Exploiting the monthly data flow in structural forecasting☆

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Abstract

The paper develops a framework which allows to combine the tools provided by structural models for economic interpretation and policy analysis with those of reduced form models designed for now-casting. We show how to map a quarterly dynamic stochastic general equilibrium (DSGE) model into a higher frequency (monthly) version that maintains the same economic restrictions. Moreover we show how to augment the monthly DSGE with auxiliary data that can enhance the analysis and the predictive accuracy in now-casting and forecasting. Our empirical results show that both the monthly version of the DSGE and the auxiliary variables help in real time for identifying the drivers of the dynamics of the economy.

JEL Classification:C33, C53, E30

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☆ *The views expressed in this paper are those of the authors, and not those of the Bank of England or its committees.*

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1. Introduction

This paper develops an analytical framework to combine the structural analysis based on dynamic stochastic general equilibrium (DSGE) models with reduced form analysis designed for digesting the real-time flow of data publication. The aim is to obtain early signals on the current state of the economy and read it through the lens of a structural model.

Now-casting with DSGE models raises two challenges. First, these models are typically estimated with quarterly data on a balanced panel. Therefore, even if some of the model's variables are available at a higher frequency, this information is lost. Second, DSGE models are estimated on a set of variables that is more limited than the information set used by markets and policymakers, who can exploit more timely information as it progressively becomes available throughout the quarter according to an asynchronous calendar of data publications. But, as we will show, this information is valuable not only for pure forecasting/now-casting purposes but also for identifying economically meaningful shocks in real time.

An extensive recent now-casting literature, starting with Giannone, Reichlin and Small (2008), has made use of the state-space representation of reduced form statistical models to provide early estimates of the current value of key quarterly variables such as GDP in relation to the data flow. In this approach, given the model parameters, the newly available data, particularly those published earlier than national account quarterly data, help to produce progressively more accurate estimates of the states and therefore of the current quarter value of the data. This is true not only for “hard” data such as industrial production or employment but also for “soft” data such as surveys which are the first to provide information on the current quarter (for a survey see Banbura, Giannone and Reichlin, 2011). We exploit the fact that both the now-casting model of Giannone, Reichlin and Small (2008) and the generic DGSE have a state space form to link the two approaches in a formal way. This involves three elements.

First, we derive the monthly dynamics of the model, addressing a classic problem of time aggregation (for an early discussion, see Hansen and Sargent 1991). Our contribution here is to provide a method for assessing when a linear or linearised quarterly model has a unique monthly specification with real coefficients and to select the appropriate monthly specification, if there is more than one. Second, we make use of the monthly specification of the model to exploit the infra-quarter data which are available at a monthly frequency. Third, we augment it with data which are typically not included in structural models, because they do not have much relevance at a quarterly frequency, but that are potentially useful because of their timeliness. An obvious example are surveys whose value is only due to their short publication lag and, by the end of the quarter, do not convey any additional information beyond GDP growth itself.

The empirical application provided in the paper illustrates the potential use of the method for both policy modeling and academic research. We derive the monthly state-space that coincides, when put on quarterly data, with a variant of the model in Galí, Smets and Wouters (2012) that incorporates financial frictions as in Bernanke, Gertler and Gilchrist (1999) and augment it with auxiliary monthly macro indicators potentially useful for now-casting. We assess the method's performance in terms of forecast accuracy both on average over the whole evaluation sample, and in the specific episode of the Lehman Bros. crisis. We find that the now-cast and forecast accuracy of the monthly model augmented with the auxiliary variables is comparable to that of the survey of professional forecasters (SPF) and greatly improves over the quarterly model. These results are in line with similar findings for reduced-form models (e.g. Giannone, Reichlin and Small, 2008). But here, crucially, we have a structural model, so we can also exploit the real-time information flow to now-cast unobservables variables that are useful for understanding the economy's dynamics, such as the output gap or the shocks that drive the model.

To exploit further the possibilities that our framework offers for structural analysis, we focus on the Lehman Bros. crisis and we compare the augmented monthly model's storytelling in real-time to the one we would have obtained conditioning on the now-casts of the SPF, as suggested in Del Negro and Schorfheide (2013). Thanks to the auxiliary information, our model is able to better identify, in real time, the shocks driving the business cycle. Moreover, our approach delivers an interpretation of the auxiliary variables through the lens of the model.

The paper is organized as follows. In the first section we illustrate the methodology, in the second the data and the structural model, in the third we provide a forecast evaluation while in the fourth we use the framework for real time structural analysis. Finally we comment the relation of our approach to the related literature and conclude.

2. The methodology

2.1. From monthly to quarterly specification

In what follows, we show how to obtain the monthly specification of the quarterly DSGE model that has real coefficients and we discuss under which conditions such a monthly model exists and is unique. We then discuss how to link the monthly model with the auxiliary variables for now-casting.

We consider structural quarterly models whose log-linearized solution has the form:

$$\begin{aligned} s_{t_q} &= \mathcal{T}_\theta s_{t_q-1} + \mathcal{B}_\theta \varepsilon_{t_q} \\ Y_{t_q} &= \mathcal{M}_{0,\theta} s_{t_q} + \mathcal{M}_{1,\theta} s_{t_q-1} \end{aligned} \tag{1}$$

where t_q is time in quarters, $Y_{t_q} = (y_{1,t_q}, ..., y_{k,t_q})'$ is a set of observable variables which are transformed to be stationary, s_t are the states of the model and ε_t are structural orthonormal shocks. The autoregressive matrix $\mathcal{T}_\theta$, the coefficients $\mathcal{B}_\theta$, $\mathcal{M}_{0,\theta}$ and $\mathcal{M}_{1,\theta}$ are function of the deep, behavioural parameters of the DSGE model, which are collected in the vector θ. $\mathcal{M}_{1,\theta}$ accounts for the fact that often a part of the observables are defined in first differences. We consider the model and its parameters as given. The vector s_t can also include the lags of the state variables and shocks.[1]

Let us define t_m as the time in months and denote by $Y_{t_m} = (y_{1,t_m}, ..., y_{k,t_m})'$ the vector of the possibly latent monthly counterparts of the variables that enter the quarterly model. The latter are transformed so as to correspond to a quarterly quantity when observed at end of the quarter, i.e. when t_m corresponds to March, June, September or December (e.g. see Giannone, Reichlin and Small, 2008).

For example, let y_{i,t_m} be the unemployment rate u_{t_m} and suppose that it enters the quarterly model as an average over the quarter, then:

$$y_{i,t_m} = \frac{1}{3}(u_{t_m} + u_{t_m-1} + u_{t_m-2})$$

In accordance with our definition of the monthly variables, we can define the vector of monthly states s_{t_m} as a set of latent variables which corresponds to its quarterly model-based concept when observed on the last month of each quarter. Hence, it follows that our original state equation

$$s_{t_q} = \mathcal{T}_\theta \; s_{t_q-1} + B_\theta \varepsilon_{t_q}$$

[1] The inclusion of the states and their lag in the observation equation is useful to model variables that enter the system in difference. An alternative consists in including the differences of the states as additional states and setting $\mathcal{M}_{0,\theta} = S_{k,n}$ and $\mathcal{M}_{0,\theta} = 0$, where $S_{k,n}$ is a matrix of zeros and ones that just selects the appropriate rows of s_{t_q}. The problem with this approach is that it generates more redundant states and this makes more difficult to derive the minimal state representation, a step that as we will see is particularly important in the proposed procedure.

can be rewritten in terms of the monthly latent states as

$$s_{t_m} = \mathcal{T}_\theta \; s_{t_m-3} + B_\theta \varepsilon_{t_m} \tag{2}$$

when t_m corresponds to the last month of a quarter, i.e. when t_m corresponds to March, June, September or December.

We assume that the monthly states can be written as

$$s_{t_m} = \mathcal{T}_m \; s_{t_m-1} + \mathcal{B}_m \varepsilon_{m,t_m} \tag{3}$$

and that $\mathcal{T}_m$ is real and stable and ε_{m,t_m} are orthonormal shocks[2]. This implies:

$$s_{t_m} = \mathcal{T}_m^3 \; s_{t_m-3} + [\mathcal{B}_m \varepsilon_{m,t_m} + \mathcal{T}_m \mathcal{B}_m \varepsilon_{m,t_m-1} + \mathcal{T}_m^2 \mathcal{B}_m \varepsilon_{m,t_m-2}]. \tag{4}$$

We are interested in finding a mapping from the quarterly model to the monthly model: the relation between equations (1), or equivalently (2), and (4) imply that the monthly model can be recovered from the following equa-

[2]If the variables considered are stocks, the formulation (3) implies no approximation, because selecting a lower frequency just means sampling at a different frequency. If instead the variables considered are flows, then our definition of the monthly variables as an average over the quarter implies that we are introducing a non-invertible moving average in the growth rates. Therefore modeling this monthly concept as autoregressive introduces some misspecification. Doz, Giannone and Reichlin, 2012 show the effect of such miss-specification is small.

tions:

$$\mathcal{T}_m = \mathcal{T}_\theta^{\frac{1}{3}} \tag{5}$$

$$vec(\mathcal{B}_m\mathcal{B}_m') = (I + \mathcal{T}_m \otimes \mathcal{T}_m + \mathcal{T}_m^2 \otimes \mathcal{T}_m^2)^{-1} vec(\mathcal{B}_\theta\mathcal{B}_\theta'). \tag{6}$$

From (5) it is clear that finding such mapping is equivalent to finding the cube root of $\mathcal{T}_\theta$.

If the autoregressive matrix of the transition equation is diagonalizable, *i.e* if there exist a diagonal matrix D and an invertible matrix V such that $\mathcal{T}_\theta = VDV^{-1}$, then the cube root of $\mathcal{T}_\theta$ can be obtained as

$$\mathcal{T}_\theta^{\frac{1}{3}} = VD^{\frac{1}{3}}V^{-1},$$

where $D^{\frac{1}{3}}$ is a diagonal matrix containing the cube roots of the elements of D. The real elements of D, which are associated with real-valued eigenvectors, have a unique real cube root, which is the only one that gives rise to real values when combined with its associated eigenvector. For the eigenvalues that are complex conjugate instead there are three complex cube roots. These, when combined with their associated eigenvalue, return a real-valued vector. So, effectively, if k is the number of complex conjugate couples of eigenvalues in D, then there will be 3^k real-valued cube roots for $\mathcal{T}_\theta$. To select among these alternative cube roots of $\mathcal{T}_\theta$ we proceed as follows. In the case of real eigenvalues, we simply select their real cube root. In the case of complex conjugate couples, we choose the cube root which is characterized by less oscillatory behaviour, i.e. the cube root with smaller argument.

