Nowcasting, Business Cycle Dating and the Interpretation of New Information when Real Time Data are Available*

by

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Abstract

A canonical model is described which reflects the real time informational context of decision-making. Comparisons are drawn with 'conventional' models that incorrectly omit market-informed insights on future macroeconomic conditions and inappropriately incorporate information that was not available at the time. It is argued that conventional models are misspecified and misinterpret news. However, neither diagnostic tests applied to the conventional models nor typical impulse response analysis will be able to expose these deficiencies clearly. This is demonstrated through an analysis of quarterly US data 1968q4-2006q1. However, estimated real time models considerably improve out-of-sample forecasting performance, provide more accurate 'nowcasts' of the current state of the macroeconomy and provide more timely indicators of the business cycle. The point is illustrated through an analysis of the US recessions of 1990q3–1991q2 and 2001q1–2001q4.

Keywords: Structural Modelling, Real Time Data, Nowcasting, Business Cycles.

JEL Classification: E52, E58

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1 Introduction

The recent increased availability of detailed real-time data sets, consisting of the successive vintages of data that have been released over time, makes it possible to analyse more systematically the informational context in which decisions are made. It has been argued that this could be important both for understanding policy decisions made in the past and for providing policy advice in the future (see Blinder, 1997, Orphanides et al, 2000, Orphanides, 2001, and Cogley and Sargent, 2005 for example) although the use of real time data in macroeconomic analysis remains relatively rare. This paper considers the circumstances and extent to which models based on real time data can improve on more conventional models, focusing on the interpretation of new information as it arrives and on decision making that is sensitive to accurate business cycle dating.

Real-time data focuses attention on two interrelated aspects of the informational context within which macroeconomic decisions are made. The first is concerned with *end-of-sample issues* that arise because decisions are based on the currently-available data in the context of measurement and future uncertainty. This aspect includes issues surrounding forecasting (or "nowcasting" if information on today's position is published only with a delay) and the problems encountered in finding the appropriate model and econometric techniques to minimise and accommodate forecast uncertainties. These problems are compounded when variables are measured with error and there has developed a considerable literature concerned with the need to accommodate and anticipate the effects of revisions in published data in decision-making at the end-of-sample (as highlighted in Kishor *et al* (2003) or Croushore and Evans (2006), for example).

The second aspect of macroeconomic decision-making highlighted by real time data concerns *processing issues*. This includes the interpretation of the "news" that becomes available in each period and has been discussed in the literature concerned with the identification and impulse response analysis of monetary policy or other types of shocks. Here, attention has frequently focused on the timing and sequencing of decisions to obtain impulse responses that describe the impact of particular policy innovations.[1] The role of the timing of decisions in the analysis highlights that it is important to use the relevant vintage of data to properly reflect the real-time informational context. But 'processing issues' also include questions on how to best interpret and exploit the wealth of information that is available to describe the current and expected future prospects of the economy, including direct measures of expectations available from surveys and market information (in financial markets, say).[2] The macroeconomic implications of the processing issues have been highlighted by Mankiw, Reis and Wolfers (2003), for example, who propose a 'sticky-information' model to explain business cycle properties. Similarly, Orphanides and Williams (2002) emphasise the importance of understanding the nature of inflation expectations to properly interpret the successes and failures of monetary policy. And, more recently, Gali and Gertler (2007) discuss the significance of the role of private sector expectations of the future performance of the economy and future policy actions in the monetary transmission mechanism.[3]

The importance of the two aspects of real time data for any modelling activity will depend on the purpose of the modelling. If the purpose of the analysis is to test a particular economic theory or to interpret and understand past policy episodes, then the analysis is likely to place more emphasis on the interpretation and processing of data. If the purpose of the modelling is to facilitate real-time decision-making and forecasting, then the focus will be on end-of-sample issues. The aim of the paper, then, is to evaluate the use of real time data in modelling in principle and in practice, distinguishing between the use of the data in interpreting new information and its use in nowcasting/forecasting and in making decisions influenced by business cycle conditions. In the first part of the

[1] Important examples are provided in Bernanke and Mihov (1998), Sims and Zha (1998), Christiano *et al.* (1999), Rotemberg and Woodford (1999) and Brunner (2000), inter alia.

[2] There is a well-established empirical literature showing that direct measures of expectations contain useful information to explain future economic outcomes; see Batchelor (1986), Lee (1994), Smith and McAleer (1995), Roberts (1995, 1997) and Lee and Shields (2000) on the use of surveys, and Estrella and Trubin (2006) and Bordo and Haubrich (2008) on the use of yield curve information, say.

[3] The literature on learning is also relevent here; see Evans and Honkapohja (2001) for a comprehensive review.

paper, we describe a canonical model that explicitly reflects the real-time information context of decision-making, accommodating the end-of-sample and the processing issues raised above. The model captures the simultaneous determination of first-release measures of macroeconomic variables, their expected future values and their subsequent revisions and illustrates the (typically extensive) restrictions required to identify economically-meaningful relations and the associated structural innovations. The canonical model also provides a means of considering the nature of conventional models found in the literature. Conventional models are based on "final vintage" datasets which measure variables after all the revisions have taken place and they omit the direct measures of expected future values that were available at the time. They both incorporate information on revisions that was not available at the time and ignore survey-based and market-informed insights on future macroeconomic conditions that were available. These provide the standard framework within which macroeconometric analysis takes place though, so it is useful to consider how the results of conventional analyses should be interpreted in the light of the canonical model framework and whether standard statistical tools will expose the misspecification.

The second part of the paper examines the extent to which these issues are important empirically through an analysis of quarterly US data over the period 1968q4 – 2006q1 using the empirical counterparts of the canonical and the conventional models. The analysis shows that the misspecification of the conventional models is not exposed either by diagnostic tests applied to the models or by typical impulse response analysis. However, their out-of-sample forecasting performance is considerably weaker than that of the fully-specified real time model. The real time analysis is particularly powerful in providing 'nowcasts' to accurately describe the current state of the macroeconomy and in providing more timely indicators of the business cycle. Therefore, in contrast to the conclusions of Croushore and Evans (2006), we argue that real time considerations do have practical significance for economic decision-making and policy analysis. The power of the real time model is illustrated through a case study of the use of information in recognising the recessions experienced in the US in 1990q3–1991q2 and 2001q1–2001q4.

The layout of the paper is as follows. Section 2 introduces the canonical modelling framework proposed to take into account the information available in real time. The section illustrates the identification issues involved and discusses the links between this model and the conventional models typically found in the literature. Section 3 describes the US real time data, including a summary of the sequencing of data releases. It also introduces three alternative and increasingly sophisticated empirical models that can be estimated making progressively greater use of the data available in real time. This aims to establish quantitatively the importance of taking into account the various sources of information available in real time in macroeconomic policy analysis. Section 4 reports on the use of the models in constructing nowcasts and forecasts of recessions in real time. The section describes a case study analysing the information flows that would have informed decision makers in the recession of 2001q1 – 2001q4 and compares this with the use of information in the recession that occurred a decade earlier in 1990q3 – 1991q3. Finally, section 5 concludes.

2 A Modelling Framework to Accommodate Real Time Information

In this section, we describe a canonical model that is able to accommodate explicitly the information available in real time, including the release of different vintages of data and of direct measures of expected future outcomes. Comparison of the canonical model with a "conventional" model of macroeconomic dynamics helps establish the ways in which real-time data might improve macroeconomic analysis and those where it might be less useful. Broadly-speaking, we argue that the real-time data are important in dealing with 'end-of-sample' issues but are probably less helpful in addressing 'processing issues'.

In what follows, ${}_tx_{t-s}$ is the measure of the (logarithm of the) variable x at time $t-s$ as released at time t and ${}_tx^e_{t+s}$ is a direct measure of the expected value of the variable at $t+s$, with the expectation formed on the basis of information available at the time the measure is released, t. The sample of data runs from $t = 1, ..., T$. We write ${}_t\mathbf{x}_t = ({}_tx_{1t}, ..., {}_tx_{mt})'$, an $m \times 1$ vector of variables, so that $\mathbf{x}_t$ might be a 4×1 vector containing data on the interest rate, output growth, price inflation, and money growth, for example. For ease of exposition, we assume in the first instance that the determination and first-measurement of variables is synchronised and that data are revised once following its first release. In this case, the model is:

$$\mathbf{A}_{11}\ {}_t\mathbf{x}_t = -\mathbf{A}_{12}\ {}_t\mathbf{x}^e_{t+1} - \mathbf{A}_{13}\ {}_t\mathbf{x}_{t-1} + \mathbf{B}_{11}\ {}_{t-1}\mathbf{x}_{t-1} + \mathbf{B}_{12}\ {}_{t-1}\mathbf{x}^e_t + \mathbf{B}_{13}\ {}_{t-1}\mathbf{x}_{t-2} + \boldsymbol{\varepsilon}_{bt} \quad (2.1)$$

$$\mathbf{A}_{22}\ {}_t\mathbf{x}^e_{t+1} = -\mathbf{A}_{21}\ {}_t\mathbf{x}_t - \mathbf{A}_{23}\ {}_t\mathbf{x}_{t-1} + \mathbf{B}_{21}\ {}_{t-1}\mathbf{x}_{t-1} + \mathbf{B}_{22}\ {}_{t-1}\mathbf{x}^e_t + \mathbf{B}_{23}\ {}_{t-1}\mathbf{x}_{t-2} + \boldsymbol{\varepsilon}_{et} \quad (2.2)$$

$$\mathbf{A}_{33}\ {}_t\mathbf{x}_{t-1} = -\mathbf{A}_{31}\ {}_t\mathbf{x}_t - \mathbf{A}_{32}\ {}_t\mathbf{x}^e_{t+1} + \mathbf{B}_{31}\ {}_{t-1}\mathbf{x}_{t-1} + \mathbf{B}_{32}\ {}_{t-1}\mathbf{x}^e_t + \mathbf{B}_{33}\ {}_{t-1}\mathbf{x}_{t-2} + \boldsymbol{\varepsilon}_{rt} \quad (2.3)$$

where $\mathbf{A}_{ij}$ and $\mathbf{B}_{ij}$, $i, j = 1, 2, 3$, are $m \times m$ matrices of coefficients and $\boldsymbol{\varepsilon}_{bt}$, $\boldsymbol{\varepsilon}_{et}$ and $\boldsymbol{\varepsilon}_{rt}$ are $m \times 1$ vectors of shocks with mean zero and diagonal covariance matrices Ω_b, Ω_e and Ω_r, respectively. We can normalise the diagonal elements of $\mathbf{A}_{11}$, $\mathbf{A}_{22}$ and $\mathbf{A}_{33}$ to unity so that the equations of the system explain, respectively, the time-t measure of each of the variables in $\mathbf{x}_t$, the time-t expectation of $\mathbf{x}_{t+1}$ and the time-t revised measures of $\mathbf{x}_{t-1}$.[4] The structural model (2.1)-(2.3) reflects the fact that three interrelated processes occur here simultaneously and in real time: (i) 'behavioural' economic decisions are made by economic agents to determine the actual values of the variables at each time; (ii) expectations are formed on the variables by those same economic agents; and (iii) the economic outcomes are measured reflecting the data collection and survey practices of the statistical agencies.

