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A Tale of Two Rigidities: Sticky Prices in a Sticky-Information Environment

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Abstract

Macroeconomic models with microeconomic foundations afford the opportunity to compare the model's behavior with empirical evidence at the macro and micro levels. This paper proposes a model that combines two strands of the literature on stickiness to match both sets of empirical facts. (1) Firms acquire information infrequently, as in Mankiw and Reis (2002), resulting in sticky information. (2) Firms face menu costs to change prices, leading to state-dependent sticky prices at the micro level. I estimate key structural parameters via indirect inference and show that a model of sticky prices in a sticky-information environment, combined with considerable real rigidity, is consistent with micro and macro evidence. In this context, sticky prices are not only useful in matching micro data on the size of price changes and the duration between adjustments; they also improve the model's ability to fit the macro data, as embodied in an empirical Phillips curve.

Key words: sticky prices; sticky information; indirect inference
JEL codes: E31, E32, E40

I   Introduction

Macroeconomic models with microeconomic foundations afford the opportunity to compare the behavior of the model with empirical evidence at the macro and micro levels. In a series of recent papers, Mankiw and Reis (2002, 2003, 2006, 2007) and Reis (2006b) have proposed a model with informational frictions among price setters that fits a number of basic macro facts. One drawback to this model, however, is that it generates pricing behaviors at the micro level that are at odds with empirical evidence.

This paper proposes a model that combines two strands of the literature on stickiness in order to match both macro and micro facts. First, because it is costly to acquire, absorb, and process information, firms infrequently update their information on aggregate conditions. Thus, at a given moment in time firms hold a variety of beliefs about the state of the economy.

Second, firms face explicit "menu" costs which they must pay to change their prices. These costs lead to state-dependent pricing decisions and price rigidity at the firm level. This is true even though the model includes positive trend inflation.

Putting sticky prices into a sticky-information environment takes a step toward Carroll's (2003, p. 295) suggestion that the "real world presumably combines some degree of price stickiness and a degree of expectational stickiness." This paper lends support to such a conjecture. Estimation of the model via indirect inference finds that a considerable combination of informational rigidity, real rigidity, and menu costs is necessary for the model to match both the macro and the micro data. I estimate that 31% of firms update their information in an average quarter, and the average duration between updates is 3.2 quarters. Matching the data requires strong real rigidities, with a reduced-form parameter estimate of 0.061. The

representative firm faces menu costs equal to approximately 1.5% of steady-state revenues and large idiosyncratic shocks, with a standard deviation of nearly 7%.

While the baseline estimates favor inclusion of sticky prices, sticky information, and real rigidities, the model allows for estimation of nested cases as well. Doing so yields substantively different quantitative results, capturing some substitutability between the frictions. For instance, omitting either sticky prices or sticky information increases the need for extremely strong real rigidity in matching the data; under only sticky information, the average duration between information updates also rises to 4.8 quarters. Most importantly, the estimation also reveals that the model with sticky prices and sticky information provides not only a closer fit to the *micro* data but also a closer fit to the *macro* data than the model with only sticky information. These results suggest that matching the microfoundations of the model with the empirical micro data has payoffs for macro performance as well.

Both assumptions underlying the model—that information acquisition and price adjustment are costly activities—are supported by empirical evidence. For instance, in a case study of an industrial firm Zbaracki et al. (2004) document and quantify these and other costs associated with changing prices and find that they sum to more than 1% of revenues. A variety of other studies have inferred the existence of information and price-adjustment costs through case studies, observation of prices or expectations, or estimation of reduced-form models.

The fact that firms make state-dependent pricing decisions is significant. State-dependent pricing invokes what is known as the "selection effect": firms whose prices are farthest from their targets are the ones most likely to adjust.[1] As Caplin and Spulber (1987) and Golosov and Lucas (2007) show, this selection effect can eliminate or diminish monetary non-neutrality.

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[1] See, e.g., Gertler and Leahy (2008). The selection effect is intuitive given the nature of costly price adjustment. Such an effect is absent under the typical Calvo-pricing framework, however, where adjustment is random: a firm close to its target has the same probability of adjusting as a firm extraordinarily far from it.

Infrequent information updating in a state-dependent pricing model mitigates this selection effect, since firms do not always know exactly how their actual price compares with their optimal price. Especially when combined with real rigidities, this helps to generate considerable monetary non-neutrality in the model.

The structure of the paper is as follows. Section II presents the model and its nested variants. The estimation technique used in this paper, indirect inference, is outlined in Section III. Section IV presents the empirical findings and the dynamics that arise from the estimated parameters, and Section V discusses the results. Section VI concludes. An Appendix assesses the approximating aggregate law of motion from the model.

II   A Model of Sticky Prices in a Sticky-Information Environment

This paper constructs a model in which firms face implicit costs to acquiring new information and pay explicit menu costs to change prices. This approach combines two strands of the literature on stickiness. Recent work on sticky information has focused attention on the fact that not all agents in an economy have the most up-to-date information, as in Mankiw and Reis (2002), since information acquisition and processing are costly. At the same time, there is a vast literature exploring the causes and consequences of sticky prices. In this section, I combine Mankiw-Reis information updating with state-dependent pricing to produce a model of sticky prices in a sticky-information environment.[2]

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[2] This distinguishes the present paper from others that blend elements of sticky prices and incomplete information, such as Ball and Cecchetti (1988), Kiley (2000), Bonomo and Garcia (2001), and Bonomo and Carvalho (2004); and Dupor et al. (forthcoming) and Bruchez (2007) employing Mankiw-Reis information updating and Calvo pricing; and Klenow and Willis (2007) using fixed-duration information updating rules and state-dependent pricing. Gorodnichenko (2009) and Woodford (2009) present models that endogenize the acquisition of information in the presence of state-dependent pricing decisions.

The Profit Function

To emphasize the interaction between sticky prices and sticky information and maintain tractability, the model is kept simple. Demand for firm i's product at time t is $Y_{it} = Y_t (P_{it} / P_t)^{-\theta}$, with $-\theta$ the elasticity of demand for good i and P_{it} the price of good i. With a continuum of firms, aggregate output is $Y_t = \left[\int Y_{it}^{(\theta-1)/\theta} di \right]^{\theta/(\theta-1)}$ and the price level is $P_t = \left[\int P_{it}^{1-\theta} di \right]^{1/(1-\theta)}$.

Real marginal costs for firm i depend on two components: an idiosyncratic term χ_{it} and the economy-wide gross output gap.

$$(2.1) \qquad MC_{it} = \delta \chi_{it} \left(Y_t / Y_t^N \right)^{\gamma}$$

The idiosyncratic component of marginal cost follows

$$(2.2) \qquad \ln \chi_{it} = \rho_\chi \ln \chi_{it-1} + \varepsilon_{\chi,it}, \; \varepsilon_{\chi,it} \sim \text{i.i.d. } N(0,\sigma_\chi^2).$$

In theory, the idiosyncratic component of marginal cost could represent firm-specific productivity shocks, as in Golosov and Lucas (2007), among others. These firm-specific productivity shocks buffet individual firms and thereby have a direct impact on their marginal costs that is orthogonal to aggregate economic activity. The parameter δ is used to normalize the symmetric, flexible-price/full-information natural rate of output, Y_t^N, to one for all t. The parameter γ is a measure of real rigidity, in the spirit of Ball and Romer (1990): marginal costs—and thereby firms' prices—respond less to the output gap if γ is small (i.e., there is a lot of real rigidity) compared with the case in which it is large.

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Aggregate demand is determined by the quantity equation (or, alternatively, from a cash-in-advance constraint), $M_t=P_tY_t$, with M_t interpreted as nominal aggregate demand or money with constant velocity of one. Combining the above, firm i's profit function is

$$(2.3) \qquad \Pi\left(\frac{P_{it}}{P_t}, \frac{M_t}{P_t}, \chi_{it}\right) = \left(\frac{P_{it}}{P_t}\right)^{1-\theta}\frac{M_t}{P_t} - \delta\chi_{it}\left(\frac{M_t}{P_t}\right)^{\gamma+1}\left(\frac{P_{it}}{P_t}\right)^{-\theta}.$$

Money or nominal demand growth, $\Delta m_t=(M_t/M_{t-1})-1$, is exogenous and grows at rate μ in the steady state. It takes the form

$$(2.4) \qquad \Delta m_t = \mu(1-\rho) + \rho\Delta m_{t-1} + \varepsilon_t, \ \ \varepsilon_t \sim \text{i.i.d. N}(0,\sigma^2).$$

The Firm's Optimization Problem

In a frictionless world, firm i obtains information on χ_{it}, M_t, and P_t each period and sets P_{it} to maximize profits. Such a world, however, contrasts with reality. Acquiring and processing information are costly, time-consuming endeavors. Similarly, implementing price changes typically requires paying a "menu" cost, via either literally printing new menus or labor costs. Extensive empirical research has documented the existence and size of these costs.[3]

This paper captures these real-world features by combining infrequent information updating with state-dependent pricing. Each period, a firm updates its information about the state of the aggregate world with probability $\lambda \in (0,1]$, as suggested by Mankiw and Reis (2002, 2003), independent of the firm's information-updating history. Implicitly, this process is a reduced form that captures the costs of acquiring, absorbing, and processing information; Reis

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[3] Zbaracki et al. (2004) document a variety of costs for a large industrial firm associated with changing prices, including information-acquisition costs, customer-negotiation costs, and the costs associated with physically implementing price changes. In this paper, "menu costs" exclude information-acquisition costs.

(2006b) provides a theoretical justification for how such a framework can arise if producers face an explicit information cost.[4] With probability $1-\lambda$, the firm does not acquire new information on aggregate conditions. Following Klenow and Willis (2007), firms obtain information on their idiosyncratic component of marginal cost χ_{it} in each period. However, because the idiosyncratic component of marginal cost is an independent process, knowing χ_{it} does not offer any information on aggregate variables.

