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Sticky information and sticky prices ☆

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Abstract

In the U.S. and Europe, prices change at least once a year. Yet nominal macro shocks seem to have real effects lasting well beyond a year. ''Sticky information'' models, as posited by Mankiw and Reis [2002. Sticky information versus sticky prices: a proposal to replace the new Keynesian Phillips curve. Quarterly Journal of Economics 117, 1295–1328], Sims [2003. Implications of rational inattention. Journal of Monetary Economics 50(3), 665–690], and Woodford [2003. Princeton University Press: Princeton, NJ], can reconcile micro flexibility with macro rigidity. We simulate a sticky information model in which price setters update information on macro shocks less frequently than information on micro shocks. We then examine price changes in the micro data underlying the U.S. CPI. Empirical price changes react to old information, just as sticky information models predict.

JEL classification: D8; E3; L16

Keywords: Sticky information; State dependent pricing

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1. Introduction

Individual consumer and producer prices change every six months to one year.[1] In contrast, many studies find that nominal macro shocks have real effects with a half-life well over a year.[2] "Sticky information" theories can reconcile macro price rigidity with micro price flexibility.[3] These theories, advanced recently by Sims (1998, 2003), Mankiw and Reis (2002, 2006), and Woodford (2003), feature imperfect information about macro shocks. As a result, many rounds of micro price changes are needed to fully reflect a given macro shock. In Sims' version of sticky information, the micro flexibility is at the expense of macro flexibility, as firms face convex costs of processing information.

The aim of this paper is to explore whether the tell-tale predictions of sticky information models are borne out in data on micro price changes. Do price changes reflect dated information on macro states? Answering this question is difficult given the lack of consensus on a measure of monetary policy shocks, especially one that explains inflation movements well. We therefore simulate simple GE models to derive responses of price changes to past inflation movements.

The simulated models feature exogenous money growth, a cash-in-advance constraint, and monopolistically competitive firms. The firms face idiosyncratic productivity and aggregate money shocks, but do not change prices every period because they face costs of implementing price changes (i.e., menu costs). Nominal prices are sticky alongside the sticky information for two reasons. First, 80–90% of prices do not change in the typical month, an important fact for a monetary business cycle model to match. Second, the lumpiness of price changes is useful for testing for sticky information. When a firm changes its price, does the change reflect only inflation innovations since their last price change, or does it put weight on older innovations?

A model with flexible information is used as a benchmark (i.e., constant updating on macro states). Staggered updating of information on macro states is then introduced as in Taylor (1980). This model is closest to Mankiw–Reis in having periodic full updating of macro information. The model also shares some of the spirit of Sims, however, in having firms observe their idiosyncratic shocks every period. As expected, the less frequent the updating of macro information in the model, the more persistent the real output effects of money shocks. And the stickier the information, the more individual price changes reflect old inflation innovations as opposed to recent ones.

Moments from the CPI Research Database maintained by the U.S. Bureau of Labor Statistics are used to calibrate model parameters. The mean, standard deviation and serial correlation of money growth in the model are chosen to approximate the mean, standard deviation and serial correlation of inflation in the data. The size of menu costs and the size of idiosyncratic productivity shocks are chosen to match the frequency and size of micro price changes in the data.

The empirical test hinges on whether price changes in the data respond to old inflation innovations, or only those arriving since the firm last changed its price. The evidence

[1]See Bils and Klenow (2004) and Nakamura and Steinsson (2006) for U.S. evidence, and Dhyne et al. (2005) for studies of Euro Area countries.

[2]See, for example, Christiano et al. (1999), Romer and Romer (2003), and Bernanke et al. (2004).

[3]Strategic complementarities can also generate a "contract multiplier", i.e., real effects lasting well beyond price durations. We neglect such real rigidities to focus on sticky information theories.

suggests that price changes do reflect macro inflation innovations older than they should according to the flexible information model. The empirical regression results more closely resemble those obtained from the sticky information models than the flexible information model.[4]

We also examine whether specific types of price changes reflect macro information or, instead, purely idiosyncratic forces. The BLS labels each price as either a "sales" price or a "regular" price, and also keeps track of when products turn over ("substitutions"). Price changes related to sales and substitutions are often filtered out of price data by macro researchers (e.g., Golosov and Lucas, 2007; Nakamura and Steinsson, 2006) on the grounds that they may reflect idiosyncratic considerations rather than macroeconomic information. Sales- and substitution-related price changes respond to macro information in much the same way that regular price changes do, which suggests that they should not be dropped from the data in macro studies.

The rest of the paper is organized as follows. Section 2 lays out the general equilibrium models featuring sticky prices (due to menu costs) and exogenously sticky information. Section 3 describes the CPI micro data set, and reports statistics used to set parameter values in the models. Section 4 compares the price changes produced by the models to those in the CPI micro data. Section 5 offers conclusions.

2. Model

To investigate the role of sticky information in the micro data, we construct a model with several key features. The basic structure of the model follows from Blanchard and Kiyotaki (1987). Households consume a wide variety of goods with a constant elasticity of substitution between them. Monopolistically competitive firms produce goods to meet demand at their posted prices. To generate a motive for holding money, households must pay for their consumption goods in cash before receiving their income. In order to generate the nominal price rigidities observed in the data, firms face a "menu" cost of implementing a price change. To examine the role of sticky information, information on macro variables (exogenous and endogenous) arrives in staggered fashion. By changing the frequency of information arrival we can investigate different degrees of information stickiness. Finally, firms use a boundedly rational forecast for inflation. This assumption permits a solution to the model with a finite state space.

2.1. Households

Households consume a variety of m goods and provide labor for production of the goods. Their choices are made to maximize

$$\mathrm{E}_t\left[\sum_{t=0}^{\infty}\beta^t(C_t-\varphi L_t)\right],$$

where L_t is labor input and C_t is the consumption good. Linear utility reduces the number of aggregate states, allowing to incorporate more heterogeneity while retaining

[4]Knotek (2006) also concludes that a model containing both sticky information and sticky prices is consistent with micro- and macro evidence.

computational feasibility. The consumption good is a Dixit–Stiglitz composite of individual goods with elasticity of substitution θ:

$$C_t = \left(\sum_{j=1}^{m} C_{j,t}^{(\theta-1)/\theta} \right)^{\theta/(\theta-1)}.$$

Households make their spending decisions at the beginning of the period before receiving their income, and their purchases must be paid for out of money holdings, M_t. Money holdings are used to purchase consumption goods and real bonds, B_t:

$$\sum_{j=1}^{m} P_{j,t} C_{j,t} + P_t B_t = M_t. \tag{1}$$

Real bonds are priced using the cost of purchasing a unit of the aggregate consumption good, which is given by

$$P_t = \left(\sum_{j=1}^{m} P_{j,t}^{1-\theta} \right)^{1/(1-\theta)}. \tag{2}$$

Households receive income at the end of each period in the form of money. Income consists of wages earned by working for firms at a per-period wage rate, W_t, profits from their ownership of firms, Π_t, real returns from bond holdings, r_t, and lump sum transfers of money from the central bank, X_{t+1}.[5] Income earned in period $t-1$ provides money holdings for consumption in period t:

$$M_t = W_{t-1} L_{t-1} + \Pi_{t-1} + P_{t-1}(1 + r_{t-1}) B_{t-1} + X_t. \tag{3}$$