The equations in (2.1)-(2.3) can be stacked to obtain

$$\mathbf{A}\ \mathbf{z}_t = \mathbf{B}\ \mathbf{z}_{t-1} + \boldsymbol{\varepsilon}_t, \quad (2.4)$$

where $\mathbf{z}_t = ({}_t\mathbf{x}_t,\ {}_t\mathbf{x}^e_{t+1}, {}_t\mathbf{x}_{t-1})'$, $\mathbf{A} = \begin{bmatrix} \mathbf{A}_{11} & \mathbf{A}_{12} & \mathbf{A}_{13} \\ \mathbf{A}_{23} & \mathbf{A}_{22} & \mathbf{A}_{23} \\ \mathbf{A}_{31} & \mathbf{A}_{32} & \mathbf{A}_{33} \end{bmatrix}$, $\mathbf{B} = \begin{bmatrix} \mathbf{B}_{11} & \mathbf{B}_{12} & \mathbf{B}_{13} \\ \mathbf{B}_{21} & \mathbf{B}_{22} & \mathbf{B}_{23} \\ \mathbf{B}_{31} & \mathbf{B}_{32} & \mathbf{B}_{33} \end{bmatrix}$ and $\boldsymbol{\varepsilon}_t = (\boldsymbol{\varepsilon}_{bt},\ \boldsymbol{\varepsilon}_{et}, \boldsymbol{\varepsilon}_{rt})'$ with covariance $\Omega = \begin{bmatrix} \Omega_b & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \Omega_e & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \Omega_r \end{bmatrix}$. The corresponding reduced form VAR is

$$\mathbf{z}_t = \mathbf{C}\ \mathbf{z}_{t-1} + \mathbf{u}_t, \quad (2.5)$$

[4]The equation in (2.3) can obviously be written in the 'revision' form $\mathbf{A}_{33}\ ({}_t\mathbf{x}_{t-1} -\ {}_{t-1}\mathbf{x}_{t-1}) = ... +$ $(\mathbf{B}_{31} - \mathbf{A}_{33})\ {}_{t-1}\mathbf{x}_{t-1} + ...$.

where $\mathbf{C} = \mathbf{A}^{-1}\mathbf{B}$ and $\mathbf{u}_t = \mathbf{A}^{-1}\boldsymbol{\varepsilon}_t$ with covariance matrix $\Sigma = \mathbf{A}^{-1}\Omega\mathbf{A}^{-1}$. Given that the contemporaneous interactions between variables are accommodated explicitly in the $\mathbf{A}$ matrix, it is typically assumed that the structural innovations in Ω are orthogonal to each other.[5] Identification of the parameters of the structural model in (2.4), and the associated structural innovations, from the parameters in (2.5) requires $\frac{9m^2+3m}{2}$ restrictions based on *a priori* theory, although subsets of the parameters and innovations might be identified on the basis of fewer relevant restrictions.

It is worth reflecting on how the canonical model of (2.4) and the associated reduced form of (2.5) relate to the more conventional models of macroeconomic variables found in the literature. These ignore real-time considerations by making use only of the final vintage of data and, usually, by eschewing the direct measures of expectations that are available. The relationship between the models becomes clearer by noting that conventional models effectively focus on the post-revision series ${}_t\mathbf{x}_{t-1}$ only. If data are revised only once (and remains unchanged thereafter), then ${}_T\mathbf{x}_{t-1} = {}_t\mathbf{x}_{t-1}, \quad t = 1, ..., T..$ In this case, apart from the observation at the end of the sample, the final vintage of data ${}_T\mathbf{X}_t$ is the same series as the post-revision series ${}_t\mathbf{X}_{t-1}$ measured at time T

$$\begin{aligned} {}_T\mathbf{X}_t &= \{\ {}_T\mathbf{x}_1,\ \ {}_T\mathbf{x}_2,\ \ ...,\ \ {}_T\mathbf{x}_{T-2},\ \ {}_T\mathbf{x}_{T-1},\ \ {}_T\mathbf{x}_T\ \}, \\ {}_t\mathbf{X}_{t-1} \text{ measured at time } T &= \{\ {}_2\mathbf{x}_1,\ \ {}_3\mathbf{x}_2,\ \ ...,\ \ {}_{T-1}\mathbf{x}_{T-2},\ \ {}_T\mathbf{x}_{T-1},\ \ \emptyset\ \}, \end{aligned}$$

where $\emptyset$ represents a missing entry. If the sample of data is sufficiently long (so that the difference at the end of the series is unimportant), any model estimated using the final vintage of data will be equivalent to that obtained using the post-revision series only. Further, the canonical model of $\mathbf{z}_t$ determines the nature of the model that should be estimated for any subset of the variables in $\mathbf{z}_t$. The reduced form (2.5) means $\mathbf{z}_t = (\mathbf{I} - \mathbf{C}L)^{-1}\mathbf{u}_t$ and the time series model of any variable or subset of variables in $\mathbf{z}_t$ is determined by the lag structure of $(\mathbf{I} - \mathbf{C}L)^{-1}$ and the properties of the $\mathbf{u}_t$. The point is

[5] This 'standard' assumption has important implications for the interpretation of the structural innovations. Realistically even structural innovations could be correlated with each other. The orthogonality assumption implicitly means that one of the innovations is reconfigured so that the correlation is subsumed into the structural parameters in $\mathbf{A}_0$ and the innovation is redefined as that part of the original which is orthogonal to the rest.

illustrated simply if we consider $\mathbf{x}_t$ to contain just one variable. In this case, the system in (2.5) is a three-variable VAR of order 1. But each individual series also admits a univariate ARMA(3,2) specification so that we can write, for example,

$$ {}_t x_{t-1} = \lambda_1 \; {}_{t-1}x_{t-2} + \lambda_2 \; {}_{t-2}x_{t-3} + \lambda_3 \; {}_{t-3}x_{t-4} + v_t - \theta_1 \; v_{t-1} - \theta_2 \; v_{t-2}, \qquad t = 1, ..., T, \tag{2.6} $$

where the λ_1, λ_2 and λ_3 are functions of the parameters in $\mathbf{C}$ while the θ_1, θ_2 and properties of the errors v_t are determined by matching its correlelogram with that of the combination of shocks given by $(\mathbf{I} - \mathbf{C}L)^{-1}\mathbf{u}_t$.[6] Estimation of (2.6), or the corresponding univariate autoregressive approximation, will provide the same estimates of the λ and θ parameters whether we use use the post-revision series or the final vintage series, subject to the sample not being dominated by the differences at the end of the data.

2.1 Real time data and information processing

An argument put forward for the use of models that employ real-time data is that they can help clarify the processing issues surrounding the use of information and the interpretation of news. The canonical model of (2.4) illustrate the potential for identification provided by the detail of real-time data. But it also shows that considerable *a priori* information is required to define meaningful structural relations, and this will include information on the nature and measurement of data and on the expectation formation process as well as on the decision-making of economic agents. For example, if the system of (2.4) included data on the four variables, interest rates, output, inflation and money, we would require 78 identifying restrictions to be imposed to identify the structural model and all of the underlying behavioural shocks from the associated reduced form VAR. The availability of these restrictions will vary from one modelling exercise to another, but it is worth elaborating on three particular sources here to clarify the real time issues that are involved.

[6] Noting that $(\mathbf{I} - \mathbf{C}L)^{-1} = [\det(\mathbf{I} - \mathbf{C}L)]^{-1}\mathrm{adj}(\mathbf{I} - \mathbf{C}L)$, the autoregressive element is based on $\det(\mathbf{I} - \mathbf{C}L) = 1 - \lambda_1 L - \lambda_2 L - \lambda_3 L$ and the moving average element depends on the combination of reduced form errors given $\mathrm{adj}(\mathbf{I} - \mathbf{C}L)$. See Hamilton (1994, p. 349) for details.

One source of potential identifying restrictions is from economic theory. For example, recently, there have been many 'New-Keynesian' models described in the literature which have clearly specified micro-foundations and which provide well-defined dynamic relationships between key macroeconomic variables; see the references in Gali and Gertler (2007), for example. If measurement issues are ignored, then such models can be readily accommodated within a VAR framework and the structure suggested by the theory provides (many) over-identifying restrictions, on the contemporaneous and lagged parameters, with which the theory can be tested.[7] The identifying restrictions for recovering these structural relationships in estimation would be more complex, however, if consideration is given to the type and nature of the information set that is available in real time. This is because the microfoundations of a New Keynesian Phillips curve, say, would require assumptions to be made not only on firms' price setting behaviour but also on *which* information the firms use to form expectations; i.e. whether they based their decisions on first-releases of published data or on expectations of post-revision data, and so on.[8] Agents in the model would also need to form a view on the extent to which the statistical agency publishes the 'raw 'data obtained as the outcome of a clearly defined data collection exercise (even if this includes systematic measurement error of unknown source) or whether the agency attempts to purge the data of systematic error prior to publication.[9]

A second potential source of identifying restrictions on the system in (2.4) is through assumptions on the nature of the expectations formation process. The characterisation of expectations in (2.1) makes no assumptions on the expectation formation process but can accommodate many alternative assumptions through the imposition of restrictions on the parameters of the model. This includes the rational expectation (RE) hypothesis, for example. However, implementing the identifying restrictions arising from the RE assumption in (2.4) requires assumptions to be made on which measure of the variables

[7]See Kim and Pagan (1995) or Pesaran and Smith (2006), for example.

[8]See Croushore and Evans's (2006) related discussion on whether policy decisions are based on observed first release data or the 'true' underlying state of the economy when estimating policy rules.

[9]See Jacobs and van Norden (2006) for discusson of the sources of revision error in published data and the extent to which the revisions reflect the 'news' or 'noise' described in Mankiw and Shapiro (1983).

agents had in mind when reporting their expectations. For example, the identifying restrictions relating to (2.2) will be quite different depending on whether respondents in a survey report their expectation of the first release measure, so ${}_{t-1}\mathbf{x}_t^e = E[{}_t\mathbf{x}_t \mid I_{t-1}]$, or they report their expectation of the "actual" post-revision measure, so ${}_{t-1}\mathbf{x}_t^e = E[{}_{t+1}\mathbf{x}_t \mid I_{t-1}]$. In the former case, for example, we can write $\mathbf{B}_{12} = \mathbf{I}_m$, $\mathbf{A}_{12} = \mathbf{A}_{13} = \mathbf{B}_{12} = \mathbf{B}_{13} = \mathbf{0}$ so that ${}_t\mathbf{x}_t = {}_{t-1}\mathbf{x}_t^e + \boldsymbol{\varepsilon}_{et}$ in (2.1) and $\boldsymbol{\varepsilon}_{bt}$ has a clear interpretation in terms of "news on the first release measure becoming available at time t".[10] The identifying structure would be quite different if ${}_{t-1}\mathbf{x}_t^e = E[{}_{t+1}\mathbf{x}_t \mid I_{t-1}]$ however.

A third form of *a priori* information used to provide identifying restrictions on the system in (2.4) is through assumptions on the timing and/or sequencing of decisions. These assumptions are typically used to motivate a diagonal, or block diagonal, structure in the 'contemporaneous' matrix corresponding to $\mathbf{A}$ in VAR models of macroeconomic variables. This approach is well illustrated in studies of the effects of monetary policy where the use of identifying restrictions based on the timing and sequencing of decisions are particularly common. The use of real-time data allows a more precise description of the timing of new information, including the sequence of the arrival of news within the period if quarterly data are used. This might enable some if not all shocks to be identified. For example, given that interest rate data are available at any point during a quarter while quarterly output, price and money data are published at various specified times during the quarter, one could choose to use the beginning-of-quarter measure of the interest rate to unambiguously place this *first* in the sequence of behavioural decisions determining these four variables.[11] On the further assumption that interest rate and other forecasts are also determined after the policy decision, then we can place the interest rate first in the vector of variables $\mathbf{z}_t$ and write the first row of $\mathbf{A} = (1, 0, 0, 0, ...)'$ in (2.4). The reduced form equation for the interest rate will then provide an estimate of the structural interest rate equation and the shocks to the reduced form interest rate equation can be

[10]Here, $\mathbf{z}_t = \mathbf{A}^{-1}\mathbf{B}\ \mathbf{z}_{t-1} + \mathbf{A}^{-1}\boldsymbol{\varepsilon}_t$ and $E[\mathbf{z}_t|I_{t-1}] = \mathbf{A}^{-1}\mathbf{B}\ \mathbf{z}_{t-1}$. Focusing on the first row, we have $E[{}_t\mathbf{x}_t|I_{t-1}] = (\mathbf{I}, \mathbf{0}, \mathbf{0})\mathbf{A}^{-1}\mathbf{B}\ \mathbf{z}_{t-1} = {}_{t-1}\mathbf{x}_t^e$ so $(\mathbf{I}, \mathbf{0}, \mathbf{0})\mathbf{A}^{-1}\mathbf{B} = (\mathbf{0}, \mathbf{I}, \mathbf{0})$. For this to hold for any behavioural relation and any measurement process, we have $\mathbf{B}_{12} = \mathbf{I}_m$ and $\mathbf{A}_{12} = \mathbf{A}_{13} = \mathbf{B}_{12} = \mathbf{B}_{13} = \mathbf{0}$.