If monthly observations for some variables are available, we can use them to identify the cube root by choosing the one that maximizes the likelihood of the data. The cube root selected is generally unique. Indeed, Anderson *et al.* (2014) have shown that having mixed frequency observation typically implies identifiability. In our case the two procedures produce the same results.

If $\mathcal{T}_\theta$ is not diagonalizable, it is possible to obtain the Jordan form[3] and to derive the cube root based on that. An interesting result is that the procedure described for diagonalizable matrices extends to this situation in most cases (see Higham, 2008). However there is a caveat that is of particular relevance for DSGE models. Namely, Higham (2008) proves that there exists no p-th (so also no cube) root of a matrix that has zero-valued eigenvalues that are defective, *i.e.* that are multiple but not associated to linearly independent eigenvectors. In the case of DSGE models, this situation arise mainly, but not

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[3]Any matrix $A \in \mathbb{C}^{n\times n}$ can be expressed in the canonical Jordan form

$$Z^{-1}AZ = J = diag(J_1, J_2, ..., J_p),$$

with

$$J_k = J_k(\lambda_k) = \begin{bmatrix} \lambda_k & 1 & & \\ & \lambda_k & \ddots & \\ & & \ddots & 1 \\ & & & \lambda_k \end{bmatrix} \in \mathbb{C}^{m_k \times m_k},$$

where Z is non-singular and $m_1 + m_2 + +... + m_p = n$ with p the number of blocks. We will denote by s the number of distinct eigenvalues (see, for example, Higham (2008) for further details).

exclusively, when there are redundant states. It is hence important to work on the model to try to reduce it to a minimal state space. When defective zero-valued eigenvalues appear even in the transition matrix of the minimal state space (for example because of the choice of observables), then we suggest considering whether there are ways to render the model diagonalizable.

We can obtain $\mathcal{B}_m\mathcal{B}_m'$ as the solution of equation (6). As we are interested in recovering $\mathcal{B}_m$, we make the additional assumption that the three monthly shocks are the same and coincide with the quarterly shock, *i.e.* $\varepsilon_{m,t_m} = \varepsilon_{m,t_m-1} = \varepsilon_{m,t_m-2} = \varepsilon_{t_q}$. Under this assumption, we can obtain $\mathcal{B}_m$ directly from the following equation:

$$\mathcal{B}_m + \mathcal{T}_m\mathcal{B}_m + \mathcal{T}_m^2\mathcal{B}_m = \mathcal{B}_q.$$

Let us now turn to the equation that links the states to the observables. We start by analyzing the (not very realistic) case in which all variables are observable at monthly frequency. The monthly observation equation would then be:

$$Y_{t_m} = \mathcal{M}_m s_{t_m} \tag{7}$$

where

$$\mathcal{M}_m = \left(\mathcal{M}_{0,\theta} + 0 \cdot L + 0 \cdot L^2 + \mathcal{M}_{1,\theta}L^3\right)$$

The equations (3) and (7) therefore describe the monthly dynamics that are compatible with the quarterly model.

2.2. *Mixed frequency and jagged edged data*

If all the observables of the model were available at a monthly frequency, we could simply use the monthly model defined by equations (3) and (7) to immediately incorporate this higher frequency information. However, some variables - think of GDP, for example - are not available at monthly frequency. So let us assume that the variable in the i-th position of the vector of observables Y_{t_m}, i.e. y_{i,t_m}, is not available at a monthly frequency, but only at the quarterly frequency. This means that y_{i,t_m} is a latent variable when t_m does not correspond to the end of a quarter. Moreover, due to the unsynchronised data release schedule, data are not available on the same span (the dataset has jagged edges). The unavailability of some data does not prevent us from still taking advantage of the monthly information that is available using a Kalman filter. To do so, we follow Giannone, Reichlin and Small (2008) and define the following state space model

$$s_{t_m} = \mathcal{T}_m \ s_{t_m-1} + \mathcal{B}_m \varepsilon_{m,t_m}$$
$$Y_{t_m} = \mathcal{M}_m(L) s_{t_m} + V_{t_m}$$

where $V_{t_m} = (v_{1,t_m}, ..., v_{k,t_m})$ is such that $\text{var}(v_{i,t_m}) = 0$ if y_{i,t_m} is available and $\text{var}(v_{i,t_m}) = \infty$ otherwise.

2.3. *Bridging the model with the additional information*

We denote by $X_{t_m} = (x_{1,t}, ..., x_{n,t})'$ the vector of these auxiliary stationary monthly variables transformed so as to correspond to quarterly quantities at the end of each quarter, as described above.

Let us now turn to how we incorporate the auxiliary monthly variables in the structural model. As a starting point we define the relation between the auxiliary variables X_{t_q} and the model's observable variables at a quarterly frequency:

$$X_{t_q} = \mu + \Lambda Y_{t_q} + e_{t_q} \tag{8}$$

where e_{t_q} is orthogonal to the quarterly variables entering the model. We will use this equation to estimate the coefficients Λ and the variance-covariance matrix of the shocks $E(e_{t_q} e'_{t_q}) = R$. We use a flat prior on all the parameters, so that the posterior model corresponds to the OLS estimate.

Let us now focus on incorporating the auxiliary variables in their monthly form. As stressed above, $X_{t_m} = (x_{1,t}, ..., x_{n,t})'$ is the vector of these auxiliary stationary monthly variables transformed so as to correspond to quarterly quantities at the end of each quarter. We can relate X_{t_m} to the monthly observables Y_{t_m} using the equivalent of equation (8) for the monthly frequency (the bridge model):

$$X_{t_m} = \mu + \Lambda Y_{t_m} + e_{t_m} \tag{9}$$

where $e_{t_m} = (e_{1,t_m}, ..., e_{k,t_m})$ is such that $\text{var}(e_{i,t_m}) = [R]_{i,i}$ if X_{i,t_m} is available and $\text{var}(e_{i,t_m}) = \infty$ otherwise. In this way we take care of the problem of the jagged edge at the end of the dataset, due to the fact that the data is released in an unsynchronized fashion and that the variables have different publishing lags (e.g. capacity utilization releases refer to the *previous* month's total capacity utilization, while the release of the Philadelphia Business Outlook Survey refers to the *current* month). We will use equation (9) to expand the original state-space derived in Section 2.2. Summing up, the state space takes the form:

$$\begin{aligned} s_{t_m} &= \mathcal{T}_m \; s_{t_m-1} + \mathcal{B}_m \varepsilon_{m,t_m} \\ Y_{t_m} &= \mathcal{M}_m(L) s_{t_m} + V_{t_m} \\ X_{t_m} - \mu &= \Lambda Y_{t_m} + e_{t_m} \end{aligned} \tag{10}$$

where V_{t_m} and e_{t_m} are defined above. The state-space form (10) allows us to account for and incorporate all the information about the missing observables contained in the auxiliary variables.

The choice of modeling X_{t_m} as solely dependent on the observables Y_{t_m} rather than depending in a more general way from the states s_{t_m}, is motivated by the fact that we want the auxiliary variables to be relevant *only* in real time, but we do not want them to affect the inference about the history of the latent states and shocks. In this way the procedure is minimally invasive with respect to the original quarterly model.

3. Empirical analysis

3.1. The structural model

We implement the methodology described above on a variant of the medium-scale model presented in Galí, Smets and Wouters (2012; henceforth GSW) that includes financial frictions as in Bernanke, Gertler and Gilchrist (1999). The GSW reformulates the well known Smets-Wouters (2007; henceforth SW) framework by embedding the theory of unemployment proposed in Galí (2011a,b). The main difference of the GSW with respect to the SW is the explicit introduction of unemployment, and the use of a utility specification that parameterizes wealth effects, along the lines of Jaimovich and Rebelo (2009). We add the financial frictions building on the work of Christiano, Motto and Rostagno (2003), De Graeve (2008) and Del Negro, Hasegawa and Schorfheide (2014). In this set-up, banks collect deposits from households and lend to entrepreneurs, who are hit by idiosyncratic shocks to their net wealth. The entrepreneurs use a mix of these funds and their wealth to acquire physical capital, but because of their idiosyncratic shocks, their revenues may be too low to repay the loans. The banks therefore protect themselves charging a spread over the deposit rate, which will be a function of the entrepreneurs' leverage and riskiness. We present the main log-linearized equations of the model in Appendix A and refer to Galí, Smets and Wouters (2012) for an in depth discussion of the model.

The model is estimated on nine data series for the US: per capita GDP growth, per capita consumption growth, per capita investment growth, a measure of real wage inflation based on compensation per employee, the GDP deflator inflation, per capita employment, the policy rate, the unemployment rate and a measure of the spread, namely, the annualized Moody's Seasoned Baa Corporate Bond Yield spread over the 10-Year Treasury Note Yield at Constant Maturity. The policy rate is the effective Fed Funds rate in the part of the sample when it is not constrained by the zero lower bound. From January 2009 onward, the policy rate corresponds to the shadow rate computed by Wu and Xia (2014), which is intended to capture the effects on the term structure of unconventional policy tools such as large-scale asset purchases and forward guidance.

GDP growth, investment growth, wage growth are available at a quarterly frequency only, while nominal consumption growth, employment, unemployment, the policy rate and the spread are available at monthly frequency, at least. The model however is specified and estimated at quarterly frequency: we report the model's priors in Appendix A, while the model's posterior distribution is estimated annually at the beginning of each year of the evaluation sample, which goes from 1995 to 2014.

The model includes nine structural shocks: risk premium, monetary policy, exogenous spending, investment-specific technology shock, neutral technology, price mark-up, wage mark-up, net worth and exogenous labour supply shocks.[4] Figure 1 shows the decomposition of GDP growth.

[4]All the shocks are AR(1) bar the monetary policy shock, which is white noise.

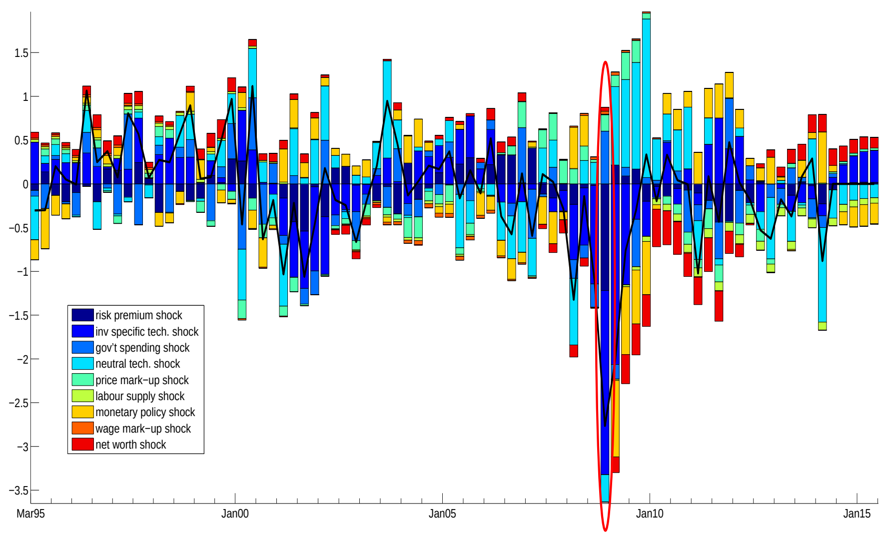

Figure 1: **Shock decomposition of quarterly GDP growth**

Results confirm that over the whole sample the investment specific shock plays a sizeable role (as in Justiniano, Primiceri and Tambalotti, 2010) though the presence of the net worth shock in the model, as in Del Negro, Hasegawa and Schorfheide (2014), reduces its importance. The presence of the labour supply shock in the GSW somewhat reduces the importance of the wage mark-up shocks in the SW first pointed out by in Chari, Kehoe and Mc Grattan (2009).

