Reset Price Inflation

and the Impact of Monetary Policy Shocks

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Abstract

A standard state-dependent pricing model generates little monetary non-neutrality. Two ways of generating more meaningful real effects are time-dependent pricing and strategic complementarities. These mechanisms have telltale implications for the persistence and volatility of "reset price inflation." Reset price inflation is the rate of change of all desired prices (including goods that have not changed price in the current period). Using the micro data underpinning the CPI, we construct an empirical measure of reset price inflation. We find that time-dependent models imply unrealistically high persistence and stability of reset price inflation, especially for goods with sticky prices. This discrepancy is only exacerbated by adding strategic complementarities, even under state-dependent pricing. A state-dependent model with no strategic complementarities aligns most closely with the data.

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1. Introduction

Consumer prices change every seven or eight months in the U.S.[1] Yet the real effects of monetary shocks have been estimated to last around thirty months.[2] These figures suggest real effects lasting roughly four times longer than nominal price stickiness – i.e., a "contract multiplier" of around four in Taylor's (1980) terminology. In comparison, research on calibrated DSGE models obtains much lower contract multipliers, at least in the absence of strategic complementarities and sticky information. Chari, Kehoe and McGrattan (2000) report contract multipliers around one in a variety of time-dependent pricing models. Caballero and Engel (2007) and Golosov and Lucas (2007) arrive at contract multipliers well below one in their state-dependent pricing models. Dotsey, King and Wolman (1999) and Midrigan (2008) obtain intermediate contract multipliers in their state-dependent models.

As has been well-known since Ball and Romer (1990) and Kimball (1995), strategic complementarities in the pricing decisions of individual sellers can produce large contract multipliers.[3] A starting point for these models is that the nominal stickiness be staggered, to create the possibility of coordination failure among price setters.[4] In response to an aggregate shock, strategic complementarities mute the size of price changes for those changing prices, as price setters wait for the average price to respond.

[1] Klenow and Krystov (2008) and Nakamura and Steinsson (2008a). This figure ignores price changes involving sale prices, otherwise the number would be about four months.

[2] Christiano, Eichenbaum, and Evans (1999), Romer and Romer (2004), and Bernanke, Boivin, and Eliasz (2004), each based on U.S. data, are a few of the many examples.

[3] Recent papers in this vein include Altig et al. (2005), Carvalho (2006), Blanchard and Gali (2007), Gertler and Leahy (2008) and Nakamura and Steinsson (2008b).

[4] Staggered price setting appears to describe the U.S. data well. Klenow and Kryvstov (2008) find that the fraction of consumer prices changing does fluctuate but is not highly correlated with movements in inflation. They also find big individual price changes. Golosov and Lucas (2007) show that these facts can be explained by large idiosyncratic shocks that govern both the timing and size of price changes at the micro level.

We show that models with high contract multipliers at the macro level display slow-moving "reset" prices at the micro level. A reset price for an individual seller is that price it would choose if it implemented a price change in the current period. Actual prices often differ from reset prices, of course, because of nominal price stickiness. We define "*theoretical* reset price inflation" as the weighted average change of all reset prices, including those of current price changers and non-changers alike. We denote "reset price inflation" as the weighted average change of reset prices of actual price changers only. In the Calvo (1983) time-dependent pricing model, the probability of changing price is independent of the desired reset price change, so reset price inflation is a pure reflection of theoretical reset price inflation. In state-dependent models, sellers weigh the benefits of moving to the reset price against the (menu) costs of doing so. For these models reset price inflation can depart importantly from theoretical reset price inflation.

Strategic complementarities should dampen the volatility of reset price inflation and boost its persistence. An individual seller will move by smaller amounts, requiring multiple price changes to fully respond to a nominal shock. This may be especially true of "sticky" goods (those with less frequent price changes, such as services) compared to "flexible" goods (those with more frequent price changes, such as durable goods). The less frequently the prices of competitors change, the more cautiously a price changer may proceed.

We confirm our intuition by simulating DSGE models featuring time-dependent pricing (TDP) or state-dependent pricing (SDP), with or without strategic complementarities. The models feature a single aggregate shock (to money or aggregate productivity) plus idiosyncratic shocks to each seller's labor productivity. The complementarities take the form of intermediate goods as in Basu (1995); these slow down "monetary pass-through" because price changers have not seen their intermediate costs fully adjust due to the sticky prices of other firms. Sellers are grouped into one of two sectors: the flexible price sector (low menu cost, bigger idiosyncratic shocks) or the sticky price sector (high menu cost, smaller shocks).

Using the micro data on prices collected by the U.S. Bureau of Labor Statistics for the Consumer Price Index, we construct an empirical index of reset price inflation for the months January 1989 through May 2008. In brief, we impute to all prices, both those changing and not, the reset price changes exhibited by price changers. We compare the behavior of our empirical measure of reset price inflation to that of an identically-constructed measure from simulated data arising both from TDP and SDP models. As discussed above, this measure is the exact counterpart to theoretical reset price inflation in the Calvo model. Even though our constructed reset price inflation is not the same as theoretical reset price inflation for SDP models, we find that simulated SDP models yield clear predictions for our constructed reset price inflation. Thus our empirical measure of reset price inflation speaks to the empirical relevance of competing SDP models.

In the data, we find that reset price inflation is more volatile and less persistent than actual inflation; these qualitative features are common to all the sticky price models, with or without strategic complementarities. To delve further into the role played by price rigidity, we split goods in the CPI into one of two groups: “flexible” and “sticky”. The former reflects about 30 percent of consumer spending and displays an average monthly frequency of price changes of around 1/3. The latter constitutes about 70 percent of spending and displays an average monthly frequency of 1/10. We calibrate our models in accordance with these facts, in addition to the absolute size of price changes in each of these groups. As the models predict, reset price inflation for the sticky goods is particularly volatile compared to actual inflation for the sticky goods.

We find that the models displaying contract multipliers are fundamentally at odds with the data. TDP models, with or without strategic complementarities, and the SDP models with strategic complementarities, generate unrealistically high persistence and low volatility of reset price inflation. More specifically, these models predict that the impact of a nominal shock will build over time, not only for the overall price index, but also for an index of the level of reset prices. But in the data we see the opposite. An increase in reset price inflation predicts lower, not higher, reset price inflation in subsequent months, so that an index of reset prices responds more on impact than over time. Another robust prediction across all model specifications is that goods with infrequent price changes will display relatively more persistent inflation (overall, not reset). But we fail to see this in the data.

The SDP model with no complementarities comes closest to matching the empirical patterns. It features broadly realistic volatility and persistence of reset and actual price inflation for all goods, flexible goods, and sticky goods. Now, one potential way to rescue strategic complementarities is to incorporate endogenous monetary policy. If monetary policy quickly offsets the aggregate shock (to money itself or to aggregate productivity), then models with complementarities no longer imply outsized persistence of reset and actual inflation. This solution creates two problems, however. First, endogenous monetary policy essentially gets rid of the contract multiplier. Second, this solution crushes inflation volatility to around one-fifth of the observed level. If monetary policy offsets shocks, price setters respond little to them and inflation becomes way too smooth.

The literature on monetary policy has coalesced on strategic complementarities in order to rationalize a large contract multiplier. Our results suggest that the sticky-price models we examine are not good explanations for a high contract multiplier.

The rest of the paper proceeds as follows. Section 2 describes the dataset and the empirical properties of reset price inflation. Section 3 lays out the models and compares statistics from the simulated models to their empirical counterparts. Section 4 concludes.

2. An empirical measure of reset price inflation

The CPI Research Database

We use the micro data underlying the non-shelter portion of the CPI to construct our measure of reset price inflation. The BLS surveys the prices of about 85,000 items a month in its *Commodities and Services Survey*. Individual prices are collected at about 20,000 retail outlets across 45 large urban areas.[5] The survey covers all goods and services other than shelter, or about 70 percent of the CPI based on BLS consumer expenditure weights. The *CPI Research Database,* maintained by the BLS Division of Price and Index Number Research and hereafter denoted CPI-RDB, contains all prices in the *Commodities and Services Survey* since January 1988. We use the CPI-RDB through May 2008, and will refer to this as "1988-2008".

The BLS collects consumer prices *monthly* for food and fuel items in all areas. The BLS also collects prices monthly for all items in the three largest metropolitan areas (New

[5] The BLS selects outlets and items based on household point-of-purchase surveys, which furnish data on where consumers purchase commodities and services. The price collectors have detailed checklists describing each item to be priced — its outlet and unique identifying characteristics. They price each item for up to five years, after which the item is rotated out of the sample.

York, Los Angeles, and Chicago). The BLS collects prices for items in other categories and other urban areas only *bimonthly*. We find for our competing models that the impulse responses for reset price inflation differ markedly in the initial periods after a shock, making it valuable to have an empirical counterpart that captures the data at high frequency. For this reason, we restrict our analysis to the top three areas that have monthly data on all goods.

The BLS defines 300 or so categories of consumption as Entry Level Items (ELIs). Within these categories are prices for particular items (we call a longitudinal series of individual price quotes at the micro level a "quote-line"). The BLS provided us with unpublished ELI weights for each year from 1988-1995 and 1999-2004 based on Consumer Expenditure Surveys in each of those years. We normalize the nonshelter portion of the weights to sum to 1 in each year. We set the 1996 and 1997 ELI weights to the 1995 weights, and the 1998 weights to their 1999 level. We set the 2005 and onward weights to their 2004 level. The CPI-RDB also contains weights for each price within an ELI. We allocate each ELI's weight to individual prices in each month in proportion to these item weights to arrive at weights ω_{it} that sum to 1 across items (i's) in each month.

The BLS labels each price as either a "sale" price or a "regular" price. Sale prices are temporarily low prices (including clearance prices). Golosov and Lucas (2007), Nakamura and Steinsson (2008a), and others filter out such sale prices on the grounds that they are idiosyncratic deviations from stickier regular prices. Related, in classifying goods as "flexible" or "sticky" and in calibrating the model economies, we do so based on the frequency of *regular* price changes. We adopt this treatment because it yields more conservative results with respect to our conclusions. If, alternatively, we encompass the higher rate of price changes involving prices labeled by the BLS as sales prices, we would obtain an average frequency of price change of a little over 25 percent monthly rather than 22 percent. In turn, this would require even larger contract multipliers for our model economies to generate the same persistence in the impact of monetary shocks. But we find that the data do not support large contract multipliers. We use all prices, including sale prices, when constructing our inflation and reset price inflation series. To the extent sales are truly idiosyncratic their impact on the time series for price inflation, given the large samples of price quotes in each sector, will average close to zero. To the extent sales do affect aggregated price inflation, they are not idiosyncratic and so should not be excluded. That said, our results are robust to excluding sales prices from the series for price inflation.

Forced item substitutions occur when an item in the sample has been discontinued from its outlet and the price collector identifies a similar replacement item (e.g., new model) in the outlet to price going forward. The monthly rate of forced item substitutions is consistently about 3 percent in the sample. Essentially all item substitutions involve price changes. We include these price changes at substitutions in our statistics.[6]

About 12 percent of the prices the BLS attempts to collect are unavailable in a given month. The BLS classifies roughly 5 percent of items as out-of-season. We put zero weight on out-of-season items when calculating both inflation and the frequency of price changes. The BLS classifies the other 7 percent as temporarily unavailable. As these items may be only intermittently unavailable during the month, we treat items out of stock as available at the previously collected price. We employ this treatment both for calculating frequency of price changes and time series of inflation rates.

[6] For just over half of forced substitutions the rate of price change imparted to the CPI reflects a BLS adjustment aimed at capturing quality change across the substitution. We employ these BLS adjustments in all price change statistics.

Although the BLS requires its price collectors to explain large price changes to limit measurement errors, some price changes in the dataset appear implausibly large. We exclude price changes that exceed a factor of five. Such price jumps constitute less than one-tenth of one percent of all price changes.

Defining Reset Price Inflation

Section 3 below illustrates how models with high contract multipliers exhibit inertia, not only in price inflation, but also in reset price inflation—so the behavior of reset price inflation is a barometer for lasting real effects of monetary shocks.

