State-Dependent or Time-Dependent Pricing:
Does It Matter for Recent U.S. Inflation?

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Abstract

Inflation equals the product of two terms: the fraction of items with price changes (whose volatility figures prominently in state-dependent pricing models), and the average size of those price changes (the only source of fluctuations in time-dependent pricing models). The variance of inflation over time can be decomposed into contributions from the variance of each term and from their covariance. We use micro data collected by the U.S. Bureau of Labor Statistics to calculate this decomposition for consumer price inflation from February 1988 through April 2003. We find that 90% of the variance of monthly inflation stems solely from fluctuations in the average size of price changes. When we calibrate a prominent state-dependent pricing model to match the empirical variance decomposition, we find that the model’s shock responses are very close to those in a standard time-dependent pricing model. We conclude that, at least for recent U.S. inflation, a realistic state-dependent pricing model has aggregate implications quite similar to time-dependent pricing models.

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1. Introduction

In time-dependent sticky price models, the timing of individual price changes is exogenous. In particular, a firm might set its price $N$ periods ahead (Fischer, 1977), only every $N$ periods (Taylor, 1980), or randomly (Calvo, 1983). The Taylor and Calvo models feature exogenous staggering of price changes across firms in the economy. As a result of this staggering, the fraction of firms adjusting their prices is constant from period to period. When demand increases after a monetary expansion, only a fraction of all prices increase, so aggregate real output grows.

Exogenous and staggered timing allows for tractable aggregation of individual pricing policies, and easy solution of dynamic aggregate responses to monetary disturbances. However, time-dependent models lack microeconomic foundations. This has led to state-dependent pricing models in which firms choose when to change prices subject to “menu costs.” The implications of these models for real output and inflation can differ dramatically from the predictions of traditional time-dependent models. Caplin and Spulber (1987) consider a model of endogenous price adjustment in which, under certain assumptions on the money process and distribution of prices, money has no real effects. Subsequent research by Caballero and Engel (1993) and Caplin and Leahy (1991, 1997) examine more general money processes and include sources of heterogeneity across firms. While the Caplin and Spulber neutrality result is not robust to these generalizations, the literature continued to emphasize how state-dependent pricing (SDP) models differ from time-dependent pricing (TDP) models.

Dotsey, King and Wolman (1999)—hereafter DKW—present a general equilibrium model with iid menu costs. Because the menu costs are iid across firms at a point in time and across time for a given firm, the state space is manageable. For their chosen parameter
values, DKW find that the fraction of firms changing prices responds importantly to monetary shocks. A positive (negative) monetary shock induces more (fewer) firms to change their prices. And when more firms adjust their prices, the average size of adjustment is larger. The endogenous bunching of price changes significantly speeds up price adjustment and dampens the short run effects on real output. DKW conclude:

"... the extent of price stickiness and the extent of nonneutrality is very responsive to the nature of agents’ beliefs about the permanence of monetary disturbances, because these beliefs affect the incentives that agents have to adjust the timing pattern of their price adjustments. From the perspective of our model then, time-dependent models have been appropriately criticized for treating the pattern of price adjustment as exogenous." (p. 688)

More recent research on SDP models uses newly-available nonlinear solution methods to investigate the implications of persistent menu cost shocks (Willis, 2001), sticky plans (Burnstein, 2001), and idiosyncratic marginal cost shocks (Golosov and Lucas, 2003). Like DKW, these studies stress how and when SDP models differ from traditional TDP models because of endogenous timing of price changes.

In this paper we look for bunching of price changes in the data underlying the Consumer Price Index (CPI) compiled by the U.S. Bureau of Labor Statistics (BLS). The data consists of monthly retail prices of individual non-housing goods and services in the CPI from January 1988 through April 2003. Over this period the 12-month moving average inflation rate dipped as low as 1.4% and reached as high as 6.2%. The fraction of items changing price in the CPI micro data is typically high, with a mean of around 25% per month and a standard deviation of 4% across months. We ask how much synchronization of price changes contributed to fluctuations in inflation over this period.
To summarize the extent to which price changes are synchronized in the data, we take advantage of an inflation identity. Aggregate inflation in a given month equals the product of two terms: the fraction of items changing price, and the average size of price changes. Using this identity, the variance of inflation over time can be decomposed into (terms proportional to) the variance of the fraction of items changing price, the variance of the average size of price changes, and assorted covariance terms. When we implement this decomposition in the 1988-2003 CPI sample, we find that roughly 90% of the variance of monthly inflation is due to the variance of the size of price changes, i.e., “the TDP term.” (In TDP models, the fraction of items changing price is constant over time, so the TDP term is responsible for 100% of the variance of inflation.) The remaining terms are “SDP terms” in that they involve variation over time in the fraction of items changing price. In our sample, these SDP terms account for only 10% or so of the variance of inflation.

To develop the implications of our evidence for sticky price models, we calibrate DKW’s model to match the observed 90-10 variance decomposition. The resulting impulse responses for real output and the price level in this SDP model are very close to those generated under a Calvo TDP model: their absolute differences sum to less than 0.5%. We conclude that, at least for U.S. consumer price inflation since 1988, a realistically calibrated SDP model has aggregate implications quite close to those of a standard TDP model.

We organize the rest of the paper as follows. In section 2 we describe the U.S. CPI microdata in detail. We provide variance decompositions based on this data in section 3. In section 4 we calibrate DKW’s state-dependent pricing model to our evidence, and compare the resulting aggregate predictions to those of a popular time-dependent pricing model. We offer concluding remarks in section 5.
2. BLS Micro Data on Consumer Prices

To construct the non-shelter portion of the CPI, the BLS surveys the prices of about 85,000 items a month in its *Commodities and Services Survey*.\(^1\) Individual prices are collected by 400 or so U.S. Census agents visiting 20,000 retail outlets a month, mainly across 45 large urban areas. The outlets consist of grocery stores, department stores, auto dealerships, hospitals, etc. The survey covers all goods and services other than shelter, or about 70% of the CPI based on BLS consumer expenditure weights.

The BLS selects outlets and items based on household point-of-purchase surveys which furnish data on where consumers purchase commodities and services. The Census agents have detailed checklists describing each item to be priced — its outlet and unique identifying characteristics. The agents price each item for up to five years, after which the item is rotated out of the sample. The BLS rotates items and outlets every four or five years to try to keep the basket current.

The *CPI Research Database*, maintained by the BLS’s Division of Price and Index Number Research and hereafter denoted CPI-RDB, contains all prices in the *Commodities and Services Survey* from January 1988 to the present, currently April 2003. As we now describe, we restrict our attention to a subset of the sample that is best suited to our investigation.

