FISCAL FORESIGHT AND INFORMATION FLOWS

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ABSTRACT. News—or foresight—about future economic fundamentals can create rational expectations equilibria with non-fundamental representations that pose substantial challenges to econometric efforts to recover the structural shocks to which economic agents react. Using tax policies as a leading example of foresight, simple theory makes transparent the economic behavior and information structures that generate non-fundamental equilibria. Econometric analyses that fail to model foresight will obtain biased estimates of output multipliers for taxes; biases are quantitatively important when two canonical theoretical models are taken as data generating processes. Both the nature of equilibria and the inferences about the effects of anticipated tax changes hinge critically on hypothesized information flows. Different methods for extracting or hypothesizing the information flows are discussed and shown to be alternative techniques for resolving a non-uniqueness problem endemic to moving average representations.

Keywords: news, anticipated taxes, non-fundamental representation, identified VARs *JEL Codes*: C5, E62, H30

1. INTRODUCTION

A venerable tradition, often traced to Pigou (1927), ascribes a significant role in aggregate fluctuations to economic decision makers' responses to expectations about not-yet-realized economic fundamentals. That tradition finds voice in a recent surge of interest in the economic consequences of *news*—or *foresight*. Recent work explores how news affects the predictions of standard theories, seeks evidence of the impacts of news in time series data, and estimates dynamic stochastic general equilibrium models to quantify the relative importance of anticipated and unanticipated "shocks" to fundamentals.

Existing work typically posits a particular stochastic process for news, grounded in neither theory nor empirics. That process determines the economy's information flows and, in a rational expectations equilibrium, agents' expectations. Given the prominent role of expectations in the news literature, it is remarkable that existing work does not systematically

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examine how the specification of information flows affects the nature of equilibrium and the connection of theory to data. This paper addresses that gap.

For several reasons we focus on the difficulties associated with identifying the foreseen "shocks" to taxes. First, few economic phenomena provide economic agents with such clear signals about how important margins will change in the future: foresight is intrinsic to tax policy. Second, an institutional structure governs information flows about taxes: the process of changing taxes entails two kinds of lags—the inside lag, between when new tax law is initially proposed and when it is passed, and the outside lag, between when the legislation is signed into law and when it is implemented. That institutional structure informs the nature of tax information flows. Third, differential U.S. tax treatment of municipal and treasury bonds leads to a direct measure of tax news that offers a potential solution to modeling tax foresight. Such measures are scarce for news about nonpolicy fundamentals like total factor productivity. Despite the paper's focus on taxes, one of its key messages—that hypothesized information flows are critical to determining the impacts of news—extends immediately to other contexts.¹

Fiscal foresight poses a challenge to econometric analyses of fiscal policy because it generates an equilibrium with a non-fundamental moving average representation. Information sets of economic agents and the econometrician can be misaligned, with agents basing their choices on more information than the econometrician possesses. Structural shocks to tax policy, then, cannot be recovered from current and past fiscal data, a central assumption of conventional econometric methods. Instead, conventional methods can lead the econometrician to label as "tax shocks" objects that are linear combinations of all the exogenous disturbances at various leads and lags.²

This paper builds on and extends Hansen and Sargent's (1991b) general characterization of the implications of environments in which the history of innovations in a vector autoregression does not equal the history of information that agents observe. We go beyond treating invertibility as a 0–1 proposition by assessing the quantitative importance of failing to model foresight in two workhorse macroeconomic models. We offer a compelling economic example—tax foresight—that makes clear that non-fundamentalness and its consequences affect answers to substantive macroeconomic questions. Most importantly, we ground nonfundamentalness in economic theory, which points towards empirical lines of attack. Both Hansen and Sargent (1991b) and Fernández-Villaverde, Rubio-Ramírez, Sargent, and Watson (2007) have been read primarily as cautionary notes, in large part because they point to a serious problem, but not to a way forward.

¹In addition to taxes, studies have examined news about a wide range of fundamentals, including total factor and investment-specific productivity [Beaudry and Portier (2006), Christiano, Ilut, Motto, and Rostagno (2008), Jaimovich and Rebelo (2009), Schmitt-Grohé and Uribe (2012), Fujiwara, Hirose, and Shintani (2011)]; government military spending run ups [Fisher and Peters (2010), Ramey (2011)]; phased-in government infrastructure spending [Leeper, Walker, and Yang (2010)]; announcements of interest-rate paths by inflation-targeting central banks [Blattner, Catenaro, Ehrmann, Strauch, and Turunen (2008), Laséen and Svensson (2011)]. All of these applications lend themselves to the analysis that we conduct.

²Issues associated with non-fundamentalness were pointed out in the rational expectations econometrics literature by Hansen and Sargent (1980, 1991b) and Lippi and Reichlin (1993, 1994) and recently emphasized by Fernández-Villaverde, Rubio-Ramírez, Sargent, and Watson (2007). Leeper (1989) and Yang (2005) examine the issues in the context of tax foresight.

No consensus exists on how to handle tax foresight, a fact that is underscored by the diverse empirical findings in the literature. Research concludes that an anticipated cut in taxes may have little or no effect [Poterba (1988), Blanchard and Perotti (2002), Romer and Romer (2010)], may be mildly expansionary in the short run [Mountford and Uhlig (2009)], or may be strongly contractionary in the short run [House and Shapiro (2006), Mertens and Ravn (2011)]. By using different measures of tax news and different methodologies, these studies implicitly posit different tax information flows, which, as we show, can produce strikingly different inferences about the effects of anticipated tax changes.

The paper has three parts:

- (1) A simple analytical example makes precise how foresight and optimizing behavior create equilibria with non-fundamental moving average representations. The example makes the source of non-fundamentalness transparent: it arises as a natural by-product of the fact that agents' optimal intertemporal decisions discount future tax obligations. Although private agents discount tax *rates* in the usual way, they discount recent tax *news* more heavily than past news because with foresight the recent news informs about taxes in the more distant future. The econometrician, in contrast, discounts in the usual way, down weighting older news relative to recent news. Agents and the econometrician employ different discounting patterns because the econometrician's information set lags the agents'.
- (2) Simple analytics reveal the source of non-fundamentalness, but do not shed light on whether it matters in practice. Using two canonical dynamic stochastic general equilibrium models—Chari, Kehoe and McGrattan's (2008) real business cycle model and Smets and Wouters' (2003; 2007) new Keynesian model—as data generating processes, we quantify the inference errors an econometrician might make by failing to model foresight. We tie those errors to alternative, empirically motivated specifications of tax news processes—information flows that distinguish between the "inside" and "outside" lags associated with tax policies. Estimates of tax multipliers can be off by hundreds of percent and can even be of the wrong sign. Biases can be positive or negative, but the econometrician tends to underestimate the effects of foresight over longer horizons.
- (3) We discuss several lines of attack that offer a way forward in dealing with nonfundamental equilibria. We show that seemingly unrelated approaches—the narrative approaches of Ramey (2011) and Romer and Romer (2010) and the dynamic stochastic general equilibrium approach of Schmitt-Grohé and Uribe (2012)—are solving the problems associated with foresight in a similar fashion: by expanding the information set of the econometrician in order to resolve a non-uniqueness problem endemic to moving average representations.

2. Analytical Example

This section introduces fiscal foresight into a simple economic environment where the econometric issues can be exposited analytically. Results and conclusions reached in the simple exposition extend to more general setups, as section 2.2 discusses.

Consider a standard growth model with a representative household that maximizes expected log utility, $E_0 \sum_{t=0}^{\infty} \beta^t \log(C_t)$, subject to $C_t + K_t + T_t \leq (1 - \tau_t) A_t K_{t-1}^{\alpha}$, where C_t , K_t , Y_t , T_t , and τ_t denote time-t consumption, capital, output, lump-sum taxes, and the income tax rate respectively, and A_t is an exogenous technology shock. As usual, $0 < \alpha < 1$ and $0 < \beta < 1$. The government sets the tax rate according to a time-invariant rule and adjusts lump-sum transfers to satisfy the constraint, $T_t = \tau_t Y_t$. Government spending is identically zero. We assume complete depreciation of capital. Labor is supplied inelastically which, as section 3.3 shows, understates the problems that foresight creates.

The equilibrium conditions are well known and given by

$$\frac{1}{C_t} = \alpha \beta E_t \left[(1 - \tau_{t+1}) \frac{1}{C_{t+1}} \frac{Y_{t+1}}{K_t} \right]$$
(1)

$$C_t + K_t = Y_t = A_t K_{t-1}^{\alpha} \tag{2}$$

Let A and τ denote the steady state values of technology and the tax rate. The steady state capital stock is $K = [\alpha\beta(1-\tau)A]^{1/(1-\alpha)}$. Let lower case letters denote percentage deviations from steady state values, $k_t = \log(K_t) - \log(K)$, $a_t = \log(A_t) - \log(A)$, and $\hat{\tau}_t = \log(\tau_t) - \log(\tau)$. Log linearize and combine (1) and (2) to produce a second-order difference equation in capital

$$E_t k_{t+1} - (\theta^{-1} + \alpha) k_t + \alpha \theta^{-1} k_{t-1} = E_t [a_{t+1} - \theta^{-1} a_t] + \left\{ \theta^{-1} (1 - \theta) \left(\frac{\tau}{1 - \tau} \right) \right\} E_t \hat{\tau}_{t+1} \quad (3)$$

where $\theta = \alpha \beta (1 - \tau)$ is a particularly important constant in the analysis. Assuming an *i.i.d.* technology shock, the solution to (3) is

$$k_t = \alpha k_{t-1} + a_t - (1-\theta) \left(\frac{\tau}{1-\tau}\right) \sum_{i=0}^{\infty} \theta^i E_t \hat{\tau}_{t+i+1}$$

$$\tag{4}$$

Equilibrium investment depends negatively on the expected discounted present value of future tax rates, a well-known result [Lucas (1976), Abel (1982), Judd (1985), Auerbach (1989)]. Of course, more distant tax rates receive heavier discounting than more recent rates.

To model foresight, we must specify how news about taxes signals future tax rates. For many of the points we wish to make, it suffices to assume that tax information flows take a particularly simple form: agents at t receive a signal that tells them exactly what tax rate they will face in period t + q. In later sections we will both relax this assumption and posit more sophisticated rules for tax rates. The tax rule is $\tau_t = \tau e^{\varepsilon_{\tau,t-q}}$ or in log-linearized form

$$\hat{\tau}_t = \varepsilon_{\tau, t-q} \tag{5}$$

Assume the technology and tax shocks— $\varepsilon_{A,t}$ and $\varepsilon_{\tau,t}$ —are *i.i.d.* and the representative agent's information set at date t consists of variables dated t and earlier, including the shocks, $\{\varepsilon_{A,t}, \varepsilon_{\tau,t}\}$. Given the tax news process in (5), this implies that at t the agent has (perfect) knowledge of $\{\hat{\tau}_{t+q}, \hat{\tau}_{t+q-1}, \ldots\}$.