[11]A more detailed description of the timing of US data releases is provided in the following section.

given the standard interpretation as reflecting structural monetary policy shocks.[12]

This discussion shows that the use of real time data might help in identifying and processing information in some circumstances, especially where the sequencing of decisions is well understood. But the discussion also makes clear that the extra detail of the data typically requires a corresponding increase in the detail of the structure provided by *a priori* information for it to be useful in identification. In the absence of this detailed *a priori* structure, models that employ real time data are unlikely to have any advantage over simpler conventional models in providing insights on behavioural/structural interpretations of news, testing economic theory, policy evaluation, and so on.

The real-time models would, however, highlight difficulties in interpretation which are obscured in more conventional models. For example, in the absence of identifying restrictions, the dynamics of the macroeconomy might be characterised through a Generalised Impulse Response analysis of the reduced form system in (2.5), following Koop *et al.* (1995). This type of impulse response describes the effects of a shock to a variable of interest taking into account the innovations that are typically observed elsewhere in the system when such a shock occurs. It is acknowledged that the shock cannot be interpreted in terms of an economic innovation of a particular type and is recognised as being an amalgam of the true underlying behavioural shocks. This approach contrasts with the more straightforward interpretation of impulse responses typically offered in the literature on the basis of more conventional models estimated using final vintage data. If the conventional model is recognised as the lower-order VAR model that focuses on the post-revision series as a subset of the $\mathbf{z}_t$ in (2.4), then the discussion surrounding (2.6) shows the shocks in the conventional model are actually a convoluted combination of the true structural innovations.[13] The real time data highlight that the straightforward

[12]Garratt et al. (2006) illustrate that, assuming that interest rates are set 'first', a structural interest rate equation of this form can be derived as the outcome of the optimising decisions of a monetary authority faced with a structural model of the form in (2.4) and an objective function that is quadratic in some or all of the other variables in $\mathbf{x}_t$.

[13]As (2.6) makes clear, the time-t innovation in the lower-dimension model consists of shocks to expected future values of the series and to revisions as well as shocks to first-release and revised measures of the series.

interpretation of impulse responses based on conventional models should be treated with caution therefore.

2.2 Real time data and diagnostic testing

The discussion above suggests that, in the absence of detailed *a priori* information on the structural relations, the real time and conventional models are equally admissible as representations of the macroeconomy. In these circumstances, we might evaluate the use of the real time data by testing the statistical adequacy of the models to reflect the data. However, as the discussion surrounding the simplified model at (2.6) made clear, the conventional models will typically provide an entirely adequate representation of the data even if the true data generating process is as in the real time model of (2.4). The conventional model will have a more complicated ARMA structure than the original and, in practice, these might be approximated with high-order AR models in estimation. Standard diagnostic tests (on serial correlation, functional form, non-normality, outliers, and so on) might appear poor if the approximation is poor. But in principle, if the real time model is well-specified, then there is no reason to expect the diagnostic tests for the conventional model to indicate misspecification.

An alternative approach to testing the statistical adequacy of conventional models in the presence of data revisions is by looking for instability in models estimated using different data vintages; see Orphanides (2001) or Croushore and Evans (2006), for example. However, the arguments presented above suggest that if the underlying real time model is an adequate representation of the data, then the corresponding conventional model will also be an adequate representation. If the sample size is large enough for the final observation to have an insignificant impact on the estimation, the exercise will provide sensible, unbiased estimates of the parameters of the conventional model (which are functions of the true underlying parameters of (2.4)). These estimates will remain stable over time, irrespective of the vintage of data used in estimation.[14]

[14]The univariate conventional model of (2.6) corresponded to a three-variable VAR of order 1 where there is one revision only. If the data is revised p revisions, then the multivariate model would be a $p+2$ -variable VAR and the corresponding univariate represntation would be ARMA$(p+2, p+1)$. Nevertheless,

The structural stability of the conventional model is based on the assumption that the real time model is itself stable over time. Structural instability in the real time model will, of course, translate to structural instability in the conventional model. The extent to which this misspecification shows in diagnostic tests of the conventional model will depend on the details of the real time model. But it is intuitively reasonable to think that the conventional model might be relatively sensitive to structural breaks because a structural break in any one of the relationships of the real time model will show as instability in the corresponding conventional model. Generally speaking, then, diagnostic testing of the conventional model is unlikely to expose model misspecification, although structural instability tests might be more sensitive than other tests.

2.3 Real time data and forecasting

The most striking deficiency of conventional models relative to those using real time data is likely to be exposed in nowcasting and forecasting exercises. The estimated real time model of (2.5) can be used, of course, to produce directly the one-step-ahead forecasts of the next period's survey expectation ${}_{T+1}y_{T+2}$, of the first-release measure of ${}_{T+1}y_{T+1}$ and of the post-revision nowcast measure ${}_{T+1}y_{T}$. The forecast performance will depend on the context and it is widely recognised that forecasts based on estimated versions of the true data generating process can be outperformed by simpler misspecified models, in a mean squared error sense, if the true model includes variables with relatively little explanatory power (see Clements and Hendry, 2005). However, the direct measures of expectations are likely to have good explanatory power; indeed, the direct measures will themselves provide the optimal forecast if expectations are formed rationally and relate to the post-revision measure. Further, there is considerable evidence that there is a systematic and predictable element in data revisions which will contribute to a model's forecasting performance. This suggests that the complete real-time model, including expectations data and revisions data, will produce relatively good forecasts. The model can also be used in a straightforward way to obtain unbiased forecasts of the future values of the post-revision series at longer forecast horizons and to produce forecasts of specific events. This is the

the same arguments would apply.

case even where the events are defined by a complicated function of different variables at different forecast horizons; forecasting the probability of two consecutive periods of negative growth, for example, or the occurrence of turning points or of some other conjuncture of variable outcomes associated with recession or another business cycle feature.[15]

This contrasts with forecasting exercises obtained using the conventional model. Although the first-release observation on the data at the end-of-sample ${}_{T}y_{T}$ is available automatically in the time-T vintage of data, this will provide a biased estimate of the post-revision nowcast measure in which we are interested, assuming that there is a predictable element in revisions. The measurement error will contaminate subsequent forecasts at longer horizons and the characterisation of the uncertainty surrounding the forecasts will also be incorrect. Event probability forecasts will be biased too. In brief, it seems likely that conventional models which do not make use of direct measures of expectations or take into account revisions in data will be particularly poor at forecasts that focus on the end of the sample when decisions are made. This is ultimately an empirical issue, however, and we therefore explore the relative forecast performance of various models of US macro data in the following section.

3 The Informational Content of US Real Time Data

In this section, we provide an analysis of US data on output growth, inflation, money and interest rates to investigate the information content of the first-releases of measures of these series, of revisions in these data and of direct measures of expectations of the variables. The real time dataset is obtained from the Federal Reserve Bank of Philadelphia at *www.phil.frb.org/econ/forecast/* and consists of 161 quarterly vintages of data; the first was released in 1965q4 and the final vintage used in this paper is dated 2006q1. All vintages include variable observations dated back to 1947q1. The analysis in this section is primarily statistical aimed at illustrating the issues raised in the previous section to evaluate the usefulness of real time data. The usefulness is judged first in the context of identifying and tracing out the macroeconomic effects of monetary policy shocks and

[15]See Garratt *et al* (2003) for discussion of the simulation methods that underlie the production of the event probability forecasts.

then in the context of 'nowcasting' and forecasting the current and future state of the macroeconomy.

3.1 Timing of US Data Release

The empirical analysis starts with a description of our macroeconomic data taking proper account of the timing of the data releases in the US. For aggregate output, data on real GDP in quarter t is released for the first time at the end of the first month of quarter $t+1$. This figure is reported in the Federal Reserve Bank of Philadelphia's real time data set as the mid-point of the $(t+1)^{th}$ quarter and is it is denoted by ${}_{t+1}y_t$ in what follows, where y_t is the logarithm of real GDP, $t = 1947q1 - 2006q1$. Revisions that subsequently take place in output measures in the months up to the mid-point of the $(t+2)^{nd}$ quarter are reported in ${}_{t+2}y_t$. Likewise, ${}_{t+3}y_t$ incorporates any revisions that are then made up to the mid-point of the $(t+3)^{th}$ quarter, and so on.

Money and price measures are released monthly with a one month's delay. In this analysis, p_{t-1} refers to the *average* value of the (logarithm of) the consumer price index (CPI) over the three months of quarter $t-1$. The observation for prices in the third month of quarter $t-1$ is not released until the end of the first month of quarter t and so, matching the timing of the release of the output data, we take each quarter's price observation to be released at the mid-point of the succeeding quarter, denoted ${}_tp_{t-1}$. So, for example, the average data for the months that constitute the first quarter, January, February and March, are assumed to become available in the following May; the average data for the months that constitute the second quarter, April, May and June, are assumed to become available in the following August, and so on. The timing of the release of data on the M1 measure of the money supply is exactly the same and so ${}_tm_{t-1}$ also refers to the average of the data relating to the three months of quarter $t-1$ released for the first time at the mid-point of quarter t.

Our measure of the rate of interest, r_t, is the Federal Funds rate. The Federal Reserve's Open Market Committee usually meets eight times a year; in February, March, May, July, August, September, November and December and the outcome of its deliberations are immediately made known. The decision on how to measure the rate at the quarterly frequency is relatively arbitrary, and so we can choose to measure the rate in a way that justifies any assumptions on the timing of interest rate decisions. To be consistent with the assumption that interest rate decisions are made first within the quarter, we take as our measure of the quarterly interest rate, ${}_tr_t$, the Federal Funds rate as observed at the beginning of January, April, July, and October, i.e. the interest rate holding on the first day of the relevant quarter.

To investigate the informational content of 'forward-looking' variables, we make use of the interest rate spreads (to reflect market expectations of future rates) and experts' forecasts on output and prices as provided in the Federal Reserve Bank of Philadelphia's *Survey of Professional Forecasters* (SPF), from 1968q4 – 2006q1. The spread is denoted ${}_tsp_t$ and is defined as the difference between the three-month Treasury Bill Secondary Market Rate, converted to a bond-equivalent basis, and the market yield on US Treasury securities at a 10 year constant maturity (quoted on investment basis).[16] Both series are obtained from the *H.15: Selected Interest Rates* publication of the Board of Governors of the Federal Reserve System. The observations for the spread are taken at the beginning of each quarter to coincide with the interest rate series. Forecasts taken from the SPF are made around the mid-point of quarter t although, in fact, the forecasters have available to them the first release information on the previous quarter's output and price level, ${}_ty_{t-1}$ and ${}_tp_{t-1}$ at the time when the forecasts are made.[17] The nowcasts relating to quarter t's output and price level are denoted by ${}_ty_t^f$ and ${}_tp_t^f$, and the forecasts of quarter $t+s$ output and price level, $s > 0$, are denoted by ${}_ty_{t+s}^f$ and ${}_tp_{t+s}^f$, respectively.

3.2 Model Specifications

To investigate the informational content of the various data that become available, we estimate three simple macroeconomic models which make increasingly specialised use of the data: a 'conventional' model which ignores real time considerations; a specification that pays attention to the timing of data releases and revisions but does not include any

[16]See Estrella and Trubin (2006) for discussion.

[17]Given that the spread information becomes available at the start of quarter t, the SPF will have internalised this source of contemporaneous information also.

forward-looking information; and a model which includes all the information available in real time. Following the discussion of the previous section, attention focuses on interest rates, output, prices and money. However, preliminary investigation shows that although interest rates are stationary, output, prices and money series are integrated of order one and need to be differenced to obtain stationarity. In our models, we consider output growth, price inflation and money growth in the analysis, measuring these using changes in the (log) of the first-release data in our models that accommodate data revision. As shown in Garratt et al (2006), a model that explains this growth measure alongside the revisions data is entirely justifiable statistically on the assumption that growth in the respective series is stationary and that measurement errors and expectational errors are all stationary.[18] In all three models, shocks to interest rates and growth rates die out in the infinite horizon but have persistent effects on the levels of output, prices and money.