*Frequency of BLS Pricing*

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 York, Los Angeles, and Chicago). The BLS collects prices for items in other categories and

\(^1\) The BLS conducts a separate survey of landlords and homeowners for the shelter portion of the CPI. The sources for this section are the BLS Handbook of Methods (U.S. Department of Labor, 1997, Chapter 17) and unpublished documentation for the CPI-RDB (to be described shortly).
other geographic areas only bimonthly.\textsuperscript{2} About 72\% of observations in the sample are for monthly items, and the remaining 28\% are for bimonthly items. We concentrate our analysis on monthly items. Because our focus is on the endogenous timing of price changes, we prefer a finer and longer sample of 183 monthly observations to a pair of broader and shorter samples of 91 bi-monthly observations. We will, however, report some critical statistics for two bi-monthly samples that use price quotes from all geographic areas.

\textit{Temporary price discounts (``sales'')}

According to the BLS, a ``sale price'' is a price that is considered by the outlet to be lower than the ``regular price'' in the current period. The sale price is temporary, available to all consumers, and is usually identified by a price tag or a sign. Roughly 11\% of quotes in the sample are sale prices. Sales are especially frequent for food items, where they comprise 15\% of all quotes (vs. 8\% of all non-food price quotes). Chevalier, Kashyap and Rossi (2003) also observe frequent sales in their analysis of scanner data from grocery stores. They report that sales often generate V-shapes, as the price goes down and then returns to the regular (pre-sale) level in the next period. In the BLS data, about two-thirds of sales exhibit this pattern.

We report price changes for all prices and, separately, for regular prices. When the BLS price is a sale price, we set the unobserved regular price equal to the last observed regular price. We illustrate this in Figure 1.

Figures 2 and 3 present the distributions of the number of months between price changes and of the size of price changes, respectively. These are for regular prices in the Top 3 areas from February 1988 through April 2003. In these figures we weight quotes equally within expenditure categories, and apply BLS expenditure weights to categories (``ELIs'' in

\textsuperscript{2} In Philadelphia and San Francisco the BLS priced items monthly through 1997 and bimonthly thereafter.
BLS vernacular). We use unpublished BLS ELI weights for 1995, roughly the midpoint of our sample. Figure 2 says the most common length of time between successive regular price changes is a single month. Almost half of all regular price changes are separated by less than a quarter. This reinforces our desire to focus on the monthly price data. Figure 3 shows that both large and small regular price changes are common, as are both increases and decreases in regular prices. Almost half of all regular price changes are smaller than 5% in absolute value. We calculate that 28% of regular price changes are smaller than 2.5%, and 14% are smaller than 1%. The existence of many large and small price changes is consistent with a wide range of menu costs across items and/or time, as in the DKW model.

Forced Item substitutions

Forced item substitutions occur when the item has been discontinued from the outlet and the agent identifies a similar replacement item in the outlet to price going forward. This often takes the form of a product upgrade or model changeover. BLS commodity specialists classify roughly half of substitutions as comparable, and therefore needing no quality adjustment. The commodity specialists implement some form of quality adjustment for the remaining, noncomparable substitutions. The monthly rate of forced item substitutions hovers around 3% in the sample. Essentially all item substitutions involve price changes. Because it is not clear whether price changes associated with product turnover are what modelers of sticky prices have in mind (e.g., they might entail smaller or larger menu costs), we calculate all statistics both with and without item substitutions.
Out of season items

Although the Commodity and Services Survey attempts to price 85,000 or so items per month, the agents succeed in collecting around 74,000 price quotes in the typical month. The 11,000 unavailable quotes per month consist of out-of-season items, temporary stockouts, and permanently discontinued items. The BLS estimates that about 5% of the items they attempt to price are out-of-season in the average month. As one would expect, the fraction out-of-season is particularly high for certain fresh fruits and vegetables and for clothes. For our analysis, we do not compare a price at the beginning of a season to the last price observed in the previous season. We only compare price quotes within the same season.

Stockouts

Even when in season, almost 7% of items are temporarily unavailable in a typical month. The BLS reserves this classification for items that are temporarily out of stock from the outlet or at outlets that are temporarily closed. As the BLS does for constructing the CPI, we drop these missing observations from our sample. Since we are interested in price changes across adjacent months, we also do not compare the price quotes on opposite sides of missing quotes. Figure 1 contains an example of this treatment.

Outliers

Although the BLS requires the collection agents 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 10. Such price jumps constitute less than one tenth of one percent of all price changes.
Summary Statistics

With our sampling decisions, we arrive at a subset of the CPI-RDB consisting of about 55,000 price quotes a month. In order to summarize its properties, let $p_{ijt}$ represent the log price of item $i$ in category $j$ in month $t$, and let $\omega_j$ represent the 1995 BLS consumption expenditure weight of category $j$. $I_{ijt}$ denotes an indicator of a price change for item $i$ in category $j$ in month $t$:

$$I_{ijt} = \begin{cases} 1 & \text{if } p_{ijt} \neq p_{ijt-1} \\ 0 & \text{if } p_{ijt} = p_{ijt-1} \end{cases}$$

We will exploit the following identity for aggregate monthly inflation, $\pi_t$:

$$\pi_t \triangleq \frac{\sum_j \omega_j \sum_i (p_{ijt} - p_{ijt-1})}{\sum_j \omega_j \sum_i 1} = \frac{\sum_j \omega_j \sum_i I_{ijt}}{fr_t} \cdot \frac{\sum_j \omega_j \sum_i (p_{ijt} - p_{ijt-1})}{d_{tp_t}}$$

where $fr_t$ is the fraction of items changing price in month $t$, and $d_{tp_t}$ is the average magnitude of price changes occurring in month $t$. In words, aggregate inflation is the product of the fraction of items with price changes and the average size of those price changes.

Figures 4 and 5 plot $fr_t$ and $d_{tp_t}$, respectively, for regular price inflation in the Top 3 areas from February 1988 through April 2003. The fraction of items changing price fluctuates between 15% and 35% across months. The average size of price adjustments falls mostly between -2% and 4%. There are no visible trends in either plot. Some seasonal patterns are evident, but all of the results we report below are robust to taking out month dummies.
Table 1 contains summary statistics for four samples: the monthly Top 3 urban areas (New York, Los Angeles, Chicago) and food categories, each for all prices and for regular prices. Average monthly inflation in the Top 3 areas is 0.10%, or 1.3% in annual terms from February 1988 through April of 2003. The 12-month moving average inflation rate ranges from –1.5% to 4.2% over the period. The inflation rate is notably higher when sales are excluded (2.7% annual rate, 12-month moving average from –0.2% to 5.6%), indicating that markdowns are not entirely reversed. The fraction of items changing price in the Top 3 areas averages 28% a month, 25% when sales are excluded. This high frequency of price changes is in line with the findings of Bils and Klenow (2002), who examined monthly and bi-monthly quotes in the CPI-RDB. For food items, the average fraction of items changing price in a given month is higher at 37%. This reflects the high incidence of price discounts for food: excluding sale-related price changes, 22% of food items change price per month. Food price inflation averaged 1.8% per year, and its annual moving average spanned –1.9% and 5.4%. For all samples, the across-months standard deviation in the fraction of items changing price is 4% or less.

