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Exploiting the monthly data flow in structural forecasting

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ABSTRACT

A quarterly stochastic general equilibrium (DSGE) model is combined with a now-casting model designed to read timely monthly information as it becomes available. This implies (1) mapping the structural quarterly DSGE with a monthly version that maintains the same economic restrictions; (2) augmenting the model with a richer data set and (3) updating the estimates of the DSGE's structural shocks in real time following the publication calendar of the data. Our empirical results show that our methodology enhances the predictive accuracy in now-casting. An analysis of the Great Recession also shows that our framework would have helped tracing the DSGE's structural shocks in real time, obtaining, for example, a more timely account of the 2008 contraction.

1. Introduction

Obtaining early signals on the current state of the economy and reading them through the lens of a structural model is of interest in policymaking and academic circles alike. With this objective in mind, we develop 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.

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 this paper will show, this information is valuable not only for pure forecasting/now-casting purposes but also for monitoring economically meaningful shocks in real time.

An extensive recent now-casting literature, starting with Giannone et al. (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 et al., 2011). Exploiting the fact that both the now-casting model of Giannone et al. (2008)

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and the generic DGSE have a state space form, it is possible 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 linearized quarterly model has a unique monthly specification with real coefficients and to select the appropriate monthly specification, if there is more than one. Second, the monthly specification of the model is used to exploit the infra-quarter data which are available at a monthly frequency. Third, the monthly model is then augmented with data which are typically not included in structural models, because they do not have much relevance at a quarterly frequency, but are potentially useful because of their timeliness. An obvious example is survey data, whose value is only due to their short publication lag and, by the end of the quarter, does 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 modelling and academic research. We derive the monthly state-space that coincides, when put on quarterly data, with a variant of the model in Galí et al. (2012) that incorporates financial frictions as in Bernanke et al. (1999) and augment it with auxiliary monthly macro indicators potentially useful for now-casting. The performance of our methodology is assessed in terms of forecast accuracy both on average over the whole evaluation sample, and in the specific episode of the Lehman Bros. crisis. The now-cast 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 et al., 2008). But here, crucially, the analysis is based on a structural model, so it can also exploit the real-time information flow to now-cast unobservable 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, the empirical application focuses on the Lehman Bros. crisis and compares 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 trace, in real time, the shocks driving the business cycle. Tracing in a timely fashion the sources of the fluctuations is crucial for designing the appropriate policy response. Moreover, our approach delivers an interpretation of the auxiliary variables through the lens of the model.

The paper is organized as follows. Section 2 illustrates the methodology, Section 3 the data and the structural model, while in Section 4 we provide a forecast evaluation and use the framework for real time structural analysis. The relation of our approach to the literature is then discussed and the final section concludes.

2. Methodology

The next section shows how to obtain the monthly specification of the quarterly DSGE model that has real coefficients and discusses under which conditions such a monthly model exists and is unique. It then details how to link the monthly model with the auxiliary variables for now-casting.

2.1. From monthly to quarterly specification

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 the time in quarters, $Y_{t_q} = (y_{1,t_q}, \dots, y_{k,t_q})'$ 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 functions 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. The model and its parameters are taken 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 $Y_{t_m} = (y_{1,t_m}, \dots, y_{k,t_m})'$ 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 the end of the quarter, i.e. when t_m corresponds to March, June, September or December (e.g. see Giannone et al., 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

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

observed on the last month of each quarter. Hence, it follows that our original state equation

$$s_{t_q} = \mathcal{T}_\theta \, s_{t_q-1} + B_\theta \varepsilon_{t_q} \tag{2}$$

can be rewritten in terms of the monthly latent states as

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

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

Assume that the monthly states can be written as

$$s_{t_m} = \mathcal{T}_m \, s_{t_m-1} + \mathcal{B}_m \varepsilon_{m,t_m} \tag{4}$$

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

$$s_{t_m} = \mathcal{T}_m^3 \, s_{t_m-3} + [\mathcal{B}_m \varepsilon_{m,t_m} + \mathcal{T}_m \mathcal{B}_m \varepsilon_{m,t_m-1} + \mathcal{T}_m^2 \mathcal{B}_m \varepsilon_{m,t_m-2}]. \tag{5}$$

We are interested in finding a mapping from the quarterly model to the monthly model: the relation between Eqs. (1), or equivalently (3), and (5) implies that the monthly model can be recovered from the following equations:

$$\mathcal{T}_m = \mathcal{T}_\theta^{\frac{1}{3}} \tag{6}$$

$$vec(\mathcal{B}_m \mathcal{B}_m') = (I + \mathcal{T}_m \otimes \mathcal{T}_m + \mathcal{T}_m^2 \otimes \mathcal{T}_m^2)^{-1} vec(\mathcal{B}_\theta \mathcal{B}_\theta'). \tag{7}$$

From (6) 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 exists 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 $\mathcal{T}_\theta$. The following procedure is proposed in order to select among these alternative cube roots of $\mathcal{T}_\theta$. In the case of real eigenvalues, simply select their real cube root. In the case of complex conjugate couples, choose the cube root which is characterized by less oscillatory behaviour, i.e. the cube root with the 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. (2016) 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 arises mainly, but not 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 consider whether there are ways to render the model diagonalizable.