Using the information flows in (5) to solve for expected tax rates in (4) for various degrees of fiscal foresight yields the following equilibrium dynamics:

$$q = 0$$
 implies:

$$k_t = \alpha k_{t-1} + \varepsilon_{A,t} \tag{6}$$

q = 1 implies:

$$k_t = \alpha k_{t-1} + \varepsilon_{A,t} - \kappa \varepsilon_{\tau,t} \tag{7}$$

q = 2 implies:

$$k_t = \alpha k_{t-1} + \varepsilon_{A,t} - \kappa \bigg\{ \varepsilon_{\tau,t-1} + \theta \varepsilon_{\tau,t} \bigg\}$$
(8)

q = 3 implies:

$$k_t = \alpha k_{t-1} + \varepsilon_{A,t} - \kappa \left\{ \varepsilon_{\tau,t-2} + \theta \varepsilon_{\tau,t-1} + \theta^2 \varepsilon_{\tau,t} \right\}$$
(9)

where $\kappa = (1 - \theta)(\tau/(1 - \tau)).$

If there is no foresight, q = 0, we get the usual result that *i.i.d.* shocks to tax rates have no effect on capital accumulation. When there is some degree of tax foresight (q > 0), rational agents will adjust capital contemporaneously to yield the unusual result that even serially uncorrelated tax hikes reduce capital accumulation. Fiscal foresight manifests in the additional moving average terms present in the equilibrium representation, with the number of moving average terms increasing in the foresight horizon.

A striking, though seemingly perverse, implication of (8) and (9) is that more *recent* news is discounted (by $\theta = \alpha\beta(1-\tau) < 1$) relative to older news. This is because with two-quarter foresight, $\varepsilon_{\tau,t-1}$ affects $\hat{\tau}_{t+1}$, while $\varepsilon_{\tau,t}$ affects $\hat{\tau}_{t+2}$, so the news that affects tax rates farther into the future receives the heaviest discount. While tax *rates* are discounted in the usual way, tax *news* is discounted in reverse order. This difference in discounting between tax rates and tax news stems from optimizing behavior and underlies the econometric problems that foresight creates.

2.1. The Econometrics of Foresight. The moving average terms that foresight produces pose challenges for econometric inference. Conventional econometric analyses, such as those using identified vector autoregressions (VARs), can draw erroneous conclusions. Errors arise because models with foresight may imply that the information set of private agents is larger than the econometrician's.

An econometrician who estimates an identified VAR seeks to condition on the same information set as the economic agents in order to recover the structural shocks $\{\varepsilon_{\tau,t-j}\}_{j=0}^{\infty}$. Typically, this is achieved by conditioning the VAR estimates on current and past observables. Consider the univariate case of conditioning on current and past capital, $\{k_{t-j}\}_{j=0}^{\infty}$, and suppose that agents have two quarters of foresight. Using lag operators (i.e., $L^s x_t = x_{t-s}$), (8) may be written as

$$(1 - \alpha L)k_t = -\kappa (L + \theta)\varepsilon_{\tau,t} \tag{10}$$

Will the econometrician's conditioning set, current and past capital, span the same space as the agents' current and past structural shocks?³ The answer depends on whether $\{\varepsilon_{\tau,t-j}\}_{j=0}^{\infty}$

³More specifically, the information sets are equivalent if the Hilbert space generated by $\{k_{t-j}\}_{j=0}^{\infty}$ is equivalent (in mean-square norm) to the Hilbert space generated by $\{\varepsilon_{\tau,t-j}\}_{j=0}^{\infty}$.

is fundamental for $\{k_{t-j}\}_{j=0}^{\infty}$, using the terminology of Rozanov (1967). Fundamentalness requires the equilibrium process to be invertible in current and past k_t , so that

$$\left[\frac{1-\alpha L}{1+\theta^{-1}L}\right]k_t$$

is a convergent sequence. If $|\theta| > 1$, this condition holds and $\{k_{t-j}\}_{j=0}^{\infty}$ spans the same space as $\{\varepsilon_{\tau,t-j}\}_{j=0}^{\infty}$. But a unique saddlepath solution requires $|\theta| < 1$. Therefore, $\{\varepsilon_{\tau,t-j}\}_{j=0}^{\infty}$ is not fundamental for $\{k_{t-j}\}_{j=0}^{\infty}$.

To determine the econometrician's information set, we derive the Wold representation for k_t from the one-step-ahead forecast errors associated with predicting k_t conditional only on its past values. This representation emerges from flipping the root of the moving average representation from inside the unit circle to outside the unit circle using the Blaschke factor, $[(L+\theta)/(1+\theta L)]$ [see Hansen and Sargent (1991b) or Lippi and Reichlin (1994)]. The Wold representation for capital is

$$(1 - \alpha L)k_t = -\kappa (L + \theta) \left[\frac{1 + \theta L}{L + \theta} \right] \left[\frac{L + \theta}{1 + \theta L} \right] \varepsilon_{\tau,t}$$
$$= -\kappa (1 + \theta L) \qquad \varepsilon_{\tau,t}^*$$
$$= -\kappa \left\{ \theta \varepsilon_{\tau,t-1}^* + \varepsilon_{\tau,t}^* \right\}$$
(11)

By observing current and past capital, the econometrician recovers current and past ε_{τ}^* , rather than the news that private agents observe, current and past ε_{τ} . The econometrician's innovations are the statistical shocks associated with estimating the autoregressive representation; those shocks represent information that is mostly "old news" to the agents of the economy. Fundamental shocks map into the econometrician's shocks as

$$\varepsilon_{\tau,t}^* = \left[\frac{L+\theta}{1+\theta L}\right]\varepsilon_{\tau,t} = (L+\theta)\sum_{j=0}^{\infty} -\theta^j \varepsilon_{\tau,t-j}$$
$$= \theta\varepsilon_{\tau,t} + (1-\theta^2)\varepsilon_{\tau,t-1} - \theta(1-\theta^2)\varepsilon_{\tau,t-2} + \theta^2(1-\theta^2)\varepsilon_{\tau,t-3} + \cdots$$
(12)

This mapping shows that what the econometrician recovers as the tax innovation at time t, $\varepsilon_{\tau,t}^*$, is actually a discounted sum of the tax news observed by the agents at date t and earlier.

An econometrician who ignores foresight will discount the innovations incorrectly. In the econometrician's representation, yesterday's innovation has less effect than today's innovation, as the terms $\theta \varepsilon_{\tau,t-1}^* + \varepsilon_{\tau,t}^*$ in (11) show when $|\theta| < 1$. Agents with foresight, in contrast, discount news according to $\varepsilon_{\tau,t-1} + \theta \varepsilon_{\tau,t}$, as in (8), because yesterday's news has a larger effect on capital accumulation than today's news. Differences in discounting patterns applied by the econometrician and the agents lead to a variety of econometric problems.

By not modeling foresight, the econometrician has conditioned on a smaller information set. The extent to which private agents condition on information that is not captured by current and past variables in the econometrician's information set determines the error associated with the VAR. This error can be mapped directly into the θ parameter that governs the

non-invertibility of the equilibrium moving-average representation. The variance of the onestep-ahead forecast error for the agent is

$$E[(k_{t+1} - E[k_{t+1}|\varepsilon^t])^2] = E\left[\left(\frac{-\kappa(L+\theta)}{1-\alpha L}\varepsilon_{\tau,t+1} - L^{-1}[-\frac{\kappa(L+\theta)}{1-\alpha L} + \kappa\theta]\varepsilon_{\tau,t}\right)^2\right]$$
$$= (\kappa\theta)^2 \sigma_\tau^2$$
(13)

where ε^t denotes current and past ε . For the econometrician's information set, the variance of the forecast error is

$$E[(k_{t+1} - E[k_{t+1}|k^t])^2] = E\left[\left(\frac{-\kappa(L+\theta)}{1-\alpha L}\varepsilon_{\tau,t+1} - L^{-1}\left[-\frac{\kappa(1+\theta L)}{1-\alpha L} + \kappa\right]\left[\frac{L+\theta}{1+\theta L}\right]\varepsilon_{\tau,t}\right)^2\right]$$
$$= \kappa^2 \sigma_{\tau}^2$$
(14)

The ratio of (13) to (14) is θ^2 . As θ^2 approaches unity (zero), the difference between the agent's and econometrician's information sets gets smaller (larger). If θ is greater than or equal to 1, the representation for capital becomes fundamental with respect to $\varepsilon_{\tau,t}$ and the variances of the forecast errors in (13) and (14) coincide.

To examine the importance of the information discrepancies in this model, we plot impulse response functions conditioning on the agents' and econometrician's information sets. Impulse response functions are widely used to convey how *agents* respond to innovations, but response functions based on the econometrician's information set will not capture these responses. Consider the impulse response functions generated by (8) and (11). Figure 1a plots the responses of capital to a one-standard deviation innovation, assuming two quarters of foresight (with $\alpha = 0.36$, $\beta = 0.99$, $\tau = 0.25$, $\sigma_{\tau}^2 = 1$). With foresight, agents know exactly when the innovation in fiscal policy translates into changes in the tax rate. This creates the sharp decline in capital one quarter after the news arrives and before the tax rate changes, as the dotted-dashed line indicates. The econometrician's VAR, though, discounts the innovations incorrectly and reports that the biggest decline in capital occurs on impact, suggesting that foresight does not exist (solid line). The difference between the response functions can be quite dramatic, especially at short horizons.

Figure 1a shows that the econometrician will infer that the tax shock is unanticipated. Of course, not all shocks that affect fiscal policy are known several quarters in advance. Consider a tax rate process, $\hat{\tau}_t = e_{\tau,t}^u + \varepsilon_{\tau,t-q}$, that allows for both anticipated (ε_{τ}) and unanticipated (e_{τ}^u) shocks at time t. If these shocks are orthogonal at all leads and lags, then the equilibrium dynamics of (3) will not change because *i.i.d.* tax shocks will not alter the dynamics of capital. An econometrician who does not account for foresight will attribute *all* of the dynamics associated with the anticipated component of the tax rate to the unanticipated component. This suggests that researchers interested in the dynamic effects of fiscal policy—whether the interest is in anticipated or unanticipated changes in policy—must explicitly account for foresight to avoid spurious conclusions.

Conditioning on more variables will not always lead to better inference. In the case of two-quarter foresight, suppose the econometrician estimates a VAR that includes the tax



FIGURE 1: Responses of Capital to Tax Increase with $\alpha = 0.36, \beta = 0.99, \tau = 0.25$. Figure 1a plots the response of (13) and (14). Figure 1b plots the response to the VAR $(\tau_t, k_t)'$. Both figures assume two quarters of foresight.

rate and the capital stock as observables

$$\begin{bmatrix} \hat{\tau}_t \\ k_t \end{bmatrix} = \begin{bmatrix} L^2 & 0 \\ \frac{-\kappa(L+\theta)}{1-\alpha L} & \frac{1}{1-\alpha L} \end{bmatrix} \begin{bmatrix} \varepsilon_{\tau,t} \\ \varepsilon_{A,t} \end{bmatrix}$$
$$\mathbf{x}_t = \mathcal{H}(L)\boldsymbol{\epsilon}_t \tag{15}$$

A necessary condition for $\boldsymbol{\epsilon}_t$ to be a fundamental for \mathbf{x}_t is that the determinant of $\mathcal{H}(z)$ be analytic with no zeros inside the unit circle. Foresight creates a zero inside the unit circle (at z = 0), implying that the information set generated by { $\mathbf{x}_t, \mathbf{x}_{t-1}, \mathbf{x}_{t-2}, ...$ } is smaller than the information set generated by { $\boldsymbol{\epsilon}_t, \boldsymbol{\epsilon}_{t-1}, \boldsymbol{\epsilon}_{t-2}, ...$ }.

