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# Monetary Policy Performance and the Accuracy of Observations

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# Monetary Policy Performance and the Accuracy of Observations*

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**Abstract**

This paper evaluates the consequences for monetary policy performance of acquiring more accurate real time data. A forward looking model is set up and calibrated to fit the broad stylized facts of the U.S. economy. Two different assumptions about the information structure of the economy are made. Under the first, both policy makers and the public cannot observe potential output, but have to estimate it by applying the Kalman filter to noisy observations. Under the second structure, the public knows the true state of the economy, while the policy makers still have to estimate it. Evaluation of a standard loss function gives the counterintuitive result that less accuracy in real time data can lead to small, but positive, changes in welfare.

JEL classification: E37, E47, E52, E58

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## 1 Introduction

There are many uncertainties facing a policy maker in the business of central banking. That economic theory and econometrics are used to reduce the uncertainty about the state of the world tomorrow by building and estimating forecasting models is perhaps clear. The degree to which there is also uncertainty about the state of the world today might at first glance seem to be only a question of accurate observation. However, some quantities that are relevant for the conduct of monetary policy are not directly observable, like the output gap. Economic theory can help determine the state of unobservable variables since it tells us how the variables that are observable depend on the ones that are not. The accuracy of this technique will depend on the accuracy of the observations. The purpose of this paper is to examine how the performance of

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monetary policy is affected by a reduction in the errors of observation. This is a question of practical relevance to policy makers since it answers the question of how many resources should be devoted to obtaining high quality real time data. It is also of interest to note that without a parameterized and calibrated model, we cannot be certain of in what direction welfare will change when the accuracy of real time data is improved. Indeed, our model suggests that less accuracy can actually improve welfare.

Our methodology will be the following. A standard new Keynesian model will be set up and calibrated, taking into account the uncertainty of the real time measurement of output and the unobservability of potential output. Inflation is assumed to be measured perfectly. The size of the noise in the measurement of output will then be varied and a standard expected loss function calculated for each specification. This allows us to compare the welfare consequences, as defined by the policy makers loss function, of changing the amplitude of the measurement errors on output.

The rest of the introductory section briefly reviews the related literature. Section 2 presents the structural model. Section 3 discusses different assumptions about the information structure of the economy and shows how the Kalman filter can be applied to our model to estimate the unobservable variables. Section 4 deals with calibration issues, section 5 presents and discusses the main results and section 6 concludes by discussing what we have and have not learned from our exercise.

## 1.1 Recent developments in the literature

In models of monetary policy, it is usually assumed that the policy makers are trying to minimize some loss function. The standard formulation of the loss function consists of a discounted weighted sum of expected deviations of output and inflation from their target levels, and policy is usually expressed as a linear function of the state variables. An optimal policy is a function that attains the minimum of the loss function.

Recent theoretical developments in the field of optimal monetary policy have produced a rigorous theoretical foundation for a 'hunch' that the profession of central bankers and interested academic economists have had for some time. Specifically, the 'hunch' is that the observed smoothing of the instrument could be explained as being an optimal response to uncertainty about the output gap.[1] Building on earlier papers on control with partial information by Pearlman (1986) and Currie, Levine and Pearlman (1986) and work on signal extraction from endogenous variables by Sargent (1991), Svensson and Woodford (2002a, 2002b) constructs a general framework where uncertainty about the output gap leads to instrument smoothing, while at the same time a form of certainty equivalence still holds. Certainty equivalence still holds in the sense that the parameters in the optimal policy function does not depend on whether it is applied to a perfectly measured state or to an optimal estimate of that state. This certainty equivalence result will be used extensively in the present paper. Ex post though, it will appear as if the responses to (the revised estimates) of the output gap are too timid. This is due to the real time data problem of identifying what type of shock the economy is subject to. For instance, a

[1] See for instance Blinder (1997), Sack(1998) and Smets(1998).

decrease in inflation can be attributed to either a negative cost push shock, a decrease in demand or a positive supply shock. An actual supply shock will thus only lead to a partial adjustment of the estimate of potential output, and the other parts will be attributed to cost push and demand shocks. So not only does this framework provide a coherent explanation of some stylized fact, it also lends itself well to answering the question of this paper.

The list of previous papers that have utilized this general framework is quite short, but growing. There is one paper by Ehrmann and Smets (2001), where the authors characterize and investigate the performance of different policy regimes in a calibrated backward/forward looking model.

Papers investigating the welfare implications of real time data problems are also few. Orphanides (1998) calculates the output equivalent cost of ignoring data uncertainty in a backward looking (pre-Lucas) model, and finds that the costs are large. Kriz (2003) performs similar experiments to those in the present paper, but uses the somewhat less realistic assumptions on what is observable or not. The Kriz paper is also limited to the symmetric information case of when policy makers and the public faces the same type of uncertainty, and the calibrated parameters are taken from models that assume perfect observability.

# 2 The Model

We will use a standard new Keynesian model with Calvo pricing for the formal analysis.[2] The structural model can be characterized by the following equations.

First, an expectations augmented Phillips curve

$$\pi_t = \beta E_t \pi_{t+1} + \delta(\phi(y_t - \overline{y}_t) + \varepsilon_{\pi t}) \tag{1}$$

where $\{\pi_t, y_t, \overline{y}_t, \varepsilon_{\pi t}\}$ is inflation, output, potential output and an exogenous inflation (cost-push) shock in period t. $E_t$ is the expectations operator based on information at time t. The nature of the information available to different agents in the economy will play a crucial role for the analysis, and it will be made precise in the next section. Goods are differentiated and prices are set in a monopolistically competitive market. $\phi$ is the elasticity of substitution between the differentiated products. $\delta$ is defined as $\delta = \frac{q}{1-q}[1 - \beta(1-q)]$ where $q$ is the fraction of firms that are allowed to change prices each period and $\beta$ is the discount rate. Wether the shock $\varepsilon_{\pi t}$ is multiplied by $\delta$ or not, is a matter of defining the shock. If $\varepsilon_{\pi t}$ is viewed as a shock to marginal cost, then the extent to which it is transmitted into an increase in the price level should depend on the stickiness of prices, i.e. the parameter $\delta$. Alternatively $\varepsilon_{\pi t}$ could be viewed as a shock to inflation and should not be multiplied by $\delta$. Together $\phi$ and $\delta$ determine the slope of the (short run) Phillips curve.

