A Theory of Demand Shocks

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This paper presents a model of business cycles driven by shocks to consumer expectations regarding aggregate productivity. Agents are hit by heterogeneous productivity shocks, they observe their own productivity and a noisy public signal regarding aggregate productivity. The public signal gives rise to "noise shocks," which have the features of aggregate demand shocks: they increase output, employment, and inflation in the short run and have no effects in the long run. Numerical examples suggest that the model can generate sizable amounts of noise-driven volatility. (JEL D83, D84, E21, E23, E32)

The idea that changes in consumer expectations have a causal effect on cyclical fluctuations is widespread in business discussions and policy debates. Recent dynamic stochastic general equilibrium (DSGE) models of the business cycle include a large number of shocks (to technology, monetary policy, preferences, etc.), but typically do not include expectational shocks as independent drivers of short-run fluctuations.[1] This paper explores the idea of expectation-driven cycles, looking at a model where technology determines equilibrium output in the long run and consumers receive noisy signals about technology in the short run. The presence of noisy signals produces expectational errors. This paper studies the role of these expectational errors in generating volatility at business cycle frequencies.

The model is based on two ingredients. First, consumers take time to recognize permanent changes in aggregate fundamentals. Although they may have good information on the current state of the individual firm or sector where they operate, they have only limited information regarding the long-run determinants of aggregate activity. Second, consumers have access to public information that is relevant to estimate long-run productivity. This includes news about technological innovations, publicly released macroeconomic and sectoral statistics, financial market prices, and public statements by policy makers. However, these signals provide only a noisy forecast of the long-run effects of technological innovations. This opens the door to "noise shocks," which induce consumers to temporarily overestimate or underestimate the productive capacity of the economy.

    [1] Recent exceptions include Jean-Pierre Danthine, John Donaldson, and Thore Johnsen (1998), Paul Beaudry and Franck Portier (2004), and Nir Jaimovich and Sergio Rebelo (2006). The relation with these papers is discussed below.

In this paper, I derive the model's implications for the aggregate effects of actual technology shocks and noise shocks. In particular, the theory imposes restrictions on the relative responses of output, employment, and inflation following the two types of shocks, and it places an upper bound on the amount of short-run volatility that noise shocks can generate for a given level of fundamental volatility.

The analysis is based on a standard new Keynesian model where I introduce both aggregate and idiosyncratic productivity shocks. The average level of productivity in the economy follows a random walk. However, agents cannot observe average productivity directly. They can observe productivity in their own sector—which has a temporary idiosyncratic component—and a noisy signal of average productivity. They also observe prices and quantities that provide endogenous sources of information.

In this environment, a positive technology shock leads to a gradual adjustment in output to its new long-run level, and to a temporary fall in employment and inflation. On the other hand, a positive noise shock leads to a temporary increase in output, employment, and inflation.

The mechanism behind these effects is essentially based on the consumers' Euler equation. Current consumption depends positively on expected future consumption and negatively on the expected real interest rate. In equilibrium, agents expect future consumption to converge to a level determined by permanent changes in technology. Due to nominal rigidities, the real interest rate responds sluggishly to shocks. Therefore, consumption is driven mainly, in the short run, by changes in expectations about permanent productivity. After a technology shock, expectations respond less than one for one to the change in average productivity, given that consumers observe only noisy signals about it. Demand lags behind actual productivity, leading to a temporary fall in employment and to a deflationary pressure. A noise shock, on the other hand, has the features of a pure "aggregate demand shock." As consumers temporarily overstate the economy's productive capacity, demand increases while productivity is unchanged. This generates a temporary increase in employment and inflation.

To present my argument, I consider, first, a simple representative agent version of the model, without dispersed information, where the idiosyncratic temporary productivity shock is replaced by an aggregate temporary productivity shock. This basic model can be solved analytically and provides the essential intuition for the full model with dispersed information. However, this version of the model requires large temporary productivity shocks to prevent agents from learning long-run productivity too quickly. Dispersed information provides a more realistic way to slow aggregate learning, so that noise shocks can have sizable and persistent effects in the short run. When I turn to the model with dispersed information, I resort to numerical simulations. The computation of the model poses some technical challenges, reflecting the infinite regress problem that arises when agents "forecast the forecasts of others," as in Robert Townsend (1983). To address this problem, I develop a method of indeterminate coefficients with a truncated state space.

Numerical simulations are used both to analyze the qualitative predictions of the model and for a simple quantitative exercise. Namely, I evaluate the size of the demand disturbances generated by noise shocks in the model, under different parameterizations, and compare them with the demand disturbances in a simple bivariate VAR of output and employment, similar to Jordi Galí (1999). These simulations suggest that noise shocks may be able to produce a sizable fraction of observed demand-side volatility.

A novel element of a business cycle model based on learning and noise is that the choice of variance parameters has complex, nonmonotonic effects on the model's dynamics. This is because variance parameters affect not only the volatility of the shocks, but also the inference problem of the agents. In particular, a crucial parameter is the variance of the noise in the public signal. When this variance is either too small or too large, noise shocks generate small amounts of short-run volatility. In the first case, public signals are very precise and the economy converges

immediately to the full information equilibrium. In the second case, public signals are very imprecise and private agents tend to disregard them in their inference. Therefore, intermediate levels of noise variance are required to generate sizable amounts of short-run volatility.

Finally, I present a simple test that lends support to a central prediction of the model. According to the model, average expectations tend to underreact following an actual technology shock and to overreact following a noise shock. The reason is that, in the first case, consumers are optimistic, but actual productivity is even better than their expectations. In this case, producers tend to lower prices, leading to a stronger output response. In the second case, consumers are also optimistic, but actual productivity has not changed. Then, producers tend to increase prices, leading to a weaker output response. To test this hypothesis I look at two measures of expectations about aggregate activity, from the Survey of Professional Forecasters (SPF) and from the Michigan Consumer Sentiment Survey (CSS), and I look at their responses to identified technology and nontechnology shocks from a bivariate VAR. In both cases, nontechnology shocks tend to have a relatively larger effect on expectations than technology shocks, although the difference is significant only when using the SPF data.

The idea that expectations and expectational errors play a relevant role in explaining business cycles goes back, at least, to Arthur C. Pigou (1927) and John Maynard Keynes (1936). This idea has received renewed attention in a number of papers, including Danthine et al. (1998), Beaudry and Portier (2004, 2006), and Jaimovich and Rebelo (2006).[2] These papers emphasize the distinction between shocks to current and future productivity.[3] My paper emphasizes, instead, the difference between fundamental and noise shocks.

The signal-extraction problem faced by consumers connects this paper to a number of papers in which consumers observe noisy signals of underlying shocks. The closest are Antulio Bomfim (2001) and Rochelle M. Edge, Thomas Laubach, and John C. Williams (2007), who introduce noisy observations of total factor productivity (TFP) in standard Real Business Cycle (RBC) models. In particular, Bomfim (2001) focuses on the effects of measurement error in current TFP, which is similar to the noise shock in my model.[4] The main differences are that my paper features nominal rigidities and dispersed information, and it focuses on the conditional behavior of output, hours, and inflation after noise shocks versus fundamental shocks.

A few papers have tried to measure empirically the effects of expectational shocks due to noisy information, focusing on specific signals available in real time to the private sector. In particular, Seonghwan Oh and Michael Waldman (1990) focus on the measurement error present in the early release of the leading economic indicators, and show that shocks to this error term have sizable positive effects on aggregate activity. José V. Rodriguez Mora and Paul Schulstad (2007) show that aggregate consumption responds more to early public announcements regarding aggregate GDP than to actual movements in GDP, as measured by the revised GDP series. Both results are consistent with the approach in this paper.

Recent work on estimated DSGE models has identified intertemporal disturbances affecting the consumers' Euler equation as important drivers of the business cycle (Giorgio Primiceri, Ernst Schaumburg, and Andrea Tambalotti 2006). These intertemporal disturbances are somehow treated as a residual, as they are attributed to shocks to intertemporal preferences. In

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[2] Olivier J. Blanchard (1993) and John H. Cochrane (1994) are early papers that point attention to endogenous movements in consumption as a driving force behind cyclical fluctuation.

[3] Simon Gilchrist and John V. Leahy (2002) and Lawrence J. Christiano, Roberto Motto, and Massimo Rostagno (2006) explore the effects of shocks to future productivity on the joint behavior of aggregate activity and asset prices, and study the optimal response of monetary policy to these shocks.

[4] This formulation goes back to the original informational setup in Finn E. Kydland and Edward C. Prescott (1982). The signal-extraction problem played a minor role in their analysis and was later discarded in the development of RBC models.

this paper, I provide an alternative foundation for shocks to the consumers' Euler equation, as shocks coming from changes in average expectations about long-run fundamentals.

The modeling approach in this paper is related to various strands of literature. The idea that imperfect information can cause sluggish adjustment in economic variables and generate fluctuations driven by expectational errors goes back to Edmund S. Phelps (1969) and Robert E. Lucas (1972). More recently, Michael Woodford (2003), N. Gregory Mankiw and Ricardo Reis (2002), and Christopher A. Sims (2003) have renewed attention to imperfect information and limited information processing as sources of inertial behavior.[5] Finally, a rich literature, starting with Stephen Morris and Hyun Song Shin (2002), has emphasized that, in environments with imperfect information, public sources of information can cause persistent deviations of economic variables from their fundamental values.[6] This paper puts together ideas from these literatures to build a model of the cycle based on noisy learning.[7]

Finally, the paper is related to the literature on optimal monetary policy with uncertain fundamentals.[8] That literature focuses on the central bank's uncertainty regarding these fundamentals, while here I focus on the private sector's uncertainty.

The paper is organized as follows. Section I presents the representative agent model with common information which is used to illustrate the basic mechanism of the paper. In Section II, I introduce the model with dispersed information. In Section III, I present numerical simulations of the model. In Section IV, I present the test based on survey data. Section V concludes.

I. A Basic Model

A. *Setup*

Let me begin by considering a simple representative agent model with common information, which illustrates the basic mechanism of the paper. The model is a standard new Keynesian model with monopolistic competition and price setting *à la* Guillermo Calvo (1983). In this environment, I introduce temporary and permanent aggregate technology shocks and assume that agents cannot distinguish the two shocks and receive a noisy public signal regarding the permanent shock. I then analyze the economy's dynamic behavior, focusing on the effect of the "noise shock," which corresponds to the noise component in the public signal.

Preferences and Technology.—The preferences of the representative consumer are given by

$$E \sum_{t=0}^{\infty} \beta^t U(C_t, N_t),$$

with

$$U(C_t, N_t) = \log C_t - \frac{1}{1+\zeta} N_t^{1+\zeta},$$

[5] See also Fabrice Collard and Harris Dellas (2004), Giuseppe Moscarini (2004), Christian Hellwig (2005), Klaus Adam (2006), Philippe Bacchetta and Eric Van Wincoop (2006), Yulei Luo (2006), Reis (2006), Stijn Van Nieuwerburgh and Laura Veldkamp (2006), Fabio Milani (2007), Kristoffer Nimark (2007), and Bartosz Maćkowiak and Mirko Wiederholt (2009).

[6] See Jeffery Amato, Morris, and Shin (2002), Hellwig (2002), George-Marios Angeletos and Alessandro Pavan (2004), and Franklin Allen, Morris, and Shin (2006).

[7] Takuji Kawamoto (2004) looks at the effect of technology shocks in an environment with imperfect information. His analysis does not feature noise shocks, and focuses on the gradual adjustment of output after a technology shock. He independently derives the result that, under imperfect information, technology shocks lead to a fall in employment.

[8] See Kosuke Aoki (2003), Athanasios Orphanides (2003), Reis (2003), Lars E. O. Svensson and Woodford (2003, 2004), and Tambalotti (2003).

where N_t are hours worked and C_t is a composite consumption good given by

$$C_t = \left(\int_0^1 C_{j,t}^{(\gamma-1)/\gamma}\, dj \right)^{\gamma/(\gamma-1)},$$

$C_{j,t}$ is the consumption of good j in period t, and $\gamma > 1$ is the elasticity of substitution among goods. Each good $j \in [0,1]$ is produced by a single monopolistic firm, which has access to the linear production function

$$(1) \qquad\qquad\qquad\qquad\qquad Y_{j,t} = A_t N_{j,t}.$$

Uncertainty.—The only source of exogenous uncertainty is the productivity parameter A_t. Let $a_t = \log A_t$. From now on, a lowercase variable will denote the log of the corresponding upper-case variable. Productivity has a permanent component, x_t, and a temporary component, η_t,

$$(2) \qquad\qquad\qquad\qquad\qquad a_t = x_t + \eta_t,$$

where η_t is an i.i.d. shock, normal, with zero mean and variance σ_η^2, and x_t is a random walk process given by

$$(3) \qquad\qquad\qquad\qquad\qquad x_t = x_{t-1} + \varepsilon_t,$$

where ε_t is i.i.d., normal, with zero mean and variance σ_ε^2. Each period, all agents in the economy observe current productivity a_t and the noisy signal s_t regarding the permanent component of the productivity process, given by

$$(4) \qquad\qquad\qquad\qquad\qquad s_t = x_t + e_t,$$

where e_t is i.i.d., normal, with zero mean and variance σ_e^2. The three shocks η_t, ε_t, and e_t are mutually independent.

