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

Edward S. Knotek II*

Federal Reserve Bank of Kansas City

December 2007

Abstract

Macroeconomic models with microeconomic foundations should be consistent with macroeconomic and microeconomic facts. This paper proposes a model that combines two strands of the literature on stickiness in order to match both sets of facts. (1) Firms acquire information infrequently, as in Mankiw and Reis (2002), resulting in sticky information. (2) Firms face menu costs which they must pay to change prices, leading to state-dependent sticky prices at the micro level. I estimate key structural parameters and show that a model of sticky prices in a sticky-information environment is consistent with micro and macro evidence.

Key words: sticky prices, sticky information, indirect inference

JEL codes: E31, E32, E40

---

* I thank Jon Willis for useful discussions, Daniel Levy and Ricardo Reis for detailed comments, my discussant Bennett McCallum, and Yuriy Gorodnichenko, and seminar and conference participants at the Federal Reserve Bank of Kansas City, Federal Reserve System Macro Meeting, Missouri Economics Conference, Midwest Macro, and the Society for Computational Economics Conference on Computing in Economics and Finance for comments. The views expressed herein are solely those of the author and do not necessarily reflect the views of the Federal Reserve Bank of Kansas City or the Federal Reserve System. Contact information: Economic Research Department, Federal Reserve Bank of Kansas City, 925 Grand Boulevard, Kansas City, MO 64198. Tel.: (816) 881-2596. Fax: (816) 881-2199. Email: edward.knotek@kc.frb.org.

I Introduction

Macroeconomic models with microeconomic foundations should be consistent with both macroeconomic and microeconomic facts. In a series of recent papers, Mankiw and Reis (2002, 2003, 2006, 2007) and Reis (2006b) suggest that a model with informational frictions among price setters can fit a number of basic macroeconomic facts. The drawback to this model, however, is that it is not consistent with empirical evidence on pricing using micro level data.

This paper proposes a model that combines two strands of the literature on stickiness in order to match both sets of 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. I estimate an important role for both sticky prices and sticky information using indirect inference, based on the model's ability to match empirical evidence on macroeconomic fluctuations as embodied in an empirical Phillips curve and on microeconomic evidence on the mean size of and duration between price changes. I estimate 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 0.06. Finally, the representative firm faces menu costs equal to 1.45% of steady state revenues and large idiosyncratic shocks, with a standard deviation of 7%. Sticky prices in a sticky-information environment also produce inertial, hump-shaped responses of the output gap and inflation to a nominal shock.

Omitting price rigidity from the model is not innocuous. Without price stickiness, I show that the model fails to match empirical evidence on price adjustment at the micro level. In addition, omitting price rigidity changes the parameter estimates, with the estimated fraction of firms updating their information in an average quarter falling to 18%. But most importantly, the model with sticky prices and sticky information provides a closer fit to the *macro* data than a model with only sticky information. Such a finding suggests that macroeconomic models with the "right" microeconomic foundations may also provide a better fit to macroeconomic data.

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 use state-dependent pricing 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. Infrequent information updating in a state-dependent pricing model mitigates this selection effect, since

[1] See, e.g., Gertler and Leahy (2006). The selection effect is intuitive given the nature of costly price adjustment. Such an effect is absent under the typical Calvo (1983) 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.

firms do not always know exactly how their actual price compares with their optimal price. This helps to generate non-neutrality in the model.

The structure of this paper is as follows. Section II presents the model. Section III shows how the baseline model compares with special cases in which firms face only sticky prices or only sticky information. Section IV estimates the model and discusses the results. Section V concludes.

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

This paper constructs a model in which firms face 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; Taylor (1999) provides a brief summary. 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]

[2] This distinguishes the present paper from others that blend elements of sticky prices and incomplete information. Kiley (2000) allows firms to choose their Calvo probability of adjusting their price and whether to pay a cost to acquire the current period's information or use the previous period's information for free. The empirical results do not focus on the imperfect-information channel. Bonomo and Garcia (2001) model an economy in which firms face menu costs to change prices, and information is distributed to all firms simultaneously and at discrete intervals. Combined with the assumption that each firm's frictionless optimal price follows an exogenous, driftless Brownian motion, this implies that no firm will change its price between information updates. Bonomo and Carvalho (2004) justify fixed-price time-dependent rules in a model where firms pay a single cost to update their information and change their prices simultaneously. Such rules are analyzed in the context of a singular disinflation. Dupor, Kitamura, and Tsuruga (2006) employ Mankiw-Reis information updating and Calvo pricing, and Klenow and Willis (2007) use fixed-duration information updating rules and state-dependent pricing.

The Profit Function

To emphasize the interaction between sticky prices and sticky information and maintain tractability, exposition of the model is kept simple. Under Dixit-Stiglitz monopolistic competition, demand for firm *i*'s product at time *t* is $Y_{it} = Y_t(P_{it} / P_t)^{-\theta}$, where $-\theta$ is the elasticity of demand for good *i* and P_{it} is 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 aggregate 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} (e.g., a productivity shock) and the economy-wide gross output gap.

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

The idiosyncratic component of marginal cost follows

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

The symmetric, flexible-price/full-information natural rate of output, Y_t^N, is normalized to one for all *t* and the parameter δ ensures that output converges to it in the steady state. 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.

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

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

Money or nominal demand growth, Δm_t, is exogenous and grows at rate μ in the steady state. It takes the form

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

The Firm's Optimization Problem

In a frictionless world, the problem of firm i is trivial: in each period, obtain the necessary information on χ_{it}, M_t, and P_t so as to set P_{it} to maximize profits. Such a world, however, contrasts with reality. Acquiring and processing information are time-consuming, costly endeavors. This would be especially true for the world populated by a continuum of monopolistic competitors as set out above. 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 combines infrequent information updating with state-dependent pricing. Each period, a firm updates its information about the state of the aggregate world with probability λ, as suggested by Mankiw and Reis (2002, 2003). This probability is 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 (2006b) provides a theoretical justification for how such a framework can arise if producers face an explicit information cost. With probability $1-\lambda$, the firm does not acquire new information on aggregate conditions.