$\mathcal{B}_m \mathcal{B}_m'$ can be obtained as the solution of Eq. (7). In order to recover $\mathcal{B}_m$, 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

[2] If the variables considered are stocks, the formulation (4) 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 modelling this monthly concept as autoregressive introduces some misspecification. Doz et al. (2012) show the effect of such misspecification is small.

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

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

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 $m_1 + m_2 + \cdots + m_p = n$ with p being the number of blocks. We will denote by s the number of distinct eigenvalues (see, for example, Higham, 2008 for further details).

assumption, $\mathcal{B}_m$ can be obtained directly from the following equation:

$$\mathcal{B}_m + \mathcal{T}_m \mathcal{B}_m + \mathcal{T}_m^2 \mathcal{B}_m = \mathcal{B}_q. \tag{8}$$

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

$$Y_{t_m} = \mathcal{M}_m s_{t_m} \tag{9}$$

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

Eqs. (4) and (9) therefore describe the monthly dynamics that are compatible with the quarterly model. The discussion above proves the following proposition.

Proposition 1. *Consider the quarterly state space model (1). Let us assume that the monthly states follow an autoregressive model* $s_{t_m} = \mathcal{T}_m\, s_{t_m-1} + \mathcal{B}_m \varepsilon_{m,t_m}$, *where* $\mathcal{T}_m$ *is real and stable and* ε_{m,t_m} *are orthonormal shocks. Let us also assume that* $\mathcal{T}_\theta$ *is diagonalizable. Then the monthly counterpart of model (1) is*

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

where Y_{t_m} *are the possibly latent monthly counterparts of the original model's observables and* s_{t_m} *are the monthly states. The matrices* $\mathcal{T}_m$, $\mathcal{M}_m$ and $\mathcal{B}_m$ *are*:

$$\begin{aligned} \mathcal{T}_m &= \mathcal{T}_\theta^{\frac{1}{3}} = VD^{\frac{1}{3}}V^{-1} \\ vec(\mathcal{B}_m \mathcal{B}_m') &= (I + \mathcal{T}_m \otimes \mathcal{T}_m + \mathcal{T}_m^2 \otimes \mathcal{T}_m^2)^{-1} vec(\mathcal{B}_\theta \mathcal{B}_\theta') \\ \mathcal{M}_m &= \left(\mathcal{M}_{0,\theta} + 0 \cdot L + 0 \cdot L^2 + \mathcal{M}_{1,\theta} L^3\right) \end{aligned} \tag{11}$$

where the diagonal matrix D and the invertible matrix V that satisfy $\mathcal{T}_\theta = VDV^{-1}$. *If we also assume that* $\varepsilon_{m,t_m} = \varepsilon_{m,t_m-1} = \varepsilon_{m,t_m-2} = \varepsilon_{t_q}$, *then* $\mathcal{B}_m + \mathcal{T}_m \mathcal{B}_m + \mathcal{T}_m^2 \mathcal{B}_m = \mathcal{B}_q$.

Given the model in Proposition 1, it is relatively straightforward to handle mixed frequencies and add auxiliary higher frequency information, as shown in Sections 2.2 and 2.3.

2.2. Mixed frequency and jagged edged data

If all the observables of the model were available at a monthly frequency, one could simply use the monthly model defined by Eqs. (4) and (9) 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 unsynchronized 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 et al. (2008) and define the following state space model

$$\begin{aligned} s_{t_m} &= \mathcal{T}_m\, s_{t_m-1} + \mathcal{B}_m \varepsilon_{m,t_m} \\ Y_{t_m} &= \mathcal{M}_m(L) s_{t_m} + V_{t_m} \end{aligned} \tag{12}$$

where $V_{t_m} = (v_{1,t_m}, \dots, v_{k,t_m})$ 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

Denote by $X_{t_m} = (x_{1,t}, \dots, x_{n,t})'$ 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, define the relation between the auxiliary variables X_{t_q} and the model's observable variables at a quarterly frequency:

$$X_{t_q} = \mu + \Lambda Y_{t_q} + e_{t_q} \tag{13}$$

where e_{t_q} is orthogonal to the quarterly variables entering the model. This equation is used to estimate the coefficients Λ and the variance–covariance matrix of the shocks $E(e_{t_q} e_{t_q}') = R$. Flat priors are used on all the parameters, so that the posterior model corresponds to the OLS estimate. The choice of modelling X_{t_q} as solely dependent on the observables Y_{t_q} rather than depending in a more general way from the states s_{t_q} is motivated by the fact that we do not want them to affect the inference about the history of the latent states and shocks, therefore they must be relevant *only* in real time. In this way the procedure is minimally invasive with respect to the original quarterly model.

