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Is money informative? Evidence from a large model used for policy analysis☆

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Abstract

In this paper we assess whether monetary variables, which are observed with little delay, convey marginal information on the state of the Italian economy, taking as a benchmark the forecasting errors generated by the quarterly model of the Bank of Italy in the 1990s. We follow two approaches. First we map monetary surprises into estimates of the observed structural disturbances using a Kalman filter approach, in order to improve the forecasts. Then we look at the sample correlations among forecasting errors in monetary and real variables, thereby taking into account links that may not be accounted for by the model's structure. We find that bank interest rates have a strong information content. Monetary aggregates play no role according to the first approach; according to the second approach they do, but the economic interpretation of this finding is not straightforward. All in all, the results highlight the role of financial prices and quantities as indicators of the state of the economy. However, they do not imply a mechanical policy reaction to this information, as both the strength and the sign of the relationship between the surprises in monetary and real variables depend on the source of the shocks.

JEL classifications: C53; E52; E58; E65

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1. Introduction

Is money useful to the monetary policymaker? The role of monetary variables in guiding policy choices was downgraded by most academics and central bankers in the

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1990s, in the face of unexpected shifts in the velocity of money. Money also ceased to play an explicit role in mainstream macro models. Most modern models (both large macro-models and small, micro-founded structural models) feature a stable long-run relationship between money and prices, but monetary variables fail to serve a useful purpose for implementing policy, since they are post-recursively demand-determined, after the fundamental macro variables are set.[1]

Recently, however, the role of monetary and credit variables has returned to the spotlight of policymaking and academic interest.

At the policy level, the strategy adopted by the European Central Bank since it started operating in 1999 draws an explicit distinction between approaches that assign a central role to money and those that rely on a set of indicators, including projections obtained with econometric techniques;[2] the ECB uses both approaches. At the academic level, a number of recent quantitative studies have re-examined the issue of the information content of money, finding a meaningful role for financial variables as predictors of future inflation (Nicoletti Altimari, 2001; Trecroci and Vega, 2000).[3]

One of the reasons for assigning a role to monetary variables is that they may convey information on the underlying state variables of the economy, which are observed with lag of several months. This is because 'monetary data are measured relatively more accurately than many other economic indicators and are typically available in a more timely fashion' (European Central Bank, 2000). In this vein, a number of recent studies have used small, micro-founded structural models in order to assess whether, under specific assumptions on the structure of information lags, monetary variables possess any information content (Dotsey and Hornstein, 2003, for the US, and Coenen et al., 2001, for the euro area).

Another strand of the literature argues that money may be useful as a proxy for effects that are otherwise not well measured or more fundamentally, that it has a direct role in the transmission mechanism, which is not captured by existing models.[4] In a different perspective, the emphasis is placed on the role of money as a guidepost for avoiding major mistakes rather than on its short-run contribution to overcoming information lags in other variables.[5]

In this paper, we focus on the first set of issues and assess whether monetary variables had non-negligible information content in the 1990s. To answer this question, we rely on a large macro model, the quarterly model of the Italian economy at the Bank of Italy,

[1] See the review and discussion in Meyer (2001).

[2] See European Central Bank (2000) and Issing et al. (2001).

[3] Dotsey and Otrok (1994) question the reliability of the evidence provided by Granger-causality tests and argue that the issue of the information content of money can only be addressed within structural models.

[4] Meyer (2001) lists the main explanations proposed to justify the direct impact of money on inflation and economic activity: (i) money affects demand; (ii) money proxies for the broad range of interest rates and asset prices through which monetary policy operates; (iii) monetization causes changes in expectations about the course and effects of future policy.

[5] This underlies the position in European Central Bank (2000), according to which 'the analysis conducted under the second pillar [projections and other indicators] focuses on factors ... which influence price developments in the shorter term', while 'the analysis under the first [monetary] pillar offers particularly useful guidance over a medium-term horizon'. See also Dotsey et al. (2000).

which is extensively used for actual policymaking. The main reason for this choice, which contrasts with the attention paid by the recent literature to small models, is the practical relevance of the experiment: large macro models may have theoretical shortcomings compared with the recent stream of smaller models built on solid microfoundations, but they remain a prominent tool used by central banks for forecasting and policy evaluation.[6]

The paper analyses the properties of the forecasting errors generated by the quarterly model; we refer to surprises to the final targets of policy (GDP and prices) as well as to monetary variables (both quantities or prices). How surprising are these surprises? Can we do marginally better by considering monetary variables more carefully? We assess the information content of surprises in monetary variables following two distinct but complementary routes: one approach optimally filters the new information contained in financial variables by mapping surprises into estimates of structural disturbances and then forecasting the variables of interest exploiting this additional piece of information; the other approach looks directly at the correlations among surprises. It is worth stressing that the two approaches are complementary rather than competing. The former, whose analytical framework is based on Wallis (1986) and Harvey (1989), rests on the transmission mechanism built into the model and addresses the problem of measuring the gain in predictive accuracy achievable by optimally exploiting the information contained in monetary surprises. The latter, for which we refer to Friedman (1984), tries to answer the same question simply by looking at historical correlation among surprises. Both methods have pros and cons: the former is more efficient and informative, the latter more robust.

We depart in several respects from previous literature which engaged in a similar exercise. In contrast with Angeloni and Cividini (1990), who assess the information content of monetary variables only on the basis of the properties of the quarterly model of the Italian economy and measure it by means of stochastic simulations, we take our model to the data and assess the relevance of money as an information variable in terms of the actual forecasting performance over the 1990s. Whereas Friedman (1984) looks at the 'surprises' generated by a small econometric model in order to assess the information content of money, we rely on a large model routinely used for monetary policy purposes and on structural assumptions to filter information. Unlike Dotsey and Otrok (1994), we provide a unified framework for combining both structural and reduced-form approaches to estimate unobserved variables.

The results highlight the potential role of financial prices and quantities as measures of unobserved state variables and suggest that the effort required to implement structural filters has its own pay off. However, the policy implications of this finding are not straightforward, since the relationship between the financial and real sides of the economy is not time-invariant and it is highly dependent on the source of the shocks.

The paper is organized as follows. Section 2 describes how monetary and credit aggregates entered the policy strategy of the Bank of Italy in the two decades preceding European Monetary Union. Section 3 discusses how surprises in monetary variables may

[6] For a survey, see the special issue of *Economic Modelling,* July 1998 (Vol. 15, No. 3).

be used by the policymaker and compares two different ways of reaping the full benefits of the timely availability of financial statistics. In Section 4, a Kalman filter approach is applied to the Bank of Italy's quarterly model to gauge the gain in forecasting accuracy associated with optimally extracting the information contained in monetary variables. Section 5 addresses the same issue by studying the historical correlation among surprises generated by the quarterly model. Section 6 concludes.