The noise term e_t in the signal s_t plays two roles: it prevents the agents from perfectly identifying permanent innovations to technology *and* it generates an independent source of variation in the agents' beliefs regarding x_t. As I will show below, both roles are relevant in determining the economy's cyclical behavior.

Consumers.—I consider a simple "cashless" environment where consumers have access to a nominal one-period bond which trades at the price Q_t. The consumer's budget constraint is

$$(5) \qquad\qquad Q_t B_{t+1} + \int_0^1 P_{j,t} C_{j,t}\, dj = B_t + W_t N_t + \int_0^1 \Pi_{j,t}\, dj,$$

where B_t are nominal bonds' holdings, $P_{j,t}$ is the price of good j, W_t is the nominal wage rate, and $\Pi_{j,t}$ are the profits of firm j. In equilibrium consumers choose consumption, hours worked, and bond holdings, so as to maximize their expected utility subject to (5) and a standard no-Ponzi-game condition. Nominal bonds are in zero net supply, so market clearing in the bonds market requires that $B_t = 0$.

From consumers' optimization it follows that the demand for good j is

$$(6) \qquad Y_{j,t} = \left(\frac{P_{j,t}}{P_t}\right)^{-\gamma} C_t,$$

where P_t is the price index

$$(7) \qquad P_t = \left(\int_0^1 P_{j,t}^{1-\gamma} \, dj\right)^{1/(1-\gamma)}.$$

Firms.—Firms are allowed to reset prices only at random time intervals. Each period, a firm is allowed to reset its price with probability $1 - \theta$ and must keep the price unchanged with probability θ. Firms hire labor on a competitive labor market at the wage W_t, which is fully flexible.

The firm's objective is to maximize the expected present value of its profits. Since the firms are owned by the consumers, this present value is computed using the stochastic discount factor $Q_{t+\tau|t} = \beta^\tau (C_{t+\tau}/C_t)^{-1}$. Let P_t^* denote the optimal price for a firm that can adjust its price at time t. This firm maximizes

$$E_t \sum_{\tau=0}^{\infty} \theta^\tau Q_{t+\tau|t} \left[P_{j,t+\tau} Y_{j,t+\tau} - W_{t+\tau} N_{j,t+\tau}\right],$$

subject to $P_{j,t+\tau} = P_t^*$, the technological constraint (1), and the demand relation (6). The firm takes as given the stochastic processes for P_t, C_t, and W_t, and the stochastic discount factor $Q_{t+\tau|t}$.

Aggregate real output is defined as nominal output divided by the price index P_t,

$$Y_t \equiv \frac{\int_0^1 P_{j,t} Y_{j,t} \, dj}{P_t}.$$

Substituting (6) and (7) on the right-hand side, it follows that $Y_t = C_t$, so aggregate output is equal to aggregate consumption. Inflation is defined as the change in the log of the price index P_t, that is,

$$\pi_t \equiv p_t - p_{t-1}.$$

Monetary Policy.—To complete the description of the environment, I need to specify a monetary policy rule. The central bank sets the short-term nominal interest rate, i.e., it sets the price of the one-period nominal bond, Q_t. Letting $i_t = -\log Q_t$, I can describe monetary policy in terms of choosing i_t each period. For simplicity, I focus on a simple rule that responds only to current inflation,

$$(8) \qquad i_t = i^* + \varphi \pi_t,$$

where $i^* = -\log \beta$ and φ is a constant coefficient chosen by the monetary authority.

B. *Equilibrium*

Following standard steps, the consumers' and the firms' optimality conditions and the market clearing conditions can be log-linearized and transformed so as to obtain two stochastic difference equations that characterize the joint behavior of output and inflation in equilibrium.[9]

In particular, the consumer's Euler equation and goods market clearing give the relation[10]

$$(9) \qquad\qquad y_t = E_t[y_{t+1}] - i_t + E_t[\pi_{t+1}].$$

The firm's optimal pricing condition can be manipulated so as to obtain

$$(10) \qquad\qquad \pi_t = \lambda(w_t - p_t - a_t) + \beta E_t[\pi_{t+1}],$$

where $\lambda \equiv (1 - \theta)(1 - \beta\theta)/\theta$ is a constant parameter. The first term on the right-hand side reflects the effect of real marginal costs, captured by $w_t - p_t - a_t$, on the desired price-target of the firms that can adjust prices. Substituting in (10) the consumer's optimality condition for labor supply, $w_t - p_t - y_t = \zeta n_t$, and the labor market clearing condition, $n_t = y_t - a_t$, one obtains

$$(11) \qquad\qquad \pi_t = \kappa(y_t - a_t) + \beta E_t[\pi_{t+1}],$$

where $\kappa \equiv \lambda(1 + \zeta)$.

Equations (9) and (11), together with the monetary rule (8), can be used to derive the equilibrium dynamics of y_t and π_t. Let $x_{t|t}$ denote the agents' expectation regarding x_t based on their information at date t, that is,

$$x_{t|t} \equiv E_t[x_t].$$

To characterize the equilibrium, let me begin with the following conjectures regarding the one-step-ahead forecasts of output and inflation:

$$(12) \qquad\qquad E_t[y_{t+1}] = E_t[x_t],$$

$$(13) \qquad\qquad E_t[\pi_{t+1}] = 0.$$

Substituting these conjectures and the monetary policy rule (8) in (9) and (11) gives

$$y_t = x_{t|t} - \varphi\pi_t,$$

$$\pi_t = \kappa(y_t - a_t).$$

The first equation reflects the fact that current consumption, and hence current output, depend positively on the agents' expectations regarding the permanent component of technology and negatively on current inflation, which tends to raise the nominal interest rate and, given (13), the real interest rate. The second equation shows that current inflation depends positively on the

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[9] See Galí (2007, ch. 3).
[10] From now on, throughout the paper, I will omit constant terms in linear equations, whenever confusion is not possible.

difference between current output and "natural output," which is equal to a_t.[11] Rearranging, I obtain

$$(14) \qquad y_t = \frac{1}{1 + \varphi \kappa} x_{t|t} + \frac{\varphi \kappa}{1 + \varphi \kappa} a_t,$$

$$(15) \qquad \pi_t = \frac{\kappa}{1 + \varphi \kappa} (x_{t|t} - a_t).$$

Equation (14) shows that realized output is a weighted average of productivity and of the agents' expectation about permanent productivity, $x_{t|t}$. The relative weights depend on the parameters κ and φ, which capture, respectively, the importance of nominal rigidities in the model and the responsiveness of monetary policy to inflation. I will return to the role of these parameters below. Taking expectations on both sides of (14) and (15) at time $t - 1$ and using the fact that x_t is a random walk confirm the initial conjectures (12) and (13).

C. *Productivity Shocks and Noise Shocks*

While expressions (14) and (15) provide a compact characterization of the equilibrium behavior of output and inflation, to fully characterize the economy's response to the underlying shocks $(\varepsilon_t, e_t, \eta_t)$ it is necessary to derive an explicit expression for $x_{t|t}$. Each period, the agents observe two noisy signals regarding the aggregate state x_t: current productivity a_t and the current signal s_t. Applying standard Kalman filtering techniques, the dynamics of $x_{t|t}$ are given by

$$(16) \qquad x_{t|t} = \rho x_{t-1|t-1} + (1 - \rho)(\delta s_t + (1 - \delta) a_t),$$

where ρ and δ are scalars in $(0, 1)$, which depend on the variance parameters σ_ε^2, σ_e^2, and σ_η^2.[12] In particular, the parameter ρ is increasing in σ_e^2 and σ_η^2, given that, when these variances are larger, s_t and a_t are less precise signals of x_t and agents take longer to adjust their expectation $x_{t|t}$ to the true value of x_t. The parameter δ, instead, depends on the ratio σ_e^2/σ_η^2, that is, on the relative precision of the two signals. The more precise is s_t, relative to a_t, the larger is the value of δ.

Now it is possible to study the effect of the three underlying shocks ε_t, e_t, and η_t by deriving the impulse response functions of y_t, n_t, and π_t. Let me begin by considering a permanent productivity shock, $\varepsilon_t = 1$. The response of realized productivity, $a_{t+\tau}$, τ periods after the shock, is 1 for all $\tau \geq 0$. The response of the agents' expectation $x_{t+\tau|t+\tau}$ is equal to $\sum_{k=0}^{\tau} \rho^k (1 - \rho) = 1 - \rho^{\tau+1}$. To derive this expression, iterate (16) forward and notice that, after the shock, both $s_{t+\tau}$ and $a_{t+\tau}$ increase permanently. Substituting in (14) yields the following impulse response function for output:

$$\frac{dy_{t+\tau}}{d\varepsilon_t} = 1 - \frac{\rho^{\tau+1}}{1 + \varphi \kappa} \in (0, 1).$$

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[11] Natural output is defined as the output level that arises under flexible prices. Since prices are flexible in the limit case where $\theta \to 0$ and $\kappa \to \infty$, expression (14), below, shows that indeed natural output is equal to a_t.

[12] The expressions for ρ and δ are:
$$\rho = (1/\sigma_x^2)/(1/\sigma_x^2 + 1/\sigma_\eta^2 + 1/\sigma_e^2),$$
$$\delta = (1/\sigma_e^2)/(1/\sigma_e^2 + 1/\sigma_\eta^2),$$
where $\sigma_x^2 \equiv Var_{t-1}[x_t]$ is the solution to the Riccati equation
$$\sigma_x^2 = ((1/\sigma_x^2) + (1/\sigma_\eta^2) + (1/\sigma_e^2))^{-1} + \sigma_\varepsilon^2.$$
I assume that the prior of the agents at time $t = 0$ is $N(0, \sigma_x^2)$ so that the agents' learning problem has already reached its steady state and the coefficients ρ and δ are time invariant.

The output response to a permanent productivity shock is positive, grows with τ, and converges to 1 as $\tau \to \infty$. Since $n_t = y_t - a_t$, the response of employment is

$$\frac{dn_{t+\tau}}{d\varepsilon_t} = -\frac{\rho^{\tau+1}}{1 + \varphi\kappa} < 0,$$

giving a temporary negative response of employment which dies out as $\tau \to \infty$. Using (15), inflation also displays a temporary negative response, with an impulse response function given by

$$\frac{d\pi_{t+\tau}}{d\varepsilon_t} = -\kappa \frac{\rho^{\tau+1}}{1 + \varphi\kappa} < 0.$$

The intuition behind these responses is that agents are not able to immediately identify the permanent technology shock. Therefore, the expectation $x_{t|t}$ initially underreacts relative to the actual change in underlying productivity. This implies that consumer demand, and thus output, catch up only gradually with the increased productivity of the economy. Along the transition path, firms tend to lower prices as they face lower marginal costs, and employment falls temporarily.

Let me turn to the noise shock e_t, which is a pure shock to expectations and does not affect productivity. Again, it is useful to first derive the responses of $a_{t+\tau}$ and $x_{t+\tau|t+\tau}$ to $e_t = 1$. The response of $a_{t+\tau}$ is clearly zero for all $\tau \geq 0$. The filtering equation (16) shows that the response of $x_{t+\tau|t+\tau}$ is now given by $\rho^\tau (1 - \rho) \delta$ for $\tau \geq 0$. Using (14), it then follows that the response of output is

$$\frac{dy_{t+\tau}}{de_t} = \rho^\tau \frac{(1 - \rho)\delta}{1 + \varphi\kappa} > 0,$$

the response of employment is

$$\frac{dn_{t+\tau}}{de_t} = \rho^\tau \frac{(1 - \rho)\delta}{1 + \varphi\kappa} > 0,$$

and, using (15), the response of inflation is

$$\frac{d\pi_{t+\tau}}{de_t} = \rho^\tau \frac{\kappa(1 - \rho)\delta}{1 + \varphi\kappa} > 0.$$

Therefore, output, employment, and inflation all increase in the short run and then revert to their initial values as $\tau \to \infty$.

