Learning with Expectational Shocks in the New Keynesian Model

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Abstract

This paper examines the role expectational shocks in combination with other structural shocks in explaining post-war economic volatility within the context of a New Keynesian model. Agents form expectations using constant gain learning then augment these forecasts with judgment. These judgments may be interpreted as a reaction to current news stories or policy announcements that would influence people's expectations. I allow for the possibility that these judgments be informatively based on information about structural shocks, but judgment itself may also be subject to its own stochastic shocks. I estimate a standard New Keynesian model that includes these shocks using Bayesian simulation methods. To aid in identifying expectational shocks from other structural shocks I include data on professional forecasts along with data on output growth, inflation, and interest rates.

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1 Introduction

Having rational expectations with full information about quantities of relevant state variables and stochastic shocks is the most common assumption among research that models macroeconomies. The assumption makes solving, evaluating, and estimating macroeconomic models possible with standard tools (albeit, still rather sophisticated), but the informational requirements and information processing requirements behind the assumption are rather extreme. Least squares learning is a type of non-rational, adaptive expectations that attempts to use more realistic forecasting methods within the context of macroeconomic models to understand macroeconomic dynamics. In such a framework, economic agents gather past data and use simple least squares time series techniques to form their expectations for future outcomes before making forward looking decisions (a feasible and rather simple statistical exercise).

One drawback of least squares learning is that expectations are based only on collections of past data that are passed through some statistical procedure. Forward looking decisions might well be also guided by relevant current events that have not yet made themselves evident in historical data. Such events might include the outcome of an election, the passing of a new law, a natural disaster, a change in political landscape of a major oil exporting country, or news of a recent technological development, just to name a few. As soon as such events are made known through the media, optimizing economic agents would do well to immediately change their expectations and decisions accordingly. One could argue that rational expectations captures this realistic component of expectations formation that learning does not. Typically in dynamic stochastic general equilibrium (DSGE) models with rational expectations, the values for current stochastic shocks are realized before expectations are made.

It might also happen, however, that the implications of current events are over-interpreted, or their importance is exaggerated in the media. One example of an exaggerated news story in recent U.S. history might be the Y2K computer bug widely discussed in the late 1990s. The September 11, 2001, terrorist attacks may be an example of a very real event, but whose implications to economic activity may have been over-estimated. Rational expectations certainly cannot account for such misinterpretations of news of this type.

Judgment based on information in the news that is impractical or impossible to quantify may therefore be beneficial, detrimental, or more probably a combination of both. In this paper I examine within the context of a standard stochastic New Keynesian model expectations that are formed by least squares learning forecasts and are then augmented by judgment. The least squares forecasts incorporates historical data that can be readily obtained: the output gap, inflation rate, and the federal funds rate. If expectations were rational and agents had full information, they would also use current realizations of stochastic shocks in forming expectations. In the learning environment with judgment, values for stochastic shocks cannot be obtained or estimated, but judgments based on news and current events may incorporate some of this information. Judgment may also be subject to its own stochastic shocks that are independent to all other shocks and state variables. This stochastic component of judgment can be viewed as the detrimental component to using judgment; shocks that are unrelated to economic fundamentals affect agents expectations and forward looking decisions. One of the contributions of this paper is to provide an estimate for the degree to which judgment has influenced expectations in the post-war U.S. monetary economy, and how much of this judgment is informative (that is, correlated with current realizations of stochastic shocks) and how much is disruptive.

2 Related Literature

The literature on learning specific to the monetary economics literature can be broadly put into two categories: 1) theoretical work that examines the consequence to the stability of equilibria under learning versus rational expectations, and 2) empirical and descriptive research that examine the difference in macroeconomic dynamics between learning and rational expectations. The first branch explores the conditions for expectational stability, or E-stability, on monetary policy parameters. A model with learning that is E-stable will have expectations that converge to the rational expectations equilibrium, within the neighborhood of the rational expectations solution. Examples papers of this type are numerous, but include Bullard and Mitra (2002), Bullard and Mitra (2007), Evans and Honkapohja (2003b), Evans and Honkapohja (2003a), Preston (2005), to name a few. These papers demonstrate that conditions on monetary policy for E-stability can be different and more restrictive than conditions for determinacy, the implication being that the economy can become unstable and volatile if monetary policy strays from these restrictions.

Such concerns have motivated the second branch of literature that investigates whether learning can lead to macroeconomic dynamics we see in the data that is not well explained by traditional rational expectations models. Orphanides and Williams (2005b) use a calibrated model with learning to demonstrate that a transient inflation shocks can lead to "inflation scares" characterized by prolonged periods of high inflation. Findings like these suggests that learning can explain macroeconomics persistence. Milani (2007) estimates New Keynesian model with learning and confirms that learning can explain persistence in inflation and output without the need for common "mechanical" sources of persistence that are typically augmented to rational expectations models such as habit formation and inflation indexation. Learning has also been used to explain characteristics of the "Great Inflation" and "Great Moderation", the large run-up of inflation and macroeconomic volatility in the 1970s followed by a long period of relatively moderate volatility and low inflation since 1984. Examples of such papers include Orphanides and Williams (2005a), Primiceri (2006), Bullard and Eusepi (2005), and Bullard and Singh (2007).

Preceding this paper, relatively little work has investigated the importance of judgment or "add-factors" on expectations. Reifschneider, Stockton, and Wilcox (1997) and Svensson (2005) demonstrate the usefulness of judgment for central bankers when making monetary policy decisions. Bullard, Evans, and Honkapohja (2008) and 2010 incorporate judgment of the kind that is purely disruptive (judgments depend exclusively on stochastic shocks that are independent of economic fundamentals) into simple monetary models and demonstrate that judgment can create "exuberance equilibria", a condition that is susceptible to self-fulfilling judgments even when an equilibrium is otherwise locally determinant and/or E-stable. They go on to suggest appropriate monetary policy to prevent such unstable outcomes.