Firms do, however, obtain information on their idiosyncratic component of marginal cost χ_{it} in each period. This assumption can be justified on the grounds that—in order to replicate the

[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.

large observed size of price changes, as stressed by Golosov and Lucas (2007)—firms' pricing decisions must be heavily influenced by frequent and large idiosyncratic shocks. Models of rational inattention (e.g., Sims 2003 or Maćkowiak and Wiederholt 2007) would thus posit that firms pay close attention to χ_{it}. Because the idiosyncratic component of marginal cost is an independent process, knowing χ_{it} does not offer any information on aggregate variables.[4]

Note that in the case of λ=1, the firm always has all idiosyncratic *and* aggregate information. The model thus reduces to a full-information model.

At the same time, it is potentially costly for a firm to change its price away from its previous level. Specifically, a firm must pay a menu cost, Φ, if it wishes to implement a price change at time t. This generates 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 $j \geq 1$ 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 most recent nominal price, P_{it-1}, and its current idiosyncratic marginal cost term χ_{it}.

First, consider the case in which the firm does not acquire new aggregate information in period t. The firm is then 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. 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

[4] See footnote 1 of Reis (2006b, p. 796).

gone j+1 periods without an information update. In either case, the firm discounts the future at 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 periods ago, is

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

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 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 periods ago, is

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

The firm optimizes over these choices, such that the expected value to the firm of entering period t with price P_{it-1}, idiosyncratic marginal cost component χ_{it}, and last having updated its aggregate information j periods ago is

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

Second, consider the case in which the firm acquires new aggregate information in period t. The firm's problem then becomes a special case of the above with j=0. In that case, the firm would make its decision regarding whether to keep its price or change it using χ_{it}, P_t, M_t, Δm_t, etc. Since the firm sees current period values, there is no uncertainty over the profits the firm will earn in period t. All uncertainty regards the future facing the firm.

Note that in the case of Φ=0, price changes are costless. Because firms change prices at will, they only seek to maximize contemporaneous profits—or their expected level, when based upon old information.

Computational Issues and Expectations

When information updating occurs with constant probability λ, it is possible for a firm to go an extraordinarily long time between information updates. To avoid this, I assume there is a $j_{\max}$ beyond which a firm updates with certainty. That is, if a firm enters period t last having updated its aggregate information $j_{\max}$ periods ago and does not acquire new information today, it knows with certainty that it will update its information in the following period. 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 λ=0) that information updating is perfectly staggered across firms, as in a Taylor-type model.

As a second point, note that one could rewrite the firm's profit function (2.3) as

$$\Pi\left(\frac{P_{it}}{P_t},\frac{M_t}{P_t},\chi_{it}\right)=\Pi\left(\frac{P_{it}}{P_{t-j}}\frac{P_{t-j}}{P_t},\frac{M_t}{M_{t-j}}\frac{M_{t-j}}{P_{t-j}}\frac{P_{t-j}}{P_t},\chi_{it}\right).$$

A firm with aggregate information j periods old knows its nominal price relative to P_{t-j}, and it also knows M_{t-j}/P_{t-j}. Since money growth follows (2.4), Δm_{t-j} can be used to form expectations over all possible realizations of cumulative money growth since the last information update, $\mu_{t,t-j} = M_t / M_{t-j} = (1+\Delta m_t)(1+\Delta m_{t-1})\cdots(1+\Delta m_{t-j+1})$. The profit function also requires expectations over possible realizations of cumulative inflation since the last information update, $\pi_{t,t-j} = P_t / P_{t-j} = (1+\pi_t)(1+\pi_{t-1})\cdots(1+\pi_{t-j+1})$, along with its interactions with cumulative money growth.

To form expectations over aggregate variables, I assume that firms use a forecasting rule in the spirit of Krusell and Smith (1998) as applied by Willis (2002). Such a rule is consistent with the idea that information acquisition, absorption, and processing are costly activities and surveying a continuum of other firms would be prohibitively expensive, since the rational-expectations solution to the model would require that firms know all the state variables—including the relative prices and the complete information sets—of an arbitrarily large number of other firms. Firms make linear j-period-ahead forecasts of real money balances via

$$\left(\frac{M_t}{P_t}\right)^F = \alpha_0\left(\frac{1-\alpha_2^j}{1-\alpha_2}\right) + \alpha_1\sum_{k=0}^{j-1}\alpha_2^k\left(\Delta m_{t-k}\right)^F + \alpha_2^j\frac{M_{t-j}}{P_{t-j}}, \tag{2.8}$$

where the superscript F denotes a forecasted value and α_0 is restricted such that steady-state output converges to its flexible-price/full-information level. This rule 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. Given their last observations of nominal money growth and real money balances, firms use these variables to form expectations over the distribution of possible real money balances at any point in the future.

Based upon (2.8) and the elements laid out above, firms form all the expectations needed to solve their optimization problem. A firm that last updated its aggregate information j periods ago uses its knowledge of Δm_{t-j} to form expectations over the distribution of $\mu_{t,t-j}$ via (2.4). Using Δm_{t-j}, (2.4), and M_{t-j}/P_{t-j}, the firm forms expectations over the distribution of M_t/P_t via (2.8). Finally, the firm uses M_{t-j}/P_{t-j} and the distributions of $\mu_{t,t-j}$ and M_t/P_t to form expectations over the distribution of $\pi_{t,t-j}$ via $\pi_{t,t-j} = \mu_{t,t-j}(M_{t-j}/P_{t-j})(M_t/P_t)^{-1}$. Expectations of χ_{it+1} are formed rationally based on knowledge of χ_{it} and equation (2.2).

While expectations are made in a simple manner, they are nevertheless model-consistent, as in Krusell and Smith (1998). The methodology is as follows. Start with an initial guess $A_0=\{\alpha_0,\alpha_1,\alpha_2\}$. Using the forecast rule with A_0, simulate the model and for the case of j=1 estimate the coefficients in (2.8), $\hat{A}_0$, replacing forecasts with realized values. If the estimated parameters are close to the guess, then agents' expectations are on average consistent with the dynamics of the model (and the dynamics of the model are on average consistent with expectations). If not, form a new guess, A_1, and iterate to convergence. In the terminology of Krusell and Smith (1998, p. 875), such a procedure leads to a "computed, approximate equilibrium."

III Comparing Impulse Responses

To illustrate the dynamics that arise from the model, this section compares impulse responses generated from the baseline model with sticky prices and sticky information with the (nested) special cases in which firms face only sticky prices or only sticky information.