We noted earlier that 11% of quotes were “sale” prices. Yet for the Top 3 areas in Table 1, the mean \( \bar{r} \) is only 3.5% points lower for regular prices than for all prices. This decrease seems surprisingly small given that almost all moves from regular prices to and from sale prices involve price changes. The explanation is that categories with a larger share of sale prices happen to have smaller weight in consumer expenditures. In particular, food items constitute 39% of all price quotes in the Top 3 areas yet receive only 10% of consumption expenditure weight. Attenuation from weighting is less pronounced within food, where about

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3 By comparison, the mean CPI inflation rate for all areas over this period was 3.2%, with a 12-month moving average ranging from 1.4% to 6.2%.
15% of prices are sale prices and the frequency of regular price changes is 15% points lower than the frequency of all price changes.

In Table 1 we also report the fraction of items increasing in price ($fr^+$) and the fraction decreasing in price ($fr^-$), which sum to the fraction changing price ($fr = fr^+ + fr^-$). Although most price changes are positive, as one would expect, around 44% of price changes are negative. This is true even for regular prices, so it does not simply reflect temporary price discounts. Related, Table 1 shows that the average absolute price change is over 10% in the Top 3 areas, and almost 25% for food items. Even regular price changes are large, averaging over 7% in the Top 3 areas and in excess of 17% for food items. The combination of small average price changes and large absolute price changes suggests substantial idiosyncratic shocks to markups or marginal cost. Golosov and Lucas (2003) use this evidence to motivate a state-dependent pricing model with large and persistent idiosyncratic shocks to productivity.

3. Decomposing the Variance of Inflation

In this section we decompose the variance of inflation over time into (terms involving) the variance of the average magnitude of price changes, the variance of the fraction of items changing price, and the covariance between the two. Applying a first-order Taylor series expansion to (1) around the sample means ($\bar{dp}_t$ and $\bar{fr}_t$) and computing the variance over time, we obtain the following exact variance decomposition:

$$\text{var}(\pi_t) = \frac{\text{var}(dp_t) \cdot \bar{fr}_t^2}{TDP \text{ term}} + \frac{\text{var}(fr_t) \cdot \bar{dp}_t^2 + 2 \cdot \bar{fr}_t \cdot \bar{dp}_t \cdot \text{cov}(fr_t, dp_t) + O_t}{SDP \text{ terms}}$$

where $O_t$ denotes the higher order terms.$^4$

$^4$ In a short Appendix we discuss alternative groupings of the covariance terms in the decomposition.
Tables 2 and 3 report variance decompositions based on all prices and regular prices, respectively. Within each Table, we present results with and without item substitutions in separate columns. The rows of each Table present results for different geographic areas, and separately for food items. We present only the first term in (2)—the “TDP term”—and the sum of the other terms—the “SDP terms.” The TDP term captures changes along the intensive margin, which account for all of the variation in inflation in TDP models. The SDP terms involve changes along the extensive margin, which only contribute in SDP models.

The results in Tables 2 and 3 are striking. The term due to the variance of the average size of price adjustments (the TDP term) accounts for between 85% and 106% of inflation’s variance across the 32 permutations. In 28 of the 32 cases, the TDP term accounts for between 85% and 93% of inflation’s variance. We summarize by saying the TDP term accounts for roughly 90% of the variance of inflation in this data. Fluctuations in the fraction of items changing price—the key endogenous variable in SDP models—are a relatively unimportant source of fluctuations in inflation. This result is robust to excluding both substitution-related price changes and sale-related price changes. The result holds for food items from all areas, as well as for all items in five separate geographic areas. The result also holds up when looking at Top 3 or Top 5 areas as a whole.

Although our focus is the monthly data, we checked the robustness of our findings to aggregation over time and to inclusion of geographic areas with bi-monthly price quotes. First, we calculated variance decompositions for 91-observation “odd” and “even” bi-monthly samples for the Top 3 areas. Across the odd and even samples and for all prices and regular prices, the TDP term accounted for between 83% and 85% of the variance of bi-monthly
inflation. Second, we constructed a 60-quarter sample for the Top 3 areas. Here the TDP term represented 86% of inflation’s variance (87% for regular prices). Finally and most important, we looked at bi-monthly inflation for all geographic areas rather than just areas with monthly price quotes. Bi-monthly price quotes are on odd and even cycles, so we constructed an odd and an even bi-monthly inflation rate—again for all geographic areas in the CPI. Across the odd and even samples with all prices and regular prices, the TDP term accounted for between 93% and 96% of inflation’s variance. These figures suggest even less synchronization of price changes across geographic areas than within them. Thus, including all geographic areas reinforces our finding that the average size of price changes explains the bulk of inflation’s variance.

Table 4 contains across-time correlations between the monthly variables $\pi, f_r, fr^+, fr^-$, and $dp$. Consistent with the variance decompositions, the average size of price adjustments ($dp$) comoves almost perfectly with inflation. The correlation is 0.98 or greater across the samples. The correlation between the average fraction of items changing price ($f_r$) and inflation is small at around 0.1 for the Top 3 areas, and around 0.2 for food.

The correlation between the size ($dp$) and fraction ($fr$) of price changes in the Top 3 areas is roughly zero in all samples. This evidence is inconsistent with those SDP models which imply very positive comovement between the size and incidence of price changes. In DKW’s model, for example, the need for larger price changes is what induces firms with larger menu costs to accelerate price changes after certain shocks. We illustrate this in the next section.
4. Implications for Sticky-Price Models

In this section we will demonstrate some implications for popular sticky price models of the facts we presented in Tables 1 through 4. In particular, we will use the DKW model (Dotsey, King and Wolman, 1999). It is a tractable dynamic stochastic general equilibrium model in which firms face fixed costs of price adjustment which are iid across firms and across time. When the size of aggregate disturbances is small, the equilibrium in this model can be well-mimicked by a log-linear approximation around a stationary steady state.\footnote{A Technical Appendix with a more detailed description of the DKW model is available upon request.}

In the following subsection we briefly describe the DKW model and then discuss its predictions for business cycle dynamics under the parameter values used by DKW. We next calibrate the model to fit the empirical evidence presented in section 3. We will show that these two economies have very different responses to aggregate shocks.