These papers by Bullard, Evans, and Honkapohja fall into the first branch of learning literature mentioned above: they provide theoretical evidence that expectations formed by judgment and learning can lead to economic instability. The present work is the first attempt to bring the issue to the second branch: to determine whether judgment with learning can be used to explain characteristics of business cycle fluctuations seen in the data for the post-war United States.

3 Model

Learning and judgment are examined within the context of a standard New Keynesian model, a model that has been estimated at great length with rational expectations and learning to investigate the roles stochastic shocks play in explaining macroeconomic dynamics.[1] In this section I describe the background and log-linearization of a rational expectations version of the model. In the next section expectations are replaced with expectations formed by with learning and judgment.[2]

The model consists of three sectors that describe consumer behavior, producer behavior under imperfectly flexible prices, and monetary policy. The first sector is an equation or system of equations that describes optimal consumer behavior. When this sector can be conveniently written in one equation, this is often called the "IS equation". The second sector is a single equation, referred to as the Phillips curve, that describes optimal producer behavior when firms are subject to a pricing friction. The final sector is the monetary authority, which is usually assumed to follow a simple nominal interest rate rule. The

[1] Notable examples using rational expectations include Ireland (2004a), Ireland (2004b), Nason and Smith (2005), Smets and Wouters (2003), 2005, and 2007, just to name a few. Examples of estimated New Keynesian type models with learning include Milani (2007), Slobodyan and Wouters (2007), Slobodyan and Wouters (2008), Murray (2009b), and Murray (2009a).

[2] This is perhaps the most common way to incorporate learning into dynamic macroeconomic models. However, as Marcet and Sargent (1989) point out and Preston (2005) further demonstrates, this method is not consistent with learning in the microfoundations of the model because the least squares expectations operator does not follow the law of iterated expectations, a property that is assumed when solving the model.

sectors jointly determine the dynamics of the output gap (the percentage difference between real GDP and potential GDP), the inflation rate, and the nominal interest rate.

3.1 Consumers

There are a continuum of consumer types and a continuum of intermediate good producers, each on the unit interval. Each consumer type has a specific type of labor skill that can only be hired by a corresponding intermediate good firm. It is assumed that there many consumers of each type so that no consumer has market power over their wage. Moreover, it is assumed that there are the same number of consumers in each type, so that the output levels of intermediate goods do not depend on the distribution of consumer types. Different intermediate goods firms may pay different wages, so labor income may be different for each consumer type. To simplify the model, it is further assumed that there is a perfect asset market so despite differences in labor income, all consumers choose the same level of consumption.

Each consumer of type $i \in (0,1)$ chooses consumption, c_t, labor supply, $n_t(i)$, and purchases of real government bonds, $b_t(i)$, to maximize lifetime utility,

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{1}{1-\frac{1}{\sigma}} \xi_t \left(c_t - \eta c_{t-1}\right)^{1-\frac{1}{\sigma}} - \frac{1}{1+\frac{1}{\mu}} n_t(i)^{1+\frac{1}{\mu}} \right], \tag{1}$$

subject to the budget constraint,

$$c_t + b_t(i) = \frac{1+r_{t-1}}{1+\pi_t} b_{t-1}(i) + \frac{w_t(i)}{p_t} n_t(i) + \Pi_t - \tau_t. \tag{2}$$

where ξ_t is an aggregate preference shock, $w_t(i)/p_t$ is the real wage paid to type i labor; Π_t is the total value of profits consumers earn by owning stock in firms, and τ_t is the real value of lump sum taxes. The preference parameters are the intertemporal elasticity of substitution, denoted by $\sigma \in (0,\infty)$; the elasticity of labor supply, denoted by $\mu \in (0,\infty)$; and the degree of habit formation, denoted by $\eta \in [0,1)$.

When the degree of habit formation is greater than zero, consumers' utility from current consumption depends on their previous level of consumption. Habit formation introduces persistence in consumption, and therefore output. Significant output persistence is commonly found in empirical studies of DSGE models. For example, Smets and Wouters (2005) find point estimates of habit formation close to unity. Furthermore, Fuhrer (2000) finds that habit formation leads to "hump-shaped" impulse response functions, a characteristic commonly supported by U.S. and European data. Milani (2007) finds a significant degree of habit formation, but only under rational expectations. When estimating the model with constant gain learning, he finds an estimate for the degree of habit formation close to zero.

Log-linearizing consumers' first order conditions leads to the following log-linear Euler equation,

$$\hat{\lambda}_t = E_t \hat{\lambda}_{t+1} + \hat{r}_t - E_t \pi_{t+1}, \tag{3}$$

where $\hat{\lambda}_t$ is the percentage deviation from the steady state of the Lagrange multiplier on the budget constraint, (2), and is therefore interpreted as the marginal utility of real income. A hat indicates the percentage deviation of a variable from its steady state.[3] Utility maximization leads to the following log-linear marginal utility of income,

$$\hat{\lambda}_t = \frac{1}{(1-\beta\eta)(1-\eta)} \left[\beta\eta\sigma E_t \hat{c}_{t+1} - \sigma(1+\beta\eta^2)\hat{c}_t + \sigma\eta\hat{c}_{t-1} \right] + \left(\hat{\xi}_t - \beta\eta E_t \hat{\xi}_{t+1} \right). \tag{4}$$

The marginal utility of income, (4), and the Euler equation, (3), make up the IS sector of the model.