Let us now focus on incorporating the auxiliary variables in their monthly form. As stressed above, $X_{t_m} = (x_{1,t}, \dots, x_{n,t})'$ is the vector of these auxiliary stationary monthly variables transformed so as to correspond to quarterly quantities at the end of each quarter. X_{t_m} can be related to the monthly observables Y_{t_m} using the equivalent of Eq. (13) for the monthly frequency (the bridge model), and expanding the monthly model in Proposition 1 as follows:

$$\begin{aligned} s_{t_m} &= \mathcal{T}_m \, s_{t_m-1} + \mathcal{B}_m \varepsilon_{m,t_m} \\ Y_{t_m} &= \mathcal{M}_m(L) s_{t_m} + V_{t_m} \\ X_{t_m} &= \mu + \Lambda Y_{t_m} + e_{t_m} \end{aligned} \tag{14}$$

where $e_{t_m} = (e_{1,t_m}, \dots, e_{k,t_m})$ 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. This approach takes 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).

3. Empirical analysis

The empirical application is based on a variant of the model in Galí et al. (2012) that incorporates financial frictions as in Bernanke et al. (1999). This section provides more details on the model and on the auxiliary monthly macro indicators used to augment it.

3.1. The structural model

We implement the methodology described above on a variant of the medium-scale model presented in Galí et al. (2012; henceforth GSW) that includes financial frictions as in Bernanke et al. (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 et al. (2003), De Graeve (2008) and Del Negro et al. (2016). 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. The main log-linearized equations of the model are presented in the online appendix and refer to Galí et al. (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 (2016), 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, and 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 posterior distribution for the model's parameters is estimated annually at the beginning of each year of the evaluation sample, which goes from 1995 to 2014, using data from 1964Q1 onwards.

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] Fig. 1 shows the decomposition of GDP growth.

Results confirm that over the whole sample the investment specific shock plays a sizeable role (as in Justiniano et al., 2010), though the presence of the net worth shock in the model, as in Del Negro et al. (2016), 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 et al. (2009).

Interestingly, our model attributes the bulk of the fall in GDP at the end of 2008 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 et al. (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.

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

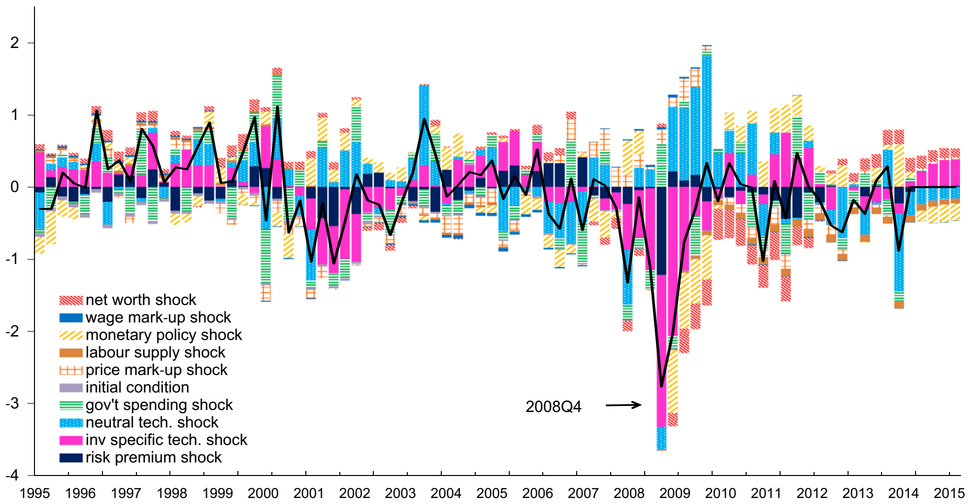

Fig. 1. Shock decomposition of quarterly GDP growth. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

3.2. The auxiliary variables

We consider a dozen 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 et al., 2016 economic policy uncertainty index) and some national accounts quantities. A full list and description of these series is reported in Table 1, which describes a stylized calendar of data releases where the variables have been grouped into 38 clusters according to their timeliness. This allows us to relate the changes in the forecast with groups of variables with similar economic content. For example, although the housing sector is not included in the model, one 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-linearized DSGE.

The first column of Table 1 indicates the progressive number associated to each “vintage” or release cluster, the second column reports the timing of the release and the third the series being released. The fourth column reports the date the release refers to, which gives us the information on the publication lag. For example, 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.

Fig. 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. For example, the variance decomposition of average weekly earnings (EGS), the economic policy uncertainty index (EPU) and the real disposable personal income (RDPI) is mostly explained by the idiosyncratic component, while the model's shocks have most explanatory power for industrial production (IP), total construction (CONST) and PCE inflation (PCEPI).

Let us focus on the three shocks that are driving the fall in GDP in 2008Q4, namely the risk premium shock, the investment specific technology shock and the neutral technology shock. Fig. 2 shows that the risk premium shock is most relevant for nominal variables (such as CPI inflation and PCE inflation) and for 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 of the real economy, like the Philadelphia Business Outlook Survey (PHBOS) and the PMIs.

3.3. The derivation of the monthly model

Let us now consider the computation of the monthly version of the model. As a first step, one must verify that $\mathcal{T}_\theta$ in (1) can be diagonalized. Indeed it can, so there exists a matrix D of eigenvalues and the corresponding matrix V of eigenvectors

[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 et al., 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.