Interestingly, our model attributes the bulk of the fall in GDP at the end of 2008 (highlighted in red) to three shocks: *i)* the risk premium shock, a perturbation to agents intertemporal Euler equation governing the accumulation of the risk-free asset, which plausibly captured the changes to risk attitudes brought about by the collapse of Lehman Brothers; *ii)* the investment specific technology shock, which also affects the net worth of the entrepreneurs in the model, and *iii)* the neutral technology shock. Our findings are broadly consistent with those of Christiano, Eichenbaum and Trabandt (2015), who analyse the Great Recession through the lens of a state-of-the-art New Keynesian model and attribute the bulk of the movements in aggregate real variables and inflation to a consumption wedge, a financial wedge and the neutral technology shock.

3.2. The auxiliary variables

We consider a dozen of additional macro and financial variables that are monitored more closely by professional and institutional forecasters[5]. These include real indicators (such as industrial production, house starts, total construction, etc...), price data (CPI, PPI, PCE inflation), financial market variables (the fed funds rate and the BAA-AAA spread), labour market variables, credit variables, a measure of uncertainty (Baker, Bloom and Davis (2015) economic policy uncertainty index) and some national accounts quantities. A full list and description of these series is reported in Table B.4 in Appendix B, which describes a stylised calendar of data releases where the variables have been grouped in 38 clusters according to their timeliness. This allows us to relate the changes in the forecast with groups of variables

[5]For a discussion of alternative ways of selecting the auxiliary variables, see Cervena and Schneider (2014), who apply the methodology proposed in the earlier version of this paper (Giannone, Monti and Reichlin, 2010) to a medium-scale DSGE model for Austria and address the issue of variable selection by proposing three different methodologies for the subsample selection.

with similar economic content. For example, although the housing sector is not included in the model, we can capture information about it thanks to the auxiliary variables. Similarly, surveys can be very informative, because they give a measure of changes in the private agents' sentiments that is not explicitly modelled in the standard log-linearised DSGE.

In the first column of Table B.4 we indicate the progressive number associated to each "vintage" or release cluster, in the second column the data release, in the third the series and in the fourth the date the release refers to, which gives us the information on the publication lag. We can see, for example, that the Philadelphia Fed Survey is the first release referring to the current month m and it is published on the third Thursday of each month. Hard data arrive later. For example, the first release of industrial production regarding this quarter is published in the middle of the second month of the quarter. GDP, released in the last week of the first month of the quarter refers to the previous quarter.

Figure 2 reports the portion of the variance of the one-quarter-ahead forecast of the auxiliary variables that is attributed to each of the shocks in the model. Looking at the variance decomposition provides interesting insights on which kind of information the auxiliary variables deliver. Notice that in addition to the structural shocks these variables are also affected by an idiosyncratic shock. The larger the idiosyncratic shock the less informative is a variable about the model dynamics.

Let us focus on the three shocks that are driving the fall in GDP in

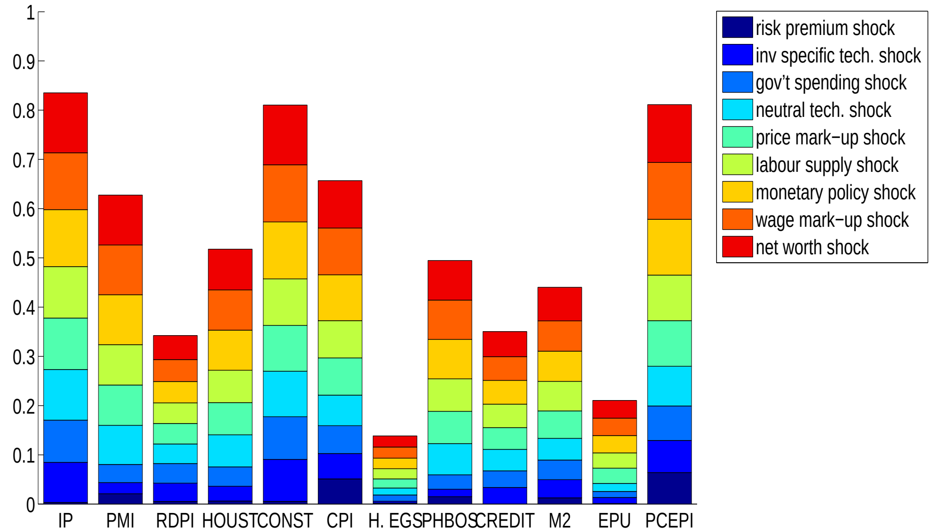

Figure 2: **Forecast error variance decomposition of the auxiliary variables one quarter ahead.**

2008Q4, namely the risk premium shock, the investment specific technology shock and the neutral technology shock. The figures show that the the risk premium shock is most relevant for nominal variables (such as CPI inflation and the PCE inflation) and surveys on the real economy such as the PMIs. On the other hand, the variables that are significantly affected by the neutral technology shock are mostly real, like industrial production, housing starts, total construction and the surveys (PHBOS and PMI).

3.3. The derivation of the monthly model

Let us now consider the computation of monthly version of the model. We first verify that $\mathcal{T}_\theta$ in (1) can be diagonalized. Indeed it can, so we obtain the matrix D of eigenvalues and the corresponding matrix V of eigenvectors that satisfy $\mathcal{T}_\theta = VDV^{-1}$. We identify the model's real-valued cube root as described in the previous Section and we also verify that it is indeed the one that maximizes the likelihood.

We then produce the now-cast with the monthly model with and without auxiliary variables and compare it both to the SPF's forecasts and to the forecast produced with the quarterly model, in which the last data point available is inputed for the higher frequency variables, as is generally done in policy institutions. And we will also obtain real-time estimates of purely model-based concepts like the output gap. As we will show in the next Section, simply taking advantage of all the information available about the observables at a monthly frequency greatly increases the forecasting performance of the model. Incorporating information from key macro variables that are more timely also helps, especially for GDP growth.

4. Forecast Evaluation

In this Section we evaluate the forecasting performance of the monthly model augmented by auxiliary variables (M Augmented) and compare it with: the quarterly DSGE model based on the balanced panel (Q balanced), and the monthly model (M model). The forecasts are evaluated at different dates within the quarter in order to assess the effect of timely monthly information on the accuracy of the forecasts. We also benchmark these forecasts against the survey of professional forecasters (SPF) although this is only possible at the middle of the quarter when the such surveys are published[6].

We show both point forecasts and density forecasts, focusing on the evaluation sample 1995Q1-2014Q2. Over this sample, the model is estimated once a year using data from 1964 to the year before the one we are evaluating. Due to availability issues we use data from 1982 to estimate the relationship between the auxiliary variables and the model (Λ in system (10)). Because only few of the auxiliary variables we consider are available in real-time from the beginning of the evaluation sample in 1995Q1, we perform the exercise in pseudo-real-time: we use the latest vintage of data, but, at each point of the forecast horizon, we only use the data available at the time.

4.1. Point Forecasts

In the main text we present now-casts and forecasts of per capita real GDP growth, GDP deflator inflation, unemployment and the output gap. In Appendix we report further results for consumption growth, the policy rate, unemployment and GDP deflator inflation. The figures and tables in this section report the root mean square forecast error (RMSFE) for the different models. In order to align the SPF's and the models' information sets as closely as possible we display it only from cluster 18 to cluster 20, *i.e.* around the beginning of the second month of the quarter when the SPF's forecasts are published.

[6] Where necessary, the SPFs forecast are adjusted by the same population growth index used in the model, in order to align them as much as possible with the models' forecasts, which are in per capita terms.

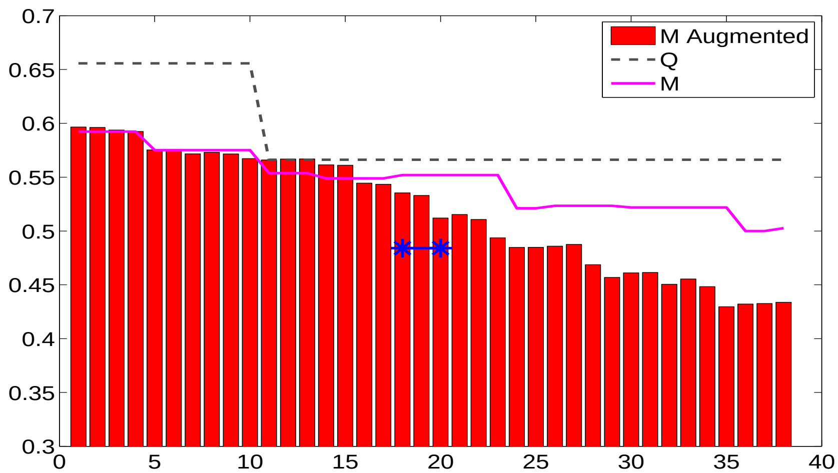

Figure 3: RMSFE of GDP growth now-casts throughout the quarter for the quarterly model (Q, the dashed line), the monthly model (M, the purple line) and the monthly model augmented with the auxiliary information (M Augmented, the red bars). We also report the SPF now-casts, in blue with an asterisk marker.

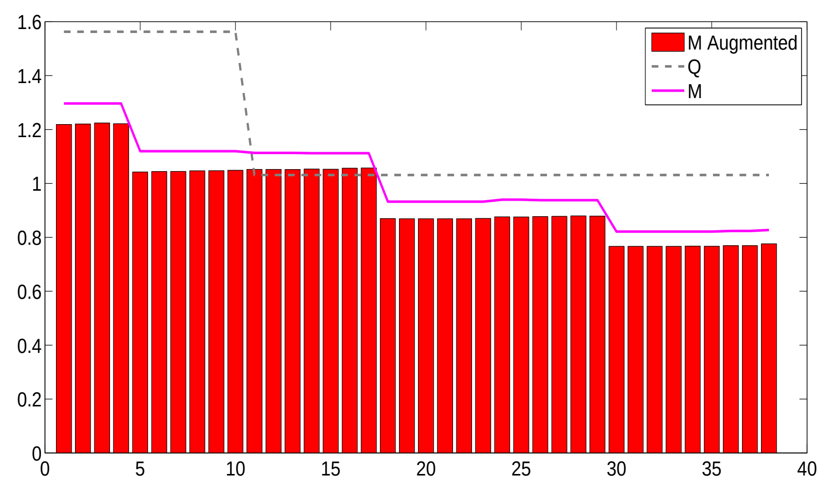

Figure 4: RMSFE of the now-cast of the output gap throughout the quarter for the quarterly model (Q, the dashed line), the monthly model (M, the purple line) and the monthly model augmented with the auxiliary information (M Augmented, the red bars).