2. The background: monetary policy in Italy

Two features make the quarterly model of the Bank of Italy a promising reference for our experiment. First, the model was extensively used for policy-making, both in a period when the announcement of monetary reference paths played an important role and when they were somewhat de-emphasized, leaving room for targeting inflation forecasts. Second, it features a post-recursive role for monetary and credit variables, which is very much in line with current macroeconomic practice.[7]

The monetary policy framework of the Bank of Italy in the last two decades employed several reference variables: target ranges for money (M2) were announced from 1985 to 1998, although with varying emphasis; the exchange rate also played a pivotal role in the EMS period, from 1979 to 1992; inflation forecasts played a major role from 1994 to 1998.[8] The common, clearly specified theoretical framework of the quarterly model ensured that the multiple objectives pursued by the monetary authority could be set in a mutually consistent way. It helped the central bank to evaluate the information content of real and monetary variables and to present and explain its actions to the general public, with a logically consistent account of the developments of the real and monetary indicators.

When M2 growth rates were announced, the model, as a forecasting tool, provided values for the M2 profile consistent with the desired path for the final targets. A normative scenario derived from a main forecasting exercise, usually performed every autumn, was used as an input for the profiles for the main financial aggregates, interest rates and monetary instruments. The use of monetary aggregates for day-to-day policy evaluation was based on monitoring and assessing their deviations from the benchmark scenario and on analysis of the causes of such deviations.[9]

However, from the mid-1990s onwards, the focus of monetary policy switched towards inflation forecasts, although the target path for M2 continued to be announced. Beginning

[7] The quarterly model of the Italian economy is described in Banca d'Italia (1986) and Galli et al. (1989). Its current version includes 96 stochastic equations and 790 identities. The model is Keynesian in the short-run and neo-classical in the long-run; capital is non-malleable and potential output depends on the vintages of installed capital; the real interest rate is exogenous and determined on the world financial market. A detailed description of the monetary transmission mechanism in the model is in Nicoletti Altimari et al. (1995). The money demand equation (in the official definition used by the Bank of Italy until 1998) is presented in Angelini et al. (1994).

[8] See Altissimo et al. (2001) for details and references.

[9] A detailed analysis of the role played by monetary indicators in different episodes is in Altissimo et al. (2001). The paper also discusses of the role played by the quarterly model in policy making.

in 1995, the Governor of the Bank of Italy announced upper limits for inflation in the following year and stated explicitly how the management of official rates would be linked to the behaviour of actual and expected inflation. The model retained an essential role, as it was the tool used to produce the internal inflation forecasts that would be announced to the public.[10]

Currently, the model is still extensively used in particular during the macroeconomic projection exercises carried out jointly with the ECB and the other national central banks of the Eurosystem (see European Central Bank, 2001). The theoretical framework underlying the monetary and financial block is to a large extent the one outlined in Ando and Modigliani (1975) and conforms to the methodology that used to underlie the MPS econometric model for the US.[11] Monetary and credit aggregates essentially play a post-recursive role, similarly to most existing macro-models.[12]

3. Money, information and surprises

Even when money and credit do not have a direct impact on aggregate supply or demand, responding to their unexpected movements could be appropriate if they signal contemporaneous, but still unobservable, changes in real income or prices. Thanks to the shorter lags with which monetary and credit data become available, surprises in the behaviour of money with respect to a benchmark profile may be used as soon as they materialize to infer something about likely forthcoming surprises in policy targets and to react accordingly.[13] The question is how to exploit this information effectively. In this section, we employ a simple mainstream model to assess the relative performance of two approaches, which can be used for this purpose.

The way in which the flow of new information is used for policy purposes can be described within a simple 'passive money' macro-model (e.g. Clarida et al., 1999; Galí, 2000). A forward-looking aggregate demand curve is joined with a forward-

[10] Siviero et al. (1999) discuss the role of inflation forecasts over the period and provide econometric evidence of the role of internal forecasts in the Bank's reaction function.

[11] The introduction of forward-looking elements in such a framework is discussed by Nicoletti Altimari et al. (1995) and Gaiotti and Nicoletti Altimari (1996).

[12] The monetary and financial section of the model is composed by more than 200 equations, of which some 30 are stochastic. It describes the financial position of seven categories of economic agents (central bank, banks, government, households, firms, mutual funds and rest-of-the-world) and how their assets and liabilities are allocated among eight groups of instruments (currency, deposits, compulsory reserves, repos, short-term securities, long-term securities, loans and mutual funds and shares). Each market is described by a demand function and an inverted supply equation, in which the endogenous variable is the relevant interest rate. The determination of interest rates is based on banks' behavioural equations and equations for the term structure. Banks have monopolistic power and can set both the lending and the borrowing rate, but take the price of interbank deposits as given. In both cases, the size of the spread depends on the elasticity of demand and on the structure of marginal costs.

[13] The vast literature on the information content of money dates from the 1970s (a survey is in Friedman, 1990). Here, we briefly summarize the main features of this approach in a simplified model, in order to clarify our subsequent analysis.

looking price equation and a money demand schedule. The system is closed with a policy rule.

$$x_t = E_t x_{t+1} - \frac{1}{\sigma}(r_t - E_t \pi_{t+1} - \overline{rr}_t)$$

$$\pi_t = \beta E_t \pi_{t+1} + \lambda E_t x_t + u_t$$

$$m_t = p_t + y_t - \eta r_t + v_t \qquad (1)$$

where $x_t \equiv y_t - \bar{y}_t$ is the output gap, π_t is inflation, m_t money and r_t the monetary policy instrument.[14] The cost-push term is assumed to be an AR(1) process, $u_t = \rho u_{t-1} + \varepsilon_t$, with $\varepsilon_t \sim IID(0, \sigma_\varepsilon^2)$, while the velocity shock v_t is assumed to be white noise with variance σ_v^2; $\overline{rr}_t$ and $\bar{y}_t$ are, respectively, the exogenously determined equilibrium level of the real interest rate and of the potential output. We assume that at time t current prices and inflation, unlike the output gap, are not observed. Correspondingly, the cost-push shock, which is the variable driving the equilibrium path of output and inflation, and the money-demand shock are known with a one-period lag, while we assume no uncertainty about the parameters of the model and the probability distribution of the shocks.