[3] A hat is omitted from π_t because it is necessary to assume the steady state level of inflation is equal to zero when deriving the log-linear supply relationship.

3.2 Producers

There is one final good used for consumption which is sold in a perfectly competitive market and produced with a continuum of intermediate goods according to the production function,

$$y_t = \left[\int_0^1 y_t(i)^{\frac{\theta-1}{\theta}} di\right]^{\frac{\theta}{\theta-1}}, \tag{5}$$

where y_t is the output of the final good, $y_t(i)$ is the output of intermediate good i, and $\theta \in (1, \infty)$ is the elasticity of substitution in production. Profit maximization leads to the following demand for each intermediate good,

$$y_t(i) = \left[\frac{p_t(i)}{p_t}\right]^{-\theta} y_t, \tag{6}$$

where $p_t(i)$ is the price of intermediate good i and p_t is the price of the final good. Substituting equation (6) into equation (5) leads to the following expression for the price of the final good in terms of the prices of intermediate goods,

$$p_t = \left[\int_0^1 p_t(i)^{1-\theta} di\right]^{\frac{1}{1-\theta}}. \tag{7}$$

Each intermediate good is sold in a monopolistically competitive market and is produced according to the production function, $y_t(i) = z_t n_t(i)$, where z_t is an aggregate technology shock. It can be shown that intermediate goods firms' optimal choices for labor demand and labor market clearing leads to the following aggregate log-linear marginal cost,

$$\hat{\psi}_t = \frac{1}{\mu}\hat{y}_t - \hat{\lambda}_t - \left(\frac{1}{\mu} + 1\right)\hat{z}_t. \tag{8}$$

Firm's pricing conditions are subject to the Calvo (1983) pricing friction, where only a constant fraction of firms are able to re-optimize their price in a given period. The firms that are able to re-optimize their price is randomly determined, completely independently of firms' prices or any other characteristics or history. I suppose that firms who are not able to re-optimize their price do adjust their price by a fraction, $\gamma \in [0,1)$, of the previous period's inflation rate. A positive degree of price indexation introduces a source of persistence in inflation which is often found to be statistically significant when estimating New Keynesian models (see for example, Smets and Wouters (2003), (2005), (2007), and Milani (2007)).

Let $\omega \in (0,1)$ denote the fraction of firms that are not able to re-optimize their prices every period. Since these firms are randomly determined, ω^T is the probability that a firm will not be able to re-optimize its price for T consecutive periods. A firm who is able to re-optimize chooses its price to maximize the following present discounted utility value of profits earned while the firm is unable to re-optimize its price again:

$$E_t \sum_{T=0}^{\infty} (\omega\beta)^T \frac{\lambda_{t+T}}{\lambda_t} \left\{ \left(\frac{p_t(i)\pi^*_{t+T}}{p_{t+T}} \right) y_{t+T}(i) - \Psi\left[y_{t+T}(i)\right] \right\}, \tag{9}$$

where $\Psi\left[y_{t+T}(i)\right]$ is the real total cost function of producing $y_{t+T}(i)$ units, given the optimal decision for labor, and $\pi^*_{t+T} = \prod_{j=1}^{T}(1+\gamma\pi_{t+j-1})$ is degree to which the firm's price is able to adjust according to inflation indexation. It can be shown that the first order condition for $p_t(i)$ combined with the final good price index, equation (7), leads to the log-linear Phillips equation,[4]

$$\pi_t = \frac{1}{1+\beta\gamma} \left[\gamma\pi_{t-1} + \beta E_t \pi_{t+1} + \frac{\mu(1-\omega)(1-\omega\beta)}{\omega(\mu+\theta)} \hat{\psi}_t \right]. \tag{10}$$

3.3 Fully Flexible Prices

The IS equations and Phillips equations can be re-written in terms of the difference from the outcome under fully flexible prices. This allows the model to be taken to data on the output gap, the percentage deviation of real GDP from real potential GDP, as measured by the Congressional Budget office.

Let $\tilde{y}_t = \hat{y}_t - \hat{y}^f_t$ and $\tilde{\lambda}_t = \hat{\lambda}_t - \hat{\lambda}^f_t$ denote the percentage deviation of output and marginal utility from their fully flexible price outcomes, where a superscript f denotes the outcome under fully flexible prices. Under flexible prices the linearized Euler equation, (3),

[4] It is assumed during the log-linearization that there is a steady state for the price level, which implicitly assumes the steady state level of inflation is equal to zero.

and marginal utility of income, (4), still hold. Using these conditions and imposing goods market clearing that consumption is equal to output implies,

$$\tilde{\lambda}_t = E_t\tilde{\lambda}_{t+1} + \hat{r}_t - E_t\pi_{t+1} - r_t^n, \tag{11}$$

$$\tilde{\lambda}_t = \frac{1}{(1-\beta\eta)(1-\eta)}\left[\beta\eta\sigma E_t\tilde{y}_{t+1} - \sigma(1+\beta\eta^2)\tilde{y}_t + \sigma\eta\tilde{y}_{t-1}\right], \tag{12}$$

where r_t^n is the percentage deviation of the natural interest rate from its steady state. The "natural interest rate" is the interest rate that would occur under fully flexible prices. I suppose that r_t^n follows the stochastic exogenous process,

$$r_t^n = \rho_n r_{t-1}^n + \epsilon_{n,t}, \tag{13}$$

where $\epsilon_{n,t}$ is an independently and identically distributed shock.