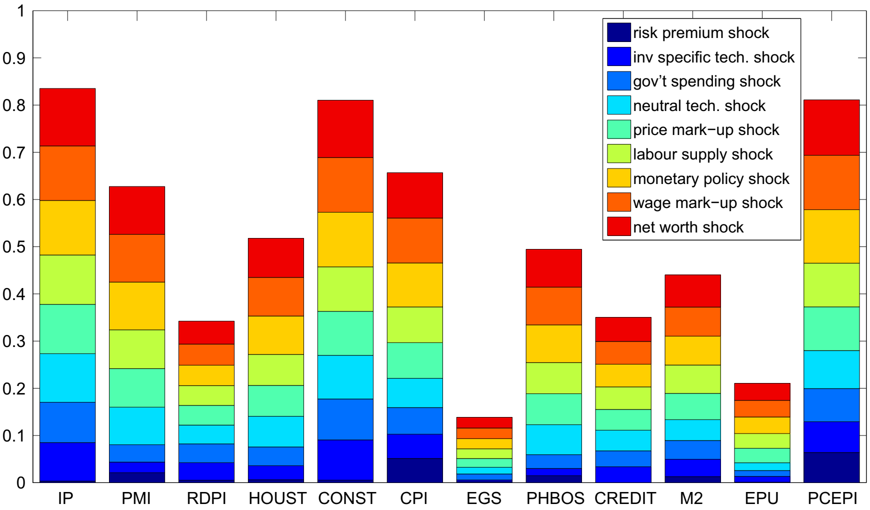

Fig. 2. Forecast error variance decomposition of the auxiliary variables one-quarter ahead.

that satisfy $\mathcal{T}_\theta = VDV^{-1}$. The model's real-valued cube root is identified as described in the previous section, and we also verify that it is indeed the one that maximizes the likelihood.

The now-cast with the monthly model with and without auxiliary variables are then produced and compared 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 shown 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

This section focuses on the evaluation of the now-casting and forecasting performance of the monthly model augmented by auxiliary variables (M Augmented) and compares it with: the quarterly DSGE model based on the balanced panel (Q), and the monthly model (M). The now-casts are evaluated at different dates within the quarter in order to assess the effect of timely monthly information on the accuracy of the now-casts. Forecasts up to 4 quarters ahead are also considered. These now-casts and forecasts are benchmarked 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]

Both point forecasts and density forecasts are shown, focusing on the evaluation sample 1995Q1–2014Q2. Over this sample, the DSGE model is estimated once a year using data from 1964 to the year before the one we are evaluating. Due to availability issues, the data used to estimate the relationship between the auxiliary variables and the model (Λ in system (11)) starts in 1982. This relationship is re-estimated every quarter. Because only few of the auxiliary variables considered are available in real-time from the beginning of the evaluation sample (1995Q1), the exercise is performed in pseudo-real-time: we use the latest vintage of data, but, at each point of the forecast horizon, using only the data available at the time.

The main text of the paper discusses results for GDP deflator inflation, unemployment, the output gap and per capita real GDP growth, our ultimate focus. The online Appendix B reports further results for consumption growth, the policy rate, unemployment and GDP deflator inflation.

4.1. Point forecasts: now-casting

The now-casts are updated 38 times throughout the quarter, corresponding to the stylized calendar 1 described in Table 1. Each update of the now-casts can thus be associated with a date and a set of information being released. We first report how the root mean square forecast error (RMSFE) of our now-casts changes with new information releases. The horizontal axis of Figs. 3 and 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

[6] Where necessary, the SPF's forecasts 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.

Table 1
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 released with 1-month delay (m-1). Column 5 indicates 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.

Vintage	Timing	Release	Publ. lag	Transf.	FRED
1	1st day of the 1st month	–	–	–	–
2	1st bus. day of the 1st m.	Economic policy uncertainty index	m-1	1	USEPUINDXM
3	1st bus. day of the 1st m.	PMI	m-1	1	NAPM
4	1st bus. day of the 1st m.	Construction	m-2	1	TTLCONS
5	1st Friday of the 1st m.	Employment situation	m-1	2	AWHNONAG, CE16OV, UNRATE
6	Middle of the 1st m.	CPI and PPI	m-1	2	CPIAUSL
7	15th to 17th of the 1st m.	Industrial production	m-1	2	INDPRO
8	3rd week of the 1st m.	Credit and M2 (H8 release)	m-1	2	LOANS, M2
9	Later part of the 1st m.	Housing starts	m-1	1	HOUST
10	3rd Thursday of the 1st m.	Business Outlook Survey: Phil. Fed	m	1	–
11	Last week of 1st m.	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 1st m.	Fed Funds rate and credit spread	m	3	FEDFUNDS, BAAY10
15	1st bus. day of the 2nd m.	Economic policy uncertainty index	m-1	1	USEPUINDXM
16	1st bus. day of the 2nd m.	PMI	m-1	1	NAPM
17	1st bus. day of the 2nd m.	Construction	m-2	1	TTLCONS
18	1st Friday of the 2nd m.	Employment situation	m-1	2	AWHNONAG, CE16OV, UNRATE
19	Middle of the 2nd m.	CPI and PPI	m-1	2	CPIAUSL
20	15th to 17th of the 2nd m.	Industrial production	m-1	2	INDPRO
21	3rd week of the 2nd m.	Credit and M2 (H8 release)	m-1	2	LOANS, M2
22	Later part of the 2nd m.	Housing starts	m-1	1	HOUST
23	3rd Thursday of the 2nd m.	Business Outlook Survey: Phil. Fed	m	1	–
24	Last week of 2nd m.	PCE, RDPI	m-1	2	DSPIC96, PCE
25	Last week of 2nd m.	PCE price index	m-1	2	PCEPI
26	Last day of the 2nd m.	Fed Funds rate and credit spread	m	3	FEDFUNDS, BAA10Y
27	1st bus. day of the 3rd m.	Economic policy uncertainty index	m-1	1	USEPUINDXM
28	1st bus. day of the 3rd m.	PMI	m-1	1	NAPM
29	1st bus. day of the 3rd m.	Construction	m-2	1	TTLCONS
30	1st Friday of the 3rd m.	Employment situation	m-1	2	AWHNONAG, CE16OV, UNRATE
31	Middle of the 3rd m.	CPI and PPI	m-1	2	CPIAUSL
32	15th to 17th of the 3rd m.	Industrial production	m-1	2	INDPRO
33	3rd week of the 3rd m.	Credit and M2 (H8 release)	m-1	2	LOANS, M2
34	Later part of the 3rd m.	housing starts	m-1	1	HOUST
35	3rd Thursday of the 3rd m.	Business Outlook Survey: Phil. Fed	m	1	–
36	Last week of 3rd m.	PCE, RDPI	m-1	2	PCE, DSPI96C
37	Last week of 3rd m.	PCE price index	m-1	2	PCEPI
38	Last day of the 3rd m.	Fed Funds rate and credit spread	m	3	FEDFUNDS, BAAY10