The central bank optimizes every period by choosing the interest rate which minimizes its current-period loss function, which is assumed to be a quadratic function of both inflation and the output gap: $1/2(\pi_t^2 + \alpha x_t^2)$. The optimal policy requires that $E_t x_t = -(\lambda/\alpha) E_t \pi_t$. In each period, the estimate of inflation can be optimally revised by applying the Kalman filter to extract information on the unobserved state variables. The revision in the estimate will depend on the 'surprises' in money and in past inflation (see Appendix A):

$$\pi_{t|t} - \pi_{t|t-1} = \left[\frac{1}{1 + \sigma_v^2/\sigma_\varepsilon^2} \quad \vdots \quad (\varphi + \rho) - \frac{\psi}{1 + \sigma_v^2/\sigma_\varepsilon^2} \right] \times \begin{bmatrix} (m_t - p_{t-1}) - (m_{t|t-1} - p_{t-1|t-1}) \\ \pi_{t-1} - \pi_{t-1|t-1} \end{bmatrix} \qquad (2)$$

where $\psi \equiv \varphi - \left(\frac{\lambda}{\alpha} + \eta\rho + \frac{\lambda}{\alpha}\eta\sigma(1-\rho)\right)(\rho + \varphi)$. Money is informative insofar as velocity shocks are not too volatile: as $\sigma_v/\sigma_\varepsilon \to \infty$, money surprises play no role at all; if the volatility of the velocity shock is equal to zero, inflation would be predicted with no error.

Eq. (2) sets a relation among 'surprises' of endogenous variables. To exploit it for policy purposes, two approaches may be used. A first approach relies on the econometric model describing the working of the economy and uses the model's estimated multipliers and covariance matrix to extract the information contained in monetary and credit data, by means of the Kalman filtering procedure used to obtain Eq. (2). We apply this approach to the quarterly model of the Italian economy in Section 4. This solution is theoretically appealing, since it provides an approximation to the optimal filter and explicitly attempts to attribute to structural shocks the innovation to previous-period forecasts. It is also

[14] All variables are in logs, except the interest rate.

related to what, less formally, is usually done in day-to-day monetary analysis, when the behaviour of money is interpreted to gain insight into the underlying economic phenomena. However, a drawback of this approach is that it is strongly model-dependent, as only the dynamic correlations among forecast errors that are built into the structure of the model are taken into account: one may not find any information content for money if the model is misspecified.

A second approach, which we apply to the quarterly model in Section 5, gauges the informative content of surprises in financial variables by analyzing the correlation between forecast errors, i.e. the surprises in endogenous variables obtained from a simulation of the model.[15] In the model described above, this would require regressing $\pi_t - \pi_{t|t-1}$ onto $[(m_t - p_t) - (m_{t|t-1} - p_{t|t-1})]$ and $(\pi_{t-1} - \pi_{t-1|t-1})$. The resulting estimates (as shown in the Appendix A) would asymptotically yield the coefficient vector:

$$\delta = \begin{bmatrix} \dfrac{1}{1 + \sigma_v^2/\sigma_\varepsilon^2} \\ (\varphi + \rho) - \dfrac{\psi}{1 + \sigma_v^2/\sigma_\varepsilon^2} \end{bmatrix} \tag{3}$$

which is clearly identical to the one in Eq. (2).

While the two approaches are equivalent under perfect knowledge of the structural coefficients in the system, the equivalence breaks down if either an incomplete set of surprises is used or model uncertainty is allowed for: under incomplete information, the estimates of the second approach could be inefficient and even biased because of an omitted variables problem; under model uncertainty, by contrast, no general conclusion can be drawn concerning the relative performance of the two methods. The advantage of using a much larger set of variables in the estimates of the structural model may be offset by the bias caused by imposing incorrect over-identifying restrictions on the reduced-form. The magnitude of these contrasting effects will depend on the source of misspecification.

All in all, the regression based approach is simpler and may possibly account for relationships among variables, which are not embodied in the structure of the model. However, it is also inefficient and more likely to arbitrarily constrain the information set used to evaluate the signalling role of financial variables. The balance of the pros and cons may go either way and so there is a case for comparing the results coming from the two approaches to extracting information from monetary data.

4. Information lags and monetary variables: a filtering approach

Several studies have examined how data which are known with time delay can be best predicted on the basis of available information. The analytic framework adopted in this

[15] Friedman (1984) provides an example of this approach.

section rests on the contribution by Wallis (1986) and Harvey (1989),[16] while the application proposed is closely related to the one outlined in Kalchbrenner and Tinsley (1976) and Sandee et al. (1984) and, for Italy, Angeloni and Cividini (1990).[17] However, the latter experiment, which contributed to justifying the role attributed to monetary aggregates in Italy in the 1980s, is based on the 'theoretical' information content built into the model's properties, i.e. on the reduction of the forecast error variance obtained from a set of stochastic simulations of the model. By contrast, we aim to test on actual data (the 1990s) the improvement in predictive accuracy.

Incorporating the additional information from new observations on money and credit variables in a full-scale simulation requires that a few steps be followed. First, surprises for financial indicators must be computed; second, such surprises must be mapped into structural shocks; finally, forecasts conditional on the information set augmented with the updated estimate of the structural shocks must be generated.

The quarterly model of the Bank of Italy may be written as

$$f(y_t, k_t; \vartheta) = f\left(\begin{bmatrix} y_t^T \\ y_t^M \\ y_t^O \end{bmatrix}, k_t; \vartheta\right) = \begin{bmatrix} \varepsilon_t^T \\ \varepsilon_t^M \\ \varepsilon_t^O \end{bmatrix} \tag{4}$$

where $f(\cdot)$ is a system of non-linear functions, ϑ are the model parameters, k_t is the vector of pre-determined variables and ε_t collects the structural white-noise disturbances. y_t, the vector of modelled variables is partitioned into three subsets, y_t^M, y_t^T and y_t^O corresponding, respectively, to policy targets, monetary indicators and other endogenous variables. The corresponding linearised reduced form is:

$$y_t \equiv \begin{bmatrix} y_t^T \\ y_t^M \\ y_t^O \end{bmatrix} = A^{-1}B(L)y_{t-1} + A^{-1}C(L)x_t + A^{-1}\varepsilon_t \equiv \Pi(L)y_{t-1} + \Gamma(L)x_t + u_t \tag{5}$$

where x_t, a subset of k_t is the vectors of exogenous variables, $B(L)$ and $C(L)$ are matrix polynomials of order $p-1$ and q, respectively, and u_t are the reduce form shocks.

[16] Harvey (1989) describes how the Kalman filter helps coping with data irregularities and provides the details of the approach used here; Wallis (1986) utilises the Kalman filter to deal with the so called 'ragged edge' problem, i.e. the fact that official statistical agencies produce data at different intervals and with different delays, so that at any time we have 'current' information on some variables but not on others.