The DKW model

We adhere as closely as possible to the baseline specification of Dotsey, King and Wolman (1999), i.e., DKW. The economy is populated with a continuum of identical households. Each household purchases bundle \{c_{it}\} of differentiated consumption goods in period \(t\), where \(i\) spans the fixed variety of goods. Households hold real money balances \(m_t\), which they demand inelastically, and supply labor \(l_t\). Current period utility is

\[
U(c_t, l_t) = \frac{c_t^{1-\sigma}}{1-\sigma} + \psi(1-l_t)
\]

where \(c_t\) is the Dixit-Stiglitz aggregate consumption index

\[
c_t = \left[ \int_0^1 c_{it}^{\theta} di \right]^{1/\theta}.
\]
Monopolistically competitive firms hire capital \((k_{it})\) and labor \((l_{it})\) in competitive markets to produce a variety \(i\) consumption good subject to Cobb-Douglas technology:

\[
y_{it} = e^{\alpha_{it}} k_{it}^{\alpha_l} l_{it}^{1-\alpha}
\]

where \(\alpha_i\) is an aggregate productivity index. We assume \(\alpha_i\) follows a random walk with drift:

\[
a_t = \mu_a + a_{t-1} + \epsilon_{at}
\]

where \(\epsilon_{at}\) is a zero mean, normally distributed error with standard deviation \(\sigma_a\). For simplicity the aggregate capital stock is fixed, but capital is perfectly mobile across firms.

Each firm faces a fixed (menu) cost of adjusting its price. These costs are iid across firms and over time. The menu costs are drawn from a differentiable, four-parameter cdf

\[
G(\xi) = c_1 + c_2 \tan(c_3 \cdot \xi - c_4), \quad \xi \in [\xi_{\min}, \xi_{\max}]
\]

with properties \(\xi_{\min} \geq 0\), \(G(\xi_{\min}) = 0\), \(\xi_{\min} < \infty\), \(G(\xi_{\max}) = 1\).

The price set by adjusting firms is equal to the present discounted value of future nominal marginal costs weighted by the unconditional probability of the price remaining in effect in each period. Since firms are \textit{ex ante} identical with respect to the menu costs they will face, adjusting firms assign the same probabilities to changing their price in each future period. Firms operate the same production technology and face the same input prices, so they also have the same marginal cost. As a result, all firms adjusting their price in a given period choose the same price.

With positive trend inflation the maximal number of periods \((J)\) the firm is willing to go without changing its price is finite. Each firm will want to adjust after \(J\) periods with probability 1 because, for any realization of menu costs \((\xi_{\max} < \infty)\), the benefit from adjusting (a higher markup) will exceed the benefit from waiting one more period (foregoing the menu cost). Firms will therefore be distributed between \(J\) cohorts, with firms choosing the same
price and output within each cohort. These features render the state space of the model small and the model tractable and easy to solve.

The government changes the supply of money in the economy via lump-sum transfers to households. The rate of growth of the money supply follows the AR(1) process

$$\mu_t = (1 - \rho_m)\mu_m + \rho_m \mu_{t-1} + \varepsilon_{mt}$$

where $\mu_m$ is the mean growth rate of the money supply and $\varepsilon_{mt}$ is a zero mean, normally distributed error with standard deviation $\sigma_m$.

**Simulating DKW economies**

An equilibrium is a sequence of prices and allocations such that the optimization problems of households and firms are solved and all markets clear. Following DKW, we implement a log-linear approximation of the equilibrium around the stationary steady state path (the equilibrium with no aggregate shocks, only idiosyncratic menu costs). We simulate equilibrium realizations for three sets of parameter values: the parameter values originally used by DKW (“Original Quarterly”), the monthly versions of the original DKW parameter values (“Original Monthly”), and, finally, parameter values calibrated to the key empirical evidence we presented in Tables 1 through 4 (“Calibrated Monthly”). We very briefly describe these economies in Table 5, and provide their parameter values in Table 6.

Column A of Table 6 contains the original parameter values used by DKW. For this quarterly SDP economy, the top panel of Figure 6 presents responses of output, the price level and the fraction of firms changing prices to a permanent +1% impulse in the money supply. These figures accurately mimic those in DKW (1999, Figure IV). Each plot contrasts responses in the SDP economy to those in a TDP economy. The TDP economy is a Calvo
economy with the fraction of firms adjusting prices always equal to the unconditional mean fraction in the SDP economy.\(^6\)

In the quarter of the money shock, output increases by about 0.4\% in the SDP economy, compared to about 0.8\% in the TDP economy. Over the next four quarters, output returns to its steady state level. The price level rises almost 0.7\% in the SDP economy on impact (vs. only 0.2\% in the TDP economy). The fraction of firms adjusting their prices jumps 7 percentage points when the money supply surges, then falls back to the pre-shock level of 20\% a quarter within a year. All three variables exhibit echo effects eight quarters after the shock, related to the number of cohorts \(J=8\). For the first few quarters after the shock, firms are accelerating price changes. This tilts the size of cohorts toward those with younger prices, and results in fewer price adjustments three to seven quarters after the shock. After 8 quarters the firms who sped up price changes in response to the shock have older prices, pushing the hazard rate up again.

To summarize the different dynamic responses of the SDP and TDP economies, we sum their absolute % response differences. We denote the cumulative absolute response differences for \(X\) (real output or the price level) as

\[
CRD_X = H \sum_{i=0}^{\infty} |X_{i}^{SDP} - X_{i}^{TDP}|
\]

where \(X_{i}^{SDP}\) (\(X_{i}^{TDP}\)) is the impulse response at the \(i\)-th lag in the SDP (TDP) economy. To make the responses comparable across quarterly and monthly economies, \(H\) is 1 for monthly responses and 3 for quarterly responses. For the Original Quarterly DKW economy in the top

\(^6\) Alternatively, we could have had the conditional probability of adjustment after \(j\) periods in the TDP economy equal the (increasing in \(j\)) steady state hazard rate in the SDP economy. We found that the impulse responses for this “generalized Calvo” economy were virtually indistinguishable from those for the Calvo economy.
The panel of Figure 6, the output responses differ by a cumulative 5.8% and the price responses by a cumulative 7.4%.

The most striking difference between the quarterly SDP and TDP economies can be seen in the variance decompositions they imply for inflation. As shown in Column A of Table 7, in the Original Quarterly DKW economy the “TDP term” accounts for only 20% of the variance of inflation on average across 100 simulations of 61 quarters. The standard deviation of the TDP term across simulations is about 5% for all simulations. Fluctuations in the fraction of firms changing prices accounts for 41% of inflation’s variance, and the positive covariance between the fraction adjusting and the size of adjustments accounts for the remaining 39%. In contrast to the empirical 90-10 decomposition (from Tables 2 and 3), the decomposition in the Original Quarterly DKW economy is 20-80; the decomposition in the TDP economy is, of course, 100-0.

To facilitate comparison to our monthly BLS data, we next simulate a monthly parameterization of the DKW model. For this purpose we adjust the discount rate, the period labor endowment, and the standard deviation of period monetary shocks appropriately. In addition, we adjust the parameters of the menu cost distribution to obtain a monthly mean fraction of firms changing prices equal to 6.7%. This implies a three-month fraction equal to the 20% in DKW’s quarterly economy. Column B of Table 6 lists the “Original Monthly” parameter values, our monthly translation of DKW’s quarterly parameterization.

