. They include the wide use of conditioning assumptions, the involvement of a variety of models, a frequent assessment for reasonableness and consistency of the outputs and a prominent role assigned to expert judgement. Furthermore, both include as a fundamental component the assessment of risks surrounding the projections. On this last point, Kilian and Manganelli (2008) point out that the same theoretical tools can be adapted easily to the risk management strategies pursued by both central banks.

2.1 Macroeconomic Forecasting at the Federal Reserve Bank of New York

The FRBNY has a long tradition of forecasting US economic conditions. These forecasts and accompanying analysis make up a part of the vast array of information on domestic and global economic and financial conditions which inform the FRBNY's role in the process of setting US monetary policy.

[3]There is, however, a continuous nowcasting process at the ECB which will be further discussed later and also revisited in section 4.

2.1.1 What is the Forecast?

Before beginning to explain how the forecast is prepared, it would be useful to explain what kind of forecast the FED produces. One component of the forecast is a “best guess”, based on a set of conditioning assumptions, of the path of macro variables such as GDP growth, the unemployment rate, and inflation over a forecast horizon of about two years. Internally, this best guess is referred to as the “modal” forecast in that it is intended to be the most likely of a wide range of potential outcomes. The modal forecast is not the output of a single model of the US economy. The science of economics has not yet developed a “consensus” model which produces reliable forecasts for a range of key variables. A variety of models of varying degrees of sophistication are used in the process, but ultimately it is a “judgemental” forecast.

The number of underlying conditioning assumptions is extensive and defining them is an important part of the process. The major conditioning assumptions include the economy’s potential growth rate, the stance of fiscal and monetary policy, the rate of growth of the economies of the major US trading partners, the path of the exchange value of the dollar, and the path of global oil prices. Putting together this modal forecast is both challenging and humbling. The FRBNY has at its disposal vast amounts of macro and micro data on the US economy covering much of the post-World War II period. In addition, the FRBNY, like many other central banks, has a team of highly trained and seasoned professionals who are able to combine state-of-the-art statistical techniques with the experience and judgment that comes from having monitored and forecasted the US economy for decades. Nonetheless, it is taken for granted that before even the forecasting process starts that the probability that events will unfold as described in the modal forecast is essentially zero. The US economy is constantly evolving. Each cycle is unique and turning points are extremely difficult to identify in real time.

For all of the reasons above, the FRBNY also produces an assessment of the risks around the modal forecast. This risk assessment is based on the construction of the most prominent risk scenarios confronting the global economy, an assessment of the most likely errors in the conditioning assumptions, and the most likely errors in the understanding of current conditions and how the economy actually works. In section 5 we will elaborate on some of the technical aspects.

2.1.2 A High Level Overview of the Process

Most major economies maintain a system of national accounts through which the level and growth rate of economic activity and prices is estimated. In the US, the National Income and Product Accounts or NIPAs are maintained by the Bureau of Economic Analysis (BEA) of the US Department of Commerce. The BEA is for the most part a data user, relying on data produced primarily by the Bureau of Labor Statistics and the Bureau of the Census. Gross Domestic Product (GDP) is the sum of all final expenditures on goods, structures, and services within the borders of the Unites States over a given period of time such as a calendar quarter or year. The main categories of final expenditures are consumption, gross private domestic investment, government consumption expenditures and gross investment, and net exports. Data are available to allow each of these major categories to be disaggregated to a quite detailed level. While GDP is the sum of all final expenditures made within the borders of the US over a given period of time, it is simultaneously equal to all of the income which accrues to the factors of production over that same time period. Gross National Product (GNP), or the income earned by factors of production owned by US citizens and corporations, is derived by adding to GDP income flowing into the US from the rest of the world and subtracting income payments made to the rest of the world. Net national product is derived by subtracting from GNP private and government capital consumed (depreciation) during the time period that income accrued. To derive national income, the statistical discrepancy is subtracted from net national product. The statistical discrepancy is, as its name suggests, an accounting identity that equates the income side to the NIPAs with the expenditure side. If the statistical discrepancy is positive, it indicates that the estimated sum of total expenditures exceeds the estimated sum of incomes. If it is negative, estimated incomes exceed estimated expenditures. Finally, national income is composed of, in order of importance, wages and salaries, corporate profits, proprietors' income, etc.

The forecast is assembled in a spreadsheet model of the expenditure and income sides of the NIPA. However, the FRBNY organizes the expenditure side of the NIPAs in a manner consistent with a "bottom up" projection of real final expenditures, the corresponding price indices, and nominal final expenditures. In this alternative presentation, GDP is composed of two main categories of expenditures, domestic demand and net exports. Domestic demand is made up of inventory investment and final sales to domestic purchasers. Final sales to domestic purchasers is divided into two categories, private, which is the sum of consumption and gross private domestic fixed investment, and government consumption expenditures and gross investment. An important metric is the ratio of the stock of inventories over total final sales, which is the sum of final sales to domestic purchasers and net exports.

The forecast process begins by making an initial projection of the quarterly rates of growth of the components of real final sales to domestic purchasers - C plus I plus G - and their corresponding price indices over the forecast horizon. This first pass is based on a judgmental assessment of recent trends, typical cyclical behavior, and exogenous factors such as upcoming changes in tax rates or government spending. To this is added a first estimate of the rate of growth of inventories, keeping the ratio of inventories over final sales on a path judged to be consistent with longer-term trends. The projected growth rate of domestic demand, along with assumptions about global growth and the path of the exchange value of dollar, are then run through a trade model, providing a first estimate of net exports.

The projected path of real GDP growth resulting from this process is then used as an input into what FRBNY staff calls the "Productivity and Costs" model. This model produces projected paths of the unemployment rate over the forecast horizon. In addition to the growth of real GDP, there are numerous assumptions that must be made for variables such as productivity growth, average weekly hours worked, population growth rate, and labor force participation rate. Finally, the FRBNY runs a "Prices and Wages" model with inputs from the preceding two steps to derive projections for core CPI and PCE deflator inflation and compensation per hour in the nonfarm business sector.

This set of "first round" results are then assessed for reasonableness and consistency with views about the major forces impacting the economy. Is the path of the personal saving rate consistent with the state of household leverage and lending standards? Is the path of the unemployment rate and inflation consistent with assumptions regarding monetary policy and the path of long term interest rates? Is the path of corporate profits consistent with the assumed path of equity prices? Is the path of the inventory/final sales ratio reasonable? Answers to questions such as these often prompt subsequent iterations of the process until a forecast is obtained that can be explained and defended to senior management. Again, as noted earlier, this exercise produces a modal forecast, or the most likely outcome. In section 3 we will examine the statistical accuracy of these point forecasts. In section 5 we elaborate on how various risk scenarios are built around the modal forecast. The latter will produce density forecasts which will be appraised in section 6.

2.2 Macroeconomic Forecasting at the European Central Bank

Eurosystem staff macroeconomic projections play an important role as a tool for aggregating and organising existing information on current and future economic developments. Conditioned on a set of assumptions, they provide projections for a range of macroeconomic variables, combining the results of models with economic experts knowledge. The forecasting process of the Eurosystem has specific characteristics due to its objectives and to the organization of the European System of Central Banks (ESCB). In this section we describe the forecasting process in place at the European System of Central Banks.

First of all it is important to note that the Eurosystem and ECB staff macroeconomic projections for the euro area are carried out four times a year with two different sets of procedures. The projections are performed twice a year in the context of the Eurosystem staff Broad Macroeconomic Projection Exercise (BMPE) and twice in the context of the ECB staff Macroeconomic Projection Exercise (MPE).[4] In the following we will describe the wider BMPE exercise, and the differences with the somewhat simpler MPE will be highlighted at the end.

Focusing on the BMPE, the responsibility of the forecast exercises rests in the hands of the staff of the ECB and that of the Eurosystem National Central Banks. The forecasts are carried out under the responsibility of the Monetary Policy Committee. The Monetary Policy Committee is composed of senior staff representatives of the ECB and the National Central Banks, provides guidance for the production of the projection figures and is responsible for the final draft of the report on the projection exercise. The Working Group on Forecasting (WGF), which is one of the three working groups reporting to the Monetary Policy Committee, is responsible for producing detailed figures for the macroeconomic projections and for producing an initial version of the report.

The forecasts are characterized by a special focus on inflation. The main process, the BMPE itself, looks at the broader macro economy, including fiscal and labor market indicators. The quarterly

[4]See *A guide to Eurosystem staff macroeconomic projection exercises*, European Central Bank, 2001.

projections extend to a horizon of two to three years. In parallel and contemporaneously, the Narrow Inflation Projection Exercise (NIPE) looks at monthly movements in inflation up to 18 months ahead. It focuses on all main components of the Harmonized Index of Consumer Prices (HICP): unprocessed and processed food, energy, services and non-energy industrial goods.

The need to coordinate the work of central banks requires the adoption of common technical assumptions underlying the forecasts. At the beginning of the exercise provisional assumptions are agreed, including interest rates, exchange rates, the international environment and fiscal variables. These assumptions are constantly reviewed and refined in the course of the forecast exercise. The ESCB forecast uses futures for oil prices and a random walk assumption for the exchange rate of the euro. Common food prices assumptions and international environment projections are produced by the ECB staff, while National Central Banks update the fiscal policy assumptions on the basis of new passed (or likely to be passed) fiscal measures. The conditioning assumptions for monetary policy are also an important element of the forecast. Before 2006 an assumption of constant short-term interest rate was used for simplicity and to avoid commitment. Since June 2006, market interest rates are used to ensure a higher consistency of projections and a better comparability with other forecasts while still maintaining a “technical” nature. For this reason, future policy rates are not published in the forecast.

The process starts by updating the assumptions and providing a first baseline forecast. An iterative process, involving the participation of the National Central Banks, leads to convergence on a new coherent forecast including all the new assumptions. The NIPE process follows a parallel and largely contemporaneous procedure. Ultimately, following general practices and similarly to the FRBNY, the ESCB forecast is a mixture of models and expert judgement. Notably for (shorter-term) inflation projections a detailed knowledge of institutional factors (e.g. administered prices, indirect taxes, fiscal policy measures) is an essential ingredient. Models used differ according to purpose and they include large-scale macro-economic models, area-wide models (ECB and some National Central Banks), the new Multi Country Model (ESCB) and NCB models. A wide array of ancillary or more specialized models pertain to the short term (bridge equations, factor models) or deal with specific aspects of the forecast (specialized models for international food commodities or the housing market, models of the global economy). An area-wide DSGE model is also used to interpret the forecasts.

An important feature of the Eurosystem staff macroeconomic projection exercises is that they combine national and euro area-wide perspectives. The euro area is a set of interacting and integrating economies. However, monetary policy decisions are based upon an assessment of euro area-wide conditions. Following these considerations, each forecast is produced via aggregation of the individual Eurozone countries forecasts, but consistency at the euro area level is constantly assured. Individual country-level assessments make full use of the detailed knowledge and experience of country experts and are able to take account of the rich set of national data sources and to include the details of the institutional frameworks for individual countries. These national projection exercises are integrated within an overall euro area perspective, for example ensuring that the individual country trade flows are made fully consistent with each other and that the final projections represent the consensus of Eurosystem staff opinion. Furthermore, a structural interpretation of the projections is done through the lenses of an euro area DSGE model. These two approaches are the subject of constant discussion and the entire process lasts between six and eight weeks. The BMPE/NIPE numbers and reports are discussed and endorsed in a final meeting of the Monetary Policy Committee. Finally, the forecast is presented to the Governing Council on the pre-set publication date.

Risk analysis plays in general an important role in central banks; at the ECB, the risk analysis reflects the view of the Monetary Policy Committee, whose assessment is complemented by model-based estimations of uncertainty. Risk factors typically discussed include whether oil prices will follow futures prices, the future dynamics of the exchange rate, risks to the global growth projections, and risks stemming from wages, housing markets or unforeseen fiscal policy measures. Given the importance of price stability in the ECB's mandate, risks to price stability are more extensively discussed.

The BMPE process involves the National Central Banks in the June and December exercises. A simpler process, the MPE exercise, is limited to the different divisions of the ECB and takes place in the March and September projections. Differently from the BMPE, in the MPE only the ECB is involved in the preparation of the projections, and the ECB staff rather than the Monetary Policy Committee and the WGF is responsible for them. The risk assessment in the MPE reflects the opinions of the ECB staff rather than the members of the Monetary Policy Committee.

The projections are published in the ECB Monthly Bulletin and are available since December 2000. The published figures include projections for inflation (as measured by the HICP), the growth of real GDP and its main expenditure components for the current year and the following year (except for the December exercise when the horizon is two years ahead). The projections are published in the form of ranges in order to reflect the degree of uncertainty attached to such exercises.

Charts appearing in Figures 1 and 2 report the published (B)MPE projections for respectively euro area real GDP growth and HICP inflation in terms of ranges for the 2000-2013 sample. The solid horizontal lines across each year denote the actual outcomes. For each target year, a total of nine forecast releases are published, with the first published in the December exercise two years prior to the target year and the last published in the December Monthly Bulletin of the target year. The midpoint of the range is also indicated for each of the nine prediction exercises.