At the same time, it is costly for a firm to change its price away from its previous level. Specifically, a firm must pay a menu cost, $\Phi \geq 0$, if it wishes to implement a price change at time t. This generates the potential for state-dependent pricing decisions at the firm level.

The assumptions of infrequent information updating and costly price adjustment lead to the following scenario. Without loss of generality, suppose that firm i last updated its information $j \geq 0$ periods ago. At that time, the firm observed the aggregate variables in the economy: the nominal money supply M_{t-j}, the money growth rate Δm_{t-j}, the aggregate price level P_{t-j}, etc. The firm always knows its nominal price, P_{it-1}, and its current idiosyncratic marginal cost term χ_{it}.

In any period t, the firm is faced with a choice. If it does not change its price, it expects to earn profits $E_{t-j,t}\Pi(P_{it-1}/P_t, M_t/P_t, \chi_{it})$ in the current period, where the notation $E_{t-j,t}$ denotes expectations formed on the basis of aggregate information from time $t-j$ and idiosyncratic information from time t.[5] In the next period, with probability λ the firm will acquire M_{t+1}, P_{t+1}, etc.; with probability $1-\lambda$, the firm will not update its aggregate information, and it will have gone $j+1$ periods without an information update. In either case, the firm discounts the future at

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[4] Caballero (1989) presents an alternative explanation for how time-dependent information updating can arise as a solution to a firm's optimal information-updating problem.
[5] In the case of $j=0$, when firm i acquires information on aggregate variables at time t, the firm knows its level of profits with certainty and the expectations operator is not needed.

constant rate β, goes into the next period with nominal price P_{it-1}, and will face χ_{it+1}. Thus the

value to the firm of keeping its old price, given it observed P_{t-j}, M_{t-j}, and Δm_{t-j} when it last

updated its aggregate information $j \geq 0$ periods ago, is

(2.5)
$$V^K\left(\frac{P_{it-1}}{P_{t-j}}, \frac{M_{t-j}}{P_{t-j}}, \Delta m_{t-j}, j, \chi_{it}\right) = E_{t-j,t}\Pi\left(\frac{P_{it-1}}{P_t}, \frac{M_t}{P_t}, \chi_{it}\right) +$$
$$\beta E_{t-j,t}\left\{\lambda V\left(\frac{P_{it-1}}{P_{t+1}}, \frac{M_{t+1}}{P_{t+1}}, \Delta m_{t+1}, 0, \chi_{it+1}\right) + (1-\lambda)V\left(\frac{P_{it-1}}{P_{t-j}}, \frac{M_{t-j}}{P_{t-j}}, \Delta m_{t-j}, j+1, \chi_{it+1}\right)\right\}$$

Alternatively, firm i can pay the menu cost Φ and change its nominal price to $\tilde{P}_{it}$. It takes

into account the expected profits from this change in the current period and the value of going

into the following period with this new price (and the probabilities that the firm will or will not

update its aggregate information). Thus the value to the firm of changing its price in period t,

given it observed P_{t-j}, M_{t-j}, and Δm_{t-j} when it last updated its information $j \geq 0$ periods ago, is

(2.6)
$$V^C\left(\frac{P_{it-1}}{P_{t-j}}, \frac{M_{t-j}}{P_{t-j}}, \Delta m_{t-j}, j, \chi_{it}\right) = \max_{\tilde{P}_{it}} E_{t-j,t}\Pi\left(\frac{\tilde{P}_{it}}{P_t}, \frac{M_t}{P_t}, \chi_{it}\right) - \Phi +$$
$$\beta E_{t-j,t}\left\{\lambda V\left(\frac{\tilde{P}_{it}}{P_{t+1}}, \frac{M_{t+1}}{P_{t+1}}, \Delta m_{t+1}, 0, \chi_{it+1}\right) + (1-\lambda)V\left(\frac{\tilde{P}_{it}}{P_{t-j}}, \frac{M_{t-j}}{P_{t-j}}, \Delta m_{t-j}, j+1, \chi_{it+1}\right)\right\}.$$

The firm optimizes over these choices, such that the value to the firm of entering period t with

price P_{it-1}, facing idiosyncratic marginal cost component χ_{it}, and last having updated its

aggregate information $j \geq 0$ periods ago is

(2.7)
$$V\left(\frac{P_{it-1}}{P_{t-j}}, \frac{M_{t-j}}{P_{t-j}}, \Delta m_{t-j}, j, \chi_{it}\right) = \max\left\{\begin{array}{l} V^K\left(\frac{P_{it-1}}{P_{t-j}}, \frac{M_{t-j}}{P_{t-j}}, \Delta m_{t-j}, j, \chi_{it}\right), \\[2ex] V^C\left(\frac{P_{it-1}}{P_{t-j}}, \frac{M_{t-j}}{P_{t-j}}, \Delta m_{t-j}, j, \chi_{it}\right) \end{array}\right\}.$$

Note that the above model nests several cases. If $\lambda \in (0,1)$ and $\Phi > 0$, the model produces

sticky prices and sticky information. With the menu cost $\Phi = 0$, price changes are costless and

firms simply maximize profits in each period; coupled with $\lambda \in (0,1)$, this produces a model with only sticky information. By contrast, a value of $\lambda=1$ would imply that firms acquire new information in each period; coupled with $\Phi>0$, this produces a model with only sticky prices.

Computational Issues

When information updating occurs with constant probability $\lambda<1$, a firm has a positive probability of going an extraordinarily long time between information updates. To avoid this, I assume that if a firm goes j_{max} periods since its last information update, it will acquire information in the next period with certainty. This assumption is plausible for real-world firms, who would not wish to be too ill-informed. A number of papers using state-dependent pricing—e.g., Ball and Mankiw (1994), Ireland (1997)—use a similar mechanism to maintain tractability. Given this assumption, the model nests the possibility (if $\lambda=0$) that information updating is perfectly staggered across firms, since in this case firms will deterministically update aggregate information based on the upper bound j_{max}.

Computing the rational-expectations equilibrium of the model with sticky prices and sticky information would require that firms know all the state variables—including the relative prices and the complete information sets—of all other firms. If information acquisition, absorption, and processing are costly activities, then surveying a continuum of firms would be prohibitively expensive. Instead, in keeping with the spirit of the model I assume that firms are boundedly rational, in the spirit of Krusell and Smith (1998), in their perception of how the aggregate economy evolves when forming expectations.

In particular, firms perceive the approximating aggregate law of motion taking the form

(2.8)
$$\frac{M_t}{P_t} = \alpha_0 + \alpha_1 \Delta m_t + \alpha_2 \frac{M_{t-1}}{P_{t-1}},$$

as in Willis (2002).[6] This law of motion is especially useful for its parsimony: firms are not required to retain more state variables to solve their pricing problem than are absolutely necessary. This keeps the state space of the problem manageable and estimation of the model feasible. At the same time, the coefficients of (2.8) contain economic significance: α_1 measures the responsiveness of real money balances to money growth, and α_2 measures the persistence of movements in real money balances. Thus, the law of motion can capture a variety of intrinsic dynamics of the model. Finally, this linear law of motion can be used iteratively by firms to form k-step-ahead forecasts of real money balances (and, by extension, cumulative inflation since their last information update). By combining the law of motion (2.8) with knowledge of the processes in (2.2) and (2.4), firms can generate all the expectations needed to solve their optimization problem in equations (2.5), (2.6), and (2.7).

As an example, consider the case in which the firm obtains aggregate information on M_t, P_t, Δm_t, etc., in period t. Because the firm perceives real money balances as evolving according to the law of motion (2.8), its expectation of real money balances at time $t+1$ conditional on time t information (using the expectation notation given above) would be $E_{t,t}(M_{t+1}/P_{t+1}) = \alpha_0 + \alpha_1 E_{t,t}(\Delta m_{t+1}) + \alpha_2 (M_t/P_t)$, with $E_{t,t}(\Delta m_{t+1})$ determined via (2.4). By extension, the firm can then generate $E_{t,t}(M_{t+2}/P_{t+2}) = \alpha_0 + \alpha_1 E_{t,t}(\Delta m_{t+2}) + \alpha_2 E_{t,t}(M_{t+1}/P_{t+1})$ and so forth to form arbitrary k-step-ahead forecasts of real money balances. By combining these forecasts of real money balances, the last observed level of real money balances, and expectations over cumulative money growth since the last information update (obtained by manipulating equation (2.4)), the firm can then

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[6] See also Klenow and Willis (2007), Midrigan (2008), and Nakamura and Steinsson (forthcoming) for applications of approximating aggregate laws of motion in state-dependent pricing frameworks.

derive expectations over cumulative inflation since the last information update, which are required to deflate its nominal price in (2.5) and (2.6).

While expectations formed via the approximating aggregate law of motion are made in a simple manner, they are nevertheless model-consistent as in Krusell and Smith (1998). The methodology is as follows. Starting with an initial guess $A_0=\{\alpha_0,\alpha_1,\alpha_2\}$ for the coefficients in (2.8), one can solve and simulate the model to generate a time series of data for the aggregate economy. After discarding initial observations, estimate the coefficients in (2.8) from this time series, producing $\hat{A}_0$. If the estimated $\hat{A}_0$ coefficients are close to the guess A_0, stop. If not, form a new guess, A_1, and iterate to convergence.

Because the model does not have a closed-form solution, value function iteration is performed on a grid of discretized state variables. The money growth and idiosyncratic marginal cost shock processes are converted into their Markov chain representations with five and three states, respectively, as in Tauchen (1986).