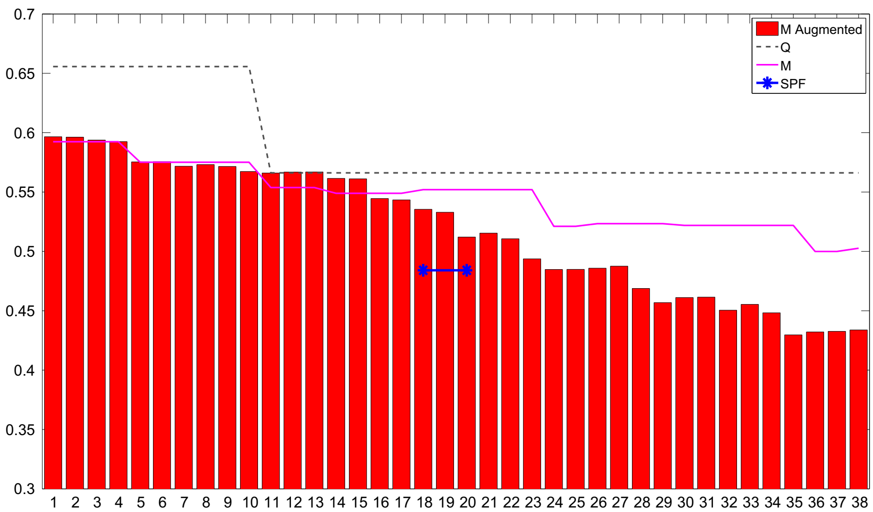

Fig. 3. RMSFE of GDP growth now-casts throughout the quarter for the quarterly model (Q), the monthly model (M) and the monthly model augmented with the auxiliary information (M Augmented). We also report the SPF now-casts, in blue with an asterisk marker. The numbers on the *x*-axis correspond to the vintages reported in Table 1. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this paper.)

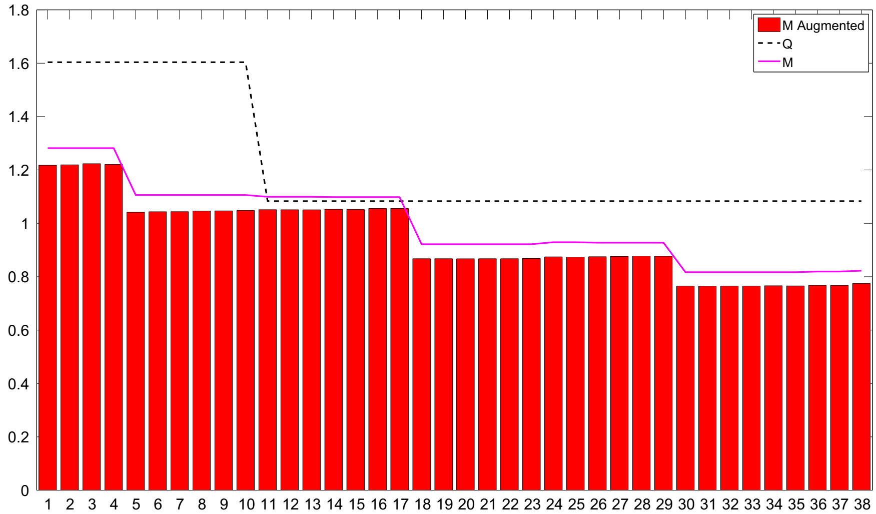

Fig. 4. RMSFE of the now-cast of the output gap throughout the quarter for the quarterly model (Q), the monthly model (M) and the monthly model augmented with the auxiliary information (M Augmented). The numbers on the *x*-axis correspond to the vintages reported in Table 1.