The Wold representation for (15) is obtained by finding Blaschke matrices $\mathcal{B}(L)$ and orthonormal matrices W, \tilde{W} that do not alter the covariance generating function of \mathbf{x}_t , but "flip" the zeros outside of the unit circle. To do this we seek a B(L), W, and \tilde{W} that satisfy $\mathcal{B}(L)\mathcal{B}(L^{-1})' = I$ and WW' = I, $\tilde{W}\tilde{W}' = I$, and produce innovations that span the space generated by $\{\mathbf{x}_t, \mathbf{x}_{t-1}, \mathbf{x}_{t-2}, ...\}$. The first step in the algorithm is to evaluate $\mathcal{H}(L)$ at L = 0, and postmultiply by W so as to put the zeros in the first column of the product matrix [Townsend (1983, appendix A), Rozanov (1967)]. Remaining columns of W can be constructed from a Gram-Schmidt orthogonalization procedure. The orthonormal W matrix ensures that the representation remains causal, preserving the assumption that the econometrician does not observe future values of the variables. Postmultiplying by B(L) flips the zero outside of the unit circle. With two zeros inside the unit circle for (15), repeat this algorithm (find an orthonormal matrix \tilde{W} that aligns the zeros in the first column, etc.). Proceeding in this fashion delivers the representation

$$\begin{bmatrix} \hat{\tau}_t \\ k_t \end{bmatrix} = \underbrace{\begin{bmatrix} L^2 & 0 \\ \frac{-k(L+\theta)}{1-\alpha L} & \frac{1}{1-\alpha L} \end{bmatrix}}_{\mathbf{X}_t} W \mathcal{B}(L) \tilde{W} \mathcal{B}(L) \underbrace{\mathcal{B}(L^{-1})}_{\mathcal{W}'} \mathcal{B}(L^{-1}) W' \begin{bmatrix} \varepsilon_{\tau,t} \\ \varepsilon_{A,t} \end{bmatrix}}_{\boldsymbol{\epsilon}_t} \mathbf{x}_t = \underbrace{\mathcal{H}^*(L)}_{\mathcal{H}^*} \mathbf{e}_t^* \tag{16}$$

where

$$W = \begin{bmatrix} \frac{1}{\sqrt{1+(\theta\kappa)^2}} & \frac{-\kappa\theta}{\sqrt{1+(\theta\kappa)^2}} \\ \frac{\kappa\theta}{\sqrt{1+(\theta\kappa)^2}} & \frac{1}{\sqrt{1+(\theta\kappa)^2}} \end{bmatrix}, \tilde{W} = \begin{bmatrix} \Delta(1+\kappa^2\theta^2) & -\Delta\kappa \\ \Delta\kappa & \Delta(1+\kappa^2\theta^2) \end{bmatrix}, \mathcal{B}(L) = \begin{bmatrix} L^{-1} & 0 \\ 0 & 1 \end{bmatrix}$$
$$\Delta = \begin{bmatrix} (1+\kappa^2\theta^2)^2 + \kappa^2 \end{bmatrix}^{-1/2}$$

and $\Delta = [(1 + \kappa^2 \theta^2)^2 + \kappa^2]^{-1/2}.$

Now the econometric problems are more severe. First, the econometrician who proceeds with VAR analysis using (16) will likely obtain an impulse response function in which foresight does not appear to exist in the data. Figure 1b depicts the response of capital to a tax increase for the agent (dotted-dashed line) and econometrician as the variance of the technology shock decreases from 1 to 0.01. Conditioning on the econometrician's information set, the path of capital is flat when $\sigma_a^2 = \sigma_{\tau}^2 = 1$. In theory, unanticipated *i.i.d.* capital tax shocks have no effect on the economy, so based on the flat response of capital, an econometrician will infer that the effects of fiscal policy are limited to unanticipated components only. By not modeling foresight, the econometrician achieves a "self-fulfilling prophesy" and wrongly concludes that foresight is not an issue.⁴

Second, as the variance of the tax shock increases relative to the technology shock, the errors associated with foresight become more pronounced. Figure 1b shows that the initial response of capital to a one-standard-deviation increase in the tax shock *increases* from 0 to 0.12 as σ_a^2 decreases from 1 to 0.01, so that an anticipated tax increase could be estimated to have no effect or a positive effect on capital and output.

Existing empirical work reports a diverse set of inferences about the effects of an anticipated tax increase on output. Figures 1a and 1b demonstrate that even this simple model can deliver diverse results that depend on the underlying information flows.

Finally, *all* conditional statistics reported by the econometrician will be misspecified. Consider the variance decompositions that Hansen and Sargent (1991b) emphasize. Let

$$E(\mathbf{x}_t - E_{t-j}^* \mathbf{x}_t)(\mathbf{x}_t - E_{t-j}^* \mathbf{x}_t)' = \sum_{k=0}^{j-1} \mathcal{H}_k^* \Sigma^* \mathcal{H}_k'^*$$

denote the *j*-step ahead prediction error variance associated with the econometrician's information set, where Σ^* is the variance-covariance matrix associated with $(\varepsilon^*_{\tau,t}, \varepsilon^*_{A,t})'$. Like impulse response functions, variance decompositions are derived using *conditional* expectations, so the discrepancy in the information sets implies that the coefficients generated by

⁴With this simple form of foresight, an econometrician who estimates a VAR in $(\hat{\tau}_{t+q}, k_t)$ will recover the true shocks. But more sophisticated information flows, as in later sections, or empirically plausible tax rules, as in Leeper, Plante, and Traum (2010), preclude that easy fix.

 $\mathcal{H}^*(L)$ will misallocate the variance across the structural shocks.⁵ Figure 1b suggests that the econometrician will treat the tax shock as nearly *i.i.d.* and infer that none of the variation in capital (and hence output) can be attributed to tax innovations; all of the variation will be attributed to the technology shock. This inference holds even if, in fact, the tax shock explained nearly all of the variation in capital (for example, when the variance of the technology shock, σ_A^2 , is arbitrarily small).

Further implications of foresight appear in the online appendix, where we show that Granger causality tests and tests of economic theory, such as tests of present value restrictions, will be misspecified in the presence of foresight. Errors associated with ignoring foresight can be quite large.

2.2. Generalizations. The previous example assumes an *i.i.d.* tax shock, but the difficulties associated with foresight extend to more general setups. Suppose the stationary tax rate follows $\hat{\tau}_t = C(L)L^q \varepsilon_{\tau,t}$, where C(L) is a polynomial in the lag operator L and q is the degree of foresight. The only restriction placed on C(L) is that the corresponding coefficients are square summable, which allows for *any* serial correlation pattern. Agents guess that the law of motion for capital is given by a square summable linear combination of tax and technology shocks, $k_t = F(L)\varepsilon_{\tau,t} + G(L)\varepsilon_{a,t}$, as Whiteman (1983) shows. Focusing on tax shocks only and substituting this guess into the difference equation for capital in (3) yields

$$\theta L^{-1}[F(L) - F_0]\varepsilon_{\tau,t} - (1 + \alpha\theta)F(L)\varepsilon_{\tau,t} + \alpha LF(L)\varepsilon_{\tau,t} = \left\{ (1 - \theta)\left(\frac{\tau}{1 - \tau}\right) \right\} E_{t+1}\hat{\tau}_{t+1}$$

where the Wiener-Kolmogorov formula is used to take expectations (i.e., $E_t x_{t+1} = L^{-1}[D(L) - D_0]\varepsilon_{x,t}$, where $D(L)\varepsilon_{x,t}$ is the Wold representation), and $\theta = \alpha\beta(1-\tau)$. Uniqueness of the rational expectations equilibrium requires $|\theta| < 1$, where the equilibrium $F(L)\varepsilon_{\tau,t}$ for q periods of foresight is given by

$$F(L)\varepsilon_{\tau,t} = -\left[\frac{\kappa[L^qC(L) - \theta^qC(\theta)]}{(1 - \alpha L)(L - \theta)}\right]\varepsilon_{\tau,t}$$
(17)

This equation makes plain how foresight impinges on optimal capital accumulation for any choice of C(L). Whenever $q \ge 2$, the equilibrium contains moving average components even when C(L) is purely autoregressive. This representation suggests that it is straightforward to construct impulse response functions that take a wide range of shapes (including hump-shaped), for which the dynamic equation for capital continues to be non-invertible in current and past k_t .

The logic that leads foresight to produce equilibria with non-fundamental moving-average representations extends to a large class of models. Consider the generic multivariate rational expectations model

$$\Gamma_0 y_t = \Gamma_1 y_{t-1} + \Psi z_t + \Pi \eta_t \tag{18}$$

where y_t is an $n \times 1$ vector of endogenous variables, z_t is an $m \times 1$ vector of exogenous random shocks, η is a $k \times 1$ vector of expectation errors, which satisfy $E_t \eta_{t+1} = 0$ for all t. Γ_0 and Γ_1 are $n \times n$ coefficient matrices, along with Ψ ($n \times m$) and Π ($n \times k$). Klein (2000)

⁵This result holds even though the statistical shocks of the VAR remain uncorrelated. Orthogonality of the Blaschke and W matrices $(\mathcal{B}(L)\mathcal{B}(L^{-1}) = I$ and $WW' = \tilde{W}\tilde{W}' = I$) implies that the unconditional second moments of the VAR system remain the same, but the conditional moments will be different.

and Sims (2002) use a generalized Schur decomposition of Γ_0 and Γ_1 to show that there exist matrices such that $Q'\Lambda Z' = \Gamma_0$, $Q'\Omega Z' = \Gamma_1$, $Q'Q = Z'Z = I_{n\times n}$, where Λ and Ω are upper-triangular. The ratios of the diagonal elements of Ω and Λ , ω_{ii}/λ_{ii} , are the generalized eigenvalues. Defining $w_t = Z'y_t$ and pre-multiplying (18) by Q, yields the decomposition

$$\begin{bmatrix} \Lambda_{11} & \Lambda_{12} \\ 0 & \Lambda_{22} \end{bmatrix} \begin{bmatrix} w_{1,t} \\ w_{2,t} \end{bmatrix} = \begin{bmatrix} \Omega_{11} & \Omega_{12} \\ 0 & \Omega_{22} \end{bmatrix} \begin{bmatrix} w_{1,t-1} \\ w_{2,t-1} \end{bmatrix} + \begin{bmatrix} Q_1 \\ Q_2 \end{bmatrix} (\Psi z_t + \Pi \eta_t)$$
(19)

The system is partitioned so that the generalized eigenvalues imply an explosive path for $w_{2,t}$. Analogous to (4), $w_{2,t}$ must be solved forward to ensure stability of the system. Sims shows that the forward solution of (18) is

$$y_t = \Theta_1 y_{t-1} + \Theta_0 z_t + \Theta_y \Theta_z \sum_{s=1}^{\infty} \Theta_f^{s-1} E_t z_{t+s}$$

$$\tag{20}$$

where $\Theta_f = \Omega_{22}^{-1} \Lambda_{22}$ is the inverse of the unstable eigenvalues, and $\Theta_z = \Omega_{22}^{-1} Q_2 \Psi$. Θ_f is the multivariate analog to θ in the simple analytical example and satisfies $\sum_{j=0}^{\infty} \operatorname{tr} \Theta_f \Theta'_f < \infty$.⁶

If the structural shocks, z_t , are *i.i.d.* and agents do not have foresight, then the last term in (20) drops out of the solution and the equilibrium has a VAR representation. In this case, conditioning on the control and state variables, y_t , allows a VAR to recover the structural shocks. But when agents have foresight, the equilibrium representation becomes a VARMA with the MA coefficients Θ_f . Suppose the structural shocks are given by $z_t = \epsilon_{t-q}$, and agents have foresight—at date t they observe ϵ 's dated t and earlier, then the equilibrium is

$$y_t = \Theta_1 y_{t-1} + \Theta_0 \epsilon_{t-q} + \Theta_y \Theta_z [\epsilon_{t-q+1} + \Theta_f \epsilon_{t-q+2} + \dots + \Theta_f^{q-1} \epsilon_t].$$
(21)

As in the univariate case, the fiscal variables in (20), z_{t+s} , are discounted in the usual way, but the news innovations in (21), ϵ_{t-q} , are discounted perversely, with more recent news discounted the heaviest. This is why models with foresight are more likely to deliver nonfundamental equilibrium representations.