Model Calibration

Table 1 contains a list of parameter values for the quarterly model. The exogenous process (2.4) is nominal GDP growth. The parameters for this equation are estimated on U.S. data for 1983.1–2005.4. The model abstracts from positive long-run output growth, hence this 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, as in Nakamura and Steinsson (2007a, 2007b). The maximum number of quarters that a firm would go without updating its information, $j_{\max}$, is set to eight. Thus 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). As an upper bound, this is above most estimates of the average duration between aggregate information updates from empirical studies that omit price stickiness.[5]

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, as in Tauchen (1986), with five and three states, respectively. The other relevant variables are discretized in 0.4% increments over all relevant outcomes.

[5] See Table 2. These studies also truncate the distribution for estimation purposes. Carroll (2003), Mankiw et al. (2004), and Reis (2006a) present additional evidence of informational stickiness.

Comparison with the Mankiw-Reis Model

The model set out in Section II nests several special cases. When $\Phi=0$, firms costlessly change prices and set the price that they expect to be optimal—based upon information acquired as of their last information update j periods ago—at time t, and firms acquire new aggregate information with probability λ in a given period. This is a sticky-information model ("SI"), similar to the model originally proposed by Mankiw and Reis (2002) with two important exceptions. First, firms go no longer than $j_{\max}$ periods between information updates. Second, firms form linear model-consistent expectations via the forecasting rule (2.8).[6]

Figure 1 compares this paper's sticky-information model to two variants of the model proposed by Mankiw and Reis ("MR," 2002). Figure 1(a) is the original MR model, in which there is no upper limit on the duration between information updates. Figure 1(b) illustrates what occurs when the distribution of information updates is truncated at $j_{\max}$, as in the SI model. In general, the dynamics of the SI model appear to be a hybrid of the two MR variants. Most notably, the SI model's linear forecasting rule (2.8) prevents the same type of large non-linear response that the rational expectations in Figure 1(b) produce.

Comparison among Forms of Stickiness

Aside from the sticky-information-only case above, the baseline model from Section II also nests the sticky-price-only case ("SP"), in which $\lambda=1$ and all firms have complete knowledge over all aggregate and idiosyncratic variables in all periods. Figure 2 presents generalized impulse responses for the sticky-information and sticky-price cases and compares them with the baseline sticky-price/sticky-information model ("SP/SI").

[6] The SI model omits idiosyncratic shocks, so $\chi_{it}=1$ for all i and t to more closely follow the Mankiw-Reis model.

In the sticky-price model, all firms immediately see the change in nominal demand growth. Furthermore, given the AR process for money growth, they know the effects of the shock will persist for several quarters. In conjunction with their idiosyncratic shocks, firms have an incentive to respond almost immediately to the shock—thus the inflation rate quickly increases, peaking in the quarter of the shock. Nevertheless, the shock does yield real effects, owing to the real rigidity parameter γ. Less real rigidity (i.e., a larger value of γ) would produce a larger inflation response and a smaller output response, pushing the results toward those of Golosov and Lucas (2007).

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). Real rigidity in the model further constrains action on the part of the informed firms, as they do not wish to have their prices too far from their competitors'. This results in a delayed inflation response and stronger real effects than in the sticky-price case.

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 real rigidity constrains firms from setting prices too different from their competitors', ceteris paribus. The ultimate result is considerable monetary non-neutrality in the model.

IV Estimation and Discussion

While a number of studies have estimated the frequency with which firms update information, these studies employ reduced-form equations based on the implicit assumption that prices are fully flexible. Empirical evidence on pricing at the micro level contradicts such an assumption.

In this section, I use simulation techniques to estimate four structural model parameters via indirect inference: (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. I assess the model's ability to match post-1983 U.S. data because it affords relative stability and because recent empirical studies on price adjustment at the micro level use data from this period.[7]

Estimation of Model Parameters via Indirect Inference

Estimation of the model is done via indirect inference. 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. To this end, the criteria used to assess the model should encompass both micro and macro data.

To capture the spirit of the latter, 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

$$\pi_t = \xi_0 + \xi_{11}\pi_{t-1} + \xi_{12}\pi_{t-2} + \xi_{13}\pi_{t-3} + \xi_{14}\pi_{t-4} + \xi_2 y_{t-1} + \zeta_t, \tag{4.1}$$

where y is the output gap derived from the HP filter. Table 3 presents estimates of the coefficients using U.S. data for the period 1983.1–2005.4. Estimation of (4.1) over this period is relatively insensitive to the inclusion of a measure of food and energy shocks, hence these are omitted for the sake of parsimony and compatibility with the model.

[7] 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.

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 will be useful in determining the size of the menu cost Φ and the size of the standard deviation of the idiosyncratic marginal cost shocks σ_χ affecting the firms. Using price data underlying computation of the consumer price index by the Bureau of Labor Statistics for the U.S., Klenow and Kryvtsov (2007) 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). Call these moments ξ_3 and ξ_4, respectively.

Indirect inference uses model simulations to estimate the structural model parameters that minimize the weighted difference between moments estimated on simulated data and those estimated using U.S. data (e.g., Gouriéroux et al. 1993). Let $\psi = [\lambda, \gamma, \Phi, \sigma_\chi]'$ be the structural parameters to be estimated, and let $\hat{\Xi} = [\xi_{11}, \xi_{12}, \xi_{13}, \xi_{14}, \xi_2, \xi_3, \xi_4]'$ 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 Ξ on the simulated data, yielding a set of coefficients and moments $\tilde{\Xi}(\psi)$. Repeating this procedure S times for each ψ, the indirect inference estimator $\hat{\psi}$ is

$$\hat{\psi} = \arg\min_{\psi} \left(\hat{\Xi} - \frac{1}{S} \sum_{s=1}^{S} \tilde{\Xi}(\psi) \right)' \Omega \left(\hat{\Xi} - \frac{1}{S} \sum_{s=1}^{S} \tilde{\Xi}(\psi) \right). \tag{4.2}$$

The positive definite weighting matrix Ω is the identity matrix. Estimation of $\hat{\psi}$ was conducted via simulated annealing (e.g., Goffe et al. 1994) with multiple starting points chosen to ensure that $\hat{\psi}$ is the global minimum.[8]

A considerable amount of informational and real rigidity is necessary for the model to match both the macro and the micro data. Table 3 presents results from the estimation. The estimate of λ is 0.297 (with standard error 0.077), implying a highly significant role for sticky information in matching the data. By itself, this value implies that a firm has a 30% probability of acquiring new information in a given quarter and that firms would update their information on average once every 3.4 quarters. This is the interpretation in the standard sticky-information model. However, this paper's model with sticky prices imposes a maximal length of time beyond which a firm acquires new information with certainty ($j_{\max}$=8 quarters). Because this upper bound causes some firms to "automatically" acquire new information, 31% of firms actually acquire new information in an average quarter, and the average length of time between information updates is 3.2 quarters.