Table 2
RMSFE at representative vintages for GDP growth, the unemployment rate and GDP deflation inflation now-casts. The first column indicates the vintages. The bold type face is used to identify forecasts that are statistically significantly better.

Vintage	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

*** Indicates 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% based on the Diebold and Mariano (1995) test, where we use Newey–West standard errors to deal with the autocorrelation that multi-period forecast errors usually exhibit.

** Indicates 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 5% level based on the Diebold and Mariano (1995) test, where we use Newey-West standard errors to deal with the autocorrelation that multi-period forecast errors usually exhibit.

* Indicates 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 10% level based on the Diebold and Mariano (1995) test, where we use Newey-West standard errors to deal with the autocorrelation that multi-period forecast errors usually exhibit.

corresponds to the flash estimate of GDP for the previous quarter and 14, 26 and 38 correspond to the last day of each month, date at which that month's financial data is accounted for. In order to align the SPF's and the models' information sets as closely as possible, the SPF's now-casts are displayed only from cluster 18 to cluster 20, i.e. around first half of the second month of the quarter when the SPF's forecasts are published.

Notice that the now-cast of the quarterly model that uses the balanced panel (Q) can be updated only once in the quarter, when the GDP for the past quarter is released (cluster 10). The now-cast of the monthly model (M) is updated 9 times throughout the quarter, at each release of the model variables that are available at a monthly frequency – consumption (12, 24, 36), the employment variables (5, 18, and 30) and the financial 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 Figs. 3 and 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 as unemployment (Table 2) and the output gap (Fig. 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 monthly observables in a more consistent way, rather than from the real-time data flow.

For quarterly GDP, on the other hand, the best performance is generated by the monthly model augmented by the auxiliary variables (see Fig. 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 et al. (2011). 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 (Table 2). This is not surprising since this variable is itself flat over the forecasting sample.

4.2. *Point forecasts further out*

We also consider forecasts up to one year ahead, focusing on per capita real GDP growth in the main text (Table 3). Results for the GDP deflator inflation are reported in the online Appendix B. The advantage of using higher frequency information is mainly related to now-casting, confirming the findings in Giannone et al. (2008).

The same evaluation is also performed for two sub-samples, 1995–2007 and 2008–2014. The relative forecasting performance of the models is quite different before and after the Great Recession for most variables and in the second sub-sample there is a significant deterioration in terms of now-casting and forecasting performance.

Table 3
Quarter-on-quarter GDP growth forecasts: RMSFE of forecasts with horizons 0–4, produced in the first half of the second month of the quarter (information cluster 20), approximately when the SPF produce their own forecasts. The bold type face is used to identify forecasts that are statistically significantly better.

Horizon	SPF	Q	M	M Augmented
GDP growth – Full sample: 1995–2014				
Q0	**0.4841****	0.5662	0.5520	**0.5121***
Q1	**0.5898****	0.6699	0.6493	0.6327
Q2	**0.6454***	0.7164	0.7090	0.7093
Q3	0.6755	0.7343	0.7351	0.7343
Q4	0.6954	0.7506	0.7544	0.7541
GDP growth – Pre-crisis sample: 1995–2007				
Q0	**0.4769*****	0.5589	**0.4865***	**0.4824***
Q1	**0.5407****	0.6698	0.6386	0.6526
Q2	**0.5493***	0.7117	0.6878	0.7031
Q3	0.5557	0.7091	0.6930	0.7054
Q4	0.5613	0.6873	0.6737	0.6877
GDP growth – Post-crisis sample: 2008–2014				
Q0	**0.4954*****	0.5777	0.6431	0.5563
Q1	0.6632	0.6696	0.6593	0.6549
Q2	0.7753**	0.7260	0.7289	0.7240
Q3	0.8553*	0.7783	0.7902	0.7902
Q4	0.8914	0.8548	0.8757	0.8670

*** Indicates 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% level based on the Diebold and Mariano (1995) test.

** Indicates 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 5% level based on the Diebold and Mariano (1995) test.

* Indicates 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 10% level based on the Diebold and Mariano (1995) test.

[7] Since the output gap is unobserved, we take its 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 this ex post estimate of the output gap.

Table 4
Log predictive score of the now-cast of unemployment and GDP growth and for all of the model's real variables at representative vintages. The first column indicates the 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 in the first half 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 release of the employment data at the beginning of the third month of the quarter. Vintage 38 is the last day of the quarter.

Vintage	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

4.3. *Density forecasts*

In order to characterize and evaluate 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:

$$S_h(\mathcal{M}) = \frac{1}{N_h} \sum_{t=T}^{T+N_h-1} \ln p(y_{t+h} | Y_{1:T-1}, \mathcal{M}), \tag{15}$$

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 4 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 of the model's 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.

4.4. *Now-casting GDP around recessions*

The role of the monthly data flow is especially important for now-casting GDP growth and, in particular, for estimating more accurately the timing and the depth of recessions, as shown in Fig. 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 the monthly model with the auxiliary data (M Augmented) gives a much timelier assessment of the 2001 recession compared to the SPF. The M Augmented model also produces a more precise real-time assessment of the depth of the Great Recession than the SPF, as well as a better assessment of the recovery.