III   Estimation Strategy: Indirect Inference

The model of sticky information and state-dependent pricing decisions does not produce a simple structural equation—compared with, for instance, the canonical New Keynesian Phillips curve under Calvo pricing—that can be estimated on U.S. data. For this reason, I use simulation techniques to estimate model parameters via indirect inference. Since solving and simulating the model is highly time-intensive, I confine estimation to four parameters: (1) the probability that a given firm will acquire new aggregate information in a given period, λ; (2) the amount of real

rigidity in the model, γ; (3) the size of the firms' menu costs, Φ; and (4) the standard deviation of the idiosyncratic shocks to marginal cost, σ_χ.

The remaining model parameters, listed in Table 1, are as follows. The discount factor β is 0.99 for the quarterly model. The parameters in the exogenous process (2.4) are estimated on U.S. data for nominal GDP growth for 1983.1–2005.4. The model abstracts from positive long-run output growth, hence mean real GDP growth over this time is subtracted from the series.

The constant desired markup is $\theta/(\theta-1)=1.2$, consistent with Rotemberg and Woodford (1992). The persistence of the idiosyncratic marginal cost shocks, ρ_χ, is set to 0.7, within the wide range of values used in the literature. I set the upper bound on the age of information, j_{max}, to eight, so a firm that has not acquired information in the last eight quarters does so with certainty in the next quarter (i.e., the ninth quarter after the last update).[7]

Because the goal of the model is to match salient features of the micro-pricing data and, at the same time, generate macroeconomic fluctuations similar to those experienced in the U.S., the criterion function to assess the model encompasses both micro and macro data. I focus attention on the period 1983.1–2005.4, because it affords relative stability and because recent empirical studies on price adjustment at the micro level use data from this period.[8]

To capture macro fluctuations, I utilize an equation that has been estimated ad infinitum in either levels (e.g., Gordon 1998) or first differences (e.g., Stock and Watson 1999): the empirical Phillips curve. The specification for this paper takes the form:

$$(3.1) \qquad \pi_t = \xi_0 + \xi_{11}\pi_{t-1} + \xi_{12}\pi_{t-2} + \xi_{13}\pi_{t-3} + \xi_{14}\pi_{t-4} + \xi_2 y_{t-1} + e_t,$$

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[7] As an upper bound, this is above most estimates of the average duration between aggregate information updates from empirical studies that omit price stickiness, as discussed in Section V; these studies also truncate the distribution for estimation purposes. Carroll (2003), Mankiw et al. (2004), and Reis (2006a) present additional evidence of informational stickiness.

[8] In particular, the CPI Research Database from the BLS that underlies Klenow and Kryvtsov (2008) begins with observations in January 1988; their study ends with the January 2005 observations. The frequency with which firms obtain new aggregate information could theoretically be a function of the level and variance of inflation. Focusing on this period is thus more likely to satisfy the implicit estimation assumption that λ is constant.

where π_t is GDP deflator inflation between periods $t-1$ and t, and y_{t-1} is a measure of the output gap derived from the HP filter at time $t-1$.[9]

While the Phillips curve coefficients comprise the macro moments of interest, I also include two moments from empirical studies on micro pricing: the mean duration between price changes and the mean (absolute) size of price changes. These moments are useful in determining the size of the menu cost Φ and the standard deviation of the idiosyncratic marginal cost shocks σ_χ affecting the firms. Using price data underlying computation of the consumer price index for the U.S., Klenow and Kryvtsov (2008) estimate a mean duration between regular price changes of 8.6 months, or 2.87 quarters, and a mean size of regular price changes of 11.3% (in absolute terms). I label these moments ξ_3 and ξ_4, respectively.

Indirect inference uses simulations to estimate the structural model parameters that minimize the weighted difference between moments estimated on simulated data and those estimated on U.S. data (e.g., Gouriéroux et al. 1993). Let $\psi = [\lambda, \gamma, \Phi, \sigma_\chi]'$ be the parameters to estimate, and let the auxiliary parameter $\hat{\Xi} = [\xi_{11}, \xi_{12}, \xi_{13}, \xi_{14}, \xi_2, \xi_3, \xi_4]'$ be the Phillips curve coefficient estimates and micro-pricing moments estimated from the U.S. data. For a given ψ, one can simulate N firms for T quarters and estimate a set of coefficients and moments on the simulated data, $\tilde{\Xi}(\psi)$. Repeating this procedure S times for each ψ, the indirect inference estimator $\hat{\psi}$ is

(3.2) $$\hat{\psi} = \arg \min_{\psi} \left(\hat{\Xi} - \frac{1}{S} \sum_{s=1}^{S} \tilde{\Xi}(\psi) \right)' \Omega \left(\hat{\Xi} - \frac{1}{S} \sum_{s=1}^{S} \tilde{\Xi}(\psi) \right).$$

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[9] Table 2 presents estimates of the coefficients using U.S. data for the period 1983.1–2005.4. Estimation of (3.1) over this period is relatively insensitive to the inclusion of a measure of food and energy shocks, hence they are omitted for the sake of parsimony and compatibility with the model.

The positive definite weighting matrix Ω is set to the identity matrix.[10] Estimation is conducted via simulated annealing (Goffe et al. 1994). Standard errors for the parameter estimates are computed using numerical derivatives.

IV Estimation Results

Parameter estimates for the model developed in Section II with sticky prices and sticky information are presented in column (a) of Table 2. The table also contains the Phillips curve coefficients and micro-pricing moments from the U.S. data (the components of the auxiliary parameter $\hat{\Xi}$) and the values from the simulated data for the parameter estimates.

Estimation of the model finds that a considerable combination of informational rigidity, real rigidity, menu costs, and large idiosyncratic shocks is necessary for the model to match both the macro and the micro data. The exogenous probability of acquiring information, λ, is estimated to be 0.297 with standard error 0.028. By itself, this estimate suggests that the typical duration between firms' acquiring new information on aggregate conditions is a little longer than three quarters.[11] Since the estimate is well below the full-information benchmark of $\lambda=1$, this implies an important role for informational frictions in matching the data.

The estimated level of real rigidity, γ, is 0.061 (with standard error 0.011). As Woodford (2003, p. 173) writes that an estimate of real rigidity (or strategic complementarity) "in the range

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[10] With the identity weighting matrix, $\hat{\psi}$ is a consistent estimator of the true ψ_0 but the variance-covariance matrix of the estimator is not asymptotically efficient. Setting Ω equal to the identity matrix has the benefit of enabling direct comparisons between the baseline sticky-price/sticky-information model and nested model variants with different auxiliary parameters $\hat{\Xi}$, as laid out in Section IV.
[11] The presence of the upper bound on information durations, j_{max}, complicates this interpretation, though only modestly for this case. I discuss this point in more detail below.

between 0.10 and 0.15 does not require implausible assumptions," this estimate suggests that considerable real rigidities are necessary to match the empirical U.S. data.

Menu costs, Φ, amount to approximately 1.5% of steady-state revenues and are statistically significantly greater than zero. This is similar to the calibration used in Klenow and Willis (2007). However, the menu cost estimate is about double the values reported using time-labor studies by Dutta et al. (1999) for drugstores and Levy et al. (1997) for grocery stores, where prices changes are more frequent. The standard deviation of the idiosyncratic shocks, σ_χ, is nearly 7%. Along the lines of Golosov and Lucas (2007), this estimate implies that firms face large shocks to partly match the observed size of price changes in the empirical data.

While unconstrained estimation of the model parameters favors the inclusion of both sticky information and sticky prices, the model from Section II nests these special cases individually when $\Phi=0$ and $\lambda=1$, respectively.[12] Columns (b) and (c) present the parameter estimates from these nested models.[13]

Estimation of the nested models has a considerable impact on the best-fitting parameters. Compared with the baseline, the model with only sticky information in column (b) has an estimated probability of acquiring new information λ about half as large, and the estimated amount of real rigidity increases to an implausibly extreme amount (i.e., γ falls toward zero and

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[12] For simplicity and to facilitate comparison with the model of Mankiw and Reis (2002), I omit idiosyncratic shocks from the sticky information only case ($\chi_{it}=1$ for all i and t). Note that this paper's model with only sticky information differs slightly from the Mankiw-Reis sticky-information model, since this paper imposes an upper bound on the duration between information updates (j_{max}) and assumes that firms are boundedly rational in their perception of how the economy evolves; see equation (2.8).

[13] Because the model with only sticky information, column (b), excludes menu costs and idiosyncratic shocks, this model would not be capable of matching the micro moments in $\hat{\Xi}$ and hence the indirect inference auxiliary parameter becomes $\hat{\Xi} = [\xi_{11}, \xi_{12}, \xi_{13}, \xi_{14}, \xi_2]'$; i.e., the model is estimated using only the Phillips curve coefficients. (The bold-faced entries in this column denote that they were not part of the estimation procedure.) The model with only sticky prices, column (c), uses all of the coefficients and micro moments. Note that very few firms are constrained by the discretization technique used to solve the problem: the mean duration between price changes for the sticky information model in column (b) is 1.008 and 1.000 under strategic neutrality in column (e), close to the expected value of 1 given that prices are flexible.

is no longer statistically significant). Estimation of the model excluding information frictions, in column (c), also finds a similarly extreme role for real rigidity compared with the baseline model. Moreover, as would be expected given that the unconstrained estimation did not favor either nested case, the fit of these models to the data is worse: the sum of squared differences between the macro moments is almost double the baseline model.[14]

Columns (d) through (f) conduct a similar set of exercises by shutting off real rigidity in the model in favor of strategic neutrality among price-setters: γ is calibrated to one in each case.[15] Because the above estimates find strong real rigidities, this change worsens the fit of the models as measured by the sum of squared differences with the macro moments.[16] To compensate for the lack of real rigidity yet still attempt to generate plausible macro and micro dynamics, the estimates of the probability of acquiring new information λ in columns (d) and (e) are driven to essentially zero in a statistical sense. In these cases, the upper bound on the duration between information updates, j_{max}, drives most information updating. Given the very small estimates of λ, expanding this upper bound to allow for very long periods between information updates would likely improve the fit of the models.