One point that should be clarified is that the ranges reported in Figures 1 and 2 are not derived by mechanically considering the point forecasts from a suite of models. The models used in the (B)MPE are many, as the ECB not only uses a suite of different tools, but so do the National Central Banks. Some models are designed to forecast variables other than GDP or inflation, e.g. oil prices or housing prices, and may yield GDP and inflation forecasts only as a by-product. Country models are also in some cases different from each other, reflecting national specificities. Moreover, hard and soft data also inform the final forecast (range), while not necessarily entering any models.

The need to take into account the monthly meeting frequency of the Governing Council leads to an additional process of constant updates of the projections between exercises. Price updates are produced by the ECB staff after each release of the flash estimate for HICP at the beginning of the month and in the middle of the month when final figures for the previous month become available. New figures are produced by updating the most recent projections to take into account the publication of additional data and changes in the assumptions (with a particular emphasis on international energy prices, food prices and exchange rates) and other information available at higher frequencies (e.g. the Weekly Oil Bulletin). These projections are of a mechanical nature, to account for the fact that judgement is already included in the quarterly exercise. On the real side of the economy a similar process of updates produces short-term mechanical early estimates for quarter-on-quarter euro area real GDP growth twice a month, namely after the release of industrial production data in the middle of the month and following the release of EC survey data at the end of the month.

3 Evaluation of Point Forecasts

In this section we start with a relatively conventional forecast evaluation: examining point forecast performance. It should be pointed out that the purpose of this exercise is not to run a horse race, as comparing the performance between the ECB and FRBNY is extremely difficult. First of all, as noted in section 2, the institutional details of the forecasting process at the ECB and FRBNY are very different. This poses some challenges for a direct comparison; in particular, the fact that the ECB and the Federal Reserve forecasting processes are driven by the schedule of respectively the meetings of the Governing Council and the FOMC. This makes the outcomes difficult to compare as they are conditioned on different information sets. For similar reasons, it is also not so straightforward to compare central bank forecasts with those of professional forecasters. In fact the results are mixed in this regards. Stockton (2012) observes that the Bank of England forecasts have been marginally worse than those of outside forecasters. In contrast, Figure 3 reported by Potter (2012a), which compares the April 2008 assessment of the downside risk by the FRBNY with that of the Survey of Professional Forecasters, shows some evidence that the FRBNY had a more sober assessment of the risk of a severe downturn than private sector forecasters did. We will elaborate more on this in section 6.

Since the crisis started in the US, it is natural to start with the FRBNY forecasts. Potter (2012a) identifies three main failures in the real-time forecasting of the FRBNY which stand out:

- The misunderstanding of the housing boom: the FRBNY staff analysis of the increase in house prices did not find convincing evidence of overvaluation. Perhaps the best illustration of this is provided in Figure 4 showing the vintage FRBNY housing starts forecasts during the Great Recession.
- A lack of analysis of the rapid growth of new forms of mortgage finance.
- The insufficient weight given to the powerful adverse feedback loops between the financial system and the real economy.

We focus first on real GDP growth forecasts - the series common to the ECB and FRBNY since the measures of inflation considered differs across the Atlantic.[5] Recall that the ECB projections are published in March, June, September and December. We focus on the December forecast prior to the target year. This is referred to as release five, and hence the middle of the nine vertical bars depicted in Figure 1 for each of the years in the sample. This particular release is picked as it is the best match with the end-of-year FOMC forecasts prior to the target year.

Table 1 shows one-year ahead ECB and FRBNY forecasts of real GDP growth. Errors are computed as predicted minus realized. The table further reports several accuracy measures: mean forecast error (MFE), mean squared forecast error (MSFE), mean absolute forecast error (MAFE), root mean squared forecast error (RMSFE), minimum forecast error (MIN) and maximum forecast error (MAX). The entire period covers 2000-2012, the *Pre-Crisis* sample covers 2000-2007Q4 and the remainder of the sample corresponds to the crisis period.

The results in Table 1 indicate that the MFE for the ECB and FRBNY are quite comparable, with the ECB featuring slightly lower numerical values. The errors for GDP growth are on average positive, meaning that growth was overestimated, with the wedge being larger during the crisis. In terms of mean squared forecast error, mean absolute forecast error, root mean squared forecast error, minimum forecast error and maximum forecast error the results are even more similar. Note that during the crisis the MSFE for the ECB and FRBNY increased respectively six and five times in comparison with the pre-crisis sample, and the MAFE and RMSFE more than doubled. This may seem a relatively poor record for both central banks, but the lower accuracy is not particularly exceptional when compared for instance with the Bank of England record reported in Stockton (2012, Table 1).[6]

The picture is quite different for inflation, however, as is evident from Table 2. In terms of MSFE and MAFE, while we see comparable numbers in the pre-crisis sample for the ECB and FRBNY, there is a clear divergence during the crisis. The FRBNY record on inflation forecasting during the crisis was identical to its pre-crisis performance. In all cases the errors are on average negative, meaning that predicted inflation was lower than realized. For the US the mean during the crisis period is for all practical purposes zero. The ECB's record in contrast worsened significantly. The MSFE and MAFE of inflation forecasts became two to three times larger for the ECB. It is important to recall the two institutions focus on different inflation measures. In particular, the high volatility of food and energy prices, included in the ECB projections, is at least partially responsible of the decrease in the ECB's forecasting performance. It would therefore be more appropriate to compare the performance of the ECB inflation forecasts with that of the Bank of England. Stockton (2012, Table 2) shows that the British central bank inflation forecasts also showed substantial deterioration, roughly of the same order of magnitude. In Table 4 - discussed later - we report the forecast performance for the GDP deflator and CORE GDP deflator of the FRBNY. We observe that the FRBNY forecast performance of the GDP deflator is also considerably worse during the crisis.

[5] In what follows, we refer to ECB/Eurosystem staff projections as "ECB" projections for brevity.

[6] See also Kenny and Morgan (2011).

In section 2 we discussed the fact that the FRBNY and the ECB have some significant operational differences in their forecasting process. As a result, the historical records that are available differ as well. In the remainder of this section we take advantage of the specific features of each central bank to highlight topics of interest.

The advantage of the ECB forecasting process setup is that we can easily appraise fixed-horizon forecasts. In Tables 1 and 2 we limited our assessment to the one-year ahead horizon only, corresponding to release 5 for the ECB, since it was the easiest for the purpose of comparing both central banks (the Federal Reserve holds a December FOMC meeting). The ECB produces 9 forecasts for a given target year, and Table 3 reports the summary statistics for three different releases: 1, 5 and 9, where the first corresponds to a two-year horizon and the last is the end-of-year forecast of the target year. The reported statistics are the same as those in the previous tables. We observe that the deterioration is across the board. For example the MSFE of release 1 pre-crisis was 2.44% and increased to 17.93% during the crisis. Interestingly, releases 1 and 5 look very similar, prior and during the crisis. Release 9, which is the last forecast in December of the target year had a minuscule MSFE of 1.10% prior to the crisis which increased five-fold to 5.74%. Based on the RMSFE for that release, the ECB overestimated GDP growth - or more accurately failed to estimate the depth of the recession - by 2.40% during the crisis.

Table 4 is specific to the FRBNY and sheds light on the forecast performance for the various components of GDP. Recall that the modal forecast is assembled in a spreadsheet model of the expenditure and income sides of the NIPA and an alternative presentation, where GDP is composed of two main categories of expenditures, domestic demand and net exports. We concentrate again on the one-year horizon. The entries to the table are Real GDP (now in terms of relative forecast errors), PCE, BFI ETS (Business Fixed Investment, Producers Durable Equipment), BFI Struc (Business Fixed Investment, Nonresidential structures), Residential Investment, Exports, Imports, Federal Government, Gov S+L (state and local), PCE deflator and Core PCE deflator. From the table we note that during the crisis, Business Fixed Investment, Producers Durable Equipment, Business Fixed Investment, Nonresidential structures, Residential Investment, Exports, Imports and PCE deflator all featured substantial forecast errors. These results are not surprising: The collapse of the housing market and the subsequent impact on the real economy were unprecedented and off the charts.

4 Were Financial Market Signals Fully Accounted For?

Economic forecasters, like most other economists, were behind the curve as the global financial crisis developed. Both theoretical models, as well as empirical ones, either ignored or failed to take fully account of the powerful adverse feedback loops between the financial system and the real economy.

The question we address in this section is whether central banks could have done a better job at reading financial market signals. The crisis was first and foremost a crisis caused by financial market turmoil. The analysis in this section is influenced by Andreou, Ghysels, and Kourtellos (2013) who suggest to rely more on financial market data to improve macro forecasting. The issue requires one to think about mixed frequency data since financial market data are intrinsically high frequency (in our case daily) whereas the forecasts pertain to low frequency macroeconomic phenomena such as GDP growth. One solution is to use MIDAS regression models, adopting a framework put forward in recent work by Ghysels, Santa-Clara, and Valkanov (2002) and Ghysels, Santa-Clara, and Valkanov (2006).[7]

We start with the Eurosystem staff Broad Macroeconomic Projection Exercise (BMPE), focussing on real GDP growth. Recall that the (B)MPE forecasts for the euro area are published four times a year, namely in the March, June, September and December issues of the ECB Monthly Bulletin. For each target year, nine forecast releases are published, as projections for each target year start to be published two years earlier in December and are last published in the December Monthly Bulletin of the target year. Considering forecasts for GDP growth in each quarter, therefore, a sequence of nine estimates is produced for a given quarter t, starting in quarter $t-8$ end ending with the nowcast in quarter t. We want to study whether the, respectively forecast errors e_t^i for i = $1, \ldots, 8$ and nowcast e_t^i for i = 9 errors are predictable with real-time financial data available at the time the fore/nowcast is made. In this respect, we assume that the cutoff date for the BMPE forecasts is the first day of the publication month, i.e. the 61^{th} day of the quarter, although the Monthly Bulletin is actually published around the 15^{th} of each month. We use the convention that $e_t^i \equiv BMPE_t^i$ - ΔGDP_t. We denote the daily financial series available at the time of the BMPE release by HF_t^i; there are in fact $j = 1, \ldots, K$ high frequency series. Moreover, e_{t-1}^i is observable for i = $1, \ldots, 9$, as data for the previous quarter are released before the forecast round in a given quarter is finalized. The following autoregressive scheme can therefore be used in the MIDAS regressions, using the vintage i of the j^{th} daily financial series denoted $HF_{j,t}^i$:

$$e_t^i = \mu_j^i + \rho_j^i e_{t-1}^i + \beta_j^i \sum_{d=0}^{D_i} w(\theta_j^i) HF_{j,t_i-d}^i + u_t^i, \qquad i = 1, \ldots, 9 \quad j = 1, \ldots, K \tag{4.1}$$

The time subscripts to the HF refer to daily lags $t_i - d$ where t_i is the day of finalization of the BMPE forecast i and d are daily lags. While there are several possible parameterizations of the MIDAS polynomial weights, to keep the parameter specification tight we take a restricted Beta polynomial with only one parameter, see Ghysels, Sinko, and Valkanov (2006) or Ghysels (2012). In other words, we are testing the assumption that financial data contain information which is useful for explaining BMPE forecast errors, because it is not contained in low(er) frequency macroeconomic variables. The financial variables we consider belong to the following five groups: fixed income, foreign exchange, commodities, stock exchange, corporate yields. The detailed list of the indicators is provided in Appendix A.

For each t we have j = $1, \ldots, K$ predictions of the fore/nowcasts e_t^i. The next step, following the strategy put forward in Andreou, Ghysels, and Kourtellos (2013) is to combine the K predictions. Timmermann (2006) provides an excellent survey of forecast combination methods. We consider two

[7] Recent surveys on the topic of MIDAS include: Andreou, Ghysels, and Kourtellos (2011) who review more extensively some of the material summarized in this document, Armesto, Engemann, and Owyang (2010) who provide a very simple introduction to MIDAS regressions and finally Ghysels and Valkanov (2012) who discuss volatility models and mixed data sampling.

strategies: (1) simple average across the MIDAS regressions each involving one of the financial series considered and (2) Bayesian model averaging (BMA).

The results are reported in Table 5. We only cover the simple model averaging, as the BMA results yielded similar findings. The sample runs from 2000Q1 to 2012Q1. The table reports the average R^2 across all MIDAS models estimated for each of the forecast releases for a given quarter. The benchmark model is a simple autoregressive model, i.e. equation (4.1) without the high frequency data. In order to test the significance of the results, we built 95% confidence intervals for the R^2 of the autoregressive model by bootstrapping its errors.[8]

We do not report all the detailed results, only summary statistics. Namely, for each release we report the average R^2 for the aforementioned MIDAS regressions. In addition, we also report the same statistics for the autoregressive models which exclude the financial series. The MIDAS regressions average R^2 for GDP forecast errors for the one-year ahead BMPE forecasts covering the sample 2000Q1 - 2012Q1 is 0.45, whereas the bootstrap confidence interval for the autoregressive model is $[0.00, 0.26]$. Results for the other BMPE releases are similar. In particular, commodity prices seem to convey relevant information, while fixed income indicators are able to best explain one-quarter ahead forecast errors. The performance of the exchange rate is in general not good, while the change in stock market volatility performs relatively well at horizons longer than one year. With respect to corporate bond spreads, their information content decreases for shorter horizons. The overall conclusion is that financial variables contain useful information for predicting euro area real GDP growth in real time. Simple MIDAS regressions using such financial series could have improved the forecast accuracy.

