Nowcasting, Business Cycle Dating and the Identification of Policy Shocks using Information Available in Real Time*

by

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Abstract

A modelling framework is proposed in which the real time informational context of decision-making is properly reflected. Comparisons are drawn with 'standard' estimated models that incorrectly omit market-informed insights on future macroeconomic conditions and inappropriately incorporate information that was not available at the time. An analysis of quarterly US data 1968q4-2006q1 shows that neither diagnostic tests applied to the standard models nor typical impulse response analysis are able to expose the misspecification clearly. 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. A case study highlights the use of information in recognising the US recessions of 1990q3 – 1991q2 and of 2001q1 – 2001q4.

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

JEL Classification:

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1 Introduction

The recent availability of detailed real time data sets allows a systematic consideration of the issues that arise when modeling data generating processes using variables whose final measured values are revealed over time. Underlying many of the papers that use these data is a concern for the problems faced by policy makers who need to respond to events in real time, and have to do so in the absence of final knowledge of the state variables that guide their decision making (see Blinder, 1997, Orphanides et al, 2000, Orphanides, 2001 and Cogley and Sargent, 2005, for example).

In this paper, we raise a related issue concerning the ability of researchers to model dynamic relationships and recover structural innovations using time series data when the data are revised over time – even when researchers are using final measured values to empirically model these relationships. This paper argues that complications in empirically identifying economically meaningful relationships arise when one recognises that agents' decision making and expectations formation, which underlie these dynamic relations, will be based on the information set that is known in real time. Although some data available in real time are subject to revisions over time, it is important to recognise that some data, such as direct measures of expectations based on point-in-time surveys, or that derived from financial markets, are not subsequently revised. Hence, complications in identification arise because the information set available to agents at the time of forming expectations consists of information which is 'final' or is 'post-revision', as well as information which is not yet 'final' due to time-lags in data collection, for instance. When forming expectations of variables at a particular point in time therefore, agents will be implicitly taking into account measurement considerations associated with data subject to future revisions.

The use of direct measures of expectations has become quite widespread in recent applied macroeconomics. For example, Mankiw, Reis and Wolfers (2003) emphasise the need to examine the expectation formation process to understand fluctuations in the business cycle, proposing a 'sticky-information' model to explain business cycle properties. 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. The significance of using direct measures of expectations in explaining these macroeconomic phenomena is entirely consistent with the large literature finding aggregate expectations data in time-series analysis contains useful information for future economic outcomes (see Batchelor (1986), Lee (1994), Smith and McAleer (1995) and Lee and Shields (2000), for example,) and the benefits in making use of direct measures of expectations in macroeconomic models (see Roberts, 1995, 1997, for example).

In the first part of this paper, we show how the existence of forward looking data available in real time, other real time data and the subsequent revisions that much of these data undergo, places restrictions on empirical models that go beyond the usual restrictions imposed by researchers derived from economic theory or from the timing of economic decisions. To illustrate this, a framework is proposed in which first release measures of macroeconomic variables, their expected future values and their subsequent revisions are jointly modelled. Using this framework as a basis, we show that in order to identify economically meaningful relations and the associated structural innovations, the complete set of restrictions, including those imposed by real time considerations and the associated measurement issues, need to be imposed. Ignoring these restrictions, which is the usual case in empirical research, means that orthogonalised structural innovations may be impossible to recover. Although information on the timing and sequencing of decisions can place some economically meaningful structure on the system, ordinarily, the number of restrictions that would be needed to identify all structural innovations will be prohibitive.

Given these concerns, in the second part of the paper, we consider the implications of reduced form models implied by the proposed structural model that omit important sources of real time information that are available at the time decisions are made. In particular, we consider the use of variables such as direct measures of expectations that are publicly-available and market-informed insights on future macroeconomic conditions (in spread data, for example) that form part of the real time data set available to decision makers. Unlike other real time data, however, these variables are not revised in the future. We also accommodate the information content contained in systematic revisions in the variables are subject to subsequent revisions. An analysis of quarterly US data over the period 1968q4 – 2006q1 shows that the misspecification of standard models is not clearly exposed either by diagnostic tests applied to the standard models or by typical impulse response analysis. However, comparison with models that properly reflect the real time informational context show that the out-of-sample forecasting performance of an analysis conducted in real time is considerably improved, considering the forecasts of the variables in turn and considering forecasts of combinations of the variables in forms suggested by the objective functions of monetary authorities. 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 propose 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 a modelling framework that can take into account the information available in real time and in particular, the issues that arise in the measurement of data. The section discusses the links between this model and those typically found in the literature, and provides an insight into the type of information required in the identification of the proposed structural model. We use impulse response analysis to highlight the robustness of identification schemes and in particular, focus on the analysis of the effects of monetary policy shocks. Section 3 describes the information content of US real time data and provides a summary of the sequencing of data releases. It also introduces three alternative and increasingly sophisticated models that can be applied to, and make 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 Model Specification, Identification and Timing

2.1 Model Specification with Synchronised Data Release

The empirical analysis of macroeconomic phenomenon raises important issues relating to measurement, structural modelling, the identification of economically-meaningful shocks and the interpretation of their effects. Using the notation that ${}_{t}x_{t-s}$ is the measure of the (logarithm of the) variable x at time $t-s$ as released at time t, these issues can be illustrated in the canonical model of (2.1)-(2.3) below. Here, for ease of exposition, we assume in the first instance that the determination and measurement of variables is synchronised but that data are revised once following its first release. In this case, the model is:

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

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

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

where ${}_{t}\mathbf{x}_{t} = ({}_{t}x_{1t}, ..., {}_{t}x_{mt})'$ is an $m \times 1$ vector of variables, where the 'e' superscript means that the variable is a direct measure of the expected value of the variable (with the expectation formed on the basis of information available at the time the measure is released), where $\mathbf{A}_{ij}$ and $\mathbf{B}_{ij}$, $i, j = 1, 2, 3$, are $m \times m$ matrices of coefficients and $\boldsymbol{\varepsilon}_{et}$, $\boldsymbol{\varepsilon}_{bt}$ and $\boldsymbol{\varepsilon}_{rt}$ are $m \times 1$ vectors of shocks with mean zero and diagonal covariance matrices Ω_e, Ω_b 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 $\mathbf{x}_{t-1}$.[1] For example, $\mathbf{x}_t$ might be a 4×1 vector containing the interest rate, output

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

growth, price inflation, and money growth.

The structural model (2.1)-(2.3) reflects the fact that three interrelated processes occur here simultaneously and in real time: (i) expectations are formed (expression (2.1)); (ii) 'behavioural' economic decisions are made to determine the actual values of the variables at each time (expression (2.2)); and (iii) the economic outcomes are measured (expression (2.3));. Characterising the underlying structural processes with (2.1) – (2.3), so that the structural innovations $\boldsymbol{\varepsilon}_{st}$, $s = e, b, r$, represent the respective innovations in the three distinct processes, requires detailed *a priori* knowledge on the underlying processes – including those that exist in real time. This involves quite fine distinctions on how agents (including the statistical agency) measure outcomes, form expectations and use information to make decisions. For example, the revision process in (2.3) will reflect the data collection and survey practices of the statistical agencies. This implies that the parameters A_{3j}, B_{3j}, $j = 1, 2, 3$, will reflect the extent to which (i) an 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 (ii) whether the agency attempts to purge the data of systematic error prior to publication.[2] Similarly, if the relationships in (2.1) reflect the expectation formation process, then the A_{1j}, B_{1j}, $j = 1, 2, 3$, will differ depending on whether agents report their expectation of the first-release data in the next period ${}_{t+1}\mathbf{x}_{t+1}$ when responding to the survey or whether they have in mind their expectation of the post-revision series ${}_{t+2}\mathbf{x}_{t+1}$. Even if these issues are resolved, interpretation of the A_{2j}, B_{2j}, $j = 1, 2, 3$, in (2.2) in terms of the behavioural relations will require a view to be formed on, for example, whether agents use time-t measures of variables in making their decisions or whether they make decisions based on their expectations of post-revision series.

This discussion highlights the fact that considerable *a priori* information is required to define meaningful structural relations, and this will include information about the nature of and measurement of data that is available in real time and consequently, many *a priori* restrictions will be required to identify the structural relations in estimation. Specifically,

[2]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).

note that the equations in (2.1)-(2.3) can be stacked to obtain

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

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 $\boldsymbol{\varepsilon}_t = (\boldsymbol{\varepsilon}_{et},\ \boldsymbol{\varepsilon}_{bt}, \boldsymbol{\varepsilon}_{rt})'$ with covariance $\Omega = \begin{bmatrix} \Omega_e & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \Omega_b & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \Omega_r \end{bmatrix}$. The corresponding reduced form VAR is

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

where $\mathbf{C} = \mathbf{A}^{-1}\mathbf{B}$ and $\mathbf{u}_t = \mathbf{A}^{-1}\boldsymbol{\varepsilon}_t$ with covariance matrix $\Sigma = \mathbf{A}^{-1}\Omega\mathbf{A}^{-1}$. Identification of *all* of the parameters of the structural model in (2.4), and the associated structural innovations, from the parameters in (2.5) requires $9m^2 - 3m$ restrictions based on a priori theory. 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.[3] In this case, identification of all the parameters in (2.4) requires a further $\frac{9m^2-3m}{2}$ restrictions, although subsets of the parameters and innovations can be identified on the basis of fewer relevant restrictions.

[3]This 'standard' assumption has important implications for the interpretation of the structural innovations. To illustrate, assume ${}_ty_t = d\ {}_{t-1}y_{t-1} + \varepsilon_{bt}$ while ${}_ty^e_{t+1} = d\ {}_ty_t + \varepsilon_{ft}$. Here, the variable y_t is set in an entirely backward-looking relationship, subject to an innovation ε_{bt}, and the expectation of the variable in the following period is determined by the same backward-looking relationship and is subject to an innovation ε_{ft}. It is quite reasonable to assume that the innovations are based on the news arriving at t and are therefore related, with $\varepsilon_{ft} = \rho\varepsilon_{bt} + \varepsilon_{et}$. The expectations equation can be written in orthogonalised form: ${}_ty^e_{t+1} = b_1\ {}_ty_t + b_2\ {}_{t-1}y_{t-1} + \varepsilon_{et}$, where $b_1 = d(1+\rho)$, $b_2 = \rho d$. But ε_{et} is interpreted as *that part of the news* becoming available at time t on y_{t+1} that is independent of news on ${}_ty_t$ and the estimated parameters implicitly accommodate the joint reliance of the variables on the same news.