The y_t vector contains endogenous variables, which, like capital in the simple analytical model of section 2, are typically forward looking. We established in the Wold representation (15) that simply adding forward-looking variables to the VAR does not always resolve the noninvertibility. In rational expectations models, endogenous variables respond contemporaneously to news about future tax rates, but (21) shows that the contemporaneous response of these variables will be discounted by Θ_f^{q-1} . Most of the adjustment in variables to news occurs at future dates (in periods t + q), rather than contemporaneously (at t). To derive a fundamental VARMA representation, we need to augment (21) with a variable whose representation does not suffer from the perverse discounting. That variable's largest response to news will occur contemporaneously and news will be discounted in the usual way, as in (20). This makes the moving average part of (21) invertible, ensuring the econometrician's information set is consistent with the agents'.

⁶Mertens and Ravn (2010) derive this restriction in a real business cycle model with one unstable eigenvalue and refer to Θ_f as the "anticipation rate" because it is the rate at which news or foresight is discounted. In line with our findings, they argue that this relationship between the anticipation rate and unstable eigenvalues is a robust feature of models with foresight.

The extent to which foresight leads to econometric errors depends on the underlying structure of the economy, the nature of information flows and econometric specifications. The next section examines these issues in two canonical macro models.

3. QUANTITATIVE IMPORTANCE OF FORESIGHT

The information flows specification in (5) was chosen for its analytical convenience, not for its plausibility. To assess the quantitative importance of foresight, this section generalizes those flows to capture actual news processes and embeds the generalized specification in two empirically motivated DSGE models. We show how the nature of information flows affects the inference errors an econometrician can make by not modeling foresight. Quantitative importance is summarized by dynamic tax multipliers, comparing those estimated by an econometrician who fits an identified VAR to the true tax multipliers.

3.1. Modeling Information Flows. Rich information flows characterize the arrival and accumulation of news about tax changes, but generally fall into two periods: between initial proposal and final enactment—or rejection—of a new tax law ("inside lag") and between enactment and when the law takes effect ("outside lag").⁷ During the inside lag, information and expectations evolve about the likelihood and the precise form of proposed legislation. Sources of information that mark the beginning of the inside lag can be formal—a president's State of the Union speech—or informal—a politician's campaign pledges. And this early information may be confirmed or contravened by subsequent actions.⁸ Outside lags arise whenever there is a delay between the legislation's passage and its implementation, as when tax changes are phased in. The two types of lags differ in important ways. During the inside lag, anticipated taxes are uncertain; news arrives regularly and induces agents to update their expectations. Agents are solving a dynamic signal extraction problem in an attempt to distinguish noise from news. During the outside lag, the tax law has been adopted, no more news arrives, and agents have perfect foresight about future tax rates.

Examples clarify the nature of information flows. The Economic Recovery Tax Act of 1981, enacted in August 1981, phased in tax reductions through the beginning of 1984 to yield an outside lag of 10 quarters. In announcing his candidacy for president in November 1979, Ronald Reagan made clear that he intended to substantially lower taxes: "The key to restoring the health of the economy lies in cutting taxes" [Reagan (1979)]. News about future taxes then arrived throughout 1980, evolving with Reagan's prospects of winning office. An additional six months passed between President Reagan's formal call for tax relief in February 1981 and the legislation's enactment. The inside lag associated with this tax change is, arguably, five or more quarters, with the weights agents place on the bits of news changing over time. Taken together, the two lags imply a foresight period of about four years.

⁷These labels date back to Friedman (1948), where we combine the "recognition" and "decision" lags to form inside lags and our outside lags refer to how long it takes legislation to change tax rates.

⁸Announcing their candidacies, both Ronald Reagan and George W. Bush made clear their intentions to cut taxes well over a year before they took office and formally proposed tax cuts. George H. W. Bush, in contrast, pledged in his announcement speech, "I am not going to raise your taxes—period." That was two-and-a-half years before he called for a tax increase. See http://www.4president.org for these speeches.

Adjustments to Social Security taxes can entail extraordinarily long lags. The National Commission on Social Security Reform was established in December 1981 to recommend solutions to the System's short- and long-term solvency problems. Its recommendations, reported in January 1983, formed the basis for the Social Security Amendments of 1983, which were enacted in April 1983. The Amendments phased in payroll tax increases beginning in 1984 and extending to 1990. Although their inside lag may have been only a few quarters, the Amendments' outside lag is over six years. Other changes in Social Security taxes had comparably long lags.

To model these intricacies, we generalize (5) with a specification of information flows about tax rates that is flexible enough to capture both inside and outside lags. For labor taxes, we posit

$$\hat{\tau}_t^L = \rho \hat{\tau}_{t-1}^L + \sum_{j=0}^J \phi_j \left[\sigma^L \varepsilon_{\tau,t-j}^L + \xi \sigma^K \varepsilon_{\tau,t-j}^K \right]$$
(22)

where $\hat{\tau}_t^L$ is the labor tax rate, ε^L and ε^K are news about labor and capital tax rates, ξ permits labor and capital tax rates to be correlated, and the ε 's are serially uncorrelated. We posit the best-case scenario for econometricians in that the tax processes are exogenous: in this case, identification is straightforward in the absence of foresight, ensuring that all errors arise solely from foresight.

As before, the sequence of innovations, $\{\varepsilon_{\tau,t-j}^L, \varepsilon_{\tau,t-j}^K\}_{j=0}^{\infty}$, enter the agent's information set directly. We interpret the moving-average coefficients as weights, imposing that $\sum_j \phi_j = 1$. Modeling information flows as moving average processes captures the idea that from quarter to quarter news about taxes evolves randomly, and generalizes the "perfect foresight" information structure. To see this more clearly, set J = 2, $\xi = 0$, $\rho = 0$, and $\sigma^L = 1$, so the tax rule becomes

$$\hat{\tau}_t^L = \theta \varepsilon_t^L + (1 - \theta) \varepsilon_{t-1}^L$$

where $\theta \in (0, 1)$. If $\theta = 0$, then agents have perfect foresight because they observe $\hat{\tau}_{t+1}^L$ perfectly. If $\theta = 1$, then agents have no foresight and receive news only about the contemporaneous tax rate. As θ moves smoothly from 1 to 0, agents receive more news about next period's tax rate.

Specification (22) embeds many of the information flows that appear in theoretical studies of foresight, including Christiano, Ilut, Motto, and Rostagno (2008), Jaimovich and Rebelo (2009), and Fujiwara, Hirose, and Shintani (2011) in the context of technology news; Ramey (2011) for government spending news; Yang (2005) and Mertens and Ravn (2011) with regard to tax news, and Schmitt-Grohé and Uribe (2012) for news about a variety of variables. These studies set $\phi_j = 0$ for all j except for $\phi_q = 1$, where q is the period of foresight.⁹ These specifications imply that once the news arrives, agents have q periods of *perfect foresight* about the object being modeled. This may be an adequate assumption about information flows that stem from outside lags, but they miss altogether the inside lags. Inside lags are periods when agents are learning about how the future may play out. Tax policies

⁹Some studies allow the news shocks, ε_{t-j} , to be drawn from distinct distributions for each j, and set $\phi_j = 1$ for each relevant j [Schmitt-Grohé and Uribe (2012), Fujiwara, Hirose, and Shintani (2011), and Mertens and Ravn (2011)]. The j = 0 shock is unanticipated, while the j > 0 shocks are anticipated given information at time t.

develop over time, from initial informal proposals to formal proposals, all the way through the legislative process. The ϕ_j coefficients in (22) reflect how agents update their views about taxes during the inside lags. Values of the ϕ_j 's describe how information flows differ from period to period.

3.2. Model Descriptions. We study a real business cycle model—closely related to Chari, Kehoe, and McGrattan (2008)—and a new Keynesian model—similar to those in Smets and Wouters (2003, 2007)—but add distorting tax rates on capital and labor income. These models are workhorses in the macroeconomics literature so we provide only brief descriptions here. The online appendix describes the models and estimation strategies thoroughly.

In the real business cycle (RBC) model, a representative agent maximizes time-separable discounted utility over consumption and leisure. The agent supplies labor and capital to a representative firm, which produces output according to a Cobb-Douglas technology. The government chooses a set of fiscal variables to satisfy the flow budget constraint, $G_t + Z_t =$ $\tau_t^L w_t l_t + \tau_t^K r_t^K k_{t-1}$, where G_t is government consumption, and Z_t is transfers. Log-linearized government consumption policy follows an AR(1) process and lump-sum transfers adjust to balance the government budget constraint each period.

Tax legislation adjusts labor and capital taxes following (22) and its analog for capital tax rates. Yang (2005) estimates the correlation between tax rates at 0.5, implying the value of ξ . Since changes in individual income tax rates affect both labor income taxes and part of capital income taxes, the two tax shocks are often correlated.

The new Keynesian (NK) model extends the RBC model to incorporate real and nominal rigidities that have been shown to help fit macroeconomic data. It also models fiscal financing by allowing spending to adjust to stabilize government debt. The NK model adds external habit formation, differentiated labor types, a monopolistically competitive intermediate goods sector, variable capital utilization, wage and price rigidities, and a monetary authority that follows a Taylor-type rule for setting nominal interest rates. Tax policies obey (22) and government spending policies follow the process

$$\hat{X}_t = \rho_X \hat{X}_{t-1} + \gamma_X \hat{s}^B_{t-1} + \sigma_X \varepsilon^X_t, \ \hat{X} \in \{\hat{G}, \hat{Z}\}$$

$$\tag{23}$$

where $\hat{s}_{t-1}^B \equiv \frac{B_{t-1}}{Y_{t-1}}$ is the debt-output ratio and $\gamma_X < 0$.

We estimate the NK model using Bayesian methods and U.S. quarterly data from 1984 to 2007. To conduct simulations, we fix parameters at the mode of the posterior distributions (see table 1 in the online appendix). For the RBC model, the structural parameters are calibrated to the values used in the literature and standard deviations of the shocks are set to the values estimated in the NK model. By calibrating one model to well-known values and estimating the other model, we aim to demonstrate that our findings are not dependent on whether parameters are calibrated or estimated.

3.3. Information Flows and Estimation Bias. The Romers' (2007; 2010) narrative analysis and Yang's (2009) timeline of inside and outside lags associated with federal tax changes reveal two critical features of information flows about taxes. First, the foresight horizon varies considerably from one piece of tax legislation to the next. Second, most tax changes

FISCAL	FORESIGHT	AND	INFORMATION	FLOWS

Process	Lags	Description	Coefficients
Ι	Inside	6 qtrs, smooth news	$\phi_j = \frac{1}{6}, \ j = 1, 2, \dots, 6$ $\phi_0 = \phi_7 = \phi_8 = 0$
II	Inside	6 qtrs, concentrated news	$\phi_1 = \phi_2 = \phi_3 = 0.05, \phi_4 = 0.25$ $\phi_5 = \phi_6 = 0.3, \phi_0 = \phi_7 = \phi_8 = 0$
III	Outside	8-qtr phase-in	$\phi_j = 0 \ j \neq 8$ $\phi_8 = 1$
IV	Outside	2-qtr phase-in	$\phi_j = 0, \ j \neq 2$ $\phi_2 = 1$

TABLE 1: Information Flow Processes. Coefficient settings in tax rule (22).

entail substantial inside and outside lags. The generalized specification (22) can model these features of information flows; simple specifications like (5) cannot.