In Table 6 we run the same type of analysis with *all* the FOMC forecasts of the FRBNY using financial data described in Appendix B. The dates are each FOMC meeting between early 2002 and the end of 2012. Recall also that the *Pre-Crisis* sample covers 2000-2007Q4 and the remainder of the sample corresponds to the crisis period. The series we consider roughly match the realm of financial instruments used in the euro area exercise, although the number of series is smaller. Note also that the setting is somewhat different, since the forecasts we consider here are the modal forecasts, not mechanically generated by models but rather subjected to a process involving judgemental corrections. The conclusions are the same as for the euro area. Note that we are also able to do a sample split before and during the crisis. While sample sizes are small, there is evidence that the usefulness of financial series increased during the crisis, when one compares the regression fits.

[8]Adding regressors necessarily raises the R^2. Hence, in order to compare whether the increase in the R^2 due to the inclusion of high-frequency regressors on top of the own lag is not spurious one should refer to the adjusted R^2, which penalizes the inclusion of additional explanatory variables. The qualitative results presented, in particular the magnitude of the improvement yield by the high-frequency regressor, do not change when considering the adjusted R^2. For ease of interpretation, we stick therefore to the R^2. The number of bootstrap repetitions is 1000.

5 The Forecasting Process: A Conceptual Framework

As noted earlier, research departments at central banks typically run a host of models. These typically range from simple bridge equation models, univariate time series models, MIDAS regressions, to multivariate models such as VARs, factor and DSGE models. The recent global financial crisis pushed central bank forecasters into unchartered territory, as models exclusively relying on historical estimates posed many challenges to forecasters. In this section we, present a framework that reflects some of the new thinking prompted by the challenging new environment faced by central banks. It is the purpose of this section to describe a conceptual framework which was developed at the FRBNY to address the challenging issues faced during the crisis.[9] The framework has two key ingredients: (1) the emphasis on what might be called scenario-driven forecasting schemes, and (2) the recognition that one should pay attention to distributional features beyond point forecasts, in line with general notions of macroeconomic risk.

The use of scenario-driven forecasting schemes, which dates back to Waggoner and Zha (1999), is not exclusively related to macroeconomic forecasting exercises. Central banks started a process of regular stress tests for the financial sector in the aftermath of the crisis. The results of a first comprehensive, forward-looking assessment of the financial conditions of the US 19 largest bank holding companies by the federal bank supervisory agencies were released early May 2009. The exercise was conducted by the Federal Reserve, the Office of the Controller of the Currency, and the Federal Deposit Insurance Corporation. The Supervisory Capital Assessment Program, more commonly referred to as the bank stress tests, used two macroeconomic scenarios, one based on baseline conditions and the other with more pessimistic expectations, to plot a "What If?" exploration into the banking situation in the rest of 2009 and into 2010. Baseline scenario assumptions for real GDP growth and the unemployment rate for 2009 and 2010 were assumed to be equal to the average of the projections of the recession's likely depth and duration published by Consensus Forecasts, the Blue Chip survey, and the Survey of Professional Forecasters in January and February 2009. This baseline scenario was intended to represent a consensus view about the depth and duration of the recession. The more adverse scenario was constructed from the historical track record of private forecasters as well as their current assessments of uncertainty and amounted for example to a 3.3% decline in GDP in 2009 measured on a year over year basis (versus -2% baseline decline) and a modest 2010 recovery with .5% growth (versus 2% growth in the baseline scenario). The subjective probability assessments provided by participants in the 2009 January Consensus Forecasts survey and the February Survey of Professional Forecasters implied a roughly 15 percent chance that real GDP growth could be at least as low, and unemployment at least as high, as assumed in the adverse scenario. This type of analysis, exemplified by the bank stress tests, also figured prominently in central bank macroeconomic forecasting.

The conceptual framework also incorporates notions of macroeconomic tail risk. This second point is not exclusively related to the crisis. Historically, linear models with certainty equivalence properties

[9] The material in this section is based on material presented by Simon Potter at the Bank of England, October 2010.

where point forecast rules are sufficient (i.e., expected values) have been a commonly used framework to discuss policy decisions. The convenience and simplicity of such a framework is widely recognized, but it is also gradually being replaced by settings where macroeconomic risk and uncertainty play a more explicit and prominent role. Several authors, including Hansen and Sargent (2008), Orphanides and Williams (2007), Woodford (2010), and many others, have stressed that, when decision makers face uncertainty about the state of or the model for the economy and have a loss function that factors in an aversion to this uncertainty, it can be optimal to react to changes in the perception of macroeconomic uncertainty.

5.1 Scenario-driven Risk Profiles

To set the stage, we let $\mathbf{Y}_t$ be a vector containing J observable economic variables, e.g. GDP growth, core inflation, etc. We are interested in future values of $\mathbf{Y}_{T+s} = \{Y_{jT+s} : s = -\tau, ..., 0, 1, ...S;$ $j = 1, ..., J\}$, where T is the current time. We let $F_T(Y_{jT+s})$ be a marginal or conditional cumulative density function of the joint cumulative forecast distribution. At some future finite date s' $Y_{T+s'}$ is known with certainty.

We noted in section 2.1.1 that one component of the forecast is a "best guess" (modal forecast), based on a set of conditioning assumptions for future paths of GDP growth, the unemployment rate, and inflation for a forecast horizon of about two years. In addition the FRBNY also makes an assessment of the risks around the modal forecast. The modal forecast is the one produced by the research staff, as described in section 2.1. This risk assessment is based on judgments of the most prominent risk scenarios confronting the global economy, an assessment of the most likely errors in the conditioning assumptions, and the most likely errors in the understanding of current conditions and how the economy actually works.

To formalize the thought process let us consider $K + 1$ unobserved states, with state 0 being a baseline state also referred to as a central scenario. More specifically, let

$$\mathbf{Y}_{T+s} = \sum_{k=0}^{K} 1(Z_{T+s} = k)\mathbf{X}_{T+s}(k),$$

where Z_{T+s} is a stochastic process that takes the values $0, 1, ..., K$ and $\mathbf{X}_{T+s}(0)$ is random vector produced by the baseline forecast and is Gaussian/symmetric:

$$\mathbf{X}_{T+s}(0) \sim N(\mu^0_{T+s}, \Sigma^0_{T+s})$$

with $\{\mathbf{X}_{T+s}(k), k = 1, ..., K\}$ having densities f^k_{T+s}.

If we add transition probabilities across the $K + 1$ states we end up with a Markovian mixture of (possibly truncated) normals. Clearly, some discipline needs to be imposed to avoid parameter proliferation in this framework and allow for relatively direct expression of prior beliefs. The approach is a generalization of the famous fan charts produced by the Bank of England starting in the late 1990s, which is based on a two-piece normal distribution.

The state of the stochastic process Z_{T+s} is associated with a specific economic scenario with the assumption that the baseline scenario is an absorbing state in the long run. Hence, the baseline model can be viewed as a long term goal for a central bank, like a 2% inflation target, a 3% GDP growth, etc.

The stochastic process is assumed to be Markovian with a non-homogenous transition probability matrix, with the property that after a move out of the baseline (for example into a recession or boom), any transition goes back into the baseline as it is an absorbing state.

For example if Z_{T+s} = 0 (i.e. baseline) $\forall$ s, then:

$$\begin{array}{c} \text{Boom} \\ \text{Baseline: Normal Growth} \\ \text{Recession} \end{array} \begin{bmatrix} p & 1-p & 0 \\ pq' & q' & nq' \\ 0 & 1-n & n \end{bmatrix},$$

whereas for all $Z_{T+s} \neq 0$, we have the transition matrix:

$$\begin{array}{c} \text{Boom} \\ \text{Baseline: Normal Growth} \\ \text{Recession} \end{array} \begin{bmatrix} p & 1-p & 0 \\ 0 & 1 & 0 \\ 0 & 1-n & n \end{bmatrix}.$$

The above example shows that the parametrization of the transition matrix is greatly simplified by assuming that the baseline state is absorbing in the long run. Note that this specification comes at a cost: recessions could simply have one quarter duration. The justification for this simplification for the absorbing state scheme is that the central bank is assumed to achieve its goals over the long-run by use of its policy instruments and the multivariate Gaussian distribution associated with state 0 captures the long run features of such a situation. Further, uncertainty about the current state of the economy can be allowed for by assuming that the stochastic process Z_{T+s} took the value 0 a certain number of quarters in the past (some negative s). Moreover, rather than making the strong assumption that the transition probabilities are known, Dirichlet distributions are used to allow for uncertainty. The choice of Dirichlet distributions is motivated by computational convenience, particularly updating of beliefs in real time. Hence, the approach essentially amounts to creating random transition matrices with some discipline imposed, notably: $\lim_{s' \to \infty} P[Z_{T+s'} = 0] = 1$. Transitions from the central scenario are drawn from Dirichlet distributions where beliefs pertaining the likelihood about certain scenarios are crucial and degrees of freedom of the distribution is used to capture confidence in these beliefs. For transitions back to the central scenario one needs to chose $2K$ additional parameters. Again this can be parameterized such that one parameter is based on beliefs about the average time spent in this scenario and another parameter reflects confidence in this belief. Finally, while in principle one could allow transitions between scenarios, they are by design set equal to zero, although it is possible, in general setting, to fill out more of the transition matrix.

Realizations of this process are stochastic sample paths with random entry into the different scenarios and conditional on entry, time in any scenario is random as well. As a consequence there is no unique way of defining the length or time of arrival into a scenario. The definition adopted by the FRBNY implementation of a path associated with a scenario k is the collection of paths which visit at least once the k^{th} discrete state. One can then compute averages across all paths with at least one visit into the scenario. The obvious advantage is computational convenience of summary statistics. Yet, the definition also has the disadvantage that it potentially combines paths from both central and alternative scenarios. An alternative would be to weight by the occupation times for each scenario.

Simulations are a natural and convenient way to construct forecast distributions from this Markovian mixture. One such simulation works by drawing standard normals for each horizon then:

- For the central scenario the scale is determined by the relevant Cholesky factorization of the covariance matrix
- For the other K scenarios take absolute values of Gaussian draws are taken with the sign then determined as positive or negative depending the characterization of the scenarios - which essentially yields sign-restricted draws.
- The draws are then scaled either deterministically or sometimes by random variable to generate fat tails if required.

A practical example, inspired by the events during the global financial crisis is as follows. Consider the joint distribution over output and inflation where one can think of a range of scenarios with random draws as follows:

1. Productivity boom: draw $+$ output, $-$ inflation
2. Loss of Credibility: draw $-$ output, $+$inflation
3. Overheating: draw large $+$inflation, $+$ then $-$ output
4. Global Credit Crunch: draw large $-$ inflation and output

Before proceeding with the details, particularly regarding the choice of parameters, it is worth visualizing the output that is produced from the above exercise. The two panels of Figure 5 display the sample paths associated with end of 2009Q3 projections of the aforementioned scenarios, namely in addition to the baseline scenario we have: (a) Productivity boom, (b) Loss of Credibility, (c) Overheating and (d) Global Credit Crunch. The simulated paths in Figure 5 feature patterns which indeed correspond to the assumed scenarios. For example *Loss of Credibility* results in rising inflation - more so that the in the scenario *Overheating*, whereas the *Global Credit Crunch* path enters deflationary territory. Likewise, GDP growth is the highest under the *Productivity boom* scenario and the smallest in the *Global Credit Crunch* one, where the latter is projecting negative or zero GDP growth until the end of 2011.

The simulations also produce a forecast distribution as displayed in the panels of Figure 6. The central scenario appears, as expected, at the center of the fan chart. The shades of the chart reflect the percentiles of the forecast distribution. These forecast distributions will be the subject of analysis in the next section.

5.2 Calibration

Where do the probabilities of the different states come from? And how are the parameters of the state-dependent schemes determined? In an abstract sense it is assumed that the policymaker knows/gives probabilities, modal forecast and history produces the other parameters. In practice, introspection and iteration take place. In this subsection we elaborate on the calibration of the simulated scenario-driven paths displayed in Figure 5.

To visualize which probability schemes are involved in the calibrations, consider the histograms displayed in Figure 7. The left panel provides the probabilities pertaining to the central scenario, namely the probability of remaining in the scenario through 2010Q4.

Broadly speaking four types of calibration methods are used. They can be characterized as: (a) Financial Markets Data-based Calibration, (b) Professional Forecasters Data-based Calibration, (c) Historical Event-based Calibration and finally (d) DSGE Model-based Calibration. In this section we cover the first three (see Potter (2012b) for a broader discussion which includes DSGE Model-based Calibration).

The first calibration method can be used to choose a subset of parameters by matching financial market data implied moments (expectations). The latter obviously requires a mapping between forecast distribution and policy rates. A good example is the *Loss of Credibility* scenario appearing in Figure 8. Each scenario-driven path implies a Fed Funds rate profile. For the purpose of comparison the plot also displays the market projections extracted from the Fed Fund Futures at different maturities.

A prominent example of Professional Forecasters Data-based Calibration was already mentioned in the context of bank stress tests where the baseline scenario assumptions for real GDP growth and the unemployment rate for 2009 and 2010 were equal to the average of the projections published by Consensus Forecasts, the Blue Chip survey, and the Survey of Professional Forecasters in February 2009. There are limitations here as well. Typically professional forecasts provide little path information and often have a year over year format which is not so easy to match with calibrations.