These results suggest that a model combining information rigidities, menu costs, and real rigidity is necessary for the model to match both the macro and the micro data. The results also

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[14] In estimating non-nested cases, Kiley (2007) presents results favoring hybrid New Keynesian sticky-price models, which include backward-looking price-setting components, over both strictly forward-looking sticky-price models and the Mankiw-Reis sticky-information model for the periods 1965Q1-2002Q4 and 1983Q1-2002Q4. When focusing solely on the canonical forward-looking New Keynesian sticky-price model, which is more comparable to the state-dependent pricing model in this paper, the Mankiw-Reis sticky-information model better fits the data over 1965Q1-2002Q4, and the forward-looking sticky-price model better fits the data for the 1983Q1-2002Q4 period.

[15] For the case with only sticky prices in column (f), the model is incapable of matching both the Phillips curve coefficients and the micro moments for reasonable parameter values for Φ and σ_χ. Consequently, the indirect inference auxiliary parameter for this case is only the two micro moments, $\hat{\Xi} = [\xi_3, \xi_4]'$. While this clearly will overstate the sum of squared differences with the macro moments, this exercise is in keeping with the spirit of Golosov and Lucas (2007).

[16] For column (f) with sticky prices only and $\gamma=1$, the model can almost perfectly match the two micro moments when estimating Φ and σ_χ; the sum of squared differences with the micro moments is 4.1×10^{-8}. Ironically, however, the relative flatness of the criterion function for this case prevents the numerical derivative procedure from obtaining a statistically significant estimate of Φ.

point to a limited amount of substitutability among these frictions. Omitting either sticky prices or sticky information tends to increase the need for extremely strong real rigidity in matching the data. For instance, moving from the baseline case to the model with only sticky information, eliminating menu costs augments firms' incentives to respond to output gap movements; additional real rigidity (smaller values for γ) reduces these incentives. Assuming strategic neutrality among price-setters yields estimates with an increased role for information frictions. This suggests that adding information frictions to state-dependent pricing models in general may be a way to lessen the need for mechanisms that generate real rigidity but also produce counterfactual results.[17]

Additionally, the model with sticky prices and sticky information should not only be viewed as improving the microfoundations of the sticky information model. The sticky-price, sticky-information model better matches the macro data for four of the five Phillips curve coefficients, and the total sum of squared differences between the coefficients is considerably smaller. Thus, the evidence suggests that the sticky-price, sticky-information model not only better matches the *micro* data than a model with only sticky information, but it also better matches the *macro* data than a model with only sticky information.

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[17] Golosov and Lucas (2007) criticize diminishing returns to labor, Klenow and Willis (2006) criticize kinked demand curves, and Dotsey and King (2005) and Knotek and Terry (2008) criticize firm-specific labor markets as mechanisms that generate real rigidity but produce inconsistencies between state-dependent pricing models and the real-world behavior of firms.

Impulse responses

    To illustrate the model's dynamics, Figure 1 displays generalized impulse responses for

the baseline model with sticky prices and sticky information and the nested versions.[18] Each

panel is constructed using the parameter estimates from Table 2.

    Under only state-dependent sticky prices, all firms immediately see the shock and—given

the AR process in (2.4)—know that its effects will persist for several quarters. Under strategic

neutrality in panel (f), the combination of the nominal shock and idiosyncratic shocks generates a

strong enough selection effect that inflation peaks immediately and by nearly the full amount of

the nominal shock. As in Golosov and Lucas (2007), the result is near-monetary neutrality.

Under strong estimated real rigidity in panel (c), however, firms have incentives to keep their

prices more aligned with non-adjusting firms. The result is that the selection effect, while still at

play, is diminished in strength, inflation does not rise as quickly, and the nominal shock produces

real effects.

    With only sticky information, prices are flexible but only a fraction of price setters see

the shock when it occurs and therefore know to respond. Even under strategic neutrality, this can

generate a real response, in panel (e). Strong estimated real rigidity, in panel (b), further

constrains action on the part of the informed firms, as they do not wish to have their prices too

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[18] Since the Markov process used to approximate (2.4) does not easily lend itself to a simple impulse response, generalized impulse responses were created by simulating the model 20,000 times. In each simulation, the exogenous money growth process took on its trend value, normalized to zero, in quarter $t=-1$. The shock in each simulation occurred in quarter $t=0$ and was 1.3% (annualized). Thereafter, money growth was determined randomly by the Markov process. For large enough S, the mean money growth response approximates the actual response of (2.4) to a single shock. Likewise, it is assumed that the mean responses over the 20,000 simulations of inflation and the output gap approximate their actual responses as well.

far from their competitors'. This results in a delayed inflation response and stronger real effects than in the case with only sticky prices where all firms see the shock immediately.[19]

The model with sticky prices and sticky information combines these mechanisms. Sticky information prevents some firms from seeing the aggregate shock immediately. Sticky prices prevent some firms from reacting to the aggregate shock immediately. And a considerable amount of estimated real rigidity, in panel (a), constrains firms from setting prices too different from their competitors', ceteris paribus. The ultimate result is considerable monetary non-neutrality: in the baseline model, inflation peaks after 8 quarters and the output gap peaks 3 quarters after the shock.[20] While the model with only sticky information in panel (b) produces generally similar dynamics, it requires larger estimates of the roles of informational and real rigidities.[21]

V   Discussion

The upper bound on the duration between aggregate information updates, j_{max}, complicates the interpretation of the frequency of aggregate information updating. Without this upper bound, the estimate of $\lambda=0.297$ in the baseline model would imply that 29.7% of firms acquire new aggregate information in any given period. By preventing firms from becoming too ill-informed,

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[19] Real rigidity combined with bounded rationality generates real effects beyond the upper bound on information j_{max}; see the Appendix for more on this issue.
[20] These results are not influenced by the fact that the upper bound on information acquisitions is set to $j_{max}=8$: increasing the bound by one does not affect the figure. The same is not true for the responses in panels (b), (d), and (e): because of the low estimates of λ, many information updates are automatic in these cases. Ceteris paribus, increasing j_{max} to 9 in these cases would move the peak inflation response to period 9 in panel (b) and would extend the dynamics of the inflation and output responses by another period in panels (d) and (e).
[21] These dynamics are also very close to the Mankiw and Reis (2002) sticky-information model, in which inflation peaks 7 quarters after the shock and output peaks after 3 quarters under a modestly different calibration.

however, this upper bound occasionally causes firms to automatically acquire new information, implying the true frequency of acquiring new information is higher than that implied by λ.

Table 3 presents information-updating statistics from tracking the simulated panels of firms. For the parameter estimates in the baseline model in column (a), 6% of aggregate information updates occur automatically because of the j_{max} bound, 31% of firms acquire new aggregate information in a given quarter, and the average duration between aggregate information updates is 3.2 quarters. Beyond the baseline model, the nested models with sticky information in columns (b), (d), and (e) have lower estimates of λ and therefore the upper bound j_{max} becomes more important in driving firms' updating.[22]

Table 4 compares these results with other estimates from the literature. The 4.8 quarter average duration for this paper's model with only sticky information is toward the lower end of the range of estimates from Andrés et al. (2005), Coibion (2010), and Kiley (2007) for the Mankiw-Reis sticky-information model using a similar sample period. For the model with sticky prices and sticky information, the average duration of 3.2 quarters is slightly longer than the estimates from Dupor et al. (forthcoming) of 2.5 quarters, using Calvo pricing and Mankiw-Reis information updating. However, Dupor et al. (forthcoming) use a sample period containing the more volatile 1960s and 1970s. Under these conditions, firms may have had incentives to stay more informed and therefore acquired information more frequently; during the more tranquil 1983-2005 period, firms may not have need to pay such close attention to macroeconomic conditions. Further development of models that endogenize information acquisition, such as Gorodnichenko (2009) and Woodford (2009), is a welcome step in this direction.

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[22] Note that in the baseline model in column (a), only 1.85% of firms have information $j_{max}=8$ periods old at any given point in time. However, all of these firms will "automatically" update their aggregate information in the next period, whereas firms with more recent information vintages will receive an aggregate information update with probability λ in the next period. As a result, the percentage of the total number of updates that are "automatic" is disproportionately higher than the percentage of firms with the highest allowed informational vintage.

An interesting feature of the model is the interaction between state-dependent pricing and the acquisition of aggregate information, a feature not available when firms make time-dependent or Calvo-style pricing decisions. Figure 2 plots how the frequency of price change varies with time since the firm's last aggregate information update in the baseline model. Compared with the average frequency of price change of 34.2% across all price setters, two patterns are notable. First, firms with information three to six quarters old are more likely to change their prices than average, in particular because more firms make price increases than normal. This is caused by positive trend inflation in the model: ceteris paribus, firms with older macro information assume their prices have fallen in real terms, which shrinks the range of inaction in their (s,S) problems given their information sets. Thus, a given idiosyncratic shock is more likely to push them into action when they have older macro information. Second, if firms know they will acquire information in the next period, they are less likely to change their prices in the current period. This occurs when it has been eight quarters since their last information update, since this coincides with j_{max}. In particular, firms are wary of cutting prices immediately prior to a known update, for fear that inflation may have been higher than anticipated, thus requiring them to quickly undo the price decrease.

The heterogeneity induced by idiosyncratic shocks to marginal costs plays an important role in the model. First and foremost, these shocks are needed to match the stylized fact that price changes are large—much larger than could be explained, given their average frequency, by macro variables alone. This point has been raised by Golosov and Lucas (2007), among others. But also important is that, as Caballero and Engel (1993) show, idiosyncratic shocks in a state-dependent pricing model desynchronize pricing decisions at the firm level, reducing the potential

for multiple equilibria.[23] By itself, sticky information would induce heterogeneity and reduce firms' abilities to perfectly synchronize. However, it would not necessarily affect their desires to (de-)synchronize as do large idiosyncratic shocks.