We examine the implications of four alternative information flows in the two DSGE models. The alternatives reflect the diversity of information flows that previous authors have documented. With a maximum length of tax foresight of eight quarters, the four information processes we employ appear in table 1.

Processes I and II model inside lags that differ in the intensity of information flows. In I, the flows are smooth, so news over the previous six quarters receives equal weight. Tax laws that make steady progress through the legislature and get implemented with little delay create flows like I. Process II concentrates the news on lags four through six, with small weight on recent news. Tax changes implemented with a lag of about one year, with only slight changes in details in the periods immediately before implementation, generate flows like II.

The outside lags in processes III and IV closely resemble the information flows that other authors posit [for example, Mertens and Ravn (2011), and Forni, Gambetti, and Sala (2011)]. These processes imply that agents have eight-quarter (III) or two-quarter (IV) perfect foresight about tax changes. Perfect foresight precludes any further changes in legislation, so these processes are exclusively about implementation delays or phased-in tax changes.¹⁰

Table 2 summarizes the actual and estimated output multipliers associated with a typical tax change in the RBC and NK models. In this exercise, the agent knows the information process and observes the actual ε_t 's. The econometrician, on the other hand, bases inference on a set of observables. We construct the innovations representation based on the econometrician's conditioning set and use the Kalman filter to back out the econometrician's inferences about the responses of output and taxes to a shock to the tax rate. For the RBC model, the econometrician conditions on the labor tax rate, income tax revenue, output, and investment; the conditioning set for the NK model adds government consumption, private consumption, labor, government debt, inflation, and the nominal interest rate. Thus, the

¹⁰Ideally, information flows would encompass both inside and outside lags, but such flows would take us outside of a linear structure. For example, one could posit the flows for the inside lag and then, conditional on legislation having been enacted, switch to the outside lag specification, a process that is inherently nonlinear.

estimated VAR contains several "forward-looking" variables. As a robustness check, we examined many combinations of alternative conditioning variables and found results that are consistent with those in table 2. We report biases as estimated less actual multipliers and biases as a percentage of the actual multipliers. In the absence of foresight, the bias is always zero.

Several general findings emerge from the table. Biases can be very large—hundreds of percent—and can change sign over time across both models. In both models, the biggest errors arise from outside lags—information processes III and IV—which are the information flows most frequently posited in work on foresight. Inside lags with moving-average terms—processes I and II—produce smaller, though still sizeable errors. Information process III, in which agents have two years of perfect foresight about tax rates, generates the largest inference errors in both models. It also confounds dynamics: the econometrician estimates that the strongest effect is contemporaneous, while the largest impact actually occurs two or three years later, depending on the model.

In the RBC model, actual multipliers change *sign*—positive in the foresight period and negative later—but estimated multipliers are uniformly negative. Frictions in the NK model propagate errors, making short versus long-run distinctions less pronounced.¹¹ In the frictionless RBC model, biases dissipate over time.

A consistent finding across the two models is that for horizons of eight quarters and beyond, the econometrician underestimates the multiplier. The lone exception is the NK model under information process I. The discounting of the tax innovations that appears in (4) and (20) explains this result. An agent with q quarters of foresight discounts the innovations so that the $\varepsilon_{\tau,t-q}$ shock receives little discount relative to shocks dated t through t-q-1. As in the analytical model, this perverse discounting occurs because $\varepsilon_{\tau,t-q}$ informs about the contemporaneous tax rate, τ_t , while shocks dated t through t-q-1 inform about future tax rates. An econometrician, who does not observe the true innovations, applies the conventional discounting to the innovations in her information set, as in (11). This makes the econometrician's impulse response functions die out faster than the true impulse response functions to yield the underestimates.

These findings establish two key points. First, failure to model fiscal foresight can produce quantitatively important errors of inference in the canonical models used for macroeconomic policy analysis. Second, the precise nature of information flows about news matters for the pattern of inference errors. Getting the information flows "right" poses a substantial challenge to DSGE modelers. We turn now to empirical approaches designed to address the errors associated with foresight.

4. Solving the Problem

This section unifies the empirical lines of attack that appear in the literature to deal with the econometric problems associated with foresight. We show how seemingly diverse approaches—for example, the narrative methods of Romer and Romer (2010) and Ramey (2011) and the dynamic stochastic general equilibrium approaches of Fujiwara, Hirose, and

 $^{^{11}}$ This echoes Leeper and Walker's (2011) results for foresight about technology.