Model 1; Specification with Conventional Timing The first model we consider is a simple four-variable Vector Autoregressive Model explaining interest rates, output growth, price inflation and money growth using the final vintage data series only; i.e. a model of the form in (2.5), using

$$\mathbf{z}_t = \left(\; {}_T r_t, \quad ({}_T y_t - {}_T y_{t-1}), \quad ({}_T p_t - {}_T p_{t-1}), \quad ({}_T m_t - {}_T m_{t-1}) \; \right)',$$

for $t = 1, ..., T$. The timing of this model is 'conventional' in the sense that this is the form of the data that is typically employed in macroeconomic analysis. Here, the investigator considers only the most recent (time-T) data series available, assuming that these were the data available at the time decisions were made (presumably subject to some innocuous measurement error) and effectively ignoring the fact that revisions have taken place. Further, the data here are aligned temporally on the basis of the time period t to which the observation refers, not of the date of release. This assumes that all of the data that relate to time period t were available at time period t despite the publication delays

[18] The VAR model can be written as a cointegrating VAR with cointegrating relations existing between, respectively, the first-release, expected values and revised values for each variable with cointegrating vectors (1, −1, 0) and (1, 0, −1).

known to operate in practice. This model provides the baseline comparator, therefore, abstracting from all real time considerations.

Model 2; Specification with Real Time Data and Revisions Our second model specification takes into account the release of information at each point in time, estimating a model of the form in (2.5), using

$$\begin{aligned}\mathbf{z}_t \;=\; (\;& {}_t r_t,\;\; ({}_t y_{t-1} -_{t-1} y_{t-2}),\;\; ({}_t p_{t-1} -_t p_{t-2}),\;\; ({}_t m_{t-1} -_t m_{t-2}),\\ & ({}_t y_{t-2} -_{t-1} y_{t-2}),\;\; ({}_t y_{t-3} -_{t-1} y_{t-3})\;\;)',\end{aligned}$$

for $t = 1, ..., T$. This model includes the real time measures of the four macroeconomic series of interest, measured taking into account the one-quarter publication lag described earlier, plus two output revisions. The model more realistically replicates the decision making context faced by agents using information actually known to policy makers and other economic agents at the time at which decisions are made. Simple variable exclusion tests lead us to include up to two revisions of output in the model only and to drop revisions in money and prices altogether.[19]

Model 3; Specification with Real Time Data, Revisions, and Economic Indicators Our third model specification supplements the system of Model 2 with direct measures of expectations of current and future economic activity available in real time, estimating a model of the form in (2.5), using

$$\begin{aligned}\mathbf{z}_t \;=\; (\;& {}_t r_t,\;\; ({}_t y_{t-1} -_{t-1} y_{t-2}),\;\; ({}_t p_{t-1} -_t p_{t-2}),\;\; ({}_t m_{t-1} -_t m_{t-2}),\\ & ({}_t p_t^f -_t p_{t-1}),\; ({}_t y_t^f -_t y_{t-1}),\; ({}_t p_{t+1}^f -_t p_t^f),\; ({}_t y_{t+1}^f -_t y_t^f),\; {}_t sp_t\\ & ({}_t y_{t-2} -_{t-1} y_{t-2}),\;\; ({}_t y_{t-3} -_{t-1} y_{t-3})\;\;)',\end{aligned}$$

for $t = 1, ..., T$. The model therefore includes, in addition to the variables of Model 2, time-t measures of the nowcast of inflation and output growth from the SPF, direct

[19] To be more specific, although the money and price series are revised, these revisions have no systematic, statistically significant pattern and their lagged values make no significant contribution to the explanation of the other variables in the system. Similar comments apply to the third (and longer) revisions in output. Test results are available from the authors on request.

measures of one-quarter ahead forecasts of the same series and the long- and short-term interest rate spread.

3.3 Estimation Results and Impulse Response Functions

A real time analysis of the models will involve their recursive estimation at each point in time.[20] However, useful insights on the nature of the conventional analyses of Model 1 can be obtained, and compared to the real time analyses of Models 2 and 3, by looking in detail at examples of the estimated models based on a particular sample. Tables 1 and 2 therefore report the estimated VARs of Models 1-3 based on the final vintage of data ($t = 1967q1, .., 2005q4$, $T = 2005q4$ for Model 1 and $t = 1968q4, .., 2006q1$, $T = 2006q1$ for Models 2 and 3).

Model 1 The results show that there is considerable complexity in the feedbacks between the variables, with standard variable addition tests showing that a VAR of order 4 is appropriate (although lagged money appears to have a relatively minor role in explaining interest rates, growth or inflation). Strong growth and/or high inflation precede interest rate rises, as might be expected with a "Taylor-type" rule, interest rate rises are associated with a subsequent slowdown in growth, and inflation is influenced by positive growth with a long (four quarter) lag.

This overview is confirmed by the impulse response functions (IRFs) plotted in Figure 1, which show the impact of a shock to the interest rate equation to each of the four variables. This is typically interpreted as a monetary policy shock, on the assumption that interest rates are set 'first', as discussed earlier. The IRFs show the effect of a monetary policy shock that raises interest rates by one standard error on impact, with the rate returning to the level obtained in the absence of the shock after one or two years. The output response is protracted, with relatively strong effects lasting some two-three years, including a substantial fall in output relative to the base for over a year (so that

[20] For Model 1, this might involve a recursive analysis of the final vintage data, using the appropriate sample periods but using measures of the data which would not have been available at the time. This is termed "quasi real-time analysis" by Orphanides and van Norden (2002).

output levels will be approximately 25% lower at the infinite horizon than in the absence of the shock). The inflation response reflects the 'price puzzle' often featured in the literature, whereby the interest rate rise is associated with a *rise* in inflation on impact but shows a small negative/neutral impact in the long run. And the response of money is a substantial reduction in money holdings, both in the short and longer term. In short, then, the 'conventional' system equations appear complex but sensible in terms of the signs and magnitudes of the coefficients and the overall system properties are exactly of the sort that are typically found in empirical exercises of this kind.

The diagnostic statistics in Table 1 also suggest that the four equations in this specification are reasonable ones according to the fit and, generally speaking, to the absence of evidence of serial correlation, functional form problems, heteroscedasticity or non-normality in the residuals. The main indicator of problems with the model is the strong evidence of structural instability, at least in the interest rate, inflation and money equations, identified through the application of the standard F-test to the sample split in half at $1986q1$.[21] Taken at face value, then, Model 1 appears to provide a reasonable characterisation of the data and one that is broadly in line with macroeconomic stylised facts. However, there is evidence of instability which would render the model inappropriate for real time forecasting or policy prescription even if the data were measured without error so that the final vintage data used here had been available at the time.

Model 2 Table 2 reports on Models 2 and 3 obtained using the first-release data and revisions in the series for $t = 1968q4, .., 2006q1$. The body of the table describes the estimated VAR for Model 2. This confirms that the analysis of data available in real time, including data on revisions, provides a distinct and even more complicated dynamic characterisation of the macroeconomic data than Model 1. Importantly, there are very clear, statistically-significant, systematic patterns in the first and second revisions of output, and the revisions themselves also play an important role in explaining the evolution of the (first-release measures of) output growth. The interest rate remains positively related

[21] Subsequent tests suggest that there was a degree of stability during the first half of the sample (between 1967q1-1986q1) but evidence of further instability within the latter half.

to output growth and inflation and the signs of the short-run and long-run elasticities in the growth and inflation equations again appear sensible. But the size and the timing of the effects are quite different to those in Table 1, with this model able to accommodate the interrelatedness of measured output growth, its revision and their impact on the other macroeconomic variables which Model 1 cannot.

The coefficient estimates of Table 2 show clearly the statistical significance of separately modelling the first-release and revised measures of output. However, the differences between the models are obscured when considering the system-wide response to an interest rate shock. This is illustrated in Figure 1 where the effects of an interest rate shock on Model 2 are traced against those in Model 1. The interest rate is assumed to be set 'first' in both Models 1 and 2, so the shock has the same interpretation in both sets of impulses. Further, the impulses have been calculated to trace the effect of the shock on comparable output, inflation and money series in both models. This is because, in Model 2, the impulses relate to the effect of the shock to the *post-revision* output, inflation and money series (i.e. to ${}_{t+3+s}y_{t+s}$ $s = 0, 1, ...,$ in the case of output, where there are systematic revisions for two periods, and ${}_{t+1+s}p_{t+s}$ and ${}_{t+1+s}m_{t+s}$ for prices and money where the revisions have no systematic content). These series are approximately equal to the final vintage series used in Model 1, therefore.[22] Nevertheless, at first sight, it is surprising to find the impulse responses looking so similar in Models 1 and 2 given the

[22]Following Koop et al. (1996), we note that an impulse response function illustrates the time profile of a variable in response to a particular shock relative to the profile when no shock occurs. The shock can be to a specific variable assuming no other shocks take place (an orthogonalised impulse response function) or it can be a system-wide shock normalised on a particular variable but taking into account simultanous innovations in other variables too. The definition of the responses of post-revision output to a shock specified by $\mathbf{u}_t = \overline{\mathbf{u}}$ for Model 1 is given by

$$E[\ {}_{T}y_{t+s} \mid I_{t-1}, \mathbf{u}_t = \overline{\mathbf{u}}] - E[\ {}_{T}y_{t+s} \mid I_{t-1}], \qquad s = 1, ...,$$

while the response of post-revision output to a shock specified by $\mathbf{u}_t = \underline{\mathbf{u}}$ for Model 2 is given by

$$E[\ {}_{t+3}y_{t+s} \mid I_{t-1}, \mathbf{u}_t = \underline{\mathbf{u}}] - E[\ {}_{t+3}y_{t+s} \mid I_{t-1}], \qquad s = 1, ...$$

For impulse responses from different models to be comparable, the responses must relate to the impact of the same shock (so $\overline{\mathbf{u}} = \underline{\mathbf{u}}$).

statistical significance of the additional dynamics made explicit in Model 2. On reflection, however, this may not be so hard to understand. Specifically, we have already noted that, even if the VAR Model 2 is the true data generating process, it is possible to estimate a VARMA time series model for any sub-set of the variables in Model 2 which will aim to approximate the true DGP. Having recognised that the post-revision series in Model 2 are approximately equal to the final-vintage series used in Model 1, it is clear that Model 1 can be interpreted as a simplified approximate version of Model 2. The estimated impulse responses of the post-revision series in Model 2 illustrate the same properties of the system dynamics captured by the responses of Models 1 to the same interest rate shock, therefore. This is reassuring if this particular impulse response exercise is the purpose of the analysis. But it is misleading if the model was to be used to trace the effect of other types of shock or in forecasting or in providing a structural interpretation to the estimated model.[23]

Further, although the estimated version of Model 1 might provide a reasonable approximation of the true data generating process (as reflected in the system properties of the estimated impulse responses discussed above), this does not mean that the *forecast* of post-revision output levels will be approximately equal to those obtained from Model 2. Hence, impulse response analysis cannot establish the importance of data revisions for the identification of policy shocks and their effects.

The equation diagnostics again provide broad reassurance on the statistical coherence of the model according to fit and the standard residual-based tests. The evidence for structural instability is weaker for the interest rate and inflation equations (being significant at the 10% but no longer at the 5% level of significance) but remains for the money equation and there is now doubt on the stability of the output equation too (at least at the 10% level of significance). In brief, then, the estimated equations of Model 2 also appear sensible in terms of signs and magnitudes of coefficients and have reasonable diagnostic properties. If estimated recursively, these equations could have been more reliably used

[23]The argument suggests that the two models would generate similar impulse responses of the post-revision series if the shock is the same in the two models. However, no shock can be specified that is defined similarly in both Models 1 and 2 apart from that to the interest rate.

to inform policy decisions in real time although some ambiguity on structural stability still remains.

Model 3 The lower section of Table 2 summarises the impact of adding to Model 2 the forward-looking variables suggested in Model 3, again focusing on the model estimated over $t = 1968q4, .., 2006q1$. A specification search suggested that six lags of the spread, ${}_{t}sp_{t}$, two lags of each of the SPF nowcasts ${}_{t}y_{t}^{f}$ and ${}_{t}p_{t}^{f}$ and two lags of the one-quarter ahead forecasts, ${}_{t}y_{t+1}^{f}$ and ${}_{t}p_{t+1}^{f}$ should be included in the equations and the $\chi_{LM}^{2}(14)$ statistic indicates the significance of these variables in each equation. The other three χ_{LM}^{2} statistics aim to isolate in turn the separate contributions of the spread, the SPF nowcasts, and the one-quarter ahead SPF forecasts. These confirm that all three series have considerable explanatory power in the interest rate, output growth and inflation equations highlighting the potential misspecification problems of macroeconomic modelling exercises that omit forward looking variables.[24] Interestingly, the forward looking data, and especially the spread, also provide significant explanatory power for the revisions, suggesting that these data may reflect agents' expectation of the true underlying data.