The household budget constraint specifies that money spent on purchases in the current period not exceed money income earned in the previous period. Combining (1) and (3):

$$\sum_{j=1}^{m} P_{j,t} C_{j,t} + P_t B_t = W_{t-1} L_{t-1} + \Pi_{t-1} + P_{t-1}(1 + r_{t-1}) B_{t-1} + X_t.$$

The solution to the household's optimization decision provides the demand function, real interest rate, and wage rate that firms use in their dynamic programming problem. Since the intertemporal marginal rate of substitution in consumption is 1 in equilibrium, the real interest rate is constant at $r = (1-\beta)/\beta$. Households are indifferent between consuming today and saving for consumption in the next period using bonds. We solve for an equilibrium in which households spend all money holdings on consumption in the current period, as bonds are in zero net supply. Using the cash-in-advance constraint, the demand for a differentiated goods can be expressed as a function of real money balances:

$$C_{i,t} = \left(\frac{P_{i,t}}{P_t} \right)^{-\theta} \frac{M_t}{P_t}. \tag{4}$$

Finally, using the households' labor supply decision, we derive a constant expected real wage. Since wage income earned today is not spent until the following period, households equate the marginal disutility of labor with the discounted expected marginal utility of

[5] Money transfer are dated the following period to signify when it affects economic activity.

consumption produced by marginal income earned from working today. This relationship is used to solve for the real wage in the current period as a function of the expected change in the price level:

$$\frac{W_t}{P_t} = \frac{\varphi}{\beta P_t \mathrm{E}_t[1/(P_{t+1})]}. \tag{5}$$

2.2. Firms

In the economy, there are m monopolistically competitive firms. Each firm produces a differentiated good, Y_i, using labor input, L_i. Firms are assumed to meet all demand at a given price, which implies that $Y_i = C_i$.

Contemporaneous real profits for firm i are given by

$$\Pi_i = \frac{P_i}{P} Y_i - \frac{W}{P} L_i,$$

where P_i is the price for good i. The firm faces the demand function given by (4), the real wage given by (5), and the production function

$$Y_i = Z_i L_i^{\eta}.$$

Here Z_i is an idiosyncratic productivity shock, and η governs returns to scale of production, allowing for decreasing returns due to a fixed factor of production.

After substituting in the demand, real wage, and production functions, we arrive at the real profit function

$$\Pi_i = \left(\frac{P_i}{P}\right)^{1-\theta} \frac{M}{P} - \frac{\kappa (Z_i)^{-1/\eta}}{P\mathrm{E}[1/P']} \left(\frac{P_i}{P}\right)^{-\theta/\eta} \left(\frac{M}{P}\right)^{1/\eta},$$

where $\kappa = \varphi/\beta$.

2.2.1. Price adjustment cost

In order to generate nominal price rigidity, we assume that firms must pay a cost, ψ, in order to implement a price change. This cost is the same for all firms and in all periods and is expressed as a fraction of revenue in the steady-state symmetric equilibrium, where steady-state (*ss*) revenue for all firms is $R_{\mathrm{ss}} \equiv \frac{M}{P_{\mathrm{ss}}}$. If firm i chooses to change its price in the current period, then net contemporaneous profits will be $\Pi_i - \psi R_{\mathrm{ss}}$.

2.2.2. Information cost

To explore the implications of sticky information, we assume information regarding macro state variables arrives in a staggered fashion. If new information does not arrive, the firm is not able to determine anything about the current innovation to money growth. This requires that pricing managers not interact with the production managers or accountants within the firm, otherwise they could see production or profits and draw inferences about current money innovations. This assumption keeps the model tractable and presents the starkest implications of sticky information. The assumption could potentially be relaxed by adding measurement error to the model. Firms would then solve a signal extraction problem when they do not have updated information. See Zbaracki et al. (2006), however, for a case study suggesting that limited communication between price setters and others within the firm is not an implausible assumption.

Ideally, one would specify a model in which firms face a cost of acquiring information about the macro state variables. In Reis (2006), firms decide each period whether to pay for updated information on the aggregate states. As we assume in this model, Reis establishes conditions under which firms find it optimal to update their information at fixed intervals.

Let $\bar{A}$ be the number of periods between observing the aggregate money growth rate, inflation rate, and real money supply. For a given firm in a given period, let A represent the number of periods since aggregate information was last observed, i.e., the age of aggregate information. If a firm has updated information, then $A = 0$. Similarly, let $\bar{I}$ represent the number of periods between observing idiosyncratic information. We set $\bar{I} = 0$ so firms always have current information on their idiosyncratic productivity shock. This assumption follows in the spirit of Sims' rational inattention story, wherein firms pay more attention to idiosyncratic than aggregate shocks because the former are much larger.

2.3. Dynamic optimization

Given the presence of an implementation cost of a price change, the firm solves a dynamic optimization problem to maximize profits. In each period the firm decides whether or not to adjust its price. If it decides to adjust, it pays the implementation cost and resets its price. If it does not adjust, its nominal price remains fixed, and its relative price, $p_i = P_i/P$, decreases at the rate of inflation.

The timing of information updating impacts the state variables of the firm's optimization problem. The seven state variables are the firm's current nominal price relative to the aggregate price level the last time aggregate information was observed ($p_{i,A}$), the money growth rate when last observed ($g_{M,A}$), the inflation rate when last observed (π_A), the level of real money balances when last observed ($m_A \equiv M_A/P_A$), the idiosyncratic productivity index (Z_i), the age of aggregate information (A), and the information set Ω used to form future expectations of the endogenous state variables.

Given the state vector, $S = \{p_{i,A}, g_{M,A}, \pi_A, m_A, Z_i, A, \Omega\}$, the firm maximizes the following value function:

$$V(S) = \max(V^{\mathrm{C}}(S), V^{\mathrm{NC}}(S)), \tag{6}$$

where $V^{\mathrm{C}}(S)$ represents the firm's value conditional on changing its price and $V^{\mathrm{NC}}(S)$ its value conditional on not changing its price. The value of a price change is expressed as

$$V^{\mathrm{C}}(S) = \max_{p^*_{i,A}}\{\mathrm{E}_{-A}[\Pi_i - \psi R_{\mathrm{ss}}] + \beta \mathrm{E}_{S'|S}[V(S')]\},$$

with $S' = \{p^*_{i,A'}, g'_{M,A'}, \pi'_{A'}, m'_{A'}, Z'_i, A', \Omega'\}$. The firm's value function is discounted by β, which reflects the household's real interest rate.

In order to solve this optimization problem, the firm must be able to form expectations over the state variables. In periods in which the firm does not observe current information, the firm computes expected profits conditional on the most recent information they have on the state variables. For example, to form an expectation of the current relative price, p_i, the firm takes the current nominal price relative to the price level A periods ago, $p_{i,A}$, and integrates over all of the possible sequences of inflation over A periods conditional on information in the state vector. Regardless of the age of the information, the firm will always compute conditional expectations of the future value function. The firm chooses the nominal price relative to the price level A periods ago, $p^*_{i,A}$, that generates the highest expected value.