The response to a temporary shock η_t is more complex, because in the first period the shock affects both the agents' beliefs and realized productivity, while in the following periods it affects only the agents' beliefs. Proceeding as in the previous cases, it is easy to show that the first period responses of output, employment, and inflation are, respectively,

$$\frac{dy_t}{d\eta_t} = \frac{(1 - \rho)(1 - \delta) + \varphi\kappa}{1 + \varphi\kappa} > 0,$$

$$\frac{dn_t}{d\eta_t} = \frac{(1 - \rho)(1 - \delta) - 1}{1 + \varphi\kappa} < 0,$$

$$\frac{d\pi_t}{d\eta_t} = \frac{\kappa((1 - \rho)(1 - \delta) - 1)}{1 + \varphi\kappa} < 0.$$

In the following periods, the responses are all positive and equal, respectively, to

$$\frac{dy_{t+\tau}}{d\eta_t} = \rho^\tau \frac{(1 - \rho)(1 - \delta)}{1 + \varphi\kappa},$$

$$\frac{dn_{t+\tau}}{d\eta_t} = \rho^\tau \frac{(1 - \rho)(1 - \delta)}{1 + \varphi\kappa},$$

$$\frac{d\pi_{t+\tau}}{d\eta_t} = \rho^\tau \frac{\kappa(1 - \rho)(1 - \delta)}{1 + \varphi\kappa}.$$

After the effect on productivity has vanished, the effect of η_t is analogous to that of a noise shock, since it affects only agents' expectations.

This simple model suggests that a setup where agents learn about long-run changes in productivity delivers interesting implications about the conditional correlations of output, inflation, and employment, following different shocks. In particular, the impulse responses derived above suggest that the noise shock has the flavor of an aggregate demand shock in traditional Keynesian models.

D. *Remarks*

Inspecting (14) immediately reveals that the two crucial parameters for the model's dynamics are κ, reflecting the importance of nominal rigidities in the model,[13] and φ, reflecting the monetary policy response to inflation. When either κ or φ are larger, equilibrium output tends to be closer to current productivity. In the flexible price limit (with $\theta \to 0$ and $\kappa \to \infty$), the long-run expectations of consumers determine the real interest rate but have no impact on equilibrium output. This emphasizes that the role of consumer expectations on equilibrium output is very different depending on the degree of price stickiness. Nominal rigidities mute the response of the real interest rate and imply that shifts in consumer expectations are translated into changes in current output. With flexible prices, instead, changes in expectations are completely absorbed by the real rate.

On the monetary policy side, as φ goes to infinity the equilibrium converges to the equilibrium of a flexible price economy irrespective of the value of κ. In that case, the central bank adjusts the nominal interest rate so as to mimic the movements in the real rate in the flexible price benchmark.[14] Notice that $\varphi \to \infty$ corresponds to the optimal monetary policy in this environment, as it delivers both zero inflation and a zero output gap. In this sense, the demand shocks identified above are the result of a suboptimal policy rule. Extending the model, there are a number of reasons why optimal monetary policy may not be able to mimic the flexible price benchmark in this type of environment. For example, one could introduce mark-up shocks, affecting the

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[13] Notice that κ is decreasing in θ, for given β and ζ.
[14] Substituting (15) into (8) shows that as $\varphi \to \infty$ the nominal interest rate, and thus the real interest rate, converge to $x_{t|t} - a_t$.

pricing equation, and assume that the monetary authority can observe only y_t and π_t. In this case, the monetary authority would not be able to identify the values of a_t and $x_{t|t}$ (which are needed to compute the "natural rate") and would have to base its actions on its best estimates of these variables. The analysis of optimal monetary policy in such an environment is outside the scope of this paper.[15]

Notice that in the model there is a nontrivial relation between the variances σ_ε^2, σ_e^2, and σ_η^2 and the output volatility generated, respectively, by the three shocks. In particular, consider the short-run (one-period) output volatility due to noise shocks, which is equal to

$$(17) \qquad \left(\frac{(1-\rho)\,\delta}{1+\varphi\kappa}\right)^2 \sigma_e^2.$$

Notice that, as σ_e^2 approaches zero the value of $(1-\rho)\delta$ converges to one, since in the limit the signal s_t conveys perfect information about x_t. When, instead, σ_e^2 goes to ∞, the expression $(1-\rho)\delta$ goes to zero, as the signal becomes completely uninformative.[16] In both cases, the expression in (17) goes to zero.[17] That is, when the signal is too precise or too imprecise, noise shocks tend to generate small levels of output volatility. In order for noise shocks to have a relevant cyclical effect, one needs to consider intermediate values for σ_e^2, so that agents put some weight on the signal s_t, while, at the same time, the noise e_t is sufficiently volatile. This nonmonotonic relation between the variance of the noise shocks and the output volatility they generate is a peculiar feature of a learning model of the business cycle. I will return to this point in the numerical analysis of the model with dispersed information, in Section IIIB.

E. *Toward Imperfect Information*

The objective of this paper is to build a model where demand disturbances are generated by informational shocks on aggregate productivity. By demand disturbances, I mean disturbances that generate positive comovement among output, employment, and inflation. The noise shocks in the simple model above have these features. However, in order to generate a sizable amount of volatility, they need to be accompanied by relatively large temporary shocks to productivity, that is, by a relatively large value of σ_η^2. From an analytical point of view, notice that, as σ_η^2 goes to zero, δ goes to zero, agents use only current productivity to forecast x_t, and the output volatility due to noise shocks in (17) goes to zero.[18] From a quantitative point of view, I have simulated the model above, using parameters consistent with those in Section III below. These simulations

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[15] See Aoki (2003) and Svensson and Woodford (2003) for related exercises in environments where the private sector has full information. In Lorenzoni (forthcoming), I analyze optimal monetary policy in an environment with dispersed information analogous to that in Section II.

[16] Using the expressions in footnote 12, it is easy to show that

$$\lim_{\sigma_e^2 \to 0} \rho = 0, \ \lim_{\sigma_e^2 \to 0} \delta = 1,$$

and

$$\lim_{\sigma_e^2 \to \infty} \rho = \frac{2\sigma_\eta^2}{2\sigma_\eta^2 + \sigma_\varepsilon^2 + \sqrt{(\sigma_\varepsilon^2)^2 + 4\sigma_\eta^2 \sigma_\varepsilon^2}}, \ \lim_{\sigma_e^2 \to \infty} \delta = 0.$$

[17] To prove this statement, in the second case, notice that

$$\lim_{\sigma_e^2 \to \infty} ((1-\rho)\,\delta)^2 \sigma_e^2 = \lim_{\sigma_e^2 \to \infty} \frac{1/\sigma_e^2}{(1/\sigma_x^2 + 1/\sigma_\eta^2 + 1/\sigma_e^2)^2} = 0.$$

[18] This follows from the expressions in footnote 12.

show that to obtain sizable and persistent effects of noise shocks on output (in the range of those obtained in Section IIIB) requires values of σ_η at least ten times larger than σ_ε. These values not only appear unrealistic, but, in a way, defeat the purpose of the exercise: the introduction of sizable demand disturbances requires much larger "supply disturbances," that is, disturbances that generate a negative correlation between output and inflation and between output and employment in the short run. In fact, numerical simulations show that these values of σ_η lead to negative unconditional correlations of these variables at business cycle frequencies.[19]

The role of the temporary shock η_t in the model of this section was essentially to add noise to the observation of x_t by the representative agent, so as to induce sluggish adjustment in expectations. A realistic alternative is to introduce idiosyncratic productivity shocks and assume that agents can directly observe productivity only in their own sector, which is a noisy signal about average productivity in the economy. This approach is appealing for several reasons. First, the introduction of large idiosyncratic shocks seems more realistic, as the available evidence points to the presence of large firm-level volatility, relative to aggregate volatility.[20] Second, this approach is consistent with the presence of considerable dispersion in expectations about macroeconomic aggregates, both in measures of consumer sentiment and in the survey of professional forecasters.[21] Third, given that idiosyncratic productivity shocks cancel out in the aggregate, they do not contribute to generate a negative correlation between output and employment and between output and inflation, that is, they allow me to introduce demand shocks without, at the same time, having to introduce large supply shocks.

Therefore, in the following section, I modify the model by introducing idiosyncratic productivity shocks and dispersed information. In particular, the temporary shock η_t will be replaced by idiosyncratic, sector-specific temporary productivity shocks $\eta_{l,t}$. I will then assume that agents can observe productivity only in their own sector and noisy price and quantity signals about the aggregate economy.

II. The Model with Dispersed Information

A. *Setup*

I now turn to the full model with heterogeneity and dispersed information. Consumers are located in a continuum of islands, indexed by $l \in [0, 1]$. Each island is analogous to the economy described in the previous section, with a representative consumer who owns a continuum of price-setting firms producing differentiated goods indexed by $j \in [0, 1]$. However, now islands are characterized by different productivity levels $A_{l,t}$. The consumer from island l consumes the goods produced in a subset of other islands. This subset is denoted by $\mathcal{B}_{l,t} \subset [0, 1]$ and is randomly selected by nature each period. Symmetrically, the firms in island l are visited by a subset $\mathcal{C}_{l,t} \subset [0, 1]$ of consumers coming from other islands. The random assignment of consumers to islands is such that the mass of goods in $\mathcal{B}_{l,t}$ is constant and so is the mass of consumers in $\mathcal{C}_{l,t}$. Labor is immobile across islands, so the consumer located in island l works only for the firms in island l.

Given this geography, I will make some crucial informational assumptions: agents in island l observe only productivity, output, prices, and wages in their own island, the prices of the goods

in the consumption basket of the local consumer, and a public noisy signal of aggregate inflation. With this information structure, agents receive only noisy price and quantity signals about the aggregate economy. The signal s_t, regarding the permanent component of the technology process, is still present and is publicly observed by all the agents in the economy.

Preferences and Technology.—Preferences are the same as in the previous section, except that consumption and labor supply now have an island index ($C_{l,t}$ and $N_{l,t}$) and the composite consumption good for the consumer from island l includes only the goods in the consumption basket $\mathcal{B}_{l,t}$, that is,

$$C_{l,t} = \left(\int_{\mathcal{B}_{l,t}} \int_0^1 C_{j,m,l,t}^{(\gamma-1)/\gamma} \, dj \, dm \right)^{\gamma/(\gamma-1)},$$

where $C_{j,m,l,t}$ is the consumption of variety j produced in island m, by the consumer from island l, at time t.

The production function is

$$(18) \qquad\qquad Y_{j,l,t} = A_{l,t} N_{j,l,t},$$

where $N_{j,l,t}$ is the labor input and $A_{l,t}$ is the island-specific productivity.

Uncertainty.—As in the basic model of Section I, productivity $a_{l,t}$ has a permanent component and a temporary component, but the temporary component is now idiosyncratic to island l and is denoted by $\eta_{l,t}$. Therefore, $a_{l,t}$ is given by

$$a_{l,t} = x_t + \eta_{l,t}.$$

For each island l, the idiosyncratic shock, $\eta_{l,t}$, is normal, with zero mean and variance σ_η^2, serially uncorrelated, and independent of the aggregate shocks ε_t and e_t. The cross-sectional distribution of $\eta_{l,t}$ satisfies $\int_0^1 \eta_{l,t} \, dl = 0$. The process for x_t and for the public signal s_t are given by (3) and (4), as in Section I.

Finally, there are two idiosyncratic shocks, $\xi_{l,t}^1$ and $\xi_{l,t}^2$, which introduce noise in the endogenous price and quantity signals observed by the agents, and a shock ω_t to the public signal about aggregate inflation. For ease of exposition, I will discuss them in detail below.

Each period, consumers and firms located in island l choose quantities and prices optimally on the basis of the information available to them, which includes: the local productivity $a_{l,t}$, the public signal s_t, the price of the one-period nominal bond Q_t, the local wage rate $W_{l,t}$, the prices of all the goods in the consumption basket of the local consumer $\{P_{j,m,t}\}_{j\in[0,1], m\in\mathcal{B}_{l,t}}$, the total sales of the local firms $\{Y_{j,l,t}\}_{j\in[0,1]}$, and the inflation index $\tilde{\pi}_t$, introduced below.