In closely related work, Klenow and Willis (2007) develop a model of state-dependent pricing in which firms face a fixed duration between information updates. Using micro pricing data from the Bureau of Labor Statistics' Consumer Price Index Research Database, they present evidence that real-world firms' prices reflect macroeconomic information at least one year older than what would be expected in a complete information framework. In contrast, this paper uses macro evidence on the relationship between inflation and the output gap to estimate the degree of Mankiw-Reis-style randomized staggering. A considerable amount of informational rigidity is needed to match real-world macroeconomic data, longer than allowed under the Klenow-Willis model (in which firms go at most eight *months* between information updates instead of eight *quarters*) but consistent with their interpretation of the micro data. Taken together, both papers suggest that sticky prices and sticky information are necessary to match microeconomic and macroeconomic facts.

As a last point, there are several ways to assess the approximating law of motion (2.8), which describes firms' perception of the evolution of real money balances. Table 3 presents the most commonly used measure of goodness-of-fit: R^2. At 0.999, the fit is very good in the baseline model and the case with only sticky information and an estimated amount of real rigidity, and it is good for the other cases outside the sticky-price model with strategic neutrality. Den Haan (2010) presents a more exhaustive set of assessments of the approximating law of

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[23] Another potential venue for multiple equilibria comes from the approximating aggregate law of motion (2.8), since in the presence of state-dependent pricing and real rigidity this could act as a sunspot to coordinate firms' actions. While lacking analytic proof, simulations begun from different starting guesses for the law of motion coefficients converge to the same final point, which suggests that the law of motion is ultimately describing the intrinsic dynamics of the model (and its parameters) rather than driving them.

motion. The Appendix shows the law of motion tends to perform quite well according to these metrics. It further shows that, for the case of pure sticky information, the model with bounded rationality is broadly similar to the rational expectations benchmark.

VI   Conclusion

This paper proposes a model that combines two forms of stickiness: sticky prices and sticky information. Estimation of the model based on U.S. data suggests that both forms of stickiness are necessary to match empirical evidence. Using indirect inference, I find that 31% of firms update their information in an average quarter, and the average duration between updates is 3.2 quarters. The data also require strong real rigidities, with a reduced-form parameter estimate of 0.061. Finally, the representative firm faces menu costs equal to approximately 1.5% of steady-state revenues and large idiosyncratic shocks, with a standard deviation of nearly 7%.

Sticky prices are not only important in improving the model's ability to match the empirical evidence on micro price adjustment. The addition of sticky prices to a sticky-information environment also tends to improve the model's ability to match the macro data, as embodied in an empirical Phillips curve. This strengthens the argument for ensuring that macroeconomic models have the "right" microeconomic foundations.

Given the complexity of combining sticky information with state-dependent sticky prices, the model and estimation strategy were kept simple to maintain tractability. This has led to the omission of a number of interesting issues, such as a more thorough treatment of the aggregate-demand side of the economy and systematic monetary policy. Further consideration of these and other issues is left for ongoing research.

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Figure 1: Generalized Impulse Responses using Estimated Parameters
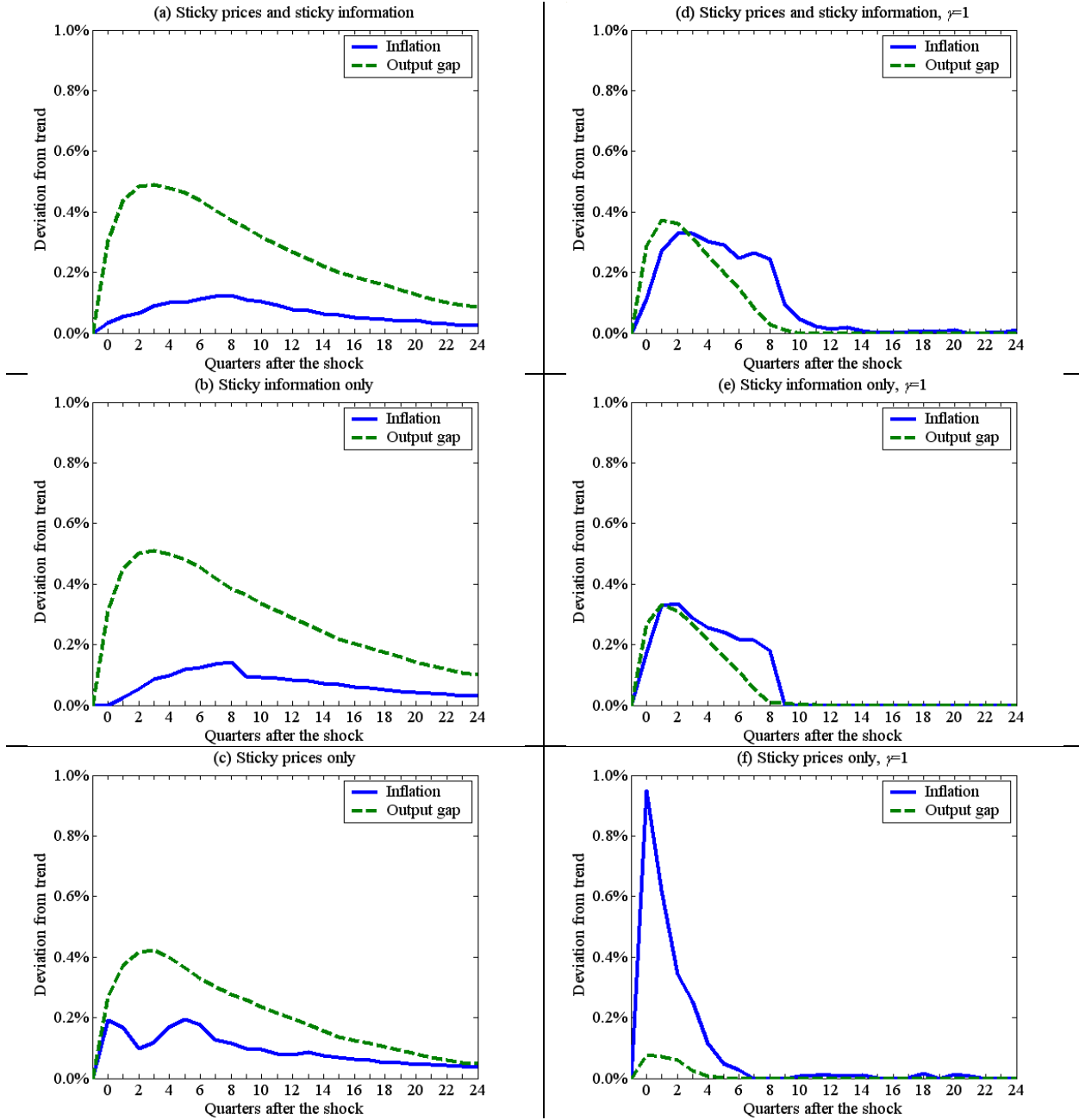
Notes: Mean responses of inflation (the solid line) and the output gap (the dashed line) over 20,000 simulations to a 1.3% shock to money growth at time $t=0$, using the parameter estimates from columns (a) through (f) of Table 2. Panels (d), (e), and (f) assume strategic neutrality ($\gamma=1$). For more details, see Section IV.

Figure 2: Frequency of Price Change as a Function of Time since Last Information Acquisition
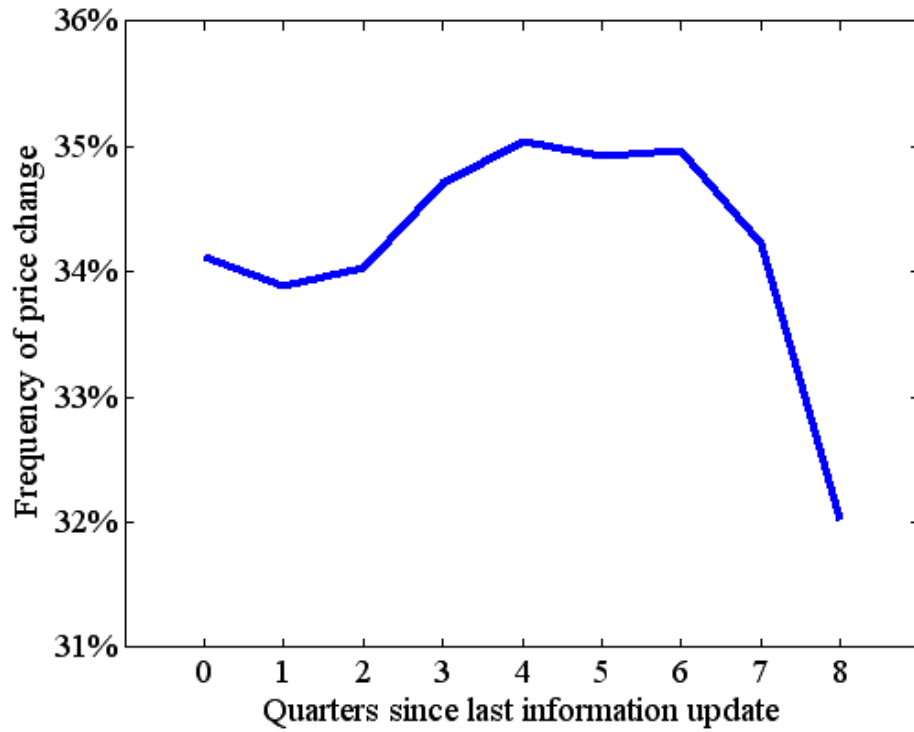
Notes: Since $j_{max}=8$, a firm that has gone eight quarters since its last information update obtains new information on aggregate variables with certainty in the next period. The unweighted average frequency of price change, regardless of time since last information update, is 34.2%.