The value conditional on no price change is expressed as

$$V^{\mathrm{NC}}(S) = \mathrm{E}_{-A}[\Pi_i] + \beta \mathrm{E}_{S'|S}[V(S')],$$

with $S' = \{p_{i,A'}, g'_{M,A'}, \pi'_{A'}, m'_{A'}, Z'_i, A', \Omega'\}$.

For the exogenous state variables, money growth and idiosyncratic productivity, we assume autoregressive processes:

$$\begin{aligned} g_{M,t} &= \mu_{g_M} + \rho_{g_M} g_{M,t-1} + v_{g_{M,t}},\ \ v_{g_M} \sim \mathrm{N}(0, \sigma^2_{v_{g_M}}), \\ \ln Z_{i,t} &= \rho_Z \ln Z_{i,t-1} + v_{Z,i,t},\ \ v_Z \sim \mathrm{N}(0, \sigma^2_{v_Z}). \end{aligned} \tag{7}$$

2.3.1. Bounded rationality

In order to compute a fully rational expectation of inflation, a firm needs to know the state variables of all firms in the economy, including the joint distribution of relative prices and idiosyncratic productivity shocks. One way to solve this model would be to reduce heterogeneity to a manageable scope, as in Dotsey et al. (1999) (hereafter DKW). An alternative is to assume firms form inflation expectations based on a limited set of information. We choose the latter for two reasons. First, the heterogeneity restrictions required for the DKW model do not match up well with the micro evidence.[6] Second, due to the heterogeneity introduced by staggered updating of information, assuming bounded rationality helps keep the model tractable.

We assume firms use the following linear forecasting rule to form expectations of inflation:

$$\pi^{\mathrm{f}}_{t+1} = \alpha_0 + \alpha_1 \pi_t + \alpha_2 \ln m_t + \alpha_3 g_{M,t} + v_{\pi,t+1}, \tag{8}$$

where $v_{\pi,t+1}$ is the forecast error. Firms will use their inflation forecast along with their forecast of money growth, from (7), to determine a forecast for real money balances, $\ln m^{\mathrm{f}}_{t+1}$:

$$\ln m^{\mathrm{f}}_{t+1} = \ln m_t + g^{\mathrm{f}}_{M,t+1} - \pi^{\mathrm{f}}_{t+1}. \tag{9}$$

The dynamic system used for forming aggregate expectations can be expressed as a three-variable autoregressive VAR using (7)–(9).

The equilibrium solution of the model requires the selection of an appropriate inflation forecast rule, $\Theta = \{\alpha_0, \alpha_1, \alpha_2, \alpha_3\}$. Using this forecast rule, the firm solves the optimization problem in (6) by determining a policy function for the updating of prices: $p^*_{i,A} = f(p_{i,A}, g_{M,A}, \pi_A, m_A, Z_i, A, \Omega)$.

The recursive equilibrium of the model consists of the functions V and f along with the inflation forecast rule, Θ, such that: (i) V and f solve the firm's optimization problem and (ii) the expected inflation dynamics from the forecast rule matches the actual inflation dynamics resulting from firms' pricing decisions in model simulations.

[6]See Klenow and Kryvtsov (2005) and Willis (2000).

Table 1
Parameter values

Parameters not based on BLS CPI data	
Discount rate (β)	0.993
Elasticity of substitution (θ)	5
Returns to scale (η)	0.9
Parameters calibrated using BLS CPI data	
Average money growth (bimonthly) (μ_{gM})	0.0038
Serial correlation of money growth (ρ_{gM})	0
Std. dev. of innovation to money growth ($\sigma_{v_{gM}}$)	0.013
Serial correlation of idiosyncratic productivity (ρ_Z)	0.46
Std. dev. of innovation to idiosyncratic productivity (σ_{v_Z})	0.083
Implementation (menu) cost (ψ)	0.013

Note: The frequency of the model is bimonthly to match the sampling frequency of the BLS CPI survey. The implementation cost is expressed as a fraction of steady-state revenue.

2.3.2. Calibration and simulation

Due to the presence of a discrete-choice decision in the optimization problem expressed in (6), the model is solved numerically using value function iteration. In this solution, all state variables are placed on discrete grids. The bounds of the relative price state are set wide enough to include all optimal pricing decisions, and prices are placed on the grid in 205 increments of 0.13%, or one-third the steady-state inflation rate for this economy. The autoregressive process for idiosyncratic productivity is transformed into a discrete-valued Markov chain following Tauchen (1986).[7] This conversion provides us with the transition matrix, $\Phi_Z(Z, Z')$, expressing the expected probability of any given realization of $Z_{i,t+1}$ as a function of the current state variables $Z_{i,t}$. The three-variable VAR for inflation, real money balances, and money growth is similarly converted into a first-order Markov chain.[8] The transition matrices are used to compute the discounted expected value of the future period as well as expected contemporaneous profits if firms have out-of-date information. Another transition matrix, $\Phi_A(A, A')$, provides the probability of moving from information of age A in the current period to information of age A' next period. The parametrization of this matrix will determine the stickiness of macro information.

Table 1 displays the parameter values used in our model simulations. The structural parameters are calibrated using information from the BLS price data and other sources. A bimonthly frequency (six periods per year) is used in order to match the sampling frequency in the BLS micro data. The discount rate, β, is set to 0.993 ($= 0.96^{1/6}$), to arrive at a 4% annual real interest rate. The elasticity of substitution between different consumer goods, θ, is 5, corresponding to a 25% markup for the firm. This is at the intersection of values used in the IO (3–5) and macro (5–10) literatures. Returns to scale in production, η, are 0.9. This is a compromise between the more conventional constant returns and labor's share of around 0.7, as the model has only labor. The results of interest from the model are

[7]The discrete grid for idiosyncratic productivity contains 5 points spread equally in terms of the cumulative distribution function of the variable.

[8]The discrete grids for inflation, real money balances, and money growth contain 11, 7, and 5 points, respectively, spread equally in terms of the cumulative distribution function of the variables.

not sensitive to changing κ, the marginal disutility of labor divided by the discount rate, which is set to 0.5.

The remaining parameter values are calibrated using statistics from the BLS price data. The parameters of the money growth process, $\{\mu_{gM}, \rho_{gM}, \sigma_{gM}\}$, are set to produce inflation dynamics similar to the data. A random walk for money ($\rho_{gM} = 0$) comes closest to mimicking the low persistence of inflation in the data. Values of $\mu_{gM} = 0.0038$ and $\sigma_{gM} = 0.013$ closely match the mean and standard deviation of actual inflation. The persistence of the idiosyncratic productivity shock, ρ_Z, is based on estimates in Klenow and Willis (2006). That study looked at the persistence of relative prices within categories of consumption, thereby controlling for different industry price trends (e.g., computers vs. medical care). Translating the monthly serial correlation of 0.68 to the bimonthly frequency here results in $\rho_Z = 0.46$. Midrigan (2006) and Golosov and Lucas (2007) use similar values based on grocery scanner data and BLS data, respectively. The value of $\sigma_Z = 0.083$ matches the absolute size of price changes in the BLS data. This value is similar to values used in Klenow and Willis (2006), Midrigan (2006), and Golosov and Lucas (2007). Finally, the cost of implementing price changes, ψ, is 1.3% of firm revenue. Combined with the other parameter values, this choice matches the frequency of price changes observed in the data of 30% per bimonth.