The estimate of γ is 0.06 (with standard error 0.026). As Woodford (2003, p. 173) writes that an estimate of real rigidity (or strategic complementarity) "in the range between 0.10 and 0.15 does not require implausible assumptions," this estimate suggests that the presence of sticky information is not a substitute for relatively strong strategic complementarities across firms.

Finally, the sizes of the menu cost and idiosyncratic shock are highly significant, indicating that both are necessary in a representative-firm model to match the micro data. Menu

[8] Note that the model utilizes the "true" output gap—i.e., the difference between actual output and the full-information, frictionless rate of output—while the latter is approximated in the U.S. data by the HP filter. To make the model's "true" output gap better conform to the estimated output gap in indirect inference, low-frequency variations in the model's "true" output gap were removed using the HP filter and a weighting parameter of 160,000.

costs Φ amount to approximately 1.5% of steady-state revenues.[9] The standard deviation of the idiosyncratic shocks σ_χ is around 7%, implying that firms face large shocks to match the observed size of price changes in the empirical data.

<u>Comparison with a Sticky-Information Model</u>

A central question that this paper asks is whether matching the micro data can improve a model's ability to match the macro data. If sticky prices are only important in matching the micro pricing data, then the model with sticky prices and sticky information should do no better in matching the U.S. macro data than a model with only sticky information.[10] This section tests this conjecture by estimating the model with only sticky information and compares its performance with the sticky-price/sticky-information model.

Indirect inference is used to estimate λ and γ for this paper's sticky-information model, using as criteria the coefficients from the Phillips curve (4.1), $\hat{\Xi} = [\xi_{11}, \xi_{12}, \xi_{13}, \xi_{14}, \xi_2]'$. Thus the model only seeks to match the macro data. The estimate of λ is 0.131 (with standard error 0.002), implying a mean duration between information updates of more than five quarters. This is within the range of estimates from studies with flexible prices that have estimated this parameter using other techniques (Table 2), though it is biased down by the fact that nearly one-third of information updates occur because firms go $j_{\max}$ periods since their previous update. In addition, the estimate of γ is less than 0.01 (and statistically insignificantly different from zero).[11]

[9] This is double the estimates provided by Dutta et al. (1999) and Levy et al. (1997) for drugstores and grocery stores, respectively. Thus these may not be "representative" firms.

[10] Since the estimated value of λ was less than one in the sticky-price/sticky-information model, this model better fits the data than a model with only sticky prices. Note the distinction with papers that compare the performance of sticky-price *versus* sticky-information models, which often find that the sticky-price model produces a better fit with the data (e.g., Kiley 2007).

[11] Eliminating menu costs augments firms' incentives to respond to marginal cost (here: output gap) movements; additional real rigidity lessens these incentives.

Naturally, the model's ability to match the empirical evidence on micro price adjustment deteriorates, as firms change prices in virtually every period by small amounts.[12] But more important is that the model with only sticky information is unable to match the macro data as well as the model with sticky information *and* sticky prices. This is evident from Table 3. The sticky-price/sticky-information model better matches the macro data for four of the five Phillips curve coefficients. Overall, the sum of squared differences between the empirically estimated coefficients and those from the simulated models is smaller for the sticky-price/sticky-information model than for the model with only sticky information. 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.

Implications and Discussion

The model affords the opportunity to track both aggregate variables and the underlying decisions of individual firms as well. This is done in depth in Figure 3 through Figure 5 and in Table 4.

Figure 3 displays impulse responses for inflation and the output gap for the baseline model, using the estimated parameter values. The nominal shock to money (demand) growth which occurs in period 0 begins a long expansion in which inflation rises gradually, peaking seven quarters after the shock occurs. 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

[12] Very few firms are constrained by the discretization (grid) technique used to solve the problem: more than 99.5% of prices change in any given quarter. Recall that the sticky-information model abstracts from idiosyncratic shocks to better correspond to the versions presented by Mankiw and Reis (2002, 2003, 2006, 2007) and Reis (2006b), which produces many small price changes.

the figure. Thus the combination of sticky prices, sticky information, and real rigidity is capable of generating substantial monetary non-neutrality.

Table 4 presents additional statistics on the microeconomic aspects of the model. While the mean duration between price changes is 2.837 quarters, the median duration is slightly lower at 2 quarters. The mean size of a price change is around 12%. In the U.S. data, Klenow and Kryvtsov (2007) report a mean duration (across categories) between regular price changes of 8.6 months (2.867 quarters), a median duration of 7.2 months (2.4 quarters), and an average size of 11%.

However, there are discrepancies between the model and the empirical data. Table 4 shows that "small" price changes—those less than 5% in absolute value—comprise less than 1% of all price changes in the model. By contrast, Klenow and Kryvtsov (2007) find that 44% of regular price changes fall into this category. Additional heterogeneity—perhaps in the form of heterogeneous menu costs—could help the model along this dimension.

The heterogeneity induced by idiosyncratic shocks to marginal costs plays an important role in the model. First and foremost, these shocks are a necessary feature to match the stylized fact that price changes are large—much larger than could be explained, given their average frequency, by macroeconomic 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. By itself, sticky information would induce heterogeneity and reduce firms' *abilities* to perfectly synchronize; however, it would not necessarily affect their *desires* to synchronize as do large idiosyncratic shocks.

An interesting feature of the model is the interaction between state-dependent pricing and the acquisition of aggregate information, a feature that is not available when firms make time-dependent pricing decisions. Figure 4 plots how the frequency of price change varies depending on the amount of time since the firm's last aggregate information update. Two patterns are notable. First, firms with information that is three to six quarters old are relatively more likely to change their prices than average, in particular because more firms make price increases than normal. This phenomenon is caused by positive trend inflation in the model: firms with slightly older macroeconomic information will assume that their prices have fallen in real terms, ceteris paribus, and this condenses 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 macroeconomic information. The second pattern of note is that, if firms know they will acquire information in the next period, they are relatively less likely to change their prices in the current period. In the figure, this occurs when it has been eight quarters since their last information update, since this coincides with $j_{\max}$. In particular, firms are especially wary of cutting prices immediately prior to a known update, for fear that inflation may have been higher than anticipated, thus requiring them to undo the price decrease more quickly than what would be optimal.