Table 1: Model Parameters

Exogenous growth process		
μ	$6.4*10^{-3}$	Estimated from $\Delta m_t = \mu(1-\rho) + \rho\Delta m_{t-1} + \varepsilon_t$, $\varepsilon_t \sim$ i.i.d. $N(0,\sigma^2)$ using
ρ	0.49	
σ	$5.1*10^{-3}$	nominal GDP growth in U.S. data, 1983.1–2005.4
Other parameters		
β	0.99	Discount factor, quarterly model
θ	6	Implies a desired markup of 1.2
ρ_χ	0.70	Persistence of idiosyncratic marginal cost shocks
j_{max}	8	Upper bound on the age of information
N	17,500	Number of firms in each simulation
T	92	Number of simulated quarters, matching 1983.1–2005.4
S	25	Number of simulations

Table 2: Estimation Results

	U.S. data	(a) Baseline: sticky prices and sticky information	(b) Sticky info. only	(c) Sticky prices only	(d) Sticky prices and sticky info., $\gamma=1$	(e) Sticky info. only, $\gamma=1$	(f) Sticky prices only, $\gamma=1$
Estimates of:							
(1) Probability of acquiring information, λ	–	0.297 *** (0.028)	0.164 *** (0.017)	–	0.033 (0.026)	0.052 (0.063)	–
(2) Real rigidity parameter, γ	–	0.061 *** (0.011)	0.013 (0.016)	0.020 (0.044)	1	1	1
(3) Menu cost parameter, Φ	–	1.46×10^{-2} *** (2.04×10^{-3})	–	9.89×10^{-3} *** (1.80×10^{-3})	1.90×10^{-2} *** (3.58×10^{-3})	–	1.44×10^{-2} (1.52×10^{-2})
(4) Standard deviation of idiosyncratic shocks, σ_χ	–	6.86×10^{-2} *** (5.26×10^{-3})	–	5.31×10^{-2} *** (1.77×10^{-2})	8.07×10^{-2} *** (6.38×10^{-3})	–	6.55×10^{-2} *** (1.23×10^{-2})
Macro moments							
Phillips curve coefficient on:							
π_{t-1}	0.225 ** (0.100)	0.168	0.147	0.153	0.274	0.203	**0.316**
π_{t-2}	0.077 (0.101)	0.078	0.124	0.043	0.048	0.053	**−0.041**
π_{t-3}	0.107 (0.100)	0.088	0.139	0.085	0.020	−0.011	**−0.004**
π_{t-4}	0.350 *** (0.096)	0.164	0.125	0.102	0.118	0.139	**−0.026**
y_{t-1}	0.048 *** (0.017)	0.042	0.043	0.041	0.158	0.204	**0.751**
Sum of squared differences, macro moments		0.038	0.060	0.068	0.077	0.083	**0.670**
Micro moments							
Mean duration, quarters	2.867	2.837	**1.008**	2.886	2.854	**1.000**	2.867
Mean (absolute) size of a price change	0.113	0.120	**0.006**	0.093	0.140	**0.008**	0.113

Notes: ** or *** denotes significance at the 5% or 1% level, respectively. Standard errors are in parentheses. Estimation of λ, γ, Φ, and σ_χ was conducted via indirect inference; see Section III for details. Columns (d), (e), and (f) assume strategic neutrality ($\gamma=1$). The empirical Phillips curve was estimated using Ordinary Least Squares with equation (3.1) on quarterly U.S. data for the period 1983.1 through 2005.4. The model-implied Phillips curve coefficients—the macro moments in columns (a) through (f)—are averages of coefficient estimates for 25 simulations of 92 quarters of data. The empirical mean duration between price changes and the mean (absolute) size of price changes for the U.S. are from Klenow and Kryvtsov (2008), for regular microdata prices underlying the Consumer Price Index between 1988 and 2004. The associated model-based micro moments in columns (a) through (f) are computed by averaging over 25 92-quarter panels of simulated firms' pricing decisions. The bold-faced simulated moments were not used in that column's estimation; see Section IV.

Table 3: Additional Statistics

	(a) Baseline: sticky prices and sticky information	(b) Sticky info. only	(c) Sticky prices only	(d) Sticky prices and sticky info., $\gamma=1$	(e) Sticky info. only, $\gamma=1$	(f) Sticky prices only, $\gamma=1$
Information-updating statistics:						
Estimated exogenous probability of acquiring information, λ	0.297	0.164	–	0.033	0.052	–
Mean actual frequency of updates (%)	31.0	20.5	–	12.6	13.6	–
Mean duration between updates (quarters)	3.2	4.8	–	7.8	7.3	–
Percentage of updates that are automatic (%)	6.0	23.9	–	76.6	65.2	–
Goodness-of-fit of the law of motion:						
R^2	0.999	0.999	0.994	0.988	0.989	0.678

Notes: Columns (d), (e), and (f) assume strategic neutrality ($\gamma=1$). With only sticky prices in columns (c) and (f), firms always have updated information by assumption; for all other cases, if a firm has gone $j_{max}=8$ periods since the last time it acquired aggregate information, it automatically acquires new information in the next period. The mean actual frequency of updates across all firms and the mean duration between updates take these automatic updates into account. The percentage of updates that are automatic is computed by dividing the number of automatic updates by the total number of information updates in the simulations.

Table 4: Comparison of Estimates of Information Rigidity among Price Setters

	Average duration between price setters' information updates, quarters	Sample period used for estimation
Andrés et al. (2005)	6.7	1979.3–2003.3
Coibion (2010)	4.2–20.0	1982.1–2004.2
Dupor et al. (forthcoming) [#]	2.5	1960.1–2005.2
Khan and Zhu (2006)	2.8–7.7	1969.2–2000.4
Kiley (2007)	2.0	1965.1–2002.4
Kiley (2007)	2.2	1983.1–2002.4
Mankiw and Reis (2006) *	1.9	1954.3–2005.3
Mankiw and Reis (2007) *	1.3	1954.3–2006.1
This paper, sticky prices and sticky information	3.2	1983.1–2005.4
This paper, sticky information only	4.8	1983.1–2005.4

Notes: All papers impose sticky information among price setters. * also imposes sticky information among wage setters and consumers. [#] also imposes sticky prices. The durations reported for this paper correspond to the cases in which the amount of real rigidity was estimated: columns (a) and (b) from Table 2 and Table 3.

Appendix: Assessing the Approximating Aggregate Law of Motion

In keeping with the idea that information acquisition, absorption, and processing are costly activities, I follow Krusell and Smith (1998) and assume that firms are boundedly rational in their perceptions of how the economy evolves. In particular, firms perceive real money balances in the economy evolving according to an approximating aggregate law of motion of the form

(A.1) $$\frac{M_t}{P_t} = \alpha_0 + \alpha_1 \Delta m_t + \alpha_2 \frac{M_{t-1}}{P_{t-1}}.$$

This Appendix provides a number of assessments of the law of motion.

Table A1 provides estimates of the coefficients α_0, α_1, and α_2 for equation (A.1) for the six variants of the model, using the parameter estimates from Table 2. The coefficient α_1 measures the responsiveness of real money balances (equivalently: real output) to movements in money growth, while the coefficient α_2 captures the persistence of output movements. In line with the impulse responses in Figure 1 for the estimated parameters, output movements are larger and more persistent for the cases in which real rigidity is estimated to be considerable (columns (a) through (c)), than for the cases with strategic neutrality (columns (d) through (f)).

Since Krusell and Smith (1998), the simplest and most commonly cited measure of goodness-of-fit to assess approximating laws of motion has been R^2. Table A1 shows that, with R^2s of 0.999, the fit of the law of motion for the baseline model with sticky prices and sticky information (column (a)) and the model with only sticky information and an estimated level of real rigidity (column (b)) is very good. The fit deteriorates very slightly but is still quite good for the model with only sticky prices and real rigidity (column (c)) and for two of the models with strategic neutrality in price-setting (columns (d) and (e)). With only sticky prices and strategic

neutrality (column (f)), however, the low R^2 value would seem to indicate a poor fit for the law of motion.

Den Haan (2010), however, documents a number of shortcomings with focusing solely on R^2. Because of this, other assessments of the law of motion are desirable.

Figure A1 plots how the actual path of real money balances compares with that predicted by the approximating aggregate law of motion for one 92-quarter simulation of the baseline model with its estimated parameters. The solid blue line is the "truth"; i.e., the actual path of M_t/P_t derived from the aggregated decisions of the individual agents in the model. The dotted green line plots the path of real money balances predicted by the law of motion, equation (A.1), given the previous actual (or "true") value of real money balances, M_{t-1}/P_{t-1}, and the current period's money growth, Δm_t. In this sense, updating is allowed since one uses the time $t-1$ actual value of real money balances to compute the time t prediction. The virtual coincidence of the paths suggests the law of motion admirably captures movements in real money balances.

Instead of using the realization of M_{t-1}/P_{t-1} in generating the prediction of real money balances at time t, as was done for Figure A1, den Haan (2010) proposes an alternative procedure. In this framework, one compares the actual ("true") level of real money balances with what would be iteratively predicted by the law of motion. That is, given the path of exogenous money growth and a starting point (e.g., the initial prediction, $\widetilde{\left(M_0/P_0\right)}$, is equal to the initial actual level of real money balances, M_0/P_0), a path of predictions can be formed via

(A.2) $$\widetilde{\left(\frac{M_t}{P_t}\right)} = \alpha_0 + \alpha_1 \Delta m_t + \alpha_2 \widetilde{\left(\frac{M_{t-1}}{P_{t-1}}\right)}, \quad t \geq 1.$$

In this sense, updating the prediction based on the previous period's actual level of real money balances is not allowed. By simulating a very long time series and comparing it with this

generated prediction, one can then observe how errors in the law of motion—and by extension agents' expectations in the model—accumulate over time.