The underlying short-run and long-run elasticities of Model 3 are not reported in Table 2 for space considerations. But they are sensible according to sign and magnitudes once more and provide reasonable system dynamics. Indeed, the impulse responses of the post-revision series to an interest rate shock based on Model 3 are again reported in Figure 1 and again correspond closely to those of Models 1 and 2. However, the interpretation now is that Model 3 provides the most comprehensive description of the DGP for these macroeconomic series and that the specifications of Models 1 and 2 are approximations that adequately capture the system dynamics (at least as far as these particular impulse responses are concerned) but would be misleading for more structural analysis.

The fit and diagnostic tests of Model 3 (not reported for space considerations but available on request) again show an improvement over the other models. Indeed, as the figures in the final row of Table 2 demonstrate, the inclusion of the additional forward-looking variables serves to eliminate any remaining evidence of structural instability. This

[24]The forward-looking data shows little explanatory power for the money growth series.

is in itself an important empirical finding, showing that a VAR model that attempts to implicitly capture the effect of expectations formation in macroeconomic models is unlikely to succeed.[25] Model 3 represents our preferred model, therefore, accommodating directly all of the information that is available to decision-makers at the time decisions are made, including measures of expected future outcomes, but avoiding the dangers of inappropriately including information that was not available at the time by using real-time data only.

3.4 Model Evaluation using Statistical Forecasts

This section provides an evaluation of the out-of-sample point forecasting performance of the different models.[26] The analysis focuses on forecasts of output growth and inflation at various horizons to judge the extent to which the use of the data on revisions and measures of expectations make a useful contribution if decisions are made in real time based on nowcasts or forecasts of these variables.

Table 3 reports root mean squared errors (RMSE's) for Models $1'$, 2 and 3, where the models are estimated recursively for $t = 1968q4, ..., \tau$, and the relevant out-of-sample forecasts are computed at each recursion for up to two years ahead; i.e. at $\tau+h$, $h = 1, .., 8$. We chose $\tau = 1985q4, ..., 2006q1 - h$ so that the RMSE's are based on up to $N = 80$ recursions. Four RMSE's are obtained using forecasts relating to output growth alone and two are obtained relating to price inflation forecasts alone. Specifically, these are based on:

[25] This should not be interpreted as evidence against rationality in expectation formation. Rather, it suggests that the information content of the direct measures of expectations cannot be captured here by linear function of lagged values and simple structural shocks. This would be the case if, for example, changes in the policy underlying the variables of interest were announced ahead of time and best represented by discrete or other non-linear regime changes.

[26] Since forecasts from Model 1 are not directly comparable to those of Models 2 and 3, we estimated a Model $1'$. This is a VAR in four variables (akin to the variables in Model 1), but obtained in real time; i.e.a model of the form in (2.5), using

$$\mathbf{z}_t = \left(\ {}_tr_t, \ \ ({}_ty_{t-1} - {}_{t-1}y_{t-2}), \ \ ({}_tp_{t-1} - {}_{t-1}p_{t-2}), \ \ ({}_tm_{t-1} - {}_{t-1}m_{t-2}) \ \right)'.$$

- – the nowcast of the first-release output level, $\widehat{_{\tau+1}y_\tau} = E\left[_{\tau+1}y_\tau \mid I_\tau\right]$, which effectively involves a one-step ahead forecast since output is released with a one quarter delay;

  – the nowcast of actual, post-revision output level, $\widehat{_{\tau+3}y_\tau}$, which will involve three-quarter ahead forecasts accounting for the one-quarter delay in the release of output and for two quarterly revisions;

  – the forecast of actual output two-quarters ahead $\widehat{_{\tau+5}y_{\tau+2}}$;

  – the forecast of actual output four-quarters ahead $\widehat{_{\tau+7}y_{\tau+4}}$;

  – the nowcast of the first-release price series, $\widehat{_{\tau+1}p_\tau}$, and

  – the forecast of prices four-quarters ahead $\widehat{_{\tau+4}p_{\tau+3}}$, where systematic revisions are assumed unimportant.[27]

In addition, we also report RMSE's based on functions of output and inflation forecasts that might be of more direct interest to decision-makers. Specifically, we also focus on

- – the nowcast of the output gap, $x_t|\Omega_{t+s} = {}_{t+3}y_t - \widetilde{y}_t$, defined as the gap between actual output at t and the trend measure, $\widetilde{y}_t$, obtained by running the Hodrick-Prescott filter through the forecast-augmented actual output series $\{.....{}_{t-1}y_{t-4},\ {}_t y_{t-3},\ \widehat{_{t+1}y_{t-2}},\ \widehat{_{t+2}y_{t-1}},\ \widehat{_{t+3}y_t},\ \widehat{_{t+4}y_{t+1}},\ ...\}$. The post-revision output available at time t is augmented with forecasts of the future post-revision series formed on the basis of Ω_{t+s} i.e. information available at time $t+s$, $s \geq 0$.[28]

[27] Clearly, the RMSE relates equally to forecasts of output growth or price inflation relative to any common baseline; for example, the nowcast of the first-release output growth is $\sqrt{\frac{1}{N-1}\sum_{\tau=1}^{N-1}\left(\left(_{\tau+1}y_\tau - _\tau y_{\tau-1}\right) - \left(\widehat{_{\tau+1}y_\tau} - _\tau y_{\tau-1}\right)\right)^2} = \sqrt{\frac{1}{N-1}\sum_{\tau=1}^{N-1}\left(_{\tau+1}y_\tau - \widehat{_{\tau+1}y_\tau}\right)^2}$, while the forecast of inflation over the coming year is $\sqrt{\frac{1}{N-1}\sum_{\tau=1}^{N-1}\left(\left(_{\tau+4}p_{\tau+3} - _\tau p_{\tau-1}\right) - \left(\widehat{_{\tau+4}p_{\tau+3}} - _\tau p_{\tau-1}\right)\right)^2} = \sqrt{\frac{1}{N-1}\sum_{\tau=1}^{N-1}\left(_{\tau+4}p_{\tau+3} - \widehat{_{\tau+4}p_{\tau+3}}\right)^2}$.

[28] Details of the computation of the gap measure are given in Garratt et al (2008), where the gap is based on a forecast-augmented Hodrick-Prescott smoother.

– the nowcast of a policy objective, $g_t|\Omega_t = \lambda(\tilde{x}_t|\Omega_t) + ({}_{t+1}p_t - {}_t p_{t-1})^2$ defined as a weighted aggregate of the output gap and inflation where the weight on the gap is varied from $\lambda = 0.1,\ 0.3,\ 0.5$.

The table also shows the outcome of two sets of tests of forecast accuracy. The first set is provided by the Diebold-Mariano (DM) statistics which test the null of equal predictive accuracy of Models $1'$ and 2 and then Models 2 and 3 respectively, based on the differences in the reported root mean square errors and an estimate of the asymptotic variance of this difference. A consistent estimate of the long run variance is obtained by taking a weighted sum of the available sample autocovariances (see Diebold and Mariano (1995)). The second set of tests compares Models 2 and 3 only and is obtained from a simulation exercise based on the assumption that the estimated Model 2 obtained using data for $t = 1968q4, ..., \tau$ is the true data generating process for $t = 1968q4, ..., \tau + h$. Under this assumption, $100,000$ replications of the data sample were generated. Then, for each replication r: Model $2^{(r)}$ and Model $3^{(r)}$ were estimated; forecasts were made for the period $\tau + 1, .., \tau + h$; corresponding RMSE$^{(r)}$ were calculated from the two alternative models; and the difference between these (i.e [RMSE$^{(r)}$ based on Model 2] - [RMSE$^{(r)}$ based on Model 3]) was recorded.[29] The $100,000$ simulated difference statistics obtained in this way provide an empirical distribution for the statistic under the null that Model 2 is true. The † and †† indicate whether the difference in RMSEs observed in the table is greater than the upper 10% or 5% of that empirical distribution. This test statistic is likely to be a more powerful test of the usefulness of the extra variables in Model 3 for forecasting than the DM test when comparing forecasts of nested models (see Clark and McCracken (2001)) and can be readily applied no matter even when the prediction criterion is a complicated function of forecasts of different variables and over different forecast horizons.

Comparison of the RMSE statistics for Models $1'$ and 2 shows that the revisions data are useful in the nowcasts of first-release and actual output growth. The RMSE of the output growth nowcasts from Model 2 are some 25% lower than those from Model $1'$

[29]Although Model 2 is nested within Model 3, the inclusion of any irrelevent variables would damage the forecasting performance of Model 3 (see Clements and Hendry (2005)).

and the DM tests show this to be very strong evidence of improved forecast accuracy. The performance of the longer horizon forecasts of output growth, or for inflation, is not enhanced by the inclusion of the revision data (with the RMSE of Model 2 actually being worse, although not significantly so). This is not so surprising for the inflation series, where revisions were seen to be unimportant. But it also means that the improved forecasting performance achieved through inclusion of the revisions data is achieved primarily on nowcasts and is less pronounced for forecasting over the medium or longer term. This is not to deny its importance; the end-of-sample forecasting performance is crucial in real-time decision-making, for example. But it shows clearly where the gains arise.

Comparison of the RMSE for Models 2 and 3 show even more strikingly the usefulness in forecasting of including all the information available at the time decisions are made, including direct measures and market-based measures of expectations. The RMSE errors calculated using Model 3 are substantially and statistically significantly less than those calculated using Model 2 for all the forecasts considered, covering all the variables and combinations of variables at every horizon (the weakest evidence again being for long horizons for output growth, although the tests based on simulations show the differences to be statistically significant here too). Improvements of up to 40% in the RMSE are observed across the various criteria with the expectations data providing particular forecast improvement on the inflation series. It is worth emphasising that these results are found without using a very sophisticated specification search; we have noted the diagnostics used to choose appropriate lag lengths, for example, but there has been no further search conducted and many variables remain in the model with relatively low t-values. The clarity of the findings on the improved forecasting performance is not the outcome of sophisticated data-mining therefore but simply reflects the importance of including these explanatory variables and fully exploiting the information that is available to forecasters at the time forecasts and decisions are made.

4 The Usefulness of Real Time Data for Nowcasting and Forecasting

The results of the previous section show that, in terms of purely statistical criteria, there is a strong argument for using real time data, including direct and market-based expectations measures, in modelling. In this section, we show that the use of the available information in modelling and forecasting is equally important using more economic criteria in the context of decision-making. To this end, we propose specific economic events of interest relating to the business cycle and use these as a basis for evaluating Model 2 and Model 3 by comparing the models' performance in forecasting the likelihood of the events taking place.

The calculation of probability forecasts (i.e. forecasts of the probability of specified events taking place) is relatively unusual in economics. This is surprising given that, compared to the point forecasts and confidence intervals that are usually reported, probability forecasts are better able to focus on events of interest to decision-makers and can convey the uncertainties associated with the event of interest more directly. Further, the methods are relatively straightforward to implement using simulation methods. Garratt et al. (2003) describe the methods in detail, but the idea can be briefly outlined if we consider an example where we calculate the probability density function (pdf) associated with the nowcast of output growth defined by $(\widehat{_{t+3}y_t} - \widehat{_{t+2}y_{t-1}})$.[30] Here, one would use the estimates from a model (i.e. Model 2 or Model 3), including the estimated variance-covariance of the innovations, to generate R replications of the future outcomes, including $\widehat{_{t+h}y_{t-3+h}}^{(r)}$, $h = 0, 1, ...$ and $r = 1, .., R$ and the '(r)' superscript denotes the value taken in the r^{th} simulation. The values of $\widehat{_{t+h}y_{t-3+h}}^{(r)}$ obtained across replications directly provides the simulated pdf of forecast post-revision output time $t - 3 + h$ and the values of $(\widehat{_{t+3}y_t}^{(r)} - \widehat{_{t+2}y_{t-1}}^{(r)})$ provide the pdf of the nowcast of actual output growth.[31] Further, counting the number of times in which $(\widehat{_{t+3}y_t}^{(r)} - \widehat{_{t+2}y_{t-1}}^{(r)})$ exceeds zero out of the R replications provides a direct estimate of the nowcast probability that output growth is positive. This statistic will be much more useful to a decision-maker concerned with this specific feature of the business cycle than the point forecast of growth and 95% confidence intervals typically reported.