Next, we have an aggregate demand curve

$$(y_t - \overline{y}_t) = E_t[y_{t+1} - \overline{y}_{t+1}] - \frac{1}{\gamma}(i_t - E_t \pi_{t+1}) + \varepsilon_{yt} \tag{2}$$

where $i_t$ is the short nominal interest rate and $\frac{1}{\gamma}$ is the demand elasticity w.r.t. the expected real interest rate. The exogenous variables in the model,

[2] See for instance Clarida, Gali and Gertler (1999).

$\{\varepsilon_{\pi t}, \varepsilon_{yt}, \overline{y}_t\}$, follow AR(1) processes

$$\varepsilon_{\pi t} = \tau_\pi \varepsilon_{\pi t-1} + \xi_{\pi t} \tag{3}$$

$$\varepsilon_{yt} = \tau_y \varepsilon_{yt-1} + \xi_{yt}$$

$$\overline{y}_t = \tau_{\overline{y}} \overline{y}_{t-1} + \xi_{\overline{y}t} \tag{4}$$

where $\xi_{\overline{y}t}$ can be interpreted as a (positive) technology shock. We can for notational convenience collect the exogenous state variables in vector form, $\{\varepsilon_{\pi t}, \varepsilon_{yt}, \overline{y}_t\} = X_t$ and describe the driving process as

$$X_t = \tau X_{t-1} + u_t \tag{5}$$

where $\tau$ is a matrix with the autoregressive parameters$\{\tau_\pi, \tau_y, \tau_{\overline{y}}\}$ on the diagonal. The vector of disturbances, $u_t = \left\{\xi_{\pi t}, \xi_{yt}, \xi_{\overline{y}t}\right\}$ has mean zero and covariance $\Sigma_{\mathsf{uu}}$.

Finally, the interest rate will be set as a linear function of the exogenous variables

$$i_t = F X_t \tag{6}$$

where $F$ is chosen to minimize the policy maker's loss function

$$L_t = E_t \left[ \sum_{i=0}^{\infty} \beta^i \left[ \lambda (y_{t+i} - \overline{y}_{t+i})^2 + \pi_t^2 \right] \right]. \tag{7}$$

This formulation of the loss function implies that the policymakers target level of output is state dependent and equal to potential output, and that the target level of inflation is zero.[3] Optimal policy is characterized by the first order condition

$$y_t - \overline{y}_t = -\frac{\delta\phi}{\lambda}\pi_t \tag{8}$$

which will hold for

$$F = \left[ \begin{array}{ccc} \rho & \gamma & 0 \end{array} \right], \ \rho = f(\delta, \phi, \lambda, \tau_\pi) \tag{9}$$

where $\rho$ can be found by a standard iteration procedure[4]. The first order condition (8) implies that the policy makers face a trade off between price level and output stabilization in the presence of cost-push shocks, while demand shocks can be perfectly offset by raising the nominal interest rate by the size of the demand shock times the inverse of the intertemporal elasticity of consumption $\frac{1}{\gamma}$. Shocks to potential output are accommodated completely, since they raise output one for one, and thus do not affect neither the output gap nor inflation.

[3]This loss function can be justified as a quadratic approximation of a representative agent's utility function, as shown by Rotemberg and Woodford (1999). The use of the representative agent to measure social welfare in business cycles has been questioned by for instance Clarida, Gali and Gertler (1999). However, the controversy is regarding the determinants of the preference parameter $\lambda$, rather than what the functional form should be.

[4]See Söderlind (1999) for a description of the iterative procedure and Clarida, Gali and Gertler (1999) for a derivation of the first order condition.

The model above can be put in state space form as

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & \beta & 0 \\ 0 & 0 & -1 & -\frac{1}{\gamma} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{\pi t+1} \\ \varepsilon_{yt+1} \\ \overline{y}_{t+1} \\ E_t\pi_{t+1} \\ E_t y_{t+1} \end{bmatrix} = \begin{bmatrix} \tau_\pi & 0 & 0 & 0 & 0 \\ 0 & \tau_y & 0 & 0 & 0 \\ 0 & 0 & \tau_{\overline{y}} & 0 & 0 \\ -\delta & 0 & \delta\phi & 1 & -\delta\phi \\ 0 & 1 & -1 & 0 & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{\pi t} \\ \varepsilon_{yt} \\ \overline{y}_t \\ \pi_t \\ y_t \end{bmatrix} + \\ + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ \frac{1}{\gamma} \end{bmatrix} i_t + \begin{bmatrix} \zeta_{\pi t} \\ \zeta_{yt} \\ \zeta_{\overline{y}t} \\ 0 \\ 0 \end{bmatrix} \tag{10}$$

or more compactly

$$A_0 \begin{bmatrix} X_{t+1} \\ E_t x_{t+1} \end{bmatrix} = A_1 \begin{bmatrix} X_t \\ x_t \end{bmatrix} + B_0 i_t + \begin{bmatrix} u_t \\ 0_{nx\times 1} \end{bmatrix} \tag{11}$$

where $x_t = \{\pi_{t,} y_t\}'$.

# 3 Information assumptions

The information set available to the agents of the economy will be either what we will refer to as 'full information' or 'partial information'. An agent having full information knows the complete structure of the economy and can observe all of the state variables without any measurement error. The full information set at time T, $I_T$ will then be

$$I_T = \{A_0, A_1, B, D, F, \Sigma_{uu}, \Sigma_{vv}, X_t, x_t, u_t, v_t \mid t \le T\} \tag{12}$$

Agents having partial information know the structure of the economy, but cannot observe all state variables. Specifically, in our case none of the exogenous variables in $X_t$ will be directly observable by agents with partial information. The partial information set, $I_T^p$ at time T will thus be defined by (12) and (13)

$$I_T^p = \{A_0, A_1, B, D, F, \Sigma_{uu}, \Sigma_{vv}, Z_t \mid t \le T\} \tag{13}$$

$$Z_t = D \begin{bmatrix} X_t \\ x_t \end{bmatrix} + v_t \tag{14}$$

where $D$ is a matrix that picks out and scales the observable variables. In our model $D$ is a 4x5 matrix with zeros in the first three columns corresponding to the assumption that only inflation and output is observable. (13) will be referred to as the measurement equation and $v_t$ are the measurement errors with covariance $\Sigma_{vv}$ . The Kalman filter offers to the partially informed a method to estimate the unobservable state variables. The intuition behind the application of the filter is the following. Since the partially informed agents know the effect of the unobservable variables on the imperfectly measured but observable variables through the structural equations, they will be able to estimate the state of all the variables in the economy. If there were no noise in the measurement, i.e. if $\Sigma_{vv} = 0$, and the number of linearly independent observable variables is larger than the number of unobservable variables, this could be done perfectly. The Kalman filter let the agents 'filter out' the noise in the measurement equation in an optimal way.[5]