Real Business Cycle Model								
Info Process		0 qtr	4 qtrs	8 qtrs	12 qtrs	20 qtrs	peak (qtr)	
Ι	actual	0.19	-1.14	-1.48	-1.11	-0.65	-1.71(6)	
	estimated	-0.31	-1.35	-1.27	-0.97	-0.59	-1.57(5)	
	bias	-0.50	-0.21	0.20	0.14	0.06		
	% bias	-263%	-19%	14%	12%	8%		
II	actual	0.15	-0.54	-1.40	-1.05	-0.61	-1.62(6)	
	estimated	-0.56	-1.46	-1.19	-0.91	-0.55	-1.48(2)	
	bias	-0.71	-0.92	0.21	0.14	0.06		
	% bias	-473%	-169%	15%	13%	9%		
III	actual	0.09	0.16	-1.51	-1.12	-0.64	-1.51(8)	
	estimated	-1.44	-1.09	-0.82	-0.64	-0.39	-1.44(0)	
	bias	-1.54	-1.24	0.69	0.49	0.25		
	% bias	-1641%	-784%	46%	43%	39%		
IV	actual	0.16	-1.34	-1.00	-0.76	-0.45	-1.56(2)	
	estimated	-1.41	-1.06	-0.81	-0.62	-0.38	-1.41(0)	
	bias	-1.57	0.28	0.20	0.14	0.07		
	% bias	-962%	21%	20%	18%	16%		
New Keynesian Model								
		Ν	ew Keynes	sian Model				
Info Process		0 qrt	ew Keynes 4 qtrs	sian Model 8 qtrs	12 qtrs	20 qtrs	peak (qtr)	
Info Process I	actual	0 qrt -0.08	$\frac{\text{ew Keynes}}{4 \text{ qtrs}}$ -0.36	$\frac{1}{8 \text{ qtrs}}$	12 qtrs -0.43	20 qtrs -0.24	peak (qtr) -0.48 (8)	
Info Process I	actual estimated	$ \begin{array}{r} 0 & \text{qrt} \\ -0.08 \\ -0.07 \\ \hline $	$\frac{4 \text{ qtrs}}{-0.36}$ -0.44	$ \begin{array}{r} \text{sian Model} \\ \hline 8 \text{ qtrs} \\ -0.48 \\ -0.57 \\ \end{array} $	12 qtrs -0.43 -0.51	20 qtrs -0.24 -0.28	peak (qtr) -0.48 (8) -0.57 (8)	
Info Process I	actual estimated bias	$ \begin{array}{r} 0 \text{ qrt} \\ -0.08 \\ -0.07 \\ 0.01 \end{array} $		$ \frac{8 \text{ qtrs}}{-0.48} \\ -0.57 \\ -0.09 $	12 qtrs -0.43 -0.51 -0.08	$ \begin{array}{r} 20 \text{ qtrs} \\ -0.24 \\ -0.28 \\ -0.04 \end{array} $	peak (qtr) -0.48 (8) -0.57 (8)	
Info Process I	actual estimated bias % bias		ew Keynes 4 qtrs -0.36 -0.44 -0.09 -24%	$ \frac{8 \text{ qtrs}}{-0.48} \\ -0.57 \\ -0.09 \\ -20\% $	$ \begin{array}{r} 12 \text{ qtrs} \\ -0.43 \\ -0.51 \\ -0.08 \\ -18\% \end{array} $	$\begin{array}{r} 20 \text{ qtrs} \\ -0.24 \\ -0.28 \\ -0.04 \\ -18\% \end{array}$	peak (qtr) -0.48 (8) -0.57 (8)	
Info Process I II	actual estimated bias % bias actual	$\begin{array}{r} & N \\ \hline 0 \ qrt \\ -0.08 \\ -0.07 \\ 0.01 \\ 11\% \\ -0.06 \end{array}$	ew Keynes 4 qtrs -0.36 -0.44 -0.09 -24% -0.27	$ \frac{8 \text{ qtrs}}{-0.48} \\ -0.57 \\ -0.09 \\ -20\% \\ -0.43 $	$\begin{array}{r} 12 \text{ qtrs} \\ -0.43 \\ -0.51 \\ -0.08 \\ -18\% \\ -0.40 \end{array}$	$\begin{array}{r} 20 \text{ qtrs} \\ -0.24 \\ -0.28 \\ -0.04 \\ -18\% \\ -0.23 \end{array}$	$\begin{array}{c} \text{peak (qtr)} \\ -0.48 (8) \\ -0.57 (8) \end{array}$	
Info Process I II	actual estimated bias % bias actual estimated		$\begin{array}{r} \text{ew Keynes} \\ \hline 4 \text{ qtrs} \\ \hline -0.36 \\ -0.44 \\ -0.09 \\ -24\% \\ \hline -0.27 \\ -0.37 \end{array}$	$\begin{array}{r} \mbox{sian Model} \\ \hline 8 \ \mbox{qtrs} \\ -0.48 \\ -0.57 \\ -0.09 \\ -20\% \\ \hline -0.43 \\ -0.42 \end{array}$	$\begin{array}{r} 12 \text{ qtrs} \\ -0.43 \\ -0.51 \\ -0.08 \\ -18\% \\ -0.40 \\ -0.37 \end{array}$	$\begin{array}{r} 20 \text{ qtrs} \\ -0.24 \\ -0.28 \\ -0.04 \\ -18\% \\ -0.23 \\ -0.19 \end{array}$	$\begin{array}{c} \text{peak (qtr)} \\ -0.48 (8) \\ -0.57 (8) \end{array}$ $\begin{array}{c} -0.43 (9) \\ -0.42 (7) \end{array}$	
Info Process I II	actual estimated bias % bias actual estimated bias			$ \frac{8 \text{ qtrs}}{-0.48} \\ -0.57 \\ -0.09 \\ -20\% \\ -0.43 \\ -0.42 \\ 0.00 $	$\begin{array}{r} 12 \text{ qtrs} \\ -0.43 \\ -0.51 \\ -0.08 \\ -18\% \\ -0.40 \\ -0.37 \\ 0.04 \end{array}$	$\begin{array}{r} 20 \text{ qtrs} \\ -0.24 \\ -0.28 \\ -0.04 \\ -18\% \\ -0.23 \\ -0.19 \\ 0.04 \end{array}$	$\begin{array}{c} \text{peak (qtr)} \\ -0.48 (8) \\ -0.57 (8) \end{array}$ $\begin{array}{c} -0.43 (9) \\ -0.42 (7) \end{array}$	
Info Process I II	actual estimated bias % bias actual estimated bias % bias			$ \frac{8 \text{ qtrs}}{-0.48} \\ -0.57 \\ -0.09 \\ -20\% \\ -0.43 \\ -0.42 \\ 0.00 \\ 1\% $	$\begin{array}{r} 12 \text{ qtrs} \\ -0.43 \\ -0.51 \\ -0.08 \\ -18\% \\ -0.40 \\ -0.37 \\ 0.04 \\ 9\% \end{array}$	$\begin{array}{r} 20 \text{ qtrs} \\ -0.24 \\ -0.28 \\ -0.04 \\ -18\% \\ -0.23 \\ -0.19 \\ 0.04 \\ 19\% \end{array}$	$\begin{array}{c} \text{peak (qtr)} \\ -0.48 (8) \\ -0.57 (8) \end{array}$ $\begin{array}{c} -0.43 (9) \\ -0.42 (7) \end{array}$	
Info Process I II II	actual estimated bias % bias actual estimated bias % bias actual	$\begin{array}{r} & N \\ \hline 0 \ qrt \\ -0.08 \\ -0.07 \\ 0.01 \\ 11\% \\ -0.06 \\ -0.09 \\ -0.03 \\ -51\% \\ -0.03 \end{array}$	$\begin{array}{r} \text{ew Keynes} \\ \hline 4 \text{ qtrs} \\ \hline -0.36 \\ -0.44 \\ -0.09 \\ -24\% \\ \hline -0.27 \\ -0.37 \\ -0.10 \\ -37\% \\ \hline -0.12 \end{array}$	$\begin{array}{r} \text{sian Model} \\ \hline 8 \text{ qtrs} \\ \hline -0.48 \\ -0.57 \\ -0.09 \\ -20\% \\ \hline -0.43 \\ -0.42 \\ 0.00 \\ 1\% \\ \hline -0.32 \end{array}$	$\begin{array}{r} 12 \text{ qtrs} \\ -0.43 \\ -0.51 \\ -0.08 \\ -18\% \\ -0.40 \\ -0.37 \\ 0.04 \\ 9\% \\ -0.37 \end{array}$	$\begin{array}{r} 20 \text{ qtrs} \\ -0.24 \\ -0.28 \\ -0.04 \\ -18\% \\ -0.23 \\ -0.19 \\ 0.04 \\ 19\% \\ -0.26 \end{array}$	$\begin{array}{c} \text{peak (qtr)} \\ -0.48 (8) \\ -0.57 (8) \end{array}$ $\begin{array}{c} -0.43 (9) \\ -0.42 (7) \end{array}$ $\begin{array}{c} -0.37 (12) \end{array}$	
Info Process I II II	actual estimated bias % bias actual estimated bias % bias actual estimated	$\begin{array}{r} & N \\ \hline 0 \ qrt \\ -0.08 \\ -0.07 \\ 0.01 \\ 11\% \\ \hline -0.06 \\ -0.09 \\ -0.03 \\ -51\% \\ \hline -0.03 \\ -0.14 \end{array}$	$\begin{array}{c} \text{ew Keynes} \\ \hline 4 \text{ qtrs} \\ \hline -0.36 \\ -0.44 \\ -0.09 \\ -24\% \\ \hline -0.27 \\ -0.37 \\ -0.10 \\ -37\% \\ \hline -0.12 \\ -0.10 \end{array}$	$\begin{array}{r} \mbox{sian Model} \\ \hline 8 \ \mbox{qtrs} \\ -0.48 \\ -0.57 \\ -0.09 \\ -20\% \\ \hline -0.43 \\ -0.42 \\ 0.00 \\ 1\% \\ \hline -0.32 \\ -0.08 \end{array}$	$\begin{array}{r} 12 \text{ qtrs} \\ -0.43 \\ -0.51 \\ -0.08 \\ -18\% \\ -0.40 \\ -0.37 \\ 0.04 \\ 9\% \\ -0.37 \\ -0.37 \\ -0.06 \end{array}$	$\begin{array}{r} 20 \text{ qtrs} \\ -0.24 \\ -0.28 \\ -0.04 \\ -18\% \\ -0.23 \\ -0.19 \\ 0.04 \\ 19\% \\ -0.26 \\ -0.01 \end{array}$	$\begin{array}{c} \text{peak (qtr)} \\ -0.48 (8) \\ -0.57 (8) \end{array}$ $\begin{array}{c} -0.43 (9) \\ -0.42 (7) \end{array}$ $\begin{array}{c} -0.37 (12) \\ -0.14 (0) \end{array}$	
Info Process I II II	actual estimated bias % bias actual estimated bias % bias actual estimated bias	$\begin{array}{r} N \\ \hline 0 \ qrt \\ -0.08 \\ -0.07 \\ 0.01 \\ 11\% \\ \hline -0.06 \\ -0.09 \\ -0.03 \\ -51\% \\ \hline -0.03 \\ -0.14 \\ -0.11 \end{array}$	$\begin{array}{c} \text{ew Keynes} \\ \hline 4 \text{ qtrs} \\ \hline -0.36 \\ -0.44 \\ -0.09 \\ -24\% \\ \hline -0.27 \\ -0.37 \\ -0.10 \\ -37\% \\ \hline -0.12 \\ -0.10 \\ 0.01 \\ \end{array}$	$\begin{array}{r} \label{eq:sian_Model} \hline 8 \ \text{qtrs} \\ \hline -0.48 \\ -0.57 \\ -0.09 \\ -20\% \\ \hline -0.43 \\ -0.42 \\ 0.00 \\ 1\% \\ \hline -0.32 \\ -0.08 \\ 0.24 \end{array}$	$\begin{array}{r} 12 \text{ qtrs} \\ -0.43 \\ -0.51 \\ -0.08 \\ -18\% \\ -0.40 \\ -0.37 \\ 0.04 \\ 9\% \\ -0.37 \\ -0.06 \\ 0.32 \end{array}$	$\begin{array}{r} 20 \text{ qtrs} \\ -0.24 \\ -0.28 \\ -0.04 \\ -18\% \\ -0.23 \\ -0.19 \\ 0.04 \\ 19\% \\ -0.26 \\ -0.01 \\ 0.25 \end{array}$	$\begin{array}{c} \text{peak (qtr)} \\ -0.48 (8) \\ -0.57 (8) \end{array}$ $\begin{array}{c} -0.43 (9) \\ -0.42 (7) \end{array}$ $\begin{array}{c} -0.37 (12) \\ -0.14 (0) \end{array}$	
Info Process I II II III	actual estimated bias % bias actual estimated bias % bias actual estimated bias % bias	$\begin{array}{r} N \\ \hline 0 \ qrt \\ -0.08 \\ -0.07 \\ 0.01 \\ 11\% \\ \hline -0.06 \\ -0.09 \\ -0.03 \\ -51\% \\ \hline -0.03 \\ -0.14 \\ -0.11 \\ -340\% \end{array}$	$\begin{array}{c} \text{ew Keynes} \\ \hline 4 \text{ qtrs} \\ \hline -0.36 \\ -0.44 \\ -0.09 \\ -24\% \\ \hline -0.27 \\ -0.37 \\ -0.10 \\ -37\% \\ \hline -0.12 \\ -0.10 \\ 0.01 \\ 13\% \\ \end{array}$	$\begin{array}{r} \label{eq:sian_Model} \hline 8 \ \text{qtrs} \\ \hline -0.48 \\ -0.57 \\ -0.09 \\ -20\% \\ \hline -0.43 \\ -0.42 \\ 0.00 \\ 1\% \\ \hline -0.32 \\ -0.08 \\ 0.24 \\ 76\% \\ \end{array}$	$\begin{array}{r} 12 \text{ qtrs} \\ -0.43 \\ -0.51 \\ -0.08 \\ -18\% \\ -0.40 \\ -0.37 \\ 0.04 \\ 9\% \\ -0.37 \\ -0.06 \\ 0.32 \\ 85\% \\ \end{array}$	$\begin{array}{r} 20 \text{ qtrs} \\ -0.24 \\ -0.28 \\ -0.04 \\ -18\% \\ -0.23 \\ -0.19 \\ 0.04 \\ 19\% \\ -0.26 \\ -0.01 \\ 0.25 \\ 95\% \\ \end{array}$	$\begin{array}{c} \text{peak (qtr)} \\ -0.48 (8) \\ -0.57 (8) \end{array}$ $\begin{array}{c} -0.43 (9) \\ -0.42 (7) \end{array}$ $\begin{array}{c} -0.37 (12) \\ -0.14 (0) \end{array}$	
Info Process I II III III	actual estimated bias % bias actual estimated bias % bias actual estimated bias % bias actual	$\begin{array}{r} N \\ \hline 0 \ qrt \\ -0.08 \\ -0.07 \\ 0.01 \\ 11\% \\ \hline -0.06 \\ -0.09 \\ -0.03 \\ -51\% \\ \hline -0.03 \\ -0.14 \\ -0.11 \\ -340\% \\ \hline -0.06 \end{array}$	$\begin{array}{r} \text{ew Keynes} \\ \hline 4 \text{ qtrs} \\ \hline -0.36 \\ -0.44 \\ -0.09 \\ -24\% \\ \hline -0.27 \\ -0.37 \\ -0.10 \\ -37\% \\ \hline -0.12 \\ -0.10 \\ 0.01 \\ 13\% \\ \hline -0.30 \end{array}$	$\begin{array}{r} \label{eq:sian_Model} \hline 8 \ \text{qtrs} \\ \hline -0.48 \\ -0.57 \\ -0.09 \\ -20\% \\ \hline -0.43 \\ -0.42 \\ 0.00 \\ 1\% \\ \hline -0.32 \\ -0.08 \\ 0.24 \\ 76\% \\ \hline -0.33 \\ \end{array}$	$\begin{array}{r} 12 \text{ qtrs} \\ -0.43 \\ -0.51 \\ -0.08 \\ -18\% \\ -0.40 \\ -0.37 \\ 0.04 \\ 9\% \\ -0.37 \\ -0.06 \\ 0.32 \\ 85\% \\ -0.28 \end{array}$	$\begin{array}{r} 20 \text{ qtrs} \\ -0.24 \\ -0.28 \\ -0.04 \\ -18\% \\ -0.23 \\ -0.19 \\ 0.04 \\ 19\% \\ -0.26 \\ -0.01 \\ 0.25 \\ 95\% \\ -0.14 \end{array}$	$\begin{array}{c} \text{peak (qtr)} \\ -0.48 (8) \\ -0.57 (8) \\ \end{array}$ $\begin{array}{c} -0.43 (9) \\ -0.42 (7) \\ \end{array}$ $\begin{array}{c} -0.37 (12) \\ -0.14 (0) \\ \end{array}$ $\begin{array}{c} -0.33 (7) \end{array}$	
Info Process I II III III IV	actual estimated bias % bias actual estimated bias % bias actual estimated bias % bias actual estimated	$\begin{array}{r} N \\ \hline 0 \text{ qrt} \\ -0.08 \\ -0.07 \\ 0.01 \\ 11\% \\ \hline -0.06 \\ -0.09 \\ -0.03 \\ -51\% \\ \hline -0.03 \\ -0.14 \\ -0.11 \\ -340\% \\ \hline -0.06 \\ -0.15 \end{array}$	$\begin{array}{r} \hline \text{ew Keynes} \\ \hline 4 \ \text{qtrs} \\ \hline -0.36 \\ -0.44 \\ -0.09 \\ -24\% \\ \hline -0.27 \\ -0.27 \\ -0.37 \\ -0.10 \\ -37\% \\ \hline -0.12 \\ -0.10 \\ 0.01 \\ 13\% \\ \hline -0.30 \\ -0.24 \\ \end{array}$	$\begin{array}{r} \label{eq:sian_Model} \hline 8 \ \text{qtrs} \\ \hline -0.48 \\ -0.57 \\ -0.09 \\ -20\% \\ \hline -0.43 \\ -0.42 \\ 0.00 \\ 1\% \\ \hline -0.32 \\ -0.08 \\ 0.24 \\ 76\% \\ \hline -0.33 \\ -0.26 \end{array}$	$\begin{array}{r} 12 \text{ qtrs} \\ -0.43 \\ -0.51 \\ -0.08 \\ -18\% \\ -0.40 \\ -0.37 \\ 0.04 \\ 9\% \\ -0.37 \\ -0.06 \\ 0.32 \\ 85\% \\ -0.28 \\ -0.22 \\ \end{array}$	$\begin{array}{r} 20 \text{ qtrs} \\ -0.24 \\ -0.28 \\ -0.04 \\ -18\% \\ -0.23 \\ -0.19 \\ 0.04 \\ 19\% \\ -0.26 \\ -0.01 \\ 0.25 \\ 95\% \\ -0.14 \\ -0.11 \end{array}$	$\begin{array}{c} \\ \hline \\ peak (qtr) \\ -0.48 (8) \\ -0.57 (8) \\ \hline \\ -0.43 (9) \\ -0.42 (7) \\ \hline \\ -0.42 (7) \\ \hline \\ -0.37 (12) \\ -0.14 (0) \\ \hline \\ -0.33 (7) \\ -0.26 (7) \end{array}$	
Info Process I II III III IV	actual estimated bias % bias actual estimated bias % bias actual estimated bias % bias actual estimated bias	$\begin{array}{r} N \\ \hline 0 \ qrt \\ -0.08 \\ -0.07 \\ 0.01 \\ 11\% \\ \hline -0.06 \\ -0.09 \\ -0.03 \\ -51\% \\ \hline -0.03 \\ -0.14 \\ -0.11 \\ -340\% \\ \hline -0.06 \\ -0.15 \\ -0.08 \\ \end{array}$	$\begin{array}{r} \hline \text{ew Keynes} \\ \hline 4 \ \text{qtrs} \\ \hline -0.36 \\ -0.44 \\ -0.09 \\ -24\% \\ \hline -0.27 \\ -0.37 \\ -0.10 \\ -37\% \\ \hline -0.12 \\ -0.10 \\ 0.01 \\ 13\% \\ \hline -0.30 \\ -0.24 \\ 0.07 \\ \end{array}$	$\begin{array}{r} \label{eq:sian_Model} \hline 8 \ \text{qtrs} \\ \hline -0.48 \\ -0.57 \\ -0.09 \\ -20\% \\ \hline -0.43 \\ -0.42 \\ 0.00 \\ 1\% \\ \hline -0.32 \\ -0.08 \\ 0.24 \\ 76\% \\ \hline -0.33 \\ -0.26 \\ 0.07 \\ \end{array}$	$\begin{array}{r} 12 \text{ qtrs} \\ -0.43 \\ -0.51 \\ -0.08 \\ -18\% \\ -0.40 \\ -0.37 \\ 0.04 \\ 9\% \\ -0.37 \\ -0.06 \\ 0.32 \\ 85\% \\ -0.28 \\ -0.22 \\ 0.06 \\ \end{array}$	$\begin{array}{r} 20 \text{ qtrs} \\ -0.24 \\ -0.28 \\ -0.04 \\ -18\% \\ -0.23 \\ -0.19 \\ 0.04 \\ 19\% \\ -0.26 \\ -0.01 \\ 0.25 \\ 95\% \\ -0.14 \\ -0.11 \\ 0.04 \end{array}$	$\begin{array}{c} \text{peak (qtr)} \\ -0.48 (8) \\ -0.57 (8) \\ \end{array}$ $\begin{array}{c} -0.43 (9) \\ -0.42 (7) \\ \end{array}$ $\begin{array}{c} -0.37 (12) \\ -0.14 (0) \\ \end{array}$ $\begin{array}{c} -0.33 (7) \\ -0.26 (7) \end{array}$	