[17] Kalchbrenner and Tinsley (1976) is the paper which is the closest to ours: they show how to decompose the forecast errors of the monetary indicators into estimates of the structural disturbances impinging on the variables which are of interest for the monetary authorities. Sandee et al. (1984) present a minimum norm estimator to extract information from current indicators so as to increase the forecasting accuracy of the KOMPAS model. Angeloni and Cividini (1990) present evidence on the information content of financial variables in Italy in the 1980s and use a previous version of the quarterly model of the Bank of Italy (see also Angeloni and Passacantando, 1991).

The n-step ahead surprises are therefore defined as:

$$y_t - y_{t\,|\,t-n} = \sum_{i=0}^{n-1} \Pi^i(L)\left[A^{-1}\varepsilon_{t-i\,|\,t-n}\right] \equiv \begin{bmatrix} g'\ \underline{\varepsilon}_t \\ h'\ \underline{\varepsilon}_t \\ f'\ \underline{\varepsilon}_t \end{bmatrix} \tag{6}$$

where $\varepsilon_{t-i|t-n}$ is equal to ε_{t-i} if $i>n$, $\underline{\varepsilon}_t$ represents the vector formed by stacking the current and lagged (up to order $n-1$) structural disturbances ε_t and g, h and f are matrices obtained from the reduced form multipliers. Eq. (6) makes clear that surprises in endogenous variables are a complex combination of the shocks buffeting the economy.

Our experiment relies on the Kalman filter to blow up the surprises in the financial indicators, $u^M_{t|t-n}$, into estimates of the disturbances of the structural equations ε_t; they may then be transformed into estimates of the unobserved states y^T_t (and y^O_t) (Appendix B). This is the main difference with respect to the—conceptually equivalent—approach suggested in Wallis (1986), which is concerned only with forecasts and operates on the reduced forms. Estimating the structural shocks is instead of the utmost importance for policy purposes, because it allows to provide an economic rationale to the revision in forecasts and in so doing it facilitates communication within the central bank and to the general public.[18]

The matrices appearing on the right hand side of Eq. (6) are functions of the reduced-form parameters and the covariance matrix of the shocks, and can be estimated via simulations, by shocking the structural errors and computing the dynamic multipliers up to order $n-1$, where n is the information lag. As the structure of the quarterly model includes some non-linearity, the reduced-form multipliers are recomputed in each period. It is worth stressing that the filter uses the information contained in $u^M_{t\mathrm{A}t-n}$ only in a way which is coherent with the causal links coded in the identities and stochastic equations built into the quarterly model. Hence, the experiment is based on the assumption that the quarterly model is a reliable description of the working of the economy, i.e. that the model is correctly specified.

The experiment is implemented in three steps. First, l-step ahead forecasts are obtained from simulating the quarterly model. Assuming that the information lag, n, is equal to 1 and common to all endogenous variables, the model in t is simulated conditional on the observations of endogenous variables up to time $t-1$ and on the actual path of the exogenous ones.[19] The time index t ranges from 1989Q1 to 1999Q2, so that, for each forecast horizon, 42 observations are available. The l-step-ahead forecast variance of the ith element of the vector y^T_t is estimated and defined as $\sigma^2_{i,l}$.

Second, in order to incorporate additional information on financial quantities and prices, the surprise $y^M_t - y^M_{t\,|\,t-1}$ is mapped into the structural disturbances applying a

[18] In addition, linearising the mapping between surprises and structural shocks, rather than the relationship between endogenous and pre-determined variables, allows preserving the accounting identities and hence improves forecasting accuracy.

[19] That is, time t projections are conditional on $I_t = \{y_j\}_{j=0}^{t-1} \cup \{x_j\}_{j=0}^{t+l}$. Simulation runs from t to $t+l$, where l is the forecast horizon and n the information lag.

Kalman filter based on Eq. (6). The latter are then used to produce a new set of projections; the associated forecast error variances $\tilde{\sigma}^2_{i,l}$ are computed:

$$\tilde{\sigma}^2_{i,l} = \frac{1}{42}\sum_t \left(y^T_{i,t+l} - \tilde{y}^T_{i,t+l\,|\,t-1}\right)^2 \tag{7}$$

Third, an additional set of projections is generated by assuming that at time t all variables dated t are known. The corresponding l-step-ahead forecast error variances, $\bar{\sigma}^2_{i,l}$, which are conditional on $\bar{I}_t = \tilde{I}_t \cup \left\{y^T_t, y^O_t\right\} = I_{t+1}$, are computed. Notice that since $I_t \subset \tilde{I}_t \subset \bar{I}_t$, it is clearly the case that $\sigma^2_{i,l} \geq \tilde{\sigma}^2_{i,l} \geq \bar{\sigma}^2_{i,l}$. The variance $\bar{\sigma}^2_{i,l}$ provides a lower bound to the forecast error variance and represents the appropriate scaling factor for gauging the contribution to the forecast accuracy of the news about monetary and financial variables.

The outcome of the experiment is reported in Table 1, which shows mean square forecast errors (MSFEs) which are obtained under different assumptions concerning the information set available to the econometrician. Projections, which ranges from 1 to 4 steps ahead, refer to nominal and real GDP. Six variables, representing money, financial aggregates or financial prices, are alternatively used as information variables. Two indices are reported to assess the information contained in y^M_t: the first, $\sigma_{i,l}/\bar{\sigma}_{i,l}$, measures the extent of the deterioration in forecast accuracy due to the existence of information lags; the second, $\Lambda_{u^M \to u^T} \equiv \left(\sigma_{i,l} - \tilde{\sigma}_{i,l}\right)/\bar{\sigma}_{i,l}$, determines how much of this loss of precision can be avoided by incorporating financial surprises. We consider innovations in financial variables one at a time.

Among the financial variables we select currency, M2,[20] credit to firms, credit to households, bank and market interest rates. Since by construction of the experiment, there are no surprises in the policy rate (which is treated as an exogenous variable), the information in the unexpected movements of bank and market rates corresponds to the information in the movements of the spread of these rates vis-à-vis the policy rate.

The results do not lend support to the view that, given the model's structure, timely information on monetary and credit aggregates may help reduce the uncertainty originating from information lags on other variables. Rather, they seem to confirm that in the 1990s monetary and credit aggregates lost the informative value they had in the previous decade. Neither M2 nor currency nor credit to the private sector contribute to reducing forecast uncertainty on nominal GDP, as is shown by the negligible value reported in Table 1 of the improvement in predictive accuracy.

By contrast, information on bank interest rates proves effective in estimating the current unobserved values of real variables.[21] Compared with the benchmark case in which there

[20] The pre-EMU definition of Italian M2 is used, since most of the sample period predates the start of Stage Three.

