Inferring Monetary Policy Objectives with a Partially Observed State

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Abstract

Accounting for the uncertainty in real-time perceptions of the state of the economy is believed to be critical for monetary policy analysis. We investigate this claim through the lens of a New Keynesian model with optimal discretionary policy and partial information. Structural parameters are estimated using a data set that includes real-time and *ex post* revised observations spanning 1965 to 2010. In comparison to a standard complete information model, our estimates reveal that under partial information: (*i*) the Federal Reserve demonstrates a significant concern for stabilizing the output gap after 1979, (*ii*) the model's fit with revised data improves, and (*iii*) the tension between optimal and observed policy is smaller.

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1 Introduction

Central banks face the difficult task of conducting monetary policy in situations where real-time uncertainty about the state of the economy is pervasive. Uncertainty of this kind has two sources. One is the noise contained in preliminary measures of economic activity, such as output and inflation, that are used by policymakers to forecast the state. Data on these variables are continually revised over time, so the true values are not known until long after they are first released and policy decisions have been made (e.g., Croushore and Stark, 2001). A second source of uncertainty concerns estimates of economic concepts that are not directly observable but still play a vital role in the policy process. The natural rates of output and unemployment are prominent examples. Forming inferences about these variables requires a statistical model that specifies how they are related to observed data. Given the uncertainty over such models and in published data, it is common for real-time estimates of the natural rates to be way off the mark (e.g., Kuttner, 1994; Orphanides and van Norden, 2002).

Because monetary policy depends on the central bank's perception of the state of the economy, correctly interpreting historical policy behavior demands that one account for the type of informational limitations described above. Athanasios Orphanides was one of the first to point this out in a series of influential papers (e.g., Orphanides, 2001; 2002; 2004) that questioned the value of policy analysis based on data other than what policymakers actually encountered at the time decisions were being made. Using the simple rule proposed by Taylor (1993) as an example, Orphanides (2001) showed that policy recommendations implied by real-time data are often at odds with those obtained from *ex post* revised data. Moreover, estimating rules using only the latest information can obscure one's view of the way monetary authorities reacted to economic conditions as they appeared at the time. To identify the policy motives of the past, it is thus imperative to understand what the central bank was seeing at the moment its policies were implemented.

The papers written by Orphanides belong to a large literature that uses the Taylor rule as a means of describing historical monetary policy (e.g., Clarida, Galí, and Gertler, 2000). Yet, some have argued that these rules are hard to interpret because the feedback coefficients do not map uniquely into the deep parameters that represent the preferences of the policy authority. The key insight is that Taylor-type rules can be derived endogenously by solving an explicit optimization problem for the central bank (e.g., Svensson, 1997). It follows that estimated policy-rule coefficients may depend on the various weights in the central bank's objective function in addition to the parameters characterizing the structure of the economy. Disentangling the two requires an econometric procedure that acknowledges the policymaker's optimization problem during the course of estimation (e.g., Favero and Rovelli, 2003; Ozlale, 2003; Dennis, 2006; Salemi, 2006). The usual strategy is to estimate a model of private behavior subject to the restriction that monetary policy is optimal. Such an exercise enables one to obtain joint estimates of the structural parameters and the weights in the policy objective function that identify central bank preferences.

To date, most of the papers that try to explain policy as the outcome of an optimization problem assume that agents are perfectly informed about the state of the economy. Since there is no conflict between real-time and revised concepts under perfect information, the models featured in this literature are typically estimated with *ex post* revised data. However, this type of analysis appears as vulnerable to the Orphanides critique as those based on the Taylor rule, which treats central bank behavior as a primitive rather than the product of rational optimization. By endowing agents with full information and ignoring the intrinsic uncertainty of real-time data, the researcher is viewing history through a distorted lens. Attempts to validate such a model empirically may produce biased estimates of the economic structure and, in particular, the policy objective function.

Our paper continues the line of research dating back to Salemi (1995) that estimates the parameters of the central bank's objective function.[1] However, we break from standard practice by utilizing a model in which agents only have partial knowledge of the state. Every period private agents and the central bank derive an optimal estimate of the state vector by filtering information contained in a small set of noisy indicators. The central bank then implements an optimal policy conditional on its current beliefs while the private sector forms expectations consistent with the chosen policy. Thus in our model policy decisions depend on real-time perceptions of the state instead of the actual state as would be the case under complete information. The optimal-filtering (signal-extraction) mechanism also provides a way to track the evolution of these perceptions through time. Orphanides (2004) contends that both features are essential for correctly identifying historical policy objectives.

Estimation is performed on a semi-structural New Keynesian model of output-inflation dynamics. The concept of natural output has a dual role; it appears as an exogenous forcing variable in the Phillips curve and as the target for real output in the policy objective function. Regarding the information structure, we assume that private agents and the central bank observe noisy current-period measures of output growth, inflation, and the unemployment rate, the latter of which is linked to the model through an Okun's Law relationship. Using the methodological approach outlined in Svensson and Woodford (2003), both sets of agents obtain an efficient estimate of the state vector by means of a Kalman-filter updating equation. Given its estimate of the state, the central bank sets the nominal interest rate to minimize a weighted quadratic loss function under discretion. The arguments in the loss function include deviations of inflation and output from target and changes in the interest rate.

To estimate our partial information model, we employ a data set that combines real-time and *ex post* revised data from 1965:Q4 to 2010:Q1. Using real-time data to estimate the loss function is a departure from much of the extant literature that relies exclusively on revised

[1]Early examples in this literature are Cecchetti, McConnell, and Perez-Quiros (2002), Dennis (2004), Söderström, Söderlind, and Vredin (2005), and Cecchetti, Flores-Lagunes, and Krause (2006). More recent contributions include Givens and Salemi (2008), Ilbas (2012), and Givens (2012).

data (e.g., Dennis, 2006; Ilbas, 2012). In those studies omitting real-time data makes sense because agents are assumed to know the true value of the state at each point in time. By contrast, our model recognizes a distinction between the true state and the indicators that agents observe in real time. The consistent approach here is to identify the former with revised data but the latter with data that was available when past decisions were made.

Since the goal of this paper is to ascertain the empirical consequences of placing information constraints on a model with optimal policy, we take a page from the previous literature by estimating a second model that differs from our preferred model only in assuming agents have complete knowledge of the state. We then report those estimates alongside our partial information estimates. Comparing the results helps clarify the effect that informational assumptions have on estimates of structural parameters and loss function weights.

We find that uncertainty about the state impacts estimates of the model and the loss function in particular. Because our sample includes the chairmanship of Paul Volcker, a period in which a shift in Federal Reserve policy is believed to have occurred, we split the data set into two subsamples. The first covers the period ending in 1979:Q2 and the second covers the period starting in 1979:Q3. The breakpoint marks the beginning of Volcker's term. Under partial information the weight on the output gap objective (i.e., the gap between actual output and the natural rate) relative to inflation is about one-fourth and is statistically significant after 1979. Under complete information the output gap weight is not significantly different from zero before or after 1979, echoing results from previous studies that disregard information frictions altogether. The interest rate objective is also sensitive to the information environment. Partial information estimates indicate that it is significant only in the second subsample, but complete information estimates suggest that it is significant in both.

One benefit of adopting an econometric framework that combines partial information and optimal policy is that it can be used to examine the separate contributions that these two features make to model fit. To assess the role of the former, we re-estimate the partial information model using a sample that excludes real-time data. This makes the data set identical to the one used to estimate the complete information model, which contains only *ex post* revised data, and enables us to compare the fit of the two models by means of the likelihood criterion. To sort out the contribution of optimal policy, we estimate versions of the partial and complete information models that replace the interest rate equation with a generalized Taylor rule that relaxes many of the coefficient restrictions imposed by optimal discretion. Because such rules have well-known empirical qualities (e.g., Smets and Wouters, 2007), a comparison of these results to the benchmark estimates gives perspective on the conflict between fitting the observed interest rate series and satisfying the optimal policy restrictions. Our findings suggest that under partial information, the semi-structural model fits the revised data better and more easily reconciles optimal and observed policy actions.

A key step in establishing the validity of our information arrangement is checking whether the uncertainties are sufficient to generate meaningful perception errors. If the estimated model tells us that agents' perceptions of the state were never far from the true state, then accounting for information constraints may not improve efforts to identify historical policy motives. We perform this check by extracting estimates of the past output gap and inflation misperceptions that agents experienced in real time from observable macroeconomic data. The estimates reveal that beliefs about the state were at times very different from reality, particularly with regard to the output gap. Moreover, counterfactual simulations show that had the Federal Reserve been able to see the true value of the output gap, its policy rate would have been higher during the 1970s as well as the 1990s.

1.1 Related Literature

Our paper is part of a growing literature that adds partial information into a New Keynesian framework. Dotsey and Hornstein (2003) and Coenen, Levin, and Wieland (2005) assess the information content of money using calibrated models. Both find that money provides little information that is useful for stabilization policy. Ehrmann and Smets (2003) and Cukierman and Lippi (2005) derive optimal policy under conditions where natural output is unknown and find that agents make systematic output gap prediction errors. Dellas (2006) and Collard and Dellas (2010) show that mismeasurement of the state helps produce an inertial response of inflation to monetary shocks. Collard, Dellas, and Smets (2009) estimate a DSGE model with the same information structure. They show that partial information acts as an endogenous propagation mechanism and improves model fit in terms of log likelihood.

Lippi and Neri (2007) estimate a model with partial information and discretionary policy, but the analysis differs from ours in some important ways. First, we estimate on US data, whereas Lippi and Neri estimate on euro area data. Second, Lippi and Neri only report estimates under partial information because their emphasis is on comparing the signal quality of real money balances and unit labor costs. Third, Lippi and Neri estimate on revised data alone. We use both real-time and revised data simultaneously during estimation.

Neri and Ropele (2012) is a recent example that uses real-time data. They apply Bayesian methods to a partial information model *à la* Svensson and Woodford (2003). In contrast to our paper, Neri and Ropele describe policy with a Taylor rule and use the model to derive the output gap-inflation volatility tradeoff facing the European Central Bank. Additionally, the authors estimate partial and complete information models using either revised or real-time data separately. They do not consider a version that uses both types at the same time.

2 An Empirical Model with Partial Information

This section presents a semi-structural New Keynesian model with partial information and optimal discretionary policy. We define partial information as the inability of agents to perfectly observe the state. The information problem is thus confined to items in the state vector; the model and its parameters are known with certainty. Each period agents update

Table 1
A New Keynesian model

IS Equation	$y_t = \phi y_{t+1\|t} + (1-\phi)[\beta y_{t-1} + (1-\beta) y_{t-2}] - \sigma(i_t - \pi_{t+1\|t}) + \varepsilon_{y,t}$	(M-1)
Phillips Curve	$\pi_t = \alpha \pi_{t+1\|t} + (1-\alpha)\pi_{t-1} + \kappa(y_t - y_t^n) + \varepsilon_{\pi,t}$	(M-2)
Natural Output	$y_t^n = \gamma y_{t-1}^n + \varepsilon_{n,t} + \eta_y \varepsilon_{y,t}$	(M-3)
Okun's Law	$u_t - u_t^n = -\chi(y_t - y_t^n)$	(M-4)
Loss Function	$\mathcal{L}_t = E\left[(1-\delta)\sum_{j=0}^{\infty}\delta^j\{(\pi_{t+j} - \pi_{t+j}^*)^2 + \lambda_y(y_{t+j} - y_{t+j}^n)^2 + \lambda_i(i_{t+j} - i_{t+j-1})^2\}\Big\vert\Omega_t\right]$	(M-5)
Inflation Target	$\pi_t^* = \omega\pi_{t-1}^* + d(\pi_{t-1} - \pi_{t-1}^*)$	(M-6)

Notes: y - real output; i - nominal interest rate; π - inflation rate; ε_y - demand shock; y^n - natural output; ε_π - cost-push shock; ε_n - natural output shock; u - unemployment rate; u^n - natural unemployment rate; $\mathcal{L}$ - policy loss; π^* - inflation target.

their beliefs with the arrival of new information (i.e., data) on the indicators. The structure consists of an IS equation, a Phillips curve, a stochastic process for natural output, an Okun's Law relationship, and a loss function describing the stabilization goals of monetary policy.[2]

2.1 The Behavioral Equations

The aggregate behavioral equations of the model are listed in Table 1. Eq. (M-1) is a hybrid IS curve in which y_t is real output, i_t is the one-period nominal interest rate, π_t is the inflation rate, and $\varepsilon_{y,t}$ is a demand shock, assumed to be *i.i.d.* $N(0, \sigma_y^2)$. For any variable z_t, $z_{\tau|t}$ denotes $E[z_\tau|\Omega_t]$, the expected value (optimal prediction) of z_τ conditional on the date-t information set Ω_t. When $\phi = 1$ (M-1) collapses to a demand specification based on the consumption Euler equation, in which case σ is the intertemporal elasticity of substitution. Augmenting the IS equation with lags ($\phi < 1$) is a departure from strict micro-foundations but is necessary to capture persistent aspects of the data (e.g., Estrella and Fuhrer, 2002).