Following Willis (2003), a rational expectations equilibrium of the model is computed using the inflation forecasting rule expressed in (8). For a given specification of the structural parameters along with the inflation forecasting parameters, $\Theta = \{\alpha_0, \alpha_1, \alpha_2, \alpha_3\}$, the model is solved and the policy function is generated. The policy function is used to simulate a panel of 6,000 firms over 500 periods (bimonths).[9]

Simulating data from the model requires an updating process to determine the evolution of the endogenous aggregate-level state variables. The collective actions of firms in the simulation determines the aggregate inflation rate and the level of real money balances. When setting prices in the current period, firms with updated information, $A = 0$, possess the current values of inflation and real money balances. To determine the current-period inflation rate while simulating the model, which in turn determines the level of real money balances using Eq. (9), we locate the grid point in the inflation state space that most closely matches Eq. (2), where the inflation rate is combined with P_{-1} to get P.

After simulating the full panel, we evaluate the inflation forecasting rule. An OLS regression of the forecasting rule in (8) is run with simulated values for inflation, real money balances, and money growth. The initial values of the forecast parameters, Θ_0, are compared to the OLS estimates, Θ_1. If these values differ, then the forecast parameters are updated based on Θ_1 and a new solution for the model is derived. This continues until a fixed point is reached. The fixed point represents a bounded rational expectations equilibrium wherein the inflation forecasting rule assumed by firms matches up with the simulated data.

2.3.3. Sticky information

The setting for $\bar{A}$ provides the interval between updates of information. The updating across firms will be staggered so that a constant fraction of firms receive new information

[9]The size of the panel was chosen as follows. First, the cross-section should have a large number of firms given the 80,000+ price observations per period in the BLS data. Increasing the number of firms above 6,000 did not alter the results in any significant fashion. Second, the number of periods should yield close to "asymptotic" results. Lengthening the sample beyond 500 did not materially affect the simulated moments. Standard errors from regressions based on simulated data are not reported, as they are quite small given the large panels.

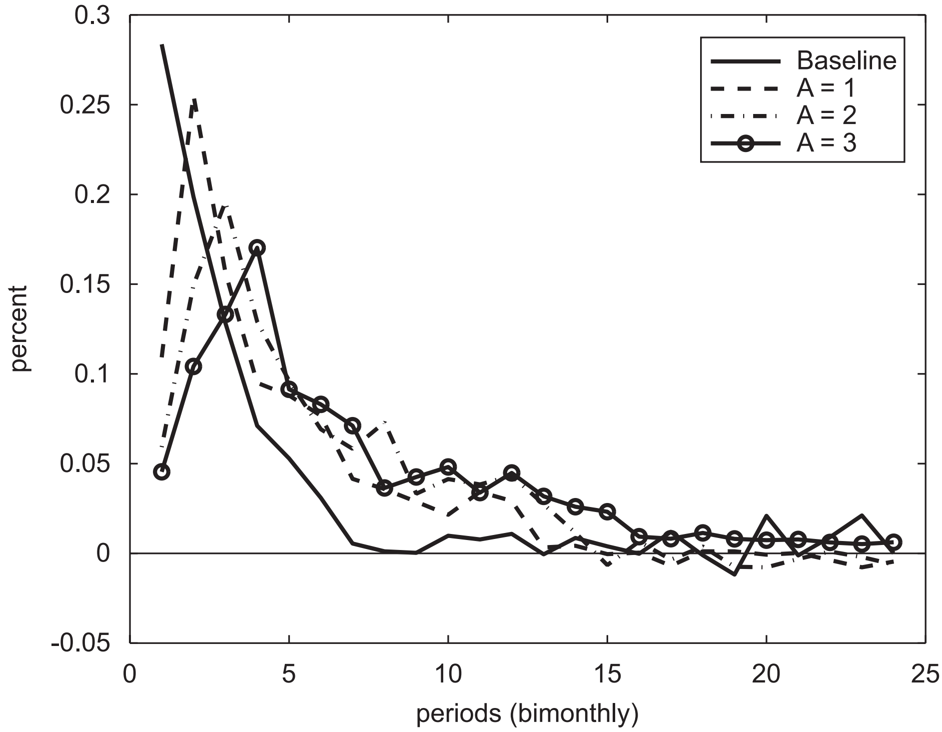

Fig. 1. Inflation response to 1% shock to the money growth rate. *Notes*: In each model specification, information on aggregate state variables arrives on a *staggered*, deterministic schedule. A indicates the maximum age of information before updating occurs. In the baseline model, $A = 0$.

each period. To illustrate the consequences of information stickiness, we will consider four cases corresponding to the maximum age of aggregate information ranging from 0 to 3 periods: $\bar{A} \in \{0, 1, 2, 3\}$.

Firms always have current information on their idiosyncratic shocks ($\bar{I} = 0$). This assumption allows us to focus on the implications of aggregate information stickiness.

To illustrate the role of sticky information, Figs. 1 and 2 display responses of inflation and real output to a 1% shock to money growth. Fig. 1 shows an increase in information stickiness leads to a delayed, hump-shaped response of inflation. The delayed inflation response suggests that there will be a stronger output response for sticky information models than for the baseline model. This pattern is clearly observed in Fig. 2.

Each of the four cases has a different equilibrium inflation process and hence different parameters values in the forecast rule (8). The parameters for each case are displayed in part (a) of Table 2. The coefficients vary modestly, but the rule's explanatory power is enhanced by sticky information as it makes inflation more persistent.[10]

2.3.4. Old information

As an alternative model of information stickiness, we also consider an economy in which all firms have equally old information. This assumption approximates a model in which

[10]Following Krusell and Smith (1998), we checked whether additional variables would improve the inflation forecasts. We regressed simulated inflation forecast errors on additional lags of the state variables as well lagged dispersion of prices (i.e., the standard deviation of relative prices in the previous period). These variables did little to explain the forecast errors.