The forecasts are updated 38 times throughout the quarter, corresponding to the stylized calendar B.4 described in Appendix B. We can thus associate to each update of the forecasts a date and a set of information being released. We first report how the root mean square forecast error (RMSFE) of our forecasts and now-casts changes with new information releases. So the horizontal axis of the Figures 3 -4 indicate the grouping of releases corresponding to the calendar. For example, clusters 5, 18, and 30 correspond to the release of the employment situation in each of the three months of the quarter, release 11 corresponds to the flash estimate of GDP for the previous quarter and 14, 26 and 38 correspond to the last day of each month where we include the financial data.

Notice that the now-cast of the quarterly model that uses the balanced panel (Q balanced) can be updated only once in the quarter, when the GDP for the past quarter is released (cluster 10). The now-casts of the monthly model (M model) is updated 9 times throughout the quarter, at each release of the variables that are released at least monthly - consumption (12, 24, 36), the employment variables (5, 18, and 30) and the term structure variables (14, 26 and 38). The monthly model augmented by auxiliary variables (M Augmented) is updated at each new release. The number of jumps in the root mean square forecast errors (RMSFE) of each of the now-casts in Figures 3-4 reflects how many times the now-cast is updated throughout the quarter.

Results indicate that the monthly specification is very useful especially when the focus is on a variable available at the monthly frequency such

	SPF	Q	M	M Augmented
		GDP growth		
5	-	0.6557	**0.5751** *	**0.5754***
20	**0.4841***	0.5662	0.5520	**0.5121** *
30	-	0.5662	**0.5219** *	**0.4611****
38	-	0.5662	**0.5027** ***	**0.4338** ***
		Unemployment		
5	-	0.2556	**0.0607****	**0.0607****
20	**0.0190****	0.0587	**0.0241***	**0.0253***
30	-	0.0587	**0.0066****	**0.0065****
38	-	0.0587	**0.0071****	**0.0070** ***
		GDP Deflator inflation		
5	-	0.0573	0.0568	0.0580
20	**0.0389***	0.0446	0.0434	0.0459
30	-	0.0446	0.0449	0.0489
38	-	0.0446	0.0482	0.0517

Table 1: **RMSFE at representative vintages for GDP growth, the unemployment rate and GDP deflation inflation now-casts**.The first column indicates the vintages. We indicate with ***, ** and * the forecasts that are statistically significantly different from the forecast produced by the model with the balanced panel (Q, second column in the tables) with a 1%, 5% and 10% level, respectively, based on the Diebold-Mariano (1995) test, where we use Newey-West standard errors to deal with the autocorrelation that multi-period forecast errors usually exhibit. The bold type face is used to identify forecasts that are statistically significantly better.

as unemployment (Table 1) and the output gap (Figure 4). Recall that the latter is defined as the difference between actual output and the output that would prevail in the flexible price and wage economy in the absence of distorting price and wage markup shocks which, in the GSW model, is very closely aligned to the total employment series, also available monthly[7]. In this case the main advantage comes from the ability to account for the

[7]Since the output gap is unobserved, we take it's ex-post estimate - *i.e.* the estimate produced by the quarterly DSGE model using all available data up to 2014Q2 - to be the "true" one, and we construct the RMSFE of the now-cast produced by the alternative models we consider with respect to it.

monthly observables in a more consistent way, rather than from the real-time data flow.

For quarterly GDP, on the other hand, we can see that the best performance is generated by the monthly model augmented by the auxiliary variables (see Figure 3). The RMSFE errors decline with the arrival of new information throughout the quarter confirming results obtained in reduced form models as surveyed by Banbura, Giannone and Reichlin (2011). The importance of the monthly data flow is confirmed by Figure 5 which reports the now-cast for the GDP growth for four representative vintages produced with information sets 5, 20, 30 and 38. Notice that with the monthly model with the auxiliary data we would have had a much timelier assessment of the depth of the Great Recession, as well as a better assessment of the recovery.

The results on the GDP deflator inflation are very disappointing for all models. All of them, including the SPF, have a similar now-casting performance the (Table 1). This is not surprising since this variable is itself flat over the forecasting sample.

In Appendix C we perform the same evaluation for the two sub-samples, 1995-2007 and 2008-2014. We show that the relative forecasting performance of the models is quite different before and after the Great Recession for most variables and that in the second sub-sample there is a significant deterioration of performances.

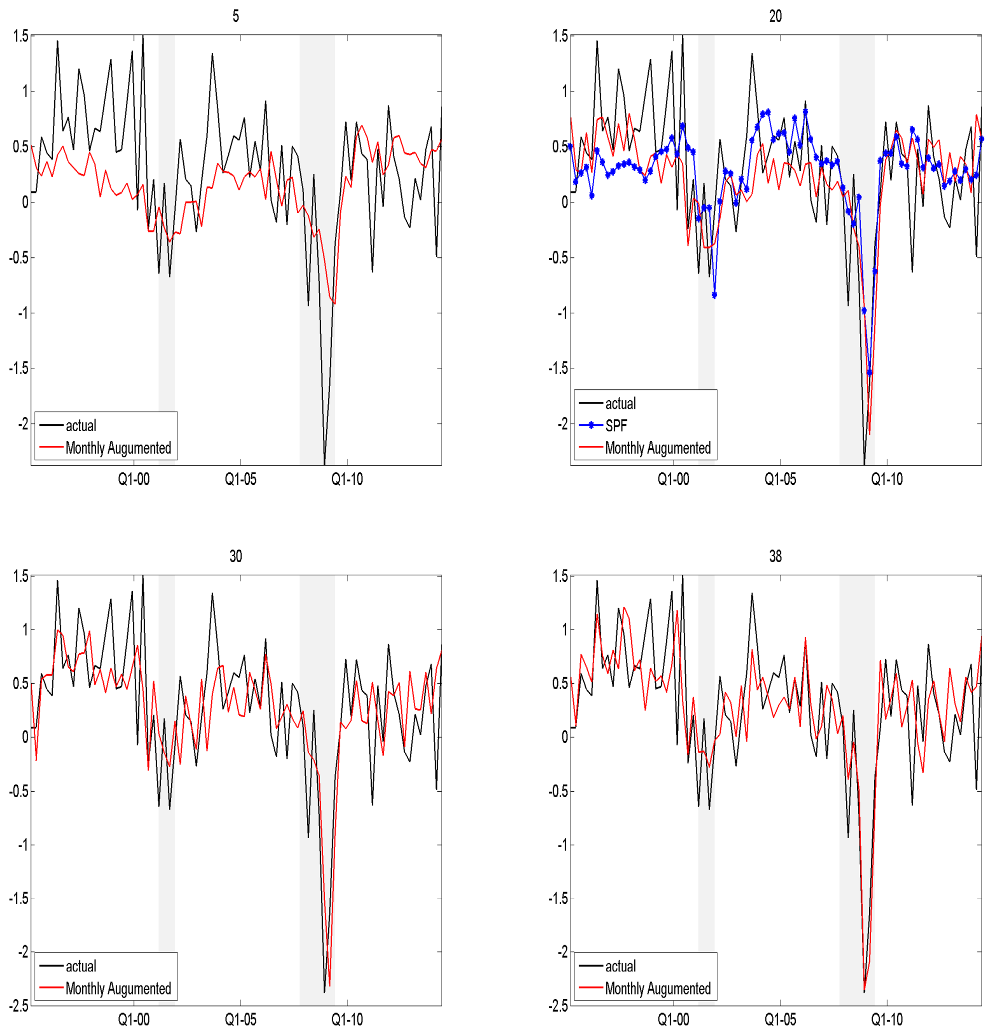

Figure 5: **The now-cast of annualised GDP growth for 4 representative vintages**. Vintage 5 corresponds to the release of the employment data on the first Friday of the first month of the quarter. Vintage 20 is the middle of the second month of the quarter and we take it to correspond to the moment at which the SPF make their forecast. Vintage 30 corresponds to the relase of the Employment data at the beginning of the third month of the quarter. The lower right panel correspond to the last day of the quarter (vintage 38). The shaded area indicates the NBER recession dates.

	GDP growth and Unemployment			All real variables		
	Q	M	M Augmented	Q	M	M Augmented
5	-1.7632	-1.2326	-1.2297	-9.9931	-8.8426	-8.6282
20	-1.225	-1.0894	-1.0651	-7.8794	-7.3741	-7.1988
30	-1.225	-0.9269	-0.8523	-7.8794	-6.1578	-5.9231
38	-1.225	-0.9054	-0.7819	-7.8794	-5.4332	-4.9318

Table 2: **Log predictive score of the now-cast of unemployment and GDP growth and for all on the models' real variables at representative vintages**.The first column indicates the vintages. Vintage 5 corresponds the release of the employment data on the first Friday of the first month of the quarter. Vintage 20 is in the first half of the the second month of the quarter and we take it to correspond to the moment at which the SPF make their forecast. Vintage 30 corresponds to the relase of the Employment data at the beginning of the third month of the quarter. Vintage 38 is the last day of the quarter.

4.2. Density Forecasts

In order to characterize and evaluating the uncertainty associated with the predictions of the model we compute the predictive density of the models and the associated log predictive scores. The log predictive score is a widely used scoring rule, used to evaluate the quality of probabilistic forecasts given a set of outcomes. Formally it is defined here as:

$$S_h(\mathcal{M}) = \frac{1}{N_h} \sum_{t=T}^{T+N_h-1} \ln p(y_{t+h}|Y_{1:T-1}, \mathcal{M}), \tag{11}$$

where h is the forecast horizon, T is the beginning of the forecast horizon and $\ln p(y_{t+h}|Y_{1:T-1}, \mathcal{M})$ is the marginal likelihood for $h = 1$.

Table 2 reports the log predictive score produced after each of the 4 representative clusters of releases (5,20,30,38), respectively for the now-cast of unemployment and GDP growth and for all on the models' real variables, i.e. all variables but the interest rate and the spread. In both cases the two monthly models are the best performing and the M augmented is consistently better than the monthly model that does not exploit the panel.