[21] Changes in the premium component of (bank and non-bank) interest rates are the amplification mechanism typically advocated by supporters of the credit channel view. Shifts in monetary policy or cyclical conditions alter the efficiency of financial markets in matching borrowers and lenders and raise the extent to which borrowers face rationing in credit markets: a deterioration in financing conditions causes firms and households to revise down their spending plans and thus amplifies the effects of the initial shock.

Table 1
Financial variables and accuracy in forecasting real and nominal GDP

		Real GDP				Nominal GDP			
		$l=1$	$l=2$	$l=3$	$l=4$	$l=1$	$l=2$	$l=3$	$l=4$
Credit to households	$\sigma_{i,l}/\bar{\sigma}_{i,l}$	1.62	1.44	1.30	1.27	1.35	1.42	1.25	1.21
	$\Lambda_{u^M \to u^T}$	0.00	0.03	0.01	0.01	0.00	0.03	0.00	0.00
Private sector credit	$\sigma_{i,l}/\bar{\sigma}_{i,l}$	1.62	1.43	1.30	1.28	1.35	1.42	1.25	1.21
	$\Lambda_{u^M \to u^T}$	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
M2	$\sigma_{i,l}/\bar{\sigma}_{i,l}$	1.61	1.44	1.30	1.27	1.35	1.42	1.25	1.21
	$\Lambda_{u^M \to u^T}$	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00
Currency	$\sigma_{i,l}/\bar{\sigma}_{i,l}$	1.62	1.44	1.30	1.27	1.35	1.42	1.25	1.21
	$\Lambda_{u^M \to u^T}$	0.01	0.02	0.00	0.00	0.00	0.02	0.00	0.00
Loan rate	$\sigma_{i,l}/\bar{\sigma}_{i,l}$	1.62	1.44	1.30	1.27	1.35	1.42	1.25	1.21
	$\Lambda_{u^M \to u^T}$	0.26	0.21	0.15	0.14	0.14	0.19	0.10	0.12
Deposit rate	$\sigma_{i,l}/\bar{\sigma}_{i,l}$	1.62	1.44	1.30	1.27	1.35	1.42	1.25	1.21
	$\Lambda_{u^M \to u^T}$	0.24	0.12	0.11	0.11	0.11	0.16	0.09	0.06

The table reports two statistics for the money/credit variables specified in the first column: (1) the standard deviation of the forecast error l-step ahead ($l=1,2,3,4$) obtained when all variables are assumed to have the same information lag, i.e. one quarter ($\sigma_{i,l}$); (2) the index measuring the efficiency gain obtained when financial variables are used to update initial conditions ($\Lambda_{u^M \to u^T}$; see text). All figures are normalised as ratios to the standard deviation of the forecast error obtained under the assumption of no information lags ($\bar{\sigma}_{i,l}$).

is a one quarter information lag for all variables, the lending rate reduces the MSFE by nearly one half; the deposits rate performs only marginally worse. Even when the forecast horizon is increased from $l=1$ to $l=4$, the improvement obtained by including financial data in the information set remains noticeable.

Similar results are obtained when real GDP is considered: the extent of the decrease in the MSFE is roughly the same and the improvement in predictive accuracy due to the use of the information in interest rates extends to all forecast horizons. This outcome suggests that news on the external finance premium mostly affect real activity and only marginally prices, which is quite consistent with the common view that changes in financing conditions are transmitted first to aggregate demand and only with a delay of several quarters to inflation. When aggregate demand components are considered, the outlook changes, though not in an unexpected way: innovations in bank interest rates appear to convey significant information about the prospective path of investments but seem silent about future consumption expenditure and trade flows.

All in all, this evidence has a straightforward interpretation. Interest rate surprises appear to contain significant information because two conditions are met: first, the model accounts for a set of channels through which bank interest rates are related to the real sector; second, the economy works in a way which is not at variance with the description provided by the model. Monetary and credit aggregates appear not to meet these requirements or to meet them only in part: they do not exert a causal influence on non-financial variables in the model, nor is the existing reverse causation from consumption/investment choices to portfolio decisions strong enough to be exploitable, since it is obscured by financial and institutional innovations and velocity shocks.

5. Information lags and monetary variables: looking at surprises

The above analysis is conditional on the structure of the model. The results could thus be an artefact, due to the limited role assigned to monetary variables in the model. The alternative strategy we follow is to estimate univariate regressions, in order to directly map surprises in y_t^M into revisions in y_t^T. The logic is the same as in the experiment run in the previous section. There is, however, an important difference. Here, by directly addressing the empirical correlations across surprises, we allow all empirical correlations between monetary and target variables to play a role beyond the assumed structure of the quarterly model.

Friedman (1984) tested the information content of monetary variables by means of a dynamic simulation of a small (six-equation) macroeconometric model over a long horizon. He derived forecast errors for nominal income growth an indefinite number of quarters ahead and estimated equations relating these forecast errors to the corresponding surprises in money growth, allowing for a rich dynamics in both variables. He found that movements of money growth contained additional information about future income growth, which, however, was statistically but not economically significant.

This approach was criticized on two grounds (Goldfeld, 1984). When dynamic simulations over a long horizon are used to generate forecast errors, the estimated equations should include the lagged surprises for all the endogenous variables in the model, with a lag structure determined by the structure of the original model and the assumptions on the information lags. Moreover, provided that the dynamics of the initial model is correctly specified, the estimated parameters in the surprise equations are a combination of parameters in the underlying model, so they can simply be written down rather than estimated.

We follow the logic of the approach, but with substantial modifications. Since we run the experiment on a large model, the parameters in the surprise equations could hardly be recovered directly from the structure of the model itself. We run the experiment under the assumption that monetary data are known one or two quarters in advance compared with other variables, which is admittedly an extreme hypothesis, as it imposes that provisional national accounts data are not informative.[22]

We simulate the quarterly model over the period 1989Q1–1999Q2, under the assumption of no uncertainty concerning exogenous variables, model coefficients and functional form specification. We compute the n-step-ahead ($n=1$, 2, 4) forecast errors of the same endogenous variables considered in the previous section. We report the properties of the one-step-ahead surprises generated by the experiment in Table 2 (all surprises are defined as percentage deviations from the baseline). As one would expect,

[22] Monetary data usually become available before national accounts data are released. In Italy, in the period under consideration, the first estimates of M2 (monthly average) were released by the last 10 days of the month, while final data were available by the following month, with usually only small revisions. National account data would be available only after one or two quarters, and still subject to substantial revisions thereafter. More timely information was available on consumer prices, whose first estimates were also available by the end of the same month, as well as consumer sentiment, wholesale prices, survey data on inflation expectations and industrial production.