Given the focus on the crisis it is worth elaborating on calibration based on historical events as past financial crises produced actual and hypothesized/feared behavior outside of the standard post-war experience. Simulation allows for construction of probabilistic information on various big events such as: (a) a Great Depression and its associated size of output drop and scale of deflation, (b) stock market crashes and depressions as well as the (c) scale of recoveries after big recessions and (d) the scale of recovery after financial crises. Figure 9 and 10 display conditional CDFs of objects of interest relative to history, namely: depth of recession and historical recovery patterns.

In Figure 9 we consider the probability distribution of the four consecutive quarters with the lowest GDP growth in a recession. The top panel represents a calibration by the FRBNY staff done in April 2008, with a 80% probability of recession. The calibrated the probability distribution of the four consecutive quarters with the lowest GDP growth in a recession is plotted against historical benchmarks, the 1990-1991 recession with a -1.0%, 1981-1982 with -2.7% and a post Great Depression observation from 1937-1938 with a -10% drop. In the lower panel of Figure 9 we plot a calibration before and after the Lehman failure. The solid line corresponds to a November 20, 2008 calibration (and therefore after Lehman) based on a 97% probability of recession (even in November 2008 the simulation had some paths that did not produce a recession), whereas the dashed line is based on a beginning of August 2008 calibration with a 46% of recession. The central forecast of -2% increases from a less than 20% probability event to a more than 60% one. As can be seen the shape of the conditional CDF also changes as more weight is placed on extreme scenarios in the underlying Markov process and the fat tail of the extreme scenarios is increased. The actual depth of the 2007-09 recession was - 5% (using the pre-2013 benchmark data). As gauged by this metric the August 2008 calibration attributed less than 3% probability to the ultimate outcome, and it was only by November 2008 that the probability of the actual outcome was close to 15 percent.

Figure 10 displays the conditional CDF of recovery relative to history with the top panel covering a calibration scale of recovery through the end of 2010 with a probability of trough by end of 2009 which was assessed in May 2009 as 73% and in October roughly the same at 75%. The probabilities are benchmarked against historical precedents. To lower panel expands the horizon by one year displaying the scale of recovery through the end of 2011 with a probability of trough by end of 2010 which was assessed in May 2009 as 95%, again measured against historical precedents.

6 Model and Density Forecast Evaluations

In the previous section we explained how to formulate and compute scenario-driven paths and noted that the simulations also produce a forecast distribution as displayed in the panels of Figure 6. In this section we compare these densities with Survey of Professional Forecasters data. We do this in two different ways.

First, we consider the cross-section of point forecasts of the SPF against the scenario-driven densities produced by the FRBNY throughout the crisis. The purpose of the exercise is to see how extreme views as well as consensus forecasts in the cross-section of the SPF compare with the FRBNY densities. Are the pessimists in the SPF completely out of sync with the FRBNY? Note that we compare point forecasts with density forecasts and this is done on purpose. What we try to address is: How far in the tails are the most optimistic and pessimistic professional forecasters? We do this via Q-Q plots of the cross-section of SPF against the FRBNY density forecasts. In Figure 11 we plot at yearly intervals such Q-Q plots in October 2007 through 2012. Hence, the plots give us yearly snapshots throughout the global financial crisis about how the cross-section of SPF measures up against the plausible scenarios considered by the FRBNY. The left tail of the SPF consists of the most pessimistic point forecasts and the right tail the most optimistic ones. In October 2007 the pessimists lined up with the left tail, and the optimists were not particularly outliers in the right tail. Hence, at the outset of the global financial crisis we note that the cross-section of the SPF and the FRBNY scenarios were well aligned. This completely changes in 2008 and 2009. The cross-section of SPF is overall more optimistic than the FRBNY. Gradually, as the US economy started to slowly recover over the next set of years we see that professional forecasters become less optimistic when measured against the range of outcomes considered in the simulated paths of the FRBNY models. Figure 11 is fascinating. It suggests that the FRBNY appears to be quicker than the forecasters in the SPF in recognizing the downside risk of the crisis. As the crisis unfolded, it also appears that the SPF showed more inertia in adjusting its range of forecasts.

Second, we compare the forecast densities of the most pessimist (in terms of point forecast of GDP growth over the subsequent year) with the scenario-driven densities produced by the FRBNY throughout the crisis. The findings are quite similar to those reported for the cross-section. In particular, FRBNY appears to be quicker than the most pessimist forecasters in the SPF in recognizing the downside risk of the crisis.

7 Concluding Remarks

Macroeconomic forecasting during the global financial crisis was a challenging task faced by the Federal Reserve Bank of New York and the European Central Bank, or any other central bank. While the forecast performance has been noticeably worse than prior to the crisis, it was comparable to that of outside forecasters. In fact, when examining density forecasts, it appears that the FRBNY was ahead of the curve, in comparison with professional forecasters.

Nevertheless, many opportunities to improve the forecast performance were missed, judged by the fact that high frequency financial data could have been used more efficiently. At a big picture level, we also should see a more prominent role of the financial sector in macroeconomic models, whether they are structural or reduced form.

It is fair to say that central banking forecasting underwent some fundamental changes. The "put out fires" crisis management has forced the research staff to think out of the box and come up with creative new approaches. We expect that the scenario-driven approaches and the mixed frequency data econometric methods, highlighted in our analysis, will be further refined and will feature prominently in the future practical implementations of forecasting at central banks.

Technical Appendices

A Euro area financial data details

The following financial data have been used for estimating MIDAS models for the euro area.

1. Fixed income
   Eonia rate; Euribor 1-month; Euribor 3-month; Euribor 6-month; Euribor 1-year; Euribor Spot week; European Union 6-year Government Benchmark bond yield; Euribor 1-year Euribor 1-month spread; change in the Euribor 3-month.
2. Foreign exchange
   Nominal effective exchange rate, euro area-17 countries vis-a-vis the EER-20 group of trading partners against Euro.
3. Commodities
   World market price of coal; change in Brent Crude; change in gold price; change in copper price; percentage change in Brent Crude; percentage change in gold price; percentage change in copper price.
4. Stock exchange
   Change in EURO STOXX 50 Volatility Index.
5. Corporate yields
   Spreads between euro area Corporate AAA and BBB Merrill Lynch Bond Indexes for maturities between 7 and 10 years; spreads between euro area Corporate AAA Merrill Lynch Bond Indexes for maturities between 7 and 10 years and 6-year Government Bond yields.

B US financial data details

The following financial data have been used for estimating MIDAS models for the US. The series is described, with the Haver DLX mnemonic given in parentheses.

1. Fixed income
   LIBOR: Overnight (T111LON@INTDAILY); LIBOR: Spot week (T111L1W@INTDAILY); LIBOR: 1 month (T111L1M@INTDAILY); LIBOR: 3 month (T111L3M@INTDAILY); LIBOR: 6 month (T111L6M@INTDAILY); LIBOR: 1 year (T111L1@INTDAILY); Government Bond Yield: 5 year (T111G5@INTDAILY); LIBOR 1 year and LIBOR 1 month spread; LIBOR: 3 month, change.
2. Foreign exchange
   Broad Trade-Weighted Exchange Rate (X111WTB@INTDAILY).
3. Commodities
   Coal: level (P112GCB@INTDAILY); Copper: percentage change, level change (PZDCOP@DAILY); Gold: percentage change, level change (PZDGEI@DAILY); Oil (Brent Crude): percentage change, level change (PZBRT@DAILY).
4. Stock exchange
   CBOE Volatility Index: percentage change (SPVIX@DAILY).

5. Corporate yields
   Corporate AAA and BBB Indexes: Spread for 15-year bonds (FMLCUA@DAILY); 15-year corporate bond index vs 5-year government bond.

References

ANDREOU, E., E. GHYSELS, AND A. KOURTELLOS (2010): "Regression Models With Mixed Sampling Frequencies," *Journal of Econometrics*, 158, 246–261.

ANDREOU, E., E. GHYSELS, AND A. KOURTELLOS (2011): "Forecasting with mixed-frequency data," in *Oxford Handbook of Economic Forecasting*, ed. by C. M., and D. Hendry, pp. 225–245.

——— (2013): "Should macroeconomic forecasters look at daily financial data?," *Journal of Business and Economic Statistics*, 31, 240–251.

ANGELINI, E., G. CAMBA-MENDEZ, D. GIANNONE, L. REICHLIN, AND G. RÜNSTLER (2011): "Short-term forecasts of euro area GDP growth," *The Econometrics Journal*, 14, C25–C44.

ARMESTO, M., K. ENGEMANN, AND M. OWYANG (2010): "Forecasting with mixed frequencies," *Federal Reserve Bank of St. Louis Review*, 92, 521–536.

BAFFIGI, A., R. GOLINELLI, AND G. PARIGI (2004): "Bridge models to forecast the euro area GDP," *International Journal of Forecasting*, 20, 447–460.

BANBURA, M., D. GIANNONE, M. MODUGNO, AND L. REICHLIN (2013): "Now-casting and the real-time data flow," in *Handbook of Economic Forecasting - Volume 2A*, ed. by G. Elliott, and A. Timmermann, pp. 195–236.

CHAUVET, M., AND S. POTTER (2013): "Forecasting Output," in *Handbook of Economic Forecasting - Volume 2A*, ed. by G. Elliott, and A. Timmermann, pp. 141–194.

CHRISTOFFEL, K., G. COENEN, AND A. WARNE (2010): "Forecasting with DSGE models," Discussion paper, European Central Bank.

CLEMENTS, M. P., AND A. B. GALVÃO (2008): "Macroeconomic Forecasting with Mixed Frequency Data: Forecasting US Output Growth," *Journal of Business and Economic Statistics*, 26, 546–554.

——— (2009): "Forecasting US Output Growth Using Leading Indicators: An Appraisal Using MIDAS Models," *Journal of Applied Econometrics*, 24(7), 1187–1206.

DEL NEGRO, M., AND F. SCHORFHEIDE (2013): "DSGE Model-Based Forecasting," in *Handbook of Economic Forecasting - Volume 2A*, ed. by G. Elliott, and A. Timmermann, pp. 57–140.

DIRON, M. (2008): "Short-term forecasts of euro area real GDP growth: an assessment of real-time performance based on vintage data," *Journal of Forecasting*, 27, 371–390.

EDGE, R., M. KILEY, AND J.-P. LAFORTE (2010): "A comparison of forecast performance between federal reserve staff forecasts, simple reduced-form models, and a DSGE model," *Journal of Applied Econometrics*, 25, 720–754.

EVANS, M. (2005): "Where Are We Now? Real-Time Estimates of the Macroeconomy," *International Journal of Central Banking*, 1, 127–176.

FORNI, M., M. HALLIN, M. LIPPI, AND L. REICHLIN (2000): "The generalized dynamic-factor model: Identification and estimation," *Review of Economics and statistics*, 82, 540–554.

GHYSELS, E. (2012): "Matlab Toolbox for Mixed Sampling Frequency Data Analysis using MIDAS Regression Models," Available at `http://www.unc.edu/~eghysels`.

GHYSELS, E., P. SANTA-CLARA, AND R. VALKANOV (2002): "The MIDAS touch: Mixed data sampling regression models," Working paper, UNC and UCLA.

——— (2006): "Predicting volatility: getting the most out of return data sampled at different frequencies," *Journal of Econometrics*, 131, 59–95.

GHYSELS, E., A. SINKO, AND R. VALKANOV (2006): "MIDAS Regressions: Further Results and New Directions," *Econometric Reviews*, 26, 53–90.

GHYSELS, E., AND R. VALKANOV (2012): "Forecasting volatility with MIDAS," in *Handbook of Volatility Models and Their Applications*, ed. by L. Bauwens, C. Hafner, and S. Laurent, pp. 383–401. Wiley.

GIANNONE, D., L. REICHLIN, AND D. SMALL (2008): "Nowcasting: The Real-Time Informational Content of Macroeconomic Data," *Journal of Monetary Economics*, 55, 665–676.

HANSEN, L., AND T. SARGENT (2008): *Robustness*. Princeton University Press: Princeton, NJ.

KENNY, G., AND J. MORGAN (2011): "Some lessons from the financial crisis for the economic analysis," Discussion paper, European Central Bank.

KILIAN, L., AND S. MANGANELLI (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.

KUZIN, V., M. MARCELLINO, AND C. SCHUMACHER (2011): "MIDAS versus Mixed-Frequency VAR: Nowcasting GDP in the Euro Area," *International Journal of Forecasting*, 27, 529–542.

——— (2013): "Pooling Versus Model Selection For Nowcasting Gdp With Many Predictors: Empirical Evidence For Six Industrialized Countries," *Journal of Applied Econometrics*, 28, 392–411.

MARCELLINO, M., AND C. SCHUMACHER (2010): "Factor MIDAS for Nowcasting and Forecasting with Ragged-Edge Data: A Model Comparison for German GDP*," *Oxford Bulletin of Economics and Statistics*, 72, 518–550.

MARCELLINO, M., J. STOCK, AND M. WATSON (2003): "Macroeconomic forecasting in the euro area: Country specific versus area-wide information," *European Economic Review*, 47, 1–18.

NUNES, L. (2005): "Nowcasting quarterly GDP growth in a monthly coincident indicator model," *Journal of Forecasting*, 24, 575–592.