Inflation dynamics are governed by the hybrid Phillips curve (M-2), which links current inflation to past and expected future inflation and the output gap. When $\alpha = 1$ (M-2) is the equilibrium condition obtained from a model of monopolistically competitive firms that

[2] Our model is similar to Ehrmann and Smets (2003) and Neri and Ropele (2012) in that the aggregate relationships are not explicitly derived from first principles. As such, none of the exercises carried out in this paper concern estimation of primitive factors reflecting tastes and technologies of households and firms.

adjust prices infrequently. In such an environment, parameter κ is inversely related to the duration of price fixity. The variable $\varepsilon_{\pi,t}$ is viewed as an exogenous cost-push shock and is assumed to be *i.i.d.* $N(0, \sigma_\pi^2)$. The rationale for including lagged inflation ($\alpha < 1$) is mainly empirical. Fuhrer (1997) argues that purely forward-looking Phillips curves produce "jump" dynamics for inflation that are at odds with the inertial responses seen in the data.

Natural output y_t^n plays a central role in the model, both as a driving force for inflation and as a target for monetary policy. Agents do not observe y_t^n, but instead must estimate it every period by solving a particular signal-extraction problem. The stochastic process for y_t^n, which is known, is given by (M-3) with $|\gamma| < 1$. Fluctuations in y_t^n originate from two shocks. The first shock, $\varepsilon_{n,t}$, affects natural output directly and is modeled *i.i.d.* $N(0, \sigma_n^2)$. Numerous studies interpret $\varepsilon_{n,t}$ as a productivity innovation (e.g., Clarida, Galí, and Gertler, 1999). The second shock is the demand shock, $\varepsilon_{y,t}$, which enters the law of motion for y_t^n with coefficient $\eta_y \geq 0$. In a micro-founded setting with nominal rigidities, natural output is driven by productivity and demand shocks, the latter of which can be attributed to shifts in consumer preferences (e.g., Erceg, Henderson, and Levin, 2000). Permitting correlation between natural output and demand shocks is therefore consistent with that class of models.

Central banks and market participants in the real world forecast the state by filtering information from numerous economic variables that are not always present in stylized models (e.g., Boivin and Giannoni, 2006). To partially capture this dynamic, we include an equation linking the unemployment rate, a key indicator of cyclical conditions, to the output gap. Specifically, unemployment enters the model by means of the Okun's Law relationship (M-4), where u_t and u_t^n denote the actual and natural rates of unemployment. Natural unemployment is understood to be the rate at which there is no incipient pressure on inflation stemming from imbalances between y_t and y_t^n. Eqs. (M-2) and (M-4) jointly imply that when $u_t = u_t^n$, the only forces acting on inflation are cost-push shocks.[3]

[3]Our definition of u_t^n differs from the long-run concept of Friedman (1968) and Phelps (1968), who describe

Like y_t^n, we assume that u_t^n is not observable, but its stochastic process is part of the information set. Our views on this process are influenced by studies that find greater empirical support for the Phillips curve when it is augmented with a time-varying natural rate of unemployment. Notable examples include Gordon (1997, 1998) and Staiger, Stock, and Watson (1997, 2001). In each case the authors model the evolution of the natural rate as a pure random walk. We follow the same approach by coupling (M-4) with the law of motion $u_t^n = u_{t-1}^n + \varepsilon_{u,t}$, where $\varepsilon_{u,t}$ is *i.i.d.* $N(0, \sigma_u^2)$. If $\sigma_u = 0$, the natural rate is constant. By contrast, a small positive value for σ_u allows some movement in u_t^n, but not so much that it dominates cost-push shocks as the main source of residual variation in the Phillips curve.[4]

The central bank selects i_t each period to minimize the intertemporal loss function (M-5). The loss function embodies the preferences of a policymaker who wants to stabilize inflation and output around target values and to achieve a smooth path for the interest rate. The inflation target π_t^* is potentially time varying, and the output target is the natural rate y_t^n. The smoothing term $\lambda_i(i_t - i_{t-1})^2$, which penalizes big swings in the policy instrument, is empirically compelling because it helps explain the serial correlation in interest rate data (e.g., Söderström *et al.*, 2005). Parameters $\lambda_y \geq 0$ and $\lambda_i \geq 0$ are weights on the output gap and smoothing objectives relative to inflation. Together they characterize policy preferences since their values determine how much the central bank trades off one stabilization goal for another. The loss function weights are the key objects of interest in this paper, and as such, are treated as free parameters to be estimated jointly with the semi-structural model.

We close the policy component of our model by specifying a stochastic process for the inflation target. As in Gürkaynak, Sack, and Swanson (2005), π_t^* is assumed to evolve

it as the rate to which an economy would converge given the structure of the labor market. While our model does not explain the sources of long-run unemployment, the fact that the Phillips curve coefficients on past and future inflation sum to one means that it is consistent with the Phelps-Friedman natural rate hypothesis.

[4] An alternative specification would allow u_t^n to follow a stationary autoregressive process (e.g., Primiceri, 2006). We explore this possibility by re-estimating the model with $u_t^n = \rho_n u_{t-1}^n + \varepsilon_{u,t}$ for $|\rho_n| < 1$. The findings are reported in a separate appendix available online. It turns out that the quantitative results are nearly unchanged because the point estimate of ρ_n exceeds 0.99 and is not significantly different from one.

according to (M-6) with $\omega \in [0, 1)$ and $d \geq 0$. Under this arrangement the inflation target follows a modified AR(1) process that partially accommodates past deviations of inflation from target. For example, inflation above the current target π_t^* will tend to raise the central bank's inflation target next period above the path implied by a conventional first-order autoregression. Inflation below target will tend to lower the trajectory for π_t^*. For the case in which $\omega = d = 0$, the inflation target is constant and normalized to zero.[5]

While a non-constant inflation target may be theoretically appealing, it can in practice lead to complications in identifying certain parameters of interest. In a landmark study Cogley and Sbordone (2008) demonstrate that inflation persistence can be explained by interaction between persistent trend inflation, pinned down by the central bank's long-run inflation target, and purely forward-looking elements in basic models of staggered price adjustment. It stands to reason then that a highly autocorrelated time-varying inflation target may soak up much of the persistence in the inflation data that a model would otherwise attribute to backward-looking sources like lags in the behavioral equations. In other words, opening one's model to alternative interpretations of the data can compromise identification of the structural parameters. In light of these established findings, we examine whether accounting for time variation in the cental bank's inflation target exposes our model to identification problems. Our strategy involves running auxiliary estimations of the partial and complete information models under the assumption of a constant inflation target ($\omega = d = 0$) and then comparing the results to the benchmark estimates discussed in section 5.[6]

[5]Gürkaynak *et al.* (2005) fix $\omega = 1$ and $d = 0.02$. When inserted into a standard monetary model, the resulting system produces a significant reaction of *long*-term interest rates to policy surprises.

[6]We report auxiliary estimates of the partial and complete information models under a constant inflation target in the online appendix.

Table 2
Indicator variables

Output Growth	$\Delta y_t^o = y_t - y_{t-1} + v_{g,t}$	(I-1)
Inflation	$\pi_t^o = \pi_t + v_{p,t}$	(I-2)
Unemployment Rate	$u_t - u_{t-1} = -\chi(y_t - y_{t-1}^n) + \chi(y_{t-1} - y_{t-1}^n) + \varepsilon_{u,t}$	(I-3)

Notes: Δy^o - observed output growth; y - real output; v_g - output growth measurement shock; π^o - observed inflation; π - inflation; v_p - inflation measurement shock; u - unemployment rate; y^n - natural output; ε_u - natural unemployment shock.

2.2 The Indicator Variables

Economic agents have limited information. At the beginning of each period, they receive signals on three variables from which they must infer the true value of the state vector. The first two signals, or indicators, are noisy measures of output growth Δy_t^o and inflation π_t^o given by (I-1) and (I-2) in Table 2.[7] The terms $v_{g,t}$ and $v_{p,t}$ are measurement shocks that capture the noise in observations of output growth and inflation first released (e.g., by a statistical agency) in period t. We allow for possible serial correlation in the measurement errors by modeling them as autoregressive processes: $v_{g,t} = \rho_g v_{g,t-1} + \varepsilon_{g,t}$ and $v_{p,t} = \rho_p v_{p,t-1} + \varepsilon_{p,t}$ with $|\rho_g| < 1$, $|\rho_p| < 1$, $\varepsilon_{g,t} \sim i.i.d.\ N(0, \sigma_g^2)$, and $\varepsilon_{p,t} \sim i.i.d.\ N(0, \sigma_p^2)$.[8]

The third indicator is the unemployment rate u_t. Because it depends on the true output gap via Okun's Law, unemployment can have significant information content in a setting where agents receive noisy signals on output growth and inflation and natural output is unknown. However, u_t also varies in response to unobserved shifts in the natural rate of unemployment, which degrades the quality of the information it provides on current output gap conditions. In fact, observations on u_t are uninformative in the course of forecasting the state if the variance of u_t^n is large. This turns out to be the case in our model because the natural rate follows a random walk, implying that the variance of u_t^n is unbounded. As a practical matter, we first difference (M-4) to obtain (I-3) and assume that agents observe the

[7] Δ denotes the first difference operator.

[8] We also consider the possibility that inflation measurement shocks follow a stationary ARMA(1,1) process $v_{p,t} = \rho_p v_{p,t-1} + \varepsilon_{p,t} - \mu\varepsilon_{p,t-1}$. The estimation results are reported in the online appendix.

change in the unemployment rate. Knowledge of Δu_t is valuable since fluctuations in $\varepsilon_{u,t}$ are stationary. Thus one implication of modeling u_t^n as a random walk is that the information content of the unemployment rate actually resides in the first difference of this series.