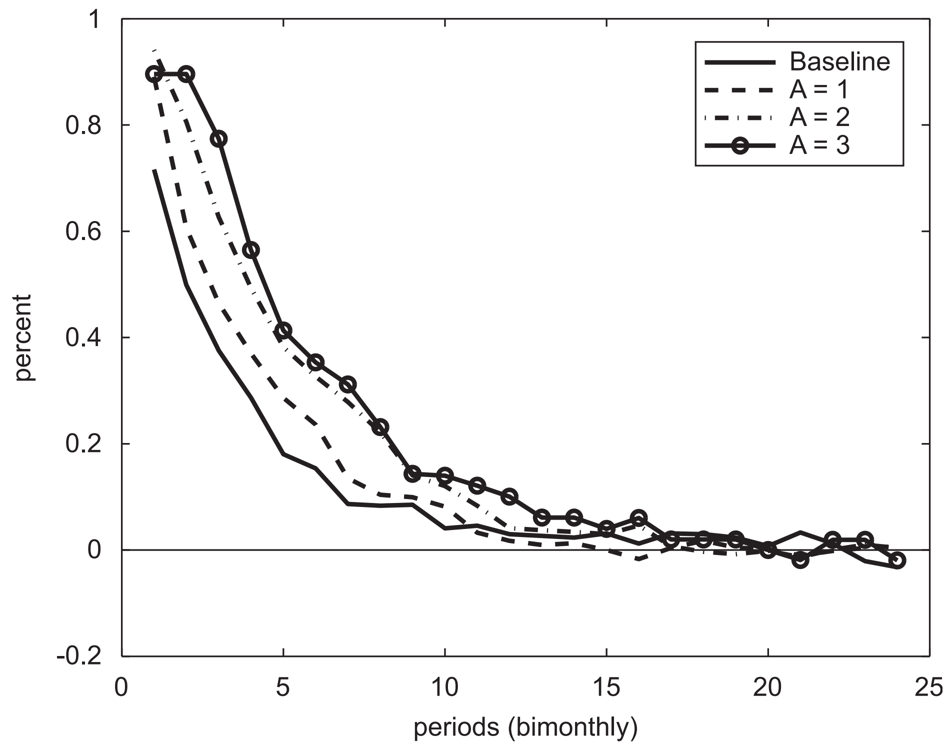

Fig. 2. Output response to 1% shock to the money growth rate. *Notes*: In each model specification, information on aggregate state variables arrives on a *staggered*, deterministic schedule. A indicates the maximum age of information before updating occurs. In the baseline model, $A = 0$.

Table 2
Equilibrium forecast rules for model

Model	α_1	α_2	α_3	R^2
(a) *With sticky information updating*				
Baseline ($\bar{A} = 0$)	0.04	0.22	−0.01	0.35
Sticky 1 ($\bar{A} = 1$)	0.08	0.22	0.02	0.79
Sticky 2 ($\bar{A} = 2$)	−0.05	0.25	−0.03	0.81
Sticky 3 ($\bar{A} = 3$)	−0.05	0.25	−0.03	0.79
(b) *With old information*				
Baseline ($\bar{A} = 0$)	0.04	0.22	−0.01	0.35
Old 1 ($\bar{A} = 1$)	−0.05	0.25	−0.03	0.94
Old 2 ($\bar{A} = 2$)	−0.30	0.27	−0.17	0.72
Old 3 ($\bar{A} = 3$)	−0.11	0.21	−0.07	0.40

Note: This table provides parameters for the following forecast rule used by firms in four separate model specifications: $\pi^{f}_{t+1} = \alpha_0 + \alpha_1 \pi_t + \alpha_2 \ln m_t + \alpha_3 g_{M,t}$. The R^2 provides the fit of the forecast rule on the simulated data. (a) With sticky information updating, information on aggregate state variables arrives on a *staggered*, deterministic schedule. $\bar{A}$ indicates the maximum age of information before updating occurs. (b) With old information, information on aggregate state variables is *identical* for all firms. $\bar{A}$ indicates the age of aggregate information.

information processing costs are such that it takes firms several periods to discern an aggregate shock. In our model, this would be represented as a case where firms *always* have aggregate information that is $\bar{A}$ periods old.

As before, we consider four different information assumptions. In the baseline model, firms always have current information. In the second case, firms always have aggregate information that is 1 period old. This differs from the previous model in that firms are now restricted so that they *never* possess current aggregate information, whereas in the sticky information model, half of firms possess current information and half possess information that is 1 period old. We also consider cases in which information is 2 and 3 periods old, respectively. Part (b) of Table 2 displays the equilibrium inflation forecast parameters. All of the coefficients change with the age of information, and the explanatory power of this equation on simulated data is strongest when information is 1 period old. This makes intuitive sense as the forecast rule only contains information lagged one period, and it suggests additional information lags should be added to the cases with older information. However, since each additional lagged variable becomes a state variable for the optimization problem, we cannot maintain tractability of the solution with an expanded forecast rule.

3. CPI data

For producing the Consumer Price Index, the U.S. Bureau of Labor Statistics conducts a monthly Commodities and Services Survey. This Survey covers all types of consumer products and services other than shelter, or around 70% of consumer spending. About 80,000 items are surveyed each month, with an item being a specific product (brand and detailed features) sold by a particular outlet. The data is collected from around 20,000 outlets located mostly in 45 large urban areas.

The CPI Research Database, maintained by the BLS Division of Price and Index Number Research, contains all prices in the Commodities and Services Survey from January 1988 to the present.[11] We base our statistics on data through December 2004. The BLS tracks individual items for about five years, affording many opportunities to observe price changes.

The BLS collects prices monthly for food and energy items in all areas, and for all items in New York, Los Angeles, and Chicago. For other areas, they check prices bimonthly for "core" items (items other than food or energy). Each bimonthly item is either odd (checked in months 1 = January, 3 = March, 5 = May, 7 = July, 9 = September and 11 = November) or even (checked in months 2 = February, 4 = April, 6 = June, 8 = August, 10 = October, and 12 = December). To use all items from all areas, and yet have a single frequency, a bimonthly data set is constructed. The disadvantage is it ignores half the price quotes for monthly items. Yet in so doing 80,000 items are incorporated, coming from all areas. Sticking with a monthly data set, in contrast, would yield only around 14,000 items from the top three cities. Just as important, looking at bimonths rather than months allows greater stickiness of information without adding as many states to the models (e.g., three bimonths as opposed to six months).

To pin down key parameters in our model, we calculate five statistics from the CPI data. Three are the mean, standard deviation, and serial correlation of the aggregate bimonthly inflation rate. In terms of our model, these help us in setting the mean, standard deviation, and serial correlation of money growth. The other two statistics are the median frequency of price changes and the median size of price changes. These two moments guide our choices for the size of menu costs and the size of idiosyncratic productivity shocks.

[11]See Klenow and Kryvtsov (2005) for a more detailed description of the CPI Research Database.

To define the statistics, let P_{sit} denote the price of item i in sector s in bimonth t, and ω_{sit} the BLS weight on item i within category s in bimonth t. The weights in sector s sum to ω_s^{95} in every bimonth, the BLS consumption expenditure weight of category s in 1995 (which themselves sum to 1). We then define the aggregate inflation rate in bimonth t to be

$$\pi_t = \sum_s \sum_i \omega_{sit}[\ln(P_{sit}) - \ln(P_{sit-1})].$$

When we calculate model moments for inflation, we use this geometric mean inflation.

We then take the simple average across the 101 bimonths from 1988 to 2004 to arrive at 0.384% per bimonth (2.3% per year) for inflation:

$$\mu_\pi = \sum_{t=1}^{101} \pi_t/101 = 0.00384.$$

In similar fashion we calculate the standard deviation (0.397%) and serial correlation (0.170) of the inflation rate:

$$\sigma_\pi = \sqrt{\sum_{t=1}^{101} (\pi_t - \mu_\pi)^2/100} = 0.00397,$$

$$\rho_\pi = \sqrt{\sum_{t=1}^{100} (\pi_t - \mu_\pi)(\pi_{t-1} - \mu_\pi)/99} = 0.170.$$

Our fourth moment is the fraction of items changing price from one bimonth to the next. Let $I(\Delta P_{sit} \neq 0)$ be a price-change indicator for item i in sector s in bimonth t, which equals 1 if the item changed price from bimonth $t-1$ to t, and 0 otherwise. We calculate the mean of this indicator for an item, then take the weighted median value across items to arrive at 0.300 (30.0% per bimonth). Easier to express explicitly is the cousin of this statistic, the weighted *mean* frequency of price changes, which is higher at 38.0%:

$$\overline{I(\Delta P \neq 0)} = \sum_s \sum_i \omega_{si} \frac{\sum_t I(\Delta P_{sit} \neq 0)}{\sum_t 1} = 0.380.$$

Here $\omega_{si} = \sum_t \omega_{sit}$. We prefer the median to the mean because, in time-dependent models at least, the median appears to better approximate a model with heterogeneity. Bils and Klenow (2004) examine this for the Taylor model, and Carvalho (2006) for the Calvo model.