ORPHANIDES, A., AND J. C. WILLIAMS (2007): "Robust monetary policy with imperfect knowledge," *Journal of Monetary Economics*, 54, 1406–35.

POTTER, S. (2012a): "The Failure to Forecast the Great Recession," Blog posted at `http://libertystreeteconomics.newyorkfed.org`.

——— (2012b): "Subjective Forecast Distributions," Bank of England Presentation - October.

STOCK, J. H., AND M. W. WATSON (2002): "Forecasting using principal components from a large number of predictors," *Journal of the American statistical association*, 97, 1167–1179.

STOCKTON, D. (2012): "Review of the Monetary Policy Committee's Forecasting Capability," Report Presented to the Court of the Bank of England.

TIMMERMANN, A. (2006): "Forecast Combinations," in *Handbook of Economic Forecasting*, ed. by G. Elliott, C. Granger, and A. Timmermann, vol. 1, pp. 136–196. North Holland.

WAGGONER, D. F., AND T. ZHA (1999): "Conditional forecasts in dynamic multivariate models," *Review of Economics and Statistics*, 81, 639–651.

WANG, M.-C. (2009): "Comparing the DSGE model with the factor model: an out-of-sample forecasting experiment," *Journal of Forecasting*, 28, 167–182.

WIELAND, V., AND M. H. WOLTERS (2013): "Forecasting and Policy Making," in *Handbook of Economic Forecasting - Volume 2A*, ed. by G. Elliott, and A. Timmermann, pp. 237–524.

WOODFORD, M. (2010): "Robustly optimal monetary policy with near-rational expectations," *American Economic Review*, 100(1), 274–303.

Table 1: One-Year ahead Forecasts of Real GDP growth - ECB/Eurosystem and FRBNY

The table reports the mean forecast error (MFE), the mean squared forecast error (MSFE), mean absolute forecast error (MAFE), root mean squared forecast error (RMSFE), minimum forecast error (MIN) and maximum forecast error (MAX). The entire period covers 2000-2012, the *Pre-Crisis* sample covers 2000-2007Q4 and the remainder of the sample corresponds to the crisis period. The ECB forecasts pertain to the fifth BMPE releases. The FRBNY are the last forecasts of each calendar year.

	MFE		MSFE		MAFE		RMSFE		MIN		MAX	
	ECB	FRBNY	ECB	FRBNY	ECB	FRBNY	ECB	FRBNY	ECB	FRBNY	ECB	FRBNY
Full sample	0.96	1.67	8.83	9.82	1.85	2.04	2.97	3.13	-3.64	-3.23	13.27	11.84
Pre-Crisis	0.46	0.92	2.56	3.33	1.28	1.38	1.60	1.82	-2.20	-3.23	2.85	4.77
Crisis	1.64	2.40	17.41	16.15	2.62	2.70	4.17	4.02	-3.64	-2.27	13.27	11.84

Table 2: One-Year ahead Forecasts of Inflation - ECB/Eurosystem and FRBNY

The table reports the mean forecast error (MFE), the mean squared forecast error (MSFE), mean absolute forecast error (MAFE), root mean squared forecast error (RMSFE), minimum forecast error (MIN) and maximum forecast error (MAX). The entire period covers 2000-2012, the *Pre-Crisis* sample covers 2000-2007Q4 and the remainder of the sample corresponds to the crisis period. The ECB forecasts pertain to the fifth (B)MPE release - the December forecast prior to the target year. This particular release is picked as it is the best match with the end-of-year FOMC forecasts prior to the target year.

	MFE		MSFE		MAFE		RMSFE		MIN		MAX	
	ECB	FRBNY	ECB	FRBNY	ECB	FRBNY	ECB	FRBNY	ECB	FRBNY	ECB	FRBNY
Full sample	-0.40	-0.15	0.94	0.30	0.79	0.45	0.97	0.55	-1.91	-1.00	2.75	1.12
Pre-Crisis	-0.49	-0.47	0.40	0.32	0.55	0.49	0.63	0.56	-1.40	-0.95	0.51	0.13
Crisis	-0.27	-0.05	1.69	0.30	1.11	0.44	1.30	0.55	-1.91	-1.00	2.75	1.12

Table 3: ECB/Eurosystem staff Real GDP growth forecasts - prediction errors across selected releases

The table reports the mean forecast error (MFE), the mean squared forecast error (MSFE), mean absolute forecast error (MAFE), root mean squared forecast error (RMSFE), minimum forecast error (MIN) and maximum forecast error (MAX). The entire period covers 2000-2012, the *Pre-Crisis* sample covers 2000-2007Q4 and the remainder of the sample corresponds to the crisis period.

	Full sample			Pre-Crisis			Crisis		
Releases	1	5	9	1	5	9	1	5	9
MFE	1.32	0.96	0.02	0.65	0.46	-0.29	2.09	1.64	0.50
MSFE	9.62	8.83	2.90	2.44	2.56	1.10	17.93	17.41	5.74
MAFE	1.84	1.85	1.11	1.26	1.28	0.86	2.51	2.62	1.49
RMSFE	3.10	2.97	1.70	1.56	1.60	1.05	4.23	4.17	2.40
MIN	-1.90	-3.64	-2.22	-1.90	-2.20	-2.22	-1.78	-3.64	-1.76
MAX	13.67	13.27	7.62	3.09	2.85	1.68	13.67	13.27	7.62

Table 4: One-Year ahead Forecasts FRBNY of Various Macroeconomic Series

The table reports the mean forecast error (MFE), the mean squared forecast error (MSFE), mean absolute forecast error (MAFE), root mean squared forecast error (RMSFE). The entire period covers 2000-2012, the *Pre-Crisis* sample covers 2000-2007Q3 and the remainder of the sample corresponds to the crisis period. The series are Real GDP, PCE, BFI ETS, BFI Struc, Residential Investment, Exports, Imports,Government: Federal, Government: State and Local, PCE Deflator, and Core PCE Deflator.

	Real GDP	PCE	BFI ETS	BFI Struc	Residential Investment	Exports	Imports	Gov Federal	Gov S+L	PCE Deflator	Core PCE Deflator
	MFE										
Full sample	1.67	1.03	4.19	3.49	7.78	2.05	2.94	-0.21	2.48	-0.51	-0.15
Pre-Crisis	0.92	0.81	5.43	-1.06	4.26	-2.29	2.21	-0.34	2.16	-1.16	-0.47
Crisis	2.40	1.24	2.99	7.93	11.21	6.28	3.66	-0.09	2.79	0.13	-0.05
	MSFE										
Full sample	9.82	5.45	115.41	235.07	325.94	109.06	109.30	44.13	12.64	3.85	0.30
Pre-Crisis	3.33	2.73	56.06	113.10	239.87	41.51	33.35	35.37	5.49	2.83	0.32
Crisis	16.15	8.09	173.24	353.91	409.81	174.88	183.30	52.67	19.60	4.84	0.30
	MAFE										
Full sample	2.04	1.62	7.82	11.84	14.98	7.60	7.62	5.57	2.97	1.45	0.45
Pre-Crisis	1.38	1.32	6.16	8.34	13.13	5.17	4.88	4.92	2.16	1.49	0.49
Crisis	2.70	1.92	9.44	15.26	16.79	9.97	10.29	6.21	3.76	1.41	0.44
	RMSE										
Full sample	3.13	2.33	10.74	15.33	18.05	10.44	10.45	6.64	3.56	1.96	0.55
Pre-Crisis	1.82	1.65	7.49	10.63	15.49	6.44	5.77	5.95	2.34	1.68	0.56
Crisis	4.02	2.85	13.16	18.81	20.24	13.22	13.54	7.26	4.43	2.20	0.55

Table 5: MIDAS Regression Analysis of Prediction Errors ECB/Eurosystem Forecasts

The table reports the estimation results for MIDAS regressions (4.1) for the (B)MPE forecasts of the ECB/ESCB staff. The predictability of $e_t^i \equiv EE_t^i$ - ΔGDP_t, i = $1, \ldots, 9$, are reported. Provided are average R^2 values for the entire sample period, with MIDAS regressions using daily high frequency series detailed in Appendix **??**. The sample runs from 2000Q1 to 2012Q1.

Releases	1	2	3	4	5	6	7	8	9
Horizon	2 years	7 quarters	6 quarters	5 quarters	1 year	3 quarters	2 quarters	1 quarter	nowcast
Avg. R^2 MIDAS Reg.	0.43	0.45	0.46	0.49	0.48	0.48	0.43	0.39	0.30
Bootstrap AR(1) R^2 C.I.	[0.00, 0.24]	[0.00, 0.26]	[0.00, 0.30]	[0.00, 0.29]	[0.01, 0.28]	[0.00, 0.31]	[0.00, 0.22]	[0.00, 0.17]	[0.00, 0.13]

Table 6: MIDAS Regression Analysis of One-year GDP growth FRBNY Forecast Errors

Provided are average R^2 values for the entire sample obtained from MIDAS models using daily high frequency series detailed in Appendix **??**, and compared with the R^2 for a simple AR(1) process for forecast errors. Also displayed is a 95% confidence interval for the AR R^2. The dates are each FOMC meeting between early 2002 and the end of 2012, the *Pre-Crisis* sample covers 2000-2007Q4 and the remainder of the sample corresponds to the crisis period.

	Full Sample	Pre-Crisis	Crisis
Avg. R^2 MIDAS Reg.	0.31	0.19	0.37
Bootstrap AR(1) R^2 CI	$[0.00, 0.08]$	$[0.00, 0.13]$	$[0.00, 0.14]$

Figure 1: Euro area Real GDP projections by the Eurosystem/ECB staff

The figures report the published Eurosystem staff Broad Macroeconomic Projection Exercise (BMPE) and ECB staff Macroeconomic Projection Exercise (MPE) projections for euro area real GDP and HICP in terms of ranges for the 2000-2013 sample. The solid horizontal lines across each year denote the actual outcomes. For each target year, nine forecast releases are published, as projections for each target year start to be published two years earlier in December and are last published in the December Monthly Bulletin of the target year. The midpoint of the range is also indicated for each of the nine prediction exercises. The solid horizontal lines denote the actual outcomes.(B)MPE projections for euro area real GDP and HICP in terms of ranges. The solid horizontal lines denote the actual outcomes. For each target year, nine forecast releases are published, as projections for each target year start to be published two years earlier in December and are last published in the December Monthly Bulletin of the target year.

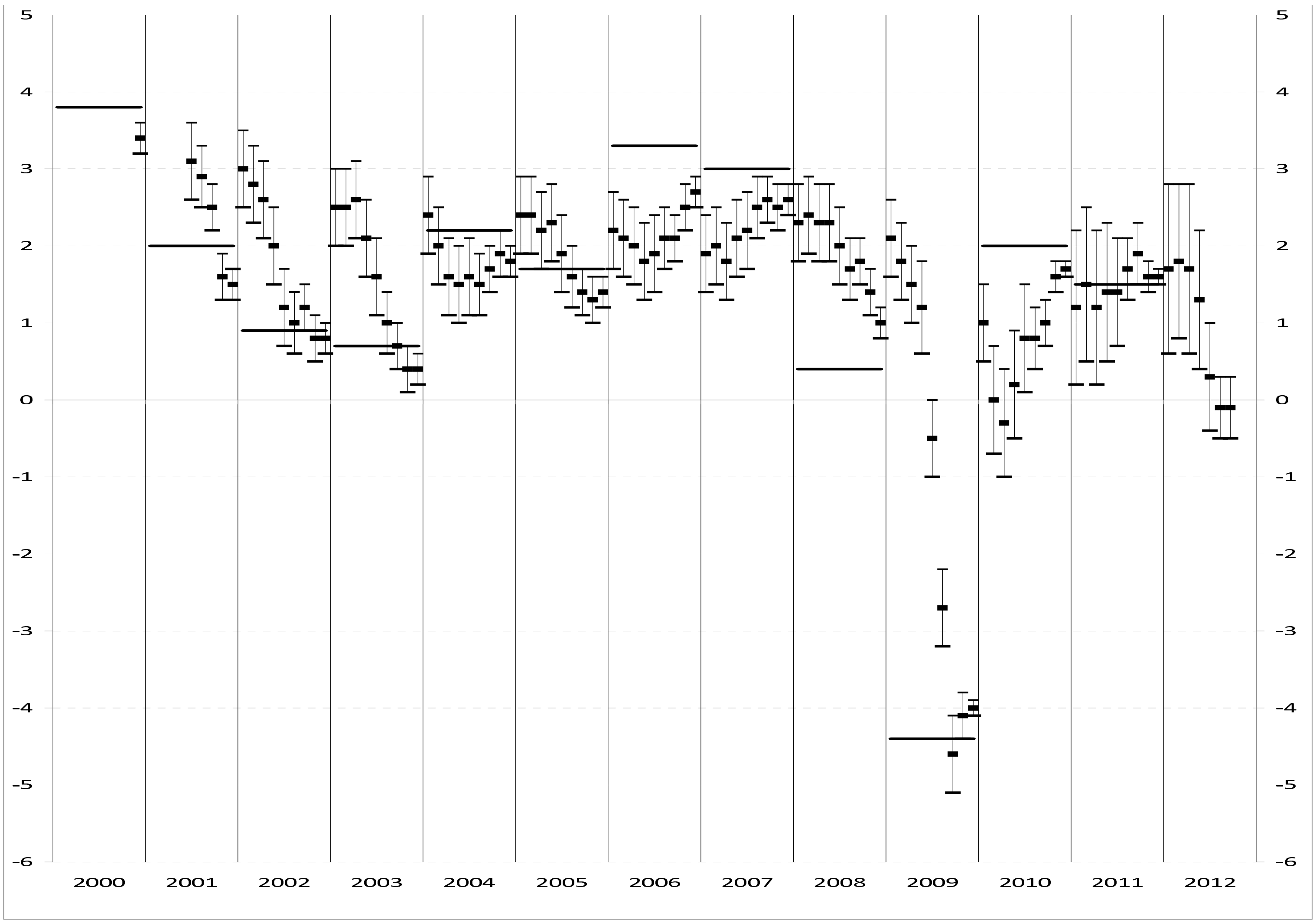


Figure 2: Euro area Harmonized Index of Consumer Prices projections by the Eurosystem/ECB staff

The figures report the published Eurosystem staff Broad Macroeconomic Projection Exercise (BMPE) and ECB staff Macroeconomic Projection Exercise (MPE) projections for euro area the Harmonized Index of Consumer Prices (HICP) in terms of ranges for the 2000-2013 sample. The solid horizontal lines across each year denote the actual outcomes. For each target year, nine forecast releases are published, as projections for each target year start to be published two years earlier in December and are last published in the December Monthly Bulletin of the target year. The midpoint of the range is also indicated for each of the nine prediction exercises. The solid horizontal lines denote the actual outcomes.(B)MPE projections for euro area HICP in terms of ranges. The solid horizontal lines denote the actual outcomes. For each target year, nine forecast releases are published, as projections for each target year start to be published two years earlier in December and are last published in the December Monthly Bulletin of the target year.