4.5. *Exploiting the model's structure in real-time: the great recession*

One of the key advantages of our methodology is the ability to exploit the structure of the model in real time. As shown, it is possible to obtain real-time estimates of unobservable variables such as the output gap and update them at each information release (see Fig. 4). The model and the structural shocks it estimates can also be used to interpret the signal coming from the data in real time.

The decomposition of the data in terms of structural shocks changes in real time with the monthly data. Let us focus, for example, on the story behind the drop in GDP in the last quarter of 2008, when Lehman Brothers collapsed. We compare the ex post decomposition for the last quarter of 2008 reported in Fig. 1, produced using the whole sample up to 2014, 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, for the quarterly balanced model (top panel of Fig. 6) and the monthly model with auxiliary information (bottom panel). The same graph is generated for the quarterly model conditioned on the now-casts produced by the SPF (middle panel of Fig. 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 Fig. 1 for ease of comparison.

One of the key messages emerging from the comparison of the graphs in Fig. 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 provides a more timely and precise assessment of 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: the monthly augmented model converges a few months earlier to the ex post decomposition. This aspect of real time analysis has been completely disregarded in the literature.

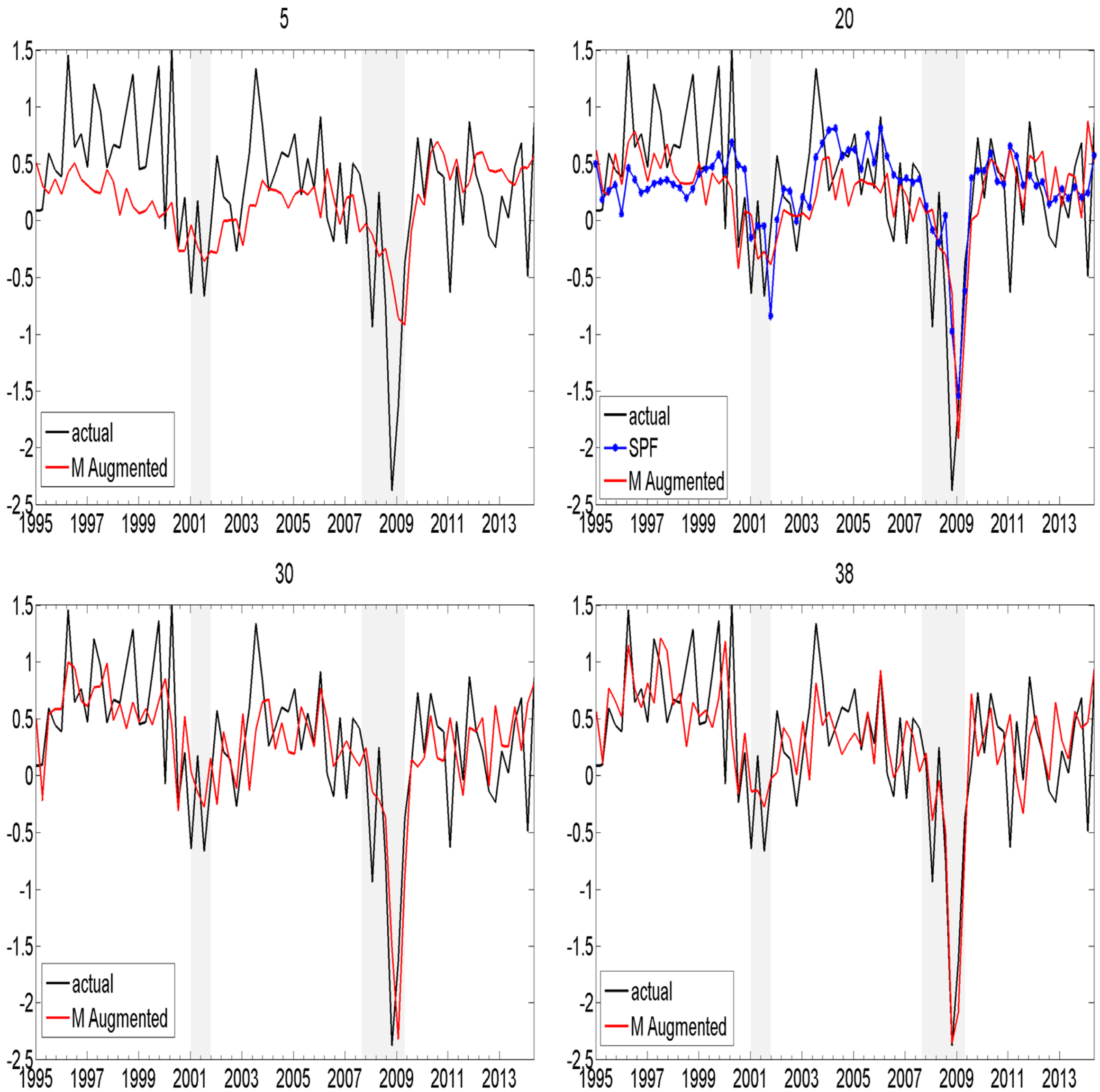

Fig. 5. The now-cast of annualized GDP growth for 4 representative vintages. Vintage 5 corresponds to the release of the employment data on the first Friday of the first month of the quarter. Vintage 20 is the middle of the second month of the quarter and we take it to correspond to the moment at which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

The charts also tell us that simply conditioning on the SPF, although providing a forecast which is at least as accurate as our M Augmented framework, does not help in recognizing in real-time the shocks that are driving the fall of GDP in 2008Q4. Clearly, each of 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 can be misleading.