3 Optimal Policy and Signal Extraction

Using the notation in Svensson and Woodford (2003), we express the model compactly as

$$\begin{bmatrix} X_{t+1} \\ \Gamma x_{t+1|t} \end{bmatrix} = A^1 \begin{bmatrix} X_t \\ x_t \end{bmatrix} + A^2 \begin{bmatrix} X_{t|t} \\ x_{t|t} \end{bmatrix} + Bi_t + \begin{bmatrix} N\varepsilon_{t+1} \\ \mathbf{0}_{4\times 1} \end{bmatrix}, \tag{1}$$

where $X_t = [\varepsilon_{y,t}\ \varepsilon_{\pi,t}\ y_t^n\ \varepsilon_{u,t}\ v_{p,t}\ v_{g,t}\ y_{t-1}^n\ y_{t-1}\ y_{t-2}\ \pi_{t-1}\ \pi_{t-1}^*\ i_{t-1}]'$ are the date-t predetermined variables, $x_t = [y_t\ \pi_t\ \pi_t^*\ \Delta u_t]'$ are the forward-looking variables, i_t is the policy instrument, and $\varepsilon_{t+1} = [\varepsilon_{y,t+1}\ \varepsilon_{\pi,t+1}\ \varepsilon_{n,t+1}\ \varepsilon_{u,t+1}\ \varepsilon_{p,t+1}\ \varepsilon_{g,t+1}]'$ are the *i.i.d.* shocks with covariance matrix Σ. The parameters of the model appear as elements of the matrices A^1, A^2, B, Γ, and N.[9]

The policymaker and the private sector do not have full information about the state of the economy, that is, about the individual elements of X_t and x_t. Instead, they only observe the indicator variables, which can be used to form optimal predictions of X_t and x_t at each point in time. The indicators are related to the state by

$$Z_t = [D_1\ D_2] \begin{bmatrix} X_t \\ x_t \end{bmatrix}, \tag{2}$$

where $Z_t = [\Delta y_t^o\ \pi_t^o\ \Delta u_t]'$ and $[D_1\ D_2]$ is a (3×16) selection matrix. The information set available to agents in period t is thus $\Omega_t \equiv \{Z_\tau, \tau \le t; A^1, A^2, B, \Gamma, N, D_1, D_2, \Sigma, \delta, \lambda_y, \lambda_i\}$.

As in Svensson and Woodford (2003), market participants and the central bank are

[9]The online appendix shows how (M-1)–(M-6) and (I-1)–(I-3) can be mapped into the general linear-quadratic form used by Svensson and Woodford (2003).

assumed to have symmetric information. This means that expectations $x_{t+1|t}$ appearing in the lower block of (1) and those in the loss function (M-5) are conditioned on the same information. Although this is a strong assumption, replacing it with asymmetric information presents other challenges. The most obvious is that it is not clear whether private agents or the policymaker should be better informed about the state. On the one hand, a case can be made that households and firms observe economic fundamentals while the central bank only sees a particular set of aggregate indicators, which are polluted by noise that is unrelated to the fundamentals (e.g., Svensson and Woodford, 2004). On the other hand, the central bank has access to private information (e.g., internal forecasts) that the public can only imperfectly infer from observed policies (e.g., Mertens, 2010). We view symmetric information as a compromise between these two competing attitudes expressed in the literature.

3.1 Optimization under Discretion

The central bank conducts optimal monetary policy under discretion. As such, it minimizes the loss function period-by-period subject to (1) conditional on Ω_t. The equilibrium is one in which the policy functions depend only on current predetermined variables.

Svensson and Woodford (2003) show that the policy setting and estimates of the forward-looking variables depend linearly on current estimates of the predetermined variables,

$$i_t = FX_{t|t}, \tag{3}$$

$$x_{t|t} = GX_{t|t}, \tag{4}$$

where F solves a particular matrix Ricatti equation, G is a fixed point of the relation

$$G = (A_{22} - \Gamma G A_{12})^{-1}[(\Gamma G A_{11} - A_{21}) + (\Gamma G B_1 - B_2)F],$$

and $\{A_{11}, A_{12}, A_{21}, A_{22}, B_1, B_2\}$ are the partitions of $A \equiv A^1 + A^2$ and B with dimensions conformable to X_t and x_t. Substituting (4) into the lower block of (1) gives

$$x_t = G^1 X_t + G^2 X_{t|t}, \tag{5}$$

with $G^1 = -(A^1_{22})^{-1} A^1_{21}$ and $G^2 = G - G^1$. It follows that predetermined variables obey

$$X_{t+1} = H X_t + J X_{t|t} + N \varepsilon_{t+1}, \tag{6}$$

where $H = A^1_{11} + A^1_{12} G^1$ and $J = A^1_{12} G^2 + A^2_{11} + A^2_{12} G + B_1 F$.

3.2 Optimal Filtering

A full characterization of the equilibrium dynamics requires a law of motion for $X_{t|t}$. Since the indicators in (2) are functions of the forward-looking variables, estimates of the predetermined variables cannot be obtained from a standard Kalman filter. Forward-looking indicators complicate the signal-extraction problem because they depend, by definition, on expected future endogenous variables. These expectations, in turn depend on an estimate of the state, which is itself a function of the indicators. Svensson and Woodford (2003) develop techniques to handle this circularity issue and present the results in terms of a modified Kalman filter.[10] The recursive updating equation for $X_{t|t}$ is given by

$$X_{t|t} = X_{t|t-1} + KL(X_t - X_{t|t-1}), \tag{7}$$

where the steady-state gain matrix $K = PL'(LPL')^{-1}$ and $L = D_1 + D_2 G^1$. Matrix P is the variance of the forecast error, $X_t - X_{t|t-1}$, satisfying $P = H[P - PL'(LPL')^{-1}LP]H' + N\Sigma N'$.

[10] These methods refine earlier work on the subject by Pearlman, Currie, and Levine (1986).

Finally, taking conditional expectations of (6) gives

$$X_{t+1|t} = (H + J)X_{t|t}, \tag{8}$$

which completes the description of the equilibrium dynamics under partial information.[11]

4 Estimation Strategy

The equilibrium admits a state-space form that can be estimated with maximum likelihood using the Kalman filter. As in Lippi and Neri (2007), the state vector appropriate for estimation augments the predetermined variables X_t with conditional forecasts $X_{t|t-1}$. For our model the state is a (24×1) object $\mathbf{s}_t \equiv [X_t' \; X_{t|t-1}']'$ governed by a *transition equation*

$$\mathbf{s}_{t+1} = \mathbf{M}\mathbf{s}_t + \mathbf{N}\boldsymbol{\varepsilon}_{t+1}. \tag{9}$$

Elements of $\mathbf{M}$ and $\mathbf{N}$ are functions of the model parameters, and $\boldsymbol{\varepsilon}_t = [\varepsilon_{y,t} \; \varepsilon_{\pi,t} \; \varepsilon_{n,t} \; \varepsilon_{u,t} \; \varepsilon_{g,t} \; \varepsilon_{p,t}]'$ is a vector of guassian shocks. Estimation requires modeling the joint dynamics of X_t and $X_{t|t-1}$ since they are determined simultaneously by (6) and (8) after substituting out $X_{t|t}$.

Closing the state-space model is a *measurement equation* linking variables observed by the econometrician to $\mathbf{s}_t$. Unlike model inhabitants who only see $Z_t = [\Delta y_t^o \; \pi_t^o \; \Delta u_t]'$, we assume that the econometrician sees not just Z_t but also the true values of output growth Δy_t and inflation π_t. This is a departure from Lippi and Neri (2007) and Neri and Ropele (2012) who require that economic agents and the econometrician observe the same data.

Our choice to give the researcher an expanded data set recognizes the distinction between economic decision making, a process carried out in real time, and model estimation, which is an exercise in retrospection. Real-time data get revised as more comprehensive information

[11] We derive the updating equation in the online appendix and provide an estimate of the gain matrix.

becomes available and as measurement techniques improve. With the benefit of hindsight, the econometrician is able to condition estimation on revised data that would not have been accessible to private agents. Below we argue that *ex post* revised data are the best measures of the true variables that the model seeks to explain but that agents never fully observe.

Defining $\mathbf{y}_t \equiv [\Delta y_t^o \ \pi_t^o \ \Delta u_t \ i_t^o \ \Delta y_t \ \pi_t]'$, the measurement equation takes the form

$$\mathbf{y}_t = \mathbf{T}\mathbf{s}_t + \mathbf{u}_t, \tag{10}$$

where $\mathbf{T}$ contains the reduced-form coefficients and $\mathbf{u}_t \equiv [0 \ 0 \ 0 \ u_{i,t} \ 0 \ 0]'$.[12] Variable $u_{i,t}$ is a measurement shock with distribution *i.i.d.* $N(0, \sigma_i^2)$; it represents a stochastic wedge between the sample interest rate i_t^o and the rate prescribed by optimal discretion i_t. The role of $u_{i,t}$ is to avoid the stochastic singularity that would occur if the observed policy rate responded only to $\mathbf{s}_t$ (e.g., Ingram, Kocherlakota, and Savin, 1994).

Estimation requires data for the variables in $\mathbf{y}_t$ observed by agents and those seen exclusively by the econometrician. In choosing Δy_t^o and π_t^o, we follow Orphanides (2001) who argues that real-time data accurately represent the information that was available to policymakers and market participants who were around at the time economic decisions were being made. Our data source is the Real-Time Data Set for Macroeconomists published by the Federal Reserve Bank of Philadelphia.[13] We define Δy_t^o as the first difference of the log of seasonally-adjusted real output (ROUTPUTQvQd). In constructing this series, we take the last output growth calculation from each vintage of data published over the sample period. Using the same procedure, readings on the annualized first difference of the log of the seasonally-adjusted output deflator (PQvQd) provide our measure of π_t^o.[14]

[12]The online appendix shows how to derive (9) and (10) and how to construct matrices $\mathbf{M}$, $\mathbf{N}$, and $\mathbf{T}$.

[13]http://www.philadelphiafed.org/research-and-data/real-time-center/real-time-data/

[14]We have assumed that error-prone measures of output growth and inflation are observed contemporaneously, even though preliminary data from the national income and product accounts is actually released with a one-quarter lag. We estimated a version of the model that accounts for the publication lag by setting $Z_t = [\Delta y_{t-1}^o \ \pi_{t-1}^o \ \Delta u_t]'$. The results were very similar to the ones reported here.

The data used to assemble real-time measures of output growth and inflation undergo a continual process of revision in the months and years following their initial release (e.g., Croushore, 2011). As a result, the true values of these concepts remain unknown for a long time after the date of first publication. In light of this fact, we assume that observations of Δy_t and π_t correspond to final published data, that is, the complete time series as recorded in the latest available release.[15] Of course, even final data is subject to uncertainty and will likely be revised again in the future. Nevertheless, we view it as offering the most reliable account of the true historical profiles of output growth and inflation.[16]

The information structure implies that private agents and the econometrician have the same data on unemployment. We base this assumption on reports showing that revisions to unemployment data are small, infrequent, and confined to seasonal factors (e.g., Kozicki, 2004). Our measure for u_t is the seasonally-adjusted civilian unemployment rate (RUC). Finally, for the interest rate series i_t^o we use the annual yield on 3-month US Treasury bills.

Fig. 1 plots the historical time series for the variables in $\mathbf{y}_t$. Each one has been demeaned, except for Δu_t whose sample mean is near zero to begin with. Observations on output growth, inflation, and the interest rate are thus interpreted as annual percentage points less their sample averages. Rather than display the actual series for Δy_t^o and π_t^o, we plot differences between their real-time and final values. Viewing the real-time data in this way makes it easier to spot periods when large *ex post* revisions occurred.

Our sample runs from 1965:Q4 through 2010:Q1. These dates span the Federal Reserve chairmanships of Burns, Miller, Volcker, and Greenspan and partially cover the terms of Martin and Bernanke. Conventional wisdom holds that a fundamental shift in US monetary

[15] We choose not to model the nature or timing of data revisions in this paper. Instead, the cumulative effect of the full history of revisions to any given data point are encapsulated by the measurement shocks $v_{g,t}$ and $v_{p,t}$, defined as the difference between real-time observations of output growth and inflation and their final values. Although agents are unable to perfectly infer $v_{g,t}$ and $v_{p,t}$ like the econometrician can, they have complete knowledge of their stochastic properties when forecasting the state.