Table 2
One-step ahead forecast errors: diagnostic tests

Variables	AR(1)	AR(2)	HET(l)	JB	ADF
Nominal GDP	0.52	0.93	0.59	0.63	– 6.80 (**)
Real GDP	0.73	0.27	0.99	0.83	– 6.30 (**)
GDP deflator	0.03	0.10	0.61	0.59	– 4.40 (**)
Currency	0.92	0.02	0.81	0.70	– 6.10 (**)
M2	0.15	0.26	0.07	0.20	– 5.00 (**)
Credit	0.00	0.00	0.21	0.59	– 3.20 (*)
Bank lending rate	0.49	0.49	0.01	0.93	– 5.60 (**)
Bank deposit rate	0.05	0.26	0.05	0.98	– 4.60 (**)

Diagnostic tests on the one-step ahead forecast error generated by the quarterly model of the Italian economy over the period 1989–1999. AR(*i*): LM test for autocorrelation of order *i*. HET(1): test for heteroscedasticity of order 1. JB: Jarque–Bera test for normality. ADF: augmented Dickey–Fuller test for the presence of a unit root (the lag length was determined with an AIC criterion). The table reports probability levels; for the ADF test, the test statistics is reported, while (*) and (**) indicate rejection of the null of a unit root at the 5% and 1% confidence level.

they exhibit reasonable properties: stationarity, normality, homoscedasticity and absence of autocorrelation.

For each horizon, we choose one monetary variable at a time ($y^M_{l,t}$ indicates a single component of the corresponding vector of variables) and run the following regression:

$$y^T_{i,t} - y^T_{i,t\,|\,t-n} = \alpha + \sum_{j=0}^{k} \gamma_j \left(y^M_{l,t-j} - y^M_{l,t-j\,|\,t-n} \right) + \sum_{j=0}^{h} \lambda_j y^M_{l,t-j} + \eta_t \qquad (8)$$

where lagged values of the monetary indicator are introduced in the regression to test whether some monetary link, neglected in the model, would be helpful in forecasting the surprise.[23] We test the statistical significance of $\Sigma\gamma_i$ in each equation by allowing for heteroscedasticity and serial autocorrelation in the error term. We evaluate the decrease in the forecast error variance.[24] Table 3 reports the results for Eq. (8), considering as a dependent variable the *n*-period-ahead (with $n = 1$, 2, 4) forecast error of real GDP, the GDP deflator and nominal GDP, respectively. Each row reports the *R*-squared from the regression, which proxies for the information content, the sum of the coefficients on the monetary surprise, $\Sigma\gamma_i$, and the *F*-test that lagged values of the monetary variable do not enter the regression.

As in the preceding experiment, the behaviour of bank interest rates (both current surprises and past values) has information content for real and nominal GDP, especially at the shorter horizons (1 and 2 quarters), with the expected (negative) sign. The percentage of variance explained by the equation is not negligible (between 30 and 40% for real GDP).

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[23] Eq. (8) was also estimated after adding the term $\left(y^T_{t-n} - y^T_{t-n\,|\,t-n-1} \right)$ on the right-hand side, to take into account the fact that, in actual forecasting practice, the recent forecasting errors in the dependent variable may also be used to update the initial conditions. The results were substantially the same as in the text.

[24] This is proxied by the R^2 of the regression.

Table 3
The information value of monetary surprises (1989–1999)

	Horizon = 1 quarter			Horizon = 2 quarters			Horizon = 4 quarters		
Dependent variable: nominal GDP									
	R^2	$\Sigma\gamma_j$	$P(\lambda_1 = .. \lambda_h = 0)$	R^2	$\Sigma\gamma_j$	$P(\lambda_1 = .. \lambda_h = 0)$	R^2	$\Sigma\gamma_j$	$P(\lambda_1 = .. \lambda_h = 0)$
Currency	0.20	− 0.15	0.66	0.05	0.00	0.90	0.21	0.04	0.79
M2	0.14	− 0.19 (*)	0.24	0.15	− 0.15	0.44	0.09	− 0.13	0.35
Credit	0.20	0.12 (*)	0.06	0.22	0.10	0.47	0.38	0.07	0.75
Bank lending rate	0.25	− 0.16 (*)	0.51	0.35	0.30 (**)	0.01 (*)	0.47	− 0.09	0.00 (**)
Bank deposit rate	0.13	− 0.08 (*)	0.40	0.22	− 0.12 (*)	0.09	0.41	− 0.17	0.06
Long term rate	0.13	0.04	0.36	0.14	0.10 (*)	0.04 (*)	0.26	− 0.05	0.04 (*)
Dependent variable: real GD									
	R^2	$\Sigma\gamma_j$	$P(\lambda_1 = .. \lambda_h = 0)$	R^2	$\Sigma\gamma_j$	$P(\lambda_1 = .. \lambda_h = 0)$	R^2	$\Sigma\gamma_j$	$P(\lambda_1 = .. \lambda_h = 0)$
Currency	0.35	− 0.18 (**)	0.32	0.38	− 0.17	0.86	0.39	− 0.38 (**)	0.57
M2	0.14	− 0.14 (*)	0.71	0.27	− 0.17 (*)	0.57	0.17	− 0.22 (*)	0.88
Credit	0.23	− 0.05	0.01 (*)	0.17	− 0.06	0.14	0.32	− 0.25	0.60
Bank lending rate	0.34	− 0.13 (*)	0.00 (**)	0.34	− 0.22 (*)	0.15	0.36	− 0.01	0.01 (*)
Bank deposit rate	0.28	− 0.08 (**)	0.03 (*)	0.33	− 0.11 (**)	0.02 (*)	0.47	− 0.18	0.00 (**)
Long term rate	0.36	0.03 (*)	0.00 (**)	0.39	0.06 (*)	0.03 (*)	0.51	− 0.01	0.00 (**)
Dependent variable: GDP deflator									
	R^2	$\Sigma\gamma_j$	$P(\lambda_1 = .. \lambda_h = 0)$	R^2	$\Sigma\gamma_j$	$P(\lambda_1 = .. \lambda_h = 0)$	R^2	$\Sigma\gamma_j$	$P(\lambda_1 = .. \lambda_h = 0)$
Currency	0.06	0.03	0.11	0.17	0.16	0.78	0.31	0.41	0.91
M2	0.08	− 0.04	0.66	0.08	0.02	0.49	0.06	0.09	0.56
Credit	0.35	0.17 (**)	0.00 (**)	0.47	0.16	0.72	0.66	0.31 (*)	0.37
Bank lending rate	0.27	− 0.03	0.73	0.56	− 0.08	0.00 (**)	0.83	− 0.07	0.00 (**)
Bank deposit rate	0.30	− 0.01	0.32	0.55	− 0.01	0.00 (**)	0.79	0.02	0.00 (**)
Long term rate	0.23	0.01	0.43	0.35	0.03	0.00 (**)	0.70	− 0.05	0.00 (**)

Estimated equation (for $n = 1, 2, 4$, y_i^T = real GDP, nominal GDP, GDP deflator; y_k^M = currency, M2, credit, Lending rate, deposit rate, long term rate):

$$y_{i,t}^T - y_{i,t|t-n}^T = \alpha + \sum_{j=0}^{k} \gamma_j \left(y_{l,t-j}^M - y_{l,t-j|t-n}^M \right) + \sum_{j=0}^{h} \lambda_j y_{l,t-j}^M + \eta_t,$$

Each panel reports the following statistics: R-squared of the regression; sum of the γ_i coefficients, where (*) and (**) indicate rejection of the null $\sum_{j=1}^{k} \gamma_j = 0$, at the 5% and 1% level; P-value from an F-test of the null H_0: $\lambda_1 = \ldots = \lambda_h = 0$.