4.3. Exploiting the model's structure in real-time

One of the key advantages of our methodology is the ability to exploit the structure of the model in real time. As we have seen, we can obtain real-time estimates of unobservable variables such as the output gap and update them at each information release (see Figure 4). We can also use the model and the structural shocks it identifies to interpret the signal coming from the data in real time.

The decomposition of the fluctuations in terms of structural shocks changes with the data arrival in real time. Let us focus, for example, on the story behind the drop in GDP in the last quarter of 2008Q4, when Lehman Brothers collapsed. Let's now compare the ex-post decomposition reported in Figure 1 with that obtained in real time. We place ourselves at the beginning of July 2008 and look at how each of the models would have attributed the shocks according to the information flow up until March 2009 in the case of the quarterly balanced model (top panel of Figure 6) and the monthly model with auxiliary information (bottom panel). We also generate the same graph for the quarterly model conditioned on the now-casts produced by the SPF (middle panel of Figure 6). Conditioning on SPFs has been suggested by Del Negro and Schorfheide (2013) as a way of indirectly exploiting timely information (as preprocessed by the SPF) in the forecast. On the right side of these graphs, we add the ex-post shock decomposition highlighted in red in Figure 1 for ease of comparison.

One of the key messages emerging from the comparison of the graphs in Figure 6 is that accounting for new information in a timely fashion not only delivers an early signal on the state of the economy but also on its drivers. In other words, it takes time to understand why the economy is slowing and, in real time, there is significant uncertainty surrounding the decomposition of the shocks. Exploiting high frequency information significantly decreases this uncertainty: we converge a few months in advance to the ex-post decomposition. This aspect of real time analysis has been completely disregarded in the literature.

The charts also tell us that simply conditioning on the SPF, although providing a forecast which is at least as accurate than that our M Augmented framework, does not help in recognising in real-time the shocks that are driving the fall of GDP in 2008Q4. Clearly, each of the the auxiliary variables carries a meaningful signal which would have been lost by simply conditioning on the view of the SPF, who pre-process the available information into a single now-cast for each observable. This confirm results in Monti (2010) showing that conditioning on the SPF as if they were actual data rather than forecasts[8] can be misleading.

[8]Del Negro and Schorfheide (2013) call this the *news* implementation of the conditioning as opposed to the *noise* implementation, in which the SPF now-casts are considered

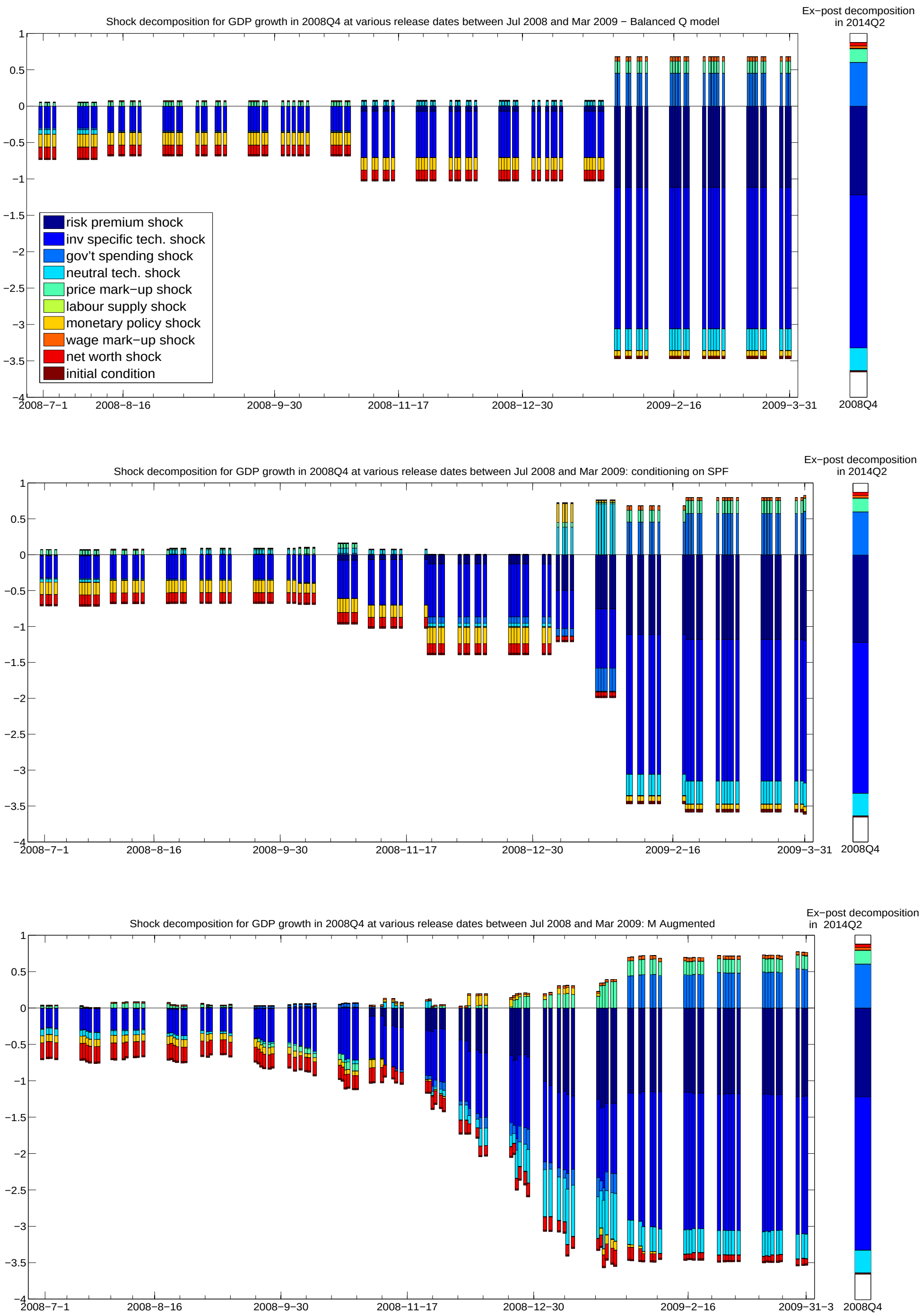

Figure 6: Shock decompositions in real tim for Q, Q+SPF and M Augmented models

In particular, the shocks decomposition obtained by conditioning on the SPF grossly underestimates the effect of the risk premium shock and, more importantly, almost misses the negative contribution of the neutral technology shock. The monthly model with auxiliary model identifies the negative contribution of the technology shock to the slowdown because the latters, as we have seen earlier, have a large impact on real variables, and the auxiliary variables related to those (e.g. surveys) are signaling at an early stage that there is a significant slowdown of the real economy and not only a large shock in the risk premium.

5. Discussion and relation with the literature

The approach proposed in this paper adds a new complementary perspective to related work in this area. A natural alternative to our approach would have been to specify the DSGE model at the monthly frequency and deal with the mixed frequency problem arising from the fact that some key macro variables are quarterly - like GDP and the GDP deflator - using, for example, the blocking technique described in Zamani *et al.* (2011). However, the problem with specifying the DSGE at a monthly frequency is that most DSGE models are quarterly and there is very little empirical experience regarding the specification of the behavioral equations and the setting of the priors in a monthly set-up. The few papers that estimate monthly DSGE models (e.g.,

noisy measures of the true signal.

Hilberg and Hollmayr 2013) somewhat mechanically adjust the parameters from their quarterly specification to the monthly equivalent. While this is relatively straightforward, it is much less obvious that the specification of the driving processes would carry through unchanged when specified at higher frequency.

A different motivation for considering mixed frequency data in structural models is to improve the estimation of the structural parameters of the quarterly DSGE by alleviating the temporal aggregation bias and mitigating identification issues (see Foroni and Marcellino, 2013, and Kim, 2010). In that approach monthly data are used to obtain better estimates of the parameters of the model. Contrary to this, and for the same reasons explained above, we keep the parameters estimated via the quarterly model untouched and use the data for obtaining progressively better estimates of the states, given those parameter estimates. Our approach is desirable especially in policy institutions where the DSGE models used for forecasting are generally very complex, they might have taken several months, or even years, to agree on, build and estimate and therefore require a lot of time and effort to change, re-estimate, and explain anew to the policymakers. In such circumstances it is unpractical and possibly unreasonable to re-estimate the model frequently. This makes our framework more desirable.

Finally, let us comment on the aspect of our approach which combines the structural model with auxiliary data. A similar idea is in Boivin and Giannoni (2006) who have proposed to estimate structural DSGE model by treating observable variables as imperfect measures of the economic concepts of the model. In this context, they show that augmenting the model with quarterly auxiliary variables can improve the identification of the states of the model and hence improve the estimation of the structural parameters in the quarterly model. Contrary to their approach, our emphasis is on exploiting the timelines of un-modelled timely data in order to obtain early estimates of modeled key variables, such as GDP growth, or latent concepts, such as the output gap, and provide a structural interpretation in real time.

The framework proposed here builds on our early work in Giannone, Monti and Reichlin (2010). In the present work we have solved an important identification problem arising to time aggregation which limited the applicability of the framework and provide a precise analytical solution which gives identification conditions that can be tested in practice. We believe that this solution is of more general interest than the specific application of this paper. Furthermore the empirical analysis highlights a wide range of applications of general use for policy and academic research which were not explored in that early work.

6. Conclusions

The paper develops a framework to combine the insights provided by structural models and the real time analysis of the flow of data publications (now-cast).

In this framework we "borrow" the quarterly parameter estimates of the

DSGE and we provide a mapping from a quarterly dynamic stochastic general equilibrium (DSGE) model to a monthly specification that maintains the same economic restrictions and has real coefficients. We then show how to adapt the monthly model so as to take into consideration realistic features of the information structure such as non-synchronous infra-quarter data releases. Finally we augment the model with data which are potentially useful for providing early signals on the state of the economy but are not included in the DSGE.

By construction, by the time quarterly data are published, the approach has no advantage with respect to the standard quarterly DSGE model. However, at any time before that date, it allows exploiting the data flow for updating, given the estimated parameters, the estimates of the states. This delivers increasingly accurate signals about the current value of key variables as well as capturing the effect of particular shocks in real time.

Our empirical application shows that timeliness matters for both the forecast and its structural interpretation. It also highlights that the shock decomposition is very uncertain in real time and that, by exploiting high frequency information, we can significantly decrease this uncertainty with the estimates of the shocks converging to the ex-post decomposition faster. Although much research has been devoted to real time analysis, the identification of structural shocks in real time has been typically overlooked in the literature. In our analysis of the great recession we have shown that our framework would have allowed to understand faster than the quarterly model that the economy was being hit not only by a risk premium shock but also by a technology shock, therefore signaling at an early stage that both the financial sector and the real economy were affected.