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.

A criticism that can be leveled against the model and the Mankiw-Reis sticky-information assumption is that—if taken literally—the cost of observing the aggregate variables necessary to make an optimal pricing decision (in this case, P_t and M_t/P_t) should be minimal. Thus one may wonder why a profit-maximizing firm would wait three quarters on average to obtain these pieces of information. Of course, the information problems of real-world firms are exceedingly more complex than the model presented here: there are many more variables and shocks, and there is much more unquantifiable uncertainty. The industrial manufacturer studied by Zbaracki et al. (2004) spent approximately $100,000 on information-acquisition costs alone. Figuring out how to use this information constitutes another important barrier to inaction—that is, the costs of processing information could be such that firms only choose to acquire *and* process information infrequently.

As a last point, there are several ways that one can assess the formation of expectations via the forecasting rule (2.8). As noted in the impulse responses of Section III, the linear model-consistent expectations combined with an upper bound on the number of quarters a firm will go between information updates yield comparable dynamics to variants of the Mankiw-Reis model with fully rational expectations. In addition, Table 4 presents the R^2s for the one-period-ahead version of the forecasting rule (whose coefficients are used iteratively to form j-period-ahead forecasts), which Krusell and Smith (1998) suggest is one way to assess the goodness-of-fit of the forecasting rule. At 0.999, the fit is quite good across the simulations. Figure 5 plots the actual realizations of M_t/P_t and the one-period-ahead forecasted series $(M_t/P_t)^F$ for a representative simulation with the estimated parameters for the sticky-price/sticky-information model, offering graphical evidence that the forecasted series appears to be quite close to the realized values.

V 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 estimate 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 0.06. Finally, the representative firm faces menu costs equal to 1.45% of steady state revenues and large idiosyncratic shocks, with a standard deviation of 7%.

This paper also finds that sticky prices are not only important in improving the model's ability to match the empirical evidence on micro price adjustment. In addition, they also improve the model's ability to match the macro data. This strengthens the argument for ensuring that macroeconomic models have the "right" microeconomic foundations.

One area where the model fails to match the empirical evidence on price adjustment at the micro level is in terms of the distribution of the size of price changes. In particular, the model fails to produce the many "small" price changes that are witnessed in the data. The introduction of heterogeneity among firms, perhaps in terms of their menu costs, could help to remedy this deficiency.

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 issues is left for ongoing research.

VI Appendix: Construction of Impulse Response Figures

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 S=10,000 times. In each simulation, the exogenous money growth process took on its trend value—normalized to zero for the sake of the figures—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 S, the mean response approximates the actual response of (2.4) to a single shock. Likewise, it is assumed that the mean responses over the S simulations of inflation and the output gap approximate their actual responses as well.

VII Works Cited

Andrés, Javier, J. David López-Salido, and Edward Nelson (2005) "Sticky-Price Models and the Natural Rate Hypothesis" *Journal of Monetary Economics* 52(5): 1025–53.

Ball, Laurence and David Romer (1990) "Real Rigidities and the Non-Neutrality of Money" *Review of Economic Studies* 57(2): 183–203.

----- and N. Gregory Mankiw (1994) “Asymmetric Price Adjustment and Economic Fluctuations” *Economic Journal* 104(423): 247–61.

Bonomo, Marco and Rene García (2001) “The Macroeconomic Effects of Infrequent Information with Adjustment Costs” *Canadian Journal of Economics* 34(1): 18–35.

----- and Carlos Carvalho (2004) “Endogenous Time-Dependent Rules and Inflation Inertia” *Journal of Money, Credit, and Banking* 36(6): 1017–41.

Caballero, Ricardo J. and Eduardo M.R.A. Engel (1993) “Heterogeneity and Output Fluctuations in a Dynamic Menu-Cost Economy” *Review of Economic Studies* 60(1): 95–119.

Calvo, Guillermo (1983) “Staggered Prices in a Utility-Maximizing Setting” *Journal of Monetary Economics* 12(3): 383–98.

Caplin, Andrew S. and Daniel F. Spulber (1987) “Menu Costs and the Neutrality of Money” *Quarterly Journal of Economics* 102(4): 703–25.

Carroll, Christopher D. (2003) “Macroeconomic Expectations of Households and Professional Forecasters” *Quarterly Journal of Economics* 118(1): 269–98.

Coibion, Olivier (2006) “Testing the Sticky Information Phillips Curve” working paper.

Dupor, Bill, Tomiyuki Kitamura, and Takayuki Tsuruga (2006) “Do Sticky Prices Need to Be Replaced with Sticky Information?” Bank of Japan IMES Discussion Paper No. 2006-E-23.

Dutta, Shantanu, Mark Bergen, Daniel Levy, and Robert Venable (1999) “Menu Costs, Posted Prices, and Multiproduct Retailers” *Journal of Money, Credit and Banking* 31(4): 683–703.

Gertler, Mark and John Leahy (2006) “A Phillips Curve with an Ss Foundation” NBER Working Paper 11971.

Goffe, William L., Gary D. Ferrier, and John Rogers (1994) “Global Optimization of Statistical Functions with Simulated Annealing” *Journal of Econometrics* 60(1–2): 65–99.

Golosov, Mikhail and Robert E. Lucas, Jr. (2007) “Menu Costs and Phillips Curves” *Journal of Political Economy* 115(2): 171–99.

Gordon, Robert J. (1998) “Foundations of the Goldilocks Economy: Supply Shocks and the Time-Varying NAIRU” *Brookings Papers on Economic Activity* 1998(2): 297–346.

Gouriéroux, Christian, Alain Monfort, and E. Renault (1993) “Indirect Inference” *Journal of Applied Econometrics* 8(supplement): S85–S118.

Ireland, Peter N. (1997) “Stopping Inflations, Big and Small” *Journal of Money, Credit, and Banking* 29(4): 759–75.

Khan, Hashmat and Zhenhua Zhu (2006) "Estimates of the Sticky-Information Phillips Curve for the United States" *Journal of Money, Credit, and Banking* 38(1): 195–207.

Kiley, Michael T. (2000) "Endogenous Price Stickiness and Business Cycle Persistence" *Journal of Money, Credit, and Banking* 32(1): 28–53.