[16] The series for Δy_t and π_t are based on data published in 2010:Q4. At the time of writing, this vintage was the most up-to-date and allowed for two consecutive revisions to the last observation in our sample.

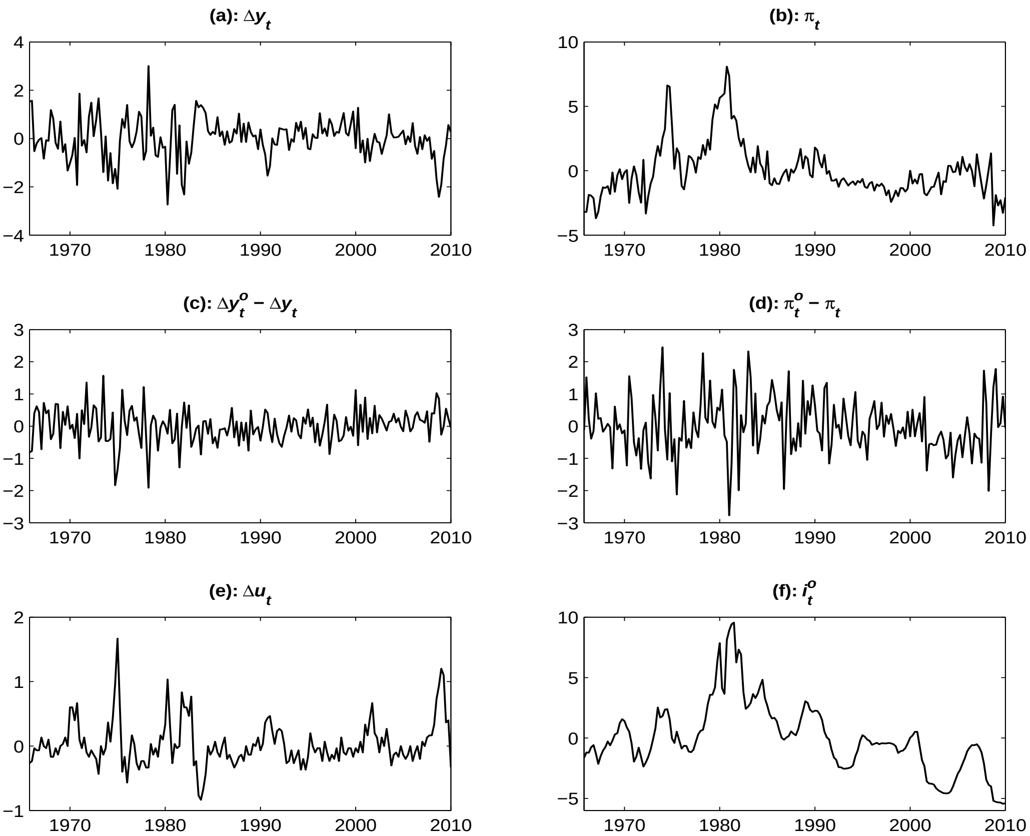

Fig. 1. Panels (a) and (b) plot the revised series for output growth, Δy_t, and inflation, π_t. Panels (c) and (d) plot the series of historical revisions to real-time output growth, $\Delta y_t^o - \Delta y_t$, and inflation, $\pi_t^o - \pi_t$. Panels (e) and (f) plot changes in the civilian unemployment rate, Δu_t, and the annual yield on 3-month US Treasury bills, i_t^o.

policy took place soon after Volcker's appointment in August 1979. It would be inappropriate then to estimate our model under the assumption of a fixed monetary regime. We therefore partition the data set into two subsamples, with the breakpoint occurring in 1979:Q3, and estimate the entire model separately using both samples. Splitting the data in this way means that we view the periods before and after 1979 as having separate but stable monetary regimes characterized by distinct sets of loss function weights.

In dealing with regime change through subsample estimation, we borrow from Dennis (2006) and Ireland (2001), both of whom select 1979:Q3 as the breakpoint. By splitting the sample on this date, however, we are immediately confronted with the task of trying to explain the high volatility and inflation of the 1970s (see Fig. 1) in the context of optimal policy. Despite these challenges, estimating the model over this period enables a systematic comparison of results for the years before and after 1979, and it strengthens our understanding of whether partial information can help reconcile optimal and observed policy outcomes during the pre-Volcker era. An added benefit of our sumbsample analysis is that it provides a framework for conducting hypothesis tests on the stability of the estimated parameters.

4.1 A Model with Complete Information

Throughout the paper we compare estimates of the partial information model to those from a version that assumes agents have complete knowledge of the state. Clearly, full information obviates the signal-extraction problem used to track agents' beliefs. The discretionary equilibrium can thus be found by applying standard solution methods for linear-quadratic control problems without a filtering component (e.g., Söderlind, 1999).[17]

An important difference between partial and complete information concerns the data used for estimation. When agents know the true values of Δy_t and π_t, the measurement shocks in (I-1) and (I-2) vanish (i.e., $\sigma_g = \sigma_p = 0$). Using real-time data on output growth and inflation along with the true values as recorded in the latest data vintage would render the model stochastically singular because $\Delta y_t^o = \Delta y_t$ and $\pi_t^o = \pi_t$ in this case. Consequently, we drop Δy_t^o and π_t^o from the measurement equation and estimate the model using only data on unemployment, the interest rate, and the revised series for output growth and inflation.

[17]A detailed exposition of the complete information model can be found in the online appendix.

5 Empirical Findings

5.1 Parameter Estimates

Table 3 displays maximum-likelihood estimates and standard errors of the parameters in (M-1)–(M-6) and (I-1)–(I-3). The first group of estimates is for the benchmark model under partial information. The second group corresponds to the complete information model. In each case we report separate estimates for the periods before and after 1979. The standard errors are the square roots of the diagonal elements of the inverse Hessian matrix.[18]

There are some similarities but also key differences in the partial and complete information estimates. Looking first at the shocks, estimates of σ_y and σ_π indicate that demand shocks are less volatile than cost-push shocks in both models and in both samples. Estimates of σ_n reveal that shocks to natural output are more volatile under partial information than under complete information in the post-1979 period but about equally as volatile in the pre-1979 period. The impact of demand shocks on natural output as measured by η_y is also weaker when agents have limited information, particularly after 1979. As to the natural rate of unemployment, the post-1979 estimate of σ_u is 0.08 under partial information but 0.18 under complete information. The estimates are 0.21 and 0.15 using pre-1979 data.

Real-time data enables us to identify the measurement shocks $v_{g,t}$ and $v_{p,t}$. Estimates of σ_g and σ_p reveal that the noise component of π_t^o is larger than that of Δy_t^o across the full sample. Each is statistically significant and of the same order of magnitude as the fundamental shocks. We also find no evidence of serial correlation. Estimates of ρ_g and ρ_p are near zero and statistically insignificant.

The effects of partial information on the aggregate behavioral equations are mixed. Post-1979 estimates of ϕ, for example, are close to one-third, implying that lagged and expected

[18]We set the discount factor δ to 0.996, which equals the average ratio of inflation to the interest rate over the full sample, and we fix d equal to 0.02 to match the value used by Gürkaynak *et al.* (2005).

Table 3
Benchmark estimates

		Partial Information			Complete Information		
Parameter	Description	1965:Q4–1979:Q2	1979:Q3–2010:Q1	W	1965:Q4–1979:Q2	1979:Q3–2010:Q1	W
σ_y	*demand shock*	0.6457 (0.0507)	0.4616 (0.0245)	0.0011	0.6015 (0.0747)	0.2730 (0.0179)	0.0000
σ_π	*cost-push shock*	0.9689 (0.0799)	0.9022 (0.1373)	0.6744	0.8848 (0.1026)	0.5607 (0.0385)	0.0031
σ_n	*natural output shock*	0.1596 (0.2285)	0.5735 (0.0702)	0.0833	0.1901 (0.1066)	0.2399 (0.0414)	0.6635
σ_u	*natural unemployment shock*	0.2083 (0.0420)	0.0789 (0.0241)	0.0076	0.1542 (0.0819)	0.1792 (0.0165)	0.7646
σ_g	*output growth noise*	0.7682 (0.0735)	0.4708 (0.0311)	0.0002	—	—	—
σ_p	*inflation noise*	0.9687 (0.1010)	0.8726 (0.0617)	0.4166	—	—	—
σ_i	*interest rate shock*	0.4890 (0.0503)	0.8428 (0.0567)	0.0000	0.8212 (0.0814)	0.6300 (0.0566)	0.0539
ρ_g	*serial correlation in* σ_g	0.0092 (0.1438)	−0.0151 (0.0927)	0.8871	—	—	—
ρ_p	*serial correlation in* σ_p	0.0975 (0.1405)	0.1131 (0.0915)	0.9262	—	—	—
ϕ	*expected future output*	0.3871 (0.0072)	0.3578 (0.0040)	0.0004	0.4425 (0.0612)	0.3711 (0.0054)	0.2454
β	*lagged output*	1.4194 (0.0071)	1.4869 (0.0058)	0.0000	0.9537 (0.0817)	1.4467 (0.0093)	0.0000
σ	*interest rate elasticity*	1.63e-6 (0.0047)	0.0009 (0.0003)	0.8566	0.1222 (0.0642)	0.0001 (0.0001)	0.0575
α	*expected future inflation*	0.5531 (0.0190)	0.1928 (0.1732)	0.0387	0.5654 (0.0295)	0.5344 (0.0140)	0.3430
κ	*output gap elasticity*	4.29e-5 (1.77e-5)	0.0223 (0.0135)	0.0990	0.0211 (0.0075)	0.0074 (0.0029)	0.0883
γ	*lagged natural output*	0.8083 (0.0535)	0.9022 (0.0184)	0.0968	0.6224 (0.0960)	0.9239 (0.0202)	0.0021
η_y	*demand shock feedback*	0.9095 (0.0527)	0.4215 (0.0919)	0.0000	1.1570 (0.1619)	1.2200 (0.1650)	0.7852
χ	*Okun coefficient*	0.4526 (0.0494)	0.3438 (0.0242)	0.0477	0.7083 (0.1398)	0.4594 (0.0383)	0.0860
λ_y	*output gap weight*	0.0338 (0.0622)	0.2262 (0.0714)	0.0422	$0^\dagger$	0.5667 (0.3544)	0.1098
λ_i	*interest-rate smoothing weight*	$0.001^\dagger$	1.1233 (0.5466)	0.0401	2.1321 (1.0176)	0.6072 (0.2719)	0.1477
ω	*inflation target persistence*	$0^\dagger$	0.9710 (0.0140)	0.0000	$0^\dagger$	0.9963 (0.0059)	0.0000
d	*inflation target accommodation*	0.02^*	0.02^*	—	0.02^*	0.02^*	—
δ	*loss discount factor*	0.996^*	0.996^*	—	0.996^*	0.996^*	—
$\ln \mathcal{L}$	*log likelihood*	−359.0435	−722.2974		−236.5502	−444.5841	

Notes: The table reports maximum-likelihood estimates of (M-1)–(M-6) and (I-1)–(I-3) under partial and complete information. Numbers in parentheses are standard errors. The columns labeled W contain the p-values of the Wald statistic for testing the null hypothesis of parameter stability. * denotes a value that is imposed prior to estimation. † denotes a value that lies on the boundary of the allowable parameter space.

future output play an important role in the IS equation. The pre-1979 estimate of ϕ is about the same under partial information but is closer to one-half under complete information. Estimates of σ, the interest-rate elasticity of output, tend to be small but significant only in the partial information case after 1979. Regarding the Phillips curve, estimates of α are around one-half and significant in all but one case, that being the post-1979 estimate under partial information. Its value is about one-fifth, raising the possibility that inflation is predominantly backward looking. In both models and across both periods, estimates of the output gap elasticity κ are small and within the range typical of the literature (e.g., Kiley, 2007). Despite this broad consistency, the partial information estimate is an order of magnitude larger than the complete information estimate in the post-1979 sample. The opposite result emerges when the models are estimated on pre-1979 data.