Finally, let us highlight that our proposed approach is simple and not invasive, as it can be applied to existing DSGEs with no need to re-estimate them frequently and without changing the model's ex-post interpretation of the data.

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References

[1] Anderson, B.D.O., M. Deistler, E. Felsenstein, B. Funovits, L. Kölbl and M. Zamani, 2014. "Multivariate AR Systems and Mixed Frequency Data: Identifiability and Estimation," *mimeo.*

[2] Baker, S.R., N. Bloom and S.J. Davis, 2015. "Measuring Economic Policy Uncertainty." NBER working paper 21633 Banbura, M. D. Giannone and L. Reichlin, 2011. "Now-casting," in Michael P. Clements and David F. Hendry, editors, Oxford Handbook on Economic Forecasting, pages 193-224.

[3] Bernanke, B., M. Gertler and S. Gilchrist, 1999. "The Financial Accelerator in a Quantitative Business Cycle Framework," in *Handbook of Macroeconomics*, ed. by J.B. Taylor and M. Woodford, vol. 1, North Holland, Amsterdam.

[4] Boivin, J. and M. Giannoni,2006. "DSGE Models in a Data-Rich Environment," NBER Working Papers 12772, National Bureau of Economic Research, Inc

[5] Cervena, M. and M. Schneider, 2014. "Short-term forecasting GDP with a DSGE model augmented by monthly indicators," International Journal of Forecasting, 30(3), Pages 498-516.

[6] Chari, V. V., Patrick J. Kehoe, and Ellen R. McGrattan. 2009. "New Keynesian Models: Not Yet Useful for Policy Analysis." American Economic Journal: Macroeconomics, 1(1): 242-66.

[7] Christiano, L. J., M.S. Eichenbaum, and M. Trabandt. 2015. "Understanding the Great Recession." American Economic Journal: Macroeconomics, 7(1): 110-67.

[8] Christiano, L., R. Motto and M. Rostagno, 2003. "The Great Depression and the Friedman-Schwartz Hypothesis," Journal of Money, Credit and Banking, 35, 1119-1197.

[9] De Graeve, F., 2008. "The external Finance Premium and the Macroeconomy: US Post-WWII Evidence," Jounrla of Economic Dynamics and Control, 32(11), 3415-3440.

[10] Del Negro, M., R. Hasegawa and F. Schorfheide, 2014. "Dynamic Prediction Pools: An Investigation of Financial Del Frictions and Forecasting Performance," NBER Working Paper No. 20575.

[11] Del Negro, M., and F. Schorfheide, 2013. "DSGE Model-Based Forecasting," Handbook of Economic Forecasting, Volume 2, Part A, p.57 - 140.

[12] Del Negro M. and F. Schorfheide, 2004."Priors from General Equilibrium Models for VARs," International Economic Review, 45 (2004): 643-673.

[13] Diebold, F.X. and R.S. Mariano, 1995."Comparing Predictive Accuracy," Journal of Business and Economic Statistics, 13, 253-263.

[14] Doz, C., D. Giannone and L. Reichlin, 2012. "A Quasi-Maximum Likelihood Approach for Large, Approximate Dynamic Factor Models," Review of Economics and Statistics,Vol. 94, No. 4, Pages 1014-1024.

[15] Foroni, C., M. Marcellino, 2013. "Mixed frequency structural models: estimation, and policy analysis," Working Paper 2013/15, Norges Bank.

[16] Galí, J., F. Smets and R. Wouters, 2012. "Unemployment in an Estimated New Keynesian Model," NBER Macroeconomics Annual, University of Chicago Press, vol. 26(1), pages 329 - 360.

[17] Galí, J., 2011a. "The Return of the Wage Phillips Curve," Journal of the European Economic Association, vol. 9(3), pages 436-461, 06.

[18] Galí, J., 2011b. *Unemployment Fluctuations and Stabilization Policies: A New Keynesian Perspective*, MIT Press (Cambridge, MA).

[19] Giannone, D., Reichlin, L. and Small, D., 2008. "Now-casting GDP and Inflation: The Real Time Informational Content of Macroeconomic Data Releases," Journal of Monetary Economics, vol. 55(4), 665-676

[20] Giannone, D., F. Monti, L. Reichlin, 2010. "Incorporating Conjunctural Analysis in Structural Model." In Volker Wieland, editor, The Science and Practice of Monetary Policy Today, pages 41-57, Springer

[21] Hansen, L.P. and T. Sargent, 1991. *Rational Expectations Econometrics*, Westview Press, Boulder.

[22] Higham, N.J. 2008. " Functions of Matrices: Theory and Computation," SIAM.

[23] Hilberg, B. and J. Hollmayr, 2013. "Asset Prices, Collateral, and Unconventional Monetary Policy in a DSGE Model," Bundesbank Discussion Papers 36/2013.

[24] Jaimovich, N. and S. Rebelo, 2009. "Can News about the Future Drive the Business Cycle?," American Economic Review, American Economic Association, vol. 99(4), pages 1097-1118

[25] Justiniano, A., G. Primceri and A. Tambalotti, 2010. "Investment Shocks and Business Cycles," Journal of Monetary Economics, 57(2), pp. 132-145

[26] Kim, T.B., 2010. "Temporal Aggregation Bias and Mixed Frequency Estimation of New Keynesian Model", mimeo.

[27] Monti, F., 2010. "Combining Judgment and Models," Journal of Money, Credit and Banking, Blackwell Publishing, vol. 42(8), pages 1641-1662.

[28] Sims, C.A., 2002. "Solving Linear Rational Expectations Models," Computational Economics, Springer, 20(1-2), 1-20.

[29] Smets, F., and R. Wouters, 2007. "Shocks and Frictions in US Business Cycles: A Bayesian DSGE Approach," American Economic Review, American Economic Association, vol. 97(3), pages 586-606.

[30] Wu, J.C. and F.D. Xia, 2014. "Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound", forthcoming in Journal of Money, Credit, and Banking.

[31] Zamani, M., W. Chen, B. D. O. Anderson, M. Deistler, and A. Filler, 2011. "On the zeros of blocked linear systems with single and mixed frequency data," in Proceedings of the 50th IEEE Conference on Decision and Control and European Control Conference (CDC-ECC), pp. 4312-4317.

Appendix A. The model

Here we summarize the key log-linear equations of the GSW model. We refer to Galí, Smets and Wouters (2012) for a more detailed description of the model.

- Consumption Euler equation:

$$\hat{c}_t = c_1 E_t\left[\hat{c}_{t+1}\right] + (1-c_1)\hat{c}_{t-1} - c_2\left(\hat{R}_t - E_t\left[\hat{\pi}_{t+1}\right] - \hat{\varepsilon}_t^b\right)$$

  with $c_1 = (h/\tau)/(1+(h/\tau))$, $c_2 = (1-h/\tau)/(1+(h/\tau))$ where h is the external habit parameter. $\hat{\varepsilon}_t^b$ is the exogenous AR(1) risk premium process.

- Investment Euler equation:

$$\hat{i}_t = i_1\hat{i}_{t-1} + (1-i_1)\hat{\imath}_{t+1} + i_2\hat{Q}_t^k + \hat{\varepsilon}_t^q$$

  with $i_1 = 1/(1+\beta)$, $i_2 = i_1/(\tau^2\Psi)$ where β is the discount factor and Ψ is the elasticity of the capital adjustment cost function. $\hat{\varepsilon}_t^q$ is the exogenous AR(1) process for the investment specific technology.

- Aggregate demand equals aggregate supply:

$$\begin{aligned} \hat{y}_t &= \frac{c_*}{y_*}\hat{c}_t + \frac{i_*}{y_*}\hat{i}_t + \hat{\varepsilon}_t^g + \frac{r_*^k k_*}{y_*}\hat{u}_t && \text{(A.1)} \\ &= \mathcal{M}_p\left(\alpha\hat{k}_t + (1-\alpha)\hat{L}_t + \hat{\varepsilon}_t^a\right) && \text{(A.2)} \end{aligned}$$

  with $\mathcal{M}_p$ reflecting the fixed costs in production which corresponds to the price markup in steady state. $\hat{\varepsilon}_t^g, \hat{\varepsilon}_t^a$ are the AR(1) processes representing exogenous demand components and the TFP process.

- Price-setting under the Calvo model with indexation:

$$\hat{\pi}_t - \gamma_p\hat{\pi}_{t-1} = \pi_1\left(E_t\left[\hat{\pi}_{t+1}\right] - \gamma_p\hat{\pi}_t\right) - \pi_2\mu_t^p + \hat{\varepsilon}_t^p$$

  with $\pi_1 = \beta$, $\pi_2 = (1-\theta_p\beta)(1-\theta_p)/\left[\theta_p(1+(\mathcal{M}_p-1)\varepsilon_p)\right]$ and θ_p and γ_p are, respectively, the probability and indexation of the Calvo model, and ε_p is the curvature of the aggregator function. The price markup μ_t^p is equal to the inverse of the real marginal $\hat{mc}_t = (1-\alpha)\hat{w}_t + \alpha\widehat{rk}_t - \hat{A}_t$.

- Wage-setting under the Calvo model with indexation:

$$\pi_t^w = \gamma_w \pi_{t-1}^p + \beta E_t \left[\pi_{t+1}^w - \gamma_w \pi_t^p\right] - \lambda_w \phi u_t + \lambda_w \mu_t^w$$

  where the unemployment rate $u_t = l_t - n_t$ is defined so as to include all the individuals who would like to be working (given current labour market conditions, and while internalizing the benefits that this will bring to their households) but are not currently employed.

- Capital accumulation equation:

$$\hat{\bar{k}}_t = \kappa_1 \hat{\bar{k}}_{t-1} + (1-\kappa_1)\hat{i}_t + \kappa_2 \hat{\varepsilon}_t^q$$

  with $\kappa_1 = 1 - (i_*/\bar{k}_*)$, $\kappa_2 = (i_*/\bar{k}_*)(1+\beta)\Psi$. Capital services used in production are defined as: $\hat{k}_t = \hat{u}t + \hat{\bar{k}}_{t-1}$

- Optimal capital utilisation condition:

$$\hat{u}_t = \frac{1-\phi}{\phi}\hat{r}_t^k$$

  with ϕ being the elasticity of the capital utilisation cost function.

- Optimal capital/labour input condition:

$$\hat{k}_t = \hat{w}_t - \hat{r}_t^k + \hat{L}_t$$

- Monetary policy rule:

$$\hat{R}_t = \rho_r \hat{R}_{t-1} + (1-\rho_r)(r_\pi \hat{\pi}_t + r_y ygap_t) + r_{\Delta y}\Delta y_t + \varepsilon_t^r$$

  where $ygap_t = y_t - yflex_t$ is the difference between actual output and the output in the flexible price and wage economy in absence of distorting price and wage markup shocks.