Whether pricing is time-dependent or state-dependent, the desired price $P_{i,t}^{*}$ of item *i* in month *t* satisfies an Euler equation taking into account effects on current and future prices. Following Dotsey et al. (1999), the Euler equation is

$$\frac{\partial \Pi_{i,t}}{\partial P_{i,t}^{*}} = -E_t\left[\beta \frac{u'(c_{t+1})}{u'(c_t)}(1-\lambda_{i,t+1})\frac{\partial V_{i,t+1}}{\partial P_{i,t}^{*}}\right]$$

where $\Pi_{i,t}$ denotes current profits, E_t refers to expectations at time *t*, $\beta u'(c_{t+1})/u'(c_t)$ is the familiar stochastic discount factor, $\lambda_{i,t+1}$ is the probability of a price change for item *i* in month $t+1$, and $V_{i,t+1}$ is next period's value function. Note that the reset price can differ from the optimal flexible price (the price that maximizes current period profits) because of future price stickiness ($\lambda_{i,t+1} < 1$). Related, the actual price can differ from the reset price if the seller does not change its price in the current period.

Reset price inflation at a given seller is the log first difference of its reset price:

$$\pi_{i,t}^{*} \triangleq \ln(P_{i,t}^{*}) - \ln(P_{i,t-1}^{*}).$$

This definition does not require a price change at either t or $t-1$. Aggregate reset price inflation is then the weighted average of micro reset price inflation:

$$\pi_t^* \triangleq \sum_i \omega_{i,t}\pi_{i,t}^* \ , \quad (2.1)$$

where the weights $\omega_{i,t}$ add to 1. By comparison actual inflation is $\pi_t \triangleq \sum_i \omega_{i,t}\pi_{i,t}$ where $\pi_{i,t} \triangleq p_{i,t} - p_{i,t-1}$ and $p_{i,t}$ denotes the log of the actual BLS price of item i at time t.

Whereas starred variables denote reset values, those without stars represent actual values. Let $I_{i,t}$ be a price-change indicator:

$$I_{i,t} = \begin{cases} 1 \text{ if } p_{i,t} \neq p_{i,t-1} \\ 0 \text{ if } p_{i,t} = p_{i,t-1} \end{cases}.$$

To construct an empirical measure of aggregate reset price inflation, each month we divide items into those that change price ($I_{i,t} = 1$) and those that do not change price ($I_{i,t} = 0$). For prices that change, the reset price is simply the current price. For prices that do not change, we index our estimate of the reset price to the rate of reset price inflation among price changers in the current period. Specifically,

$$\hat{p}_{i,t}^* = \begin{cases} p_{i,t} \text{ if } p_{i,t} \neq p_{i,t-1} \\ \hat{p}_{i,t-1}^* + \hat{\pi}_t^* \text{ if } p_{i,t} = p_{i,t-1} \end{cases}$$

where ^'s denote our estimates. In turn, our estimate of aggregate reset price inflation is

$$\widehat{\pi}_t^* \triangleq \frac{\sum_i \omega_{i,t}(p_{i,t} - \hat{p}_{i,t-1}^*)I_{i,t}}{\sum_i \omega_{i,t} I_{i,t}} . \quad (2.2)$$

Although the estimate $\hat{\pi}_t^*$ only employs time *t* price changers, price changes from previous months are captured in the base values of $\hat{p}_{i,t-1}^*$, which are indexed to reflect prior changes.[7]

In Table 1 we present a stylized example of price changes, contrasting the rate of reset price inflation to that for actual inflation or average inflation for price changers (denote this latter rate by $\tilde{\pi}_t$). The example has two goods. Both goods change price at period 0, establishing base prices for calculating reset price inflation. Good A's price increases by 20% in period 1, with Good B's unchanged. This yields a rate of 20% for reset price inflation, same as the average rate of price increase conditional on changing price, while actual inflation is 10%. But note it also kicks up the base price for calculating reset price inflation by 20%, not only for Good A, but also Good B. Therefore, when B's price increases by 20% in period 2, while A's remain unchanged, B's price just meets its updated reset price from period 1. As a result, reset price inflation for period 2 equals zero, despite the same actual inflation rate and rate of increase for price changers, respectively 10% and 20%, as in period 1.

Our estimated reset price inflation is equivalent to theoretical reset price inflation under the special case of Calvo pricing. By contrast, under SDP the decision to change a price reflects selection on the idiosyncratic component in a seller's desired price change. For this reason, estimated reset price inflation $\hat{\pi}^*$ can differ markedly from theoretical reset price

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[7] We considered an alternative measure of $\hat{\pi}_t^*$ based on coefficients from regressing the size of each price change on a set of dummy variables that take values of one for each month that separates the date of that price change from the price-quote's most recent change. This measure parallels the construct of the Case-Shiller Home Price Index (see, for instance, Shiller, 1991), which allocates rates of price increases for homes to the months between repeat sales. The advantage of this alternative measure is that it exploits information dated after *t*. A related disadvantage is that estimates near the end of the sample period reflect considerably greater selection. We find that this alternative provides a similar measure from the data, exhibiting very similar statistics, as that based on (2.2). Moreover, for the model economies we consider, the two measures are nearly identical. Therefore, we restrict attention to results based on reset inflation defined by (2.2).

inflation π^*. We illustrate this difference for SDP models in Section 3 as a means of discriminating between the TDP and SDP models.

A key question for us is what extra information is contained in $\widehat{\pi}_t^*$ that cannot be gleaned from π_t alone. Under Calvo, one can infer π_t^* from π_t if one also knows the price-change frequency. But endogenous price changing, and especially selection of changers, breaks the simple translation from $\widehat{\pi}_t^*$ to π_t. By endogenous price changing we mean any response in the fraction of goods changing price to underlying shocks. By selection of changers we mean that, in contrast to Calvo, the changers may be those with larger gaps between actual and reset prices. Related, $\widehat{\pi}_t^*$ should be directly revealing about strategic complementarities, whereas π_t is confounded by any response of the fraction changing. Some forces for a low contract multiplier (selection) or a high contract multiplier (strategic complementarities) operate on $\widehat{\pi}_t^*$ directly, whereas their effect on π_t can be clouded by movements in frequency. The persistence of π_t may be informative about the contract multiplier, but does not say where it is coming from (frequency or reset price inflation).

Similarly, we could focus on the average price change among changers ($\widetilde{\pi}_t$) rather than constructing the less direct measure $\widehat{\pi}_t^*$. In models we simulate, however, we find that the volatility of $\widetilde{\pi}_t / \pi_t$ does not vary with the contract multiplier (e.g., SDP with or without complementarities), whereas the volatility of $\widehat{\pi}_t^* / \pi_t$ falls sharply with the contract multiplier. We revisit this issue in section 3.

Evidence on Reset Price Inflation

Table 2 contains summary statistics on our constructed measure of reset price inflation, as well as on actual inflation for comparison. All the monthly series are HP-filtered and seasonally adjusted.[8] Our measure of "all goods" excludes not only shelter, which is missing from the CPI-RDB, but also energy, fresh fruit and vegetables, and eggs. We exclude these for two reasons. First, they are arguably subject to big "sectoral" shocks that are absent from our models. If these shocks are temporary then they artificially lower aggregate inflation persistence. Second, these goods involve little or no processing, and hence lack the strategic complementarities through slow-moving input prices.

In addition to the aggregate statistics, we examine actual and reset price inflation for two sub-aggregates: "flexible" goods and "sticky" goods. As mentioned, the BLS places individual price quote-lines into one of 300 or so categories (ELIs). We calculate the average frequency of regular price changes within each ELI, then classify quote-lines as "flexible" or "sticky" based on their ELI's frequency. We choose a threshold frequency separating the two groups of 1/6, similar to the overall mean (weighted) frequency of 16.8 percent. This generates a 70 percent share of spending on the sticky group compared to 30 percent on the flexible group. We put more price quotes in the sticky group to mitigate sampling error there, given its smaller number of price changes per observed price. The flexible goods average 3,100 price quotes per month, compared to 8,300 for the sticky goods. The mean frequency of price changes is 33.3 percent in the flexible group, while only 9.5 percent for the sticky.

[8] The HP-filter we employ is very smooth, with penalty parameter of one million. It removes a downward trend in inflation during the first part of the sample, and little else. With no filtering, results for reset price inflation are nearly unchanged, but actual inflation shows modestly greater persistence for the sticky group.

The first row of Table 2 reports a standard deviation of monthly reset price inflation of 1.0 percent.[9] There is not persistence in reset price inflation as measured by its first-order autocorrelation. In fact this serial correlation is notably negative, at –0.44. We provide more evidence on persistence below. The third and fourth rows report the comparable statistics for actual inflation. Actual inflation is much less volatile than reset price inflation, with a standard deviation, 0.18%, less than one-fifth that for reset price inflation. This lower volatility for actual inflation follows mechanically by its including many zero price changes, unless variations in the frequency of changes play a major role in inflation movements–but we know from Klenow and Kryvtsov (2008) that frequency changes do not play that role. Actual inflation (serial correlation –0.12) is more persistent than reset price inflation (serial correlation –0.44). Again, this is expected under nominal price stickiness unless the frequency of price changes is highly responsive to the inflation rate; in fact, all models in Section 3 predict this result.[10]

The correlation between reset and actual price inflation is reported in the last row of the table. We highlight this statistic below in contrasting model predictions. Sticky prices break the link between reset and actual inflation in the models by causing actual inflation to lag markedly behind innovations in reset price inflation. We do not see evidence of this in the data: reset and actual price inflation are highly correlated at 0.81.

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[9] Whereas our raw sample goes from January 1988 through May 2008, our constructed series run from January 1989 through May 2008. We dropped the first year because we require a new price to initiate a reset price series for a given quote-line.

[10] If we do not HP-filter the series, the serial correlation in actual inflation is modestly higher. For several reasons, the serial correlation of our CPI inflation is lower than inflation persistence reported in some other studies with U.S. data. First, our dataset excludes shelter. Shelter exhibits high persistence, in part because of BLS interpolation between annual price quotes. Second, as is well-known, inflation persistence has fallen markedly in the U.S. since the mid-1980s. See Stock and Watson (2006), for example. Finally, the personal consumption and GDP deflators exhibit more persistence than CPI inflation in recent decades.

The second and third columns repeat these statistics first for the flexible group, then for the sticky group.[11] Looking across these two columns, we see that reset price inflation is equally volatile in the flexible and sticky sectors, both having a standard deviation of 1.3 percent. Actual inflation is more than twice as volatile in the flexible vs. sticky sector, reflecting the important smoothing effect of many unchanging prices in the sticky sector.

Table 2 also shows the persistence in reset and actual price inflation across the two sectors. The flexible and sticky sectors have similar persistence in reset and actual price inflation as all goods. This runs counter to the prediction of sticky price models that infrequent price changes act as a force for inflation inertia.[12]

The price series (reset and actual) described in Table 1 reflect sale prices as well as regular prices. The results, however, do not hinge on this treatment. Table 3 repeats all the statistics from Table 2 but treats sales prices as temporarily missing, carrying forward the most recent regular price as the price for that month. The patterns highlighted from Table 2 are nearly unchanged in Table 3. In particular, reset price inflation continues to show a strong negative serial correlation of –0.43 (vs. –0.44 in Table 2), and the serial correlation of actual inflation increases only modestly to –0.06 (vs. –0.12 in Table 2). This means that sale prices either wash out in the aggregate or mimic the movements in regular prices. Inflation is modestly more persistent for sticky goods under this treatment.

[11] The correlation between reset inflation rates in the flexible and sticky sectors is only 0.11. Similarly, the correlation between the sectors in actual inflation is only 0.10. The aggregate reset inflation rate, from column 1, is much more highly correlated with reset inflation in the flexible sector (correlation 0.91) than with reset inflation in the sticky sector (correlation 0.46) despite the expenditure weight being twice as large in the sticky sector. Likewise, the aggregate inflation rate is much more highly correlated with inflation in the flexible sector (correlation 0.95) than with inflation in the sticky sector (correlation 0.41).

[12] These results are not driven by our H-P filtering. The serial correlation in reset price inflation is almost unaffected by the filter. In particular, its serial correlation is still –0.50 for the sticky goods without filtering. Serial correlation of actual inflation in the sticky sector does rise to 0.21 (vs. –0.13) for the sticky sector absent filtering, but remains a little below that for the flexible sector (0.29).