----- (2007) "A Quantitative Comparison of Sticky-Price and Sticky-Information Models of Price Setting" *Journal of Money, Credit and Banking* Supplement to volume 39(1): 101–26.

Klenow, Peter J. and Jonathan Willis (2007) "Sticky Information and Sticky Prices" *Journal of Monetary Economics* 54: 79–99.

----- and Oleksiy Kryvtsov (2007) "State-Dependent or Time-Dependent Pricing: Does It Matter for Recent U.S. Inflation?" working paper.

Krusell, Per and Anthony A. Smith, Jr. (1998) "Income and Wealth Heterogeneity in the Macroeconomy" *Journal of Political Economy* 106(5): 867–96.

Levy, Daniel, Mark Bergen, Shantanu Dutta, and Robert Venable (1997) "The Magnitude of Menu Costs: Direct Evidence from Large U.S. Supermarket Chains" *Quarterly Journal of Economics* 112(3): 791–825.

Maćkowiak, Bartosz and Mirko Wiederholt (2007) "Optimal Sticky Prices under Rational Inattention" working paper.

Mankiw, N. Gregory and Ricardo Reis (2002) "Sticky Information Versus Sticky Prices: A Proposal to Replace the New Keynesian Phillips Curve" *Quarterly Journal of Economics* 117(4): 1295–1328.

----- and ----- (2003) "Sticky Information: A Model of Monetary Non-Neutrality and Structural Slumps" in Philippe Aghion, Roman Frydman, Joseph Stiglitz, and Michael Woodford, eds. *Knowledge, Information, and Expectations in Modern Macroeconomics: In Honor of Edmund S. Phelps* Princeton, NJ: Princeton University Press.

----- and ----- (2006) "Pervasive Stickiness" *American Economic Review* Papers and Proceedings 96(2): 164–69.

----- and ----- (2007) "Sticky Information in General Equilibrium" *Journal of the European Economic Association* 5(2–3): 603–13.

-----, -----, and Justin Wolfers (2004) "Disagreement About Inflation Expectations" *NBER Macroeconomics Annual 2003* MIT Press: Cambridge, MA.

Nakamura, Emi and Jón Steinsson (2007a) "Five Facts about Prices: A Reevaluation of Menu Cost Models" working paper.

----- and ----- (2007b) “Monetary Non-Neutrality in a Multi-Sector Menu Cost Model” working paper.

Reis, Ricardo (2006a) “Inattentive Consumers” *Journal of Monetary Economics* 53(8): 1761–1800.

----- (2006b) “Inattentive Producers” *Review of Economic Studies* 73(3): 793–822.

Rotemberg, Julio J. and Michael Woodford (1992) “Oligopolistic Pricing and the Effects of Aggregate Demand on Economic Activity” *Journal of Political Economy* 100(6): 1153–1207.

Sims, Christopher A. (2003) “Implications of Rational Inattention” *Journal of Monetary Economics* 50(3): 665–90.

Stock, James H. and Mark W. Watson (1999) “Business Cycle Fluctuations in US Macroeconomic Time Series” in John B. Taylor and Michael Woodford, eds. *Handbook of Macroeconomics* vol. 1A New York: Elsevier Science B.V.

Tauchen, George (1986) “Finite State Markov-Chain Approximations to Univariate and Vector Autoregressions” *Economics Letters* 20(2): 177–81.

Taylor, John B. (1999) “Staggered Price and Wage Setting in Macroeconomics” in John B. Taylor and Michael Woodford, eds. *Handbook of Macroeconomics* vol. 1B New York: Elsevier Science B.V.

Willis, Jonathan L. (2002) “General Equilibrium of a Monetary Model with State-Dependent Pricing” working paper.

Woodford, Michael (2003) *Interest and Prices: Foundations of a Theory of Monetary Policy* Princeton University Press: Princeton, NJ.

Zbaracki, Mark J., Mark Ritson, Daniel Levy, Shantanu Dutta, and Mark Bergen (2004) “Managerial and Customer Costs of Price Adjustment: Direct Evidence from Industrial Markets” *Review of Economics and Statistics* 86(2): 514–33.