Consumers.—The consumer in island l owns the firms in the island and, thus, receives the profits $\int_0^1 \Pi_{j,l,t} \, dj$, where $\Pi_{j,l,t}$ are the profits of firm j in island l. Nominal one-period bonds are the only financial assets traded across islands. Due to the presence of island-specific shocks, the consumer in island l is now subject to uninsurable idiosyncratic income shocks. His budget constraint is

$$(19) \qquad Q_t B_{l,t+1} + \int_{\mathcal{B}_{l,t}} \int_0^1 P_{j,m,t} C_{j,m,l,t} \, dj \, dm = B_{l,t} + W_{l,t} N_{l,t} + \int_0^1 \Pi_{j,l,t} \, dj,$$

where $B_{l,t}$ denotes holdings of nominal bonds. In equilibrium, consumers choose consumption, hours worked, and bond holdings, so as to maximize their expected utility subject to (19) and a no-Ponzi-game condition.

For each island, there are now two relevant price indexes. The first is the local price index $P_{l,t}$, which includes all the goods produced in island l and is equal to

$$P_{l,t} = \left(\int_0^1 P_{j,l,t}^{1-\gamma} \, dj \right)^{1/(1-\gamma)}.$$

The second is the consumer price index $\overline{P}_{l,t}$, which includes all the goods consumed by consumer l and is given by

$$\overline{P}_{l,t} = \left(\int_{\mathcal{B}_{l,t}} P_{m,t}^{1-\gamma} \, dm \right)^{1/(1-\gamma)}.$$

The demand for good j in island $m \in \mathcal{B}_{l,t}$ by consumer l is then

$$C_{j,m,l,t} = \left(\frac{P_{j,m,t}}{\overline{P}_{l,t}} \right)^{-\gamma} C_{l,t}.$$

Aggregating the demand of all consumers in $\mathcal{C}_{l,t}$ gives the demand for the good produced by firm j,l, which is equal to

$$(20) \qquad Y_{j,l,t} = \int_{\mathcal{C}_{l,t}} \left(\frac{P_{j,l,t}}{\overline{P}_{m,t}} \right)^{-\gamma} C_{m,t} \, dm.$$

The economy-wide price index is defined, conventionally, as

$$P_t = \left(\int_0^1 P_{l,t}^{1-\gamma} \, dl \right)^{1/(1-\gamma)}.$$

Firms.—Firms are price-setters *à la* Calvo (1983), as in the baseline model of Section I. Each period, on each island, a fraction $1 - \theta$ of firms are allowed to reset their price. Let $E_{l,t}[.]$ denote the expectation of the agents located in island l. Let $P_{l,t}^*$ denotes the optimal price for a firm who can adjust its price in island l at time t. The problem of this firm is to maximize

$$E_{l,t} \sum_{\tau=t}^{\infty} \theta^\tau Q_{t+\tau|t}^l \left(P_{j,l,t+\tau} Y_{j,l,t+\tau} - W_{l,t+\tau} N_{j,l,t+\tau} \right),$$

subject to $P_{j,l,t+\tau} = P_{l,t}^*$, the technological constraint (18), and the demand relation (20). The firm takes as given the stochastic processes for $W_{l,t}$ and for $\overline{P}_{m,t}$ and $C_{m,t}$ for all $m \in [0,1]$, and the stochastic discount factor of consumer l, given by $Q_{t+\tau|t}^l = \beta^\tau (C_{l,t+\tau}/C_{l,t})^{-1}$.

Endogenous Signals.—I can now discuss the endogenous price and quantity signals observed by the agents and introduce the sampling shocks $\xi^1_{l,t}$ and $\xi^2_{l,t}$. I assume that the random selection of islands in $\mathcal{B}_{l,t}$ is such that the consumer price index for island l is, in log-linear approximation,

$$(21) \qquad \bar{p}_{l,t} = p_t + \xi^1_{l,t},$$

where $\xi^1_{l,t}$ is i.i.d., normal, with zero mean and variance $\sigma^2_{\xi,1} > 0$, and satisfies $\int_0^1 \xi^1_{l,t}\, dl = 0$. This assumption basically says that, each period, nature selects a biased sample of islands for each consumer l, so that the price index $\bar{p}_{l,t}$ is not identical to the aggregate price index p_t. The role of this assumption is to limit the ability of agents to infer the aggregate shocks from their observation of the prices of the goods they buy.[22]

The demand faced by firm j in island l, (20), can be rewritten, in log-linear approximation, as

$$y_{j,l,t} = \int_{\mathcal{C}_{l,t}} (c_{m,t} + \gamma \bar{p}_{m,t})\, dm - \gamma p_{j,l,t}.$$

I assume that the random selection of islands in $\mathcal{C}_{l,t}$ is such that the expression on the right-hand side takes the form

$$(22) \qquad y_{j,l,t} = y_t - \gamma(p_{j,l,t} - p_t) + \xi^2_{l,t},$$

where $\xi^2_{l,t}$ is i.i.d., normal, with zero mean and variance $\sigma^2_{\xi,2} > 0$, and with $\int_0^1 \xi^2_{l,t}\, dl = 0$. The underlying assumption is that the sample of consumers who buy goods in island l is a biased sample, so that firms receive only a noisy signal regarding $y_t + \gamma p_t$. Again, the role of this assumption is to limit the agents' ability to infer aggregate shocks by observing the quantities produced in their island.[23]

Monetary Policy.—Monetary policy is described by an interest rate rule which extends the rule in (8) by allowing for inertia in the response to inflation and for measurement error in the central bank's observation of current inflation. In particular, the nominal interest rate is given by

$$(23) \qquad i_t = (1 - \rho_i) i^* + \rho_i i_{t-1} + \varphi \tilde{\pi}_t,$$

where $\rho_i \in [0, 1)$ and φ are coefficients chosen by the monetary authority and $\tilde{\pi}_t$ is a noisy measure of realized aggregate inflation,

$$\tilde{\pi}_t = \pi_t + \omega_t,$$

where ω_t is an i.i.d. normal shock, with zero mean and variance σ^2_ω. Consumers also observe $\tilde{\pi}_t$. In fact, given that they observe the nominal interest rate and there are no monetary policy shocks, they can perfectly infer $\tilde{\pi}_t$ from their observation of i_t and i_{t-1}.

An immediate interpretation of the shock ω_t is in terms of measurement error. The evidence in David E. Runkle (1998) and Dean Croushore (2007) shows that early releases of inflation data

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[22] Given that nature selects the island-prices $p_{\bar{l},t}$ from the distribution $\{p_{\bar{l},t}\}_{\bar{l}\in[0,1]}$, consistency requires that the variance $\sigma^2_{\xi_1}$ is bounded above by the cross-sectional variance of prices across islands.

[23] As in the case of prices, consistency requires that the variance $\sigma^2_{\xi_2}$ is bounded above by the cross-sectional variance of $c_{l,t} + \gamma \bar{p}_{l,t}$ across islands.

contain considerable amounts of noise.[24] However, the shock ω_t can also be interpreted more broadly as a stand-in for all those shocks and specification errors not explicitly modeled, which make inflation a noisy measure of the distance between realized output and natural output (e.g., mark-up shocks). In Section IIIB, I will discuss how the interpretation of the shock ω_t is relevant for the quantitative implications of the model.

In general, the role of the error terms $\xi^1_{l,t}$, $\xi^2_{l,t}$, and ω_t, is to limit the consumers' ability to infer the value of the underlying aggregate fundamentals from local and aggregate observations of prices and quantities. In a simple model, with a small number of aggregate shocks, it is relatively easy for consumers to back out the fundamentals from these observations. In practice, the consumers' ability to estimate the economy's fundamentals is likely to be impaired by the presence of a larger number of shocks, with richer patterns of serial correlation, by model misspecification, and by the possible presence of structural breaks. The approach of this paper is to keep the model relatively simple, assume that consumers know exactly the model's parameters, and complicate their inference problem only by adding noise to their information.

B. Equilibrium

Unlike in the basic environment of Section I, the equilibrium dynamics of inflation and output can no longer be derived analytically, so the model will be solved numerically. As before, I study a log-linear approximation to a rational expectations equilibrium. In a setup with dispersed information, a log-linear approximation helps in three dimensions: it simplifies the inference problem of the individual agents, the state space for individual decision rules, and aggregation.

Individual Optimality Conditions.—Let me first derive the individual optimality conditions that will be used to characterize an equilibrium. The consumers' Euler equation takes the form[25]

$$(24) \qquad c_{l,t} = E_{l,t}[c_{l,t+1}] - i_t + E_{l,t}[\bar{p}_{l,t+1}] - \bar{p}_{l,t}.$$

The two differences with equation (9) are that both expected consumption and expected inflation are island-specific. On the other hand, as I will argue in the next section, consumption in each island l still tends to converge toward the common level dictated by the permanent productivity x_t. Therefore, $c_{l,t}$ is still driven by the agents' expectations of x_t, through the term $E_{l,t}[c_{l,t+1}]$, as in Section I.

To complete the characterization of the consumption side, it is useful to provide the individual budget constraint in log-linearized form:

$$(25) \qquad \beta h_{l,t+1} = h_{l,t} + p_{l,t} + y_{l,t} - \bar{p}_{l,t} - c_{l,t},$$

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[24] Runkle (1998) looks at the implicit GDP deflator, and Croushore (2007) examines the personal consumption expenditure price index, which is the main inflation variable used by the Federal Reserve since 2000. Both evaluate measurement error, comparing early releases of the price index with the revised series available at later dates. Measurement error in CPI inflation is harder to quantify, given that the CPI is not subject to revisions.

[25] To obtain log-linear approximations of the optimality conditions, I take as a reference point the stochastic equilibrium of an economy with no heterogeneity and full information (i.e., where all variances except σ^2_ε are set to zero). The full derivations are in the Web Appendix (available at http://www.aeaweb.org/articles.php?doi=10.1257/aer.99.5.2050).

where $h_{l,t} \equiv B_{l,t}/E_{l,t}[P_t Y_t]$ is the ratio of nominal bond holdings to expected aggregate nominal output. The variable $B_{l,t}$ is kept in levels rather than in logs, since it can take both positive and negative values.

Optimality for a firm that can update its price at date t gives

$$(26) \qquad p_{l,t}^* = (1 - \beta\theta) \sum_{\tau=0}^{\infty} (\beta\theta)^\tau E_{l,t}[w_{l,t+\tau} - a_{l,t+\tau}],$$

where $w_{l,t+\tau} - a_{l,t+\tau}$ represents the marginal cost in nominal terms in island l. This condition can be rewritten in recursive form as

$$p_{l,t}^* = (1 - \beta\theta)(w_{l,t} - a_{l,t}) + \beta\theta E_{l,t}[p_{l,t+1}^*].$$

The law of motion for the local price index is

$$p_{l,t} = \theta p_{l,t-1} + (1 - \theta)p_{l,t}^*.$$

Rearranging the last two equations and using the consumer's optimality condition for labor supply, $w_{l,t} - \bar{p}_{l,t} - c_{l,t} = \zeta n_{l,t}$, the labor market clearing condition, $n_{l,t} = y_{l,t} - a_{l,t}$, and the demand relation (22), I then obtain

$$(27) \qquad p_{l,t} - p_{l,t-1} = \lambda(\bar{p}_{l,t} + c_{l,t} - p_{l,t} - a_{l,t}) + \lambda\zeta(d_{l,t} - \gamma p_{l,t} - a_{l,t})$$

$$+ \beta E_{l,t}[p_{l,t+1} - p_{l,t}],$$

where $\lambda \equiv (1 - \theta)(1 - \beta\theta)/\theta$ and

$$(28) \qquad d_{l,t} \equiv y_t + \gamma p_t + \xi_{l,t}^2.$$

The quantity $d_{l,t}$ corresponds to the intercept of the demand function faced by the producers in island l in period t (in log-linear terms).

Expression (27) shows that prices in island l tend to increase when either the consumption of the local consumer or the demand for the goods produced in island l are high relative to the local productivity $a_{l,t}$. The consumption of the local consumer matters since it determines the location of the labor supply curve in island l. The demand of external consumers matters because it determines the amount of labor input required. Both variables jointly determine equilibrium wages and thus equilibrium marginal costs in island l.

The presence of imperfect information makes it impossible to aggregate (27) across islands and obtain a simple equation linking aggregate inflation to the aggregate output gap, as in (11). However, the underlying logic survives, as I will show in Section III.