2.1.1 Sources of identifying restrictions

One form in which *a priori* theory is often used to provide identifying restrictions 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. Such assumptions usually focus on the behavioural relations only and are based on a view of the order in which specified agents make their decisions. Identification based on sequencing is still possible, but the extended model of (2.1)-(2.3) shows that the assumptions on the timing/sequencing of behavioural decisions are much more demanding if they are to provide identification in this more realistic setting. This is because the *a priori* assumptions have to specify carefully (i) agents' use of information in forming expectations on possible future outcomes, (ii) possible data revisions and (iii) describing the sequencing of the behavioural decisions themselves. We return to this in the section below.

A related 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 contained in Gali and Gertler (2007) who provide a review of the main features of the recent vintage of macroeconometric models, 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.[4] The identifying restrictions for recovering these structrural 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 and where 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. In other words, whether they based their decisions on first-releases of published data or expectations of post-revision data,

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

and so on.[5]

A third 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 these processes and can accommodate many alternative assumptions. This includes the rational expectation (RE) hypothesis, for example, in which the direct measure of an expected variable is the mathematical expectation of the variable based on all the available information, including the form of the model in (2.1)-(2.3). However, implementing the identifying restrictions arising from the RE assumption in the context of the information set available in real time requires assumptions to be made on which measure of the variables agents had in mind when forming their expectations. For example, the identifying restrictions relating to (2.2) will be quite different if 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 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 $\boldsymbol{\varepsilon}_{et}$ has a clear interpretation in terms of "news on the first release measure becoming available at time t".[6] 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.

Of course, identification of the innovations at the least requires the use of direct measures of the expectations series and real time data. However, direct measures of expectations are either not available or are not used in most studies of macroeconomic shocks. Similarly, the revision process is also typically ignored and the analysis is conducted on the most recent, 'final vintage' dataset available when the analysis conducted. The estimation of a VAR system involving only the post-revision data ${}_t\mathbf{x}_{t-1}$ and its lags, say,

[5] Equivalent assumptions on the use of information would be required in the estimated policy rule. See Croushore and Evans' (2006) discussion on whether policy decisions are based on observed first release data or the 'true' underlying state of the economy.

[6] 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 $\mathbf{A}_{12} = \mathbf{A}_{13} = \mathbf{B}_{12} = \mathbf{B}_{13} = \mathbf{0}$.

is entirely consistent with the model in (2.4) and (2.5).[7] However, the nature of the innovations in such a model need careful interpretation because they will be functions of the behavioural shocks $\boldsymbol{\varepsilon}_{bt}$, the expectations shocks $\boldsymbol{\varepsilon}_{et}$ and the revision shocks $\boldsymbol{\varepsilon}_{rt}$, and this is a potentially important distinction. For example, in impulse response analyses of the effects of monetary policy shocks, the responses are typically interpreted as the direct reaction of a monetary policy choice and not as a complicated amalgam of the reaction to this choice plus agents' revised judgement on the policy stance in the future.

Moreover, in the context of a larger system, the complex VARMA representation of the ${}_t\mathbf{x}_{t-1}$ that corresponds to the (simpler) underlying VAR specification for $({}_t\mathbf{x}_t,\ {}_t\mathbf{x}^e_{t+1},\ {}_t\mathbf{x}_{t-1})'$ will typically be estimated not in its VARMA form but with a VAR approximation (i.e. with a high order VAR in ${}_t\mathbf{x}_{t-1}$). This approximation will further complicate the interpretation of the estimated parameters. But, perhaps even more importantly, it will also render the model less useful for forecasting and model-based decision-making as the effects of small (but economically-meaningful) feedbacks are dropped from the model in the approximation.

2.2 Model Specification with Asynchronised Data Release

The discussion above shows that there are considerable problems in identifying economically meaningful relations and the associated structural shocks when the determination and measurement of time-t variables is synchronised. In practice, this complexity is compounded by the fact that, for example, working with quarterly data, decisions can be made and expectations formed at different points within the period and the measured series relating to these decisions/expectations can be released simultaneously or with a protracted lag. This issue has been 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. For example, Christiano *et al* (1999) describe various

[7]The point is 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 in which the errors in each are linear combinations of the three shocks in $\mathbf{u}_t = (\ u_{et},\ u_{bt},\ u_{rt})'$.; see Hamilton (1994, p. 349) for details.

alternative structures in a VAR analysis of interest rates, output, prices and different monetary aggregates to investigate monetary policy decisions. Although 'final vintage' rather than real time datasets are used in the analysis, the structures imposed to identify the monetary policy shocks are motivated by sequencing/timing considerations and based on the view that "the assumption that the Fed sees output and prices when they choose the policy instrument seems at least as plausible as assuming that they don't" [p. 83]. Bernanke and Mihov (1998) and Gertler and Gilchrist (1994) make similar assumptions on the sequencing of decisions. On the other hand, Brunner (2000), Rotemberg and Woodford (1999) and Sims and Zha (1998), for example, emphasise the delays in the release of measures of economic activity, and in the decision-making processes themselves, to motivate the assumption that policy decisions precede output measures. The lack of consensus on these sequencing issues shows the relative frailty of the corresponding identifying restrictions.