To further investigate the persistence properties of these inflation rates, we next show impulse responses derived from univariate AR(6) regressions. (The choice of 6 monthly lags is based on the Akaike criterion.) Figure 1 gives the accumulated response of reset prices to a 1% impulse, first for flexible goods, then sticky. Both plots show that the (level) response in reset prices is much greater on impact than its accumulated response over time. For flexible goods the impact response is more than double the long-run response; for sticky goods it is triple the long-run response. That is, an increase in reset price inflation predicts lower reset price inflation in subsequent months, with this force being strongest for the sticky goods. This mean reversion in reset prices does not reflect temporarily sales, as the patterns are extremely similar for series purged of sale prices.

One concern for Figure 1 is that it may not be the endogenous price responses to shocks that are transitory, but rather the shocks themselves. Responses to permanent shocks may exhibit far greater persistence. In Figure 2 we plot the responses of actual prices and (reset prices – actual prices) to a shock with a permanent 1% impact on actual prices. These were obtained by imposing a long run restriction on a bivariate VAR. We see that reset prices get out ahead of actual prices initially, as one expects, but that reset prices do not stay out in front. This pattern holds for both the flexible group and the sticky group, and will provide a useful point of comparison to the models below.

3. Sticky price models and reset price inflation

The leading TDP and SDP models have predictions for the behavior of reset price inflation. We will illustrate using a Calvo TDP model and an SDP model in the spirit of Golosov and Lucas (2007), respectively. They will be two-sector models with and without strategic complementarities, so Carvalho (2006) and Nakamura and Steinsson (2008b) are even closer antecedents. We first sketch the models, then report statistics from model simulations for comparison with the facts documented in the previous section.

The Models

A representative consumer has discounted utility

$$U_0 = E_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{C_t^{1-\gamma}}{1-\gamma} - \omega \frac{L_t^{1+\psi}}{1+\psi} \right] \tag{3.1}$$

where C is composite consumption and L is labor supply. Composite consumption is a CES aggregate of individual consumption varieties $c(i)$:

$$C = \left[\int_0^1 c(i)^{1-1/\theta} di \right]^{\frac{\theta}{\theta-1}}. \tag{3.2}$$

The consumer's budget constraint is

$$P_t C_t + B_{t+1} = (1+r_t)B_t + W_t L_t + P_t \int_0^1 \Pi_t(i)\, di \tag{3.3}$$

where P is the nominal price of a unit of composite consumption, W is the nominal wage, B_t denotes holdings of state-contingent bonds (in zero net supply) that pay off in period t at (gross) nominal interest rate $(1+r_t)$, and $\Pi(i)$ are the (real) profits of firm i.[13]

The consumer chooses bond holdings, consumption of the composite, labor supply, and consumption of individual varieties to satisfy the following first-order conditions:

[13] The unit price of composite consumption is the dual of consumption aggregator (3.2): $P_t = \left[\int_0^1 p_t(i)^{1-\theta} di \right]^{\frac{1}{1-\theta}}$.

(3.4) $$1=\beta E_t\left[\left(1+r_{t+1}\right)\left(\frac{C_{t+1}}{C_t}\right)^{-\gamma}\frac{P_t}{P_{t+1}}\right]$$

(3.5) $$\frac{W_t}{P_t}=\omega L_t^{\psi}C_t^{\gamma}$$

(3.6) $$\frac{c_t(i)}{C_t}=\left[\frac{p_t(i)}{P_t}\right]^{-\theta}.$$

Turning to production, there are a continuum of monopolistically competitive firms indexed by i, which denotes the one variety each produces. Firm i has productivity $A(i)$ and combines labor $L(i)$ and a composite intermediate good $X(i)$ to produce good i:

(3.7) $$y_t(i)=A_t(i)L_t(i)^{1-\alpha_x}X_t(i)^{\alpha_x}$$

where α_x denotes the share of the composite intermediate good. The intermediate composite is a CES aggregate of individual intermediate goods:

(3.8) $$X(i)=\left[\int_0^1 x_t(i,j)^{1-1/\theta}dj\right]^{\frac{\theta}{\theta-1}}$$

where $x(i, j)$ is the quantity of intermediate good *j* used by firm *i*. For $\alpha_x>0$, each firm uses intermediate inputs produced by all other firms in the economy, with this demand taking the same form as the demand of the representative consumer. Finally, firms are grouped into two sectors, to be indexed by *s*, with the two sectors distinguished by how frequently firms change price. Note that symmetry between (3.8) and the consumption aggregator (3.2) means that the unit price of *X* is equal to *P*, the unit price of the consumption composite.

Production function (3.7) exhibits two key features commonly used in macro models of price stickiness. Following Golosov and Lucas (2007), a firm's productivity is subject to idiosyncratic shocks. We assume

$$\ln A_t(i) = \rho \ln A_{t-1}(i) + \varepsilon_t(i)$$

where $\varepsilon_t(i) \sim \text{iid}\, N\left(0, \sigma^2_{A,s}\right)$. Idiosyncratic productivity shocks will be important for capturing the dispersion of individual price changes seen in the data. The sectors will have different idiosyncratic shock volatilities as one way to rationalize the differing size and frequency of price changes observed for different types of goods in our BLS data.

A second key feature of production function (3.7) is the inclusion of intermediate goods, following Basu (1995) and Dotsey and King (2006). Intermediate goods are a potentially realistic way of generating strategic complementarities in price-setting, as firm costs fully respond to a shock only when other firms' prices respond.[14]

Firm i in sector s maximizes its discounted (real) profits

$$E_0 \sum_{t=0}^{\infty} \tilde{\beta}_{0,t} \, \Pi_t(i) \tag{3.9}$$

where $\tilde{\beta}_{0,t} = \beta^t \left(\frac{C_t}{C_0} \right)^{-\gamma}$ is the stochastic discount factor and current profits are given by

$$\Pi_t(i) = \frac{p_t(i)}{P_t} y_t(i) - \frac{W_t}{P_t} L_t(i) - X_t(i) - k_t(i) I_t(i) \frac{W_t}{P_t}. \tag{3.10}$$

[14] In a recent survey, Mackowiak and Smets (2008) suggest such "macro rigidities" are especially promising avenues for obtaining high contract multipliers.

A firm's profits equal revenue less input costs, including the cost of changing prices (the last term). $I_t(i)$ is an indicator function for whether firm *i* changes its price in period *t* at a cost of $k_t(i)$ units of labor. For the SDP models, we set $k_t(i) = k_s$. That is, in the SDP models the menu cost is fixed over time for each firm, but does vary across firms depending on the firm's sector. This will be another way to generate heterogeneity in the frequency and size of price changes observed across sectors in the BLS data. For the TDP models, $k_t(i) \in \{0, \infty\}$. Specifically, we mimic the Calvo model by having firms in sector *s* face a menu cost of 0 with probability λ_s and a menu cost of ∞ with probability $1-\lambda_s$. These Calvo menu cost realizations are independent both across firms within sectors and over time.

Firm choices of intermediates satisfy a first-order condition comparable to consumer choices of final consumption varieties:

(3.11)
$$\frac{x_t(i,j)}{X_t(i)} = \left[\frac{p_t(j)}{P_t}\right]^{-\theta} .$$

Setting production equal to total demand (from consumers and others firms) for firm *i* yields

(3.12)
$$y_t(i) = c_t(i) + \int_0^1 x_t(j,i)\,dj = \left[\frac{p_t(i)}{P_t}\right]^{-\theta} (C_t + X_t)$$

where $X_t = \int_0^1 X_t(j)\,dj$. The aggregate resource constraints for output and labor are then

(3.13)
$$C_t + X_t = \left[\int_0^1 y_t(i)^{1-1/\theta} di\right]^{\frac{\theta}{\theta-1}} \equiv Y_t \text{ and } L_t = \int_0^1 \left[L_t(i) + k_t(i) I_t(i)\right] di .$$

Finally, we assume a cash-in-advance constraint on a consumer's nominal spending

(3.14) $$P_t C_t \le M_t .$$

In turn, we assume the money supply evolves as follows:

(3.15) $$\ln M_t = \mu + \ln M_{t-1} + \rho_m \left[\ln\left(\frac{M_{t-1}}{P_{t-1}}\right) - \ln\left(\frac{M}{P}\right) \right] + \xi_t$$

where $\xi_t \sim N\left(0, \sigma_m^2\right)$, and $\ln\left(\frac{M}{P}\right)$ is steady-state aggregate real demand. When $\rho_m = 0$, the money supply evolves exogenously according to a geometric random walk with drift. We will also consider an "endogenous monetary policy" case, in which $\rho_m < 0$ and money growth is inversely related to lagged aggregate real demand. Below we will set the value of μ so that simulated inflation has the same mean as actual inflation in the BLS data, and we will set the value of σ_m to match the standard deviation of nominal non-shelter PCE growth.[15]

Additional details on the model solution and simulation are provided in an appendix.[16]

Calibration

Table 4 reports the values of economy-wide parameters in the TDP and SDP models. We consider three specifications: a baseline case featuring no strategic complementarities, a strategic complementarities specification that generates a "contract multiplier" of 4, and a specification with strategic complementarities and "endogenous monetary policy." Most parameters remain constant across the three specifications. The monthly discount factor is

[15] We deliberately do not calibrate the money supply process to data on money supply as our exogenous money supply process is a stand-in for monetary policy shocks, not actual money growth.

[16] We thank Emi Nakamura and Jon Steinsson for making the solution routines for these models available on their website. See Nakamura and Steinsson (2008b) for a detailed description of the solution procedure.

$\beta = 0.96^{1/12}$. We consider log utility in consumption ($\gamma = 1$) and linear labor supply ($\psi = 0$), while the parameter governing the disutility of labor supply (ω) is set so that steady state labor supply is 1/3. The elasticity of demand for consumption varieties is $\theta = 4$, within the range of values estimated in the trade and IO literatures, e.g., Broda and Weinstein (2006) and Hendel and Nevo (2006).[17] We set the parameters for the money growth process (μ, σ_m, ρ_m) to match the mean growth rate of inflation (0.2%), the standard deviation of nominal non-shelter PCE growth (0.48%), and, for the "endogenous monetary policy" case, the serial correlation of nominal PCE growth (-0.31) over our sample period. The serial correlation of the idiosyncratic productivity shock is set to $\rho = 0.7$, based on the estimates in Klenow and Willis (2006) using the serial correlation of new relative prices in the CPI-RDB.

Table 4 also presents parameter values determining the degree of strategic complementarity in pricing. Following Ball and Romer (1990), we define strong real rigidities (more strategic complementarities in this model) as low responsiveness of a firm's real price to changes in aggregate real demand. The firm's optimal price in the absence of menu costs can be expressed (ignoring constants) as

$$\text{(3.16)} \qquad \ln\left(p_t(i)\right) = \left(\gamma + \psi\right)\left(1 - \alpha_x\right)\ln(M_t) + \left[1 - \left(\gamma + \psi\right)\left(1 - \alpha_x\right)\right]\ln(P_t) - \ln A_t(i)\,.$$

As in Woodford (2003), we define strategic complementarity as a positive weight on the aggregate price, rather than having all weight on the aggregate money stock. Thus, when $\left(\gamma + \psi\right)\left(1 - \alpha_x\right)$ is small, prices exhibit greater complementarity. Our baseline model has log utility in consumption ($\gamma = 1$), linear labor supply ($\psi = 0$), and no intermediate goods

[17] It is also in the range used by other sticky price papers; Midrigan (2008) uses $\theta = 3$, Nakamura and Steinsson (2008b) use $\theta = 4$, and Golosov and Lucas (2007) set $\theta = 7$.

($\alpha_x = 0$), so that $(\gamma + \psi)(1-\alpha_x) = 1$. This baseline case has no strategic complementarity (the coefficient is 0 on the aggregate price level). In our "strategic complementarities" case we choose the intermediate input share to generate a contract multiplier of 4, where the contract multiplier is calculated as the ratio of the duration of real effects of a monetary policy shock to the number of periods in a typical contract.[18] This requires an intermediate share of $\alpha_x = .95$ in the SDP model ($\alpha_x = .67$ for TDP) and yields $(\gamma + \psi)(1-\alpha_x) = 0.05$, or strong strategic complementarities (a coefficient of 0.95 on the aggregate price level).[19] As emphasized by Basu (1995), more intensive use of intermediate inputs makes the response of marginal cost to monetary shocks a function of not only the nominal wage but the extent of price adjustment at other firms – a strategic complementarity.