[30] We abstract from parameter uncertainty in this example although this feature can be readily accommodated. See Garratt et al (2003) for details.

[31] It is worth emphasising that this growth nowcast involves forecasts of series at different forecast horizons which are not independent. However, the simulated pdf automatically reflects all the uncertainties associated with these forecasts.

To illustrate the importance of using real time information in this context, we focus on two events relating to the time-t perception of the business cycle at time t. The first considers the likely occurrence of two periods of consecutive negative growth at t and $t-1$; i.e. $\Pr\{A\}$ where event A is defined by $A: \{\ [({}_{t+2}y_{t-1} - {}_{t+1}y_{t-2}) < 0]\ \cap\ [({}_{t+3}y_t - {}_{t+2}y_{t-1}) < 0]\ \}$. This is one simple but frequently used definition of "recession". Figure 2 plots these probabilities for the period 1986q1 – 2006q1 as calculated from the estimates of Model 2 (dashed line) and the estimates of Model 3 (solid line) obtained recursively in real time and on the basis of $R = 200,000$ replications. The figure also plots the actual occurrence of two periods of consecutive negative growth (the dotted line), given by $[({}_{t+2}y_{t-1} - {}_{t+1}y_{t-2}) < 0] \cap [({}_{t+3}y_t - {}_{t+2}y_{t-1}) < 0]$. As it happens, this is a relatively unusual event and occurred in only two out of the 80 quarters of the last two decades of our sample (namely 1991q1 and 2001q4). This profile is reflected in the nowcasts of the probability of the event occurring which remain close to zero in most periods for both models (rising above 10% on just three occasions for Model 2 and six occasions for Model 3). Both models also recognise the increased likelihood of recession in 1991q4, with the probability rising to 52% for Model 2 and 80% for Model 3. Importantly, though, only Model 3 recognised the 2001q4 recession, providing a 56% probability of recession compared to Model 2's 4%. A formal evaluation of the two models' nowcasting performance requires a complete description of the decision-maker's loss function (identifying the costs and benefits of the decisions based on the nowcast probabilities from the two models). But the exercise illustrates clearly Model 3's ability to rapidly identify this unusual event reflecting the fact that, in reality, economic agents are well informed about the current state of the economy. This information is captured by those agents' statements on the business cycle, as measured in business surveys and market-based information. Model builders that fail to use this information may not identify events that other economic agents are aware of, therefore there is a risk of providing poor advice.

The second business cycle event considered here is the occurrence of recession as defined by the NBER (available from www.nber.org). The NBER definition of recession is based on a number of economic indicators and the recession dates are published only after a significant delay. For instance, the end of the recession in November 2001 was only announced by the NBER in July 2003. In our exercise, we evaluate our alternative models from the perspective of decision-makers who need to know whether we are in an NBER-defined recession today. The first step in this process is to relate the NBER categorisation to observable data. To this end, a probit model is estimated to explain a dummy variable, $NBER_t$, which takes a value of one for all quarterly dates of contraction as defined by the NBER and zero otherwise. Following a relatively straightforward specification search, based on the joint insignificance of longer lags, the regressors in the model consist of the current and one lag of actual output growth $({}_{t+3}y_t - {}_{t+2}\, y_{t-1})$, and the current and one lag of a 'current depth of recession' (CDR) dummy variable. The CDR variable is defined as the gap between the current level of actual output and its historical maximum where $CDR_t = \max\left\{{}_{t+3}y_{t-s}\right\}_{s=0}^{t} - {}_{t+3}\, y_t$. Therefore, the CDR dummy variable will take the value of one when output dips below its 'trend' value due to a negative shock and zero otherwise.[32] The estimated Probit model obtained using data for $1965q4 - 2006q1$ is as follows:

$$\begin{aligned} NBER_t \;=\; & \underset{[-1.2594]}{-0.6452} - \underset{[-3.4663]}{158.3721}({}_{t+3}y_t - {}_{t+2}\, y_{t-1}) - \underset{[-2.0243]}{58.8598}\,({}_{t+2}y_{t-1} - {}_{t+1}\, y_{t-2}) \\ & + \underset{[0.0579]}{0.0316} CDR_t + \underset{[2.3515]}{1.1532} CDR_{t-1} + \widehat{\epsilon}_t, \end{aligned} \tag{4.7}$$

where $\epsilon_t \sim N(0,1)$ and where t-statistics are reported in [.].

To calculate the "nowcast" probabilities of a NBER-recession, it is assumed that the relationship between $NBER_t$ and the measurables in (4.7) is known to agents throughout our sample. We then calculate $\Pr\{B\}$ where event B is defined by $B : \{\ NBER_t > 0\ \}$, obtained recursively in real time using the same the $R = 200,000$ simulations of the future as described above. It should be clear here that the nowcast values of $NBER_t$ are complicated non-linear functions of forecasts of variables measured at different forecast

[32] The asymmetry implied by the CDR term is reflected in the "bounce-back" effect, the tendency for output growth to recover relatively strongly following a recent recession. Hence, the CDR approach treats the historical maximum level of output as an attractor which influences the dynamics of output growth when output falls below its previous peak. Beaudry and Koop (1993) hypothesise that there is a non-linearity in this "peak reversion"; the further output falls from its peak, the greater is the pressure that builds up for output to return to its historical maximum. As a result, the speed at which output recovers varies according to the severity of the recession.

horizons, so that the uncertainty surrounding the likely occurrence of an NBER-recession would be extremely difficult to calculate analytically. The estimated probabilities are relatively easily obtained through the simulation exercise, however, and are illustrated for $1986q1 - 2006q1$ in Figure 3. This figure shows that contraction was actually observed, according to the NBER, in nine of the 80 quarters considered in the diagram; namely during $1990q3 - 1991q3$ and $2001q1 - 2001q4$ inclusive. Model 2 performs relatively poorly in identifying these periods in real time. The nowcast probability of NBER-contraction based on Model 2 exceeds 20% on only two occasions through the period and neither correspond to periods subsequently labelled as contractions by NBER. Model 3 on the other hand performs relatively well, with the nowcast probability exceeding 20% on ten occasions, seven of which correspond to NBER dates. Again, a full evaluation of the forecast success requires a detailed description of the loss function faced by the decision-maker. But the correspondence with the event outcomes based on Model 3 is striking and again shows the considerable information content of survey data and market-based expectations in judging where the economy currently stands.[33]

In order to see more precisely the nature of the information content contained in the survey and yield curve data, Table 4 provides further details of the estimated nowcasts of the contraction probabilities for the two periods identified by NBER as periods of contraction. Here, the first row shows the probabilities reported in Figure 3 and based on Model 3 including the spread data sp_t, plus the current realisations and one-quarter ahead expectations of inflation and output growth, respectively given by $[({}_tp_t^f -_t p_{t-1})$, $({}_ty_t^f -_t y_{t-1})]$, and $[({}_tp_{t+1}^f -_t p_t^f)$, $({}_ty_{t+1}^f -_t y_t^f)$, obtained from surveys. The subsequent three rows show the corresponding probabilities obtained if only the spread data were included in the model, only the realisation data were included, and only the one-step ahead expectations data were included, respectively. The results in these three rows are based on misspecified models (having incorrectly dropped statistically significant variables) and should be treated with caution. But they provide indicative information on the source

[33] The evaluation criterion here is how well the contraction probabilities match the NBER dates. But the continuum provided by the estimated probabilities, and particulalry the fact that these rose to close to 50% in 1988q2 and 1990q1, is potentially important information in its own right.

of the information useful in forecasting. As it turns out, the relatively high probabilities (>35%) observed in $1990q3$ – $1991q2$ and $2001q1$ – $2001q4$ in Model 3 appear to be driven primarily by the use of the survey-based realisation data. The one-step ahead expectations data are useful too, if used in isolation, but it is the realisation data, $[({}_tp_t^f -_t p_{t-1}), ({}_ty_t^f -_t y_{t-1})]$,which, in the context of the model that accommodates both first-release and revisions data, allows the model to rapidly identify the state of the business cycle.

The lower half of the table reports in an analogous fashion the contraction probabilities for the same period but based on information available one year before the contraction. Interestingly, these set of results show that it is the spread data which seems most useful. This conclusion is based on the figures provided in the lower half of Table 4 which show reasonably high (>20%) contraction-probabilities even at this forecast horizon based on Model 3, but with the high probabilities showing most clearly in the sub-models incorporating spread data.

5 Concluding Comments

This paper addresses issues that arise in both structural and reduced form empirical modelling of macroeconomic time series. For both types of modelling exercises, this paper argues that real time considerations will be of importance and a modelling framework is proposed in which the real time informational context of decision-making is properly reflected.

Structural modelling exercises, ideally, should be cognizant of the real time informational context of decision making. In particular, the fact that expectations formation takes place in real time and that, for many variables, real time values will be different to post revision values, defines a set of restrictions that would be needed to identify structural innovations that is considerably broader than the restrictions typically imposed in empirical analysis. These restrictions would reflect the processes associated with agents' underlying decision making, including expectations formation, and the methodology by which data are measured and subsequently revised. In the absence of a sufficient set of implied restrictions, very careful interpretation of the innovations is required.

The implied reduced form model incorporates market-informed insights on future macroeconomic conditions and information that was available at the time. Comparisons with 'standard' models, that incorrectly omit this information, can reveal potential specification errors. A real time analysis of quarterly US data, 1968q4-2006q1, shows that the misspecification problems are clearly highlighted using out-of-sample forecasting exercises, and not through the use of diagnostic tests applied to the standard models or typical impulse response analysis. In other words, mispecification issues can be revealed through an analysis which is real time in nature. The empirical findings show that estimated real time models considerably improve out-of-sample forecasting performance, provide more accurate 'nowcasts' of the current state of the macroeconomy and provide more timely indicators of recessions.

Table 1: Model 1: VAR with Conventional Timing: 1967q1 - 2005q4

Independent Variable	Dependent Variable			
	${}_Tr_t$	$({}_Ty_t -_T y_{t-1})$	$({}_Tp_t -_T p_{t-1})$	$({}_Tm_t -_T m_{t-1})$
intercept	-0.0170 (0.0054)	0.0071 0.0021	-0.0012 (0.0011)	0.0036 (0.0024)
${}_Tr_{t-1}$	0.2054 (0.0948)	-0.0988 (0.0379)	-0.0265 (0.0192)	0.0723 (0.0431)
${}_Tr_{t-2}$	0.1244 (0.0958)	0.0267 (0.0383)	0.0153 (0.0195)	-0.0530 (0.0436)
${}_Tr_{t-3}$	0.3150 (0.0957)	0.0837 (0.0383)	-0.0309 (0.0194)	0.0060 (0.0436)
${}_Tr_{t-4}$	0.2234 (0.0989)	-0.0392 (0.0395)	0.0222 (0.0201)	-0.0035 (0.0450)
$({}_Ty_{t-1} -_T y_{t-2})$	0.4358 (0.2127)	0.1669 (0.0851)	0.0605 (0.0432)	-0.2082 (0.0968)
$({}_Ty_{t-2} -_T y_{t-3})$	0.5588 (0.2145)	0.2185 (0.0858)	0.0181 (0.0435)	-0.0567 (0.0976)
$({}_Ty_{t-3} -_T y_{t-4})$	0.4157 (0.2205)	-0.0087 (0.0881)	0.0513 (0.0448)	0.0676 (0.1003)
$({}_Ty_{t-4} -_T y_{t-5})$	0.0736 (0.1938)	0.0242 (0.0857)	0.1011 (0.0393)	0.0579 (0.0882)
$({}_Tp_{t-1} -_T p_{t-2})$	1.4051 (0.4376)	-0.2082 (0.1750)	0.6782 (0.0888)	-0.5781 (0.1992)
$({}_Tp_{t-2} -_T p_{t-3})$	-0.1927 (0.4786)	0.0150 (0.1914)	-0.0646 (0.0972)	0.4954 (0.2178)
$({}_Tp_{t-3} -_T p_{t-4})$	0.7009 (0.4843)	0.0123 (0.1936)	0.5416 (0.0983)	-0.4783 (0.2204)
$({}_Tp_{t-4} -_T p_{t-5})$	-0.5794 (0.4581)	0.0221 (0.1832)	-0.1457 (0.0930)	0.4874 (0.2085)
$({}_Tm_{t-1} -_T m_{t-2})$	0.0320 (0.1940)	0.0414 (0.0776)	0.0220 (0.0394)	0.5657 (0.0883)
$({}_Tm_{t-2} -_T m_{t-3})$	-0.0555 (0.2205)	0.1356 (0.0882)	0.0374 (0.0448)	0.1687 (0.1004)
$({}_Tm_{t-3} -_T m_{t-4})$	-0.1694 (0.2194)	-0.0790 (0.0877)	0.0138 (0.0445)	0.0821 (0.0998)
$({}_Tm_{t-4} -_T m_{t-5})$	0.1261 (0.1901)	-0.0106 (0.0760)	-0.0216 (0.0386)	-0.0545 (0.0865)
R^2	0.7904	0.2839	0.7745	0.5390
$\hat{\sigma}$	0.0185	0.0074	0.0038	0.0084
$F_{SC(4)}$	{0.28}	{0.14}	{0.16}	{0.01}
F_{FF}	{0.12}	{0.02}	{0.00}	{0.29}
F_H	{0.00}	{0.20}	{0.04}	{0.18}
F_N	{0.00}	{0.00}	{0.34}	{0.65}
F_{STAB}	{0.02}	{0.58}	{0.00}	{0.00}

Notes: Standard errors are given in (.). R^2 is the squared multiple correlation coefficient, and $\widehat{\sigma}$ is the standard error of the regression. The remaining diagnostics are p-values, in {.}, for F-test statistics for serial correlation (SC), functional form (FF), normality (N), heteroscedasticity (H), and a Chow test of the stability of regression coefficients (STAB).