In particular, the shock 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 variables traces more accurately the negative contribution of the technology shock to the slowdown. This is because the neutral technology shock, as we have seen earlier, has a large impact on real variables: the auxiliary variables related to real variables, such as the surveys, are signalling at an early stage that there is a significant slowdown of the real economy, and not only a large shock in the risk premium.

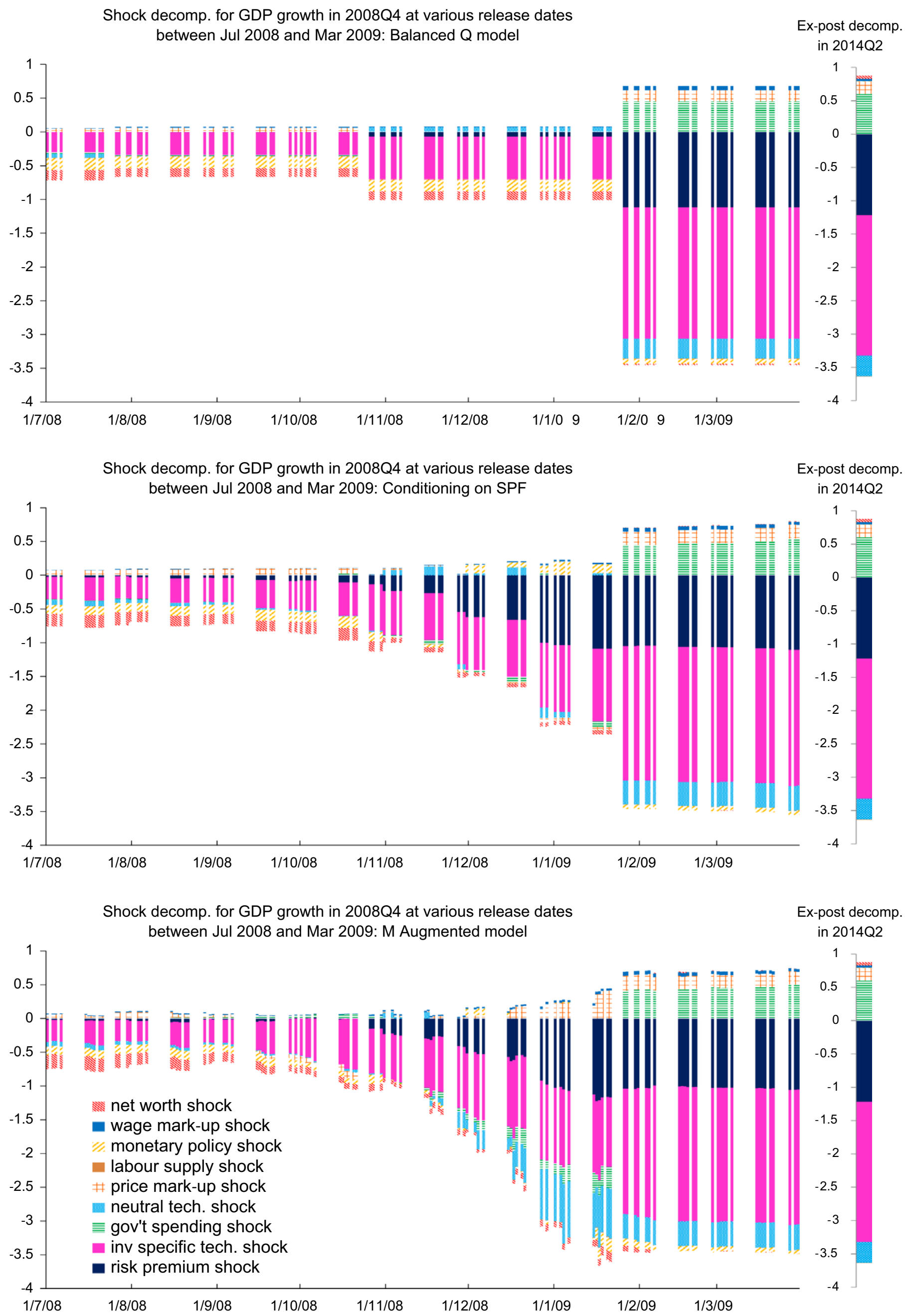

Fig. 6. Shock decompositions in real time for Q, Q+SPF and M Augmented models.

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 behavioural equations and the setting of the priors in a monthly set-up. The few papers that estimate monthly DSGE models (e.g., 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, 2014; 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 a 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 modelled 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 et al. (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. This solution is, in our opinion, 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 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. The monthly model is then adapted so as to take into consideration realistic features of the information structure such as non-synchronous infra-quarter data releases. Finally the model is augmented 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, it is possible to 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 estimation 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 signalling 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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The opinions in this paper are those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of New York, the Federal Reserve System, the Bank of England and its committees.

Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.jmoneco.2016.10.011.

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