The bottom panel of Figure 6 shows responses to a permanent and unanticipated 1% money supply increase for this Original Monthly economy. The responses are qualitatively similar to those in the Original Quarterly economy. Differences between the SDP and TDP monthly economies are smaller, mostly because the fraction of firms adjusting prices is
smaller in a month than in a quarter. As shown in Column B of Table 7, the cumulative absolute response differences are modestly lower for the monthly version (1 percentage point smaller for real output and 1.2 percentage points smaller for the price level). If we compare the responses in the fraction of firms adjusting to the steady state fraction, however, the response is larger in the monthly economy (a 42% increase above the steady state fraction in the monthly economy vs. 35% in the quarterly economy).

Comparing Columns A and B of Table 7, we see very similar variance decompositions in the quarterly and monthly versions of DKW’s parameterization. For the monthly parameterization the TDP term is 22% and the SDP first-order and second-order terms are 37% and 41%, respectively. The 20-80 variance decompositions in the quarterly and monthly DKW economies contrast starkly with the 90-10 variance decomposition in the BLS data.

To test whether the discrepancy is due to the higher trend inflation in the DKW parameterization than in the BLS data, we repeated the simulations of the DKW economies setting trend money growth to fit the average monthly (regular price) inflation in the Top 3 areas of 2.7% per year from February 1988 through April 2003. The TDP terms in the variance decomposition did rise to 31%, but this is still far from the empirical 90-10 decomposition. We next pursue the question of whether a DKW model calibrated to match the empirical 90-10 split exhibits impulse response functions very different from a simple TDP model (a 100-0 split).

Column C of Table 6 lists the parameter values for the “Calibrated Monthly” DKW economy. The parameter values we explicitly calibrate to data are as follows. We set the productivity drift to 1.5% per year and its monthly standard deviation to 0.4%, consistent with the behavior of quarterly U.S. TFP growth from 1988 through 2002. We chose trend money
growth, $\mu_m$, and the standard deviation of its innovation, $\sigma_m$, to fit the mean (0.22% per month) and standard deviation (0.39%) of regular price inflation in the Top 3 areas from February 1988 through April 2003. We selected the four parameter values of the menu cost distribution to fit the 25% mean fraction of items changing their regular price and the 90% TDP term in the variance decomposition for regular price inflation, both for the Top 3 areas over February 1988 through April 2003. We set the minimal menu cost, $\xi_{\min}$, to zero, and the maximal menu cost, $\xi_{\max}$, to 0.2% of the labor endowment. We set the minimum menu cost to zero because small price changes are common in the micro data. We set the maximal menu cost far below the 3.25% in DKW’s parameterization because we found a smaller value was necessary to match the empirical 90-10 variance decomposition.

Figure 7 contrasts the distribution of menu costs in Original Monthly and Calibrated Monthly DKW economies. The top panel of Figure 7 shows the distribution of menu costs for the Original Monthly economy. For comparison, the cdf of a Calvo TDP economy is shown—a step function dividing unit probability between realizations of either zero or maximal fixed cost. A firm facing such a distribution of menu costs will make its decision to adjust or not independently of the realization of the aggregate state: when the realized menu cost is zero, the firm will always adjust; conversely, the firm will essentially never adjust when the menu cost is prohibitively high. This is not true for a firm facing a smooth cdf, which puts positive probability on menu costs between 0 and $\xi_{\max}$. In this case, a firm facing an intermediate value of menu costs will adjust only if the aggregate shocks that have accumulated since its last price change are sufficiently large.

The bottom panel of Figure 7 shows the menu cost distribution in our Calibrated DKW economy. It is very close to the step-like cdf in the Calvo TDP model. The probability
of intermediate menu costs is much smaller than the probability of extreme (0 or $\xi_{\text{max}}$) menu costs. Hence, in the Calibrated DKW economy, most of the time firms will be adjusting (or not) independently of the realization of aggregate shocks.

Figure 8 illustrates responses to money and productivity impulses (respectively) for the Calibrated Monthly DKW economy. The responses of real output and the price level are very similar in this economy to those in the TDP economy. The absolute response differences for output cumulate to only 0.2% for the monetary shock and 0.2% for the productivity shock; for the price level they come to only 0.5% for the monetary shock and 0.2% for the productivity shock (see Table 7). These cumulative differences are an order of magnitude smaller than those under the DKW parameter values. In short, a menu cost distribution that produces a 90-10 variance decomposition yields impulse response functions quite close to those of a TDP model with its 100-0 decomposition.

As shown in the rightmost plots of Figure 8, firms do alter the timing of their price changes in the Calibrated DKW economy, but the responses are smaller and much shorter-lived than under the DKW parameter values. Relative to the steady state fraction, 19% more firms change prices after a monetary expansion, compared to 43% after a similar monetary shock under DKW parameter values. The fraction falls back to the steady state level over a few months, rather than lingering for five months or more. In order to match the 90-10 variance decomposition, firms must have limited incentive to synchronize their price changes in response to aggregate shocks.

Table 8 compares correlations in the two monthly DKW economies to those in the Top 3 areas (regular prices). In each case the Calibrated DKW economy comes closer to the data than the Original Monthly DKW economy. Still, in many cases the discrepancy between
the Calibrated economy and the data remains large. A model with persistent shocks to
average menu costs, rather than iid menu costs over time, might come closer to the data. In
particular, such shocks might lower the correlation between the fraction and size of price
changes, and raise the serial correlation of the fraction. As we will discuss in the conclusion,
a more computationally-challenging generalization would be to add firm-specific shocks to
marginal cost and/or desired markups.

Simulating a 1970s economy

A potential criticism of our findings is that inflation was too low and stable in the U.S.
over 1988-2003 to provide a useful testing ground for SDP models. As mentioned above,
one-year moving average CPI inflation ranged from a maximum of 6.2% in October 1990 to a
minimum of 1.4% in September 1998. But the mean was only 3.4% and the standard
deviation only 1.1%.