Table 5 reports the values of sector-specific parameters in our models. In the SDP model, we calibrate the standard deviation of each sector's idiosyncratic productivity shock and each sector's menu costs to generate frequencies of price change by sector of 0.33 (flexible) and 0.10 (sticky), as well as an average size of price change of 8% and 9.5% in the respective sectors. These figures correspond closely to the frequency and average size of price changes in the BLS data by sector, excluding energy and raw goods. The required shocks have standard deviation around 4.94% for the flexible sector and 4.75% for the sticky sector. Expended menu costs average 0.20% of revenue, somewhat lower than the estimates of Levy et al. (1997) and Zbaracki et al. (2004). Finally, 30% of firms are in the flexible sector and 70% are in the sticky, to match the BLS expenditure shares on these two groups.

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[18] Specifically, we follow Christiano et al. (2005) by calculating the amount of time it takes the expansion in aggregate real demand caused by a positive policy shock to drop below 10% of its initial response. We then multiply this number by the aggregate frequency of price changes.

[19] A realistic share based on BEA Input-Output Tables would be around 0.7 (Nakamura and Steinsson, 2008b).

For the TDP model, only the menu cost parameters differ from the SDP model. We actually embed Calvo in an SDP model with time-varying menu costs. Each period, the menu cost is zero for a fraction λ_s of firms, while prohibitively large value for a fraction $1-\lambda_s$.

Results and Interpretation

We now compare statistics from model simulations to the corresponding data statistics. We run 100 simulations of 240 periods each, and report the average and standard deviation of the statistics across simulations. We find that models generating large contract multipliers, either through the use of TDP or strategic complementarities, display unrealistically high persistence and low volatility of reset price inflation. Compared to the empirical data, reset price inflation in the models is way too persistent and stable.

In Table 6 we present statistics for the Calvo TDP model without strategic complementarities. This model has a contract multiplier around two.[20] Here reset inflation rates are too smooth relative to the data by a factor of two or more. Reset price inflation is too persistent in the sticky sector (–0.01 in the model vs. –0.52 in the data), and the discrepancy is even greater for actual inflation (0.88 in the model vs. –0.15 in the data). TDP also makes the correlation between actual and reset inflation too low for sticky goods (0.44 in the model vs. 0.73 in the data). Figure 3 presents the univariate IRF for model reset prices, first for flexible then sticky goods. The model IRFs are flat, meaning that the average desired price fully responds on impact. Equation (3.16) shows that the average desired price (i.e, idiosyncratic

[20] Chari et al. (2000) obtain a contract multiplier near one in a Taylor model. Using their definition (the half-life of real effects relative to the half-life of a price), we also obtain near one in our Calvo TDP model. We report higher numbers in the text using the Christiano et al. (2005) definition of the duration of real effects relative to the duration of prices. The differences owe to slower-than-exponential decay of the real effects in the models.

shocks $A_t(i)$ wash out) moves one-for-one with a change in money supply in the absence of strategic complementarities, and because money growth follows a random walk, the result is a flat impulse response function.[21] Figure 3 shows the confidence intervals from the data for comparison; the empirical IRFs are, in contrast, highly transitory.

Table 7 presents results from a Calvo TDP model *with* strategic complementarities. The contract multiplier here is approximately four. The excess smoothness of model inflation rates intensify, with empirical rates two to four times as volatile. The excess persistence problems seen in Table 6 (TDP without strategic complementarities) only worsen as well. Figure 4 shows why: the univariate IRFs build for reset prices, because of the strategic complementarities, in contrast to the diminishing empirical IRFs.

Table 8 presents the SDP model without strategic complementarities. As in Golosov and Lucas (2007), the contract multiplier in this model is well below one at 0.4. This model more closely matches the empirical statistics for actual and reset inflation in Table 2. It actually generates too much inflation volatility for sticky goods, and all goods combined, but is off by a factor of 1.5 rather than two to four as in the TDP models. Inflation persistence is markedly reduced relative to the TDP models—a model result anticipated by Caballero and Engel (2007). But inflation persistence is still too high relative to that for the data (–0.31 model vs. –0.44 data for reset price inflation, 0.41 model vs. –0.12 data for actual inflation).

[21] An alternative intuition is that the desired price is a constant markup over current and future expected discounted marginal costs, where the discounting combines the probability the price is still active in the future periods, the time-varying stochastic discount factor, and future demands for the firm's good. With no complementarities and random-walk money or aggregate productivity, marginal costs are constant over time leading to the impulse response that is basically flat. The small fluctuation in the impulse response function in periods 2 and 3 are due to minor fluctuations in the stochastic discount factor used by firms to discount profits.

The reduced persistence and greater volatility of actual inflation for the SDP model in Table 8, compared to the TDP models in Tables 6 and 7, do not reflect important fluctuations in the frequency of price changes under the SDP model. The standard deviation of the frequency of price changes is very low for the SDP model, equaling about 0.2 and 0.4 percentage points respectively for flexible and sticky goods. Directly related to this, the statistic average rate of price increase conditional on changing, $\widetilde{\pi}_t$, provides little information beyond that in actual inflation. For instance, for sticky goods under TDP, with or without complementarities, the standard deviation of $\widetilde{\pi}_t$ equals exactly 10 times the standard deviation of actual inflation. For the SDP model this ratio remains very similar, equaling 9.4. But reset price inflation is much more volatile for the SDP model than under TDP, making it a much more discriminating statistic. In particular, for the TDP model with strategic complements the standard deviation of reset inflation for sticky goods is only 2.7 times its standard deviation for actual inflation, whereas for the SDP model this ratio is 7.9. Based on the CPI data (Table 2), the observed ratio is 8.0.

Inspecting the accumulated impulse response functions for reset prices proves particularly helpful for better understanding why the models with time-dependent pricing and/or strategic complementarities predict excessively high persistence and low volatility for reset price inflation. Moreover, because we can produce time series for *theoretical* reset price inflation in the model economies, we can use these plots to document the impact of the "selection effect" on our estimated reset price inflation.

Figure 5 presents the accumulated IRFs for reset prices separately for flexible and for sticky goods. Much like the data, the responses are highly transitory. By contrast, the IRF's for theoretical reset prices would appear essentially flat, essentially the same as the IRF's under TDP pictured in Figure 3. Constructed reset price inflation differs sharply from theoretical reset price inflation because of a strong "selection effect" (see Caballero and Engel, 2007, and Golosov and Lucas, 2007). The firms changing price in a given period are not an unbiased sample of the population, but rather those who most benefit from a price change. The response of reset price inflation is much greater on impact because only firms in the tails of the distribution change price. For example, in response to a positive monetary shock, the average productivity of the price changers is below the average productivity of all firms, causing the measured reset price inflation (which depends only on price changers) to be much higher than theoretical reset price inflation. In the long-run, the accumulated response of these two measures is the same. Thus, the selection effect explains much of the greater volatility found in the SDP models relative to the TDP models.

In Table 9 we add strategic complementarities (intermediate share $\alpha_x = 0.95$) to produce a contract multiplier of around four. Doing so makes reset inflation much smoother, to the point that empirical rates are two to six times as volatile as those in the model. Model inflation rates become too persistent as well. Most problematic, strategic complementarities essentially eliminate any negative serial correlation for reset price inflation, whereas for the data reset price inflation displays strong negative serial correlation (–0.4 to –0.5). Related, complementarities, by creating inertia in prices, lower the correlation between actual and reset inflation (e.g., down to 0.44 for sticky goods in the model, vs. 0.73 in the data).

Figure 6 displays the accumulated responses for *theoretical* reset price inflation in the SDP model with strategic complementarities. The key feature of these responses, for both flexible and sticky goods, is their upward sloping trajectory. Strategic complementarities mute the size of price changes for those changing prices, as price setters wait for the average price to respond. Thus, theoretical reset price inflation is small on impact but accumulates over time as more firms change price.

Figure 7 presents the accumulated IRFs for constructed reset prices both for flexible and for sticky goods. The constructed reset price inflation differs from theoretical reset price inflation again because of a “selection effect”. Still, the trajectories slope upward, in sharp contrast to their responses without complementarities (Figure 5), and in even sharper contradiction to the plunging profiles in the data.

Again, a concern may be that there are temporary shocks in the data, whereas the model shocks are permanent (either to money or to aggregate productivity). Figure 8 displays responses to a permanent actual price shock for both flexible and sticky goods. As shown, the reset prices stay ahead of actual prices far too long relative to the data. This result is driven by the strategic complementarities.

Another possibility is that the literature has estimated big contract multipliers over long periods (such as 1950 to 2000), but that the Fed has succeeded in reducing inflation persistence and volatility dramatically in the 20 years covered by our sample (1988-2008). Indeed, many authors (e.g. Nason, 2006) have documented such regime changes in the U.S. inflation process over the past two decades, as well as for many inflation targeting countries (e.g., Benati, 2008). In this spirit, we simulate the SDP model with complementarities *and* a version of endogenous monetary policy. Specifically, we set $\rho_m = -0.6$ (the response of money growth to lagged real money balances) in (3.15) to match the serial correlation of nominal PCE growth (–0.31) over our sample period. Here money growth offsets movements in the real money stock. As shown in Table 10 (summary statistics) and Figure 9 (univariate IRFs for flexible and sticky groups), this specification succeeds in driving down the persistence of reset and actual inflation substantially. On the persistence dimension, this model succeeds about as well as the SDP model without complementarities. But there are two problems. First, there is no longer a contract multiplier above one. Of course, this might be what structural VARs show for the last twenty years.[22] Second and more problematic, endogenous money growth saps away inflation volatility. Empirical inflation rates are five to nine times as volatile as in this model. The intuition is this: if endogenous monetary policy undoes the impact of strategic complementaries on reset and actual inflation persistence, then there is little reason for reset and actual prices to change. If prices are sticky, one will not want to incorporate very transitory shocks into new prices. Thus we are left with the problem of reconciling a model with strong strategic complementarities simultaneously with the observed persistence and volatility of empirical inflation rates.

Another robustness check we perform is to replace the aggregate monetary shock with an aggregate productivity shock. Indeed, Altig et al. (2005) argue that shocks to aggregate productivity are much more responsible for inflation movements than are monetary policy shocks. With random walk aggregate productivity, instead of random walk money, our results are virtually identical (e.g., for SDP with strategic complementarities, with or without endogenous money growth).

Finally, although our models reflect a continuum of firms, sampling error is potentially important for the data. As a result, we have also calculated statistics for a finite sample of firms, setting the number of firms in each sector to match the average number of price quotes in the respective sector in the CPI-RDB (3,100 in the flexible group, 8,300 in the

[22] As one exercise, we re-ran the structural VAR of Altig et al. (2005) on our 1988-2008 sample. The estimated IRF to a monetary shock is naturally less precise given the shorter sample, but the point estimates exhibit essentially no contract multiplier for output and a very transitory inflation response.

sticky group). In no case are the IRFs materially affected. Absent strategic complementarities, the summary statistics (standard deviations and serial correlations) are little changed. In the presence of strategic complementarities, however, the persistence of reset price inflation *does* fall markedly—narrowing the gap with the data substantially. Complementarities severely dampen the volatility of "population" reset price inflation (i.e., with a continuum of goods), so that sampling error looms large in the total variance of finite-sample inflation. Because idiosyncratic shocks are so transitory (monthly serial correlation of only 0.7), the sampling error drives down the persistence of finite-sample reset price inflation.

We do not report finite-sample statistics because inflation volatility is *counterfactually tiny* under strong complementarities. Comparing the first rows of Tables 2 (data), 7 (TDP with complementarities), and 9 (SDP with complementarities), empirical reset price inflation has nine times the variance of model reset price inflation. Explaining this discrepancy would require that sampling error contribute almost 90% (8/9) of the variance of empirical reset price inflation. To gauge the actual contribution, we split the BLS sample in half. The resulting increase in the variance suggests about 25% of the variance of aggregate inflation is due to sampling error. More to the point, there is no drop in the persistence of reset price inflation when going from full to half-samples (it actually increases). Thus sampling error does not appear responsible for the low persistence of empirical reset price inflation.