Table 2: Model 2: VAR with Real Time Data and Revisions: 1968q4 - 2006q1

Independent Variable	Dependent Variable					
	${}_tr_t$	$({}_ty_{t-1} -_{t-1} y_{t-2})$	$({}_tp_{t-1} -_{t-1} p_{t-2})$	$({}_tm_{t-1} -_{t-1} m_{t-2})$	$({}_ty_{t-2} -_{t-1} y_{t-2})$	$({}_ty_{t-3} -_{t-1} y_{t-3})$
intercept	−0.0122 (0.0055)	0.0050 (0.0021)	0.0013 (0.0011)	0.0018 (0.0023)	−0.0015 (0.0011)	−0.0010 (0.0009)
${}_tr_{t-1}$	0.2967 (0.0883)	−0.0371 (0.0342)	0.0810 (0.0179)	−0.1554 (0.0364)	−0.0320 (0.0175)	−0.0097 (0.0152)
${}_tr_{t-2}$	0.0145 (0.0943)	−0.0444 (0.0365)	−0.0393 (0.0191)	0.1070 (0.0389)	0.0492 (0.0187)	0.0311 (0.0163)
${}_tr_{t-3}$	0.4013 (0.0999)	−0.0152 (0.0387)	−0.0018 (0.0202)	−0.0010 (0.0412)	−0.0118 (0.0198)	−0.0083 (0.0172)
${}_tr_{t-4}$	0.1304 (0.0945)	0.0619 (0.0366)	−0.0364 (0.0191)	0.0536 (0.0390)	−0.0082 (0.0187)	−0.0084 (0.0163)
$({}_{t-1}y_{t-2} -_{t-2} y_{t-3})$	0.9307 (0.2626)	0.5320 (0.1017)	0.0542 (0.0532)	−0.0785 (0.1084)	0.1351 (0.0521)	0.0448 (0.0453)
$({}_{t-2}y_{t-3} -_{t-3} y_{t-4})$	0.1928 (0.2623)	0.0711 (0.1015)	−0.0688 (0.0531)	0.1186 (0.1082)	0.0176 (0.0520)	0.0366 (0.0452)
$({}_{t-1}p_{t-2} -_{t-2} p_{t-3})$	0.4666 (0.4136)	−0.4952 (0.1601)	0.6215 (0.0838)	−0.2543 (0.1707)	−0.0785 (0.0820)	−0.0579 (0.0713)
$({}_{t-2}p_{t-3} -_{t-3} p_{t-4})$	0.7847 (0.4323)	0.3932 (0.1674)	0.1913 (0.0876)	0.3560 (0.1784)	0.1718 (0.0857)	0.0763 (0.0745)
$({}_{t-1}m_{t-2} -_{t-2} m_{t-3})$	0.0396 (0.1959)	0.0211 (0.0758)	0.0475 (0.0397)	0.5671 (0.0809)	0.0634 (0.0388)	0.0323 (0.0338)
$({}_{t-2}m_{t-3} -_{t-3} m_{t-4})$	−0.0072 (0.1954)	0.0966 (0.0757)	0.0048 (0.0396)	0.1989 (0.0807)	−0.0115 (0.0388)	0.0075 (0.0337)
$({}_{t-1}y_{t-3} -_{t-2} y_{t-3})$	−1.1746 (0.9334)	−0.9674 (0.3614)	0.1128 (0.1891)	−0.8357 (0.3853)	−0.5678 (0.1851)	−0.3279 (0.1608)
$({}_{t-2}y_{t-4} -_{t-3} y_{t-4})$	1.2681 (0.9581)	0.6950 (0.3709)	0.0070 (0.1941)	−0.3191 (0.3955)	−0.1550 (0.1900)	−0.2149 (0.1651)
$({}_{t-1}y_{t-4} -_{t-2} y_{t-4})$	0.1534 (1.0169)	0.7188 (0.3937)	−0.2581 (0.2060)	0.9939 (0.4197)	0.4068 (0.2017)	0.2507 (0.1752)
$({}_{t-2}y_{t-5} -_{t-3} y_{t-5})$	−1.0178 (1.0193)	−0.7758 (0.3946)	0.0601 (0.2065)	0.1909 (0.4207)	0.1777 (0.2022)	0.1654 (0.1756)
R^2	0.7715	0.4107	0.7556	0.5885	0.1761	0.0940
$\hat{\sigma}$	0.0191	0.0074	0.0075	0.0117	0.0037	0.0033
$F_{SC(4)}$	{0.20}	{0.59}	{0.00}	{0.08}	{0.06}	{0.33}
F_{FF}	{0.77}	{0.13}	{0.05}	{0.03}	{0.94}	{0.47}
F_H	{0.00}	{0.64}	{0.11}	{0.00}	{0.91}	{0.30}
F_N	{0.00}	{0.33}	{0.95}	{0.04}	{0.00}	{0.00}
F_{STAB} (Model 2)	{0.05}	{0.06}	{0.07}	{0.00}	{0.02}	{0.06}
$\chi^2_{LM}(14)$ (for Model 3 variables)	{0.00}	{0.00}	{0.00}	{0.43}	{0.08}	{0.26}
$\chi^2_{LM}(4)$ (Model 3: $({}_tp^f_t -_t p_{t-1})$ and $({}_ty^f_t -_t y_{t-1})$	{0.00}	{0.00}	{0.00}	{0.34}	{0.23}	{0.60}
$\chi^2_{LM}(4)$ (Model 3: $({}_tp^f_{t+1} -_t p^f_t)$ and $({}_ty^f_{t+1} -_t y^f_t)$)	{0.01}	{0.09}	{0.02}	{0.68}	{0.98}	{0.98}
$\chi^2_{LM}(6)$ (for Model 3: sp_t)	{0.00}	{0.00}	{0.00}	{0.67}	{0.05}	{0.08}
F_{STAB} (Model 3)	{0.58}	{0.22}	{0.19}	{0.43}	{0.04}	{0.52}

Notes: Standard errors are given in (.). R^2 is the squared multiple correlation coefficient, $\widehat{\sigma}$ the standard error of the regression and $F_{SC(4)}$, F_{FF}, F_H, F_N and F_{STAB} report p-values in {.} for F-test statistics for serial correlation (SC), functional form (FF), normality (N) and heteroscedasticity (H) and a Chow test of the stability of regression coefficients. The $\chi^2_{LM}(14)$ gives p-values in {.} from a chi-squared test statistic (with 14 d.f.) for the joint test of zero restrictions on the coefficients of two lags each of forecasts of inflation and output growth $({}_tp^f_t -_t p_{t-1})$, $({}_ty^f_t -_t y_{t-1})$, $({}_tp^f_{t+1} -_t p^f_t)$ and $({}_ty^f_{t+1} -_t y^f_t)$, provided by the SPF, and of six lags of the spread sp_t. The remaining χ^2_{LM} statistics provide a breakdown of the contribution of each of these respective variables in Model 3.

Table 3: RMSE's and Diebold-Mariano Statistics

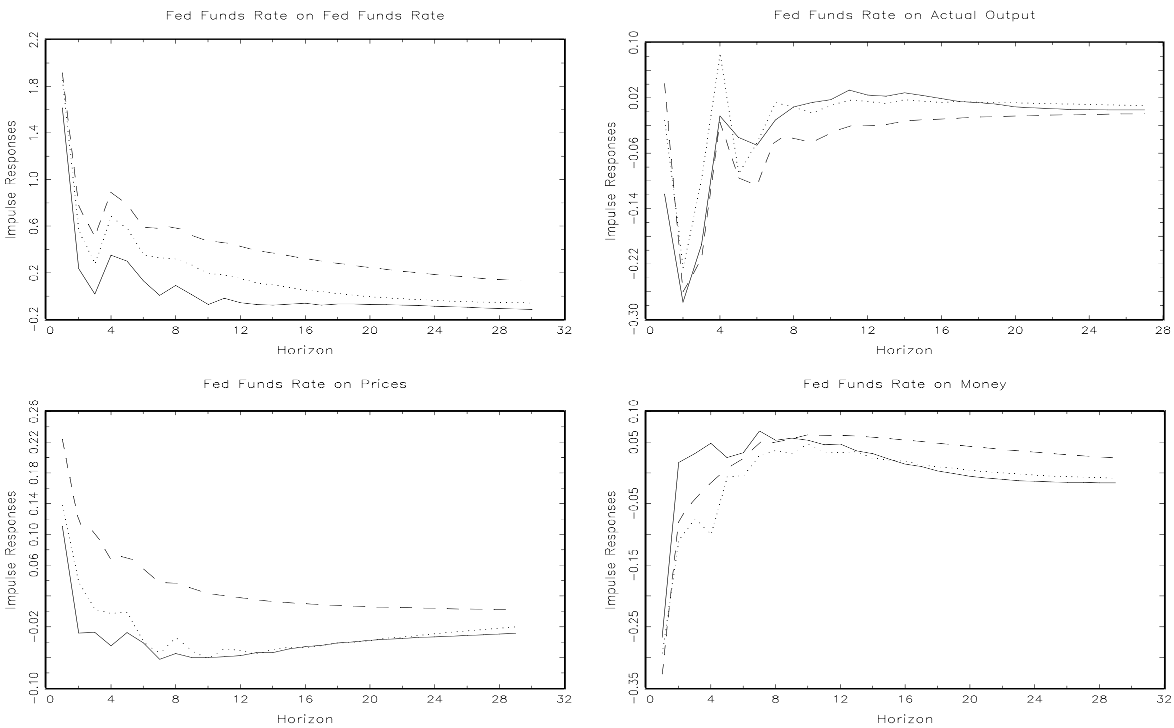
	RMSE's			Diebold-Mariano Statistics	
	Model 1′	Model 2	Model 3	Model 1′ vs 2	Model 2 vs 3
$\sqrt{\frac{1}{N-1}\sum_{\tau=1}^{N-1}\left({}_{\tau+1}y_{\tau}-\widehat{{}_{\tau+1}y_{\tau}}\right)^2}$	0.0108	0.0073	$0.0064^{\dagger\dagger}$	3.3508 [0.001]	1.9328 [0.057]
$\sqrt{\frac{1}{N-3}\sum_{\tau=1}^{N-3}\left({}_{\tau+3}y_{\tau}-\widehat{{}_{\tau+3}y_{\tau}}\right)^2}$	0.0127	0.0092	$0.0091^{\dagger\dagger}$	2.6287 [0.010]	0.1063 [0.916]
$\sqrt{\frac{1}{N-5}\sum_{\tau=1}^{N-5}\left({}_{\tau+5}y_{\tau+2}-\widehat{{}_{\tau+5}y_{\tau+2}}\right)^2}$	0.0183	0.0187	$0.0165^{\dagger\dagger}$	−.21033 [0.834]	1.2359 [0.220]
$\sqrt{\frac{1}{N-7}\sum_{\tau=1}^{N-7}\left({}_{\tau+7}y_{\tau+4}-\widehat{{}_{\tau+7}y_{\tau+4}}\right)^2}$	0.0236	0.0265	$0.0247^{\dagger\dagger}$	−1.4565 [0.150]	0.6654 [0.508]
$\sqrt{\frac{1}{N-1}\sum_{\tau=1}^{N-1}\left({}_{\tau+1}p_{\tau}-\widehat{{}_{\tau+1}p_{\tau}}\right)^2}$	0.0057	0.0058	$0.0035^{\dagger\dagger}$	−.73011 [0.467]	3.8269 [0.000]
$\sqrt{\frac{1}{N-1}\sum_{\tau=1}^{N-1}\left({}_{\tau+4}p_{\tau+3}-\widehat{{}_{\tau+4}p_{\tau+3}}\right)^2}$	0.0039	0.0041	$0.0030^{\dagger\dagger}$	−1.1854 [0.240]	2.6333 [0.010]
$\frac{1}{N}\sum_{\tau=1}^{N}\left(\widetilde{x}_{\tau}^{r}\vert\Omega_{\tau}-\widetilde{x}_{\tau}^{f}\vert\Omega_{T}\right)^2$		0.0084	$0.0078^{\dagger\dagger}$		
$\frac{1}{N}\sum_{\tau=1}^{N}\left(g_{\tau}^{r}\vert\Omega_{\tau}-g_{\tau}^{f}\vert\Omega_{T}\right)^2$ for $\lambda=0.1$		2.07×10^{-5}	$1.87\times10^{-5\dagger}$		
$\frac{1}{N}\sum_{\tau=1}^{N}\left(g_{\tau}^{r}\vert\Omega_{\tau}-g_{\tau}^{f}\vert\Omega_{T}\right)^2$ for $\lambda=0.3$		0.0017	$5.60\times10^{-5\dagger\dagger}$		
$\frac{1}{N}\sum_{\tau=1}^{N}\left(g_{\tau}^{r}\vert\Omega_{\tau}-g_{\tau}^{f}\vert\Omega_{T}\right)^2$ for $\lambda=0.5$		0.0017	$9.34\times10^{-5\dagger\dagger}$		