A natural question to ask is whether SDP terms would explain much more of the
variance of inflation in a period of higher, more volatile inflation such as the U.S. in the
1970s. While the ultimate answer is contingent on the availability of micro data from such
episodes, here we conduct a counterfactual experiment by re-calibrating the DKW model to
U.S. inflation in the 1970s. From January 1970 through December 1979, one-year moving
average CPI inflation in the 1970s averaged 6.8%. It ranged from 2.9% in August 1972 to
12.4% in December 1979, and exhibited a standard deviation of 2.5%. We take the parameter
values in Column C in Table 6, and adjust the trend and standard deviation of money growth
so that the model matches the proportionately higher mean and standard deviation of monthly
CPI inflation from January 1970 through December 1979. The discipline is that we keep the
rest of the parameter values, in particular for the distribution of menu costs.
When we simulate the 1970s DKW economy, the average fraction of firms changing price is higher at 28% than the 25% for the DKW economy calibrated to 1988-2003 inflation. This reflects firms’ choice to change prices more frequently in the presence of higher trend money growth. The main contributor to higher mean inflation in the 1970s simulation, however, is bigger individual price changes. The average price change is more than twice as high at 2% than the 0.7% in the simulation of the 1988-2003 DKW economy. Surprisingly, the over-time standard deviation of the fraction of firms changing their price is only 0.9% in the 1970s economy, compared to 3.8% in the 1988-2003 data. As a consequence, the TDP term in the variance decomposition is actually higher, at 96%, in the 1970s economy than in the 1988-2003 economy.

Figure 9 presents responses to 1% permanent money supply and productivity shocks. The fraction of firms changing price responds, but an order of magnitude less than in the economy calibrated to 1988-2003 inflation. Nevertheless, the real output and price responses to shocks differ little here compared to the 1988-2003 calibration.

Our intuition for these unexpected findings is as follows. There are two effects that shape the output and price responses to, for instance, a monetary shock. First, higher average inflation implies a higher average fraction of firms adjusting prices. Since firms that adjust in the period of the shock contribute least to the change in output, the initial output response is smaller. Second, firms have less incentive to accelerate or postpone their price changes because the average time between price changes is smaller. This latter effect increases the output response, so that the overall impact of a monetary shock on output can be higher or smaller when average inflation is higher.7

---

7 This ambiguous effect of higher trend inflation on the output effect of a monetary shock was also emphasized by Dotsey, King and Wolman (1999, page 685).
More important for our investigation, the 1970s SDP and TDP economies exhibit very similar output and price responses to money and productivity shocks in Figure 9. The cumulative absolute response differences are below 0.5% for all four cases (see Table 9). To recap, our 1970s DKW economy—with a menu cost distribution calibrated to the 1988-2003 variance decomposition and money growth calibrated to 1970s inflation—looks a lot like a simple TDP economy. As in the 1988-2003 data, in this 1970s economy movements in the fraction of firms changing prices contribute little to movements in aggregate inflation.

5. Conclusions

We employed micro data from the U.S. Bureau of Labor Statistics to assess the importance of synchronized price changes for fluctuations in CPI inflation from January 1988 through April 2003. We decomposed the variance of inflation over this period into (terms proportional to) the variance of the average size of price changes, the variance of the fraction of items changing price, and the covariance of these two. We found that the variance of the average size of price adjustments, by itself, accounted for 90% of the variance of inflation.

When we calibrated the general equilibrium menu cost model of Dotsey, King and Wolman (1999) to fit the empirical variance decomposition, the model produced impulse responses quite close to those in a simple time-dependent model. We conclude that, at least for the U.S. from 1988-2003, a realistic state-dependent pricing model has aggregate implications similar to conventional time-dependent models. Although inflation has been moderate in the U.S. since 1988, this has also been true for most OECD economies. So our results could be relevant for much of the OECD for the recent past and foreseeable future.

To explore whether a more inflationary era might suggest a bigger need for state-dependent pricing models, we altered the money growth process in the calibrated economy to
match the 1970s inflation episode in the U.S. We found that higher trend inflation increased the average fraction of firms adjusting prices, but actually decreased the over-time volatility of this fraction. This rendered fluctuations in the fraction (i.e., synchronization of price changes) even less important for aggregate inflation dynamics than in the more recent inflation data. Thus it is not clear that a realistic state-dependent pricing model has very different aggregate implications from simple time-dependent models even in episodes of higher, more volatile inflation. But the availability of more data on individual prices for the U.S. and other countries is needed to answer this question.

Throughout, we used the DKW model because of its tractability. In this model the only source of firm heterogeneity is iid menu costs across firms and over time, keeping the state space manageable. But one aspect of the data that the DKW model cannot match is the large absolute size of price changes (averaging 7% in the BLS micro data). In an environment of low average inflation, such large absolute price adjustments would seem to require sizable idiosyncratic shocks, for example to firm marginal costs as in Golosov and Lucas (2003). Given the computational difficulty of incorporating such shocks, we leave this for future research. But we note that, conditional on fitting the observed 90-10 variance decomposition for inflation, such a model might have aggregate implications close to those of time-dependent pricing. The idiosyncratic shocks to marginal costs could simply take the place of idiosyncratic shocks to menu costs.
Appendix. Alternative variance decompositions.

In this appendix we present two alternative decompositions of the variance of aggregate inflation.

We note the following statistical equalities

$$\overline{XY} = \overline{X} \cdot \overline{Y} + \text{cov}(X,Y)$$
$$\overline{X^2} = \overline{X}^2 + \text{var}(X)$$

where $X$ and $Y$ are vectors of the same length, and overline indicates sample mean.

First, we decompose $\text{var}(\pi_t)$ precisely as

$$\text{var}(\pi_t) = \overline{fr_t^2} \cdot \text{var}(dp_t) + \overline{dp_t^2} \cdot \text{var}(fr_t) + \text{var}(fr_t) \cdot \text{var}(dp_t) + R(fr_t, dp_t) \quad (A.1)$$

where the last term includes all covariance terms:

$$R(fr_t, dp_t) = \text{cov}(fr_t^2, dp_t^2) - 2 \cdot \overline{fr_t} \cdot \overline{dp_t} \cdot \text{cov}(fr_t, dp_t) - [\text{cov}(fr_t, dp_t)]^2$$

Note that the first two terms in our benchmark decomposition (2) coincide with the first two terms of (A.1); and the covariance term approximates the last two terms in (A.1).

Secondly, utilizing the the following identity

$$\ln(|\pi_t|) = \ln(|dp_t|) + \ln(|fr_t|)$$

we can also precisely decompose the variance of the logarithm of absolute inflation

$$\text{var}(\ln(|\pi_t|)) = \text{var}(\ln(|dp_t|)) + \text{var}(\ln(|fr_t|)) + 2 \cdot \text{cov}(|dp_t|, |fr_t|)$$
**Figure 1:** A hypothetical sequence of prices for an individual item in the CPI.