4. Conclusions

A large empirical literature has estimated that monetary policy shocks affect real variables for several years, much longer than the duration of nominal prices. A popular explanation for this contract multiplier combines sticky prices and strategic complementarities. The complementarities make reset prices build slowly after permanent shocks, prolonging the real effects beyond the duration of nominal prices. That is, strategic complementarities impart persistence to reset price inflation. Our key finding is that we do not see persistence in reset price inflation using data underlying the U.S. CPI from 1988-2008.

We can see two possible reactions to our findings. One is that there are other models of strategic complementarities that we have not explored here that can explain all of the facts. This is certainly possible, but our intuition is that other sources of complementarities (e.g., sticky wages rather than sticky intermediates), or even sticky information, should have similar predictions for the persistence of reset price inflation. Another reaction is that the contract multiplier may not be so high after all. Perhaps the high inflation persistence over longer samples reflects the persistence of monetary shocks ("extrinsic persistence") rather than strategic complementarities ("intrinsic persistence"). The low inflation persistence of recent decades could be because the Fed stopped adding extrinsic persistence, leaving only the low intrinsic persistence in the data.

The conclusions of several recent studies overlap with ours. Cogley and Sargent (2002), Primiceri (2006), and Cogley and Sbordone (2008) all argue that U.S. inflation persistence over long samples stems from changes in trend inflation (i.e., monetary regime changes) rather than from a high contract multiplier. Klenow and Willis (2006) find large idiosyncratic price changes in the micro data hard to square with strategic complementarities among close competitors. Kryvtsov and Midrigan (2008) suggest strong countercyclicality of inventory-sales ratios is similarly difficult to reconcile with market-wide strategic complementarities (i.e., sticky input prices). In contrast, Gopinath, Itskhoki and Rigobon

(2007) and Gopinath and Itskhoki (2008) find evidence consistent with strategic complementarities in the response of (reset) import prices to exchange rate shocks.[23]

[23] Like us, Klenow and Willis (2008) focus on reset price changes in the CPI. They find slow responses of individual reset price changes to the previous reset price changes of other items. This evidence is more in line with sticky information than strategic complementarities.

Appendix

This appendix discusses solving and simulating the price-setting models.

For setting up the firm's value function, it is useful to substitute a few variables out of the firm's profit function. This (along with one assumption described below) will allow us to express the firm's value as a function of only three states: $p_{t-1}(i)/P_t$, $A_t(i)$, and M_t/P_t. First, we use firm cost-minimization to substitute $X_t(i)$ out of profits using

$$\text{(A1)} \qquad X_t(i) = \frac{\alpha_X}{1-\alpha_X}\frac{W_t L_t(i)}{P_t}.$$

Second, we use the firm's production function to substitute $L_t(i)$ out of profits:

$$L_t(i) = \left(1-\alpha_X\right)^{\alpha_X}\left(\alpha_X \frac{W_t}{P_t}\right)^{-\alpha_X}\frac{y_t(i)}{A_t(i)}.$$

We next substitute $y_t(i)$ out of profits using the demand curve (3.12) and aggregate resource constraint $Y_t = C_t + X_t$, and substitute W_t/P_t out of profits using labor supply (3.5). Thus, (real) profits are given by

$$\text{(A2)} \qquad \Pi_t(i) = Y_t\left(\frac{p_t(i)}{P_t}\right)^{1-\theta} - \frac{\left(\omega L_t^{\psi} C_t^{\gamma}\right)^{1-\alpha_x} Y_t\left(\frac{p_t(i)}{P_t}\right)^{-\theta}}{\left(1-\alpha_x\right)^{1-\alpha_x}\alpha_x^{\alpha_x}A_t(i)} - k_t(i)I_t(i)\omega L_t^{\psi}C_t^{\gamma}.$$

We then log-linearize the production function (3.7), labor supply (3.5), resource constraints (3.13) and equation (A2) around the flexible-price steady state to express $\hat{Y}_t$ and $\hat{L}_t$ as linear functions of $\hat{C}_t$, where ^'s denote log deviations from steady state values. Specifically,

$$\hat{L}_t = \left[\frac{\frac{C}{Y} + \gamma\left(\frac{X}{Y} - \alpha_x\right)}{1 + \psi\alpha_x - \left(1+\psi\right)\left(\frac{X}{Y}\right)}\right]\hat{C}_t$$

where C, X and Y denote steady state values, and

$$\widehat{Y}_t = (1+\psi\alpha_x)\hat{L}_t + \gamma\alpha_x\hat{C}_t .$$

Finally, the cash-in-advance constraint implies $C_t = M_t / P_t$. Thus, profits – equation (A2) – can be expressed as a function of just the three state variables $p_{t-1}(i)/P_t$, $A_t(i)$, and M_t / P_t. (In the Calvo case, the menu cost $k_t(i)$ is a fourth state variable.)

To write the firm's value function in terms of these same three state variables, we must make one more simplifying assumption. The state space of the firm's problem is actually infinite dimensional since the evolution of the price level depends on the entire distribution of all firms' prices and productivity levels. In the spirit of Krusell and Smith (1998), we assume that firms perceive the evolution of the price level as being a function of a single moment of this distribution. Specifically,

$$\frac{P_t}{P_{t-1}} = \Gamma\left(\frac{M_t}{P_{t-1}}\right).$$

Nakamura and Steinsson (2008b) show that this assumption makes the model tractable while still providing highly accurate forecasts of the price level.

In the end, the firm's value function takes the recursive form

(A3) $$V_t\left(\frac{p_{t-1}(i)}{P_t}, A_t(i), \frac{M_t}{P_t}\right) = \max_{p_t(i)}\left\{\Pi_t(i) + \tilde{\beta}_{t,t+1}E_t V_{t+1}\left(\frac{p_t(i)}{P_{t+1}}, A_{t+1}(i), \frac{M_{t+1}}{P_{t+1}}\right)\right\}$$

where $\tilde{\beta}_{t,t+1}$ is the stochastic discount factor between periods t and $t+1$. The model is then solved using value function iteration, with the additional requirement that the forecast rule Γ be consistent with the aggregation of firm pricing decisions.

Table 2

Constructing Reset Price Inflation: A Simple Example

	Period 0	Period 1	Period 2
Price of Good A	1	1.22	1.22
Inflation for Good A		20%	0%
Reset price for Good A	1	1.22	1.22
Reset Inflation for Good A		20%	na
Price of Good B	1	1	1.22
Inflation for Good B		0%	20%
Reset price for Good B	1	1.22	1.22
Reset Inflation for Good B		na	0%
Inflation (π_t)		10%	10%
Inflation for changers ($\tilde{\pi}_t$)		20%	20%
Reset inflation ($\widehat{\pi}_t^*$)		20%	0%

Note: The example assumes equal expenditure shares, equaling one half, for both goods. It also assumes that both Good A and Good B exhibited a price change in period 0, establishing the base price for calculating reset price inflation for period 1. The number 1.22 in the table represents exp(0.2) to two decimal places.

Table 2

Summary Statistics for Reset and Actual Price Inflation

Statistic	All Goods	Flexible Goods	Sticky Goods
Standard deviation of π^*	1.02% (0.05)	1.31% (0.06)	1.28% (0.06)
Serial correlation of π^*	−0.44 (0.06)	−0.39 (0.05)	−0.52 (0.06)
Standard deviation of π	0.18% (0.01)	0.41% (0.02)	0.16% (0.01)
Serial correlation of π	−0.12 (0.06)	−0.10 (0.06)	−0.15 (0.08)
Correlation of π and π^*	0.81 (0.02)	0.86 (0.02)	0.73 (0.03)

Notes: All data are from the CPI-RDB. Samples run from January 1989 through May 2008. The threshold frequency of regular price changes is one sixth per month: quote-lines in ELIs with average frequency higher than one sixth are in the flexible group, and those with lower frequency are in the sticky group. All series are monthly, are HP-filtered with smoothing parameter 1,000,000, and are seasonally adjusted. Standard errors are in parentheses.

Table 3

Summary Statistics Excluding Sales Prices

Statistic	All Goods	Flexible Goods	Sticky Goods
Standard deviation of π^*	1.13% (0.05)	1.39% (0.06)	1.25% (0.06)
Serial correlation of π^*	−0.43 (0.05)	−0.39 (0.05)	−0.40 (0.04)
Standard deviation of π	0.14% (0.01)	0.39% (0.02)	0.10% (0.01)
Serial correlation of π	−0.06 (0.06)	−0.05 (0.06)	0.09 (0.08)
Correlation of π and π^*	0.77 (0.03)	0.83 (0.02)	0.53 (0.05)

Notes: All data are from the CPI-RDB. Samples run from January 1989 through May 2008. The threshold frequency of regular price changes is one sixth per month: quote-lines in ELIs with average frequency higher than one sixth are in the flexible group, and those with lower frequency are in the sticky group. All series are monthly, are HP-filtered with smoothing parameter 1,000,000, and are seasonally adjusted. Standard errors are in parentheses.

Table 4

Economy-Wide Model Parameters

Parameter	Baseline	Strategic Complements	Endogenous Monetary Policy
Monthly Discount Factor (β)	$0.96^{1/12}$	Same	Same
Coefficient of Relative Risk Aversion (γ)	1	Same	Same
Inverse of Frisch elasticity of labor supply (ψ)	0	Same	Same
Steady-state Labor Supply (L)	0.333	Same	Same
Elasticity of demand (θ)	4	Same	Same
Intermediate Input Share (α_x)			
SDP	0	0.95	0.95
TDP	0	0.67	-
Persistence of Idio. Productivity Shock (ρ)	0.7	Same	Same
Mean Growth Rate of Money (μ)	0.2%	Same	Same
S.D. of Innovation to Money Growth (σ_m)	0.48%	0.48%	0.41%
Money Growth's reaction to M/P (ρ_m)	0	0	-0.6

Notes: Parameter values apply to both the TDP and SDP models, unless otherwise noted. As shown in the text, prices are strategic complements if $(\gamma+\psi)(1-\alpha_x)<1$. The target steady state labor supply is obtained by varying the utility function parameter ω. The intermediate input share in the non-baseline cases is chosen to generate a contract multiplier of 4. The parameters for the money growth process are chosen to match the mean growth rate of inflation, the standard deviation of nominal non-shelter PCE, and, for the "endogenous monetary policy" case, the serial correlation of nominal PCE.

Table 5

Sector-Specific Model Parameters

Parameter	Baseline	Strategic Complements	Endogenous Monetary Policy
Menu Costs (SDP Only)			
Flexible	0.168%	Same	Same
Sticky	0.218%	Same	Same
S.D. of Idiosyncratic Productivity Shocks			
Flexible ($\sigma_{A,f}$)	4.93%	4.94%	4.94%
Sticky ($\sigma_{A,s}$)	4.70%	4.75%	4.75%
Probability of Zero Menu Cost (TDP Only)			
Flexible (λ_f)	0.333	Same	-
Sticky (λ_s)	0.100	Same	-
Sector Weights			
Flexible	0.3000	Same	Same
Sticky	0.7000	Same	Same

Notes: Expended menu costs are evaluated at the steady state wage and scaled by steady state revenue, $\frac{\lambda_s k_s W_{SS}}{P_{SS} Y_{SS}}$.

Although the *expended* menu costs are similar across sectors, the labor cost (k_s) of changing prices is actually more than four times greater in the sticky sector because the frequency of price change (λ_s) is 3/10 as large in the sticky sector. The labor cost of changing prices also varies greatly across the model specifications. One can show expended menu costs are proportional to $\lambda_s k_s (1-\alpha_x)$, so specifications with higher intermediate input shares have larger labor costs of changing prices.