TABLE 2: Output Multipliers for a Labor Tax Change, Correlated with a Capital Tax Change. Multipliers are output responses scaled by the peak response of revenues, converted to dollars, as in Blanchard and Perotti (2002). Agent knows the information process and observes the actual ε_t 's. Econometrician bases inference on a set of observable variables, as described in text. Biases equal estimated less actual multipliers.

Shintani (2011) and Schmitt-Grohé and Uribe (2012)—are closely related attempts to solve the problems caused by foresight. Each approach aims to resolve a non-uniqueness problem intrinsic to moving average representations. We briefly discuss three lines of attack.¹²

4.1. An Organizing Principle. Moving average representations are not unique for two distinct reasons that Hansen and Sargent (1991a) emphasize. Understanding the reasons for non-uniqueness provides a useful way to characterization solutions to the problems that

 $^{^{12}}$ Detailed calculations in support of the discussion in this section appear in an online appendix.

for esight creates. Consider the Wold representation for the $n\times 1$ vector stochastic process \mathbf{x}_t

$$\mathbf{x}_t = \sum_{j=0}^{\infty} H_j^* \boldsymbol{\epsilon}_{t-j}^* \tag{24}$$

where $\sum_{j=0}^{\infty} \operatorname{tr} H_j^* H_j^{*'} < \infty$ and ϵ_t^* is an *n*-dimensional white noise process defined as the innovation in predicting \mathbf{x}_t linearly from its semi-infinite past ($\epsilon_t^* \equiv \mathbf{x}_t - P[\mathbf{x}_t | \mathbf{x}^{t-1}]$).

Two transformations are observationally equivalent to (24). The first comes from multiplying by a nonsingular matrix U

$$\mathbf{x}_t = \sum_{j=0}^{\infty} (H_j^* U^{-1}) (U \boldsymbol{\epsilon}_{t-j}^*)$$
(25)

where the innovation is now defined as $U\epsilon_t^*$ and $H_j^*U^{-1}$ represents the altered impulse responses. If U is nonsingular, then the new innovations process spans the same space as \mathbf{x}^t and the information content of $U\epsilon_t^*$ is identical to that of ϵ_t^* . This is the type of non-uniqueness that Sims (1980) describes. Researchers confront this non-uniqueness with different orthogonalization schemes that rotate the covariance matrix through recursive orderings [Sims (1980)], short-run restrictions [Bernanke (1986), Sims (1986)], long-run restrictions [Blanchard and Quah (1989)], a combination of short and long-run restrictions [Galí (1999)], or sign restrictions [Faust (1998), Canova (2002), Uhlig (2005)].

For sight produces a second type of non-uniqueness. It is also observationally equivalent to (24), and is described by the non-fundamental representation

$$\mathbf{x}_t = \sum_{j=0}^{\infty} H_j \boldsymbol{\epsilon}_{t-j} \tag{26}$$

where now $\{\epsilon_{t-j}\}_{j=0}^{\infty}$ spans a larger space than $\{\mathbf{x}_{t-j}\}_{j=0}^{\infty}$, and H(L) satisfies

$$H^*(z)E\boldsymbol{\epsilon}_t^*\boldsymbol{\epsilon}_t^{*'}H^*(z^{-1})' = H(z)E\boldsymbol{\epsilon}_t\boldsymbol{\epsilon}_t'H(z^{-1})'.$$

where H(z) denotes the z-transform [see Sargent (1979)]. Under the typical assumption that agents observe the structural shocks ϵ_t directly, while the econometrician observes only data \mathbf{x}_t , models with sufficient foresight belong to this class of non-fundamental representations. The covariance generating functions of $H(L)\epsilon_t$ and $H^*(L)\epsilon_t^*$ are identical, but only $H^*(L)$ possesses an invertible representation in \mathbf{x}_t . Letting $A(L) = H^*(L)^{-1}$, the typical VAR methodology delivers

$$\mathbf{x}_{t} = A_{0}^{-1} [A_{1} \mathbf{x}_{t-1} + A_{2} \mathbf{x}_{t-2} + \dots + \boldsymbol{\epsilon}_{t}^{*}].$$
(27)

Identifying A_0^{-1} in the usual way recovers the shocks $\boldsymbol{\epsilon}_t^*$, but not the structural shocks, $\boldsymbol{\epsilon}_t$, that agents observe; the econometrician conditions on a smaller information set than do agents.

Hansen and Sargent's non-uniqueness point sends a clear message: to identify structural shocks in a vector autoregression, *both* types of non-uniqueness must be confronted. Confronting the non-uniqueness in (25) does *not* solve the non-uniqueness of representation (26),

and vice versa. A large literature focuses on the non-uniqueness associated with (25). Identifying (26), though, receives less attention and requires the econometrician to condition on the same information set as the agents they are modeling.

4.2. Lines of Attack. Casting the problem as resolving the two distinct forms of nonuniqueness sheds light on three approaches that appear in the empirical macro literature. One line of attack estimates conventional VARs, identified in a variety of creative ways to isolate anticipated effects, and then examines the impacts of foresight [Sims (1988), Blanchard and Perotti (2002), Yang (2007), Mountford and Uhlig (2009), Beaudry and Portier (2006), Fisher and Peters (2010), Barsky and Sims (2011)]. For example, Beaudry and Portier (2006) and Fisher and Peters (2010) condition on stock prices to capture news about expected changes in technology and government spending, respectively. Barsky and Sims (2011) identify news about productivity as the shock that is orthogonal to current utilization-adjusted productivity that best explains future variations in adjusted productivity.

A second line of attack argues that conventional VARs cannot adequately measure the impacts of foreseen changes in fiscal policy and pursues a narrative approach that introduces new information to aid identification [Ramey and Shapiro (1998), Edelberg, Eichenbaum, and Fisher (1999), Burnside, Eichenbaum, and Fisher (2004), Ramey (2011), Romer and Romer (2010)]. A third approach uses standard methods to estimate a model with fore-sight. To execute these methods, Schmitt-Grohé and Uribe (2012) and Fujiwara, Hirose, and Shintani (2011) make very particular assumptions about the information flows that give rise to foresight about technology and government spending. The tradeoff is that the modeler must be explicit about the role of information in the economy. Each line of attack tries to align agents' and the econometrician's information sets to address the second type of non-uniqueness that (26) describes.

4.2.1. The Narrative Approach. Narrative approaches to fiscal policy—pioneered by Ramey and Shapiro (1998), Romer and Romer (2010), Ramey (2011), and Mertens and Ravn (2011)—expands the econometrician's information set by using fresh data sources to identify fiscal news. For example, Ramey (2011) derives a direct measure of spending news by culling from *Business Week* dates when there were significant increases in the expected present value of military spending. To the extent that this fiscal news is triggered by non-economic factors, it may be treated as exogenous for inferring the impacts of news on macroeconomic time series. Ramey augments the econometrician's usual information set by adding this news to fiscal VARs and infers that anticipated expansions in federal government spending reduce most measures of consumption and real wages, a strikingly non-Keynesian finding.

Recognizing the intrinsic endogeneity of tax policy decisions, Romer and Romer (2010) compile a data series on the forecasted revenue consequences of federal tax changes since World War II. Romer and Romer identify as "exogenous" those revenue changes that were a response to concerns about long-run economic growth or about the state of government debt. Using this measure of tax news, Mertens and Ravn (2011) apply a timing convention to distinguish between unanticipated and anticipated news. They append tax news as exogenous

regressors to a VAR with a time trend

$$X_{t} = A + Bt + C(L)X_{t-1} + D(L)T_{t}^{u} + F(L)T_{t,0}^{a} + \sum_{i=1}^{K} G_{i}T_{t,i}^{a} + e_{t}$$
(28)

where X is a standard vector of macro time series (e.g., consumption, investment, hours), $D(L)T_t^u + F(L)T_{t,0}^a$ reflects dependence on current past unanticipated (T_t^u) and anticipated (T_0^a) news, and $\sum_{i=1}^{K} G_i T_{t,i}^a$ yields the impacts of known, but not-yet-implemented tax changes. Mertens and Ravn obtain provocative results: anticipated tax cuts induce sharp economic slowdowns during the period of foresight, and may even produce recessions.