It is worth elaborating a little on this issue in the context of the identification of monetary policy shocks in the US. Precise details of the timing of data releases are provided in the section below. However, a broad characterisation of the process is that data on interest rates are available at any point during a quarter while first release data on output, prices and money are released mid-way through the quarter with a one quarter lag. Revisions on the last three series are also published mid-quarter (with interest rates being un-revised of course so that ${}_{t}r_{t-1} = {}_{t-1}r_{t-1}$). Direct measures of 'nowcasts' of the output and price series (i.e. the time-t forecast of time-t output and price level produced before the first-release of measures of time-t values) are published quarterly along in the Survey of Professional Forecasters (Federal Reserve Bank of Philadelphia) with subsequent periods' forecasts. Further, market data on expected future interest rates, such as spread data are available at any point during the quarter and at any forecast horizon. In this case, the time-t macroeconomic data can be characterised by

$$
\begin{aligned}
{}_t\mathbf{x}_t &= [\ {}_tr_t,\ {}_ty_{t-1},\ {}_tp_{t-1},\ {}_tm_{t-1}]',\\
{}_t\mathbf{x}^e_{t+1} &= \left[\ {}_tr^e_{t+1},\ {}_ty^e_t,\ {}_tp^e_t,\ {}_tm^e_t\right]',\ {}_t\mathbf{x}^e_{t+2} = \left[\ {}_tr^e_{t+2},\ {}_ty^e_{t+1},\ {}_tp^e_{t+1},\ {}_tm^e_{t+1}\right]', && (2.6)\\
&\quad \text{(for available forecast horizons)}, && (2.7)\\
\text{and}\ \ {}_t\mathbf{x}_{t-1} &= [\ {}_tr_{t-1},\ {}_ty_{t-2},\ {}_tp_{t-2},\ {}_tm_{t-2}]',\ {}_t\mathbf{x}_{t-2} = [\ {}_tr_{t-2},\ {}_ty_{t-3},\ {}_tp_{t-3},\ {}_tm_{t-3}]',\\
&\quad \text{(for available revision horizons)}, && (2.8)
\end{aligned}
$$

where the staggered timing of decisions and data releases are reflected in the detail of the various subscripts.

Given that interest rate data are available at any point 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 interest rates, output, prices and money.[8] Moreover, on the further assumption that interest rate forecasts are also determined after the policy decision, then we can stack the ${}_t\mathbf{x}_t$, ${}_t\mathbf{x}^e_{t+1}$, and ${}_t\mathbf{x}_{t-1}$ as in (2.4) and write the first row of $\mathbf{A} = (1, 0, 0, 0, ...)'$.[9] 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 given the standard interpretation as reflecting structural monetary policy shocks.[10] The interpretation requires careful use of real time data though, measuring the variables as they were observed at the time, accommodating subsequent revisions, and explicitly noting and taking account of the timing of data releases. Moreover, as the discussion of the previous section made clear,

[8] Alternatively, one could choose the end-of-quarter measure so that policy makers do indeed see output and prices when they choose the policy instrument.

[9] It is important to note that if, for instance, the spread between long term and short term interest rates is being used to capture interest rate foreacasts, the shock to the interest rate equation will be correlated with the shock to the spread equation. In this case, the interest rate shock cannot be interpreted as the structural monetary policy shock.

[10] 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 $\mathbf{x}_t$.

identification of any further economically-meaningful shocks requires considerably more structure to be placed on the system.

Croushore and Evans (2006) also address the issue of the identification of monetary policy shocks in the context of their effects in real time analysis. They consider the issue of whether the identification of monetary policy shocks is compromised through the econometricians's use of more information than that available to the Federal Reserve. They note, for example, that the identification of monetary policy shocks cannot be uncovered simply through the recursive estimation of a VAR analysis of ${}_t\widetilde{\mathbf{x}}_t = [\ {}_tr_t,\ {}_ty_t,\ {}_tp_t,\ {}_tm_t]'$, $t = 1, ..., T$. Moreover, they establish, in Section 3 of the paper, that such an analysis shows little variation either in the size and magnitude of estimated policy shocks or their associated impulse responses when conducted using different vintages of data. Their more thorough analysis of monetary policy shocks that accommodates data revision issues is based on some quite strong assumptions on the information available to policy makers and on the revision process, however. Specifically, it is assumed that the policy reaction function is based only on the most up-to-date reported measures of macroeconomic variables available at the time (and not on the actual or expected 'true', post-revision measures; i.e. ${}_{t+1}\mathbf{x}_t$ in our canonical model above). This assumption allows the monetary policy shock to be identified directly from the reduced form OLS interest rate equation (as in the paragraph above).[11] The estimation of the remainder of the system, as required for their impulse response analysis of other types of shock, is more complicated because it is assumed that the true values of variables other than the interest rate are never directly observed and are functions only of their own (unobserved) history and lagged interest rates. The estimation issue is addressed through the use of an instrumental variables approach in which the final vintage data is used as the instrument for the unobserved true data. This modelling approach can be accommodated within the general framework described in (2.4) and (2.5) above since it implicitly assumes an underlying model linking the post-revision data to the currently observed and revised data, ${}_t\mathbf{x}_t$ and ${}_t\mathbf{x}_{t-1}$. But the restrictions imposed through instrumentation may or may not be valid and the model

[11] The paper suggests that ${}_ty_t$ is available at the time interest rates are set and therefore abstracts from accommodating the one-quarter publication lag in the analysis.

does not include direct measures of the expected future macroeconomic variables (implicitly solving these out in terms of lagged values). The paper's conclusions (that using real time data has little impact on the estimation of monetary policy shocks and their effects) depends crucially on these implied restrictions therefore, and it remains of interest to investigate these feedbacks more explicitly using the framework of (2.4) and (2.5).