Figure 1: Generalized Impulse Responses under Sticky Information

Figure 1(a): Comparison with Mankiw-Reis

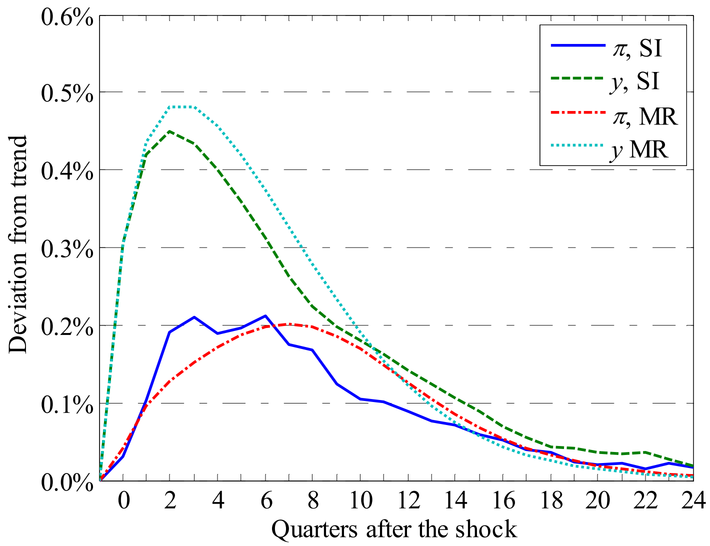
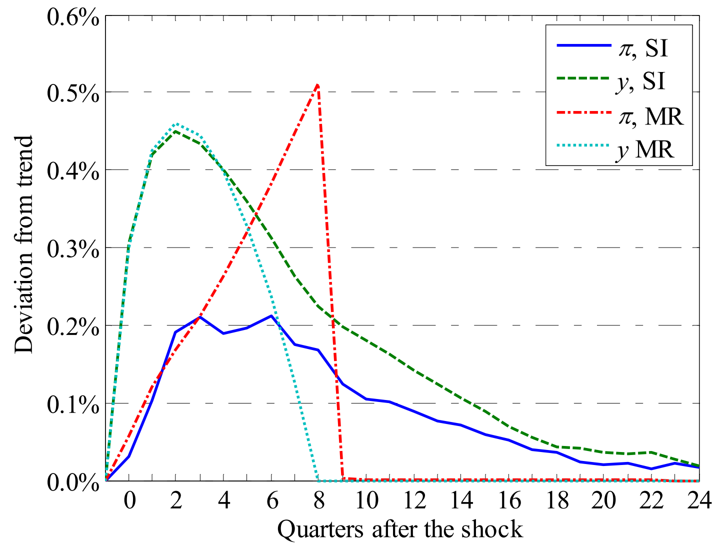
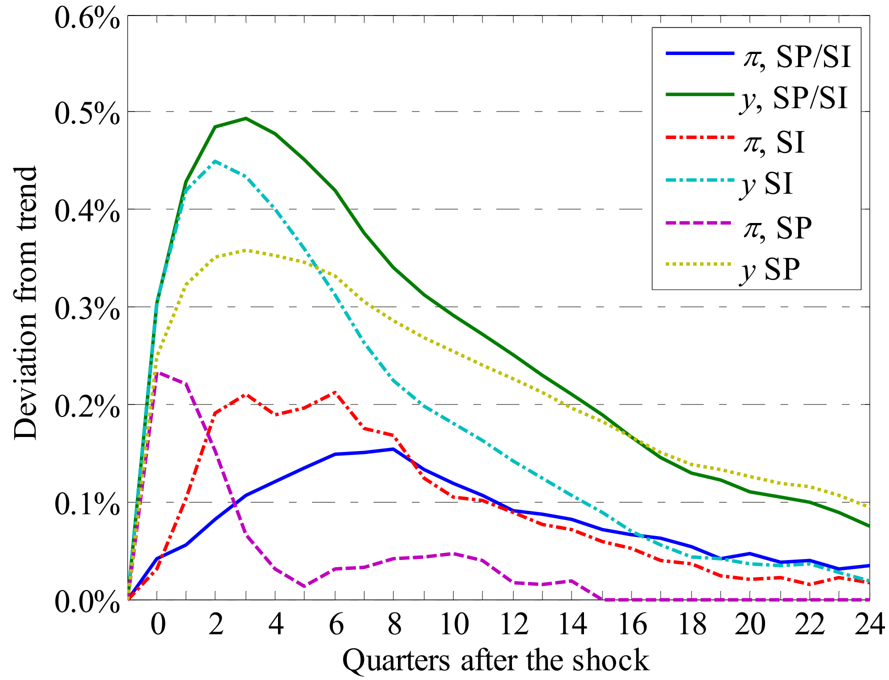


Figure 1(b): Comparison with Truncated Mankiw-Reis



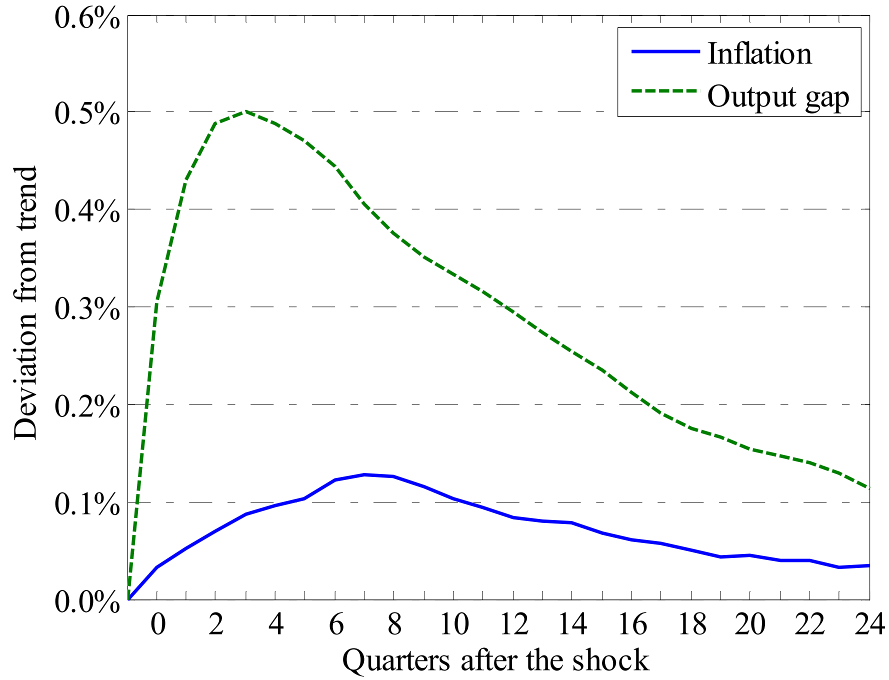
Note: Mean responses over 10,000 simulations of the output gap y and inflation π to a 1.3% shock to money growth at time t=0 with λ=0.25 and γ=0.1, as in Mankiw and Reis (2002).

Figure 2: Generalized Impulse Responses under Sticky Prices and Sticky Information



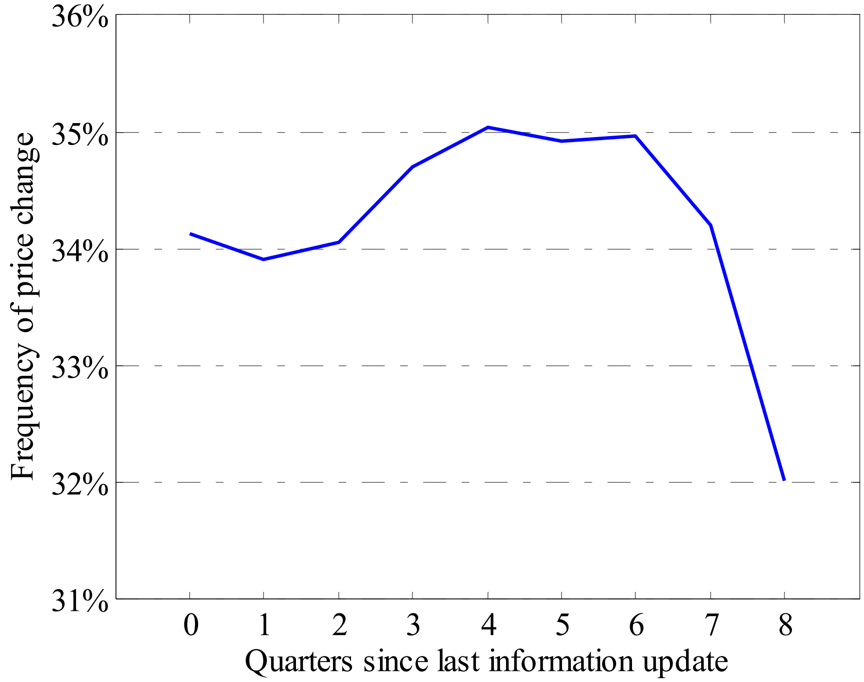
Notes: Mean responses over 10,000 simulations of the output gap y and inflation π to a 1.3% shock to money growth at time t=0. The baseline model uses λ=0.25, γ=0.1, Φ=0.0145, and σ_χ=0.06875. The SI model uses Φ=0 and omits idiosyncratic shocks. The SP model uses λ=1.