The bottom of Table A1 provides the maximum absolute errors between actual real money balances and those predicted by (A.2) over a period of 2300 simulated quarters, a time span 25 times larger than the one under consideration in this paper. For four of the six models, the maximum forecast error is less than 1%. Average absolute forecast errors are much smaller. Thus, with the exception of perhaps the model with only sticky prices in column (c), agents' forecasts for arbitrarily long horizons made via the approximating aggregate law of motion are not inconsistent with actual outcomes, conditional on the future path of money growth. Figure A2 plots the actual path of real money balances, M_t/P_t, along with the predicted path, $\widehat{(M_t/P_t)}$, for the baseline model. (Den Haan 2010 calls this the "fundamental accuracy plot.") In spite of not updating the prediction, the path generated by the aggregate law of motion very closely follows actual movements in real money balances.

As another check, den Haan (2010) recommends comparing the properties of the law of motion with the actual realizations of the simulated agents. Figure A3 performs this comparison with impulse responses. The solid lines show the deviations of real money balances from trend, based on the aggregated decisions of the individual agents in each model variant using the parameter estimates. These generalized impulse responses were computed as in Figure 1. The dashed lines show impulse responses based solely on the law of motion (A.1), subject to the same shock to money growth. In all cases, the results are similar both qualitatively and quantitatively, indicating that the law of motion performs favorably for the types of analyses carried out in this paper. The greatest discrepancies come for the model with only sticky prices and lots of estimated real rigidity (panel (c)), which also exhibited the largest absolute forecast

errors; and for the cases with sticky information and strategic neutrality (panels (d) and (e)).

Under strategic neutrality, the nominal shock quickly turns neutral once all agents have had the

opportunity to acquire new information. By contrast, the linear law of motion cannot pick up

this behavior and smoothes through the path instead.[24]

Finally, there is an alternative way to assess the accuracy of the approximating law of

motion—and bounded rationality using this particular law of motion more broadly—in the

special case of the model with only sticky information: one can compare it with the model of

Mankiw and Reis (MR, 2002). Compared with the MR sticky-information model, this paper's

model with only sticky information contains two crucial differences. First, it assumes firms that

have gone j_{max} periods since their last information update acquire information with certainty in

the following period; the baseline MR model does not impose an upper bound on the duration

between information updates. Second, it assumes that firms are boundedly rational and perceive

the economy evolving according to (A.1), which they then use to form model-consistent

expectations over real money balances and, by extension, cumulative inflation; in the MR model,

firms use rational expectations.

Figure A4 shows how the model with only sticky information compares with (1) the MR

model, which does not impose an upper bound on the duration between information updates; and

(2) the MR model, subject to the same j_{max} constraint between information updates as in the

model in this paper.[25] In general, the dynamics of the model with only sticky information appear

to be a hybrid of the two MR variants. For the first few quarters after the shock, the model

closely follows the truncated MR dynamics. Thereafter, the linear expectations formed via the

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[24] Note that, in spite of the relatively low R^2 value for the model with only sticky prices and strategic neutrality (column (f) in Table A1), the law of motion produces small non-updated maximum and average forecast errors, along with generally similar results for the impulse responses for the actual and predicted paths in Figure A3.
[25] As in Mankiw and Reis (2002), the parameters of the models are calibrated to $\lambda=0.25$ and $\gamma=0.1$, and idiosyncratic shocks and menu costs are omitted.

approximating law of motion (A.1) prevent the same type of large non-linear response that

rational expectations induce in the truncated MR model, and the model more closely resembles

the baseline MR model.[26]

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[26] Imposing an explicit upper bound on the duration between information updates by truncating the distribution of information vintages can change the dynamics of the MR model in non-trivial ways, as illustrated in Figure A4. In this case, not only do agents know that they will never be too ill-informed regarding macroeconomic conditions; via rational expectations, they also know that all other agents who have gone j_{max} periods since their last information update will acquire new information in the next period with certainty. Moreover, the ability to change prices freely in this framework allows firms the opportunity to tailor their price paths to both the period in which not all firms have information about the shock as well as the period in which all firms would have acquired information at least once following the shock. As such, nominal shocks are neutral even under substantial real rigidity within $j_{max}+1$ periods.

**Figure A1: Comparison of True and Predicted Real Money Balances for One Simulation, Updating Allowed**
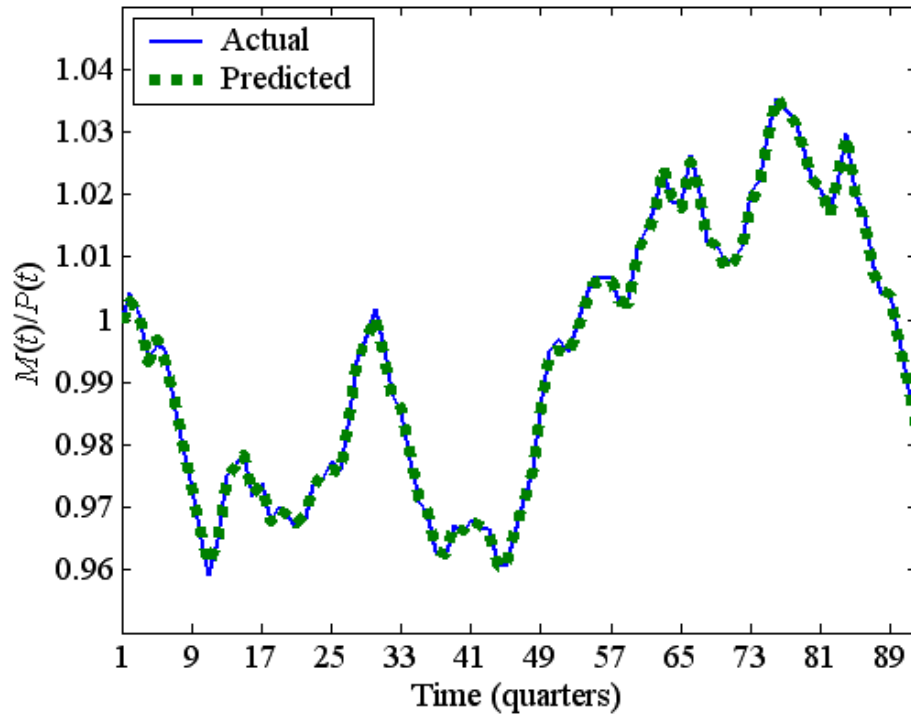
Notes: The solid line shows the actual ("true") path of real money balances, M_t/P_t, for one 92-quarter simulation of the model with sticky prices and sticky information and the parameter estimates from Table 2. The dotted line shows the predicted path of real money balances based on the approximating aggregate law of motion, equation (A.1). For each period t, the prediction is made using information on actual money growth, Δm_t, and the previous period's actual value of M_{t-1}/P_{t-1}.

Figure A2: Comparison of True and Predicted Real Money Balances, Updating Not Allowed
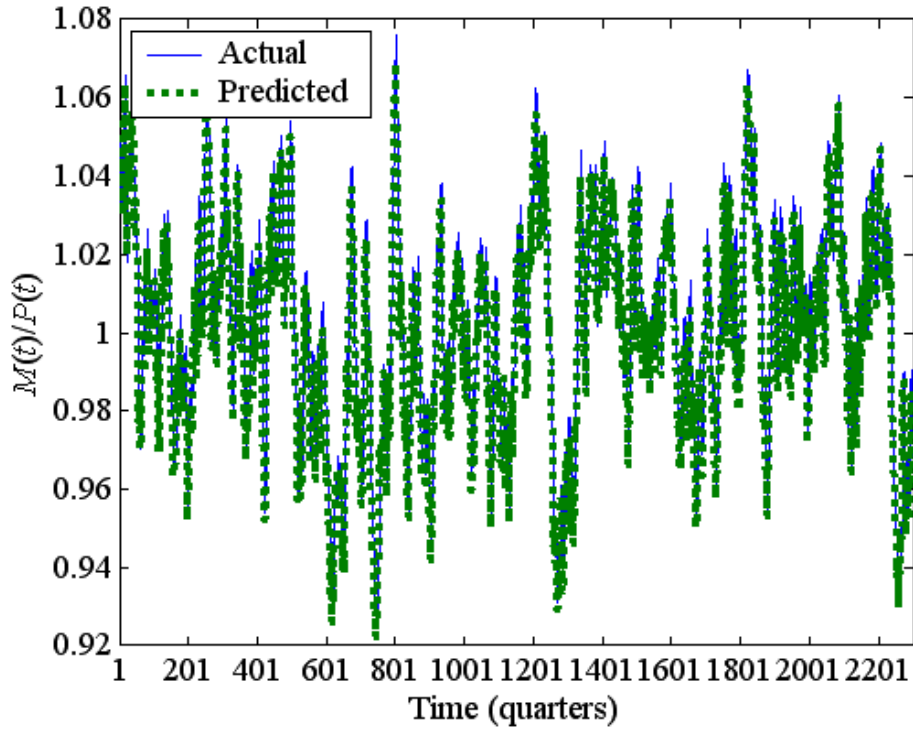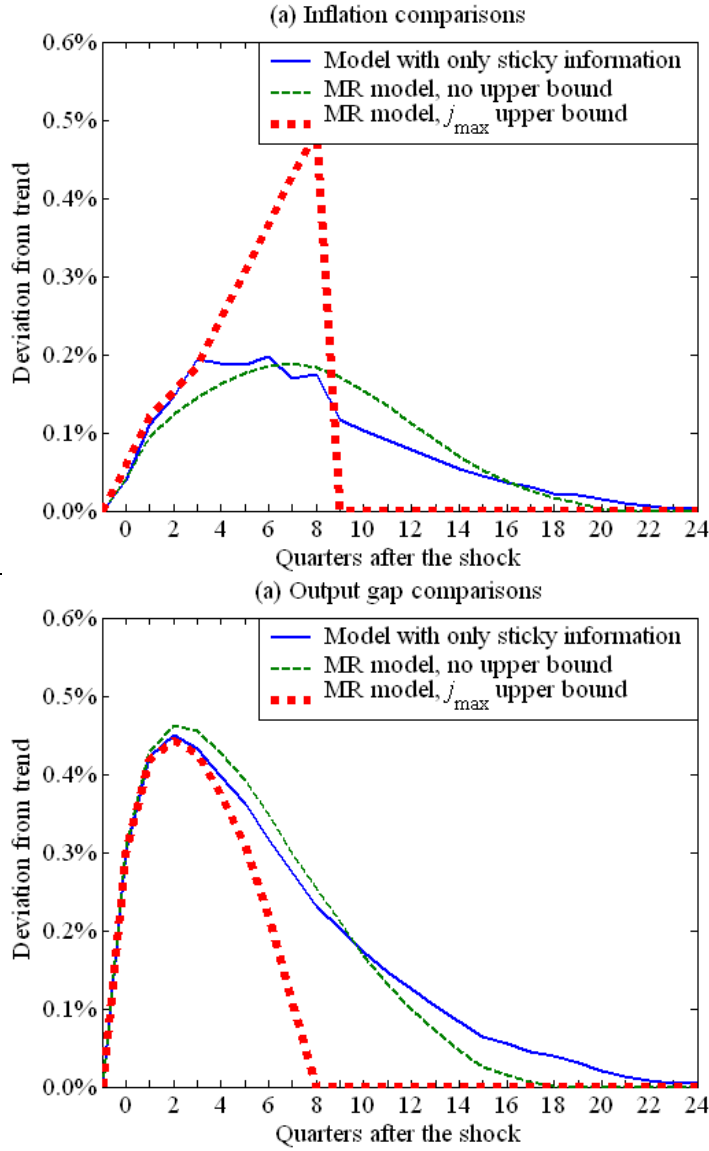