- In practice, as Del Negro, Hasegawa and Schorfheide (2014) show for the SW, adding the financial frictions to this model simply amount to replacing the equation for the value of the capital stock with the following conditions:

$$E_t\left[\hat{R}_t^k - \hat{R}_t\right] = b_t + \zeta_{sp,b}(\hat{Q}_t^k + \bar{k}_t - n_t) + \sigma_{\omega,t}$$

$$\hat{R}^k_t - \pi_t = \frac{r^k_*}{r^k_* + 1 - \delta} r^k_t + \frac{1-\delta}{r^k_* + 1 - \delta} \hat{Q}^k_t - \hat{Q}^k_{t-1}$$

$$n_t = \zeta_{nrk}(\hat{R}^k_t - \pi_t) - \zeta_{nr}(\hat{R}_t - \pi_t) + \zeta_{nqk}(\hat{Q}^k_{t-1} + \bar{k}_{t-1}) + \zeta_{nn} n_{t-1} - \frac{zeta_{n\sigma}}{sp\sigma} \sigma\omega, t-1,$$

which define respectively the spread, the return on capital and the evolution of the entrepreneurial net worth. Unlike Del Negro, Hasegawa and Schorfheide (2014) we estimate the parameters in this last equation directly. The measure of spreads in the observables is related to the model variables $E_t\left[\hat{R}^k_t - \hat{R}_t\right]$ as follows:

$$Spread = SP^* + 100 + E_t\left[\hat{R}^k_t - \hat{R}_t\right]$$

We calibrate the δ, $\frac{c}{g}$ and h to standard values of 0.025, 0.18 and 0.7 respectively, while we calibrate the following parameters to their mean posterior values in GSW (2012): $\beta = (0.31/100 + 1)^{-1}$, $\Psi = 3.96$, $\zeta_p = 10$, $\rho_{chi} = 0.99$, and $cgy = 0.69$.

The priors of the estimated parameters are reported below.

	Prior Distribution				Prior Distribution		
	Distr.	mean	st.dev		Distr.	mean	st.dev
ν	B	0.5	0.2	γ_p	B	0.5	0.1
ρ_π	N	1.5	0.125	γ_w	B	0.5	0.1
ρ_{ygap}	N	0.12	0.01	ψ	B	0.5	0.15
$\rho_{\Delta ygap}$	N	0.12	0.01	ρ_r	B	0.75	0.10
θ_w	B	0.5	0.1	ϕ	N	2	0.5
θ_p	B	0.5	0.1	$\zeta_{n\sigma}$	N	2	0.5
τ	N	0.40	0.1	σ_χ	U	2.5	1.44
SP^*	N	2	0.5	Π^*	G	0.62	0.1
l^*	N	0	0.1	ζ_{spb}	B	0.2	0.1
ζ_{rk}	N	0.2	0.1	ζ_{nr}	N	0.2	0.1
ζ_{nq}	N	0.2	0.1	ζ_{nn}	B	0.8	0.1
ρ_b	B	0.5	0.2	σ_b	U	2.5	1.44
ρ_q	B	0.5	0.2	σ_q	U	2.5	1.44
ρ_g	B	0.5	0.2	σ_g	U	2.5	1.44
ρ_a	B	0.5	0.2	σ_a	U	2.5	1.44
ρ_{ms}	B	0.5	0.2	σ_r	U	2.5	1.44
ρ_p	B	0.5	0.2	σ_p	U	2.5	1.44
ρ_w	B	0.5	0.2	σ_w	U	2.5	1.44
ρ_{nw}	B	0.5	0.2	σ_{nw}	U	2.5	1.44

Table A.3: Prior distribution of the parameters of the model

Appendix B. Auxiliary data and Calendar

	timing	release	publ. lag	transformation	FRED
1	1^{st} day of the 1^{st} month	-	-	-	-
2	1^{st} bus. day of the 1^{st} month	Economic Policy Uncertainty Index	m-1	1	USEPUINDXM
3	1^{st} bus. day of the 1^{st} month	PMI	m-1	1	NAPM
4	1^{st} bus. day of the 1^{st} month	construction	m-2	1	TTLCONS-
5	1^{st} Friday of the 1^{st} month	Employment situation	m-1	2 (earnings)	AWHNONAG, CE16OV, UNRATE
6	Middle of the 1^{st} month	CPI and PPI	m-1	2	CPIAUSL
7	15^{th} to 17^{th} of the 1^{st} month	Industrial Production	m-1	2	INDPRO
8	3^{rd} week of the 1^{st} month	Credit and M2 (H8 release)	m-1	2	LOANS, M2
9	later part of the 1^{st} month	housing starts	m-1	1	HOUST
10	3^{rd} Thursday of the 1^{st} month	Business Outlook Survey: Phil. Fed	m	1	-
11	Last week of 1^{st} month	GDP release	q-1		COMPNFB, FPI, GDPC1, GDPDEF
12	Day after GDP release	PCE, RDPI	m-1	2	PCE,DSPIC96
13	Day after GDP release	PCE price index	m-1	2	PCEPI
14	Last day of the 1^{st} month	Fed Funds rate and credit spread	m	3	FEDFUNDS, BAAY10
15	1^{st} bus. day of the 2^{nd} month	Economic Policy Uncertainty Index	m-1	1	USEPUINDXM
16	1^{st} bus. day of the 2^{nd} month	PMI	m-1	1	NAPM
17	1^{st} bus. day of the 2^{nd} month	construction	m-2	1	TTLCONS
18	1^{st} Friday of the 2^{nd} month	Employment situation	m-1	2 (earnings)	AWHNONAG, CE16OV, UNRATE
19	Middle of the 2^{nd} month	CPI and PPI	m-1	2	CPIAUSL
20	15^{th} to 17^{th} of the 2^{nd} month	Industrial Production	m-1	2	INDPRO
21	3^{rd} week of the 2^{nd} month	Credit and M2 (H8 release)	m-1	2	LOANS, M2
22	later part of the 2^{nd} month	housing starts	m-1	1	HOUST
23	3^{rd} Thursday of the 2^{nd} month	Business Outlook Survey: Phil. Fed	m	1	-
24	Last week of 2^{nd} month	PCE, RDPI	m-1	2	DSPIC96, PCE
25	Last week of 2^{nd} month	PCE price index	m-1	2	PCEPI
26	Last day of the 2^{nd} month	Fed Funds rate and credit spread	m	3	FEDFUNDS, BAA10Y
27	1^{st} bus. day of the 3^{rd} month	Economic Policy Uncertainty Index	m-1	1	USEPUINDXM
28	1^{st} bus. day of the 3^{rd} month	PMI	m-1	1	NAPM
29	1^{st} bus. day of the 3^{rd} month	construction	m-2	1	TTLCONS
30	1^{st} Friday of the 3^{rd} month	Employment situation	m-1	2 (earnings)	AWHNONAG, CE16OV, UNRATE
31	Middle of the 3^{rd} month	CPI and PPI	m-1	2	CPIAUSL
32	15^{th} to 17^{th} of the 3^{rd} month	Industrial Production	m-1	2	INDPRO
33	3^{rd} week of the 3^{rd} month	Credit and M2 (H8 release)	m-1	2	LOANS, M2
34	later part of the 3^{rd} month	housing starts	m-1	1	HOUST
35	3^{rd} Thursday of the 3^{rd} month	Business Outlook Survey: Phil. Fed	m	1	-
36	Last week of 3^{rd} month	PCE, RDPI	m-1	2	PCE, DSPI96C
37	Last week of 3^{rd} month	PCE prce index	m-1	2	PCEPI
38	Last day of the3^{rd} month	Fed Funds rate and credit spread	m	3	FEDFUNDS, BAAY10

Table B.4: Data releases are indicated in rows. Column 1 indicates the progressive number associated to each "vintage". Column 2 indicates the official dates of the publication. Column 3 indicates the releases. Column 4 indicates the publishing lag: e.g. IP is release with 1-month delay (m-1). Column 4 indicate the transformation: 1 indicates monthly differences, 2 indicates monthly growth rates, 3 stands for no transformation. All data are available from the FRED database of the St. Louis Fed

Appendix C. Additional Figures and Tables

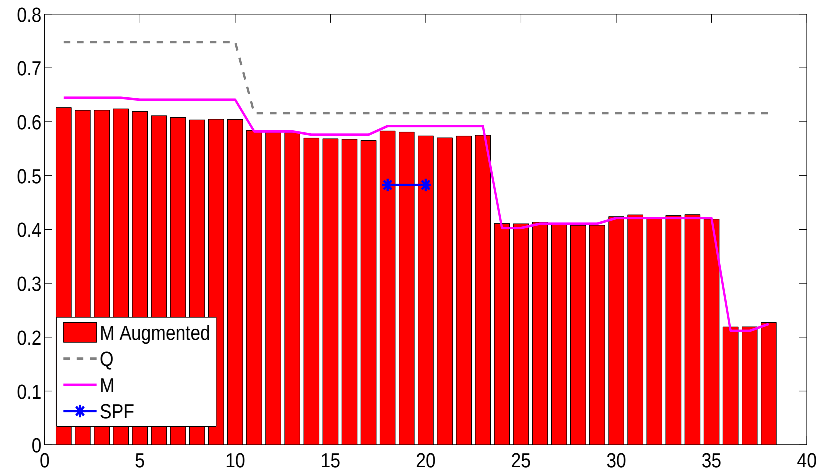

Figure C.7: **RMSFE of Consumption growth now-casts: full sample**

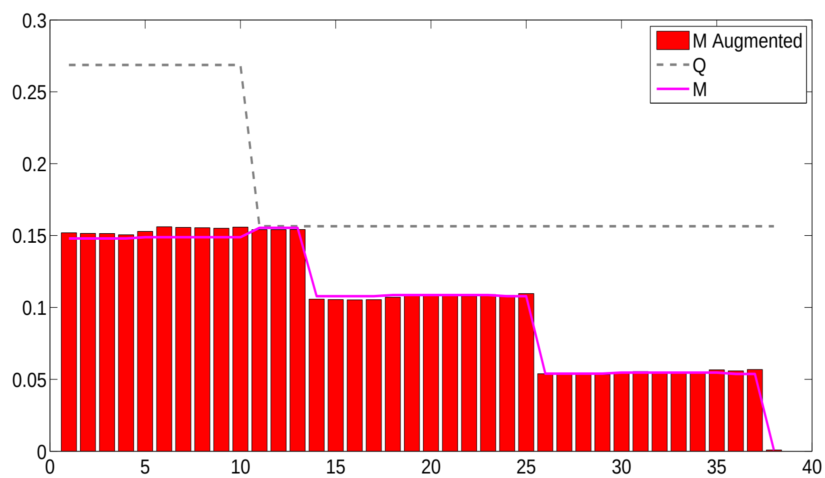

Figure C.8: **RMSFE of policy rate now-casts: full sample**

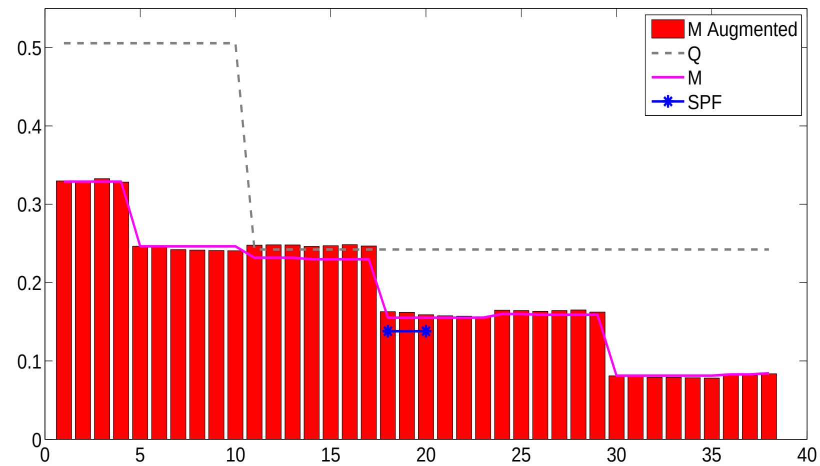

Figure C.9: **RMSFE of unemployment, estimated in real time throughout the quarter**