When prices are fully flexible, it can be shown that intermediate goods firms will all choose the same price in a given period, and the marginal cost of production is constant, and therefore always will be equal to its steady state value. Under fully flexible prices, equation (8) implies,

$$\hat{\psi}_t^f = \frac{1}{\mu}\hat{y}_t^f - \hat{\lambda}_t^f - \left(\frac{1}{\mu}+1\right)\hat{z}_t = 0.$$

One can solve this equation for $\hat{z}_t$ and substitute it back into the equation for marginal cost, (8). Plugging this expression for marginal cost into equation (10) yields the following Phillips curve in terms of the output gap,

$$\pi_t = \frac{1}{1+\beta\gamma}\left[\gamma\pi_{t-1} + \beta E_t\pi_{t+1} + \frac{(1-\omega)(1-\omega\beta)}{\omega(\mu+\theta)}(\tilde{y}_t - \mu\tilde{\lambda}_t)\right].$$

While this expression for the Phillips curve is not subject to a structural shock, when estimating the model by maximum likelihood it is convenient to have a shock here to avoid the problem of stochastic singularity. The Phillips curve is amended with a "cost-push" shock so the form that is estimated is given by,

$$\pi_t = \frac{1}{1+\beta\gamma}\left[\gamma\pi_{t-1} + \beta E_t\pi_{t+1} + \kappa(\tilde{y}_t - \mu\tilde{\lambda}_t) + u_t\right], \tag{14}$$

where κ is the reduced form coefficient on the marginal cost and u_t is an exogenous cost-push shock that evolves according to,

$$u_t = \rho_u u_{t-1} + \epsilon_{u,t}, \tag{15}$$

where $\epsilon_{u,t}$ is an independently and identically distributed shock.

3.4 Monetary Policy

The nominal interest rate is determined jointly with output and inflation by monetary policy. In this paper I assume the monetary authority follows a Taylor (1993) type rule where the interest rate is set in response to expected output and inflation, with a preference for interest rate smoothing, according to,

$$\hat{r}_t = \rho_r\hat{r}_{t-1} + (1-\rho_r)\left(\psi_\pi E_t\pi_{t+1} + \psi_y E_t\tilde{y}_{t+1}\right) + \epsilon_{r,t} \tag{16}$$

where $\rho_r \in [0,1)$ is the degree of exogenous interest rate persistence, $\psi_\pi \in (0,\infty)$ is the degree to which monetary policy responds to expectations of future inflation above the steady state level of inflation, $\psi_y \in (0,\infty)$ is the degree to which monetary policy responds to the expected output gap, and $\epsilon_{r,t}$ is an independently and identically distributed exogenous monetary policy shock with mean zero and variance given by σ_r^2.

Alternative policy rules may replace expected inflation and output with current or lagged realizations. For example, McCallum (1997) argues that a policy rule that depends on current realizations of output and inflation does not accurately depict actual information available to central banks when monetary policy decisions are made, since it takes about a full quarter to produce actual data on real GDP and price levels. He argues that the monetary policy rule should instead be expressed as a function of past data. The Taylor rule in (16) is subject to this criticism under rational expectations, but it is shown in the next section that when agents learn, expectations of future variables are completely functions of past data.

3.5 Complete Model

The complete linear New Keynesian model is represented by "IS relationship", given in equations (12) and (11); the Phillips curve in equation (14), and the Taylor rule in equation (16). These equations determine the dynamics of the output gap ($\tilde{y}_t$), the marginal utility of income gap ($\tilde{\lambda}_t$), the inflation rate (π_t), and the interest rate ($\hat{r}_t$). The model so far is subject to three structural shocks: the natural rate shock, the cost push shock, and the monetary policy shock.

4 Expectations

4.1 Learning

The log-linearized model in the previous section can be expressed in the general form:

$$\Omega_0 x_t = \Omega_1 x_{t-1} + \Omega_2 x^e_{t+1} + \Omega_2 x^e_{t+2} + \Psi z_t, \tag{17}$$

$$z_t = A z_{t-1} + \epsilon_t \tag{18}$$

where the notation x^e_{t+1} has replaced $E_t x_{t+1}$ to denote possibly non-rational expectations, x_t is a vector of minimum state variables, and z_t is a vector of structural shocks. For the New Keynesian model, $x_t = [\tilde{y}_t \ \pi_t \ \hat{r}_t]'$ and $z_t = [r^n_t \ u_t \ \epsilon_{r,t}]'$. The variable $\tilde{\lambda}_t$ can be eliminated by substituting equation (12) into equation (11) which leads to the inclusion of the two-period ahead expectation for the output gap, $E_t \tilde{y}_{t+2}$. The minimum state variable solution of the model implies the rational expectation for x_{t+1} is given by,

$$E_t x_{t+1} = G x_t + H E_t z_{t+1}, \tag{19}$$

where the elements of the matrices G and H are a function of the parameters of the model and may be determined by the method of undetermined coefficients. Agents that learn do not know the the parameters that govern the economy, but do use the reduced form of the economy for their forecasting model. Agents' information sets are restricted only to past data on x_t, so they are unable to collect data on past structural shocks to estimate matrix H. Therefore, agents collect past data on x_t to form least squares estimates for the non-zero columns of G.

In period t agents are able to assemble data sets only through period $t-1$. At this point the agents estimate G using a least squares method and use the model to make make forecasts for future output and inflation. There is no constant term in the general form of the model, equation (17), or in the rational expectation, given in equation (19), since all variables are expressed in terms of percentage deviations from the steady state or flexible price outcome. Since agents are not endowed with information about the parameters of the model, it is realistic to suppose that agents also estimate a constant term in equation (19). Let $\hat{G}_t^*$ denote agents' time t estimate for the columns of matrix G and a column for a constant term so that $\hat{G}_t^* = [\hat{g}_t \ \hat{G}_t]$, where $\hat{g}_t$ is the time t estimate of the constant term.