Table 6

Summary Statistics on Reset and Actual Price Inflation

TDP Model (no strategic complementarities)

Statistic	All Goods	Flexible Goods	Sticky Goods
Standard deviation of π^*	0.49% (0.02)	0.49% (0.02)	0.49% (0.02)
Serial correlation of π^*	-0.01 (0.07)	-0.01 (0.07)	-0.01 (0.07)
Standard deviation of π	0.13% (0.01)	0.21% (0.02)	0.11% (0.02)
Serial correlation of π	0.78 (0.04)	0.66 (0.05)	0.88 (0.03)
Correlation of π and π^*	0.61 (0.01)	0.74 (0.003)	0.44 (0.009)

Notes: Statistics are averages across 100 model simulations, each of 240 periods. Standard deviations across simulations are in parentheses.

Table 7

Summary Statistics on Reset and Actual Price Inflation

TDP Model (strategic complementarities)

Statistic	All Goods	Flexible Goods	Sticky Goods
Standard deviation of π^*	0.26% (0.01)	0.23% (0.01)	0.31% (0.01)
Serial correlation of π^*	0.10 (0.07)	0.11 (0.08)	0.05 (0.07)
Standard deviation of π	0.09% (0.01)	0.11% (0.01)	0.08% (0.01)
Serial correlation of π	0.87 (0.04)	0.78 (0.05)	0.92 (0.03)
Correlation of π and π^*	0.61 (0.01)	0.75 (0.01)	0.44 (0.02)

Notes: Statistics are averages across 100 model simulations, each of 240 periods. Standard deviations across simulations are in parentheses.

Table 8

Summary Statistics on Reset and Actual Price Inflation

SDP Model (no strategic complementarities)

Statistic	All Goods	Flexible Goods	Sticky Goods
Standard deviation of π^*	1.55% (0.07)	1.30% (0.07)	1.96% (0.09)
Serial correlation of π^*	-0.31 (0.06)	-0.37 (0.05)	-0.27 (0.06)
Standard deviation of π	0.29% (0.02)	0.40% (0.02)	0.25% (0.02)
Serial correlation of π	0.41 (0.06)	0.19 (0.07)	0.56 (0.05)
Correlation of π and π^*	0.68 (0.02)	0.79 (0.01)	0.53 (0.02)

Notes: Statistics are averages across 100 model simulations, each of 240 periods. Standard deviations across simulations are in parentheses.

Table 9

Summary Statistics on Reset and Actual Price Inflation

<u>SDP</u> Model (strategic complementarities)

Statistic	All Goods	Flexible Goods	Sticky Goods
Standard deviation of $\pi*$	0.32% (0.02)	0.22% (0.01)	0.48% (0.02)
Serial correlation of $\pi*$	0.05 (0.08)	0.09 (0.09)	-0.05 (0.07)
Standard deviation of π	0.11% (0.01)	0.12% (0.01)	0.11% (0.01)
Serial correlation of π	0.86 (0.03)	0.80 (0.04)	0.88 (0.03)
Correlation of π and $\pi*$	0.60 (0.01)	0.76 (0.01)	0.44 (0.01)

<u>Notes</u>: Statistics are averages across 100 model simulations, each of 240 periods. Standard deviations across simulations are in parentheses.

Table 10

Summary Statistics on Reset and Actual Price Inflation

SDP Model (endogenous monetary policy)

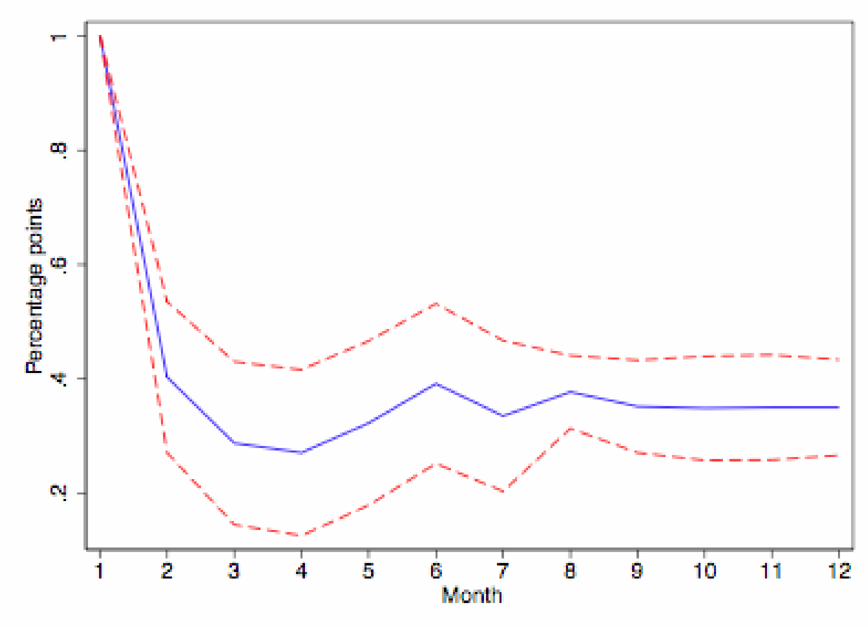
Statistic	All Goods	Flexible Goods	Sticky Goods
Standard deviation of $\pi*$	0.19% (0.01)	0.15% (0.01)	0.25% (0.02)
Serial correlation of $\pi*$	-0.28 (0.06)	-0.34 (0.06)	-0.25 (0.06)
Standard deviation of π	0.03% (0.002)	0.05% (0.003)	0.03% (0.002)
Serial correlation of π	0.38 (0.06)	0.18 (0.07)	0.52 (0.05)
Correlation of π and $\pi*$	0.69 (0.01)	0.79 (0.01)	0.55 (0.02)

Notes: Statistics are averages across 100 model simulations, each of 240 periods. Standard deviations across simulations are in parentheses.

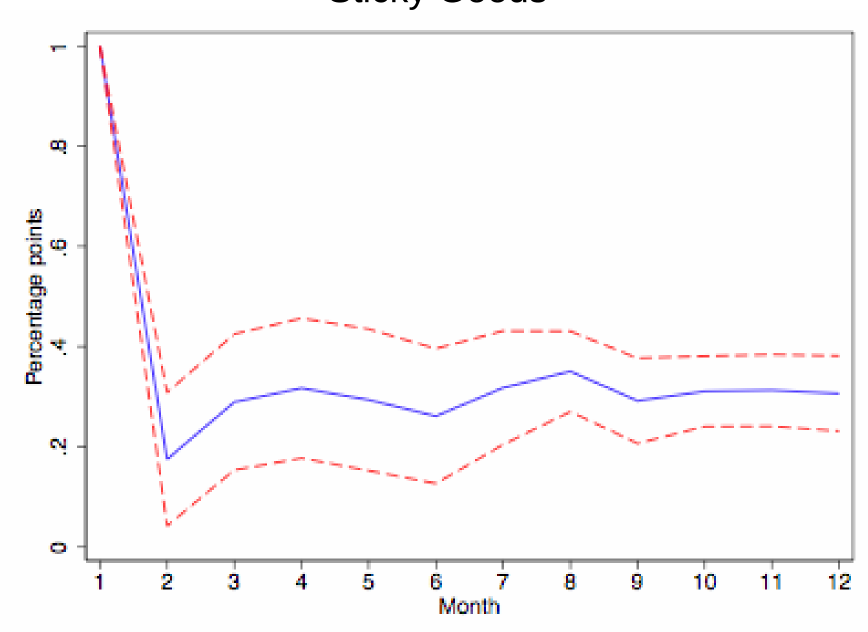
Figure 1

Empirical Impulse Response of Reset Prices

Flexible Goods



Sticky Goods

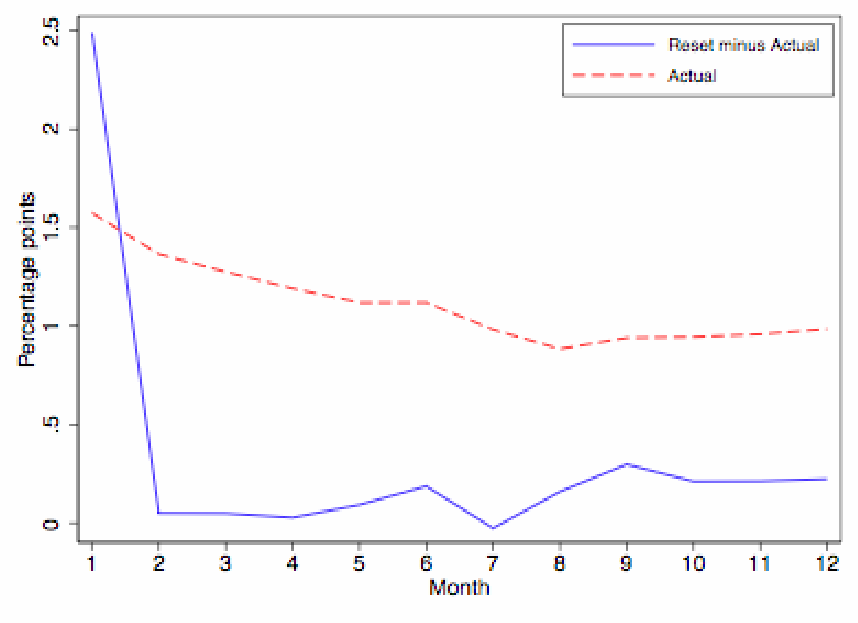


Notes for Figure 1: Dashed lines denote 95% confidence interval. Estimates reflect accumulated responses to a univariate VAR for reset price inflation with 6 monthly lags.