The results for monetary aggregates depart from the findings of the previous experiment. In particular, M2 surprises now have some information content for real GDP, as the sum of the coefficients is statistically significant and the share of explained variance is approximately 20%. In contrast, past values of M2 do not significantly enter the regression, suggesting that no major mis-specification of the money-GDP link affects the model.

However, a closer inspection of the results shows that the sum of the coefficients on monetary surprises, although significant, always has a negative sign. This finding proved to be rather robust to the introduction of other explanatory variables in the equation or to estimation over various sub-samples. Conceptually, this is not in contrast with the analysis presented in this paper; the relation between surprises is a reduced form result whose relation to the structural parameters may be complex enough. In particular, it is conceivable that particular values of the sample covariances among different shocks are driving our result.[25]

A plausible interpretation of these findings is indeed available. In a few episodes, an increase (or decrease) in uncertainty has determined both an adverse effect on aggregate demand and an increase (or decrease) in the liquidity preference. In 1992–1993, the Lira abruptly abandoned the EMS, causing a marked portfolio shift towards money and a sharper contraction in GDP and economic activity; in 1994, improved expectations fostered a shift from money to bonds, while the reduction in risk premia partially contributed to the economic recovery; in 1996, market tensions linked to uncertainty about the sustainability of the government debt determined a new shift towards money and possibly contributed to the contraction in activity; in 1997–1998, the successful convergence to EMU prompted optimism among economic agents, which was reflected in a new reduction of risk premia, a shift to less liquid assets and a (mild) recovery of GDP. In all these cases, the larger (smaller) than expected growth in money M2 was not signalling excess demand; rather, it was anticipating a decrease (increase) in activity.

Although the finding of a negative correlation can be justified, it stands in contrast with a simplistic interpretation of the role that new information on money can play for the policymaker. It shows that monetary data can be useful as indicators, but they call for a careful interpretation.

6. Conclusions

We tested whether data on monetary and credit variables, thanks to their prompt availability and higher reliability, had marginal information content for output or inflation.

In the first experiment, we filtered data on monetary and credit aggregates based on the structure of the model, to assess whether they could be used to gather information on the underlying shocks and consequently to improve upon the forecasting performance in the 1990s. We found they could not. However, we found that timely data on lending and

[25] Should one allow for a negative covariance between the cost-push and the money-demand shocks in the model in Section 3, it could be shown that the coefficient on money surprises in Eq. (2) could turn negative.

deposit rates did provide such information and could be usefully exploited by the policymaker. Interest rate surprises appear to contain significant information because the model accounts for a set of channels through which bank interest rates are related to the real sector. By contrast, monetary and credit aggregates do not exert a causal influence on non-financial variables in the model, while their role as signals of unobservable state variables is obscured by the variance of velocity shocks embodied in the model's structure.

In the second experiment, we tested whether the forecasting errors in monetary variables (and their past values) could help explain the forecast errors for output and inflation. This approach is complementary to the first one, as it also considers links not accounted for by the model structure. We found that the information content of monetary aggregates is higher than that implied by the previous experiment. However, its interpretation is difficult; in the equation explaining the forecast errors in real GDP, monetary surprises have the opposite sign than expected.

The results highlight the potential role of financial prices and quantities as measures of unobserved state variables. However, the policy implication of this finding are not straightforward, since the relationship between the financial and real sides of the economy are complex, far from time-invariant and highly dependent on the source of the shocks. A careful interpretation is needed and no mechanical reaction to monetary developments is warranted.

Appendix A

The solution of system Eq. (1) is obtained by applying the method of undetermined coefficient. The minimal state variable solution is provided by:[26]

$$\pi_t = u_t + \frac{\rho(\alpha\beta\rho - \lambda^2)}{\alpha(1-\beta\rho) + \lambda^2} u_{t-1} = u_t + \varphi u_{t-1} \tag{A1}$$

$$x_t = E_t x_t = -\frac{\lambda}{\alpha}(\rho + \varphi) u_{t-1} \tag{A2}$$

$$m_t - p_{t-1} = (\bar{y}_t - \eta \overline{rr}_t) + u_t + \underbrace{\left(\varphi - \left(\frac{\lambda}{\alpha} + \eta\rho + \frac{\lambda}{\alpha}\eta\sigma(1-\rho)\right)(\rho + \varphi)\right)}_{\psi} u_{t-1} + v_t \tag{A3}$$

[26] Real money balances are expressed in terms of previous-period prices because p_{t-1} is included in the information set I_t. Notice that $m_t - p_{t-1} = \pi_t + x_t + \bar{y}_t - \eta(\overline{rr}_t + E_t\pi_t + \sigma(E_t x_{t+1} - x_t)) + v_t$, where the equilibrium real interest rate and potential output are exogenous variables, so that the solution is immediately obtained by replacing inflation and the output gap with their representation in terms of fundamental shocks.