If agents use ordinary least squares (OLS), then,

$$\left(\hat{G}_t^*\right)' = \left(\frac{1}{t-1}\sum_{\tau=1}^{t-1} x_{\tau-1}^* {x_{\tau-1}^*}'\right)^{-1} \left(\frac{1}{t-1}\sum_{\tau=1}^{t-1} x_{\tau-1}^* x_\tau'\right), \tag{20}$$

where ${x_t^*}' = [1 \ x_t]$ is the vector of explanatory variables including the constant. This equation can be conveniently rewritten in the following recursive form:

$$\hat{G}_t^* = \hat{G}_{t-1}^* + g_t(x_{t-1} - \hat{G}_{t-1}^* x_{t-2}^*){x_{t-2}^*}' R_t^{-1}, \tag{21}$$

$$R_t = R_{t-1} + g_t(x_{t-2}^* {x_{t-2}^*}' - R_{t-1}), \tag{22}$$

where $g_t = 1/(t-1)$ is the learning gain.[5] The recursive form shows precisely how expecta-

[5]To show this, let $R_t = \frac{1}{t-1}\sum_{\tau=1}^{t-1} x_{\tau-1}^* {x_{\tau-1}^*}'$ and $\left(\hat{G}_t^*\right)' = R_t^{-1}\left(\frac{1}{t-1}\sum_{\tau=1}^{t-1} x_{\tau-2}^* x_{\tau-1}'\right)$.

tions are adaptive. The term enclosed in parentheses in equation (21) is the realized forecast error for the previous estimate $\hat{G}^*_{t-1}$. The degree to which agents adjust their expectations depends on the size of this forecast error, the variance of the estimated coefficients, captured by the inverse of matrix R_t, and the size of the learning gain, g_t. The larger is the learning gain, the more expectations respond to the latest forecast error. When agents use OLS, g_t approaches zero as time approaches infinity. Under constant gain learning, g_t remains at some constant level, g, so the degree to which new observations can affect expectations is always the same.

Agents use the least squares estimate of the coefficients in G to form the econometric forecasts,

$$\begin{aligned} E^*_t x_{t+1} &= \hat{g}_t + \hat{G}_t E^*_t x_t = (I + \hat{G}_t)\hat{g}_t + \hat{G}^2_t x_{t-1}, \\ E^*_t x_{t+2} &= \hat{g}_t + \hat{G}_t E^*_t x_{t+1} = \left[I + \hat{G}_t(I + \hat{G}_t)\right]\hat{g}_t + \hat{G}^3_t x_{t-1}. \end{aligned} \tag{23}$$

4.2 Judgment

Agents are not able to use realizations of stochastic shocks, z_t, in their forecasts.[6] However, it is realistic to suppose that current events reveal some noisy information about structural shocks, which becomes part judgment when forming expectations. Examples of such events may be natural disaster's, onset of war or political instability among trading partners, changes in weather effecting agricultural production, etc. These events cannot be instantly mapped into data to make econometric forecasts, but are nonetheless valuable information when forming expectations. Let agents' final expectations be the following sum of the econometric forecast above and judgment,

$$x^e_{t+1} = E^*_t x_{t+1} + \eta_t, \tag{24}$$

[6]Central banks do use a number of such sophisticated models that incorporate the presence of latent structural shocks when forming forecasts (indeed all much more sophisticated than what is presented in this paper). Reifschneider, Stockton, and Wilcox (1997) and Svensson (2005) point out that judgment is nonetheless an important component of central bank expectations and decisions.

where η_t includes judgment concerning the future output gap ($\eta_{y,t}$) and future inflation rate ($\eta_{\pi,t}$). The judgment vector depends on current events that includes some information about z_t, but also includes its own stochastic component that is independent of economic fundamentals. Let judgment evolve according to,

$$\begin{aligned}\eta_t &= \phi_0 + \Phi z_t + \zeta_t,\\ \zeta_{y,t} &= \rho_{\zeta,y}\zeta_{y,t-1} + \xi_{y,t},\\ \zeta_{\pi,t} &= \rho_{\zeta,\pi}\zeta_{\pi,t-1} + \xi_{\pi,t},\end{aligned} \tag{25}$$

where matrix Φ captures the degree to which judgment successfully picks up information about structural shocks and ϕ_0 is a vector of constants, and ζ_t is a vector of autocorrelated disturbances to the judgment variables. The second and third equations allow these disturbances to be autocorrelated. Therefore, agents' ill-informed judgment about a particular variable may persist for multiple quarters. The degree of persistence is given by parameters $\rho_{\zeta,y}$ and $\rho_{\zeta,y}$; and $\xi_{y,t}$ and $\xi_{\pi,t}$ are independently and normally distributed with mean zero and standard deviation given by $\sigma_{\xi,y}$ and $\sigma_{\xi,\pi}$, respectively. The vector of constants, ϕ_0, should be zero unless judgment leads to a consistent over-estimate or under-estimate of either output or inflation. I leave open the possibility that elements of ϕ_0 are non-zero to account for the observation that the forecasts reported by the Survey of Professional Forecasters often consistently under-estimate output and inflation.[7]

5 Estimation

The model is estimated using U.S. quarterly data from 1968:Q3 through 2007:Q1 on the output gap (percentage difference between real GDP reported by the Bureau of Economic Analysis and the measure of potential real GDP from the Congressional Budget Office), the

[7]Kim and Kim (2009) find persistent bias in professional forecast errors and furthermore show these past forecast errors have significant predictive power. Including past professional forecast errors as explanatory variables is shown to significantly improve upon professional forecasts for inflation.

inflation rate of the GDP deflator, and the Federal Funds Rate. Quarterly data from the same period on one quarter ahead expectations from the Survey of Professional Forecasters is also used to help identify the parameters of the learning and judgment process. The median responses were obtained for the one quarter ahead forecast for real GDP and the GDP deflator. The expectation for the output gap is found by computing the percentage difference between the forecast for real GDP and the CBO estimate for potential GDP in the next quarter. The expectation for inflation is found by computing the percentage difference between the forecast for the GDP deflator next period and the current GDP deflator. The base year used for the forecasts from the Survey of Professional Forecasters changes throughout the sample, so the data was first appropriately rescaled.