One approach would be to explicitly specify restrictions on the three processes in (2.1), (2.2) and (2.3). This would involve defining meaningful structural relationships of not only the behavioural relations that underlie decision making but also expectations formation and the information that is used to form those expectations, and the processes by which economic outcomes are measured. One would also take account of asynchronised data release. These additional considerations could be evaluated according to whether different insights are revealed regarding issues such as the timing and effect of monetary policy shocks.[12]

An alternate approach is to work with the implied reduced form derived from (2.1), (2.2) and (2.3) and conduct an analysis which is real time in nature. This analysis, in the context of an out of sample forecasting exercise, would consider the extent to which the omission of forward looking information available in real time and the failure to recognise measurement issues are important mispecifications in macroeconomic modelling. Such an analysis would focus on aspects of macroeconomic modelling that would be of most interest to policy makers operating in real time;. specifically, forecasts of events such as timely indicators of the business cycle and nowcasts providing information of the current state of the economy. This empirical exercise is undertaken 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

[12]This is the subject of ongoing research.

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, conducted in real time and focuses on the usefulness of the various forms of data that become available; i.e. first-release, revisions and direct measures of expectations. The usefulness is judged first in the context of 'nowcasting' and forecasting the current and future state of the macroeconomy and then in the context of identifying and tracing out the macroeconomic effects of monetary policy shocks.

3.1 Timing of US Data Release

Following the discussion of the previous section, the analysis of macroeconomic dynamics requires careful treatment of the data taking proper account of the timing of the data releases. It is worth providing some discussion of this aspect of the data first, therefore. For US 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).[13] 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.[14] The nowcasts relating to quarter

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

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

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 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.[15] 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

$$\mathbf{z}_t = (\ {}_Tr_t,\ \ ({}_Ty_t - {}_Ty_{t-1}),\ \ ({}_Tp_t - {}_Tp_{t-1}),\ \ ({}_Tm_t - {}_Tm_{t-1})\ \ )',$$

[15]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).

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 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

$$\begin{aligned}\mathbf{z}_t = (& {}_tr_t, \ ({}_ty_{t-1} - {}_{t-1}y_{t-2}), \ ({}_tp_{t-1} - {}_tp_{t-2}), \ ({}_tm_{t-1} - {}_tm_{t-2}), \\ & ({}_ty_{t-2} - {}_{t-1}y_{t-2}), \ ({}_ty_{t-3} - {}_{t-1}y_{t-3}) \ )',\end{aligned}$$

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.[16]

Model 3; Specification with Real Time Data, Revisions, and Economic Indicators Our third model specification supplements the system of Model 2 with direct

[16] 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 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 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.[17] 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.

[17]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).

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 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 $1986q1$.[18] 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 was measured without error so that the final vintage data used here had been available at the time.

[18] 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.

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 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.[19] Nevertheless, at first sight, it is

[19]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

surprising to find the impulse responses looking so similar in Models 1 and 2 given the 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.[20]

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.

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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 $\overline{\mathbf{u}} = \underline{\mathbf{u}}$).

[20]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.

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 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 $\chi^2_{LM}(14)$ statistic indicates the significance of these variables in each equation. The other three χ^2_{LM} 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.[21] 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

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

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 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.[22] 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.[23] 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

[22] 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.

[23] 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

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

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:

-
  - 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.[24]

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

[24] 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 $\sqrt{\frac{1}{N-1}\sum_{\tau=1}^{N-1}\left(\left({}_{\tau+4}p_{\tau+3} -_{\tau} p_{\tau-1}\right) - \left(\widehat{{}_{\tau+4}p_{\tau+3}} -_{\tau} p_{\tau-1}\right)\right)^2} = \sqrt{\frac{1}{N-1}\sum_{\tau=1}^{N-1}\left({}_{\tau+4}p_{\tau+3} - \widehat{{}_{\tau+4}p_{\tau+3}}\right)^2}$.

- – 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 $t+s$, $s \geq 0$.[25]

  – the nowcast of a policy objective, $g_t|\Omega_t = \lambda(\widetilde{x}_t|\Omega_t) + ({}_{t+1}p_t - {}_t\,p_{t-1})^2$ 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.[26] 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

[25] 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.

[26] 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)).

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 $1'$ 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 the 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 $(\widehat{{}_{t+3}y_t} - \widehat{{}_{t+2}y_{t-1}})$.[27] 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 pro-

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

vides 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.[28] 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.

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).

[28] 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.

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.[29] The estimated Probit model obtained using data for $1965q4 - 2006q1$ is as

[29] 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.

follows:

$$NBER_t = \underset{[-1.2594]}{-0.6452} - \underset{[-3.4663]}{158.3721}({}_{t+3}y_t -{}_{t+2} y_{t-1}) - \underset{[-2.0243]}{58.8598}\,({}_{t+2}y_{t-1} -{}_{t+1} y_{t-2}) \qquad (4.9)$$
$$+ \underset{[0.0579]}{0.0316}CDR_t + \underset{[2.3515]}{1.1532}CDR_{t-1} + \widehat{\epsilon}_t,$$

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 (4.9) 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 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.[30]