Figure 3: Generalized Impulse Responses under Sticky Prices and Sticky Information



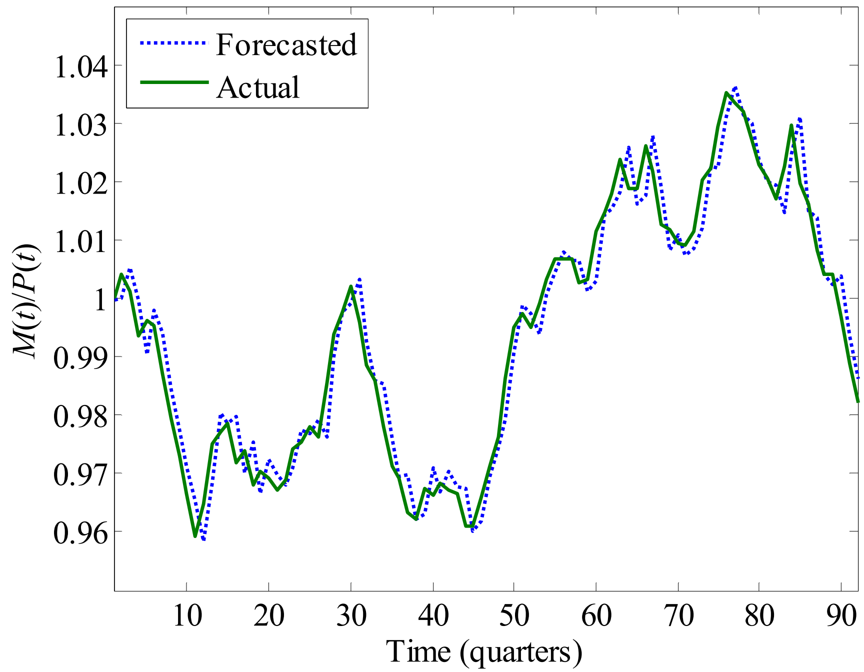
Note: Mean responses over 10,000 simulations of the output gap y and inflation π to a 1.3% shock to money growth at time t=0, using the baseline model and the parameter estimates from Section IV.

Figure 4: Frequency of Price Changes as a Function of Time since Last Information Acquisition



Note: Since $j_{\max}$=8, a firm that has gone eight quarters since its last information update obtains new aggregate information with certainty in the next period.

Figure 5: Comparison of Actual and Forecasted Real Money Balances for One Simulation



Note: Plotted are the actual series M_t/P_t and the one-step-ahead forecasted series $(M_t/P_t)^F$ for one simulation of the baseline model with sticky prices and sticky information using the parameter estimates from Section IV and the forecasting rule (2.8).

Table 1: Estimated and Calibrated 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. $\mathrm{N}(0,\sigma^2)$ using nominal GDP growth in U.S. data, 1983.1–2005.4
ρ	0.49	
σ	$5.1*10^{-3}$	
Other parameters		
θ	6	Implies a desired markup of 1.2
β	0.99	Discount factor, quarterly model
ρ_χ	0.70	Persistence of idiosyncratic marginal cost shocks
$j_{\max}$	8	Maximal number of quarters without an information update
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: Estimates of Information Rigidity among Price Setters

	Average duration between price setters' information updates (quarters)	Time series start and end dates
Andrés et al. (2005)	6.7	1979.3–2003.3
Coibion (2006)	4.2–20.0	1982.1–2004.2
Dupor et al. (2006) #	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 #	3.2	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.

Table 3: Estimation Results

	U.S. data	Baseline model: sticky prices and sticky information	Sticky information only
$\hat{\lambda}$	–	0.297 *** (0.077)	0.131 *** (0.002)
$\hat{\gamma}$	–	$6.03*10^{-2}$ ** ($2.63*10^{-2}$)	$8.98*10^{-3}$ (0.021)
$\hat{\Phi}$	–	$1.45*10^{-2}$ *** ($2.29*10^{-3}$)	–
σ_{χ}	–	$6.86*10^{-2}$ *** ($7.50*10^{-3}$)	–
Macro moments			
π_{t-1}	0.225 ** (0.100)	0.163	0.155
π_{t-2}	0.077 (0.101)	0.080	0.142
π_{t-3}	0.107 (0.100)	0.094	0.107
π_{t-4}	0.350 *** (0.096)	0.160	0.148
y_{t-1}	0.048 *** (0.017)	0.042	0.038
Sum of squared differences, macro moments		0.040	0.050
Micro moments			
Mean duration	2.867	2.837	1.005
Mean (absolute) size of a price change	0.113	0.120	0.006

Notes: $\overline{R}^2$=0.45 for the Phillips curve in the U.S. data. The mean duration between price changes and the mean (absolute) size of price changes for the U.S. are from Klenow and Kryvtsov (2007), for regular prices. ** or *** denotes significance at the 5% or 1% level. Standard errors are in parentheses.

Table 4: Micro Statistics and Expectations

	Baseline model: sticky prices and sticky information	Sticky information only
Price-change statistics		
Mean duration (quarters)	2.837	1.005
Median duration (quarters)	2.0	1.0
Mean frequency	0.342	0.995
Mean (absolute) size	0.120	0.006
"Small" price changes	0.001	1.000
Information-updating statistics		
Mean frequency	0.31	0.18
Mean duration (quarters)	3.16	5.37
Automatic updates	0.06	0.33
Forecasting and expectations		
α_0	0.06	0.05
α_1	0.94	0.97
α_2	0.94	0.94
R^2	0.999	0.999

Notes: "Small" price changes are price changes smaller than five percent in absolute value. Automatic updates are the percentage of aggregate information acquisitions that occur automatically because $j=j_{max}+1$.