Price in $ 1.10

Month 1 2 3 4 5 6 7 8 9

Price change indicator R 1 1 0 1 1 1 1 1

Size of price change × -0.10 +0.10 × +0.10 -0.05 × × -0.05

Regular price change indicator R 0 0 0 1 1 1 1 1

Size of regular price change × × × × +0.10 -0.05 × × -0.05

R = regular price  
S = sale price

Notes: An × indicates that the variable is unavailable for that month. In the inflation identity (1), \(fr\) is the across-item average of the price change indicator, and \(dp\) is the across-item average size of price change.
Figure 2
Distribution of Months Between Regular Price Changes

Top 3 CPI areas
Feb 1988 through Apr 2003
Expenditure-Weighted

% of Regular Price Changes

Months Between Regular Price Changes
Figure 3
Distribution of Regular Price Changes

Top 3 CPI areas
Feb 1988 through Apr 2003
Expenditure-Weighted
Figure 4
Fraction of items adjusting price

Figure 5
Average size of price adjustments
Figure 6: Original Quarterly and Monthly DKW Economies

Responses to a permanent +1% money impulse: Quarterly Economy

Responses to a permanent +1% money impulse: Monthly Economy
Figure 7

C.D.F. of Fixed Cost, Original Monthly DKW Economy

C.D.F. of Fixed Cost, Calibrated DKW Economy
Figure 8: Calibrated DKW Economy

Responses to a permanent +1% money impulse

Responses to a permanent +1% TFP impulse
Figure 9: 1970s DKW Economy

Responses to a permanent +1% money impulse

Responses to a permanent +1% TFP impulse
### Table 1

Across-Time Means (and Standard Deviations), in %

| Sample       | $\pi$ | $fr$ | $fr^+$ | $fr^-$ | $dp$  | $|dp|$ |
|--------------|-------|------|--------|--------|-------|-------|
| **TOP 3 AREAS** |       |      |        |        |       |       |
| All prices   | 0.10  | 28.3 | 15.6   | 12.7   | 0.33  | 10.5  |
|              | (0.38) | (4.0)| (3.1)  | (3.0)  | (1.27)| (1.2) |
| Regular prices | 0.22  | 24.8 | 14.0   | 10.8   | 0.86  | 7.3   |
|              | (0.39) | (3.8)| (3.1)  | (2.9)  | (1.47)| (1.2) |
| **FOOD**     |       |      |        |        |       |       |
| All prices   | 0.18  | 36.8 | 19.9   | 17.0   | 0.46  | 24.7  |
|              | (0.61) | (2.3)| (2.1)  | (1.2)  | (1.60)| (2.5) |
| Regular prices | 0.22  | 21.9 | 12.6   | 9.3    | 0.96  | 17.5  |
|              | (0.48) | (3.8)| (2.7)  | (1.6)  | (2.02)| (1.0) |

**Notes:** Samples run from February 1988 through April 2003. All data is from the CPI-RDB. The entries above are means and (in parentheses) standard deviations across time of the monthly values of each variable. The monthly values are defined as follows:

- $\pi_t$ = the weighted mean inflation rate from month $t-1$ to month $t$.
- $fr_t$ = the weighted mean fraction of items with changing prices from month $t-1$ to month $t$.
- $fr^+_t$ = the weighted mean fraction of items with rising prices from month $t-1$ to month $t$.
- $fr^-_t$ = the weighted mean fraction of items with falling prices from month $t-1$ to month $t$.
- $dp_t$ = the weighted mean size of price changes from month $t-1$ to month $t$.
- $|dp|_t$ = the weighted mean absolute size of price changes from month $t-1$ to month $t$.

These monthly values are across-item means. The category weights are unpublished BLS weights for 1995 based on the BLS consumer expenditure survey.
## Table 2

Variance Decompositions (using all prices)

<table>
<thead>
<tr>
<th>Sample</th>
<th>Number of observations per month</th>
<th>Including substitutions</th>
<th>Excluding substitutions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>TDP term</td>
<td>SDP terms</td>
</tr>
<tr>
<td><strong>TOP 3 AREAS</strong></td>
<td>13,194</td>
<td>90%</td>
<td>10%</td>
</tr>
<tr>
<td>New York</td>
<td>5,691</td>
<td>91</td>
<td>9</td>
</tr>
<tr>
<td>Los Angeles</td>
<td>4,459</td>
<td>85</td>
<td>15</td>
</tr>
<tr>
<td>Chicago</td>
<td>3,044</td>
<td>90</td>
<td>10</td>
</tr>
<tr>
<td><strong>TOP 5 AREAS</strong></td>
<td>16,989</td>
<td>90</td>
<td>10</td>
</tr>
<tr>
<td>Philadelphia</td>
<td>1,657</td>
<td>106</td>
<td>-6</td>
</tr>
<tr>
<td>San Francisco</td>
<td>2,017</td>
<td>86</td>
<td>14</td>
</tr>
<tr>
<td><strong>Food</strong></td>
<td>28,800</td>
<td>93</td>
<td>7</td>
</tr>
</tbody>
</table>

**Notes:** All samples go from February 1988 through April 2003, except the * samples, which only go through December 1997. The number of observations per month includes substitutions. See equation (2) in the text for the definition of the TDP term and the SDP terms. All data is from the CPI-RDB.
## Table 3

Variance Decompositions (using regular prices)

<table>
<thead>
<tr>
<th>Sample</th>
<th>Number of observations per month</th>
<th>Including substitutions</th>
<th>Excluding substitutions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>TDP term</td>
<td>SDP terms</td>
</tr>
<tr>
<td>TOP 3 AREAS</td>
<td>13,084</td>
<td>90%</td>
<td>10%</td>
</tr>
<tr>
<td>New York</td>
<td>5,645</td>
<td>83%</td>
<td>17%</td>
</tr>
<tr>
<td>Los Angeles</td>
<td>4,425</td>
<td>87%</td>
<td>13%</td>
</tr>
<tr>
<td>Chicago</td>
<td>3,014</td>
<td>87%</td>
<td>13%</td>
</tr>
<tr>
<td>TOP 5 AREAS *</td>
<td>16,876</td>
<td>87%</td>
<td>13%</td>
</tr>
<tr>
<td>Philadelphia *</td>
<td>1,646</td>
<td>98%</td>
<td>2%</td>
</tr>
<tr>
<td>San Francisco *</td>
<td>2,006</td>
<td>83%</td>
<td>17%</td>
</tr>
<tr>
<td>Food</td>
<td>28,632</td>
<td>86%</td>
<td>14%</td>
</tr>
</tbody>
</table>

Notes: All samples go from February 1988 through April 2003, except the * samples, which only go through December 1997. The number of observations per month includes substitutions. See equation (2) in the text for the definition of the TDP term and the SDP terms. All data is from the CPI-RDB.
Table 4
Cross-Correlations