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

[30]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 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 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			
	${}_T r_t$	$({}_T y_t -_T y_{t-1})$	$({}_T p_t -_T p_{t-1})$	$({}_T m_t -_T m_{t-1})$
intercept	−0.0170 (0.0054)	0.0071 0.0021	−0.0012 (0.0011)	0.0036 (0.0024)
${}_T r_{t-1}$	0.2054 (0.0948)	−0.0988 (0.0379)	−0.0265 (0.0192)	0.0723 (0.0431)
${}_T r_{t-2}$	0.1244 (0.0958)	0.0267 (0.0383)	0.0153 (0.0195)	−0.0530 (0.0436)
${}_T r_{t-3}$	0.3150 (0.0957)	0.0837 (0.0383)	−0.0309 (0.0194)	0.0060 (0.0436)
${}_T r_{t-4}$	0.2234 (0.0989)	−0.0392 (0.0395)	0.0222 (0.0201)	−0.0035 (0.0450)
$({}_T y_{t-1} -_T y_{t-2})$	0.4358 (0.2127)	0.1669 (0.0851)	0.0605 (0.0432)	−0.2082 (0.0968)
$({}_T y_{t-2} -_T y_{t-3})$	0.5588 (0.2145)	0.2185 (0.0858)	0.0181 (0.0435)	−0.0567 (0.0976)
$({}_T y_{t-3} -_T y_{t-4})$	0.4157 (0.2205)	−0.0087 (0.0881)	0.0513 (0.0448)	0.0676 (0.1003)
$({}_T y_{t-4} -_T y_{t-5})$	0.0736 (0.1938)	0.0242 (0.0857)	0.1011 (0.0393)	0.0579 (0.0882)
$({}_T p_{t-1} -_T p_{t-2})$	1.4051 (0.4376)	−0.2082 (0.1750)	0.6782 (0.0888)	−0.5781 (0.1992)
$({}_T p_{t-2} -_T p_{t-3})$	−0.1927 (0.4786)	0.0150 (0.1914)	−0.0646 (0.0972)	0.4954 (0.2178)
$({}_T p_{t-3} -_T p_{t-4})$	0.7009 (0.4843)	0.0123 (0.1936)	0.5416 (0.0983)	−0.4783 (0.2204)
$({}_T p_{t-4} -_T p_{t-5})$	−0.5794 (0.4581)	0.0221 (0.1832)	−0.1457 (0.0930)	0.4874 (0.2085)
$({}_T m_{t-1} -_T m_{t-2})$	0.0320 (0.1940)	0.0414 (0.0776)	0.0220 (0.0394)	0.5657 (0.0883)
$({}_T m_{t-2} -_T m_{t-3})$	−0.0555 (0.2205)	0.1356 (0.0882)	0.0374 (0.0448)	0.1687 (0.1004)
$({}_T m_{t-3} -_T m_{t-4})$	−0.1694 (0.2194)	−0.0790 (0.0877)	0.0138 (0.0445)	0.0821 (0.0998)
$({}_T m_{t-4} -_T m_{t-5})$	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	0.0050	0.0013	0.0018	−0.0015	−0.0010
	(0.0055)	(0.0021)	(0.0011)	(0.0023)	(0.0011)	(0.0009)
${}_tr_{t-1}$	0.2967	−0.0371	0.0810	−0.1554	−0.0320	−0.0097
	(0.0883)	(0.0342)	(0.0179)	(0.0364)	(0.0175)	(0.0152)
${}_tr_{t-2}$	0.0145	−0.0444	−0.0393	0.1070	0.0492	0.0311
	(0.0943)	(0.0365)	(0.0191)	(0.0389)	(0.0187)	(0.0163)
${}_tr_{t-3}$	0.4013	−0.0152	−0.0018	−0.0010	−0.0118	−0.0083
	(0.0999)	(0.0387)	(0.0202)	(0.0412)	(0.0198)	(0.0172)
${}_tr_{t-4}$	0.1304	0.0619	−0.0364	0.0536	−0.0082	−0.0084
	(0.0945)	(0.0366)	(0.0191)	(0.0390)	(0.0187)	(0.0163)
$({}_{t-1}y_{t-2} -_{t-2} y_{t-3})$	0.9307	0.5320	0.0542	−0.0785	0.1351	0.0448
	(0.2626)	(0.1017)	(0.0532)	(0.1084)	(0.0521)	(0.0453)
$({}_{t-2}y_{t-3} -_{t-3} y_{t-4})$	0.1928	0.0711	−0.0688	0.1186	0.0176	0.0366
	(0.2623)	(0.1015)	(0.0531)	(0.1082)	(0.0520)	(0.0452)
$({}_{t-1}p_{t-2} -_{t-2} p_{t-3})$	0.4666	−0.4952	0.6215	−0.2543	−0.0785	−0.0579
	(0.4136)	(0.1601)	(0.0838)	(0.1707)	(0.0820)	(0.0713)
$({}_{t-2}p_{t-3} -_{t-3} p_{t-4})$	0.7847	0.3932	0.1913	0.3560	0.1718	0.0763
	(0.4323)	(0.1674)	(0.0876)	(0.1784)	(0.0857)	(0.0745)
$({}_{t-1}m_{t-2} -_{t-2} m_{t-3})$	0.0396	0.0211	0.0475	0.5671	0.0634	0.0323
	(0.1959)	(0.0758)	(0.0397)	(0.0809)	(0.0388)	(0.0338)
$({}_{t-2}m_{t-3} -_{t-3} m_{t-4})$	−0.0072	0.0966	0.0048	0.1989	−0.0115	0.0075
	(0.1954)	(0.0757)	(0.0396)	(0.0807)	(0.0388)	(0.0337)
$({}_{t-1}y_{t-3} -_{t-2} y_{t-3})$	−1.1746	−0.9674	0.1128	−0.8357	−0.5678	−0.3279
	(0.9334)	(0.3614)	(0.1891)	(0.3853)	(0.1851)	(0.1608)
$({}_{t-2}y_{t-4} -_{t-3} y_{t-4})$	1.2681	0.6950	0.0070	−0.3191	−0.1550	−0.2149
	(0.9581)	(0.3709)	(0.1941)	(0.3955)	(0.1900)	(0.1651)
$({}_{t-1}y_{t-4} -_{t-2} y_{t-4})$	0.1534	0.7188	−0.2581	0.9939	0.4068	0.2507
	(1.0169)	(0.3937)	(0.2060)	(0.4197)	(0.2017)	(0.1752)
$({}_{t-2}y_{t-5} -_{t-3} y_{t-5})$	−1.0178	−0.7758	0.0601	0.1909	0.1777	0.1654
	(1.0193)	(0.3946)	(0.2065)	(0.4207)	(0.2022)	(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 $({}_tp^f_t -_t p_{t-1})$, $({}_ty^f_t - {}_ty_{t-1})$, $({}_tp^f_{t+1} - {}_tp^f_t)$ and $({}_ty^f_{t+1} - {}_ty^f_t)$, 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$\dagger$ and $\dagger\dagger$ 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, $({}_tp^f_t -_t p_{t-1})$, $({}_ty^f_t -_t y_{t-1})$, and the time-$t+1$ SPF forecasts of output growth and inflation. $({}_tp^f_{t+1} -_t p^f_t)$, $({}_ty^f_{t+1} -_t y^f_t)$. 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.