5.1 State Space Representation

Equations (17), (18), (21), (22), (23), and (25) can be combined into following single state equation convenient for evaluating a Kalman filter,[8]

$$s_t = f_t + F_t s_{t-1} + v_t \tag{26}$$

where $s_t = [\tilde{y}_t \; \pi_t \; \hat{r}_t \; \tilde{y}^e_{t+1} \; \tilde{y}^e_{t+2} \; \pi^e_{t+1} \; \eta_{y,t} \; \eta_{\pi,t} \; r^n_t \; u_t \; \zeta_{y,t} \; \zeta_{\pi,t}]'$ is a vector of state variables, and $v_t = [\epsilon_{n,t} \; \epsilon_{u,t} \; \epsilon_{r,t} \; \xi_{y,t} \; \xi_{\pi,t}]$ is a vector of all the independently and identically distributed stochastic shocks. The time-varying component of vector f_t and matrix F_t comes from the coefficients in $\hat{g}_t$ and $\hat{G}_t$ determined by the learning process in (23). You can see from this equation that f_t and F_t depend only on lagged realizations of some of the state variables, so they can be treated as predetermined when evaluating the Kalman filter.

Let GAP_t denote the data on the output gap, INF_t denote data on inflation, FF_t denote

[8]Habit formation causes the two period ahead expectation, $\tilde{y}^e_{t+2}$ to appear in the model, which in turn requires an evaluating a time t expectation for judgment $\eta_{y,t+1}$. For simplicity, I suppose this judgment is formed using the mathematical expectation operator on the equations in (25), advanced to period $t+1$. This implies that when using judgment for expectations two periods ahead, agents already discount this judgment depending on the degree of persistence, $\rho_{\zeta,y}$; and the degree to which stochastic shocks z_t impact judgment two periods ahead is determined by the actual degree of persistence dictated persistence of the natural rate and cost-push shocks (given by parameters ρ_n and ρ_u).

data on the Federal Funds Rate, and SPF_GAP_t and SPF_INF_t denote data on expected one-quarter ahead output gap and inflation rate, respectively, implied by the Survey of Professional Forecasters. The observation equations are given by,

$$
\begin{aligned}
&GAP_t = 100\tilde{y}_t, \\
&INF_t = \pi^* + 400\pi_t, \\
&FF_t = r^* + \pi^* + 400\hat{r}_t. \\
&SPF\_GAP_t = 100\tilde{y}^e_{t+1}, \\
&SPF\_INF_t = \pi^* + 400\pi^e_{t+1}.
\end{aligned}
$$

The state variables are multiplied by 100 to convert the decimals into percentages, and the inflation rate, expected inflation rate, and federal funds rate are multiplied by 4 to convert the quarterly rates to annualized rates. The New Keynesian model assumes that the steady state inflation rate is equal to zero, but since this is not likely the case in the data, the annualized steady state inflation rate, given by π^*, is estimated along with the other parameters of the model. The steady state gross real interest rate is set equal to the inverse of the discount factor; therefore $r^* = 400(1 - 1/\beta)$.

5.2 Initial Conditions

Aside from standard initial conditions for the Kalman filter and Hamilton filter, it is necessary to specify initial conditions for $\hat{g}_0$, $\hat{G}^*_0$, and R_0, the initial values for learning process given in equations (21) and (22). I use pre-sample data from 1954:Q2 through 1968:Q2 on the output gap, inflation rate, and federal funds rate and and transform these into the same terms as the state vector, x_t, according to,

$$
\begin{aligned}
\tilde{y}_t &= \frac{1}{100} GAP_t, \\
\pi_t &= \frac{1}{400}(INF_t - \pi^*), \\
\hat{r}_t &= \frac{1}{400}(FF_t - r^* - \pi^*).
\end{aligned}
$$

I estimate a VAR(1) (the same reduced form as used in the least squared learning process described in Section 4) on this data using ordinary least squares to set initial values for the learning matrices. The coefficients from the regression are used to initialize $\hat{g}_0$, $\hat{G}_0^*$, and the elements from the sum of squares component of the estimate of the variance of the coefficients is used to initialize R_0.

5.3 Bayesian Estimation

Table 1 lists the parameters to be estimated, along with the prior distribution imposed for the Bayesian estimation. The parameters include the learning gain, the parameters of the New Keynesian Model described in Section 3, the coefficients in ϕ_0 and Φ in equation (25) governing how stochastic shocks informatively impact judgment, the persistence of stochastic component to judgment, also in equation (25), and the standard deviation of the structural shocks and stochastic disturbances to judgment.