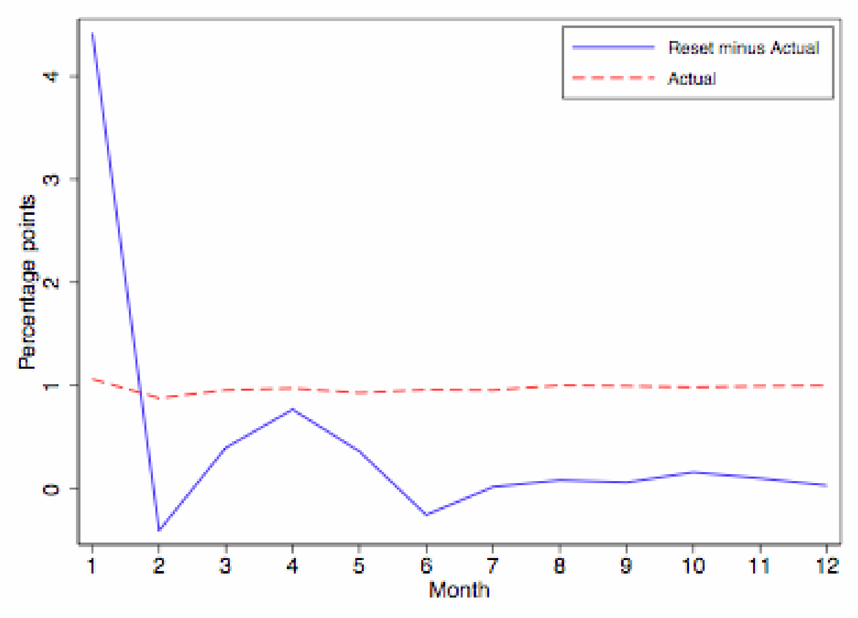
Figure 2

Empirical Impulse Response of Reset vs. Actual Prices

Flexible Goods



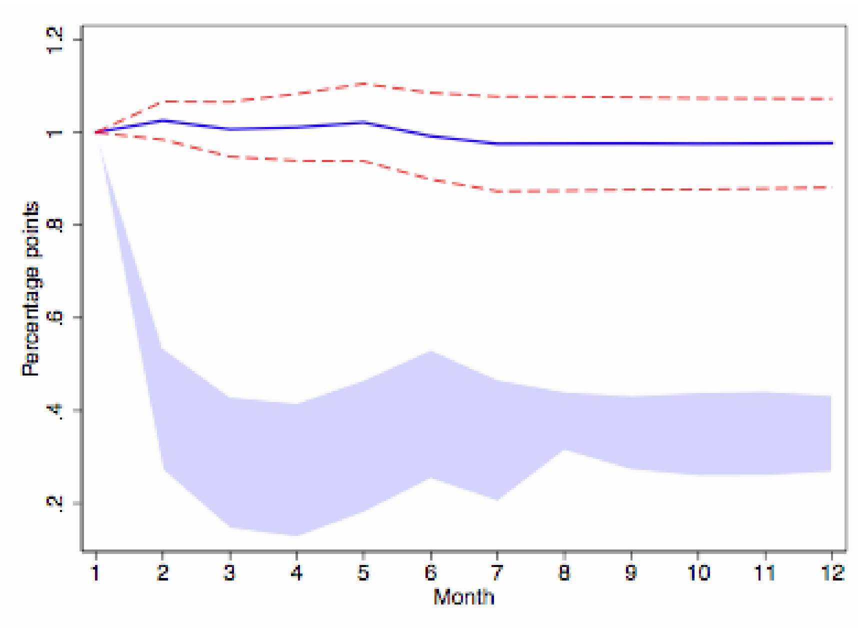
Sticky Goods



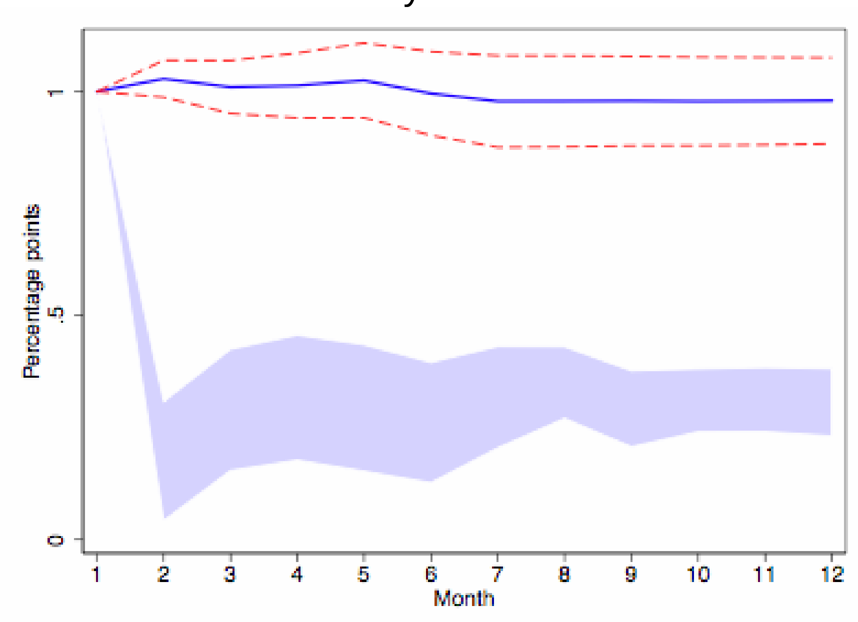
Notes for Figure 2: Displayed are accumulated responses to a structural impulse with long-run impact of one percentage point on actual prices. Impulse response functions are based on a bivariate VAR for reset inflation and actual inflation with 6 monthly lags.

Figure 3: Impulse Response of Reset Prices
(TDP Model, No Strategic Complementarities)

Flexible Goods



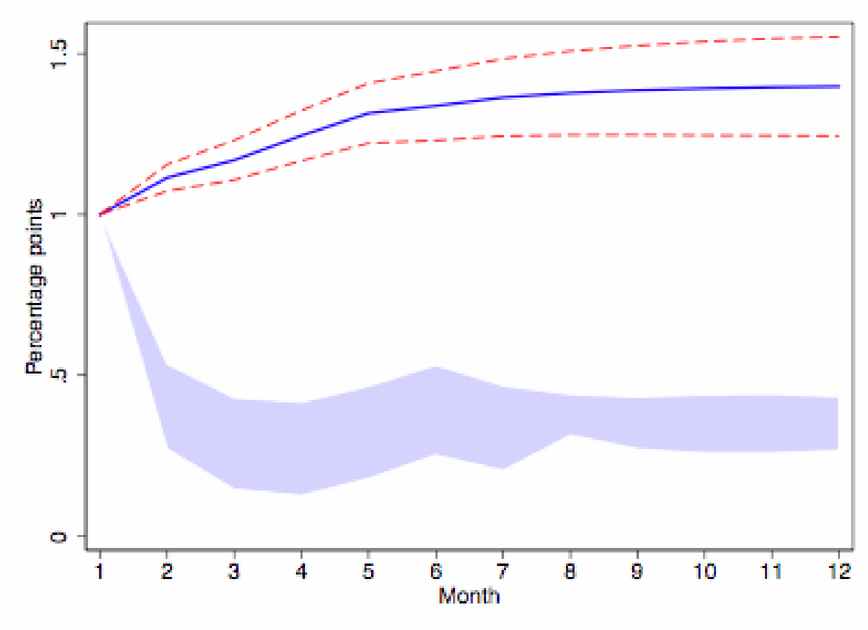
Sticky Goods



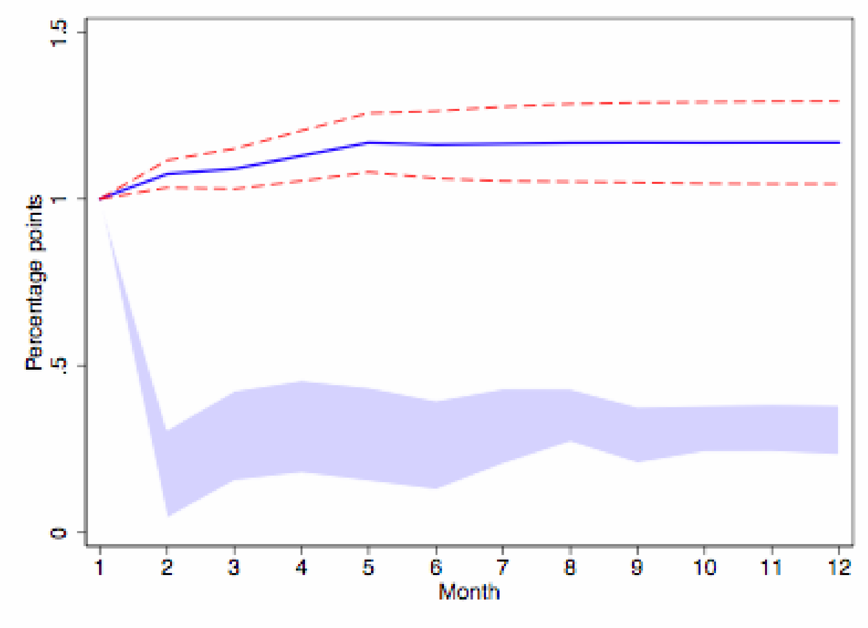
Notes for Figure 3: Dashed lines denote 95% confidence interval. Estimates reflect accumulated responses to a univariate VAR for reset price inflation with 6 monthly lags. Shaded area denotes the 95% confidence interval for estimates based on CPI-RDB data.

Figure 4: Impulse Response of Reset Prices
(TDP Model with Strategic Complementarities)

Flexible Goods



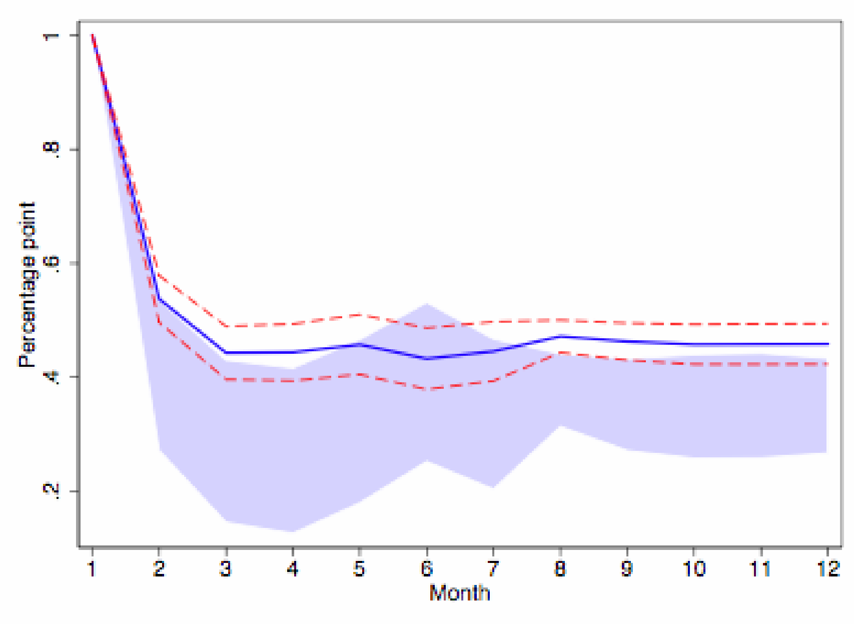
Sticky Goods



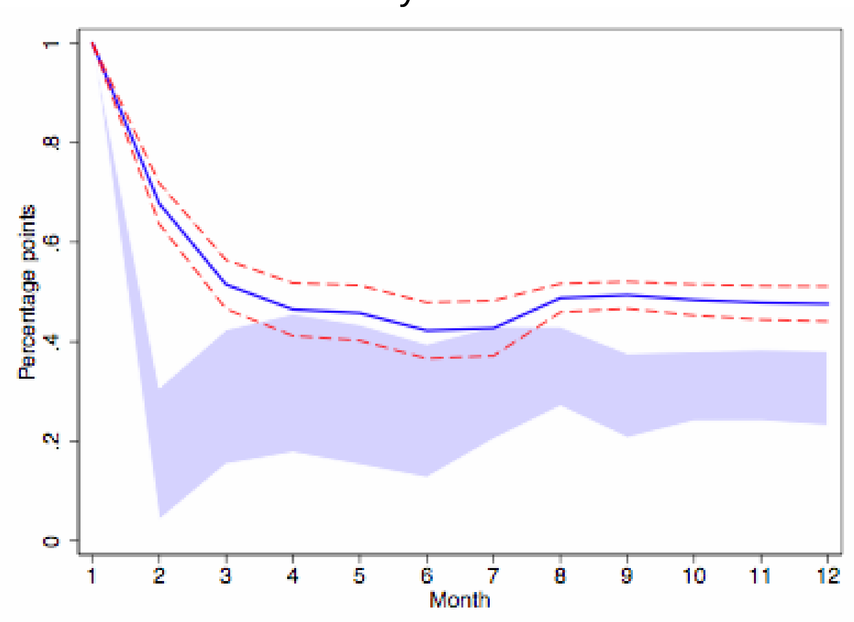
Notes for Figure 4: Dashed lines denote 95% confidence interval. Estimates reflect accumulated responses to a univariate VAR for reset price inflation with 6 monthly lags. Shaded area denotes the 95% confidence interval for estimates based on CPI-RDB data.

Figure 5: Impulse Response of Reset Prices
(SDP Model, no Strategic Complementarities)

Flexible Goods



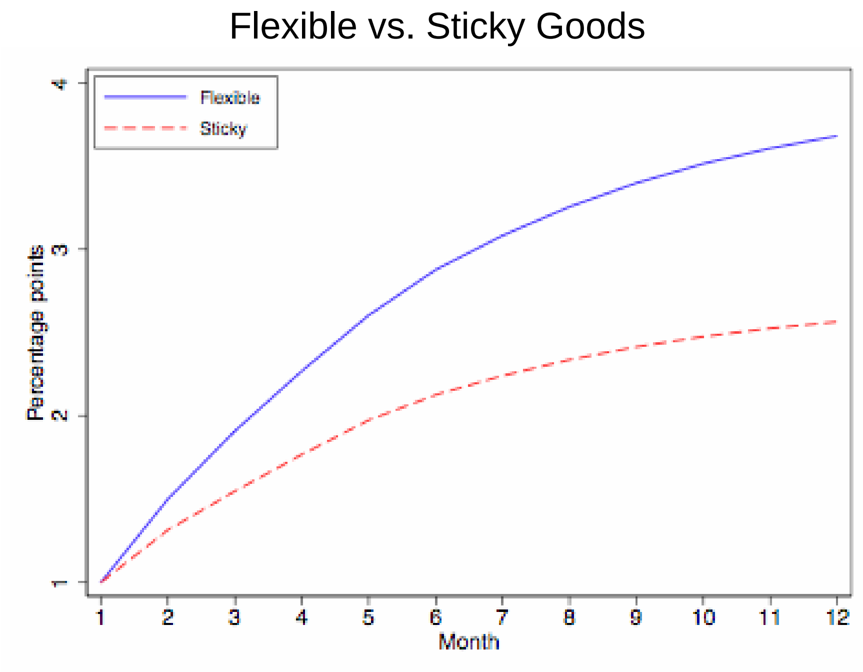
Sticky Goods



Notes for Figure 5: Dashed lines denote 95% confidence interval. Estimates reflect accumulated responses to a univariate VAR for reset price inflation with 6 monthly lags. Shaded area denotes the 95% confidence interval for estimates based on CPI-RDB data.