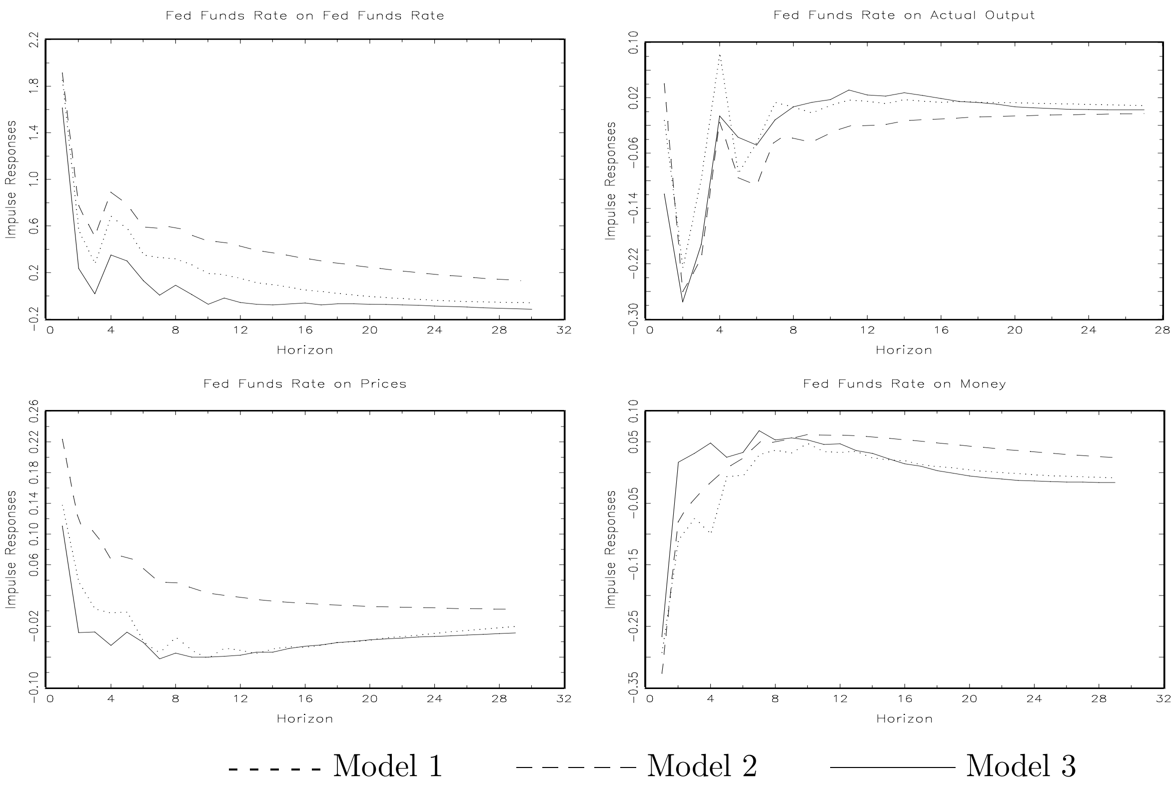

Figure 1: Impulse Responses of a Federal Funds Rate Shock

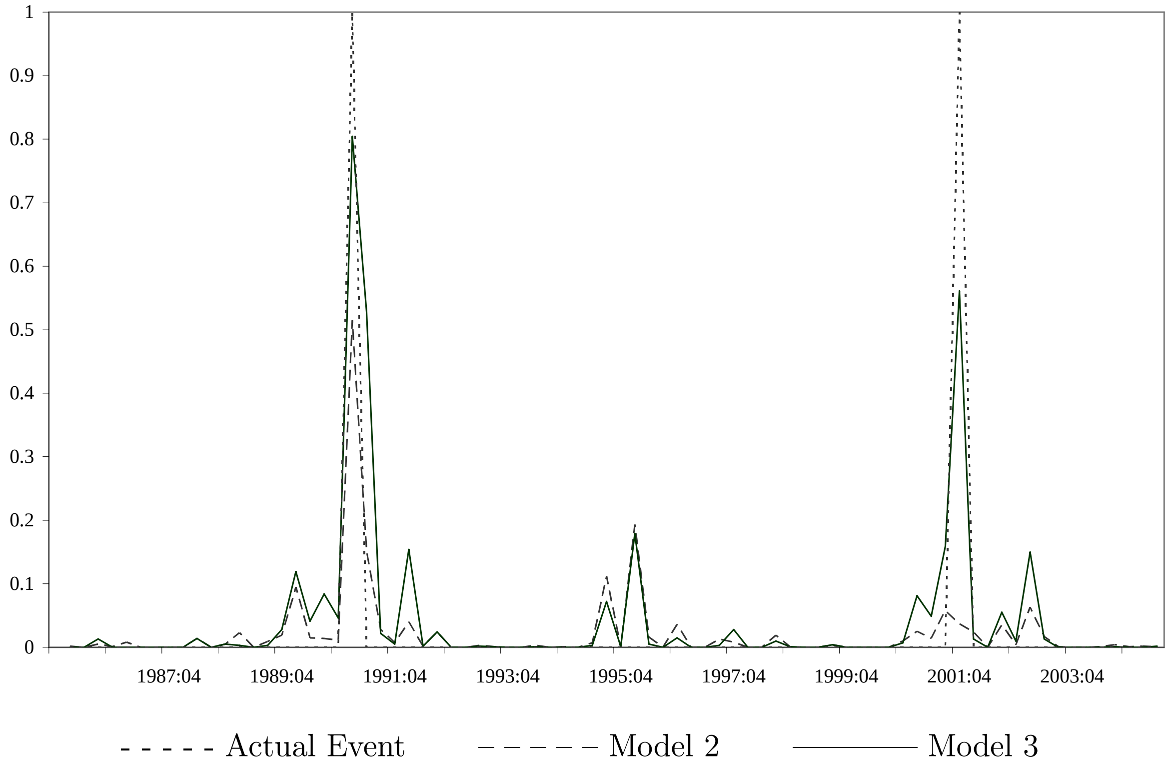

Figure 2: "Nowcast" probabilities of two periods of consecutive negative growth; $pr\left\{\left[\left({}_{t+2}y_{t-1} -_{t+1} y_{t-2}\right) < 