In the analysis below, two different assumptions will be made about who knows what in our economy. In the first case, it will be assumed that neither policy makers nor the private agents have full information, i.e. neither can observe the output gap directly. This will be referred to as symmetric information. In the other case, it will be assumed that the private agents have full information, while the policy makers still have partial information. This will be called asymmetric information. The relative realism of the assumptions have been briefly discussed by Ehrmann and Smets (2001), and Svensson and Woodford (2002a, 2002b). The arguments in favor of fully informed private agents are two. Ehrmann and Smets argue that the economy is atomistic, and that every agent (or firm) in the economy knows exactly what their own potential and current output are. Svensson and Woodford argue out of model coherence. According to them, economically relevant quantities must be known to some agents in the economy, or otherwise fail to be relevant. Then it is convenient, for aggregation purposes, to let all agents of the economy have the same full information set. However, these arguments do not hold up perfectly. One can argue against the 'atomistic' economy by noting that unless the economy is divided into completely self reliant and isolated islands, atomistic firms too will be affected by the aggregate output gap. Their optimal own good price is relative to the aggregate price level, which in turn is dependent on the aggregate output gap. Since the aggregate output gap is no more observable to the individual firm than to the policy makers, it has to be estimated. Regarding the argument of the irrelevance of unknown quantities, one can note that the structural parameters on potential and current output in our model can be interpreted as the aggregate effect of atomistic firms, without any reliance on knowledge of any aggregate quantities. Since which information structure is more realistic is still an open question, the analysis in later sections will be performed for both cases.

The next section describes how the Kalman filter can be applied to our structural model to estimate the state variables. In notation and technique, it closely follows Svensson and Woodford (2002a, 2002b). In what follows $E_t[X_{t+1}]$ will denote the rational, or mathematical, expectation of $X_{t+1}$ at time t. This will be the expectations of the fully informed agents in our model. Trivially, $E_t[X_t] = X_t$. The notation $X_{t+1|t}$ will be used to denote the partially informed agents expectations of $X_{t+1}$ at time t. Generally, $X_{t|t}$ will differ from $X_t$. When the term 'beliefs' is used, it is synonymous with 'partially informed estimate' and the term 'prediction' is synonymous with 'partially informed expectations'.[6]

## 3.1 The Kalman filter and the unobservable variables

For the later analysis it will be useful to be able to describe the dynamics of the system treating both the observation vector $Z_t$ and the estimated state

[5] Here 'optimal' refers to the Kalman filter's properties of being the minimum MSE unbiased estimator under normality assumptions, and the MSE in the class of linear estimators when the assumption of normality of the noise and innovations cannot be maintained. See Harvey(1989).

[6] This terminology is similar to the one used in the learning and macroeconomics literature. An alternative to 'beliefs' that also is used in the literature is 'perception'.

variables $X_{t|t}$ as separate state variables and write their dynamics together with the original state variables $X_t$ and $x_t$ as an AR(1) process. To achieve this, first rewrite (11) as

$$E_t \begin{bmatrix} X_{t+1} \\ x_{t+1} \end{bmatrix} = A \begin{bmatrix} X_t \\ x_t \end{bmatrix} + Bi_t + A_0^{-1} \begin{bmatrix} u_t \\ 0_{nx \times 1} \end{bmatrix} \tag{15}$$

where $A = A_0^{-1} A_1$ and $B = A_0^{-1} B_0$. It will be convenient to partition $A$ as

$$A = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \tag{16}$$

At the moment, there is no need to distinguish between the rational expectation and the partially informed expectation of the left hand side of (15). Assume that the expectation of the endogenous variables is a linear function of a given associated $X_t$.

$$E[x_t \mid X_t] = GX_t \tag{17}$$

and further define $G^1$ such that the following will hold

$$x_t = G^1 X_t + (G - G^1) X_{t|t} \tag{18}$$

The matrix $G^1$ will depend on the information structure of the economy. The derivations below of the dynamics of the system can be kept very general if we note that the matrix $G^1$ will be the only difference between the symmetric and asymmetric information case. When the general dynamics of the system has been written down, we can distinguish the two information structures by inserting the appropriate $G^1$. Now, from the structural equation, the exogenous variables (recall that they are the inflation shock, demand shock and potential output) will follow

$$X_t = A_{11} X_{t-1} + u_{t+1} \tag{19}$$

since $A_{12} = 0$ (by the definition of an exogenous variable). Combining the mapping of the state and estimated state into the endogenous variables (18) with the measurement equation (14) we get the evolution of the observations available to the partially informed agents

The observations follow

$$Z_t = LX_t + MX_{t|t} + v_t \tag{20}$$

where $L$ and $M$ are defined as

$$L \equiv D_1 + D_2 G^1 \tag{21}$$

$$M \equiv D_2 (G - G^1) \tag{22}$$

$$D = \begin{bmatrix} D_1 & D_2 \end{bmatrix} \tag{23}$$

We can now write the updating equation of the beliefs as

$$X_{t|t} = X_{t|t-1} + K(Z_t - LX_{t|t-1} - MX_{t|t}) \tag{24}$$

taking into account the contemporaneous effects of beliefs on the state variables through $M$. The estimate of $X_t$ in time t is a weighted average of the previous period prediction of $X_t$, $X_{t|t-1}$, and the noisy observation at time t, $Z_t$. The Kalman gain matrix, $K$, weighs the prediction error (the term inside brackets) optimally given the structure of the economy, the covariance of noise and the covariance of the structural shocks. Intuitively, for a given prediction error, it updates an estimate of a variable more, the less noise it is in its measurement and the larger variance the corresponding structural shock has. On top of this, the Kalman gain matrix also takes into account the covariances of the variables. For instance, when updating the cost-push shock estimate less weight will be attached to an observed increase in inflation if output is rising at the same time, everything else equal. It is calculated as

$$K = PL'(LPL' + \Sigma_{vv})^{-1} \tag{25}$$

where $P$ is the one-period-ahead prediction error covariance that for the time invariant case fulfills

$$P = A_{11}[P - PL'(LPL' + \Sigma_{vv})^{-1}LP]A'_{11} + \Sigma_{uu} \tag{26}$$

The effects of the measurement errors on the Kalman gain matrix can be understood by looking at limit cases. When the elements in $\Sigma_{vv}$ approaches infinity, the elements of $K$ will approach zero, i.e. there will be zero weight put on an infinitely noisy observation. The role of $P$ in the expression for $K$ will depend on $L$ and $\Sigma_{vv}$ and is not as easily interpreted, but in general a large element in $P$ will lead to a larger corresponding element in $K$.