The model is estimated with Bayesian methods using the Metropolis-Hastings algorithm. The vector of parameters were drawn from the posterior distribution 400,000 times and the first 100,000 draws were discarded for a burn-in period. Table 1 shows the prior distributions used for the estimation. The prior distributions for the New Keynesian parameters are similar to others used in the literature. The prior mean for the learning gain is set to 0.02, with a rather large standard deviation of 0.3. The value of the learning gain two standard deviations above the mean is 0.08, which implies the approximate sample size agents use to develop their least squares forecasts is only $0.08^{-1} = 12.5$, or just over only 3 years of data. The large standard deviation for the prior on the learning gain allows for a relatively large probability that the learning gain is close to zero, implying agents use a large number of observations and agents adjust the coefficients for their least squares forecasts only very slowly. The prior distributions for the coefficients in judgment process are intentionally made very wide in recognition that no previous literature has attempted to measure or even discuss such coefficients.

6 Results

6.1 Parameters

The prior and posterior distributions for the parameters are listed in Table 2. The last three columns present the median, 5th percentile and 95th percentile of the posterior distributions for the parameters. The estimate for the learning gain is found to be 0.0322 with a relatively tight posterior distribution relative to the prior. This implies that agents use approximately $0.0322^{-1} = 31.06$ observations for forming least squares forecasts, which corresponds to about 7.75 years. This is a magnitude similar to that found by Milani (2007), and Slobodyan and Wouters (2007), 2008. Habit formation is found to be a significant source of persistence, with an estimate $\eta = 0.6871$. Price indexation was found to be less important in explaining persistence with an estimate $\gamma = 0.1407$. Other significant sources of persistence come from the natural rate shock ($\rho_n = 0.95$), cost shock ($\rho_u = 0.78$), and the persistence of disturbances to judgment on output and inflation ($\rho_{\zeta,y} = 0.94$ and $\rho_{\zeta,\pi} = 0.89$, respectively). The most volatile shock driving business cycles is the natural rate shock, where the cost shock, monetary policy shock, and judgment shocks have standard deviations with similar magnitudes significantly below the standard deviation of the natural rate shock. Only the preference parameters σ and μ were poorly identified by the data; these posterior distributions largely mirror the priors.

6.2 Judgment

The posterior distributions for the coefficients in ϕ_0 and Φ in the judgment process were very significantly informed by the data; these prior distributions are considerably tight given very wide posterior distributions. The 5th and 9th percentiles for posterior distributions on both $\phi_{y,0}$ and $\phi_{\pi,0}$ are all negative, implying that agents make judgments with a consistent downward bias on output and inflation. The parameters in matrix Φ determine how much judgment depends on actual stochastic shocks. Using equation 25, the variance of judgment can be decomposed into variance caused by structural parameters (informed judgment) and variance from the stochastic component (mal-informed shocks to judgment) as follows,

$$Var(\eta_t) = \Phi Var(z_t)\Phi' + Var(\zeta_t). \tag{27}$$

Both z_t and ζ_t are autoregressive stochastic processes whose variances depend on the variances for the shocks. To illustrate, the variance for z_t can be derived from the variance of the underlying independently and identically distributed shocks using equation (18) as follows,

$$Var(z_t) = AVar(z_{t-1})A' + Var(\epsilon_t)$$

Take the *vec* operator on both sides of this equation,

$$vec(Var(z_t)) = A \otimes Avec(Var(z_t)) + vec(Var(\epsilon_t)).$$

Solving for the variance of z_t leads to the expression,

$$vec(Var(z_t)) = (I - A \otimes A)^{-1} vec(Var(\epsilon_t)). \tag{28}$$

The off-diagonal elements of $Var(\epsilon_t)$ are zero, and the diagonal elements are given by squares of σ_n, σ_u, σ_r, whose estimates are reported in Table 2. The output $vec(Var(z_t))$ is then appropriately re-sized to yield $Var(z_t)$ to substitute into equation (27). A symmetric exercise performed on the autoregressive equations in (25) can yield $Var(\zeta_t)$.

Table 3 reports the percentage of the variance in judgment that is explained by actual shocks to the economy (z_t) and how much is explained by disturbances to judgment. About 85% of the variability judgment in output is explained by the variance of the shock to judgment and the remaining 15% of variability is explained primarily by the variance of the natural rate shock. This implies judgment on output is primarily ill-informed: only a small amount of judgment is based on information related to fundamentals in the economy. The second column of Table 3 shows the result is very similar for judgment regarding inflation. About 62% of the judgment in inflation is ill-informed, and the remaining 38% depends on information from the cost shock. The impact of monetary policy shocks on judgment of both variables was essentially equal to zero.

Its interesting that both the natural rate shock and cost shock help inform judgment, but strangely, the natural rate shock is not used for judgments regarding inflation, and the cost shock is not used for judgments regarding output. Both of these shocks influence output and inflation in equilibrium - yet agents irrationally believe that cost shocks only drive inflation, and natural rate shocks only drive output.

7 Conclusion

Rational expectations is a prominent assumption used in evaluating economic issues built into DSGE models, but in reality people consider statistical forecasts then use judgment to adjust these numbers when forming their actual expectations. I estimate a standard New Keynesian model using data on output, inflation, and interest rates along with data on expectations from the Survey of Professional Forecasters. Fundamental structural shocks in the model include the natural rate shock, cost shock, and monetary policy shock. I allow judgment to be based on these shocks, indicating it can be informed by current fundamental shocks, but it can also be subject to its own stochastic disturbances that are orthogonal to current structural shocks and past state variables. Stochastic shocks to judgment is found to be a significant source of economic persistence and economic volatility in U.S. history. Furthermore, judgment is found to be determined primarily by its own stochastic disturbances; very little of the variability in judgment is shown to depend on fundamental shocks.