0\right] \cap \left[\left({}_{t+3}y_{t} -_{t+2} y_{t-1}\right) < 0\right]\right\}$

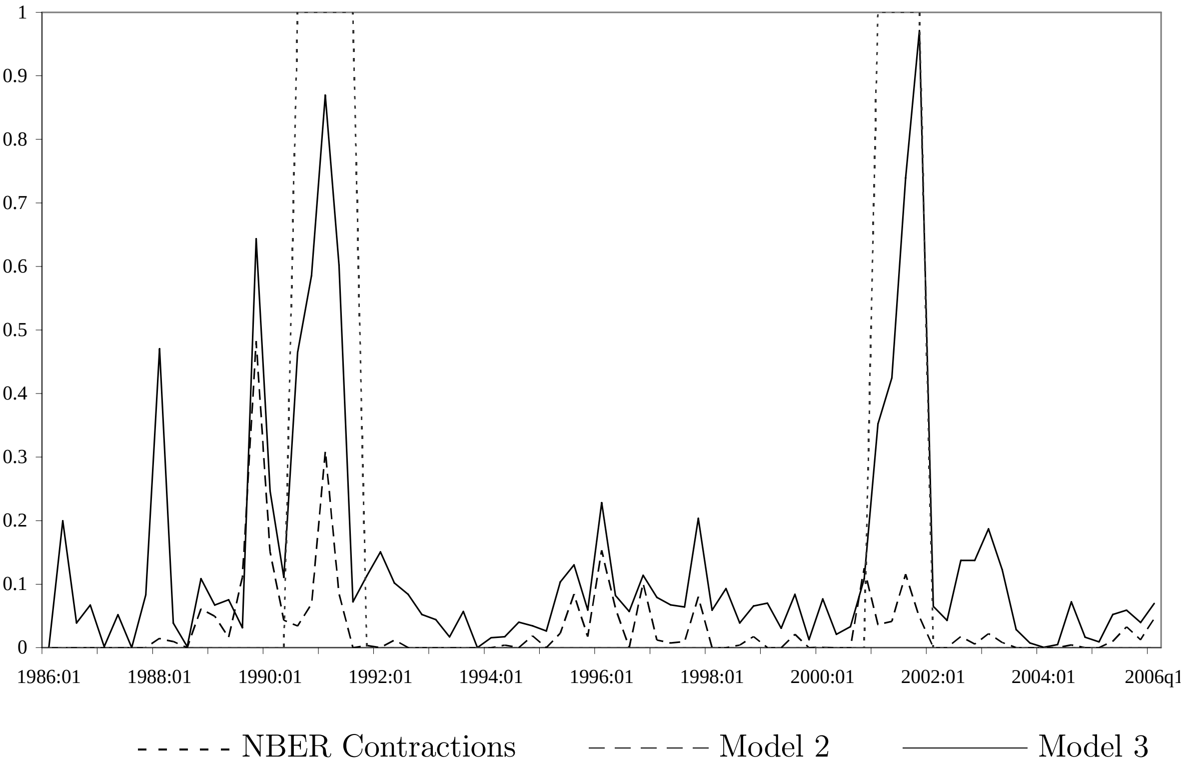

Figure 3: "Nowcast" probabilities of NBER Periods of Contraction

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