Figure 6

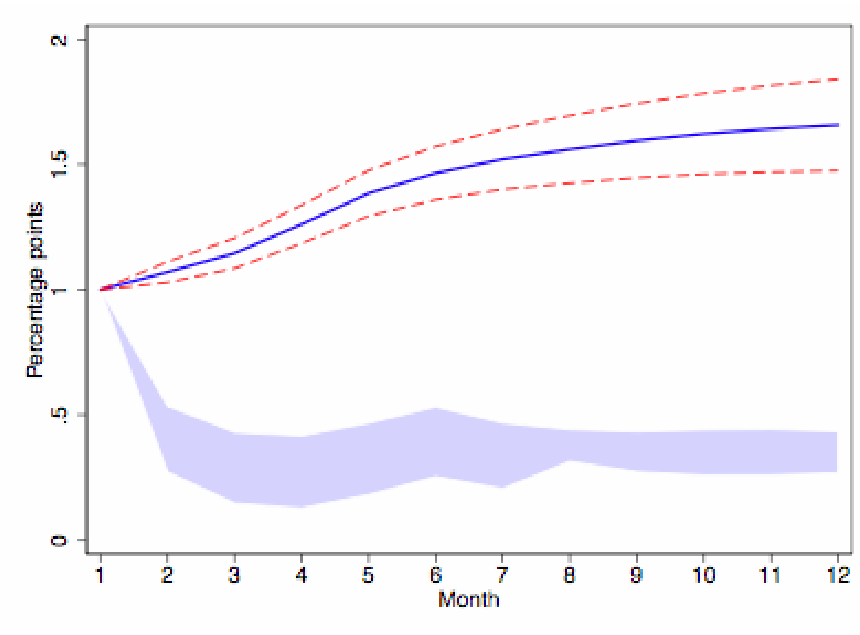
Impulse Response of Theoretical Reset Prices
(SDP Model with Strategic Complementarities)



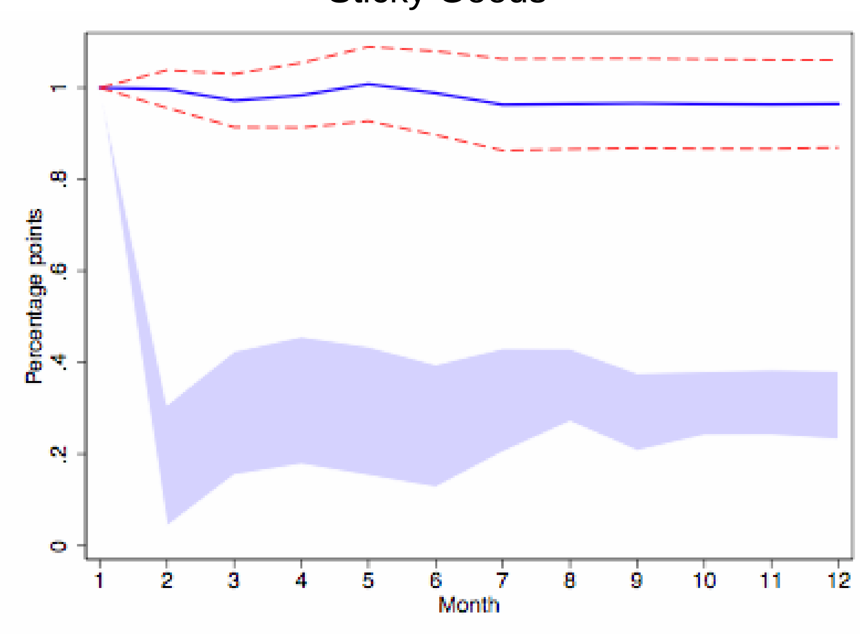
Note for Figure 6: Estimates reflect accumulated responses to a univariate VAR for reset price inflation with 6 monthly lags.

Figure 7: Impulse Response of Reset Prices
(SDP Model with Strategic Complementarities)

Flexible Goods



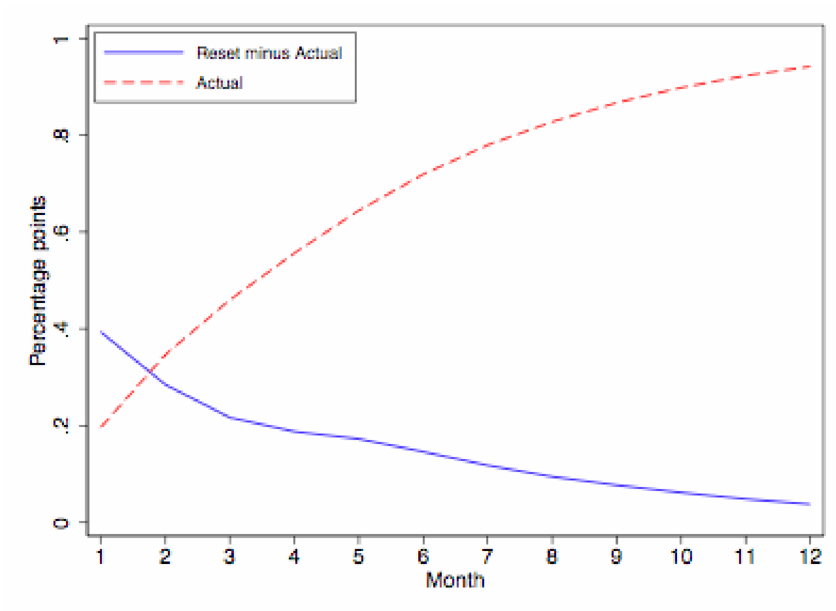
Sticky Goods



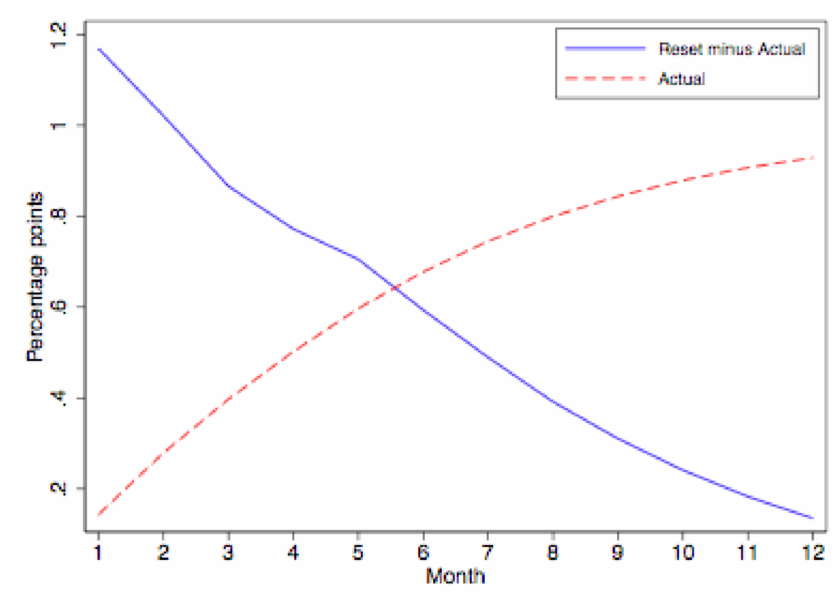
Notes for Figure 7: Dashed lines denote 95% confidence interval. Estimates reflect accumulated responses to a univariate VAR for reset price inflation with 6 monthly lags. Shaded area denotes the 95% confidence interval for estimates based on CPI-RDB data.

Figure 8: Impulse Response of Reset vs. Actual Prices, (SDP Model, Strategic Complementarities)

Flexible Goods



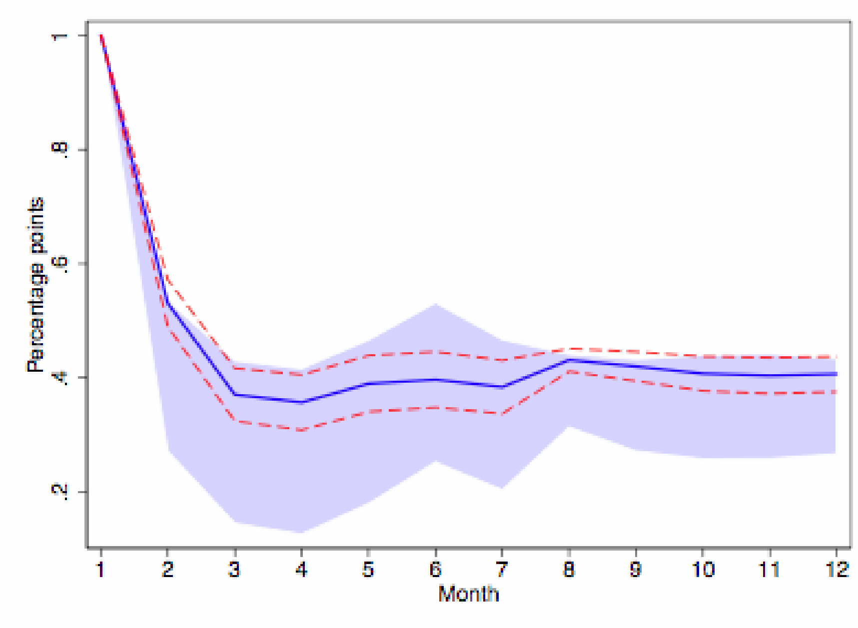
Sticky Goods



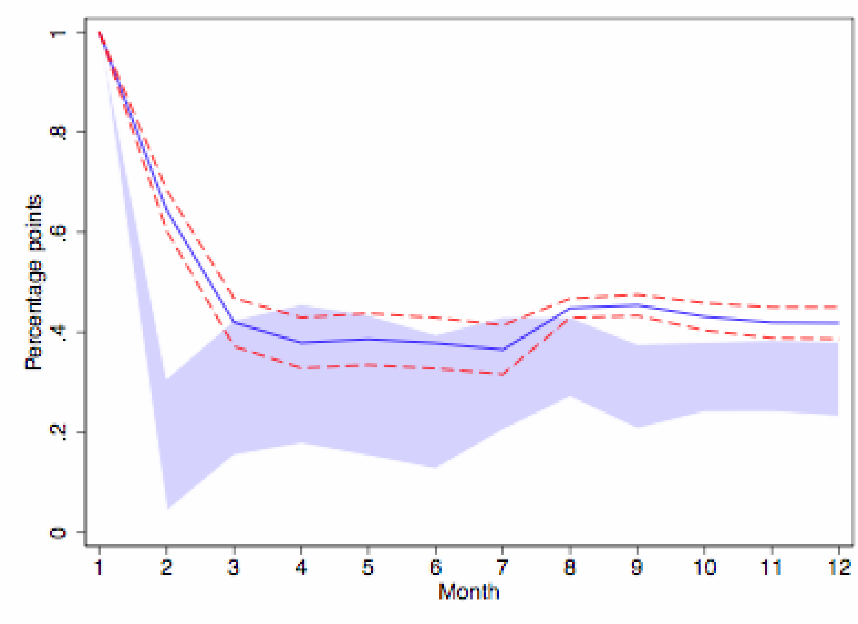
Notes to Figures 8: Displayed are accumulated responses to a structural impulse with long-run impact of one percentage point on actual prices. Impulse response functions are based on a bivariate VAR for reset inflation and actual inflation with 6 monthly lags.

Figure 16: Impulse Response of Reset Prices
(SDP Model, Strategic Complementarities, Endogenous Money)

Flexible Goods



Sticky Goods



Notes to Figures 16 and 17: Dashed lines denote 95% confidence interval. Estimates reflect accumulated responses to a univariate VAR for reset price inflation with 6 monthly lags. Shaded area denotes the 95% confidence interval for estimates based on CPI-RDB data.

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