We now have almost all the ingredients necessary to write down the dynamics of $X_t, x_t, Z_t,$ and $X_{t|t}$ as functions of their own lagged values and the measurement errors and the structural shocks. But first we need to make the updating equation (24) operational by eliminating the simultaneity in the estimation of $X_{t|t}$. Rearranging (24) yields

$$X_{t|t} = (I + KM)^{-1}(I - KL)A_{11}X_{t-1|t-1} + (I + KM)^{-1}KZ_t \tag{27}$$

where we used that by the optimality of he Kalman filter $X_{t|t-1} = A_{11}X_{t-1|t-1}$.

We can now put (18), (19), (20) and (27) together in state space form

$$\begin{bmatrix} I & 0 & 0 & 0 \\ 0 & I & -(I+KM)^{-1}K & 0 \\ -L & -M & I & 0 \\ -G^1 & -(G-G^1) & 0 & I \end{bmatrix} \begin{bmatrix} X_t \\ X_{t|t} \\ Z_t \\ x_t \end{bmatrix} = \tag{28}$$

$$= \begin{bmatrix} A_{11} & 0 & 0 & 0 \\ 0 & (I+KM)^{-1}(I-KL)A_{11} & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} X_{t-1} \\ X_{t-1|t-1} \\ Z_{t-1} \\ x_{t-1} \end{bmatrix} + \begin{bmatrix} u_t \\ 0 \\ v_t \\ 0 \end{bmatrix}$$

It now remains to determine $G$ and $G^1$.

## 3.2 The dynamics of the endogenous variables under the different information structures

To determine the evolution of the forward looking variables as functions of the exogenous state variables we recall equation (15)

$$E_t \begin{bmatrix} X_{t+1} \\ x_{t+1} \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \begin{bmatrix} X_t \\ x_t \end{bmatrix} + \begin{bmatrix} B_1 \\ B_2 \end{bmatrix} i_t + A_0^{-1} \begin{bmatrix} u_t \\ 0_{nx\times 1} \end{bmatrix} \tag{29}$$

where $B$ has been partitioned such that $B_1$ fits the upper, exogenous, block and $B_2$ fits the lower, forward looking, block. Our first task is to determine $G$ in (18). Use that by (17) $E_t[x_{t+1}] = GE_t[X_{t+1}]$ and that $i_t = FX_{t|t}$ to rewrite (29) as

$$\begin{bmatrix} I \\ G \end{bmatrix} E_t[X_{t+1}] = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \begin{bmatrix} X_t \\ x_t \end{bmatrix} + \begin{bmatrix} B_1 \\ B_2 \end{bmatrix} FX_{t|t} + A_0^{-1} \begin{bmatrix} u_t \\ 0_{nx\times 1} \end{bmatrix} \tag{30}$$

Take expectations of both sides at time t, using that by the unbiasedness property of the Kalman filter $E_t[X_{t|t}] = X_t$. The lower block of (30) then becomes

$$GA_{11}X_t = A_{21}X_t + A_{22}GX_t + B_2FX_t \tag{31}$$

where we used that $A_{12} = 0, B_1 = 0$. $G$ must then fulfill

$$G = A_{22}^{-1}\left[GA_{11} - A_{21} - B_2F\right] \tag{32}$$

where the appropriate $F$ can be found by standard optimization under discretion. This is due to the certainty equivalence result of Svensson and Woodford (2002a, 2002b), which shows that the optimal policy to be applied to an optimal estimate of the state is the same as the optimal policy function of a perfectly observable state. For a given $F$, (32) can be solved by numerical methods.

### 3.2.1 The symmetric case

Our next task is to determine $G^1$ in

$$x_t = G^1X_t + (G - G^1)X_{t|t} \tag{33}$$

for the symmetric and asymmetric case respectively. For the symmetric case, that is, when both the public and the policy makers have to estimate the current state, the rational expectation on the left hand side of (30) should be replaced by the agents predictions. Use this to rewrite (31) as

$$GA_{11}X_{t|t} = A_{21}X_t + A_{22}GX_t + B_2FX_{t|t} \tag{34}$$

For (17), (18) and (34) to all hold

$$G^1 = -A_{22}^{-1}A_{21} \tag{35}$$

must be true.

### 3.2.2 The asymmetric case

In the asymmetric case, the determination of $G^1$ becomes more complex. The reason is that unlike before, when $G^1$ was determined solely by the structural coefficients in the model, it will now also depend on the estimation algorithm of the policy makers. The estimation algorithm in turn depends on the dynamics of the observable variables, which again depends on $G^1$ through (21) and (22). The problem is thus a problem of finding a fixed point of a system of simultaneous equations. To specify the equations in question, we will again utilize the method of undetermined coefficients.