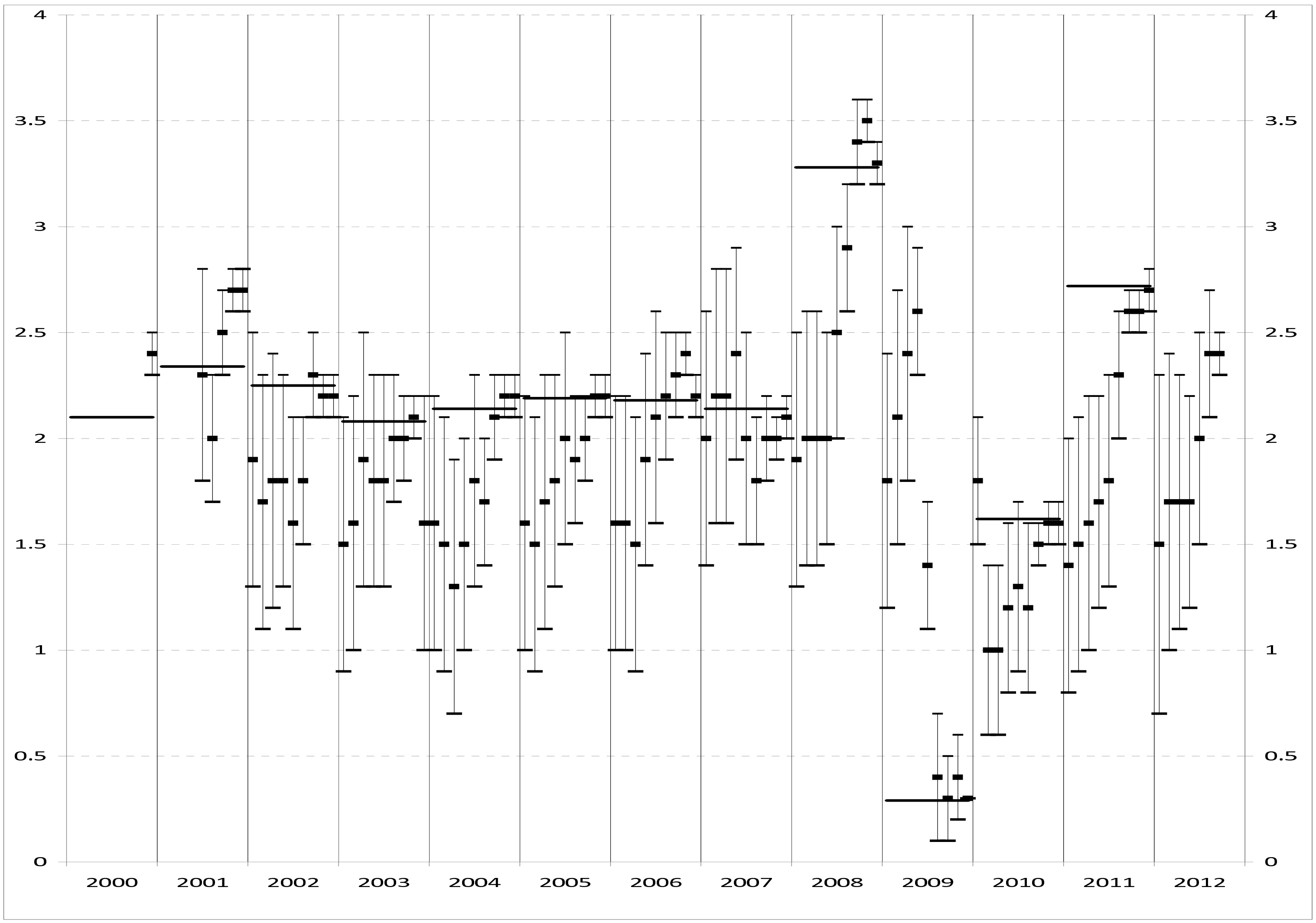


Figure 3: Probability of Real GDP Growth: Federal Reserve Bank of New York Forecasts against Survey of Professional Forecasters - April 2008

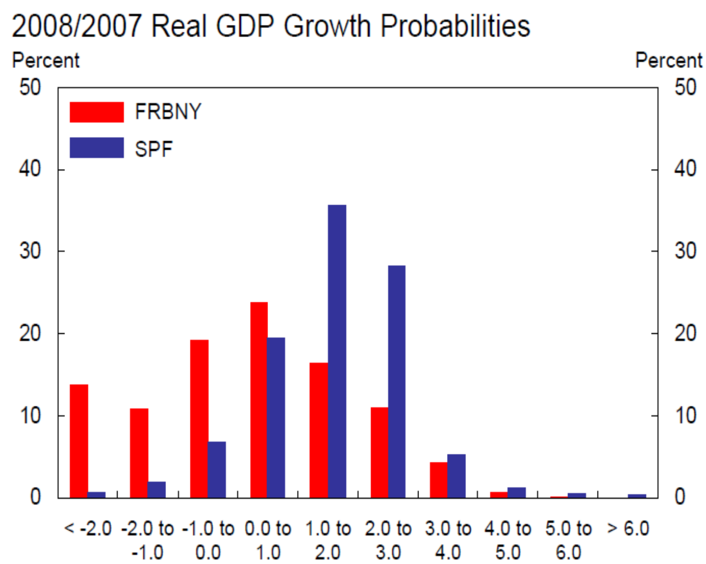


Figure 4: Housing Starts: Vintage Federal Reserve Bank of New York Forecasts During Great Recession

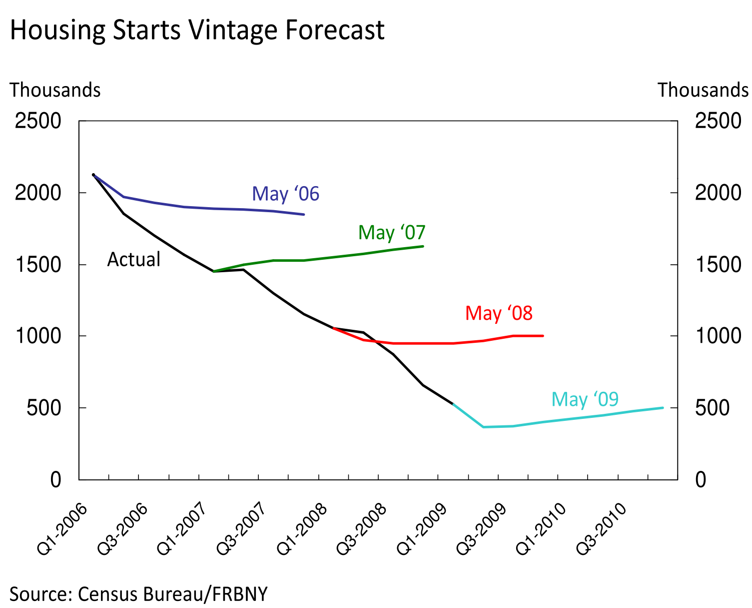


Figure 5: Real GDP growth and Core PCE Inflation under Alternative Scenarios

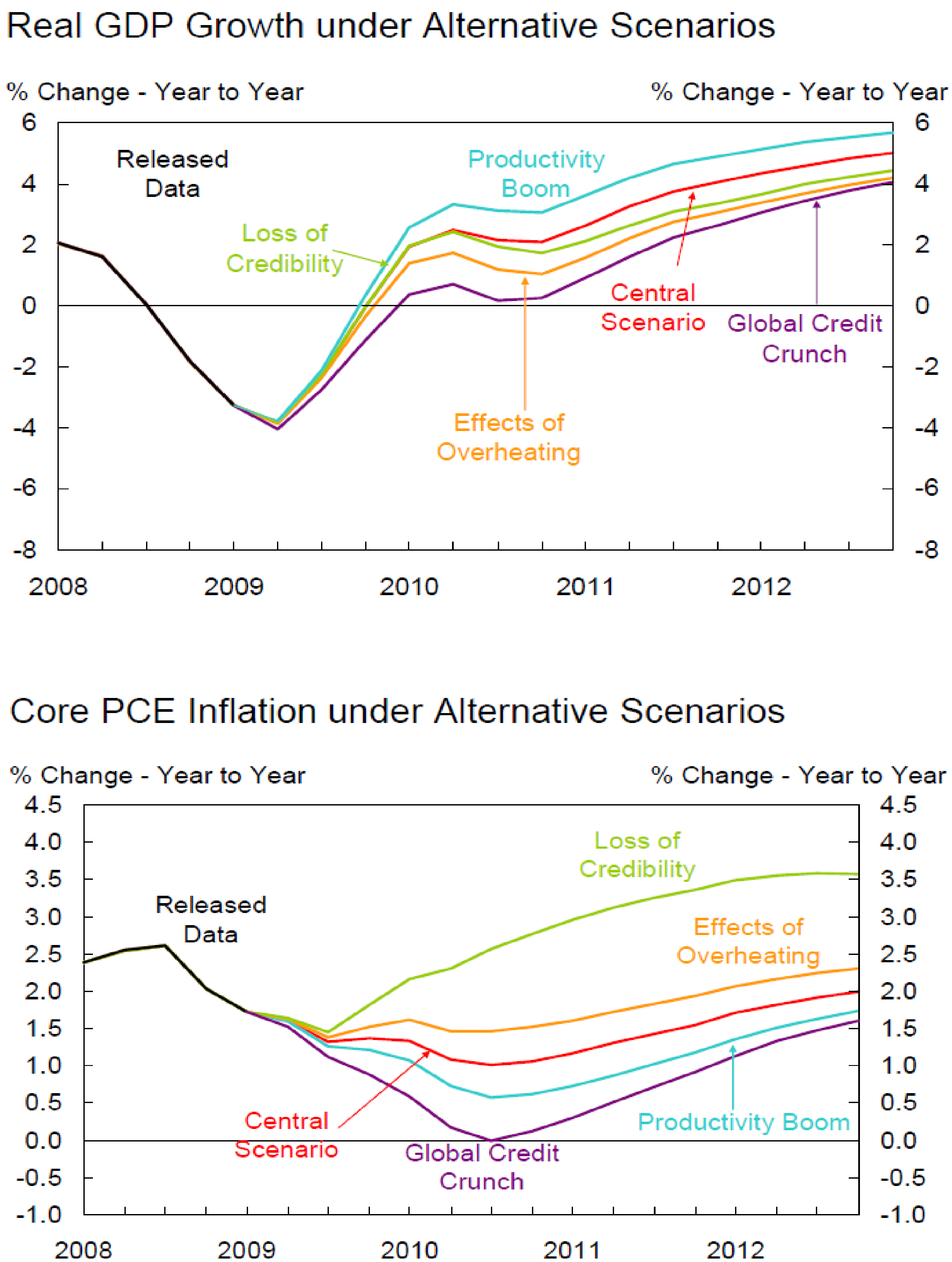
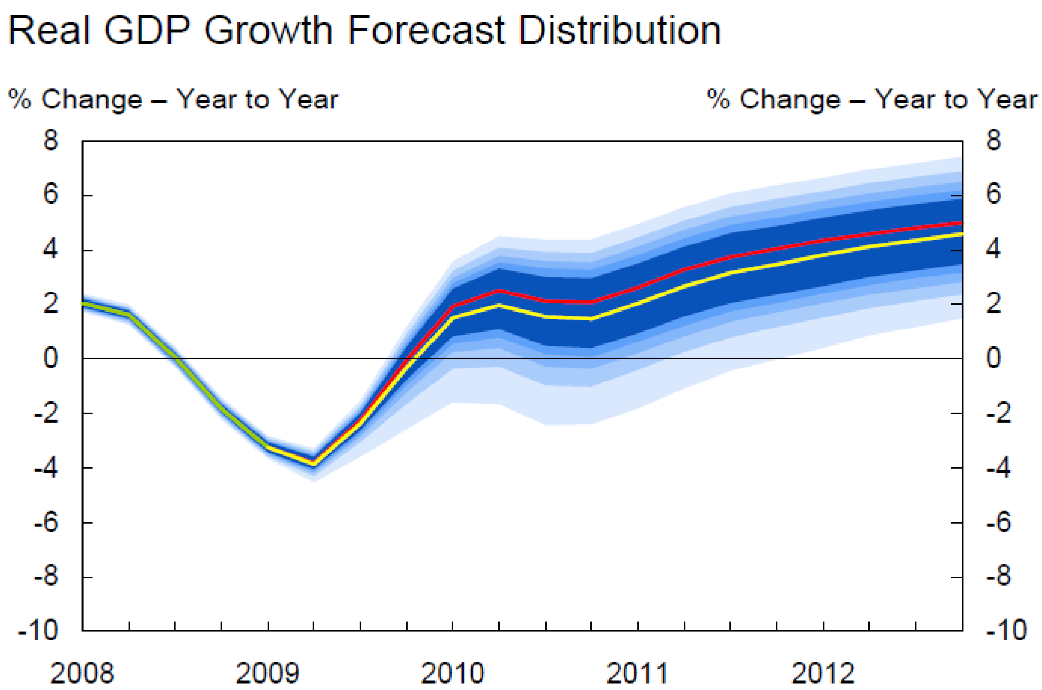