Learning and Aggregation.—The economy's aggregate dynamics will be described in terms of the variables $z_t = (x_t, e_t, p_t, i_t)$. The state of the economy is captured by the infinite dimensional vector $\mathbf{z}_t = (z_t, z_{t-1}, \ldots)$. I am looking for a linear equilibrium where the law of motion for $\mathbf{z}_t$ takes the form

$$(29) \qquad \mathbf{z}_t = \mathbf{A}\mathbf{z}_{t-1} + \mathbf{B}\mathbf{u}_t^1,$$

with

$$\mathbf{u}_t^1 \equiv (\ \varepsilon_t \ \ e_t \ \ \omega_t \ )',$$

and the appropriate rows of $\mathbf{A}$ and $\mathbf{B}$ conform with the law of motion of x_t in (3) and with the monetary policy rule (23).[26]

To solve for a rational expectations equilibrium, I conjecture that $p_{l,t}$ and $c_{l,t}$ follow the rules

(30)
$$p_{l,t} = q_h h_{l,t} + q_p p_{l,t-1} + q_a a_{l,t} + q_d d_{l,t} + q_z E_{l,t}[\mathbf{z}_t],$$

(31)
$$c_{l,t} = -\overline{p}_{l,t} + b_h h_{l,t} + b_p p_{l,t-1} + b_a a_{l,t} + b_d d_{l,t} + b_z E_{l,t}[\mathbf{z}_t].$$

The expressions (30) and (31) represent, respectively, the optimal pricing policy of the firms in island l (aggregated across firms) and the optimal consumption policy of the representative consumer in island l. Notice that $h_{l,t}$, $p_{l,t-1}$, and $E_{l,t}[\mathbf{z}_t]$ are the relevant individual state variables to describe the average behavior of consumers and firms on island l. I need to keep track of $h_{l,t}$ because of the consumer's budget constraint, I need $p_{l,t-1}$ because of Calvo pricing, and I need $E_{l,t}[\mathbf{z}_t]$ to form agents' expectations about current and future values of the aggregate state $\mathbf{z}_t$. The dynamics of $E_{l,t}[\mathbf{z}_t]$ can be characterized recursively using the Kalman filter,

$$E_{l,t}[\mathbf{z}_t] = \mathbf{A} E_{l,t-1}[\mathbf{z}_{t-1}] + \mathbf{C}(\mathbf{s}_{l,t} - E_{l,t-1}[\mathbf{s}_{l,t}]),$$

where $\mathbf{s}_{l,t}$ is the vector of signals observed by the agents in island l,[27]

$$\mathbf{s}_{l,t} = (\ a_{l,t} \ \ s_t \ \ \overline{p}_{l,t} \ \ d_{l,t} \ \ i_t \ )',$$

and $\mathbf{C}$ is a matrix of Kalman gains, which is derived explicitly in the Appendix. Let $\mathbf{z}_{t|t}$ denote the average expectation regarding the aggregate state $\mathbf{z}_t$, defined as

$$\mathbf{z}_{t|t} \equiv \int_0^1 E_{l,t}[\mathbf{z}_t]\, dl.$$

The individual updating rules can then be aggregated to find a matrix Ξ such that

(32)
$$\mathbf{z}_{t|t} = \Xi \mathbf{z}_t.$$

In equilibrium, aggregate output y_t is given by

(33)
$$y_t = \psi \mathbf{z}_t,$$

where ψ is a vector of constant coefficients. The solution of the model requires finding matrices $\mathbf{A}$, $\mathbf{B}$, $\mathbf{C}$, Ξ, and vectors ψ, $\{q_h, q_p, q_a, q_d, q_z\}$ and $\{b_h, b_p, b_a, b_d, b_z\}$ that are consistent with

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[26] See the Appendix for explicit expressions for $\mathbf{A}$ and $\mathbf{B}$.

[27] For computational reasons, it is convenient to include i_t instead of $\tilde{\pi}_t$ in the set variables observed by the agents. This allows me to simplify the Kalman filter, since, in this way, aggregate shocks do not appear in the observation equation. Since the agents know the monetary policy rule, (23), they can recover $\tilde{\pi}_t$ from their observation of i_t and i_{t-1}.

TABLE 1—BASELINE PARAMETERS

σ_ε	0.0077	σ_η	0.15
σ_e	0.03	$\sigma_{\xi,1}$	0.02
σ_ω	0.0006	$\sigma_{\xi,2}$	0.11

agents' optimality, with Bayesian updating, and with market clearing in the goods, labor, and bonds markets. The details of the algorithm used for computations are in the Appendix.

Computing an equilibrium requires dealing with the infinite histories $\mathbf{z}_t$. Here, I replace $\mathbf{z}_t$ with a truncated vector of states $\mathbf{z}_t^{[T]} = \{z_t, \ldots, z_{t-T}\}$. Numerical results show that when T is sufficiently large the choice of T does not affect the equilibrium dynamics. For the simulations presented below, I use $T = 50$. Kenneth Kasa (2000) uses frequency domain methods to deal explicitly with infinite histories, and explores in what cases infinite histories lead to a fully revealing equilibrium. In particular, he shows that in the model of Townsend (1983) with a continuum of industries, imperfect information does not go away when looking at infinite histories.[28] My numerical results suggest that my model belongs to the same class of models, given that increasing T in my simulations does not lead to smaller expectational errors.[29]

III. Noise Shocks and Aggregate Volatility

In this section, I use numerical simulations to explore the qualitative implications of the model with dispersed information. The model is too stylized for a full quantitative analysis, so I will take only a first pass at a basic quantitative question: how large are the cyclical movements generated by noise in public information? To address this question, I will compare the demand shocks generated by the model, under different parameterizations, with those generated by a simple bivariate VAR.

The discount factor β is set equal to 0.99, so the time period can be interpreted as a quarter. The inverse Frisch elasticity of labor supply ζ is set to 0.5 and the elasticity of substitution γ is set to 7.5. The parameter θ is set equal to **2/3**, corresponding to an average price duration of three quarters. These values are in the range of those used in existing DSGE studies with monopolistic competition and sticky prices. The parameters for the monetary policy rule are set at $\rho_i = 0.9$ and $\varphi = 1.5$, which corresponds to a relatively inertial Taylor rule with a response to inflation broadly consistent with existing empirical estimates.[30]

It remains to choose values for the variance parameters. Unlike standard linearized models, models with imperfect information do not display a "certainty equivalence" property; that is, variance parameters do not simply determine the size of the shocks, leaving the behavioral responses unchanged. These parameters also affect the filtering problem faced by the agents and thus contribute to determine the size and shape of the responses of the endogenous variables. I have chosen variance parameters so as to replicate as well as possible the impulse responses derived from a simple bivariate VAR in output and employment. The choice of these parameters is discussed in detail in Section IIIB. The baseline parameters are reported in Table 1.

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[28] See Section 2 of Kasa (2000).

[29] See also Giacomo Rondina (2008) for an application of frequency domain methods to a related monetary environment, and Nimark (2008), who uses a truncation method in the space of higher-order expectations.

[30] See, for example, Richard Clarida, Galí, and Mark Gertler (2000), and Christiano et al. (2005).
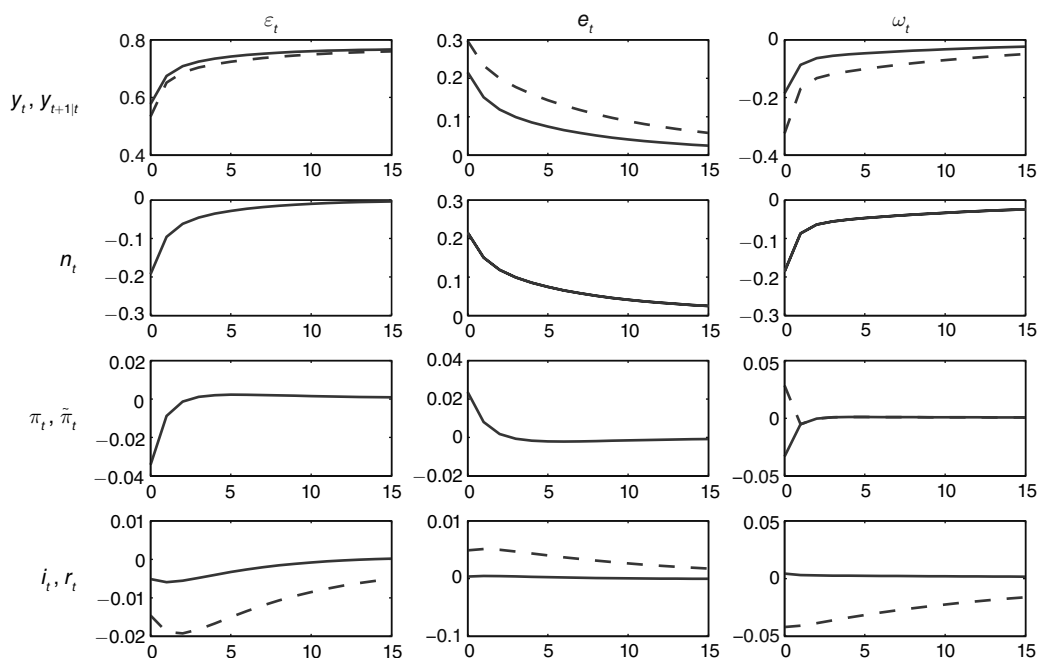
FIGURE 1. IMPULSE RESPONSES OF OUTPUT, EMPLOYMENT, INFLATION, AND THE INTEREST RATE

A. *Responses to the Three Shocks*

Figure 1 depicts the responses of output, employment, inflation, and the interest rate to the three shocks ε_t, e_t, and ω_t. In the first row of graphs, I plot both the response of y_t (solid line) and that of $y_{t+1|t} = \int E_{l,t}[y_{t+1}] \, dl$, representing the average expectation of next period's output y_{t+1} (dashed line). In the second row, I plot the response of hours. In the third row, I plot both the response of actual inflation π_t (solid line) and of the noisy inflation measure $\tilde{\pi}_t$ (dashed line). In the fourth row, I plot the nominal interest rate i_t (solid line) and the average expected real rate, given by $r_t = i_t - p_{t+1|t} + p_t$ (dashed line). For all three shocks, I plot the responses to a one-standard-error shock.[31]

From a qualitative point of view, the shocks ε_t and e_t have effects similar to those in the common information model of Section I. The technology shock leads to a gradual adjustment of output to its new long-run level and to a temporary fall in employment and inflation. The noise shock e_t leads to a joint, temporary increase in output, employment, and inflation.

The intuition behind the output response to the noise shock is that forward looking consumers expect their future incomes and consumption levels to be driven by the permanent, common component of technology, x_t. A noise shock temporarily increases their expectation of x_t. This increases expected future consumption on the right-hand side of the Euler equation (24). At the same time, the real interest rate, also on the right-hand side of (24), responds sluggishly, due to the combination of nominal rigidities and of a partially responsive monetary rule. This implies

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[31] In all figures, the scale of the responses is multiplied by 100 to make the graphs more readable.

that the pressure from increased consumer demand translates into a temporary increase in output and employment. The last row of graphs confirms this intuition, showing that the response of the real interest rate is relatively small after all three shocks, so that movements in consumption are dominated by movements in income expectations.

To understand the effects of the shock ω_t, notice that this shock operates through two channels: a monetary policy channel and an information channel. First, a positive shock ω_t leads to a temporary increase in measured inflation and thus to a nominal interest rate increase. Second, agents know that positive inflation tends to be associated with an overestimate of natural output. Thus, the shock ω_t leads agents to revise downward their expectations about x_t. Both channels lead to a reduction in spending and aggregate output. In particular, with the parameters given above, the information channel explains virtually all of the output decline following the shock. This can be seen both in the strong comovement of y_t and $y_{t+1|t}$ after an ω_t shock (in the top-right graph of Figure 1) and in the small response of the nominal interest rate (in the bottom-right graph). Therefore, in this example, ω_t is essentially an additional noise shock, leading to qualitative responses analogous to those following an e_t shock (with the opposite sign).

This leads to an interesting observation. The presence of a noisy public statistic (here about inflation) can have ambiguous effects on noise-driven volatility. On the one hand, it allows agents to better estimate the economy's fundamentals. On the other hand, it introduces an additional source of correlated expectational errors. I will return to this point below and discuss further the role of the shock ω_t.

B. *How Much Noise-Driven Volatility Can the Model Generate?*

In Figure 2, I report the impulse responses obtained from a simple bivariate VAR of GDP and hours, using US quarterly data. To identify the technology shock, I use a long-run identification restriction *à la* Blanchard and Danny Quah (1989), following Galí (1999).[32] In Figure 3, I report the impulse responses obtained from performing the same exercise on a 10,000-period sample generated using the simulated theoretical model.[33] The solid lines correspond to the baseline parameters in Table 1 and the dashed lines to an alternative parameterization, with $(\sigma_e, \sigma_\omega) = (0.04, 0.0015)$ and the remaining parameters as in Table 1.

Comparing the top-left panels of Figures 1 and 3 shows that the long-run identification strategy allows me to identify the productivity shock ε_t in the model, despite the presence of three shocks in the model. At the same time, the "nontechnology" shock obtained from the VAR on the simulated series reflects the combined effect of the shocks e_t and ω_t. As argued above, both e_t and ω_t are essentially two noise shocks and have similar implications for output and employment. Therefore, here I will not attempt to separate them with a richer identification strategy and I will concentrate on evaluating their joint role in generating short-run volatility.