We want to find a $G^1$ that satisfies

$$E_t x_{t+1} = G^1 E_t X_{t+1} + (G - G^1) E_t X_{t+1|t+1} \tag{36}$$

If we can express the right hand side in terms of $X_t$ and $X_{t|t}$ , then the resulting expression can be equated to the lower block of (30)

$$E_t x_{t+1} = (A_{21} + A_{22} G) X_t + B_2 F X_{t|t} \tag{37}$$

By using (19), (20) and (27) to find the expectations in (36), we get the expression

$$E_t x_{t+1} = G^1 A_{11} X_t + (G - G^1)[A_{11} X_{t|t} + KLA_{11}(X_t - X_{t|t})] \tag{38}$$

equate with (37)

$$G^1 A_{11} X_t + (G - G^1)[A_{11} X_{t|t} + KLA_{11}(X_t - X_{t|t})] = (A_{21} + A_{22} G) X_t + B_2 F X_{t|t} \tag{39}$$

then

$$G^1 = A_{22}^{-1}\{-A_{21} + [G^1 + (G - G^1) KL] A_{11}\} \tag{40}$$

must hold. We now have a system of simultaneous equations consisting of the expressions for $L, P, K$ and $G^1$. The fixed point of the system can for our specification be found by iterating on (21), (25), (26) and (40).[7]

# 4 Calibration issues

To investigate the quantitative and qualitative implications of changing the accuracy of real time data, we need to parameterize the model from section 2. The structural parameters will be set to fit some of the empirical characteristics of the U.S. economy and we will calibrate the parameters separately for the two different information assumptions. The behavioral parameters of the public will be taken as given and set as $\{\beta, q, \phi, \gamma\}$=$\{0.99,\ 0.75,\ 2/7,\ 2\}$ for both the symmetric and asymmetric information case. Recall that they are, in order of appearance, the discount rate, the proportion of firms that are allowed to change prices each period, the degree of market power for the individual firm, the inverse of the demand elasticity w.r.t. the expected real interest rate. This configuration is within the standard bounds in the literature.[8] The autoregressive parameters $\boldsymbol{\tau}$, the standard errors[9] of the exogenous variables (i.e. the square root of the diagonal of $\Sigma_{\mathsf{u}u}$) and the parameter of the central banks relative preference for output gap stabilization $\lambda$ will be set as

| Model | $\tau_\pi$ | $\tau_y$ | $\tau_{\overline{y}}$ | $\sigma_\pi$ | $\sigma_y$ | $\sigma_{\overline{y}}$ | $\lambda$ |
|---|---|---|---|---|---|---|---|
| Symmetric | 0.5 | 0.6 | 0.985 | 1.75 | 0.69 | 0.175 | .13 |
| Asymmetric | 0.66 | 0.6 | 0.986 | 1.4 | 0.52 | 0.135 | .24 |

The measurement errors interact both with the relative variances and with the persistence of the variables, and it is therefor important that they are taken

[7] A MatLab routine is available from the author upon request.

[8] See Clarida, Gali and Gertler (1999).

[9] To avoid any confusion: A reported standard error of for instance 1.5 percentage points implies a variance of $(0.015)^2$, not $(1.5)^2$.

into account when calibrating the model. The benchmark standard errors on the measurement of output will be set to equal the standard deviation of revisions to U.S. real GDP, where the estimate after eight quarters will serve as a proxy for the 'true' output.[10] For the period 1987:Q4-1999:Q4 the standard deviation of these revisions are approximately 0.8 percentage points of GDP. The price level is assumed to be perfectly observable. Accordingly, the benchmark measurement error covariance matrix is set as

$$\Sigma_{vv} = \begin{bmatrix} 0 & 0 \\ 0 & [0.008]^2 \end{bmatrix}$$

Table 1 displays the actual and calibrated standard deviations and autocorrelations of output and inflation.

*Table* 1

| Model | Inflation | | Output | |
|---|---|---|---|---|
| | St.Dev.[b] | Autocorrelation | St.Dev.[c] | Autocorrelation |
| Actual data[a] | 1.04 | 0.65 | 1.67 | 0.91 |
| Symmetric | 1. 07 | 0.55 | 1. 65 | 0.90 |
| Asymmetric | 1. 04 | 0.65 | 1. 662 8 | 0.91 |

[a]Quarterly U.S. data, 1987:Q4-1999:Q4 [b]Percentage points.

[c]Percentage points of GDP.

# 5 Dynamics under partial information

As mentioned in the introduction, more accurate observations does not necessarily improve the performance of monetary policy. In this section, the theory behind this counterintuitive result will be made explicit and we will see how the calibrated models respond to changes in the size of the measurement error on output.

There are two theoretically distinct reasons why improved accuracy may lead to a deterioration of policy performance, and each one is associated with a different assumption about the information structure of the economy. We start with what we may call the "muted response" channel and then follow with the perhaps more familiar stabilization bias channel.

## 5.1 Symmetric partial information and the response to shocks

Before examining the complexities arising from imperfect information, it is helpful to first look at the responses of the endogenous variables to a shock in the full information case. Recall the structural equations and the first order condition

$$\pi_t = \beta E_t \pi_{t+1} + \delta(\phi(y_t - \overline{y}_t) + \varepsilon_{\pi t}) \quad (41)$$

[10]Data of different 'vintages' are available from the Federal Reserve Bank of Philadelphia's webpage:
http://www.phil.frb.org/econ/forecast/reaindex.html

$$(y_t - \overline{y}_t) = E_t[y_{t+1} - \overline{y}_{t+1}] - \frac{1}{\gamma}(i_t - E_t\pi_{t+1}) + \varepsilon_{yt} \tag{42}$$

$$y_t - \overline{y}_t = -\frac{\delta\phi}{\lambda}\pi_t \tag{43}$$

When policy reacts to a perfect measure of the exogenous variables, only cost push shocks will induce volatility in the target variables, i.e. for demand and potential output shocks both sides of (43) will equal zero. The numerical values of the endogenous responses to shocks in our parameterized model are displayed in the elements of the $G$ matrix below

$$\begin{aligned} x_t &= GX_t, & (44)\\ x_t &\equiv \{\pi_t,\ y_t\}',\ X_t \equiv \{\varepsilon_{\pi t},\ \varepsilon_{\pi t},\ \overline{y}_t\}' & (45)\\ G &= \begin{bmatrix} 0.61076 & 0 & 0 \\ -3.0202 & 0 & 1 \end{bmatrix} & (46) \end{aligned}$$

We can decompose $G$ in to three channels: The direct effect, the effect through the instrument $i_t = FX_t$ , and the effect through the expectations of the endogenous variables next period value. This is illustrated below

$$\overbrace{\begin{bmatrix} \delta & 0 & 0 \\ 0 & 1 & 1 \end{bmatrix}}^{Direct} + \overbrace{\begin{bmatrix} F_{\varepsilon\pi} & 0 & 0 \\ F_{\varepsilon y} & -1 & 0 \end{bmatrix}}^{i_t = FX_t} + \overbrace{\begin{bmatrix} \beta g_{11}\tau_\pi & 0 & 0 \\ g_{21}\tau_\pi & 0 & 0 \end{bmatrix}}^{E_t x_{t+1}} \equiv G \tag{47}$$