Figure 6: Fan Charts Real GDP growth and Core PCE Inflation



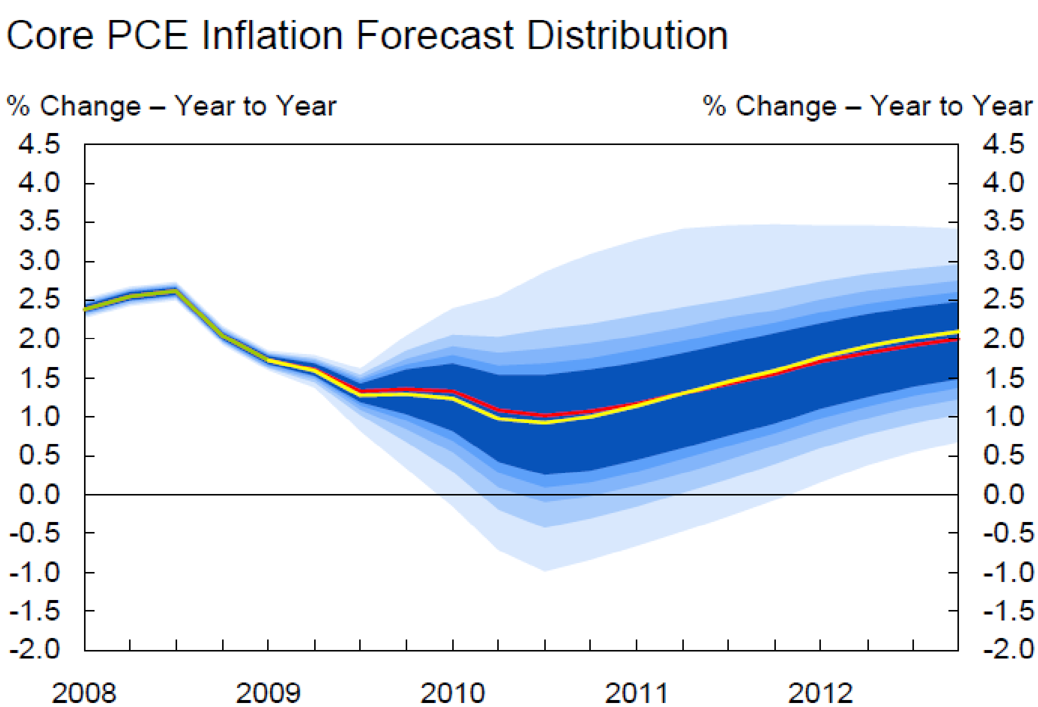
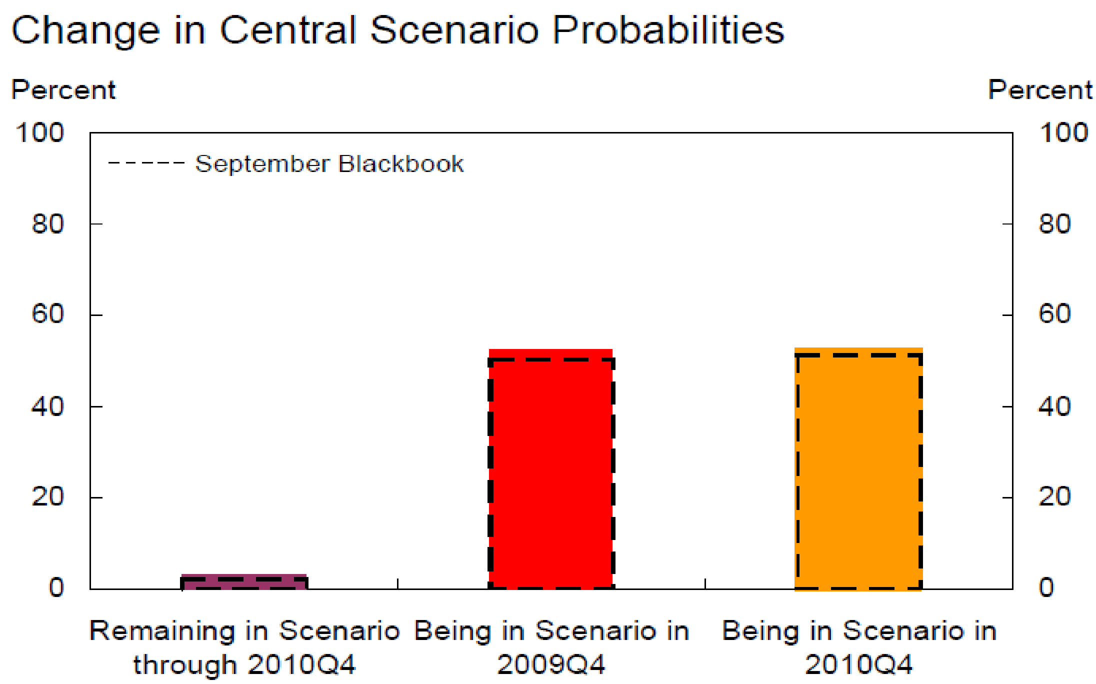


Figure 7: Scenario Probabilities and their Changes



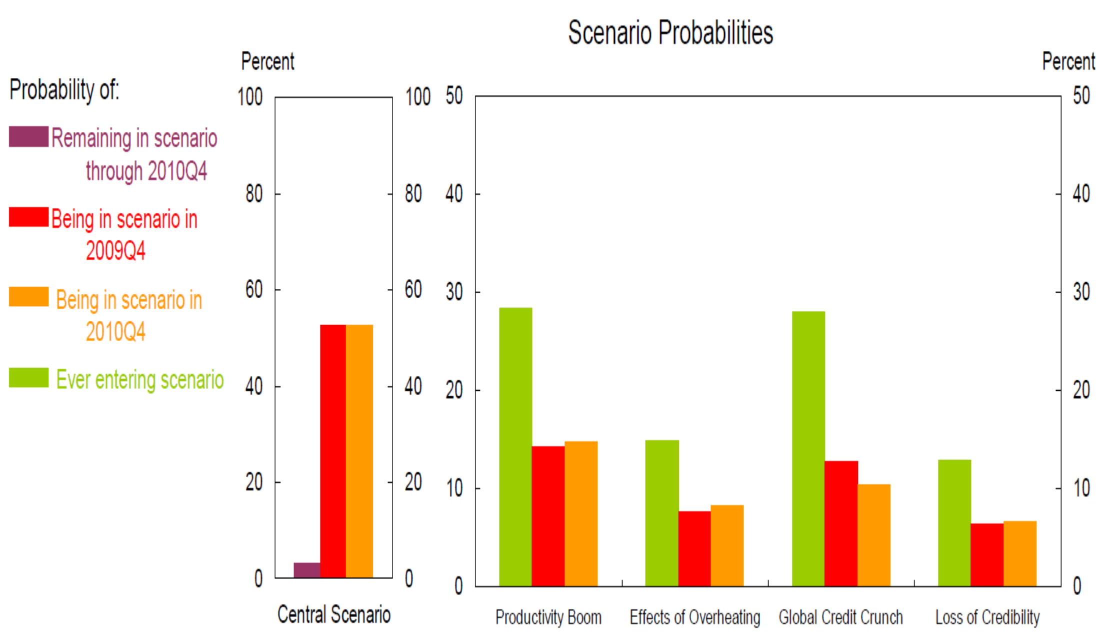
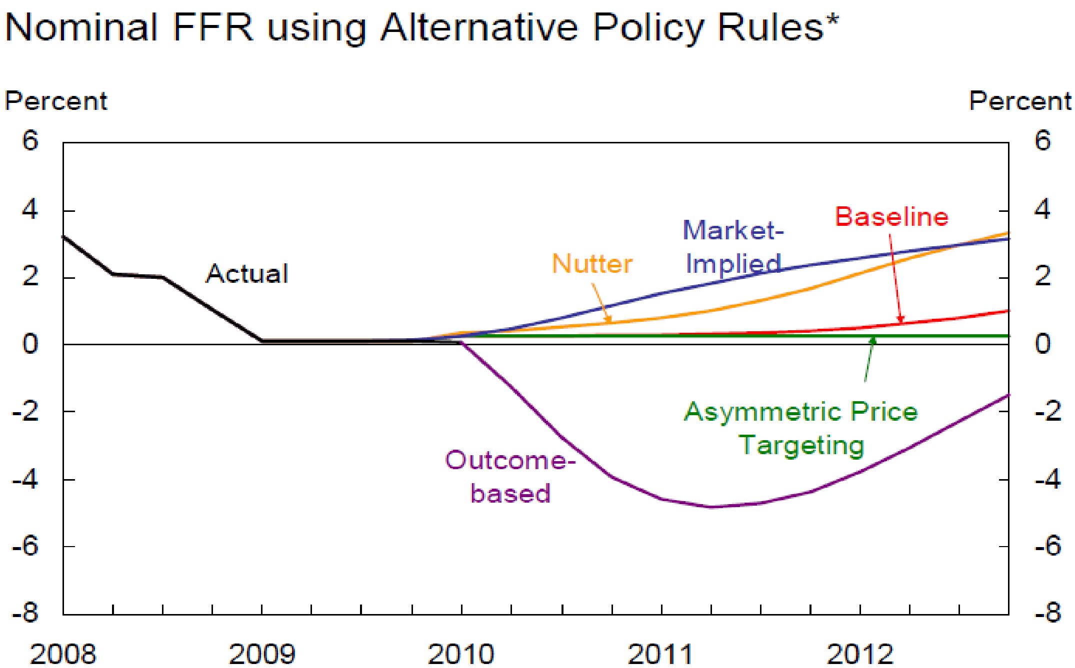