Turning to the loss function, estimates of λ_i are large and statistically significant after 1979. These findings are consistent with Dennis (2004, 2006) and Söderström *et al.* (2005) showing that optimal and observed policy during the Volcker-Greenspan era can be reconciled with a heavy weight on interest-rate smoothing, albeit in a full information environment. Our results suggest that fitting the post-1979 data in the context of partial information requires an even bigger smoothing penalty than would be necessary under complete information, as the point estimate nearly doubles from 0.61 to 1.12.

Partial information evidently has different implications for λ_i before 1979. For this period the partial information estimate approaches zero while the corresponding value under complete information exceeds two. Thus analyzing the 1970s with a complete information model points to interest-rate smoothing as the foremost policy objective. Viewing the same data through a partial information lens suggests that it was of negligible concern to policymakers.

Information restrictions also have an effect on inferences concerning the output gap objective after 1979. For this period the estimate of λ_y under partial information is 0.23 with a standard error of 0.07, while under complete information the estimate is 0.57 with a standard error of 0.35. It follows that macroeconomic objectives, if viewed from a partial information perspective, are consistent with the notion that policymakers placed significant weight (both economically and statistically) on stabilizing the output gap.[19] This is an important result because it offers an interpretation of historical policy motives that could not have been formed with much confidence had we confined our analysis to the case of full information. It may also provide an answer for why studies often find λ_y to be statistically insignificant (e.g., Dennis, 2006; Salemi, 2006) despite public statements from leading central bankers implying that output and inflation are independently important as exemplified by the Federal Reserve's dual mandate. Our findings suggest that it could be due to the failure of these studies to account for the type of information constraints that policymakers face in real time.

As mentioned in the last section, inserting a breakpoint in the data set allows us to conduct hypothesis tests on the stability of the estimated parameters. There is already a large body of research that examines whether the structural parameters common to most New Keynesian models have remained stable over time (e.g., Ireland, 2001; Inoue and Rossi, 2011). Of course the vast majority of this work has been done within a complete information framework. Whether the results of these stability tests differ in the context of partial information is a topic that has received far less scrutiny. We take up this issue here.

To identify which parameters of our model changed around the time of Volcker's appointment, we employ the Wald test developed by Andrews and Fair (1988). The test statistic is formed by squaring the difference between the first and second subsample estimates of a given parameter and dividing that quantity by the sum of their respective covariances. Under the null hypothesis of parameter stability, it is asymptotically distributed chi-square with one degree of freedom. Table 3 lists the p-values of the Wald statistics for each estimated parameter in both the partial and complete information models.

Incorporating limited information changes our assessment of instability in the aggregate

[19] A likelihood ratio test of $\lambda_y = 0$ produces a chi-square statistic of 5.53 (p-value < 0.02).

behavioral equations. Most notable are the IS and Phillips curves. For parameters ϕ and α, the Wald test easily rejects the null of stability (at the 5 percent significance level) in the partial information model but fails to reject the same hypotheses under complete information. There is also evidence of structural change in other non-policy components of the model. Using estimates obtained under partial information, tests reject the hypotheses that the Okun coefficient χ and the feedback term η_y in the natural output equation have remained stable. Under complete information, however, differences in the estimates across subsamples are not statistically significant enough to reach the same conclusions. Thus, on balance, our benchmark results point to some clear shifts in the semi-structural model that would have gone undetected in a full information environment.

What can be said about the stability of the loss function? In the partial information model we find compelling evidence in favor of a break in the output gap weight λ_y at the onset of Volcker's term. The p-value for the stability test is close to 0.04. We do not find the same evidence under complete information. In this case the pre-1979 point estimate converges to zero, the lower bound of the admissible parameter space. The post-1979 estimate of λ_y is not significantly different from the same value.[20] Similar results emerge for the interest-rate smoothing penalty. Under complete information a test of the hypothesis that estimates of λ_i are the same in both samples has a p-value of 0.15. By contrast, a Wald test applied to the partial information estimates has a p-value of 0.04.[21] Thus, as is true of the behavioral equations, our partial information estimates reveal instability in the Federal Reserve's loss function that would not have been recognized in the complete information model.[22]

[20] A Wald test of the hypothesis $\lambda_y = 0$ in the complete information model after 1979 has a p-value of 0.11.

[21] The p-values reported in Table 3 for λ_y under complete information, λ_i under partial information, and ω under both correspond to standard Wald tests of the hypotheses that the post-1979 estimates equal their pre-1979 values, which are located on the boundary of the allowable parameter space. The Andrews and Fair (1988) test is invalid in these cases since standard errors are not available for the pre-1979 estimates.

[22] We extract historical estimates of the time-varying inflation target π_t^* from the partial and complete information models and plot the two series together in the online appendix.

5.2 Tests of Partial Information and Optimal Policy

Results of the previous section make clear that partial information and discretionary policy together are central to our interpretation of historical macroeconomic objectives. Although evidence of their joint significance is important in and of itself, it would be useful to have a deeper understanding of the separate contributions that these two aspects of the model are making. Unfortunately, the benchmark analysis does not provide this level of insight, so our goal now is to explain how the estimation procedure can be modified to help disentangle the effects of optimal policy from mistaken beliefs about the state. In examining their individual contributions, we will focus our discussion on the consequences for parameter inference and, most importantly, for model fit.

Sorting out the empirical content of partial information requires an orderly comparison of models that differ only in their information structure. The side-by-side analysis featured in the last section, however, fails to meet this standard and, as a result, does not necessarily identify the specific effects of partial information. The basic problem is that the data set used to estimate the partial information model contains real-time observations that are not found in the complete information model. These extra dependent variables, in addition to the information mechanism itself, affect all of the estimates and preclude any likelihood-based ranking of fit across the two models. To distinguish the role of partial information, we re-estimate the model with a sample that omits real-time data on output growth and inflation. This makes the data set invariant within our comparison group and sharpens identification of the partial information component. Estimates for both subsamples are listed in Table 4.[23]

The contrast between partial and complete information seen in Table 3 is mostly preserved when we exclude real-time data from the sample. Partial information estimates of the policy weights, λ_y and λ_i, are still large and significant after 1979 but near zero before 1979. The IS

[23] Without real-time data, shocks $v_{g,t}$ and $v_{p,t}$ are not identified. We therefore set σ_g, σ_p, ρ_g, and ρ_p equal to the values reported in Table 3 before re-estimating the partial information model using only revised data. The complete information estimates are the same as the ones found in Table 3.

Table 4
No real-time data

Parameter	Description	1965:Q4–1979:Q2 Partial	1965:Q4–1979:Q2 Complete	1979:Q3–2010:Q1 Partial	1979:Q3–2010:Q1 Complete
σ_y	*demand shock*	0.5910 (0.0474)	0.6015 (0.0747)	0.3731 (0.0188)	0.2730 (0.0179)
σ_π	*cost-push shock*	0.9407 (0.0759)	0.8848 (0.1026)	0.9193 (0.1896)	0.5607 (0.0385)
σ_n	*natural output shock*	0.0010 (0.4793)	0.1901 (0.1066)	0.3733 (0.0402)	0.2399 (0.0414)
σ_u	*natural unemployment shock*	0.2398 (0.0268)	0.1542 (0.0819)	0.0337 (0.0367)	0.1792 (0.0165)
σ_g	*output growth noise*	0.7682*	—	0.4708*	—
σ_p	*inflation noise*	0.9687*	—	0.8726*	—
σ_i	*interest rate shock*	0.4506 (0.0573)	0.8212 (0.0814)	0.5205 (0.0562)	0.6300 (0.0566)
ρ_g	*serial correlation in* σ_g	0.0092*	—	−0.0151*	—
ρ_p	*serial correlation in* σ_p	0.0975*	—	0.1131*	—
ϕ	*expected future output*	0.3976 (0.0130)	0.4425 (0.0612)	0.3589 (0.0047)	0.3711 (0.0054)
β	*lagged output*	1.3959 (0.0236)	0.9537 (0.0817)	1.4850 (0.0075)	1.4467 (0.0093)
σ	*interest rate elasticity*	0.0025 (0.0051)	0.1222 (0.0642)	0.0013 (0.0005)	0.0001 (0.0001)
α	*expected future inflation*	0.5515 (0.0144)	0.5654 (0.0295)	0.1905 (0.2418)	0.5344 (0.0140)
κ	*output gap elasticity*	7.70e-6 (1.99e-6)	0.0211 (0.0075)	0.0274 (0.0205)	0.0074 (0.0029)
γ	*lagged natural output*	0.8737 (0.0982)	0.6224 (0.0960)	0.9617 (0.0173)	0.9239 (0.0202)
η_y	*demand shock feedback*	0.9715 (0.1183)	1.1570 (0.1619)	0.9327 (0.0741)	1.2200 (0.1650)
χ	*Okun coefficient*	0.4260 (0.0658)	0.7083 (0.1398)	0.4757 (0.0348)	0.4594 (0.0383)
λ_y	*output gap weight*	0.0004 (0.0004)	$0^\dagger$	0.2162 (0.1156)	0.5667 (0.3544)
λ_i	*interest-rate smoothing weight*	$0.001^\dagger$	2.1321 (1.0176)	1.4622 (0.5714)	0.6072 (0.2719)
ω	*inflation target persistence*	0.0005 (3.2885)	$0^\dagger$	0.9425 (0.0545)	0.9963 (0.0059)
d	*inflation target accommodation*	0.02*	0.02*	0.02*	0.02*
δ	*loss discount factor*	0.996*	0.996*	0.996*	0.996*
$\ln \mathcal{L}$	*log likelihood*	−230.4972	−236.5502	−429.6916	−444.5841

Notes: The table reports maximum-likelihood estimates of (M-1)–(M-6) and (I-1)–(I-3) under partial and complete information. The data set used to estimate the partial information model excludes real-time measures of output growth and inflation. Numbers in parentheses are standard errors. * denotes a value that is imposed prior to estimation. † denotes a value that lies on the boundary of the allowable parameter space.

and Phillips curve parameters are also quite robust and, in the case of α and κ, very different from the complete information estimates post-1979. The same can not be said of the process for natural output. In the absence of real-time data, partial information estimates of σ_n become much smaller for both samples, but estimates of the feedback coefficient η_y become larger. This suggests that inferences about the volatility of natural output, while dependent on the information setup, are heavily influenced by the application of real-time data *per se*.

As explained above, the benchmark analysis leaves open the question of whether partial information by itself improves model fit. We can now answer this question by appealing to the likelihood values reported in Table 4 since the two models have been estimated on identical data sets. Shifting from complete to partial information raises maximized log likelihood from -236.55 to -230.50 in the first sample and from -444.58 to -429.69 in the second. Here the likelihood criteria provide summary measures of the congruence between the models and the *ex post* revised data. We conclude then that partial information enables our semi-structural model to fit the revised data better both before and after 1979.

Up to this point we have assumed that policy decisions are the outcome of discretionary optimization. Without variation in the monetary arrangement, however, it is difficult to distinguish the empirical content of optimal policy from the other features of our model. So what kind of change would be sufficient to separate out the effects we are looking for? Recall that discretion imposes certain restrictions on how the interest rate responds to elements of the state vector. A logical way to assess the validity of these restrictions, in the context of either partial or complete information, is to compare results already obtained in the previous section to those from a version of the model that does not force central bank actions to be the product of loss minimization. Determining how well the models fit the data in the two cases should give better perspective on the individual contribution of optimal policy.