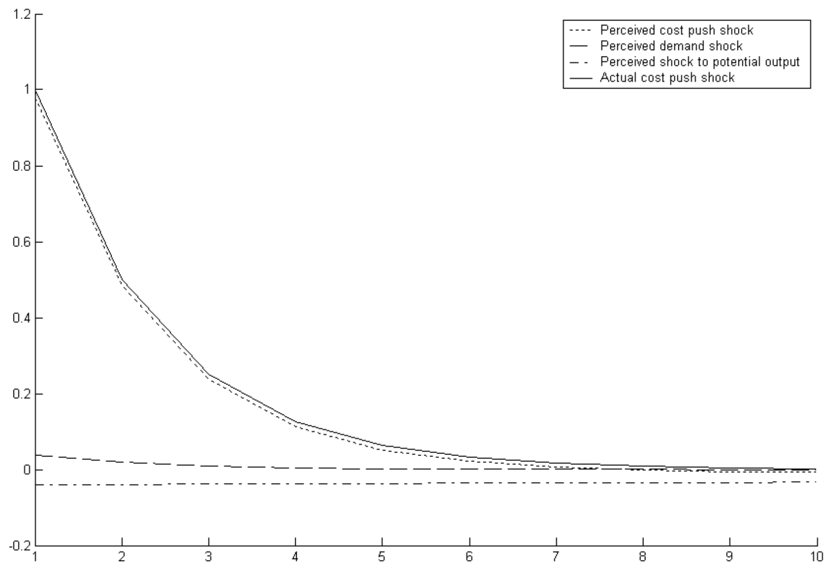
where $F_{\varepsilon\pi}$ and $F_{\varepsilon y}$ are the (negative) impacts of the policy instrument on the endogenous variables, $g_{ij}$ is the element in the i'th row and j'th column of $G$. If we now go back to the partially informed agents setting, the policy function will be $i_t = FX_{t|t}$, i.e. the instrument will react to an estimate $X_{t|t}$ rather than the true value $X_t$. Since information is symmetric, the same holds for expectations and $E_t x_{t+1} = G\boldsymbol{\tau} X_t$ should thus be replaced by $x_{t+1|t} = G\boldsymbol{\tau} X_{t|t}$. Equation (18)

$$x_t = G^1 X_t + (G - G^1)X_{t|t} \tag{48}$$

can be reinterpreted as

$$G^1 = \overbrace{\begin{bmatrix} \delta & 0 & 0 \\ 0 & 1 & 1 \end{bmatrix}}^{Direct},\ (G - G^1) = \overbrace{\begin{bmatrix} F_{\varepsilon\pi} & 0 & 0 \\ F_{\varepsilon y} & -1 & 0 \end{bmatrix}}^{i_t = FX_{t|t}} + \overbrace{\begin{bmatrix} \beta g_{11}\tau_\pi & 0 & 0 \\ g_{21}\tau_\pi & 0 & 0 \end{bmatrix}}^{x_{t+1|t}} \tag{49}$$

Partial information prevents the agents from correctly identifying the shocks that hit the economy which implies that in general $X_t \neq X_{t|t}$.The graph below illustrates how the estimates in $X_{t|t}$ evolves as a unit cost push shock hits the economy (from a prior of $X_{t-1|t-1} = \mathbf{0}$).




Response of beliefs to a unit cost push shock

*Figure* 1

This failure to correctly identify shocks will have consequences for the dynamics of the endogenous variables. In (48) above the direct effect through $G^1$ will be unaffected, while the effect through $(G-G^1)$ will change since $X_t \neq X_{t|t}$. The current shock $X_t$ will only work through $(G-G^1)$ in so far as it influences the estimate $X_{t|t}$. Below we examine the direction of changes as $X_{t|t} \neq X_t$ and thus as $G^1X_t + (G-G^1)X_{t|t} \neq GX_t$. Specifically, we will look in detail at the different response of $x_t$ to a pure positive cost push shock under partial information as compared to the response under full information.

### 5.1.1 A pure cost push shock

The Kalman filter splits the observation into its most likely components. A pure positive cost push shock will thus be partly interpreted as a positive demand shock and a negative shock to potential output. This also means that the magnitude of the actual shock is underestimated. The effects of a positive cost push shock will thus differ under partial information in the following way and through the following channels as compared to the full information case.

- The direct effect: Unchanged.
- The effect through the instrument: The perceived demand shock leads to higher interest rates, which will decrease inflation and output as compared to the full information case, while the perceived shock to potential output do not cause a response in the interest rate since these shocks accommodated completely. The underestimated actual shock will cause higher

inflation and output, through the smaller increase in the interest rate, as compared to the full information case.

- The expectations channel: The perceived positive demand shock will have no effect on expectations, since it is expected to be perfectly offset in the next period. The part attributed to the true source will be smaller than the actual shock, which will lower inflation but raise output.

The effect and channels of partial information on the endogenous variables are illustrated below. A zero means no change compared to the full information case while a plus(minus) sign indicates a higher(lower) value.

$$\overset{Direct}{\begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}} + \overset{i_t = FX_{t|t}}{\begin{bmatrix} + & - & 0 \\ + & - & 0 \end{bmatrix}} + \overset{x_{t+1|t}}{\begin{bmatrix} - & 0 & 0 \\ + & 0 & 0 \end{bmatrix}}$$

Since we have effects in both directions for both our variables, we cannot say whether partial information will increase or decrease the volatility of our target variables from cost push shocks.

### 5.1.2 Demand shocks and shocks to potential output

The cases of demand shocks and shocks to potential output are a lot simpler. Under perfect information, the former can be perfectly off set, and the latter perfectly accommodated. In their presence, partial information unambiguously leads to increased volatility in the target variables.