Notes: The table reports RMSE and Diebold-Mariano statistics for the model specifications described in the text. $\widetilde{x}_{\tau}^{r}|\Omega_{\tau}$ and $\widetilde{x}_{\tau}^{f}|\Omega_{T}$ respectively denote the real time and final output gap, as described in the text, and $g_{\tau}|\Omega_{\tau}=\lambda(\widetilde{x}_{\tau}|\Omega_{\tau})+({}_{\tau+1}p_{\tau}-{}_{\tau}p_{\tau-1})^2$. The models are estimated for $t=1968q4,...,\tau$, $\tau=$1985q4-2006q1 and $T=80$. The statistics in square brackets denote p-values. The† and †† denote the results of the test that the difference between the RMSE of Model 2 and 3 are the same under the null that the data is generated under Model 2; the symbols denote significance at the 10% and 5% levels, respectively.

Table 4: Model 3 Nowcast and Forecast Conditional Event Probabilities of NBER-dated Contractions

	1990q3	1990q4	1991q1	1991q2	1991q3	2001q1	2001q2	2001q3	2001q4
Nowcast ($h = 0$)									
$[sp_t]$, $[({}_tp^f_t -_t p_{t-1}), ({}_ty^f_t -_t y_{t-1})]$, $[({}_tp^f_{t+1} -_t p^f_t), ({}_ty^f_{t+1} -_t y^f_t)]$	0.5503	0.4774	0.9134	0.6887	0.0933	0.3520	0.4249	0.7392	0.9712
sp_t	0.1446	0.1012	0.5404	0.3480	0.0954	0.2087	0.2736	0.3246	0.0797
$({}_tp^f_t -_t p_{t-1})$ and $({}_ty^f_t -_t y_{t-1})$	0.5373	0.7871	0.9688	0.7097	0.1136	0.4695	0.3975	0.7915	0.9885
$({}_tp^f_{t+1} -_t p^f_t)$ and $({}_ty^f_{t+1} -_t y^f_t)$	0.4261	0.3664	0.7758	0.4557	0.1269	0.2250	0.2210	0.3876	0.2528
Four period ahead forecast ($h = 4$)									
$[sp_t]$, $[({}_tp^f_t -_t p_{t-1}), ({}_ty^f_t -_t y_{t-1})]$, $[({}_tp^f_{t+1} -_t p^f_t), ({}_ty^f_{t+1} -_t y^f_t)]$	0.6373	0.2379	0.2681	0.2379	0.1682	0.1481	0.1783	0.2152	0.1835
sp_t	0.8238	0.2718	0.2359	0.2248	0.1525	0.1330	0.1554	0.2625	0.2099
$({}_tp^f_t -_t p_{t-1})$ and $({}_ty^f_t -_t y_{t-1})$	0.1386	0.0969	0.1006	0.1813	0.0906	0.1090	0.0799	0.0664	0.0498
$({}_tp^f_{t+1} -_t p^f_t)$ and $({}_ty^f_{t+1} -_t y^f_t)$	0.2604	0.2394	0.2246	0.3129	0.3131	0.2993	0.2271	0.2182	0.2824

Notes: The table reports nowcast event probabilities of NBER-dated contractions, conditioning on information sets consisting of various combinations of the forward-looking variables. The variables are categorised into three sets of information set, namely, the spread, ${}_tsp_t$, the SPF time-t forecasts of inflation and output growth, $({}_tp^f_t -_t p_{t-1})$, $({}_ty^f_t - {}_ty_{t-1})$, and the time-$t+1$ SPF forecasts of output growth and inflation. $({}_tp^f_{t+1} - {}_tp^f_t)$, $({}_ty^f_{t+1} - {}_ty^f_t)$. The information sets listed in the table implies their inclusion in the respective simulation experiment. The simulation experiment underlying the computation of these probabilities is the same as that for the nowcast probabilities plotted in Figure 3, and is as detailed in the text.



- - - - - Model 1 — — — — — Model 2 ———— Model 3

Figure 1: Impulse Responses of a Federal Funds Rate Shock

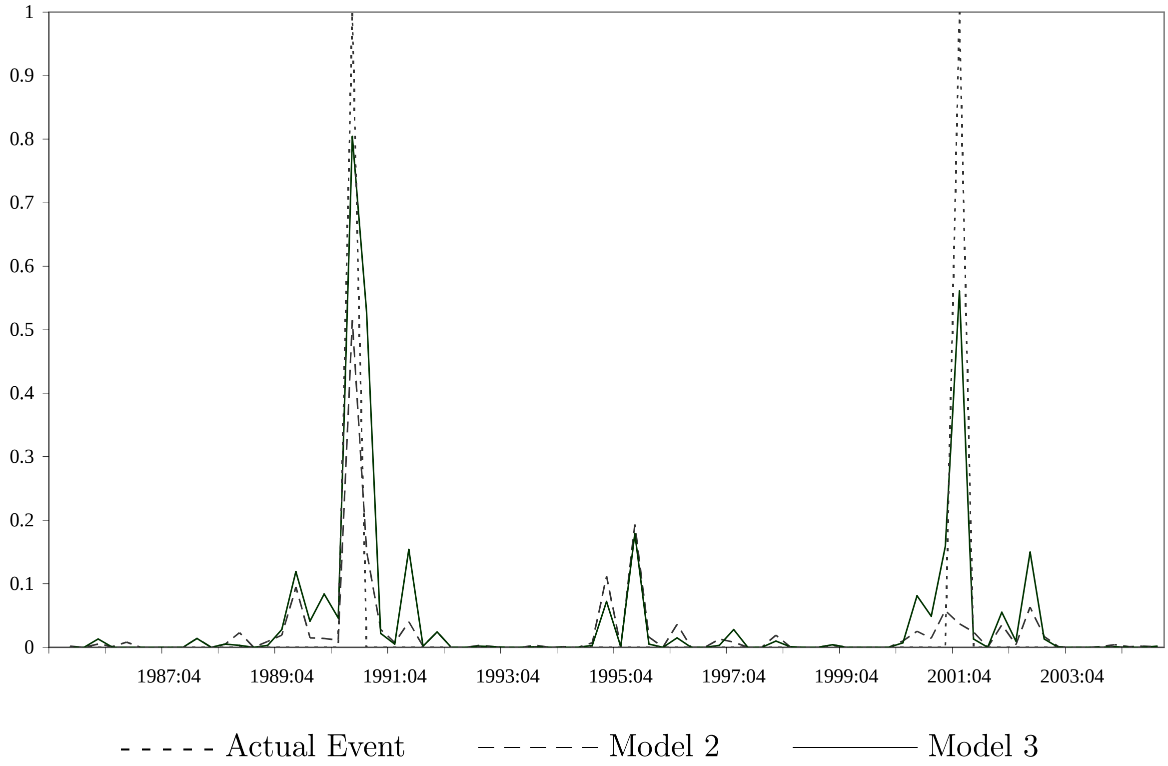


Figure 2: "Nowcast" probabilities of two periods of consecutive negative growth; $pr\left\{[({}_{t+2}y_{t-1} - {}_{t+1}\, y_{t-2}) < 0] \cap [({}_{t+3}y_t - {}_{t+2}\, y_{t-1}) < 0]\right\}$

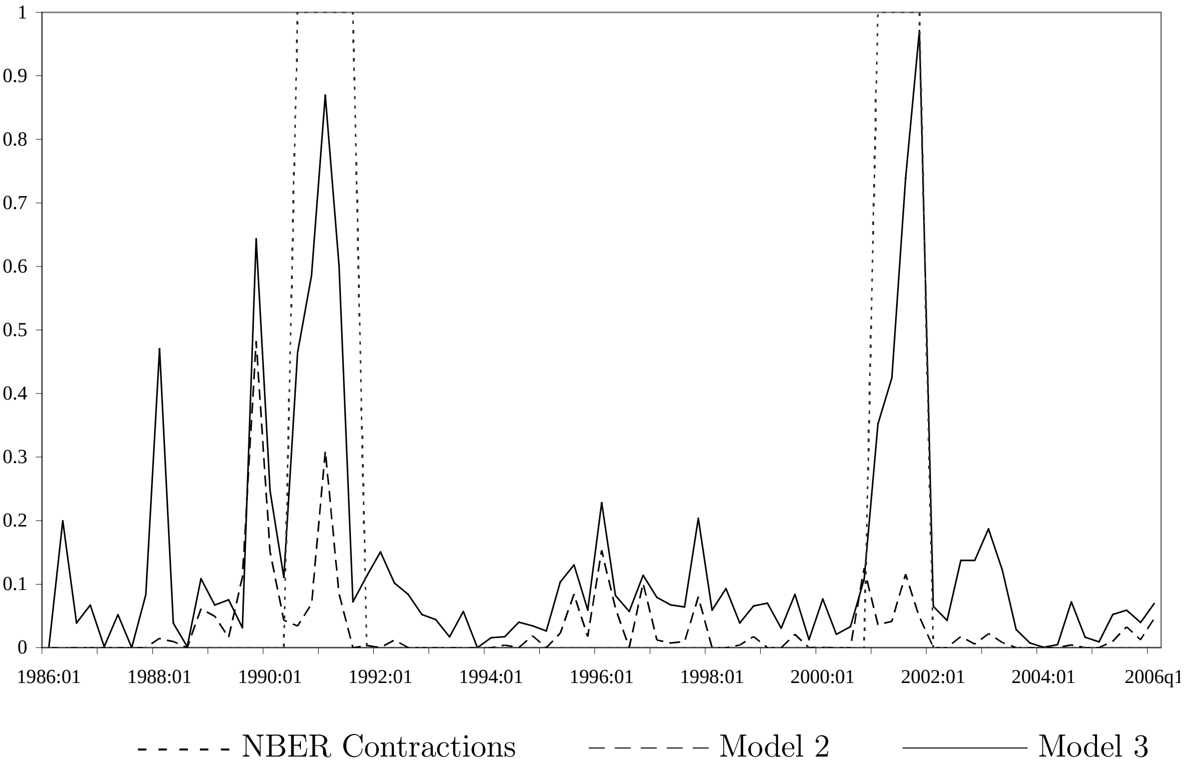


Figure 3: "Nowcast" probabilities of NBER Periods of Contraction

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