Notes: The solid line shows the actual ("true") path of real money balances, M_t/P_t, for 2300 simulated quarters of the model with sticky prices and sticky information and the parameter estimates from Table 2. The dotted line shows the predicted path of real money balances based on the approximating aggregate law of motion, equation (A.1). For period $t=1$, the prediction is made using information on actual money growth, Δm_t, and the previous period's actual value of M_0/P_0. For periods $t>1$, the prediction is made using actual money growth, Δm_t, and the previous period's *prediction* of real money balances in that period, $\widetilde{\left(M_{t-1}/P_{t-1}\right)}$. See the Appendix for details.

Figure A3: Generalized Impulse Responses and Predictions from the Law of Motion
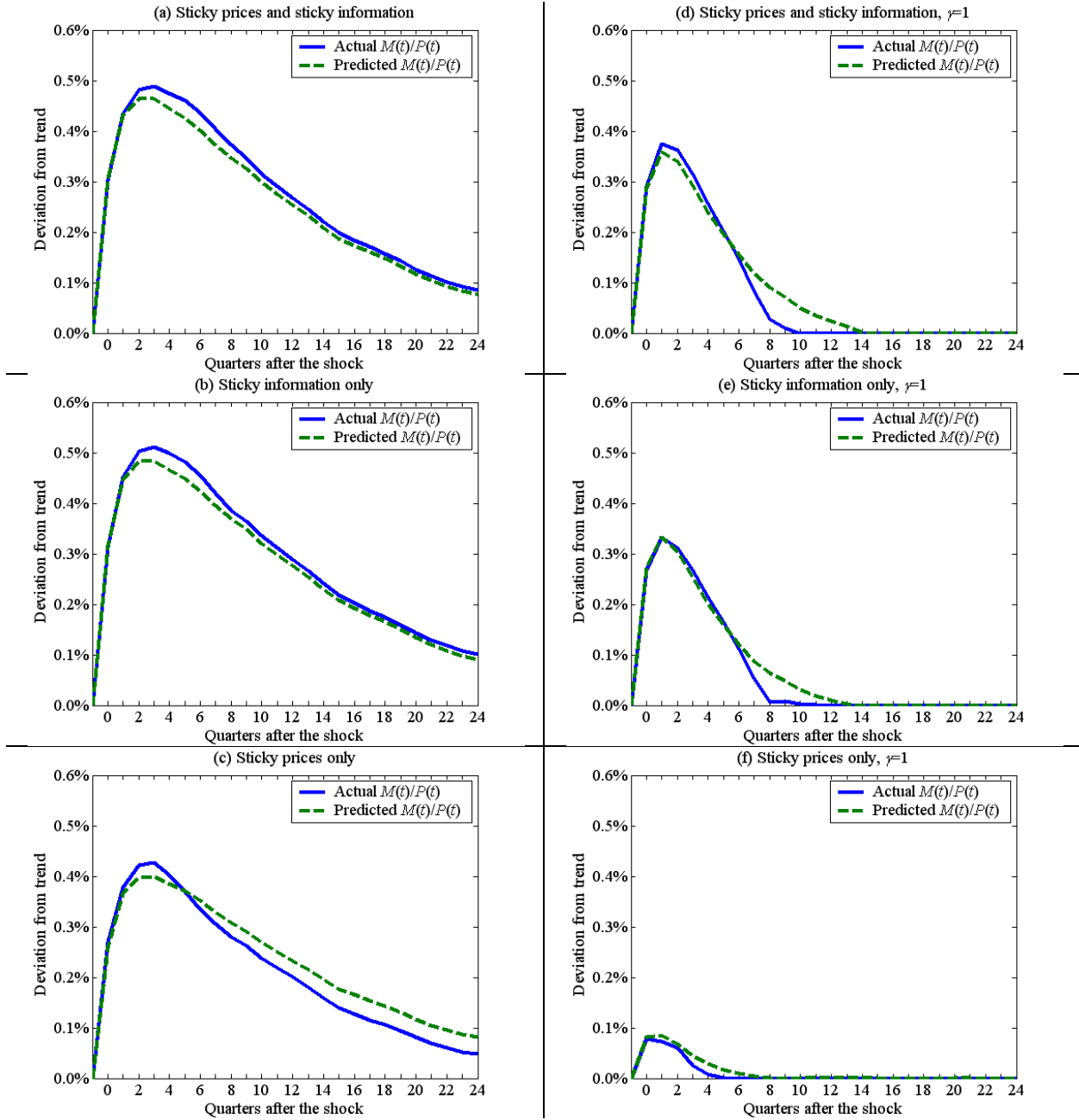
Notes: The solid line shows the actual ("true") mean responses of real money balances, M_t/P_t, over 20,000 simulations to a 1.3% shock to money growth at time t=0, using the parameter estimates from columns (a) through (f) of Table 2. Panels (d), (e), and (f) assume strategic neutrality (γ=1). The dashed line shows the predicted responses of real money balances to the same money growth shock based on the approximating aggregate law of motion, equation (A.1), and the coefficient estimates for the law of motion in Table A1. See the Appendix for details.

Figure A4: Comparing the Model with Sticky Information Only with Mankiw-Reis

(a) Inflation comparisons

- Model with only sticky information
- MR model, no upper bound
- MR model, j_{max} upper bound

(a) Output gap comparisons

- Model with only sticky information
- MR model, no upper bound
- MR model, j_{max} upper bound

Notes: Mean responses of inflation and the output gap over 20,000 simulations to a 1.3% shock to money growth at time t=0. The model with only sticky information uses the model from Section II, which assumes firms never have information more than j_{max}=8 periods old, sets the menu cost to zero, and omits idiosyncratic shocks. The dashed line uses the Mankiw and Reis (MR, 2002) model, which does not impose an upper bound on the duration between information updates. The dotted line modifies the MR model so that firms never have information more than j_{max}=8 periods old. All three models follow Mankiw and Reis (2002) and set the probability of exogenously acquiring information, λ, to 0.25 and the real rigidity parameter, γ, to 0.1.

Table A1: Details on the Approximating Aggregate Law of Motion

	(a) Baseline: sticky prices and sticky information	(b) Sticky info. only	(c) Sticky prices only	(d) Sticky prices and sticky info., $\gamma=1$	(e) Sticky info. only, $\gamma=1$	(f) Sticky prices only, $\gamma=1$
Coefficients on the law of motion						
α_0	0.06	0.06	0.05	0.21	0.24	0.43
α_1	0.94	0.97	0.79	0.92	0.87	0.28
α_2	0.94	0.94	0.95	0.78	0.75	0.57
Goodness-of-fit measure						
R^2	0.999	0.999	0.994	0.988	0.989	0.678
Assessment of non-updated forecast errors						
Maximum absolute forecast error	0.94%	0.82%	3.50%	1.13%	0.55%	0.74%

Notes: The approximating aggregate law of motion is given by equation (A.1), $M_t/P_t = \alpha_0 + \alpha_1 \Delta m_t + \alpha_2 M_{t-1}/P_{t-1}$. The coefficients on the law of motion—α_0, α_1, and α_2—and the goodness-of-fit measure in columns (a) through (f) were generated using the corresponding parameter estimates presented in Table 2. Following den Haan (2010), the maximum absolute forecast error is computed by comparing the actual path of real money balances, M_t/P_t, for 2300 simulated quarters with the value for real money balances predicted by the law of motion using only information on actual money growth, Δm_t, and the initial value of M_0/P_0 (i.e., updating the forecast of real money balances with its true value is not allowed). See the Appendix for details.