Narrative approaches face an important criticism. Theoretical and empirical models often do not line up in their treatments of information flows. Romer and Romer (2007, 2010) base their tax-shock series on narrative sources that report both enacted and proposed tax changes, but Mertens and Ravn's (2011) theory treats all anticipated tax changes as stemming from outside lags. The Romers also limit themselves to actions that actually change tax liabilities, so their data series excludes proposals that do not reach fruition, while news specifications like those in section 3 allow for revisions in expectations when proposals fail. Ramey's (2009a; 2011) narrative analysis identifies a number of instances where the news about major military build ups arrived well before any explicit legislative actions were taken, which are clear examples of inside lags. But Ramey's (2009b) theoretical specification posits a military spending rule as an autoregressive process with a news shock lagged two periods, capturing only the outside lag. This misalignment of information flows loosens the connection between theory and empirics and muddies the interpretations of empirical findings.

4.2.2. Conditioning on Asset Prices. If asset markets are efficient, the information contained in asset prices should coincide with all available information to agents and adding asset prices to a VAR should help align the information sets of the econometrician and agent. With respect to fiscal foresight, there is an asset class that is particularly useful for isolating news about future tax shocks. In the United States, municipal bonds are exempt from federal taxes and the differential tax treatment of municipal and treasury bonds can help identify news about tax changes.¹³ If \mathcal{Y}_t^M is the yield on a municipal bond at t and \mathcal{Y}_t is the yield on a taxable bond, and assuming the bonds have the same term to maturity, callability, market risk, credit risk, and so forth, then an "implicit tax rate" is given by $\tau_t^I = 1 - \mathcal{Y}_t^M/\mathcal{Y}_t$. This is the tax rate at which investors are indifferent between tax-exempt and taxable bonds. With forward-looking bond traders, the implicit tax rate predicts subsequent movements in individual tax rates: if investors expect individual tax rates to rise (fall), they drive up (down) yields on taxable bonds until they are indifferent between taxable and nontaxable bonds.¹⁴

¹³Depending on the type of bond, municipal bonds can also be exempt from the Alternative Minimum Tax, state, and local taxes. Ang, Bhansali, and Xing (2010) describe the municipal bond market.

¹⁴There is a large literature demonstrating the ability of the municipal bond market to forecast changes in fiscal policy [Poterba (1989), Fortune (1996), Park (1997), Kueng (2011)].

More precisely, a newly issued tax-exempt bond with maturity T, a par value of \$1, and per-period coupon payments C_M , will sell at par if

$$1 = \frac{C^M}{\sum_{t=1}^T (1 + R_t^{\tau})^t} + \frac{1}{(1 + R_T^{\tau})^T},$$
(29)

where R_t^{τ} is the *after-tax* nominal interest rate for payments made in period t. No-arbitrage conditions imply that an identical taxable bond paying coupon C, and selling at par satisfies

$$1 = \frac{\sum_{t=1}^{T} C(1 - \tau_t^e)}{\sum_{t=1}^{T} (1 + R_t^{\tau})^t} + \frac{1}{(1 + R_T^{\tau})^T},$$
(30)

where τ_t^e is the future tax rate expected to hold in period t.

Bonds that sell at par have a yield-to-maturity that equals the coupon payments, so the implicit tax rate is $\tau_T^I = 1 - C_M/C$. Subtracting (30) from (29) and solving for C_M/C gives

$$\tau_T^I = \sum_{t=1}^T \omega_t \tau_t^e, \tag{31}$$

where $\omega_t = \delta_t / \sum_{t=1}^T \delta_t$ and $\delta_t = (1+R_t^{\tau})^{-t}$. The current implicit tax rate is a weighted average of discounted expected future tax rates from t = 1 to T and should respond immediately to news about anticipated *future* tax changes.

Equation (31) reveals the advantages of using municipal bond spreads to capture information flows about pending tax changes. First, there is no need to specify *a priori* the period of foresight. Under efficient markets, the implicit tax rate reflects the extent to which agents do or do not have foresight about pending tax changes, which could vary with time. In periods of substantial news, one would expect substantial spreads between the implicit tax rate and the current tax rate. Second, there is no need to specify a functional form for information flows. In section 3, we modeled information flows as one of several possible information processes. We would have to conduct a similar sensitivity analysis if we were estimating a DSGE model. Using the implicit tax rate avoids taking an *a priori* stand on the nature of information flows. Finally, conditioning on the implicit tax rate resolves the non-uniqueness associated with moving-average representation (26). Like the capital accumulation equation in section 2, the implicit tax rate depends on the discounted future path of taxes. Unlike the capital equation, the yield curve of municipal bonds isolates the about taxes at different horizons.¹⁵

Employing exactly the identification scheme and data set of Blanchard and Perotti (2002) (BP), we ask how augmenting the econometrician's information set with a direct measure of tax news affects inferences.¹⁶ To conserve space, we report the data construction and estimation procedure in Leeper, Walker, and Yang (2011) and the online appendix. We find that municipal bonds respond to news about tax policy and that implicit tax rates

¹⁵As an oversimplified example, suppose that agents have two quarters of foresight and the econometrician has access to the implicit tax rate with maturities of one and two quarters. The one-quarter implicit tax rate identifies one-quarter news, while the difference between the implicit tax rates identifies two-quarter news.

¹⁶We do the same exercise for Mountford and Uhlig (2009). While the results are not as striking as for BP, we do find that conditioning on implicit tax rates qualitatively alters the findings of Mountford-Uhlig. For example, investment multipliers, which Mountford-Uhlig estimated to be zero, become significantly positive. See Leeper, Walker, and Yang (2011) and the online appendix for more details.

22

are Granger-causally prior relative to the information sets in the fiscal VAR system that Blanchard and Perotti (2002) estimate.

Adding implicit tax rates dramatically changes the VAR results of BP: anticipated tax increases *raise* output substantially for about three years before output begins to decline. This contrasts sharply to the anemic response of output to an anticipated tax shock in BP (Figure III, p. 1343), which led them to conclude, "there is not much evidence of an effect of anticipated tax changes on output [p. 1353]." The difference in the results can be attributed to how fiscal foresight is identified. By conditioning on one- and five-year municipal bond yield spreads, we allow for a much longer foresight horizon than the BP approach, which assumes agents have only one-quarter of foresight. These differences underscore the importance of modeling information flows.

Our finding that news of higher taxes increases economic activity over much of the anticipation period echoes results from two very different methodologies. In a case study, House and Shapiro (2006) argue that the phased-in tax reductions enacted by the 2001 Economic Growth and Tax Relief Reconciliation Act played a significant role in creating the unusually slow recovery from the 2001 recession. By feeding the legislated paths of marginal tax rates on labor and capital into an RBC model, the authors generate a path of equilibrium GDP that declines in response to an anticipated tax reduction. Our results are also consistent with Mertens and Ravn (2011) whose augmented VAR, (28), implies that an anticipated tax increase induces a boom in output whose amplitude and duration increase with the period of foresight. In contrast to our approach with muni-treasury spreads, Mertens and Ravn must specify a priori the period of foresight and maintain that anticipated taxes are exogenous—assumptions that are critical to the quantitative effects they obtain. Nonetheless, the qualitative effects closely resemble our results.

There are obvious limitations to using municipal bonds as a measure of anticipated tax changes. First, fiscal news must be separated from other factors that influence municipal bonds—callability, liquidity risk, default risk, etc.—factors whose influence can be controlled for and limited by using high-quality municipal bond data. Leeper, Richter, and Walker (2012) show how to construct a risk-adjusted implicit tax rate based on the methodology of Fortune (1996). They argue that for AAA-rated municipal bonds, the risk adjustment is not substantial. Using state municipal bonds, Kueng (2011) shows that default risk and liquidity factors are nearly negligible for maturities of longer horizons and that municipal bonds contain substantial news about pending tax changes. Second, the marginal investor may be high-income households and not representative of the typical taxpayer. Kueng (2011)provides supporting evidence but argues that it does not invalidate using municipal bonds to back out news about pending tax changes for other tax brackets because the economic response to tax news depends on the path of expected taxes, not the level. If municipal bonds provide an accurate indication of this path, the levels are irrelevant. Third, municipal bonds respond to changes in individual income taxes only. While this is true, often changes to various components of the tax code (personal, corporate, etc.) occur simultaneously, so municipal bonds may not accurate indicate how corporate taxes change, but they will can indicate *when* corporate taxes will change. Finally, municipal bonds are an asset that is unique to the United States, which limits the implementability of this approach.

4.2.3. Direct Estimation of DSGE Model. A third approach uses standard econometric methods, such as An and Schorfheide (2007), to estimate a DSGE model in which agents have foresight about shocks that hit the economy. Specifying the entire structure of the economy, including the information sets of the agents, yields a likelihood function that contains sufficient information to overcome the non-uniqueness of section 4.1. In models with foresight, the likelihood will be a vector ARMA process similar to the equilibrium processes of section 2 and (21). When estimating the model directly (via maximum likelihood or Bayesian techniques), one does not need to put the equilibrium into VAR form, so invertibility of the moving average process is irrelevant. By defining the information sets explicitly, it is no longer critical whether the MA representation is fundamental or non-fundamental because the likelihood function can distinguish between the two.

This benefit comes at a cost. Modelers must make very particular assumptions about the information flows that give rise to foresight about technology, government spending, taxes, and so forth. Solutions are conditional on the specified information flows, aspects of the economic structure about which economists rarely have well developed prior beliefs or direct empirical evidence. For example, in models with foresight, the length of foresight (the q in section 3) and the strength of foresight (the MA coefficients, θ , in section 3) must be specified prior to estimation. As table 2 shows, the dynamic properties of the equilibria can vary dramatically conditional on the news process.

Leeper and Walker (2011) argue that the information sets specified to achieve identification in this regard are chosen largely arbitrarily, grounded in neither theory nor empirics. Alternative, equally plausible processes for news, can deliver strikingly different equilibrium dynamics. Surprisingly, despite the centrality of information structures to the burgeoning news literature, there has been essentially no exploration of alternative, equally plausible, assumptions about how information about critical economic variables flows to agents.

5. Concluding Remarks

We have shown how foresight introduces econometric difficulties that complicate the interpretation of conventional econometric analyses. Foresight, of *any* type, can introduce non-fundamental moving average terms into the linear equilibrium process, changing the mapping between the true news that agents observe and the "shocks" that the econometrician identifies. Many of the econometric techniques in macroeconomists' toolboxes can be distorted by empirical methods that do not adequately estimate the non-invertible moving average components of equilibrium time series. Section 2 uses simple analytics to describe the nature of the problem. Section 3 demonstrates that failing to model foresight can produce quantitatively important inference errors in data generated by models now in wide use for macro policy analysis. Section 4 explains that existing empirical methods to handle foresight aim to resolve the same non-uniqueness, but in different ways.

This paper focuses on tax policy as a particularly relevant and tangible form of foresight. There is little doubt that agents know and react to tax changes before they are implemented. But the econometric difficulties that fiscal foresight creates are entirely general: they emerge anytime agents respond to news about future realizations of fundamentals. Although the problem is general, we suspect the solution is not. A general solution, if one exists, lies in the future.

Foresight poses a challenging mix of structural and measurement problems. Hypothesized information flows that are uninformed by observations and information sets that are unrestricted by theory are unlikely to resolve the foresight problem. Answers lie in blending theory with measurement.

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