### 5.1.3 Expected losses and the variance of the output measurement errors

As shown above, the qualitative implications of partial information are ambiguous. We can use our parameterized model to simulate a change in the accuracy of observations and see how the expected loss of the policy makers change. The experiment we will perform will be to calculate the expected loss when the measurement standard error on actual output is varied between zero and 3.2 percentage points of GDP. Inflation will be assumed to be measured perfectly. One should note that a zero measurement error on both output and inflation is not enough to identify all the shocks in our model. Since we only have two observable variables, inflation and output, we cannot identify all three exogenous shocks. Setting the measurement error to zero is thus not equivalent to having full information, though decreasing the measurement errors unambiguously leads to more accurate estimates. Below the expected loss is plotted against the output measurement error variances (recall that our benchmark measurement error variance is 0.8 percentage points of GDP).

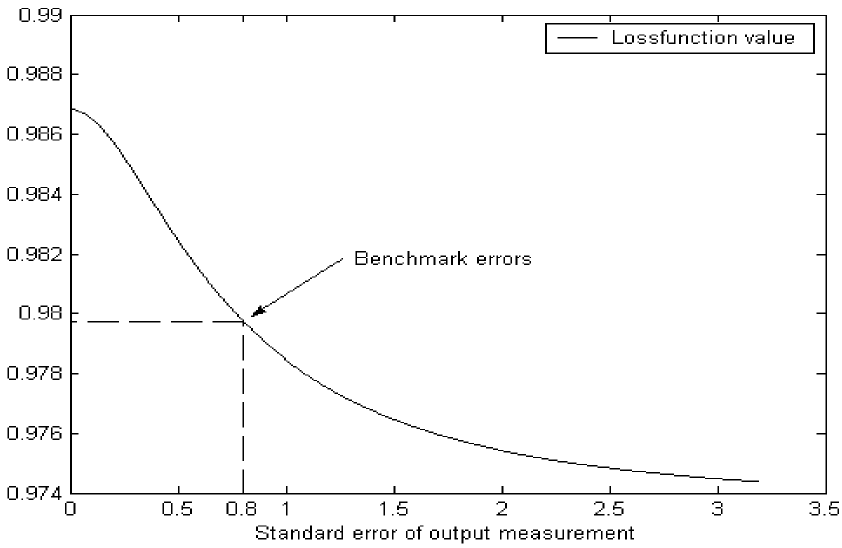



Figure 2

We can see from the figure that losses are actually decreasing in the size of the measurement errors and that moving from the current situation to having a more accurate measure of output would lead to deterioration of policy performance. Where the graph flattens out, the observations on output becomes more or less useless as signals and losses are similar to what would be the case if output was unobservable and the policy makers had to rely only on the perfectly measured inflation.

Are these changes important? We can get more intuitive numbers by calculating the 'inflation equivalent' to the change in the loss function value. It is calculated as

$$(1-\beta)\sqrt{|L^{BM}-L|} \tag{50}$$

where $L^{BM}$ is the benchmark loss and $L$ is the after-the-change loss. (If $L^{BM} - L > 0$, losses are smaller after the change, and a minus sign should be put in front of (50)). This number should be interpreted as the permanent deviation of inflation from its target level that would induce a welfare loss of the same magnitude as the change in the lossfunction value.[11]

*Table* 2

| Measurement standard error$^a$ | Loss function equivalent change in $\pi$.$^b$ |
|---|---|
| 0 | 0.08 |
| Benchmark (0.8) | 0 |
| 3.2 | -0.07 |

$^a$Percentage points of GDP. $^b$Percentage points.

Table 2 displays the inflation equivalents of the changes in central bank losses for selected changes in the measurement error variances. As we can see,

[11]See Dennis and Söderström (2002) for details.

the changes in losses are quite small. Acquiring a perfect measure of output would result in an increase in losses equivalent to a permanent increase in inflation (from the target level) of less than one tenth of a percentage point. A fourfold increase would be equivalent to reducing inflation to the target level from a permanent level of approximately the same order, 7/100 of a percentage point. While the amplitude of the changes are small, the signs are interesting and counterintuitive. Can we equate this decrease in expected losses with higher expected utility of the representative agents in the model? The staggered Calvo pricing mechanism is the only distortion in the model, but it introduces two different inefficiencies.[12] First, output can be at an inefficient level, i.e. the output gap can be non-zero. Reducing the output gap variance thus unambiguously improves welfare. Secondly, staggered prices lead to an inefficient composition of the goods produced in the economy since it implies that inflation changes not only the price level, but also relative prices. This distortion is increasing in the rate of inflation. This suggests that welfare is indeed improved in our model by less accurate real-time data. But what prevents the utility maximizing agents from achieving this outcome when they have full information? One can imagine that the agents agreed, before a shock arrived, that the firms that can change prices when the shock is observed change them by a lesser amount than what would be privately optimal. But in the absence of a enforcing mechanism it will always pay for the individual firm to cheat by adjusting prices more. Partial information can thus work as a coordination mechanism, that make society as a whole better off.

Before taking the argument above as advocating the closure of the statistics departments of central banks, one should note the critical nature of the assumption of the common information set between the policy makers and the public. If the policy makers were to acquire better real time data and could keep it from the public, policy performance would likely be increasing in the accuracy of observations. This type of information asymmetry leads to questions of central bank transparency and will not be discussed here, but further research will treat the mixed incentives of central bankers to reveal their knowledge of the state of the economy to the public. The opposite type of information asymmetry, when the public knows more than the policy makers, plays an important role in the next section since it provides another potential source of why policy performance may be decreasing in the accuracy of observations.

## 5.2 Discretionary policy, the stabilization bias and the accuracy of observations

It is a well known result that policy makers can achieve better outcomes if they can credibly commit to a future policy path. The difference between the variance around targets achieved with a optimal policy with commitment and the variance achieved with an optimal discretionary policy is called the stabilization bias.[13] To intuitively understand how discretionary policy, i.e. complete freedom of the instrument in each period, can be detrimental to welfare we can imagine a very simplified world. This world will exist only for two periods, today and tomorrow. The inflation rate today will depend on the output

[12]See for instance Woodford (1999).