Our final moment is the weighted median absolute size of price changes, which is 0.0853 (8.53%). Again, this value is easier to explicitly define as the weighted *mean*, which is higher at 12.0%:

$$\overline{|\Delta P|} = \sum_s \sum_i \omega_{si} \frac{\sum_t |\Delta P_{sit}|}{\sum_t I(\Delta P_{sit} \neq 0)} = 0.120.$$

As stressed by Klenow and Kryvtsov (2005) and Golosov and Lucas (2007), absolute price changes are much larger than needed to keep up with the trend inflation rate. The trend is about 0.4% per bimonth and the frequency of price changes is around $\frac{1}{3}$, so price changes only need average about 1.2% to keep up with trend inflation. Yet the average price change is an order of magnitude larger at 12%. These large price changes do not merely

Table 3
Moments

	μ_π	σ_π	ρ_π	$\overline{I(\Delta P \neq 0)}$	$\overline{\lvert\Delta P\rvert}$
BLS CPI data	0.0038	0.0040	0.170	0.300	0.0853
Baseline model	0.0039	0.0042	0.510	0.301	0.0865

Note: The data moments are computed using the BLS CPI survey with a bimonthly frequency from 1988 to 2004. μ_π is weighted mean bimonthly inflation for items in the CPI survey, σ_π is the standard deviation of inflation, ρ_π is the serial correlation of inflation, $\overline{I(\Delta P \neq 0)}$ is the median frequency of price adjustment, and $\overline{\lvert\Delta P\rvert}$ is the median absolute size of a price change.

reflect different sectoral mean inflation rates, as Klenow and Kryvtsov report large price movements even relative to a sectoral price index defined for around 300 separate categories of consumption. Given the relative stability of the aggregate inflation rate, idiosyncratic shocks will need to be large to generate such price changes in our model. Such idiosyncratic shocks will dominate individual firm decisions about when and how much to change prices, with aggregate conditions of much less importance.

In Table 3 we collect these moments. Klenow and Willis (2006) report small bootstrapped standard errors for similar statistics, which reflect the large number of observations underlying them (about 8 million prices and 3 million price changes). We also give the corresponding moments in our baseline model. We chose the parameter values in our baseline model to try to match these moments. The moments from the baseline model match the empirical moments well, with the exception of the serial correlation of inflation. Even without sticky information and with iid money growth, sticky prices generate more persistent inflation than observed in the data. Making money growth negatively correlated over time actually increases the serial correlation of model inflation, so iid money growth produces the closest serial correlation to the low level in the data.

4. Simulation and estimation

To empirically discriminate flexible and sticky information, we first express firm price changes as a function of variables in the information set for the "null" flexible information model.

Conditional on a fully-informed firm choosing to adjust its price, the Euler equation for the price decision is expressed as

$$\frac{\partial \Pi_{i,t}}{\partial P^*_{i,t}} + \beta \mathrm{E}_t \left[(1-\vartheta) \frac{\partial V(S_{i,t+1})}{\partial P^*_{i,t}} \right] = 0,$$

where ϑ is the probability of a firm changing its price. Here the probability of price adjustment is independent of the time since the previous change. This assumption matches the flat hazard rate found in the micro data by Klenow and Kryvtsov (2005). A flat hazard rate is also a reasonable approximation of the hazard function in the model because the volatility of idiosyncratic shocks dominates the small, but increasing, incentive to adjust due to the upward drift in the nominal money supply.[12]

[12] This begs the question of why not assume Calvo pricing to begin with. We chose to model state dependent pricing because of the "selection effect" in who chooses to change prices. We would like our test to reveal the

After iterating forward on the Euler equation and assuming all prices last at most J periods, we solve for the optimal price:

$$P^*_{i,t} = \left(\frac{\theta}{\theta - 1} \frac{\sum_{j=0}^{J-1} \varrho^j \mathrm{E}_t \Psi_{i,t+j}}{\sum_{j=0}^{J-1} \varrho^j \mathrm{E}_t \Upsilon_{t+j}} \right)^{\chi_1}, \tag{10}$$

with Υ_{t+j} representing terms associated with marginal revenue ($\Upsilon_{t+j} \equiv P_{t+j}^{\theta-1}(M_{t+j}/P_{t+j})$), $\Psi_{i,t+j}$ representing terms associated with marginal cost $\left(\Psi_{i,t+j} \equiv \kappa Z_{i,t+j}^{-1/\eta} P_{t+j}^{\theta/\eta}(M_{t+j}/P_{t+j})^{1/\eta}/(\eta P_{t+j} E_t[1/P_{t+j+1}])\right)$, and $\chi_1 \equiv \eta/(\eta + \theta(1-\eta))$.

The difficulty in using (10) to test the responsiveness of price changes to new vs. old information is that we only observe price changes and inflation in the BLS data. We do not observe any disaggregate information nor do we have a good sense of what constitutes an aggregate nominal shock for the economy. We would like to use an estimated process for exogenous monetary and/or technology shocks, and then test to see how long it takes prices to fully respond to those shocks. Such shocks are difficult to consider, however, because there is no consensus on how best to identify them. Moreover, existing identification strategies have had more success replicating empirical output dynamics than inflation dynamics.

As an alternative, we focus on the change in price one would expect based only on current information about inflation. A drawback is that we will be ignoring all other aggregate variables to which firms may be responding. Ignoring the idiosyncratic information should not be as problematic because we will be using a large panel of observations in which idiosyncratic shocks should wash out (the selection effect being an important caveat here).

We take the logarithm of (10) and then difference using the equation corresponding to the previous price change that occurred τ periods ago:

$$\begin{aligned}\Delta \ln P_{i,t} = \chi_1 \sum_{j=0}^{J-1} \rho_j (\chi_2 (\mathrm{E}_t[\ln P_{t+j}] - \mathrm{E}_{t-\tau_{i,t}}[\ln P_{t-\tau_{i,t}+j}]) \\ + (\mathrm{E}_t[\ln P_{t+j+1}] - \mathrm{E}_{t-\tau_{i,t}}[\ln P_{t-\tau_{i,t}+j+1}])) + \Xi_{i,t},\end{aligned} \tag{11}$$

where $\Xi_{i,t}$ contains additional terms corresponding to real money balances and the idiosyncratic productivity shock.

Since inflation is the only aggregate variable we can use in the actual data, we do not use the firms' forecast rule from the model to evaluate expected changes in the price level in the simulated data.[13] Instead, we search for an ARMA(p, q) specification that best captures inflation dynamics in the baseline model. We find that an MA(4) specification maximizes

(*footnote continued*)
presence of sticky information even if such selection operates. We will check this by running our test on simulated data from state dependent pricing models.