Figure 8: Nominal FFR Scenarios



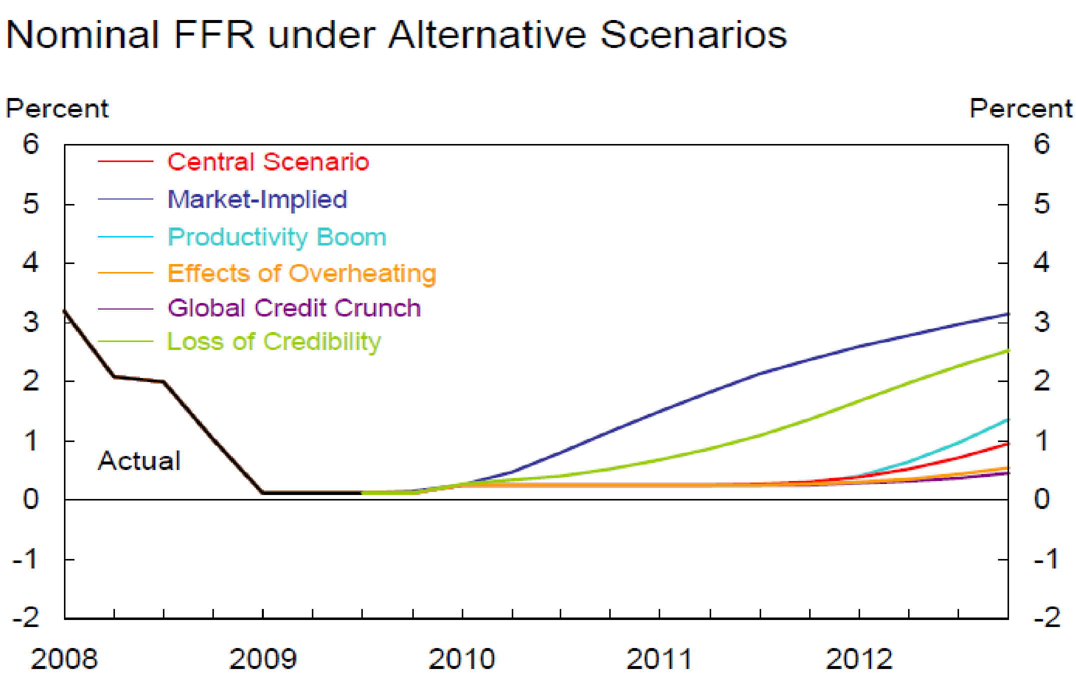
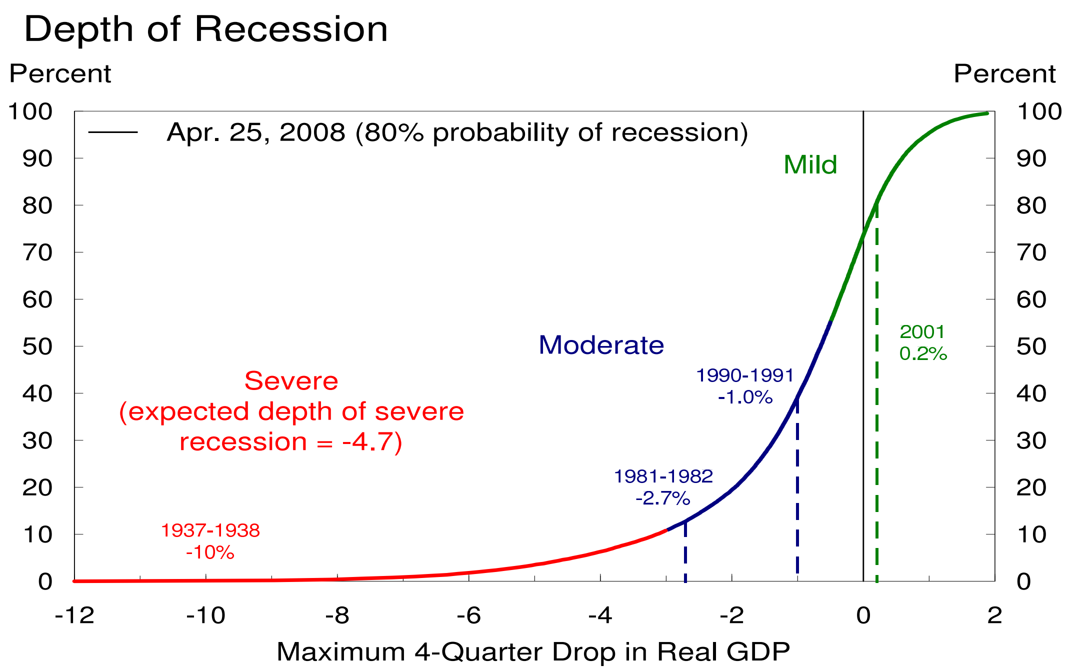


Figure 9: Historical Event-based Calibration: Depth of Recessions



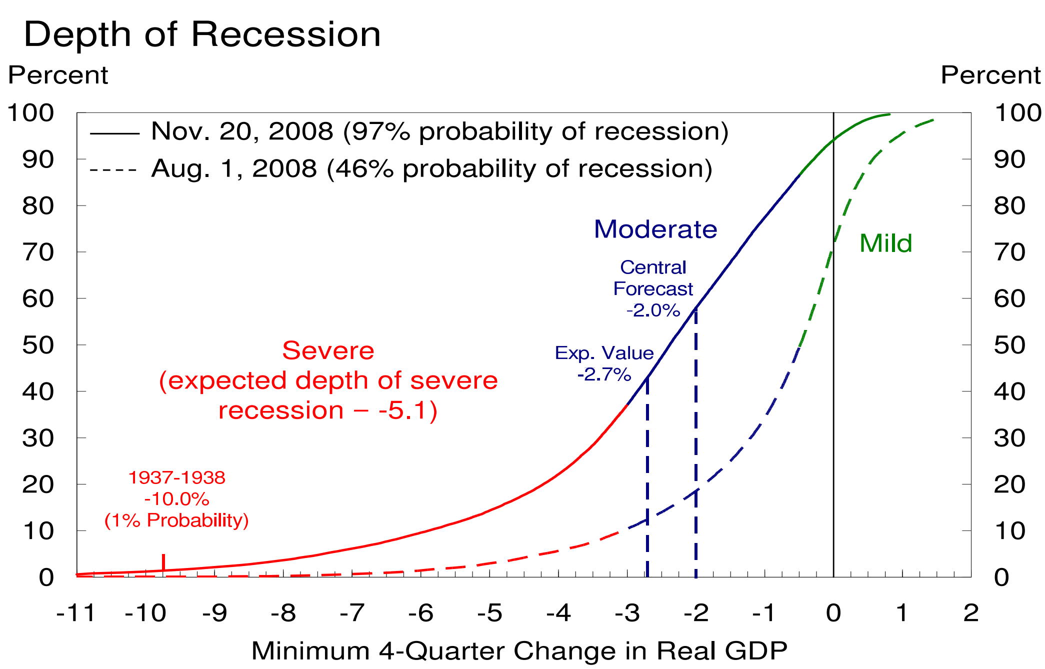
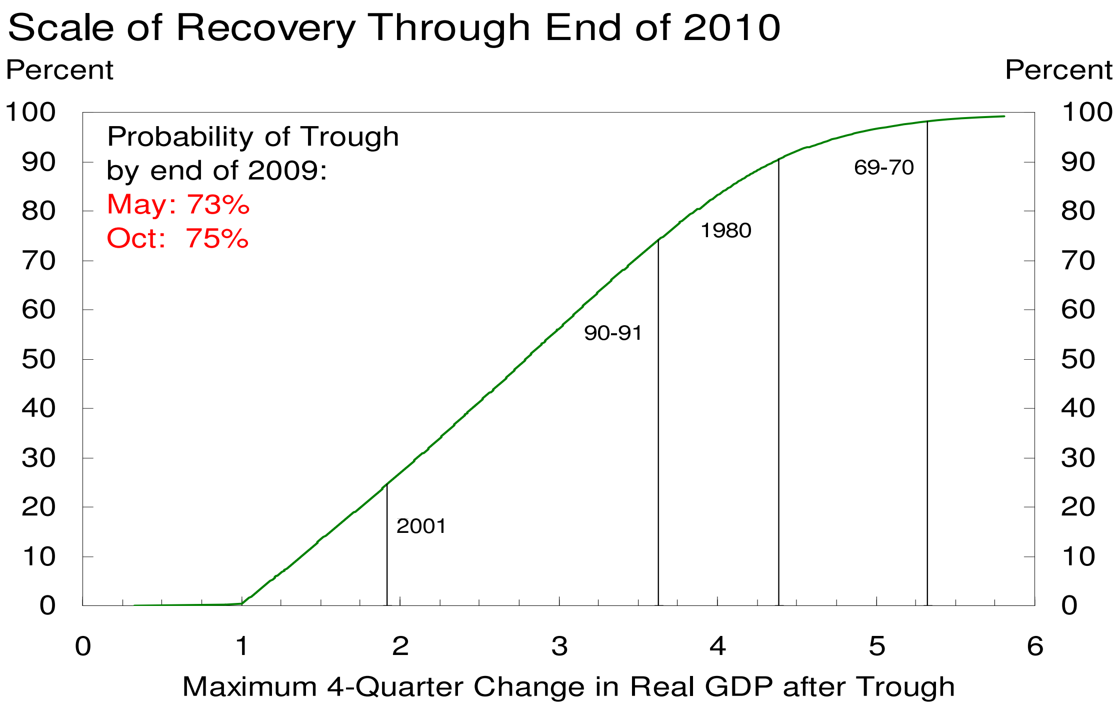


Figure 10: Historical Event-based Calibration: Recovery Probabilities



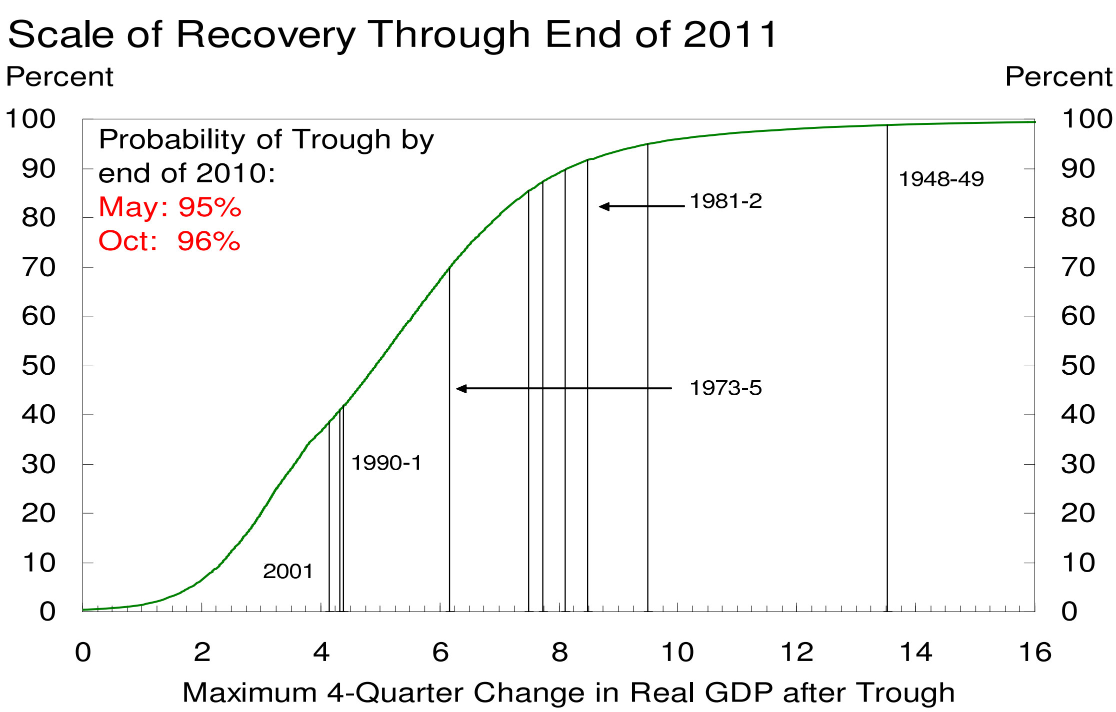
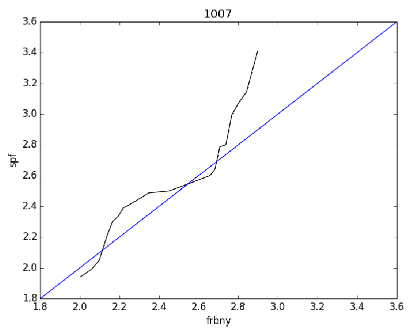
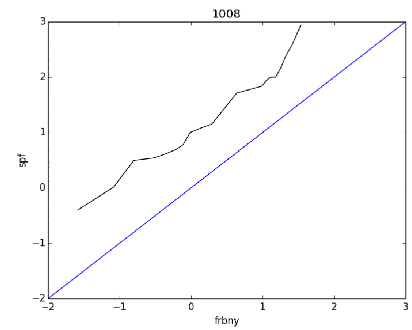


Figure 11: Q-Q Plots - FRBNY Density Forecasts versus Cross-Section Survey of Professional Forecasts

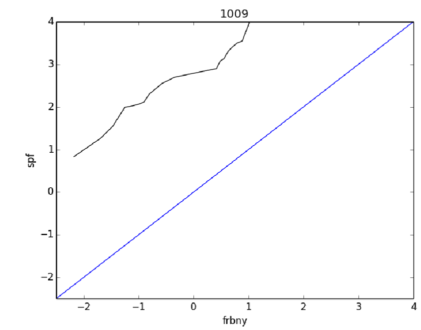
The plots display Q-Q plots of the cross-section of SPF GDP growth forecasts against the FRBNY density forecasts produced in October of 2007-2012. The methodology to compute the density forecasts is described in section 5.



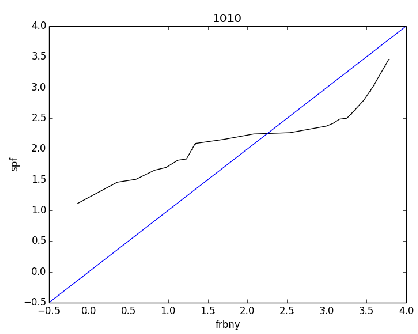
(a) October 2007



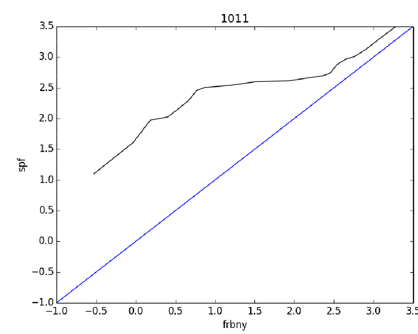
(b) October 2008



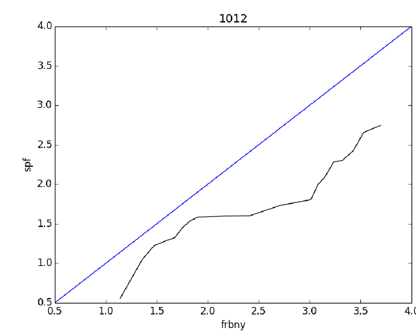
(c) October 2009



(d) October 2010



(e) October 2011



(f) October 2012