To organize a test along these lines, we replace the loss function (M-5) with a generalized

Taylor rule of the form

$$
\begin{aligned}
i_t = \rho i_{t-1} + (1-\rho)[\pi_{t|t} + \theta_\pi(\pi_{t|t} - \pi^*_{t|t}) + \theta_y(y_{t|t} - y^n_{t|t})] \\
+ \theta_{\Delta y}[(y_{t|t} - y^n_{t|t}) - (y_{t-1|t} - y^n_{t-1|t})] + \theta_{\Delta\pi}(\pi_{t|t} - \pi_{t-1|t}).
\end{aligned} \quad (11)
$$

This policy rule loosens the optimality restrictions by permitting separate response coefficients on key items in the state vector; namely, estimates of current and lagged inflation and the output gap, the perceived inflation target, and the lagged interest rate. Recent studies have found that broad feedback rules of this type do a good job of matching fluctuations in the actual US policy rate over time (e.g., Smets and Wouters, 2007; Primiceri, 2010). Fitting the interest rate series is critical for us because a central task of this paper is to judge whether observed policy outcomes can even be reconciled within an optimal policy framework. A horse race between optimal discretion and a policy rule like (11) is only useful then if the latter gives a reliable account of historical policy behavior.

Table 5 reports estimates of the partial and complete information models with interest rates determined by (11) instead of optimal discretion. In estimating both models, we only use data from the second subsample covering 1979:Q3 to 2010:Q1. Empirical work by Lubik and Schorfheide (2004) and others has shown that policy rule estimates based on pre-Volcker data often lead to equilibrium indeterminacy when examined as part of a fully specified DSGE model. Multiple equilibria would no doubt obscure any comparisons between optimal and Taylor-rule policy. To avoid these complications, we focus solely on the period after 1979.[24]

Estimation results indicate that the conflict between fitting the post-1979 data and satisfying the optimal-policy criteria is greatly diminished in the partial information model. Evidence of this can be seen by comparing log likelihood values obtained under Taylor rule

[24] Attempts to estimate (11) over 1965:Q4 to 1979:Q2 sent $\{\rho, \theta_\pi, \theta_y, \theta_{\Delta y}, \theta_{\Delta\pi}\}$ to a region of the parameter space consistent with indeterminacy. Lubik and Schorfheide (2004) show how to modify likelihood estimation to accommodate indeterminacies. Application of their methods could be useful for studying the interaction of indeterminacies and partial information, but such an extension is probably beyond the scope of this paper.

Table 5
Taylor rule estimation (1979:Q3–2010:Q1)

		Partial Information		Complete Information	
Parameter	Description	Taylor	Discretion	Taylor	Discretion
σ_y	*demand shock*	0.4625 (0.0274)	0.4616 (0.0245)	0.2796 (0.0201)	0.2730 (0.0179)
σ_π	*cost-push shock*	0.9511 (0.1489)	0.9022 (0.1373)	0.5595 (0.0385)	0.5607 (0.0385)
σ_n	*natural output shock*	1.27e-6 (0.0966)	0.5735 (0.0702)	0.5427 (0.1464)	0.2399 (0.0414)
σ_u	*natural unemployment shock*	0.1668 (0.0130)	0.0789 (0.0241)	0.2343 (0.0217)	0.1792 (0.0165)
σ_g	*output growth noise*	0.5108 (0.0355)	0.4708 (0.0311)	—	—
σ_p	*inflation noise*	0.8577 (0.0581)	0.8726 (0.0617)	—	—
σ_i	*interest rate shock*	1.1028 (0.0717)	0.8428 (0.0567)	0.4412 (0.0725)	0.6300 (0.0566)
ρ_g	*serial correlation in* σ_g	0.1452 (0.1048)	−0.0151 (0.0927)	—	—
ρ_p	*serial correlation in* σ_p	0.1014 (0.0887)	0.1131 (0.0945)	—	—
ϕ	*expected future output*	0.3640 (0.0123)	0.3578 (0.0040)	0.4233 (0.0142)	0.3711 (0.0054)
β	*lagged output*	1.4635 (0.0286)	1.4869 (0.0058)	1.3100 (0.0397)	1.4467 (0.0093)
σ	*interest rate elasticity*	0.0012 (0.0007)	0.0009 (0.0003)	0.0029 (0.0012)	0.0001 (0.0001)
α	*expected future inflation*	0.1436 (0.1798)	0.1928 (0.1732)	0.5389 (0.0126)	0.5344 (0.0140)
κ	*output gap elasticity*	0.0303 (0.0171)	0.0223 (0.0135)	1.18e-5 (3.92e-5)	0.0074 (0.0029)
γ	*lagged natural output*	0.6274 (0.0842)	0.9022 (0.0184)	0.9822 (0.0204)	0.9239 (0.0202)
η_y	*demand shock feedback*	0.7056 (0.0673)	0.4215 (0.0919)	0.7731 (0.4839)	1.2200 (0.1650)
χ	*Okun coefficient*	0.4189 (0.0282)	0.3438 (0.0242)	0.3047 (0.0858)	0.4594 (0.0383)
θ_π	*inflation response*	1.5091 (0.2256)	—	1.6783 (0.3327)	—
θ_y	*output gap response*	0.1340 (0.0755)	—	0.0015 (0.0339)	—
ρ	*lagged interest rate response*	0.8439 (0.0273)	—	0.8936 (0.0189)	—
$\theta_{\Delta y}$	*response to output gap changes*	0.8280 (0.0886)	—	0.7807 (0.1578)	—
$\theta_{\Delta\pi}$	*response to inflation changes*	−0.1481 (0.2208)	—	−0.1685 (0.0665)	—
ω	*inflation target persistence*	0.9041 (0.0501)	0.9710 (0.0140)	0.9887 (0.0111)	0.9963 (0.0059)
d	*inflation target accommodation*	0.02*	0.02*	0.02*	0.02*
$\ln \mathcal{L}$	*log likelihood*	−735.4110	−722.2974	−443.4405	−444.5841
BIC	*bayesian information criteria*	−790.7511	−770.4193	−489.1563	−483.0815

Notes: The table reports maximum-likelihood estimates of (M-1)–(M-4), (M-6), and (I-1)–(I-3) under partial and complete information for the period 1979:Q3–2010:Q1. The loss function (M-5) is replaced with a generalized Taylor rule of the form $i_t = \rho i_{t-1} + (1-\rho)[\pi_{t|t} + \theta_\pi(\pi_{t|t} - \pi^*_{t|t}) + \theta_y(y_{t|t} - y^n_{t|t})] + \theta_{\Delta y}[(y_{t|t} - y^n_{t|t}) - (y_{t-1|t} - y^n_{t-1|t})] + \theta_{\Delta\pi}(\pi_{t|t} - \pi_{t-1|t})$. Numbers in parentheses are standard errors. * denotes a value that is imposed prior to estimation.

and discretionary policies. With complete information, dropping loss minimization in favor of (11) raises log likelihood from -444.58 to -443.44. Although it does not translate into a formal hypothesis test (because the models are non-nested), this finding suggests that the generalized Taylor rule outperforms discretion in a full information environment. To facilitate a more direct comparison between the two, we also report the Bayesian information criterion (BIC), which penalizes log likelihood by an amount that increases with the number of estimated parameters. Because the Taylor rule expands the parameter space by three, the BIC actually points to discretion as the preferred model under complete information. The contrast is more dramatic when the data are viewed through the partial information model. Substituting the Taylor rule now lowers log likelihood from -722.30 to -735.41 and lowers the BIC from -770.42 to -790.75, implying that the relative fit of optimal discretion is much better when the surrounding model accounts for real-time uncertainty about the state.

Evidence on the validity of the optimal policy restrictions can also be seen in the coefficient estimates. As shown in Givens and Salemi (2008), imposing false optimality conditions on a class of models similar to ours tends to bias estimates of the behavioral parameters but not the policy rule coefficients. In Table 5 signs of parameter bias are more visible under complete information. Notice there are only a few parameters in the partial information case for which the estimates recovered under discretion are significantly different from those associated with (11). Most obvious are the persistence and volatility of natural output, with γ and σ_n decidedly smaller under the Taylor rule. By comparison, the discrepancies under complete information are more prevalent. Notably, estimates of ϕ and β point to greater forward-looking emphasis in the IS equation when policy is not optimal, and the estimate of κ implies a much flatter short-run Phillips curve.

5.3 Historical Misperceptions

Correctly interpreting the actions of policymakers requires that one take into account how their perceptions of the state evolved over time. This argument, which is central to our paper, hinges on an implicit assumption that beliefs are often far from reality; if not, policy behavior would be very similar to the behavior suggested by estimates based on revised data and perfect information. It follows that if perception errors turn out to be negligible, using a model that distinguishes the true state from real-time estimates of the state may not be important for obtaining valid inferences. We investigate this concern by deriving historical estimates of the misperceptions that agents experienced throughout the sample period. An assessment of the size and nature of those misperceptions can provide evidence on whether incorporating partial information is critical for policy analysis.

In estimating historical misperceptions, we focus on the output gap and inflation since they jointly summarize most of the information in the state vector.[25] To be clear, by misperceptions we mean differences between the *true* paths, $\{q_t, \pi_t\}_{t=1}^T$, and the paths *perceived* by model inhabitants, $\{q_{t|t}, \pi_{t|t}\}_{t=1}^T$. Thus for any date t, output gap and inflation misperceptions are given by $q_{t|t} - q_t$ and $\pi_{t|t} - \pi_t$. Keep in mind that both of these sequences are functions of a specific model, with the perceived series in particular being determined internally by the Kalman filter procedure described in section 3.2. Our task as econometricians is to infer the values of $q_{t|t} - q_t$ and $\pi_{t|t} - \pi_t$ for all t using an estimated model of the economy along with observations on just a subset of the variables represented in that model.

To that end, we apply the fixed-interval Kalman smoother described in de Jong (1989) to our partial information model evaluated at the maximum-likelihood point estimates. Here we treat the estimated model as the true data generating process and use the smoother to "backcast" the unobserved components characterizing agents' perception errors from 1965:Q4

[25]In this section we denote the output gap as $q_t \equiv y_t - y_t^n$.