[13]Although we could use money stock data to construct series for the real money supply and money growth innovations, we do not do so because in our model "money" is merely a stand-in for a variety of macro shocks that push around the inflation rate.

the adjusted R^2. This implies that $\ln P$ dynamics are expressed by

$$\ln P_t = \mu + \ln P_{t-1} + \varepsilon_t + \sum_{j=1}^{4} \delta_i \varepsilon_{t-j}.$$

Table 4 presents the moving average coefficients in the data and in the baseline model. Note that we estimate an MA(4) process in the data as well as in the model. An MA(7) actually fits better in the data, but this could reflect precisely the sticky information we want to identify. Rather than incorporate such lagged information into the ''flexible information'' predicted price change, we maintained the same order MA(4) in the data as in the model.

With this specification for price-level dynamics, we can evaluate (11) as

$$\Delta \ln P_{i,t} = \underbrace{\sum_{s=0}^{\tau_{i,t}-1} \pi_{t-s} + \chi_1 \sum_{j=0}^{3} \chi_3 \Delta_{\tau_{i,t}} \varepsilon_{t-j}}_{PPC_{i,t}} + \Xi_{i,t}, \tag{12}$$

where $\Delta_{\tau_{i,t}} \varepsilon_t \equiv \varepsilon_t - \varepsilon_{t-\tau_{i,t}}$ and $\chi_3 = \sum_{k=0}^{3-j} ((1+\chi_2)(1 - \sum_{l=0}^{k-1} \rho_l) - \chi_2 \rho_k) \delta_{j+k+1}$. The MA terms affect price changes because they help forecast future inflation. Price setters wish to respond to forecastable movements in the aggregate price level over the life of a price. To simplify, we define $PPC_{i,t}$ in (12) as the predicted price change due to new information on the aggregate price level since the previous change $\tau_{i,t}$ periods ago.

Evaluating this expression using the estimated MA(4) for inflation for each case of the model, we run the following regression on the simulated data:

$$\Delta \ln P_{i,t} = \gamma PPC_{i,t} + \upsilon_{i,t}. \tag{13}$$

To reiterate, this specification estimates how price changes respond to inflation that has accumulated since the previous change $\tau_{i,t}$ periods ago. In the baseline model, wherein firms always have current information on the aggregate state variables, we expect an estimate of $\gamma = 1$ if the omitted terms contained in $\Xi_{i,t}$ are uncorrelated with inflation information. This test has a close antecedent in Reis (2006), who regresses consumption growth on income innovations and shows that the coefficient falls as information becomes stickier.

The estimates from four model cases are displayed in part (a) of Table 5. In the baseline case, all firms have current information on aggregate state variables. In the case with 1 period of information stickiness (labeled Sticky 1), one-half of firms have new information

Table 4
Moving-average representation for inflation

	δ_1	δ_2	δ_3	δ_4	R^2
BLS CPI data	0.17	0.07	−0.06	−0.03	0.038
	(0.10)	(0.10)	(0.10)	(0.10)	
Baseline model	0.46	0.31	0.22	0.10	0.264

Note: This table displays estimates for the following MA(4) inflation specification: $\pi_t = \mu + \varepsilon_t + \sum_{j=1}^{4} \delta_i \varepsilon_{t-j}$. The mean inflation rate, μ, is shown in Table 3. BLS CPI data are measured at a bimonthly frequency from 1988 to 2004.

Table 5
Response of price changes to price-level information

	γ	R^2
(a) *Sticky information model*		
Model		
Baseline ($\bar{A}=0$)	0.550	0.009
Sticky 1 ($\bar{A}=1$)	0.466	0.006
Sticky 2 ($\bar{A}=2$)	0.330	0.003
Sticky 3 ($\bar{A}=3$)	0.219	0.001
(b) *Old information model*		
Model		
Baseline ($\bar{A}=0$)	0.550	0.009
Old 1 ($\bar{A}=1$)	0.367	0.003
Old 2 ($\bar{A}=2$)	0.212	0.001
Old 3 ($\bar{A}=3$)	0.159	0.001
BLS data	0.606	0.001
	(0.016)	

Note: This table displays the coefficient from a regression of price changes on the predicted price change due to new information on the aggregate price level since the previous change. For details on this specification, see Eqs. (12) and (13). A panel of 6000 firms and 500 periods is simulated for each model. BLS CPI data are measured at a bimonthly frequency from 1988 to 2004. (a) With sticky information, information on aggregate state variables arrives on a *staggered*, deterministic schedule. $\bar{A}$ indicates the maximum age of information before updating occurs. (b) With old information, information on aggregate state variables is *identical* for all firms. $\bar{A}$ indicates the age of aggregate information.

on aggregate state variables and one-half of firms have information that is one period old. In the case with 2 periods of information stickiness (labeled Sticky 2), one-third have new information, and so on. The estimate of γ in the baseline is 0.55, markedly lower than the unit value in our specification. This discrepancy presumably reflects the various approximations we have made (linearization, flat hazard, discrete grids, MA(4) forecast rule) plus the selection effect and omitted variables. But the γ coefficient is not uniform across the baseline and sticky information models: as information becomes stickier, the γ coefficient steadily falls to 0.22 in the Sticky 3 case. The older the information, the less related price changes are to the price change predicted under flexible information. The final row of Table 5 displays the estimate from the BLS micro data based on over 3 million consumer price changes from 1988 to 2004. The estimate of γ is 0.61, modestly above the baseline, flexible information case.

Part (b) of Table 5 shows similar behavior of the γ coefficient when firms have equally old information. In this alternative model, firms always possess information that is A periods old.

To try to gauge the age of information, we augment the estimation equation above to include lagged information. If firms all have current information on the aggregate state variables, then their price changes should not respond to innovations older than those found in Eq. (12). If firms set their prices based on old information, however, then they should respond to the lagged information. In order to test this hypothesis, we add six lagged inflation innovation terms (one year of old information) to the estimation equation:

$$\Delta \ln P_{i,t} = \gamma PPC_{i,t} + \sum_{j=1}^{6} \lambda_j \Delta_{\tau_{i,t}} \varepsilon_{t-3-j} + \upsilon_{i,t}. \tag{14}$$

Estimation results for four cases are displayed in part (a) of Table 6. In the baseline case, where all firms have current information, the coefficients on lagged innovations are small and often negative, indicating that firms are not putting a lot of weight on old information. However, as the amount of information stickiness is increased in cases Sticky 1–Sticky 3, we find that the λ coefficients steadily increase. This result is true only for the three information lags, corresponding to the degree of information stickiness in each case. If we simulated older information, however, we would presumably see additional lags attracting higher coefficients.

The final row of Table 6 displays estimates from the BLS data. Here we find some very positive and significant coefficients on old information terms. Five of the six appear economically and statistically significant when compared to the predictions of the baseline vs. sticky information models. These results provide evidence consistent with information being up to a year old.