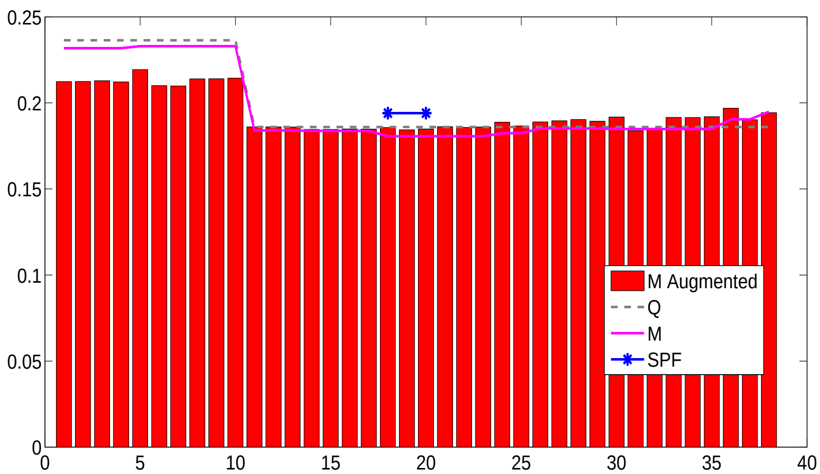

Figure C.10: **RMSFE of annual GDP deflator inflation now-casts throughout the quarter**

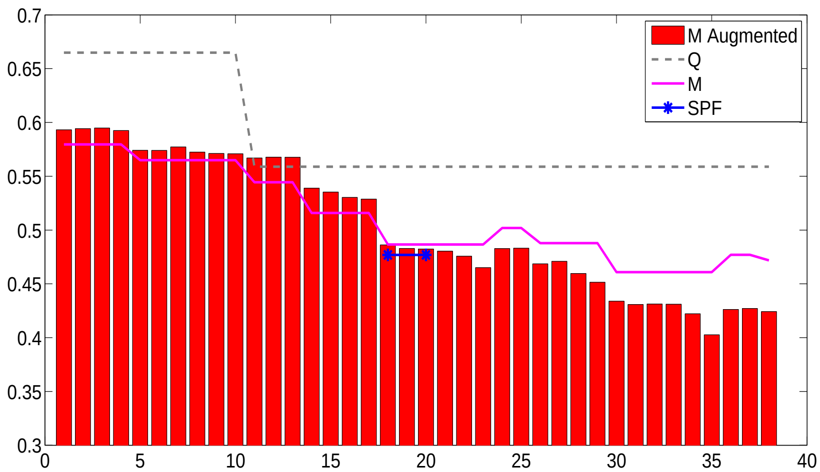

Figure C.11: **RMSFE of GDP growth now-casts: 1995-2007**

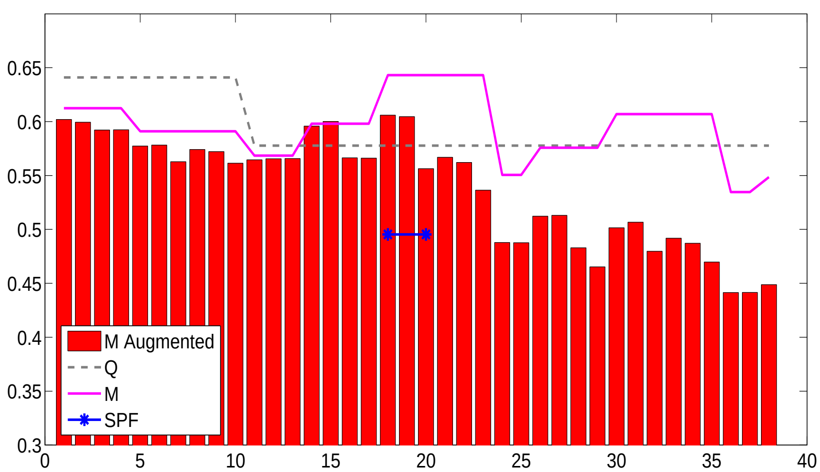

Figure C.12: **RMSFE of GDP growth now-casts: 2008-2014**

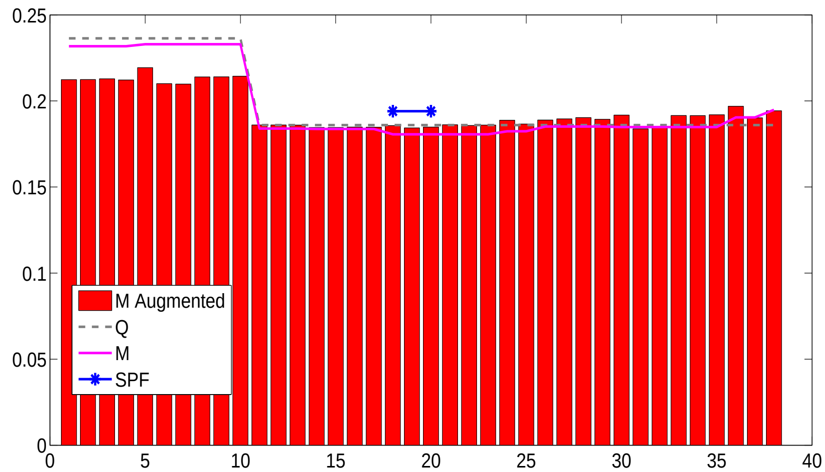

Figure C.13: **RMSFE of GDP deflator inflation now-casts: 1995-2007**

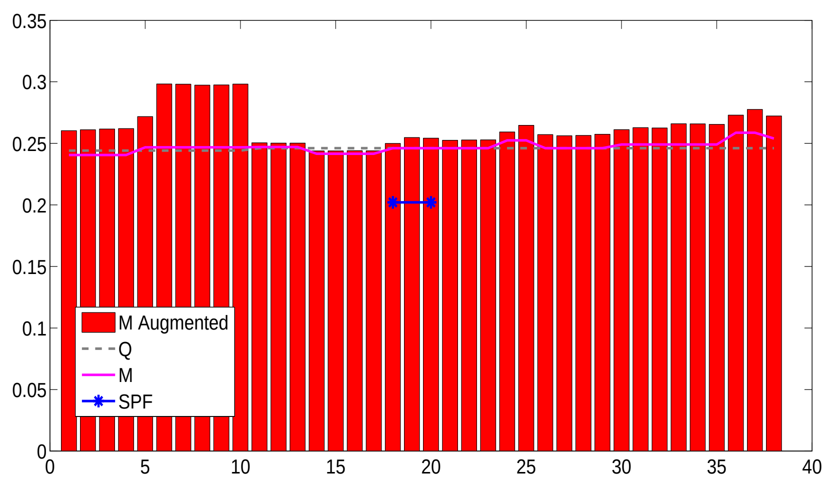

Figure C.14: **RMSFE of GDP deflator inflation now-casts: 2008-2014**

Table C.5: quarter-on-quarter GDP growth forecasts: pre-crisis sample -1995-2007

	SPF	Q	Q+cond	M	M+panel
Q0	**0.4769*** **	0.5589	0.5598	**0.4865***	**0.4824***
Q1	**0.5407** **	0.6698	0.6683	0.6386	0.6526
Q2	0.5557	0.7117	0.7122	0.6878	0.7031
Q3	**0.5493***	0.7091	0.7119	0.6930	0.7054
Q4	0.5613	0.6873	0.6915	0.6737	0.6877

Table C.6: annual GDP deflator inflation: pre-crisis sample - 1995-2007

	SPF	Q	Q+cond	M	M+panel
Q0	0.1940*	0.1861	0.1865 8	0.1804	0.1844
Q1	0.3754	0.3805	0.3799	0.3680	0.3737
Q2	**0.5549** **	0.6026	0.7064**	**0.5796***	**0.5824***
Q3	**0.7547** **	0.8517	0.8519	0.8204	**0.8173***
Q4	0.9949	0.9926	0.9932	**0.8669***	0.9544

Table C.7: quarter-on-quarter GDP growth forecasts: 2008-2014 sample

	SPF	Q	Q+cond	M	M+panel
Q0	**0.4954*** **	0.5777	0.5776	0.6431	0.5563
Q1	0.6632	0.6696	0.6719	0.6593	0.6549
Q2	0.7753**	0.7260	0.7237	0.7289	0.7240
Q3	0.8553*	0.7783	0.7744	0.7902	0.7902
Q4	0.8914	0.8548	0.8552	0.8757	0.8670

Table C.8: annual GDP deflator inflation forecasts: 2008-2014 sample

	SPF	Q	Q+cond	M	M+panel
Q0	**0.2020** **	0.2460	0.2454	0.2461	0.2547
Q1	**0.3131*** **	0.4104	0.4073	0.4091	0.4233
Q2	**0.4663** **	0.5882	0.5533	0.5821	0.5866
Q3	**06211** **	0.7696	0.7610	0.7568	0.7605
Q4	1.0191**	0.8197	0.8071	0.8137	**0.7853***

RMSFE of forecasts with horizons 0 to 4, produced in the first half of the second month of the quarter (information cluster 19), approximately when the SPF produce their own forecasts. We indicate with ***, ** and * the forecasts that are statistically significantly different from the forecast produced by the model with the balanced panel (Q, third column in the tables) with a 1%, 5% and 10% level, respectively, based on the Diebold-Mariano (1995) test