Notice also that, in comparing the model with the data, I am implicitly attributing all nontechnology disturbances in the empirical VAR to noise shocks. This is clearly an extreme assumption, as it leaves out a number of additional shocks that one would like to include on the demand side (e.g., monetary shocks and shocks to government spending). However, this assumption is in line with the spirit of the exercise, which is to generate as much demand-side volatility as possible, using *only* noise shocks.

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[32] The data are from the Haver USECON database, the sample period is 1948:I–2006:III, the measure of output is the GDP quantity index (GDPQ), and the measure of hours worked is hours in the business sector (LXBH). Both variables are in logs, multiplied by 100. Hours are detrended using a quadratic trend, and the VAR is estimated using four lags. The dashed lines represent 10 percent confidence bands, computed following Sims and Tao Zha (1999).

[33] See Fabio Canova (2007, ch. 4.7) for a systematic discussion of this type of "first-pass" evaluation of DSGE models using VARs.

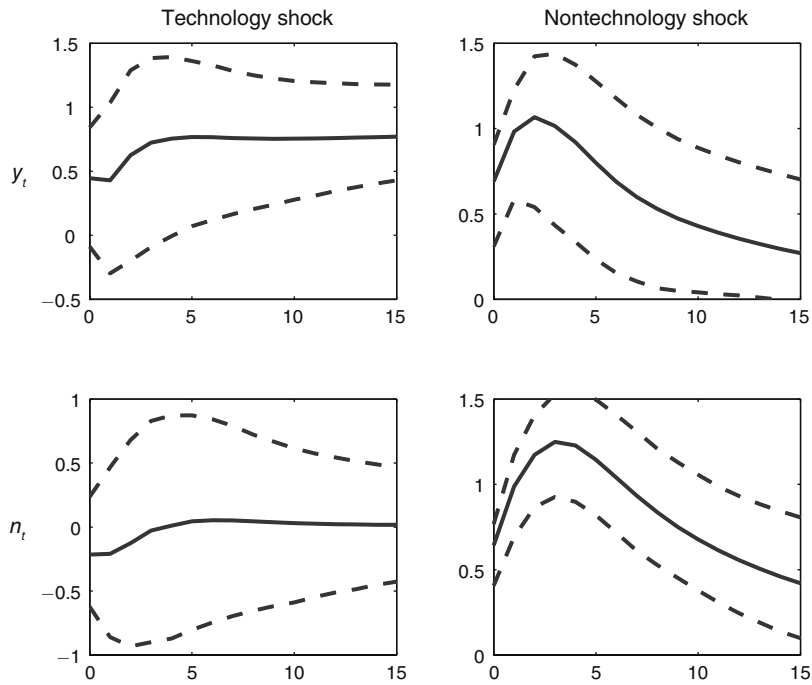Technology shock | Nontechnology shock

FIGURE 2. IMPULSE RESPONSES: BIVARIATE VAR ON US DATA,
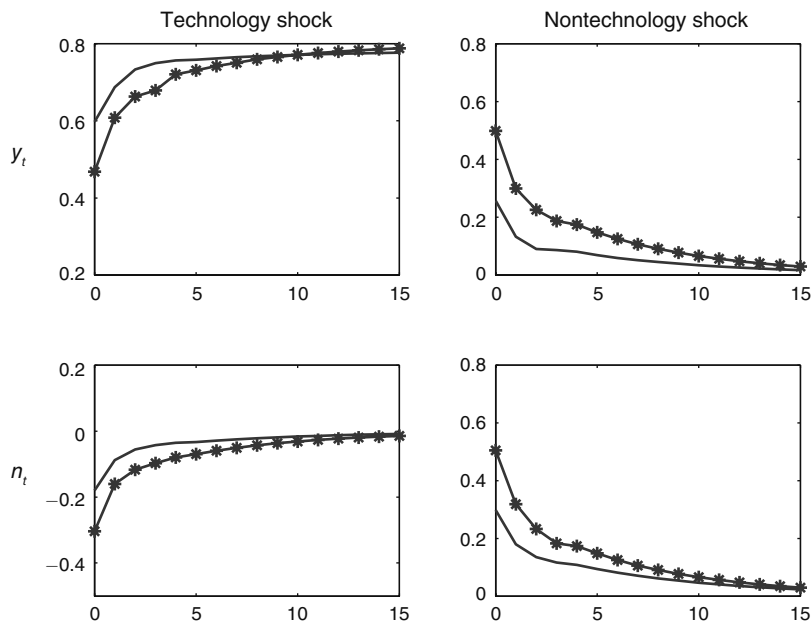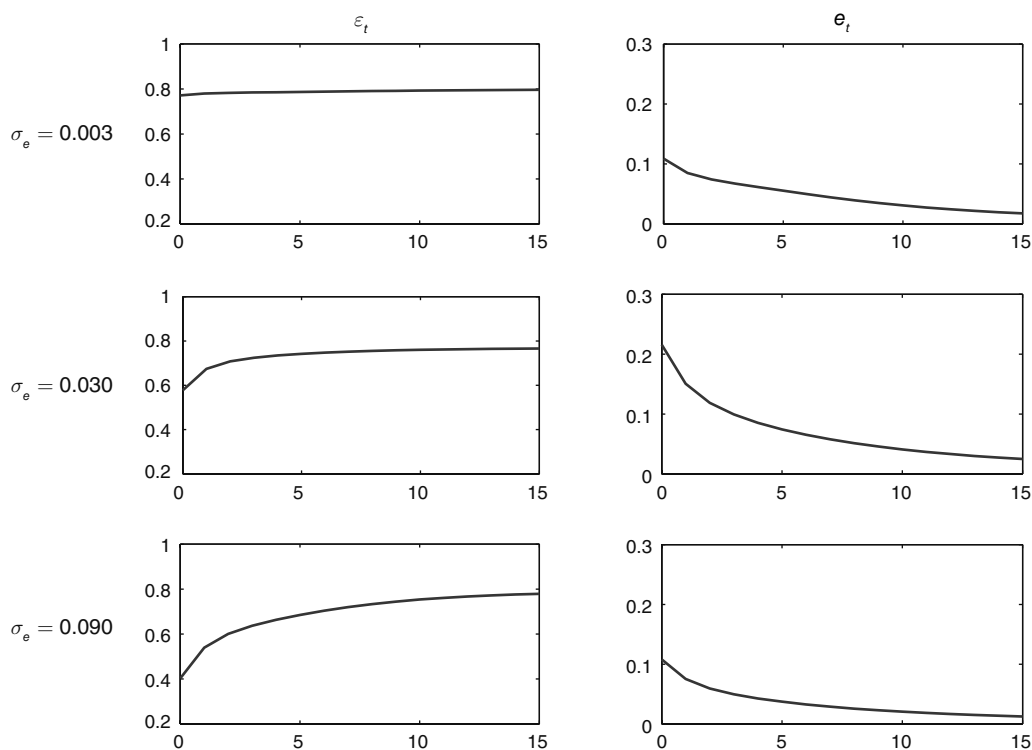WITH A LONG-RUN RESTRICTION

FIGURE 3. IMPULSE RESPONSES: BIVARIATE VAR ON SIMULATED DATA,
WITH A LONG-RUN RESTRICTION

Note: Solid lines: baseline parameterization; starred lines: high-variance parameterization.

FIGURE 4. OUTPUT RESPONSES FOR DIFFERENT VALUES OF σ_e

Let me discuss the choice of the variance parameters. The standard deviation of the technology shock, σ_ε, is set so as to replicate the empirical long-run output response to an identified technology shock in the data, which is 0.0077.

The noise shock volatility σ_e is chosen in order to obtain the maximum amount of noise-driven output volatility in the short run. That is, to maximize the impact response of output to nontechnology shocks. Notice that there is a nonmonotone relation between σ_e and noise-driven volatility, as in the common information model of Section I. As I increase the variance of the noise associated to the signal s_t, the precision of the signal deteriorates and agents put less weight on it. To illustrate this, in Figure 4, I plot the output response to the shocks ε_t and e_t, for different values of σ_e, keeping all other parameters at their baseline levels.[34] This figure illustrates the rich effects that the choice of variance parameters has on the model dynamics. The maximum output response to the e_t shock arises for intermediate values of σ_e. Changing σ_e also modifies the shape of the output response to a productivity shock, by changing the speed at which agents learn the underlying value of x_t. When σ_e is larger, learning is slower, and the output response to a technology shock is more gradual.

To choose σ_ω, I interpret ω_t as measurement error in early releases of inflation data and try to match the signal-to-noise ratio in these data. Namely, I interpret $\tilde{\pi}_t$ as the first release of the inflation rate and π_t as the final revision.[35] Then, I choose σ_ω to obtain a realistic value for the ratio between the standard deviation of the measurement error and the standard deviation of

[34] Recall that the impulse responses are normalized to represent responses to a one-standard-deviation shock.
[35] This is a conservative assumption, as the last revision will still contain some measurement error.

the innovation in "true" inflation. The latter is measured running a simple univariate autoregression of inflation with two lags (using data for the last revision). Runkle (1998) follows this approach and obtains a ratio of 0.77 using GDP deflator inflation. I performed similar calculations for PCE inflation, using the data in Croushore (2007), and obtained a ratio of 1.97.[36] Matching these two values, I obtain the alternative parameterizations $(\sigma_e, \sigma_\omega) = (0.03, 0.0006)$ and $(\sigma_e, \sigma_\omega) = (0.04, 0.0015)$ depicted in Figure 3.

Finally, the idiosyncratic volatilities σ_η, $\sigma_{\xi,1}$, and $\sigma_{\xi,2}$ are assumed to be large relative to the volatilities of the aggregate shocks. In particular, σ_η is taken to be 20 times as large as σ_ε. For a given value of σ_η, the parameters $\sigma_{\xi,1}$ and $\sigma_{\xi,2}$ are chosen so that they satisfy the upper bounds described in footnotes 22 and 23.[37] As argued above, the assumption of large idiosyncratic shocks is not unrealistic, given recent empirical findings on firm-level volatility (see footnote 20). This choice of parameters implies that agents learn little about the underlying aggregate shocks from their local observation of productivity, prices, and quantities; they learn primarily from the exogenous signal s_t and from the endogenous signal $\tilde{\pi}_t$. As long as the values of σ_η, $\sigma_{\xi,1}$, and $\sigma_{\xi,2}$ are greater than or equal to those in Table 1, their specific values have little effect on the model's aggregate implications.

Comparing Figures 2 and 3 shows that the model is able to capture well some features of the empirical impulse response functions. In particular, two patterns are present both in the data and in the model (under both parameterizations). First, following a nontechnology shock, hours tend to increase roughly one for one with output. Second, following a technology shock, hours tend to fall and the drop in hours is of the same size as the difference between the impact response of output and its long-run response.[38]

There are other features of the empirical responses that are not captured by the model, in particular, the hump-shaped responses of output and hours following the nontechnology shock. At this stage of the analysis, however, the major quantitative challenge for the model is whether it is able to generate relatively large nontechnology disturbances. The answer to this question depends on the parameterization. In both versions of the model the effects of nontechnology shocks are smaller than in the data, but the model with larger volatilities for e_t and ω_t generates a larger amount of short-run volatility.[39] In particular, it generates an output response to the nontechnology shock on impact, which is not too far from the empirical one (0.0050 in the model, 0.0069 in the data). It also displays an output response to the technology shock more in line with the data, with a smaller effect on impact and a more gradual convergence afterward. This is due to the fact that greater volatility in the public signals s_t and $\tilde{\pi}_t$ implies that the agents take more time to learn the value of x_t. Therefore, in terms of matching the empirical impulse responses, the second parameterization is preferable.

As argued above, the shock ω_t can be interpreted as pure measurement error, or, more generally, as a "reduced-form" way of introducing shocks and specification errors that make inflation

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[36] Croushore (2007, table 1) reports a standard deviation of the difference between the first release and the last revision of quarterly PCE inflation equal to 0.89. An autoregression of quarterly PCE inflation with two lags gives a standard deviation of the innovation equal to 0.45. This gives me the ratio 0.98/0.45 = 1.97. The difference with Runkle (1998) probably reflects the greater accuracy of PCE revisions.

[37] In particular, I use (30) and (31) to evaluate the cross-sectional volatilities in prices and demand which are solely due to the idiosyncratic shocks $\eta_{l,t}$ and use these as conservative upper bounds for $\sigma_{\xi,1}$ and $\sigma_{\xi,2}$.