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Table 1: Parameters and Prior Distributions

			Prior Distribution		
Parameter	Description	Domain	Distribution	Mean	Std.Dev.
g	Learning gain	R^+	Gamma	0.02	0.03
η	Habit Formation	$(0,1)$	Beta	0.70	0.10
σ	Elasticity of Substitution	R^+	Normal	1.50	0.25
μ	Labor Elasticity	R^+	Normal	2.00	0.50
κ	Phillips Curve Slope	R^+	Gamma	0.10	0.05
γ	Price Indexation	$(0,1)$	Beta	0.50	0.15
ρ_r	Policy Persistence	$(0,1)$	Beta	0.75	0.10
ψ_y	Policy Feedback Output	R	Normal	0.50	0.25
ψ_π	Policy Feedback Inflation	R	Normal	1.50	0.25
ρ_n	Natural Rate Persistence	$(0,1)$	Beta	0.50	0.20
ρ_u	Cost Shock Persistence	$(0,1)$	Beta	0.50	0.20
$\rho_{\zeta,y}$	Output Judgment Persistence	$(0,1)$	Beta	0.75	0.20
$\rho_{\zeta,\pi}$	Inflation Judgment Persistence	$(0,1)$	Beta	0.75	0.20
σ_n	Std.Dev. Natural Rate	R^+	InvGamma	0.10	0.10
σ_u	Std.Dev. Cost Shock	R^+	InvGamma	0.10	0.10
σ_r	Std.Dev. Policy Shock	R^+	InvGamma	0.10	0.10
$\sigma_{\zeta,y}$	Std.Dev. Output Judgment	R^+	InvGamma	0.10	0.10
$\sigma_{\zeta,\pi}$	Std.Dev. Inflation Judgment	R^+	InvGamma	0.10	0.10
$\phi_{y,0}$	Output Judgment Constant	R	Normal	0.00	4.00
$\phi_{y,n}$	Nat.Rate Impact on Output Judgment	R	Normal	0.00	4.00
$\phi_{y,u}$	Cost Shock Impact on Output Judgment	R	Normal	0.00	4.00
$\phi_{y,r}$	Policy Shock Impact on Output Judgment	R	Normal	0.00	4.00
$\phi_{\pi,0}$	Inflation Judgment Constant	R	Normal	0.00	4.00
$\phi_{\pi,n}$	Nat.Rate Impact Inflation Judgment	R	Normal	0.00	4.00
$\phi_{\pi,u}$	Cost Shock Impact Inflation Judgment	R	Normal	0.00	4.00
$\phi_{\pi,r}$	Policy Shock Impact Inflation Judgment	R	Normal	0.00	4.00

Table 2: Estimation Results

		Prior Distribution			Posterior Distribution		
Parameter	Domain	Distribution	Mean	Std.Dev.	Median	5th Percentile	95th Percentile
g	R^+	Gamma	0.02	0.03	0.0322	0.0224	0.0418
η	$(0,1)$	Beta	0.70	0.10	0.6871	0.6088	0.7482
σ	R^+	Normal	1.50	0.25	1.6858	1.3274	2.0728
μ	R^+	Normal	2.00	0.50	2.3458	1.6232	3.0770
κ	R^+	Gamma	0.10	0.05	0.0233	0.0114	0.0489
γ	$(0,1)$	Beta	0.50	0.15	0.2462	0.1407	0.3600
ρ_r	$(0,1)$	Beta	0.75	0.10	0.7528	0.6674	0.8236
ψ_y	R	Normal	0.50	0.25	0.1499	-0.0140	0.3201
ψ_π	R	Normal	1.50	0.25	1.8801	1.5013	2.2551
ρ_n	$(0,1)$	Beta	0.50	0.20	0.9532	0.9233	0.9796
ρ_u	$(0,1)$	Beta	0.50	0.20	0.7831	0.6936	0.8677
$\rho_{\zeta,y}$	$(0,1)$	Beta	0.75	0.20	0.9430	0.8872	0.9871
$\rho_{\zeta,\pi}$	$(0,1)$	Beta	0.75	0.20	0.8922	0.7918	0.9639
σ_n	R^+	InvGamma	0.10	0.10	0.1861	0.1180	0.2905
σ_u	R^+	InvGamma	0.10	0.10	0.0067	0.0059	0.0075
σ_r	R^+	InvGamma	0.10	0.10	0.0039	0.0036	0.0044
$\sigma_{\zeta,y}$	R^+	InvGamma	0.10	0.10	0.0091	0.0083	0.0101
$\sigma_{\zeta,\pi}$	R^+	InvGamma	0.10	0.10	0.0038	0.0034	0.0043
$\phi_{y,0}$	R	Normal	0.00	4.00	-0.0333	-0.0606	-0.0020
$\phi_{y,n}$	R	Normal	0.00	4.00	-0.0187	-0.0357	-0.0089
$\phi_{y,u}$	R	Normal	0.00	4.00	0.1377	-0.0965	0.3448
$\phi_{y,r}$	R	Normal	0.00	4.00	0.0715	0.0481	0.0938
$\phi_{\pi,0}$	R	Normal	0.00	4.00	-0.0024	-0.0037	-0.0005
$\phi_{\pi,n}$	R	Normal	0.00	4.00	0.0005	-0.0032	0.0052
$\phi_{\pi,u}$	R	Normal	0.00	4.00	-0.6204	-0.7316	-0.5201
$\phi_{\pi,r}$	R	Normal	0.00	4.00	-0.0064	-0.1257	0.1232

Table 3: Judgment Variance Decomposition

Stochastic Shock	Judgment Output (%)	Judgment Inflation (%)
Natural Rate Shock	14.93	0.08
Cost Shock	0.25	38.34
Monetary Policy Shock	0.00	0.00
Output Judgment Shock	84.82	–
Inflation Judgment Shock	–	61.58
Total	100.00	100.00