[13]For an account of the quantitative importance of this difference see Dennis and Söderström (2002).

gap today and the expected inflation rate tomorrow. Now assume that a positive inflation shock hits the economy today. The policy makers can counter the shock by raising interest rates and decrease demand today. When this is done optimally, the marginal welfare gain from the decrease in inflation will be equal to the marginal loss of decreasing output below its potential level. When a commitment technology exists, the same effect on inflation today can be achieved by decreasing output by a smaller amount, but in addition also promise to decrease it a little tomorrow. With a convex loss function and by Jensens inequality, this will decrease the welfare loss of reducing output. This holds as long as private agents do not discount the future at a much lower rate than policy makers. However, when no commitment technology exists, agents will not believe the promise of reduced output tomorrow, and it will be optimal for policy makers to counter the shock by a large reduction in output today. It should be noted that while sharing the time inconsistency problem with the Barro/Gordon-type inflation bias, the stabilization bias is quite a different concept.[14] The Barro/Gordon-type inflation bias is a first order effect that can be studied in a static framework, while the stabilization bias is a dynamic, second order phenomenon. The closest mechanical relative in the literature is perhaps the theory on optimal intertemporal distribution of distortionary taxes.

When policy makers have to estimate the state of the economy, larger measurement error variance tend to increase the inertial character of the instrument. A shock is at first (on average) underestimated, and policy is thus not responsive enough, but on the other hand policy will continue to respond to the shock after it has subsided, i.e. measurement errors make policy behave more like optimal policy under commitment. Under asymmetric information the public will correctly foresee this behavior, and respond as if the policy makers had made a credible commitment to follow this inertial path. This makes it possible that also under the assumption of asymmetric information (and in the absence of a commitment technology), decreasing the quality of real-time data available to centralbankers may actually increase welfare. To find out what holds for our model, we plot the asymmetric information sister figure to figure 2.

[14] Barro and Gordon (1983).

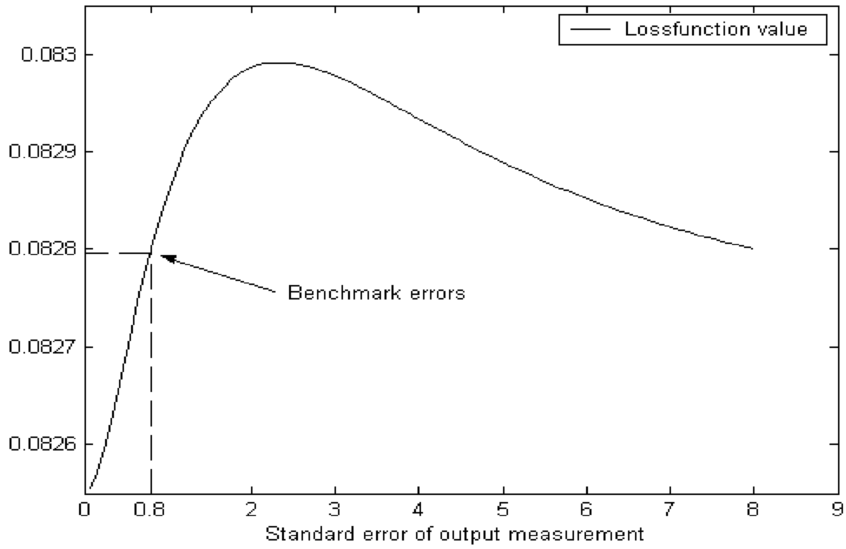



Figure 3

In figure 3 we can see that the loss function values of asymmetric case exhibits a different shape as compared to the symmetric case when the size of the measurement errors are changed. Given that we take the 0.8 measurement standard error to represent the current situation, there are two directions of change that would improve policy performance. Either through decreased measurement errors, which monotonically improves performance, or through an increase in the measurement errors that is large enough to get over the 'hump' and down to the part of the curve that lies below the current expected loss. In our model, this happens at a measurement standard error of around 8 percentage points of GDP.

The inflation equivalents of these changes are displayed in table 3.

*Table* 3

| Measurement standard error[a] | Loss function equivalent change in $\pi$.[b] |
|---|---|
| 0 | -0.02 |
| Benchmark(0.8) | 0 |
| Max Loss (2.4) | 0.01 |
| 8 | 0 |

[a]Percentage points of GDP. [b]Percentage points.

All changes in losses are small. The largest displayed inflation equivalent only amounts to 2/100 of a percentage point.

# 6 Conclusions

In this paper we have shown that under two different information assumptions, simple calibrated models suggests that one way of increasing policy performance would be to decrease the accuracy of real time data. To make a serious claim that we can improve matters by decreasing the accuracy of real time data, we need to make one out of two further assumptions depending on the assumed information structure. For the symmetric information case, we have to assume that the public also gets its real time data from the very same statistics department as the policy makers do. If not, reducing the accuracy of the policy makers data would only lead to inaccurate policy, but not more muted responses to shocks from the public.

For the asymmetric case, we would have to assume that the policy makers could credibly claim that they from now on would use less accurate data. If the policy makers enjoyed this amount of credibility, they would be better off taking the first best choice of pursuing a optimal policy under commitment, with the highest possible accuracy of real time data.

The case for closing statistics departments may thus be weak. What we can say with some confidence though, is that only limited resources should be spent on acquiring more accurate real time data.

# Appendix
# Computing the loss function

The procedure is a slightly modified version of the one described in Söderlind (1999). Start by rewriting the loss function (8) in matrix form as

$$L_t = E_t \left[ \sum_{i=0}^{\infty} \beta^i Y'_{t+i} Q' D Q Y_{t+i} \right]. \tag{51}$$

where $Y_t = \{X_t, X_{t|t}, Z_t, x_t\}$ and

$$Q = \begin{bmatrix} 0 & 0 & -1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix}, D = \begin{bmatrix} \lambda & 0 \\ 0 & 1 \end{bmatrix} \tag{52}$$

The loss function can now be calculated as

$$L_t = Y'_t V Y_t + \frac{\beta}{1-\beta} trace\,(V\Sigma) \tag{53}$$

where

$$\Sigma = H' \begin{bmatrix} \Sigma_{uu} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & \Sigma_{vv} & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} H \tag{54}$$

and

$$H = \begin{bmatrix} I & 0 & 0 & 0 \\ 0 & I & -(I+KM)^{-1}K & 0 \\ -L & -M & I & 0 \\ -G^1 & -(G-G^1) & 0 & I \end{bmatrix}^{-1} \tag{55}$$

$V$ can be found by iterating (backwards in 'time') on

$$V_s = Q'DQ + \beta W' V_{s+1} W \tag{56}$$

where $W$ is the coefficient matrix from the reduced form AR(1) process

$$Y_t = WY_{t-1} + \mathsf{e}_t \tag{57}$$

that can be found be premultiplying the right hand side of (27) appropriately.

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