[38] The finding that hours respond negatively to an identified technology shock is the subject of a heated debate (Christiano et al. 2003; Neville Francis and Valerie Ramey 2003; V. V. Chari, Patrick J. Kehoe, and Ellen R. McGrattan 2004; Galí and Pau Rabanal 2005). This debate has highlighted the need of a theory-based rationale for identification assumptions. The present model has at least the virtue of being consistent with the identification assumptions in the VAR exercise.

[39] This is not as obvious as it sounds, given the nonmonotone relation between noise variance and noise driven volatility.

a noisy measure of the distance between current and natural output. Under this broader interpretation, one might parameterize the model with larger values of σ_ω, magnifying the effects of noise shocks.

In sum, the model ability to generate sizable noise-driven shocks rests crucially on the assumptions made about the volatility of the various shocks. Clearly, the model is highly stylized so it is relatively easy for the agents in the model to figure out the underlying value of x_t from observing public statistics of productivity and inflation. A richer model that allows, for example, for monetary policy shocks and shocks to government expenditure would make this inference problem more complicated. Monetary policy shocks would confound the inference problem of the agents, by breaking the tight connection between inflation and the estimation error of x_t. Therefore, introducing additional shocks might be useful not only to increase directly demand-side volatility, but also to magnify the effect of noise shocks.

Thus far, I have concentrated on the model's ability to replicate *conditional* correlations of output and employment, which are estimated using VAR methods. An alternative is to evaluate the model looking at its implication in terms of simple *unconditional* correlations. It is interesting to recast the conclusions of this section in terms of unconditional implications. Notice that the model generates a negative correlation of output and employment following a technology shock, and a positive correlation following a noise shock. Therefore, to obtain a positive unconditional correlation (as observed in the data), I need noise shocks to explain a large fraction of total volatility. In particular, under the baseline parameterization described above, I obtain a correlation between output and employment which is basically zero (looking at HP-filtered simulated series), while under the high-variance parameterization used for Figure 3, the correlation is 0.25. Both fall short of the empirical correlation, which is around 0.8. The model does better in terms of total employment volatility. The standard deviation of (HP-filtered) hours relative to that of output is 0.37 in the baseline parameterization and 0.62 in the high-variance parameterization. The corresponding empirical value is close to one. Therefore, both conditional and unconditional moments show that, although noise shocks can generate a sizable fraction of demand-side volatility, they are not enough to explain all of it in the present model.

IV. A Test Using Survey Data

A crucial distinction between a noise shock and an actual technology shock is that, when a noise shock hits, agents' expectations tend to overreact, while, when a technology shock hits, they tend to underreact. In both cases agents receive a positive signal regarding x_t. However, given imperfect information, in the first case the actual change in x_t exceeds the expected change. In this case, firms lower prices, the expected real interest rate falls, and realized output ends up responding more than expected output. In the second case, firms tend to increase prices, the expected real interest rate increases, and realized output responds less. The difference $y_t - y_{t|t}$ is then positive in the first case and negative in the second case. This is illustrated in the top row of Figure 1.[40] This is a robust prediction of the model, which holds across a wide range of parameter values and captures the central role played by expectational errors in the model.

In this section, I attempt to test this prediction, using survey data to obtain a measure of the agents' average expectations, corresponding to $y_{t|t}$ in the model. The idea of the test is to use the simple bivariate semi-structural VAR introduced in the previous section to identify technology and nontechnology shocks, and then to test the hypothesis that output expectations underreact

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[40] To help the Euler equation interpretation of consumption movements, the figure displays the path of the one-period-ahead average forecast $y_{t+1|t}$. However, the path for the contemporary average forecast $y_{t|t}$ is virtually identical to that of $y_{t+1|t}$.

TABLE 2—REGRESSION OF EXPECTATION MEASURES ON IDENTIFIED SHOCKS

	Coefficient	Standard error
Survey of professional forecasters data		
Technology shock	0.9063	0.2515
Nontechnology shock	1.5582	0.1582
Test of the difference between coefficients		
$F(1,133) = 4.7144$ (significance level: 0.0317)		
Consumer sentiment survey data		
Technology shock	404.46	219.78
Nontechnology shock	644.76	149.18
Test of the difference between coefficients		
$F(1,167) = 0.8692$ (significance level: 0.3525)		

following a technology shock and overreact following a nontechnology shock. As measures of expectations, I use data from the Survey of Professional Forecasters (SPF) and from the Michigan Consumer Sentiment Survey (CSS). From the SPF, I take the median forecasts of nominal GDP and of the GDP deflator in the coming quarter to form a forecast of real GDP.[41] From the CSS, I take the third component of the Index of Consumer Sentiment which reflects the consumers' expectations regarding the state of the economy in the coming 12 months.[42]

To make the coefficients easier to interpret, I normalize the technology and the nontechnology shock from the VAR, so that each has a 1 percent impact effect on output. Then, letting Y_t^e denote the expectation variable, I regress Y_t^e on contemporaneous values of the technology and nontechnology shocks, on lagged values of Y_t^e, and on lagged values of GDP and hours.[43] In Table 2, I report the regression coefficients of the two shocks for each dataset. In the same table, I report the F-statistic for a test of the difference between the coefficients of the two shocks.

These results lend support to the model's prediction, as the coefficients for both the technology and the nontechnology shock are positive, and the coefficient for the nontechnology shock is larger using both datasets. However, the difference between the two coefficients is only significant when I use the SPF data. This may be due to the fact that the SPF variable is defined in terms of an explicit estimate of aggregate GDP, while the CSS index is an aggregate of qualitative responses, which is more loosely connected to the respondents' quantitative expectations about aggregate output.[44] This also implies that the values of the coefficients have a more meaningful interpretation in the case of the SPF data. In this case, the coefficients can be used for a stronger test of the model's predictions. That is, I can look at the absolute value of the two coefficients and not just at their difference. This version of the test also provides support to the model's mechanism. In particular, the coefficient on the technology shock is smaller than one (although not significantly different from one), and the coefficient on the nontechnology shock is larger than one (and here the difference is statistically significant).

[41] The mnemonics for the two variables used are NGDP2 and PGDP2. The sample is 1968:IV–2006:III.
[42] This is the component denominated "business condition, 12 months." The sample is 1960:I–2006:III.
[43] In the reported regressions I use four lags for Y_t^e, GDP, and hours.
[44] The index used here is based on the respondents' answers to the question: "Now turning to business conditions in the country as a whole—do you think that during the next 12 months we'll have good times financially, or bad times, or what?" The index is equal to the percentage of positive answers minus the percentage of negative answers (plus 100).

To check the robustness of the result, I have repeated the exercise using different VAR specifications to estimate the technology and nontechnology shocks, obtaining very similar results.[45] I have also tried different measures of expectations, obtaining similar qualitative results, although the difference in the coefficients is significant only when using one- and two-quarter-ahead SPF forecasts.[46]

Notice that the VAR identification approach used here bunches together all nontechnology shocks as if they were all driven by noise. Richer identification strategies, which are able to tease out monetary shocks and shocks to government spending, may yield sharper conclusions regarding the effect of noise shocks on expectations.

V. Concluding Remarks

In this paper, I interpret the business cycle as a process of noisy learning by the consumers, who can temporarily overstate or understate the economy's productive capacity. This idea is incorporated into a standard dynamic general equilibrium model and gives rise to noise shocks, which have the features of aggregate demand shocks.

For the sake of simplicity, the model makes sharp assumptions regarding the processes for aggregate and individual technology: the aggregate technology shock is a permanent level shock; the idiosyncratic shock is purely a temporary shock. Both assumptions could be relaxed. Introducing persistent shocks to the growth rate of aggregate TFP, rather than to the level, may help to better capture the uncertainty about medium-run swings in productivity growth. This modification may lead to potentially larger consumption responses, given that the same short-run increase in TFP would be associated to larger increases in the expected present value of income. Introducing persistence in idiosyncratic shocks would have two effects. On the one hand, it would induce agents to rely more on their private productivity signal, since it is a better predictor of future individual income. This would tend to reduce the effect of noise shocks. On the other hand, it would introduce serial correlation in the private productivity signal, inducing slower learning and increasing the effect of noise shocks.

Further, the model features no capital and has a very limited role for financial markets. This choice was made to concentrate on consumers' learning dynamics and to introduce dispersed information in the simplest setup. However, uncertainty about long-run technology innovations is clearly crucial for investment decisions. Adding investment may help to generate larger demand responses following a noise shock, improving the model's ability to fit the data.

Finally, the model requires high levels of idiosyncratic uncertainty in order to generate relatively slow aggregate learning. One reason is that the agents in the model know exactly the model's structure and have unlimited capacity to acquire and process information. It would be interesting to extend the model to relax these assumptions. In particular, the model is well suited to the introduction of limited attention *à la* Sims (2003).[47]

The analysis in Section III suggests that noise shocks may generate sizable levels of short-run volatility. However, a number of issues remain open. In particular, how should one calibrate the idiosyncratic noise in the private signals observed by individual agents and the aggregate noise in the public signals? Is it possible to obtain direct measures of noise shocks to test their effect directly?

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[45] I have tried a VAR using total employment (LE) and hours in the nonfarm sector (LXNFH), and I have used output in the business and nonfarm sectors instead of GDP (LXBO, LXNFO) paired with the respective hours' measure. I have also tried a bivariate VAR of output and inflation, still using a long-run restriction to identify the technology shock.

[46] I have tried the SPF median forecasts of output in the coming two to three quarters, and I have tried the index of "business conditions, 5 years," from the Consumer Sentiment Survey.

[47] See Maćkowiak and Wiederholt (2007).

To calibrate idiosyncratic noise, one possibility is to look at measures of cross-sectional dispersion in quantities and prices. However, this is subject to the caveat that agents' private information is probably richer than just individual price and quantity observations. Moreover, limited attention may imply that not all private information is efficiently processed to forecast aggregate changes in fundamentals. An alternative approach may be to calibrate idiosyncratic noise by looking at measures of cross-sectional dispersion in expectations, obtained from survey data.

To calibrate the noise in aggregate signals, an approach is to use data on revision errors in early releases of aggregate statistics, as I did in Section IIIB for the inflation signal. These can also be used for direct tests of the transmission of noise shocks, as in the papers by Oh and Waldman (1990) and Rodriguez Mora and Schulstad (2007). However, aggregate statistics are only a subset of the public signals available to the private sector. Again, survey-based data on average expectations may help calibrate the total volatility in common noise. They can also be used for direct testing of the model implications, which is the strategy I followed in Section IV.

Finally, an alternative approach is to estimate the model solely looking at its implications for aggregate macroeconomic variables, as it is commonly done in estimated DSGE exercises. In this paper, it was possible to use a simple long-run identification assumption to compare the model with time series evidence on output and employment. In richer models, this is less likely to be feasible, and interesting questions open up about estimation and identification in environments where agents have imperfect information on aggregate shocks.[48]

APPENDIX

In this appendix, I provide a more detailed characterization of the equilibrium of the model with dispersed information and describe the algorithm used for computations. The matrices $\mathbf{A}$ and $\mathbf{B}$ are given by

$$
\mathbf{A} = \begin{bmatrix} 1 & \mathbf{0} \\ 0 & \mathbf{0} \\ & \mathbf{A}_p \\ (\ 0\ \ 0\ \ -\varphi\ \ \rho_i\ \ 0\ ) + \varphi \mathbf{A}_p \\ I & 0 \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} 1\ 0\ 0 \\ 1\ 0\ 0 \\ \mathbf{B}_p \\ \varphi(\mathbf{B}_p + (0\ \ 0\ \ 1\ )) \\ \mathbf{0} \end{bmatrix},
$$

where $\mathbf{A}_p$ and $\mathbf{B}_p$ are vectors to be determined, and $\mathbf{0}$ represents a vector of zeros.

A. *Optimal Decision Rules*

First, let me substitute the demand relation (22) (aggregated across the firms in island l) to rewrite the budget constraint (25) as

$$
(34) \qquad \beta h_{l,t+1} = h_{l,t} + (1 - \gamma)p_{l,t} + d_{l,t} - \bar{p}_{l,t} - c_{l,t},
$$

where $d_{l,t}$ is defined by (28).