The results for the alternative model with old information are displayed in part (b) of Table 6. The pattern is not as clear: the old information coefficients are not as significant, and do not increase steadily with the degree of information stickiness. The empirical

Table 6
Response to new and old information

	γ	λ_1	λ_2	λ_3	λ_4	λ_5	λ_6	R^2
(a) *Sticky information model*								
Model								
Baseline ($\bar{A}=0$)	0.553	0.017	0.024	−0.090	−0.105	−0.173	−0.099	0.009
Sticky 1 ($\bar{A}=1$)	0.462	0.261	0.091	−0.003	−0.123	−0.191	−0.176	0.006
Sticky 2 ($\bar{A}=2$)	0.315	0.526	0.333	0.164	−0.009	−0.046	−0.016	0.003
Sticky 3 ($\bar{A}=3$)	0.203	0.500	0.457	0.307	0.038	0.114	0.050	0.001
(b) *Old information model*								
Model								
Baseline ($\bar{A}=0$)	0.553	0.017	0.024	−0.090	−0.105	−0.173	−0.099	0.009
Old 1 ($\bar{A}=1$)	0.363	0.211	0.069	0.050	−0.118	−0.069	−0.027	0.004
Old 2 ($\bar{A}=2$)	0.202	0.355	0.071	0.145	−0.072	0.082	0.060	0.001
Old 3 ($\bar{A}=3$)	0.152	0.162	−0.248	0.202	0.100	−0.154	0.003	0.001
BLS data	0.455	0.730	0.164	1.020	0.332	−0.018	0.416	0.001
	(0.018)	(0.037)	(0.041)	(0.044)	(0.044)	(0.042)	(0.038)	

Note: This table displays the coefficients from a regression of price changes on the predicted price change due to new information on the aggregate price level since the previous change ($\gamma PPC_{i,t}$) and additional lags of inflation innovations ($\lambda_j \Delta_{\tau_{i,t}} \varepsilon_{t-3-j}$). For details on this specification, see Eq. (14). A panel of 6000 firms and 500 periods is simulated for each model. BLS CPI data are measured at a bimonthly frequency from 1988 to 2004. (a) With sticky information, information on aggregate state variables arrives on a *staggered*, deterministic schedule. $\bar{A}$ indicates the maximum age of information before updating occurs. (b) With old information, information on aggregate state variables is *identical* for all firms. $\bar{A}$ indicates the age of aggregate information.

results, therefore, appear more in line with staggered information than with uniformly old information.

4.1. Responses of sales and substitutions to aggregate information

Certain types of price changes may exhibit an extreme form of sticky information, reflecting no macro information at all. Consider regular price changes vs. sales-related price changes. Golosov and Lucas (2007) and Nakamura and Steinsson (2006) focus on regular price changes by excluding temporary price discounts. Their rationale is that sales may follow a sticky plan (e.g., 10% off Cheerios the first weekend of every month). Such sales should be purely idiosyncratic and unconnected from aggregate inflation. To test this hypothesis, we split the sample of price changes into those involving only regular prices (both the old and new prices are "regular" prices according to the BLS) and those involving a sales price (either the old and/or the new price is a "sale" price according to the BLS). In this breakdown, about 1 million of the roughly 3 million price changes are sales-related. Given that many sales are temporary, sales-related price changes might, by construction, be negatively correlated with cumulative inflation since the last price change for an item. We therefore add a "down" dummy for regular-to-sales price changes and an "up" dummy for sales-to-regular price changes:

$$\Delta \ln P_{i,t} = \gamma_1 PPC_{i,t} + \gamma_{\text{down}} D_{i,t} + \gamma_{\text{up}} U_{i,t} + \upsilon_{i,t}. \tag{15}$$

Table 7 presents the results. For the full sample the dummies have the expected sign and improve the fit dramatically. Their inclusion more than doubles the coefficient on the predicted price change to about 1.3. When we look at regular price changes alone (those not involving sales prices), the coefficient is approximately equal to 1. For sales-related

Table 7
Response of sales and substitutions to new price-level information

	γ_1	γ_{down}	γ_{up}	R^2
BLS data				
Full sample	1.307	−0.324	0.312	0.319
	(0.013)	(0.0004)	(0.0004)	
Regular	0.996	NA	NA	0.003
	(0.014)			
Sales-related	1.861	−0.285	0.352	0.489
	(0.030)	(0.0007)	(0.0007)	
Same product	1.205	−0.324	0.301	0.339
	(0.014)	(0.0004)	(0.0004)	
Substitution-related	0.657	−0.300	0.385	0.189
	(0.056)	(0.003)	(0.002)	

Note: This table displays the coefficients from a regression of price changes on the predicted price change due to new information on the aggregate price level since the previous change ($\gamma_1 PPC_{i,t}$) along with dummy variables for a regular-to-sale price change ($\gamma_{\text{down}} D_{i,t}$) and a sale-to-regular price change ($\gamma_{\text{up}} U_{i,t}$). For details on this specification, see Eq. (15). BLS CPI data are measured at a bimonthly frequency from 1988 to 2004. The various specifications consider all price changes (full sample), price changes unrelated to sales (regular), sales-related price changes (sales-related), price changes that do not involve a product substitution (same product), and price changes where a product substitution has occurred (substitution-related).

price changes, the down and up dummies are helpful as expected. But, perhaps surprisingly, the coefficient on macro information is over 1.8. Thus, it appears that sales are at least as responsive to recent inflation as are regular price changes. Since sales tend to be temporary, the upshot is that their declines are not as deep and they give way to higher regular prices when recent inflation has been high. These results appear to undermine the hypothesis that sales do not reflect recent information on the aggregate price level.

Finally, we split the sample of price changes into those related to product turnover, or ''substitutions'' in the BLS vernacular, and those involving precisely the same product. About 7% of all price changes involve substitutions in the BLS data. Golosov and Lucas (2007) and Nakamura and Steinsson (2006) likewise filter out these price changes. The regression results are in the bottom panel of Table 7. The same-product regression looks similar to the full-sample regression (1.21 for same product price changes only vs. 1.31 for all price changes). More striking, substitution-related price changes appear less related to recent inflation (0.66 at turnover vs. 1.21 within-product). This finding supports the idea that substitutions reflect some idiosyncratic or longer-range forces, rather than being responses to recent inflation. Still, substitution-related price changes are very related to macro price trends and should probably not be excluded from macro research on price stickiness.

5. Conclusion

Researchers are striving to develop micro foundations for apparently long-lasting real effects of nominal shocks. Nominal rigidities may be an important component, but prices do not appear to be sticky for long enough to do the job alone. Hence, Sims, Woodford and Mankiw–Reis have formulated theories in which macro information is stickier than micro prices. In Sims' incarnation the two are tightly related: micro shocks demand micro flexibility, thereby undercutting macro flexibility because of convex costs of processing all types of information.

We have argued that sticky information theories have testable implications for micro price changes. Simple GE models demonstrate that the stickier the information, the older the inflation innovations firms respond to when they change prices. Just as these theories predict, price changes in the U.S. CPI micro data reflect information older than predicted by a flexible information model.

In addition, sales-related price changes respond to macro information at least as much as regular price changes do. This suggests that sales prices should not be filtered out of data used for analysis of macroeconomic responsiveness. More muted statements apply to substitution-related price changes, which respond very much to overall inflation, but still half as much as price changes at other times.

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