All three variables can be cast into state-space form, which allows using the Kalman filtering technique for revising projections (Harvey, 1989). The minimal state space representation is given by the transition equation:

$$\alpha_t \equiv \begin{bmatrix} \pi_t \\ m_t - p_{t-1} \\ \varepsilon_t \\ v_t \\ \pi_{t-1} \end{bmatrix} = \begin{bmatrix} \rho & 0 & \varphi & 0 & 0 \\ 0 & \rho & \psi & -\rho & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \pi_{t-1} \\ m_{t-1} - p_{t-2} \\ \varepsilon_{t-1} \\ v_{t-1} \\ \pi_{t-2} \end{bmatrix} + d_t + \begin{bmatrix} 1 & 0 \\ 1 & 1 \\ 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \varepsilon_t \\ v_t \end{bmatrix} \tag{A4}$$

where α_t is the vector of state variables and d_t collects the exogenous components of the system. The measurement equation is:

$$w_t \equiv \begin{bmatrix} m_t - p_{t-1} \\ \pi_{t-1} \end{bmatrix} = Z\alpha_t \equiv \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \pi_t \\ m_t - p_{t-1} \\ \varepsilon_t \\ v_t \\ \pi_{t-1} \end{bmatrix} \tag{A5}$$

The information set evolves according to: $I_t = I_{t-1} \cup \{\pi_{t-1}, \varepsilon_{t-1}, v_{t-1}, m_t\}$. When new data on inflation and money balances are released, the estimate of the state vector $\alpha_{t|t-1} \equiv E(\alpha_t | I_{t-1})$ can be updated as $\alpha_{t|t} = \alpha_{t|t-1} + P_{t|t-1} Z' F^{-1}(w_t - Z\alpha_{t|t-1})$, where $\alpha_{t|t} \equiv E(\alpha_t | I_t)$. $F = ZP_{t|t-1}Z'$ and $P_{t|t-1}$ is the covariance matrix of the estimation error one-step-ahead and it is updated according to the Kalman recursion as in (Harvey, 1989). The revision to the estimate of the state vector is:

$$\alpha_{t|t} - \alpha_{t|t-1} = \underbrace{\begin{bmatrix} [1+\psi(\varphi+\rho)]\sigma_\varepsilon^2 & (\varphi+\rho)\sigma_\varepsilon^2 \\ (1+\psi^2)\sigma_\varepsilon^2 + \sigma_v^2 & \psi\sigma_\varepsilon^2 \\ \sigma_\varepsilon^2 & 0 \\ \sigma_v^2 & 0 \\ \psi\sigma_\varepsilon^2 & \sigma_\varepsilon^2 \end{bmatrix}}_{P_{t|t-1}Z'} \underbrace{\begin{bmatrix} \dfrac{1}{\sigma_\varepsilon^2 + \sigma_v^2} & -\dfrac{\psi}{\sigma_\varepsilon^2 + \sigma_v^2} \\ -\dfrac{\psi}{\sigma_\varepsilon^2 + \sigma_v^2} & \dfrac{1+\psi^2+\dfrac{\sigma_v^2}{\sigma_\varepsilon^2}}{\sigma_\varepsilon^2 + \sigma_v^2} \end{bmatrix}}_{F^{-1}} \underbrace{\begin{bmatrix} \varepsilon_t + \psi\varepsilon_{t-1} + v_t \\ \varepsilon_{t-1} \end{bmatrix}}_{w_t - Z\alpha_{t|t-1}} \tag{A6}$$

The above equation implies that

$$\pi_{t\,|\,t} - \pi_{t\,|\,t-1} = \left[\frac{1}{1+\xi} \quad \vdots \quad (\varphi+\rho) - \frac{\psi}{1+\xi}\right] \begin{bmatrix} \varepsilon_t + \psi\varepsilon_{t-1} + v_t \\ \varepsilon_{t-1} \end{bmatrix} \tag{A7}$$

where $\xi\frac{\sigma_v^2}{\sigma_\varepsilon^2}$. As expected, money is informative insofar as velocity shocks are not too volatile; moreover, both surprises enhance the estimate of current period inflation, since $\pi_{t-1} - \pi_{t-1|t-1}$ makes it possible to identify the previous-period cost-push innovation, while $(m_t - p_{t-1}) - (m_{t|t-1} - p_{t-1|t-1})$ helps to estimate ε_t.[27]

The same result would be achieved by means of a regression of $\pi_{t|t} - \pi_{t|t-1}$ onto $[(m_t - p_{t-1}) - (m_{t|t-1} - p_{t-1|t-1});\ (\pi_{t-1} - \pi_{t-1|t-1})]'$, as done in the text. Under correct knowledge of the structure of the model, OLS would yield the same vector of loading, given that F and $ZP_{t|t-1}$ in the Kalman filter updating equation coincide with the second moment matrices which define the OLS estimator.

Appendix B

The way in which surprises are transformed into structural shocks can be described in terms of the Kalman filter. Eq. (6) shows that for linear models, structural shocks and n-step ahead forecast errors (surprises) are linked by the relation:

$$u_{t\,|\,t-n} = \sum_{k=0}^{n-1} \Pi^k(L)A^{-1}\varepsilon_{t-k} = M_0\varepsilon_t + \cdots + M_{n-1}\varepsilon_{t-n+1} \tag{B1}$$

which has the following state space representation:

$$\alpha_t \equiv \begin{bmatrix} u^M_{t\,|\,t-n} \\ \varepsilon_t \\ \vdots \\ \varepsilon_{t-n+2} \end{bmatrix} = \begin{bmatrix} 0 & M_1 & \cdots & M_{n-2} & M_{n-1} \\ 0 & 0 & & 0 & 0 \\ 0 & I & \ddots & 0 & 0 \\ \vdots & \vdots & & \vdots & \vdots \\ 0 & 0 & \cdots & I & 0 \end{bmatrix} \alpha_{t-1} + \begin{bmatrix} M_0 \\ I \\ \vdots \\ 0 \end{bmatrix} \varepsilon_t \tag{B2}$$

$$w_t \equiv u^M_{t\,|\,t-m} = [I \quad 0 \quad 0 \quad \cdots \quad 0]\alpha_t \tag{B3}$$

In general, this relation holds only as an approximation. In the experiment described in the paper, the matrices $\{M_k\}$, $k=0,1,\ldots,n-1$, are estimated via simulation, using dynamic

[27] It is a matter of simple algebra to check that in the sample model, $E_t\left(\pi_t - \pi_{t/t-1}\right)^2 = \left[1 + (\varphi+\rho)^2\right]\sigma_\varepsilon^2$ and $E_t\left(\pi_{t|t} - \pi_{t|t-1}\right)^2 = \left\{\left[1 + (1+\xi)(\varphi+\rho)^2\right]\sigma_\varepsilon^2\right\}/(1+\xi)$. As $\xi \to 0$, the two variances coincide, meaning that $\pi_{t|t}$ provides an exact estimate of the current-period inflation rate.

multipliers. In particular, the i–jth element of the matrix M_k is equal to $\partial y_{i(t+k)}/\partial \varepsilon_{jt}$. The recursive equations of the Kalman filter then provide the tool for optimally extracting estimates of the shocks $\varepsilon_t,\ldots,\varepsilon_{t-n+1}$. Once such estimates of the structural disturbances have been obtained, the model is simulated, $\tilde{\sigma}_{i,l}$ is computed and then compared with its lower and upper bounds $\sigma_{i,l}$ and $\sigma_{i,l}$. See Altissimo et al. (2001) for further details.

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