Prices.—Using (30) to substitute for $p_{l,t+1}$ on the right-hand side of the optimal pricing condition (27) gives

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[48] See Collard et al. (2007) and Blanchard et al. (2009).

$$\Lambda p_{l,t} = p_{l,t-1} - \lambda(1 + \zeta)a_{l,t} + \lambda(\bar{p}_{l,t} + c_{l,t}) + \lambda\zeta d_{l,t}$$
$$+ \beta(q_h h_{l,t+1} + q_p p_{l,t} + q_a E_{l,t}[a_{l,t+1}] + q_d E_{l,t}[d_{l,t+1}] + q_z E_{l,t}[\mathbf{z}_{t+1}]),$$

where $\Lambda \equiv 1 + \beta + \lambda(1 + \gamma\zeta)$. Use the budget constraint (34) to substitute for $h_{l,t+1}$ and (28) to substitute for $d_{l,t+1}$. The expected values of all aggregate variables dated $t + 1$ on the right-hand side can be expressed in terms of $\mathbf{z}_t$, using (29), (33), and the fact that $E_{l,t}[\mathbf{u}_{t+1}^1] = 0$. Moreover, the expected values of all idiosyncratic shocks dated $t + 1$ are zero. Rearranging, I then obtain

$$(\Lambda - (1 - \gamma)q_h - \beta q_p)p_{l,t} = p_{l,t-1} + q_h h_{l,t} - \lambda(1 + \zeta)a_{l,t}$$
$$+ (\lambda\zeta + q_h)d_{l,t} + (\lambda - q_h)(\bar{p}_{l,t} + c_{l,t})$$
$$+ \beta(q_a \mathbf{e}_x + q_d(\psi + \gamma\mathbf{e}_p) + q_z)\mathbf{A}E_{l,t}[\mathbf{z}_t],$$

where $\mathbf{e}_x$ and $\mathbf{e}_p$ are unitary vectors that select, respectively, x_t and p_t from the state vector $\mathbf{z}_t$. Use (30) to substitute for $p_{l,t}$ on the left-hand side and (31) to substitute for $c_{l,t}$ on the right-hand side. Matching coefficients, this gives

(35a) $$q_p = \frac{1}{\Lambda - (1 - \gamma)q_h - \beta q_p},$$

(35b) $$q_h = q_p(q_h + (\lambda - q_h)b_h),$$

(35c) $$q_a = q_p(-\lambda(1 + \zeta) + (\lambda - q_h)b_a),$$

(35d) $$q_d = q_p(\lambda\zeta + q_h + (\lambda - q_h)b_d),$$

(35e) $$q_z = q_p[\beta(q_a \mathbf{e}_x + q_d(\psi + \gamma\mathbf{e}_p) + q_z)\mathbf{A} + (\lambda - q_h)b_z].$$

Consumption.—Using (31) to substitute for $c_{l,t+1}$ on the right-hand side of the Euler equation (24) gives

$$c_{l,t} = -\bar{p}_{l,t} - i_t + b_h h_{l,t+1} + b_p p_{l,t} + b_a E_{l,t}[a_{l,t+1}] + b_d E_{l,t}[d_{l,t+1}] + b_z E_{l,t}[\mathbf{z}_{t+1}].$$

As in the case of prices, use the budget constraint (34) to substitute for $h_{l,t+1}$ and (28) to substitute for $d_{l,t+1}$. The expected values of future aggregate variables can be expressed in terms of $\mathbf{z}_t$, using (29), (33), and the fact that $E_{l,t}[\mathbf{u}_{t+1}^1] = 0$. The expected values of future idiosyncratic shocks are zero. The resulting expression is

$$c_{l,t} = -\bar{p}_{l,t} - i_t + \frac{b_h}{\beta}(h_{l,t} + d_{l,t} + (1 - \gamma)p_{l,t} - \bar{p}_{l,t} - c_{l,t})$$
$$+ b_p p_{l,t} + (b_a \mathbf{e}_x + b_d(\psi + \gamma\mathbf{e}_p) + b_z)\mathbf{A}E_{l,t}[\mathbf{z}_t],$$

where $\mathbf{e}_x$ and $\mathbf{e}_p$ are the unitary vectors defined above. Rearranging gives

$$c_{l,t} = -\overline{p}_{l,t} + \frac{b_h}{\beta + b_h} h_{l,t} + \frac{b_h(1 - \gamma) + \beta b_p}{\beta + b_h} p_{l,t} + \frac{b_h}{\beta + b_h} d_{l,t}$$

$$+ \frac{\beta}{\beta + b_h} [-\mathbf{e}_i + (b_a \mathbf{e}_x + b_d(\psi + \gamma \mathbf{e}_p) + b_z)A] E_{l,t}[\mathbf{z}_t],$$

where $\mathbf{e}_i$ is the unitary vectors that select i_t from $\mathbf{z}_t$. Use (31) to substitute for $c_{l,t}$ on the left-hand side and (30) to substitute for $p_{l,t}$ on the right-hand side. Matching coefficients, this gives

(36a) $$b_h = \frac{b_h}{\beta + b_h} + \varkappa q_h,$$

(36b) $$b_p = \varkappa q_p,$$

(36c) $$b_a = \varkappa q_a,$$

(36d) $$b_d = \frac{b_h}{\beta + b_h} + \varkappa q_d,$$

(36e) $$b_z = \frac{\beta}{\beta + b_h} [-\mathbf{e}_i + (b_a \mathbf{e}_x + b_d(\psi + \gamma \mathbf{e}_p) + b_z)A] + \varkappa q_z,$$

where

$$\varkappa \equiv \frac{b_h(1 - \gamma) + \beta b_p}{\beta + b_h}.$$

B. *Individual Inference*

To find the Kalman gains for the individual learning problem, notice that the vector of signals $\mathbf{s}_{l,t} = (\ a_{l,t} \ \ s_t \ \ \overline{p}_{l,t} \ \ d_{l,t} \ \ i_t \ )'$ can be written as

$$\mathbf{s}_{l,t} = \mathbf{F}\mathbf{z}_t + \mathbf{G}\mathbf{u}_{l,t}^2,$$

where

$$\mathbf{u}_{l,t}^2 \equiv (\ \eta_{l,t} \ \ \xi_{l,t}^1 \ \ \xi_{l,t}^2 \ )',$$

the matrices $\mathbf{F}$ and $\mathbf{G}$ are

$$\mathbf{F} \equiv \begin{bmatrix} \mathbf{e}_x \\ \mathbf{e}_x + \mathbf{e}_e \\ \mathbf{e}_p \\ \psi + \gamma \mathbf{e}_p \\ \mathbf{e}_i \end{bmatrix}, \quad \mathbf{G} \equiv \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix},$$

$\mathbf{e}_x$, $\mathbf{e}_p$, and $\mathbf{e}_i$, where defined above, and $\mathbf{e}_e$ is the unitary vector that selects e_t from $\mathbf{z}_t$. Bayesian updating for island l's agents implies that

$$E_{l,t}[\mathbf{z}_t] = E_{l,t-1}[\mathbf{z}_t] + C(\mathbf{s}_{l,t} - E_{l,t-1}[\mathbf{s}_{l,t}]).$$

Define the variance-covariance matrices

$$\mathbf{\Sigma} = \begin{bmatrix} \sigma_\varepsilon^2 & 0 & 0 \\ 0 & \sigma_\nu^2 & 0 \\ 0 & 0 & \sigma_\omega^2 \end{bmatrix}, \quad \mathbf{V} = \begin{bmatrix} \sigma_\eta^2 & 0 & 0 \\ 0 & \sigma_{\xi,1}^2 & 0 \\ 0 & 0 & \sigma_{\xi,2}^2 \end{bmatrix},$$

and let Ω be defined as

$$\Omega = \mathrm{Var}_{l,t-1}[\mathbf{z}_t].$$

Then the Kalman gains $\mathbf{C}$ are given by

(37) $$C = \Omega \mathbf{F}'(\mathbf{F}\Omega\mathbf{F}' + \mathbf{G}\mathbf{V}\mathbf{G}')^{-1},$$

and Ω must satisfy the Riccati equation

(38) $$\Omega = \mathbf{A}(\Omega - \mathbf{CF}\Omega)\mathbf{A}' + \mathbf{B}\mathbf{\Sigma}\mathbf{B}'.$$

C. *Fixed Point*

The average first-order expectations regarding the state $\mathbf{z}_t$ can be expressed as a function of $\mathbf{z}_t$ itself as

$$\mathbf{z}_{t|t} = \mathbf{\Xi}\mathbf{z}_t.$$

Using the updating equations and aggregating across consumers gives:

$$\mathbf{z}_{t|t} = (I - \mathbf{CF})\mathbf{A}\mathbf{z}_{t-1|t-1} + \mathbf{CF}\mathbf{z}_t.$$

Therefore, the matrix $\mathbf{\Xi}$ must satisfy the condition

(39) $$\mathbf{\Xi}\mathbf{z}_t = (I - \mathbf{CF})\mathbf{A}\mathbf{\Xi}\mathbf{z}_{t-1} + \mathbf{CF}\mathbf{z}_t,$$

for all $\mathbf{z}_t$. Aggregating the individual decision rules (30) and (31), I then obtain

$$p_t = q_p p_{t-1} + q_a x_t + q_d(c_t + \gamma p_t) + q_z \mathbf{\Xi}\mathbf{z}_t,$$

$$c_t = -p_t + b_p p_{t-1} + b_a x_t + b_d(c_t + \gamma p_t) + b_z \mathbf{\Xi}\mathbf{z}_t.$$

Expressing everything in terms of the state $\mathbf{z}_t$, the equilibrium coefficients must satisfy

(40) $$[\mathbf{e}_p - q_p \mathbf{e}_{p-1} - q_a \mathbf{e}_x - q_d(\psi + \gamma\mathbf{e}_p) - q_z\mathbf{\Xi}]\mathbf{z}_t = 0,$$

(41) $$[\mathbf{e}_p + \psi - b_p \mathbf{e}_{p-1} - b_a \mathbf{e}_x - b_d(\psi + \gamma\mathbf{e}_p) - b_z\mathbf{\Xi}]\mathbf{z}_t = 0,$$

for all $\mathbf{z}_t$.

An equilibrium is characterized by the vectors $\mathbf{A}_p$, $\mathbf{B}_p$, ψ describing the aggregate dynamics, the vectors $\{q_h, q_p, q_a, q_d, q_z\}$ and $\{b_h, b_p, b_a, b_d, b_z\}$ describing individual behavior, the matrices $\mathbf{C}$ and Ω describing the individual learning problem, and the matrix $\mathbf{\Xi}$ capturing the aggregate

behavior of first-order expectations. These objects characterize an equilibrium if they satisfy conditions (35)–(41).

D. *Computation*

To compute an equilibrium, I apply the following algorithm. I start with some initial value for $\{\mathbf{A}_p, \mathbf{B}_p, \psi,\}$. I derive the values of $\{q_h, q_p, q_a, q_d, q_z\}$ and $\{b_h, b_p, b_a, b_d, b_z\}$, which satisfy individual optimality, by substituting the prices and quantities (30) and (31) into (27), (24), and (25). Next, I solve for $\mathbf{C}$ and Ω in the individual inference problem. Since the vector $\mathbf{z}_t^{[T]}$ is truncated, I set to zero the value of z_{t-T-1} in $\mathbf{z}_{t-1}^{[T]}$ and replace (39) with

$$\Xi \mathbf{z}_t^{[T]} = (I - \mathbf{CF})\mathbf{A}\Xi\mathbf{M}\mathbf{z}_t^{[T]} + \mathbf{CF}\mathbf{z}_t^{[T]},$$

where

$$\mathbf{M} \equiv \begin{bmatrix} \mathbf{0} & I \\ \mathbf{0} & \mathbf{0} \end{bmatrix}.$$

This gives the following relation, which is used iteratively to compute Ξ:

$$\Xi = (I - \mathbf{CF})\mathbf{A}\Xi\mathbf{M} + \mathbf{CF}.$$

I then apply the updating rule

$$\mathbf{A}_p = (q_p\mathbf{e}_{p-1} + q_a\mathbf{e}_x + q_d(\psi + \gamma\mathbf{e}_p) + q_z\Xi)\mathbf{A},$$

$$\mathbf{B}_p = (q_p\mathbf{e}_{p-1} + q_a\mathbf{e}_x + q_d(\psi + \gamma\mathbf{e}_p) + q_z\Xi)\mathbf{B},$$

$$\psi = b_p\mathbf{e}_{p-1} + b_a\mathbf{e}_x + b_d(\psi + \gamma\mathbf{e}_p) + b_z\Xi - \mathbf{e}_p,$$

and repeat until convergence is achieved. The convergence criterion is given by the quadratic distance of the impulse response functions of y_t and p_t to the shocks in $\mathbf{u}_t^1$ (with weights given by the variances of the shocks), under the old and updated values of $\{\mathbf{A}_p, \mathbf{B}_p, \psi\}$.

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