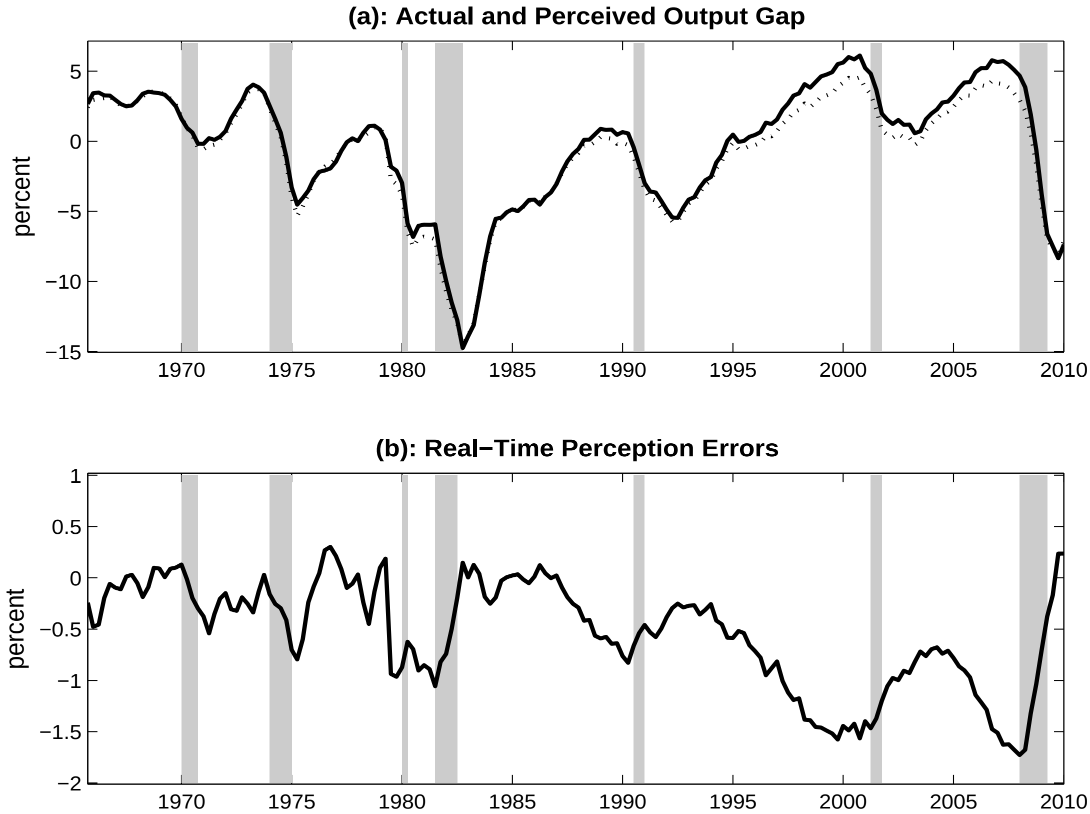

Fig. 2. Panel (a) plots the estimates of the actual output gap ($q_t \equiv y_t - y_t^n$, solid line) and the perceived output gap ($q_{t|t} \equiv y_{t|t} - y_{t|t}^n$, dotted line) obtained from the Kalman smoother. Panel (b) plots estimates of the implied real-time perception errors, $q_{t|t} - q_t$. The shaded regions correspond to NBER recessions.

to 2010:Q1. We denote the sequence of these estimates as $\{\hat{q}_{t|t} - \hat{q}_t\}_{t=1}^T$ and $\{\hat{\pi}_{t|t} - \hat{\pi}_t\}_{t=1}^T$.[26]

Figs. 2 and 3 plot the actual and perceived estimates of the output gap and inflation as well as the corresponding perceptions errors. Summary statistics on each series are reported in Table 6. Regarding the output gap, our estimates point to significant variation in agents' misperceptions over time, ranging from 0.30 percentage points in 1976:Q4 to −1.73 in 2008:Q1. Estimates of $q_{t|t} - q_t$ also appear to exhibit substantial serial correlation. The

[26]Unlike one-sided estimates produced by the standard Kalman filter, the smoother generates two-sided estimates that reflect data contained in the full sample. Two-sided estimates are useful because the state vector $\mathbf{s}_t$ in (9)–(10), which is unobserved by the econometrician, has a particular structural interpretation, and conditioning on the full sample yields a more efficient estimate of it.

Table 6
Summary statistics

	1965:Q4 - 1979:Q2					1979:Q3 - 2010:Q1				
Variable	Mean	SD	Min	Max	AR	Mean	SD	Min	Max	AR
$\hat{q}_t$	1.08	2.25	-4.51	4.04	0.97	-0.99	4.87	-14.73	6.11	0.98
$\hat{q}_{t\|t}$	0.93	2.31	-5.31	3.71	0.97	-1.70	4.48	-14.59	4.55	0.99
$\hat{q}_{t\|t} - \hat{q}_t$	-0.15	0.24	-0.80	0.30	0.78	-0.72	0.51	-1.73	0.24	0.96
$\hat{\pi}_t$	0.00	2.23	-3.68	6.62	0.74	0.00	2.03	-4.25	8.09	0.84
$\hat{\pi}_{t\|t}$	-0.04	2.01	-2.93	6.18	0.83	-0.00	1.94	-2.40	6.90	0.90
$\hat{\pi}_{t\|t} - \hat{\pi}_t$	-0.04	0.78	-2.09	1.65	0.03	-0.00	0.72	-2.09	2.29	0.25

Notes: The sample consists of 178 quarterly estimates obtained from the Kalman smoother. $\hat{q}_t$ and $\hat{q}_{t|t}$ are smoothed estimates of the actual and perceived values of the output gap (i.e., $y_t - y_t^n$), while $\hat{\pi}_t$ and $\hat{\pi}_{t|t}$ are smoothed estimates of the actual and perceived values of inflation. The statistics shown for each variable are: Mean, the mean; SD, the standard deviation; Min and Max, the minimum and maximum values; and AR, the first-order autocorrelation coefficient.

first-order autocorrelation coefficient is 0.78 in the first subsample and 0.96 in the second, meaning that errors in forecasting the output gap tended to persist for many periods. Indeed, from the end of the 1991 recession to the beginning of the Great Recession, agents underestimated the output gap by no less than 0.25 percentage points every quarter.[27]

Real-time perceptions of the output gap are also clearly biased. The mean difference between $\hat{q}_{t|t}$ and $\hat{q}_t$ is -0.15 percentage points before 1979 and -0.72 after 1979, indicating that policymakers systematically underestimated prevailing output gap conditions. This result is consistent with the evidence in Orphanides (2003, 2004) showing that the Federal Reserve's assessment of the output gap in real time was uniformly lower than its true value as recognized *ex post* throughout most of the 1970s, 1980s, and early 1990s. Comparing our results across subsamples, however, indicates that these perceptions errors were not necessarily larger during the 1970s than they were during the 1980s and 1990s as Orphanides has argued. This discrepancy could be due to the way we calculate misperceptions. Orphanides obtains them directly as the spread between a revised output gap series and the Federal Reserve's Greenbook forecast of the same concept. Outcomes are therefore strictly a func-

[27]Cukierman and Lippi (2003) prove that retrospective errors in forecasting the output gap are generally serially correlated in models with optimal monetary policy and partial symmetric information.

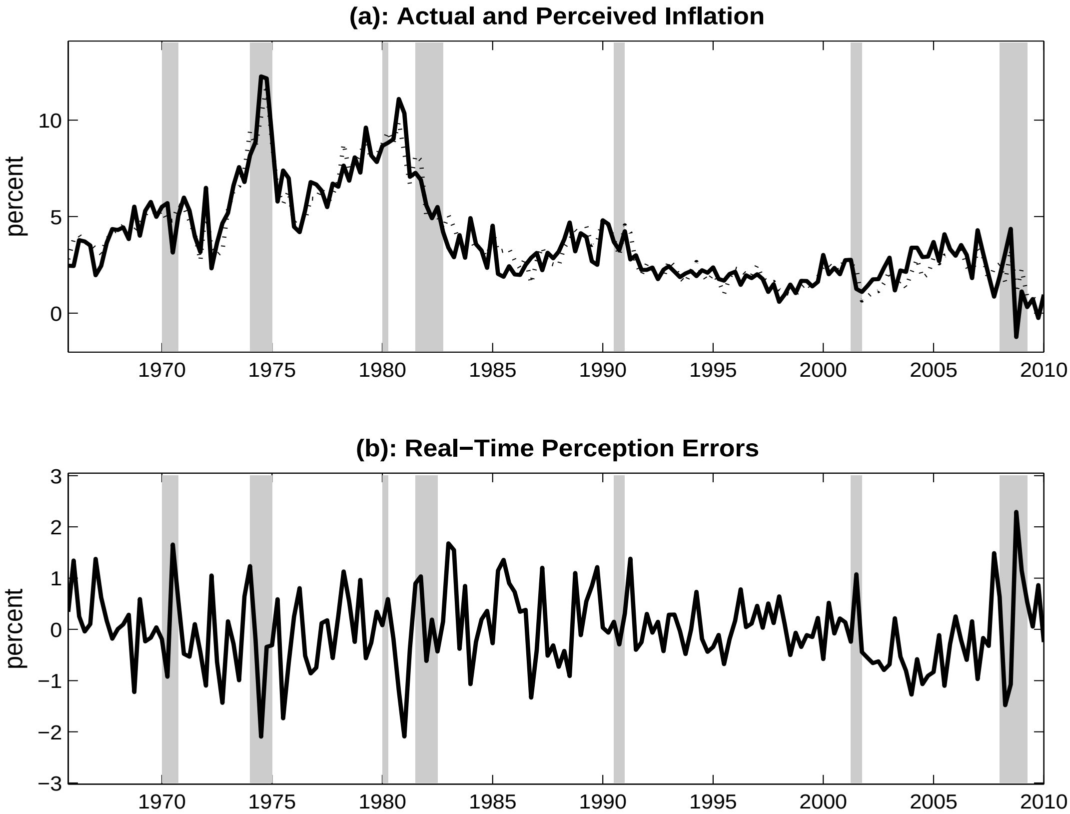

Fig. 3. Panel (a) plots the estimates of actual inflation (π_t, solid line) and perceived inflation ($\pi_{t|t}$, dotted line) obtained from the Kalman smoother. Panel (b) plots estimates of the implied real-time perception errors, $\pi_{t|t} - \pi_t$. The shaded regions correspond to NBER recessions.

tion of primary source data and determined without reference to any particular model. By contrast, we regard natural output as unobservable and assume that agents make efficient forecasts of the output gap using a set of noisy indicators and a semi-structural model of the economy. Thus our analysis characterizes misperceptions as endogenous forecast errors whose values depend on the quality of the information extracted from the indicators.[28]

Estimates of actual and perceived inflation reveal a different pattern of misperceptions

[28]The fact that output gap misperceptions became larger in the second subsample may also reflect the fact that the volatility of natural output shocks, $\varepsilon_{n,t}$, was higher after 1979 than before (see Table 3). Another possibility is that the declining volatility of real output growth and unemployment during the so-called Great Moderation period unintentionally weakened the information content of the observed indicators, particularly with regard to the true path of natural output.

than those surrounding the output gap. For example, there is little evidence of bias or serial correlation. The spread between $\hat{\pi}_{t|t}$ and $\hat{\pi}_t$ is only -0.04 percentage points in the pre-Volcker era and less than 0.01 thereafter. The autocorrelation coefficient of $\hat{\pi}_{t|t} - \hat{\pi}_t$ is also relatively small in both subsamples. Nevertheless, forecast errors were large at times, reaching highs of 2.29 percentage points in 2008:Q4 and lows of -2.09 in 1974:Q3. The overall volatility of $\hat{\pi}_{t|t} - \hat{\pi}_t$ is nontrivial; its standard deviation is about 0.75 percent before and after 1979. Interestingly, our findings are comparable to the historical account of the Federal Reserve's outlook for inflation as reported in Orphanides (2003, 2004). During the 1970s, 1980s, and early 1990s, it was not uncommon for estimates of inflation to be off by 1 or 2 percentage points. However, the Fed did not make systematic errors like they did in forecasting the output gap, and inflation misperceptions typically vanished after a few quarters.

Our estimates reveal that agents' beliefs about the output gap and inflation were at times significantly different from reality. What is less clear, but ultimately more important, is whether these perception errors had significant policy implications in real time. In other words, did the Fed's inability to observe the state have a major impact on actual policy outcomes? We answer this question by simulating optimal policy from 1965:Q4 to 2010:Q1 under different counterfactual assumptions regarding the observability of the output gap and inflation. We then compare these simulations to the true interest rate series implied by our partial information model. In the first simulation we assume agents can see the output gap in addition to the original group of indicators described in section 3. In the second simulation we remove the output gap from the information set and replace it with the revised measure of inflation. This type of analysis tells us how different the interest rate would have been had policymakers known the true value of the output gap or inflation in real time.[29]

To generate counterfactual data, we first need to recover historical estimates of the structural shocks. Like the perception errors, these are obtained by applying the Kalman smoother

[29]In the first simulation $Z_t = [\Delta y_t^o \; \pi_t^o \; \Delta u_t \; q_t]'$, and in the second $Z_t = [\Delta y_t^o \; \pi_t^o \; \Delta u_t \; \pi_t]'$.

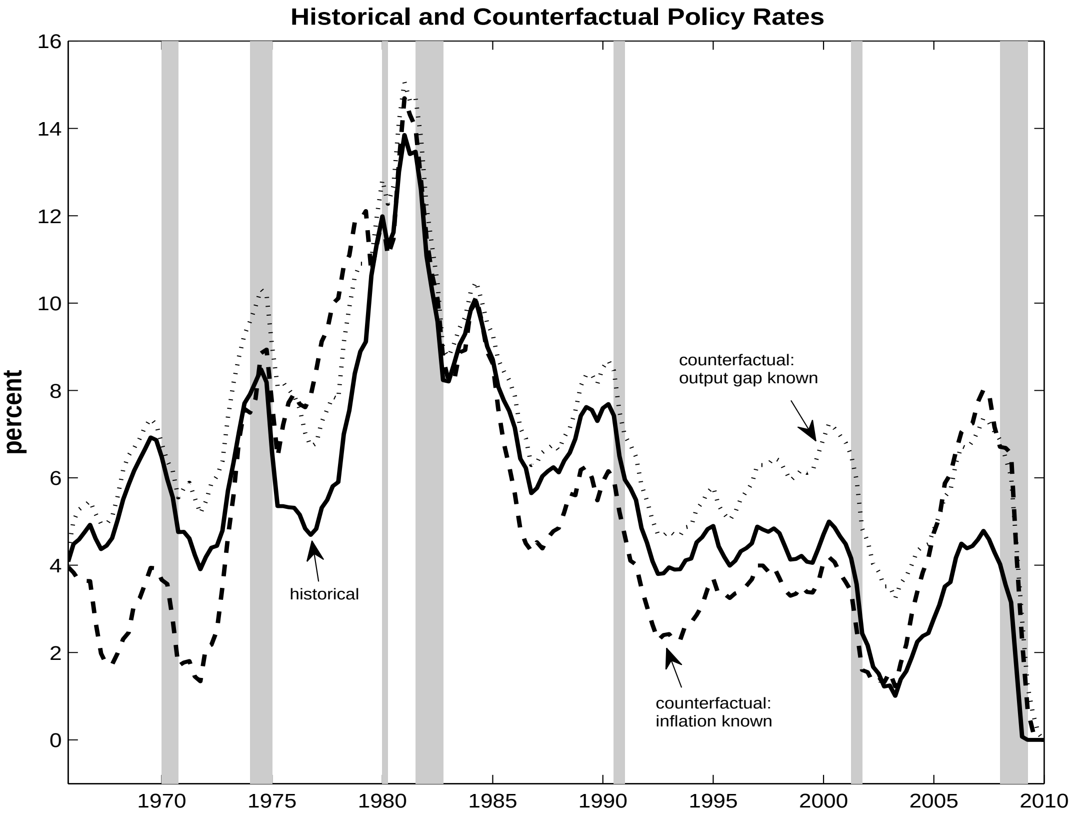

Fig. 4. The historical interest rate series (solid line) is generated from the partial information model evaluated at the point estimates reported in Table 3. The two counterfactual series are generated from the same model, but with either the output gap (dotted line) or inflation (dashed line) added to the vector of indicators. The shaded regions correspond to NBER recessions.

to the partial information model. The shocks are then reinserted into the model, holding the parameters fixed, but with either the output gap q_t or inflation π_t added to the set of indicators. The results are shown in Fig. 4.

With the exception of the Volcker disinflation and the period in which policymakers encountered the zero lower bound, uncertainty about the state had a considerable effect on policy outcomes. For example, had the Fed observed the output gap, the policy rate would have on occasion been more than 2 percentage points higher (e.g., 1975-1978 and 1999-2008). Over the full sample, the spread between the historical interest rate series and the one conditional on knowledge of q_t averaged 1.37 percentage points. Inflation uncertainty also appears to have been significant. Had the Fed possessed correct data on π_t, the policy rate would have been lower during the early 1970s but higher during the late 1970s. The same recognition would have also driven rates lower throughout most of the Greenspan era.

Fig. 4 also suggests that limited information was more problematic for policymakers during some periods than it was during others. The most prominent of these episodes appears to have been the inflationary years of 1974-1979 along with the real estate bubble and subsequent crash that took place between 2003 and 2009. In both periods the funds rate was considerably lower than what discretionary policy would have recommended had the Fed known the true values of either the output gap or inflation. By comparison, the effects of imperfect information were probably not as consequential throughout most of the Great Moderation era. From 1985 until 2003, policy would have been tighter had the Fed observed the output gap but looser had it seen the inflation rate instead. It follows that knowledge of both variables (i.e., complete information) would have shifted the Fed's policy rate in offsetting directions, resulting in an interest rate path lying somewhere between the two counterfactual series and therefore closer to the historical one.

Although simulations suggest that interest rates would have at times been different had the Fed possessed more information, it is not clear whether these differences would have altered the path of inflation. Fig. 5 plots the historical inflation series implied by optimal discretion along with two counterfactual inflation series formed using the same expanded information sets described earlier. Our estimates reveal that policymakers would not have been able to avert the rapid inflation of the mid-to-late 1970s even if the true values of inflation were known and interest rates were correspondingly higher. Inflation would still have risen dramatically in 1974 and then fluctuated between 1 and 2 percentage points above observed rates from 1975 through 1977.[30] Estimates from the second subsample indicate that

[30]Using evidence drawn from counterfactual simulations, Sims and Zha (2006) and Bianchi (2013) argue

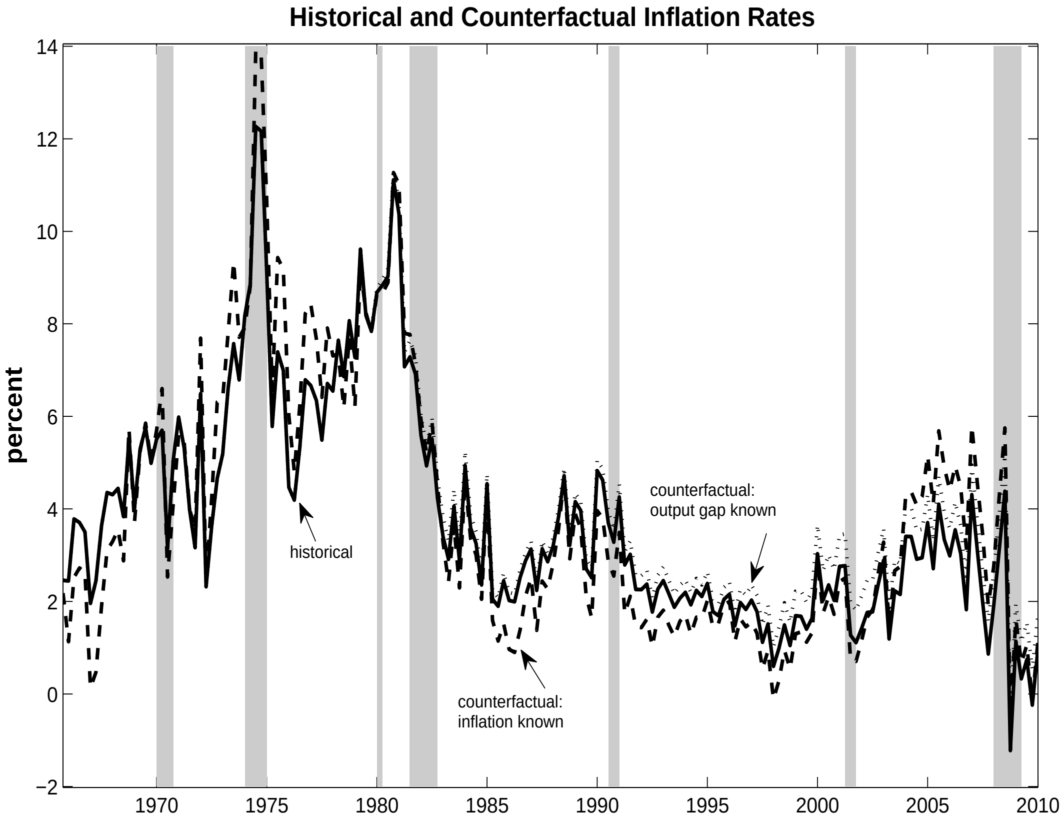

Fig. 5. The historical inflation series (solid line) is generated from the partial information model evaluated at the point estimates reported in Table 3. The two counterfactual series are generated from the same model, but with either the output gap (dotted line) or inflation (dashed line) added to the vector of indicators. The shaded regions correspond to NBER recessions.

inflation would have stabilized between one-half to one percentage point below historical levels throughout most of the 1980s and 1990s but would have drifted somewhat higher during the run-up to the Great Recession. Alternatively, had the Fed seen the true output gap in real time, inflation would have been anywhere from 0.25 to 0.75 percentage points higher during the 1990s and 2000s. At most other dates in the sample, and particularly in the pre-Volcker era, perfect knowledge of the output gap would not have changed inflation

that replacing the policy rule observed under Burns with the one observed under Volcker would not have changed the overall dynamics of inflation during the 1970s. While their work focuses on the singular role of the policy rule, our simulations demonstrate that inflation also would not have been thwarted by access to additional real-time information.

outcomes by a significant amount. This result is perhaps surprising because a popular interpretation of Orphanides (2001, 2002, 2004) is that inflation during the 1970s was driven mainly by errors in forecasting the output gap. Historical estimates based on our benchmark partial information model seem to cast doubt on this view for two reasons. One, the smoothed estimates presented in Fig. 2 show that output gap misperceptions were not manifestly larger in the mid-to-late 1970s than they were in other periods as Orhpanides contends. Two, had those misperceptions been zero, inflation would still have increased sharply as seen in Fig. 5 despite the Fed's endorsement of a loss function that assigned very little weight to output gap stability and interest-rate smoothing relative to inflation.

6 Concluding Remarks

This paper reports estimates from a semi-structural New Keynesian model with optimal discretionary policy under two different assumptions about the structure of information. In the first case market participants and the central bank only have partial (symmetric) knowledge about the state of the economy. In the the second case agents are assumed to have complete knowledge of the state. We estimate both versions separately using maximum likelihood on quarterly US data spanning 1965:Q4 to 2010:Q1, allowing for a breakpoint at the start of Volcker's chairmanship in 1979:Q3. Examining the estimates side-by-side sheds light on the ways in which accounting for informational limitations modifies our understanding of the economic structure and, in particular, the objectives of monetary policy.

Our results show that partial information affects estimates of the Federal Reserve's loss function and helps reconcile the conflict between optimal and observed policy. In contrast to the complete information results seen here and in the existing literature, we find that under partial information the relative weight on output gap stability is large and significant after 1979 and the weight on interest-rate smoothing is basically zero before 1979. According to the likelihood criterion, we also find that partial information improves the model's fit with revised data over the full sample. Additional likelihood-based comparisons reveal that discretionary policy outperforms a generalized Taylor rule in the context of partial information, whereas the opposite result emerges in the context of complete information. Given the well-known empirical properties of Taylor-type rules, this suggests that optimal and historical policies (at least since 1979) are more compatible under partial information.

To evaluate the economic significance of our findings, we use the Kalman smoother on the partial information model to recover historical estimates of both the true and perceived values of the output gap and inflation. Estimates reveal that past perceptions of the state were at times a far cry from reality. Moreover, real-time perception errors, particularly those associated with the output gap, were likely to persist for many quarters. This divergence between the perceived state and the true state exposes the magnitude of informational problems that policymakers face and therefore the importance for proper historical analysis of building realistic forms of uncertainty into macroeconometric models of optimal policy.

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