<table>
<thead>
<tr>
<th>Sample</th>
<th>Variable</th>
<th>( \pi )</th>
<th>( fr )</th>
<th>( fr^+ )</th>
<th>( fr^- )</th>
</tr>
</thead>
<tbody>
<tr>
<td>TOP 3 AREAS</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All prices</td>
<td>( fr )</td>
<td>0.09</td>
<td>0.99</td>
<td>0.04</td>
<td>0.53</td>
</tr>
<tr>
<td></td>
<td>( dp )</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Regular prices</td>
<td>( fr )</td>
<td>0.12</td>
<td>0.98</td>
<td>0.03</td>
<td>0.53</td>
</tr>
<tr>
<td></td>
<td>( dp )</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FOOD</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All prices</td>
<td>( fr )</td>
<td>0.17</td>
<td>1.00</td>
<td>0.14</td>
<td>0.53</td>
</tr>
<tr>
<td></td>
<td>( dp )</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Regular prices</td>
<td>( fr )</td>
<td>0.19</td>
<td>0.98</td>
<td>0.09</td>
<td>0.37</td>
</tr>
<tr>
<td></td>
<td>( dp )</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Samples run from February 1988 through April 2003. All data is from the CPI-RDB. The entries are correlations across time of the monthly values of the variables. The monthly values are defined as follows:

\( \pi_t \) = the weighted mean inflation rate from month \( t-1 \) to month \( t \).
\( fr_t \) = the weighted mean fraction of items with changing prices from month \( t-1 \) to month \( t \).
\( fr^+_t \) = the weighted mean fraction of items with rising prices from month \( t-1 \) to month \( t \).
\( fr^-_t \) = the weighted mean fraction of items with falling prices from month \( t-1 \) to month \( t \).
\( dp_t \) = the weighted mean size of price changes from month \( t-1 \) to month \( t \).

Monthly values are across-item means. The category weights are unpublished BLS weights for 1995 based on the BLS consumer expenditure survey.
Table 5

DKW Economies Simulated

<table>
<thead>
<tr>
<th>DKW Economy</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original Quarterly</td>
<td>Original DKW parameter values.</td>
</tr>
<tr>
<td>Original Monthly</td>
<td>Same parameter values as in “Original Quarterly” except all time-related parameters are converted to monthly rates.</td>
</tr>
<tr>
<td>Calibrated Monthly</td>
<td>Same parameter values as in “Original Monthly” except:</td>
</tr>
<tr>
<td></td>
<td>Productivity drift and monthly standard deviation are chosen to fit the behavior of quarterly U.S. TFP growth from 1988 through 2002;</td>
</tr>
<tr>
<td></td>
<td>Trend money growth and standard deviation are chosen to fit the mean and standard deviation of regular price inflation in the Top 3 areas (regular prices) from Feb 1988 through Apr 2003;</td>
</tr>
<tr>
<td></td>
<td>Menu cost distribution parameters are chosen to fit the mean fraction of items changing their regular prices and the 90% TDP term in the variance decomposition for regular price inflation, both for the Top 3 areas over Feb 1988 through Apr 2003;</td>
</tr>
<tr>
<td></td>
<td>the remaining two parameters of the menu cost distribution are chosen so that the minimal menu cost is zero and the maximal menu cost equals 0.2% of the labor endowment.</td>
</tr>
<tr>
<td>Parameter</td>
<td>Symbol</td>
</tr>
<tr>
<td>-------------------------------</td>
<td>--------</td>
</tr>
<tr>
<td>Preferences</td>
<td></td>
</tr>
<tr>
<td>Annualized discount rate</td>
<td>$R$</td>
</tr>
<tr>
<td>Risk aversion</td>
<td>$\sigma$</td>
</tr>
<tr>
<td>Technology</td>
<td></td>
</tr>
<tr>
<td>Capital share</td>
<td>$\alpha$</td>
</tr>
<tr>
<td>Markup</td>
<td>$\theta^{-1}$</td>
</tr>
<tr>
<td>Shocks</td>
<td></td>
</tr>
<tr>
<td>Money growth:</td>
<td></td>
</tr>
<tr>
<td>Annualized mean</td>
<td>$\mu_m$</td>
</tr>
<tr>
<td>Serial correlation</td>
<td>$\rho_m$</td>
</tr>
<tr>
<td>Error standard deviation</td>
<td>$\sigma_m$</td>
</tr>
<tr>
<td>Productivity growth:</td>
<td></td>
</tr>
<tr>
<td>Annualized mean</td>
<td>$\mu_a$</td>
</tr>
<tr>
<td>Error standard deviation</td>
<td>$\sigma_a$</td>
</tr>
<tr>
<td>Menu cost</td>
<td>$c_1$</td>
</tr>
<tr>
<td></td>
<td>$c_2$</td>
</tr>
<tr>
<td></td>
<td>$c_3$</td>
</tr>
<tr>
<td></td>
<td>$c_4$</td>
</tr>
</tbody>
</table>
### Table 7

Simulations of DKW Economies

<table>
<thead>
<tr>
<th>DKW Economy</th>
<th>(A) Original Quarterly</th>
<th>(B) Original Monthly</th>
<th>(C) Calibrated Monthly</th>
</tr>
</thead>
<tbody>
<tr>
<td># of cohorts, $J$</td>
<td>8</td>
<td>24</td>
<td>16</td>
</tr>
<tr>
<td>Mean fraction of prices changing</td>
<td>20%</td>
<td>6.7%</td>
<td>25%</td>
</tr>
</tbody>
</table>

**Cumulative Absolute Response Differences after a monetary shock:**
- Output: 5.8% (A), 4.8% (B), 0.2% (C)
- Price: 7.4% (A), 6.2% (B), 0.5% (C)

**Variance Decomposition of Inflation:**
- TDP term: 20% (A), 22% (B), 90% (C)
- SDP first-order terms: 41% (A), 37% (B), 3% (C)
- SDP higher order terms: 39% (A), 41% (B), 7% (C)

**Notes:** Means are across 100 simulations. Each simulation consists of equilibrium responses to stochastic disturbances for 61 periods in the quarterly model and 183 periods in the monthly model. Equation (2) in the text, reproduced here, presents the variance decomposition for inflation:

\[
\text{var}(\pi_t) = \text{var}(dp_t) \cdot \bar{fr}_{i_t}^2 + \text{var}(fr_t) \cdot \bar{dp}_{i_t}^2 + 2 \cdot \bar{fr}_{i_t} \cdot \bar{dp}_{i_t} \cdot \text{cov}(fr_t, dp_t) + O_{ij}.
\]
<table>
<thead>
<tr>
<th></th>
<th>Original Monthly</th>
<th>Calibrated Monthly</th>
<th>Top 3 areas (regular prices)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Contemporaneous</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\text{corr} \ (\pi_t, \bar{d}_t)$</td>
<td>0.89 (0.02)</td>
<td>0.98 (0.00)</td>
<td>0.98</td>
</tr>
<tr>
<td>$\text{corr} \ (\pi_t, \bar{f}_t)$</td>
<td>0.93 (0.02)</td>
<td>0.74 (0.02)</td>
<td>0.12</td>
</tr>
<tr>
<td>$\text{corr} \ (\bar{f}_t, \bar{d}_t)$</td>
<td>0.69 (0.05)</td>
<td>0.68 (0.01)</td>
<td>0.03</td>
</tr>
<tr>
<td>$\text{corr} \ (\pi_t,</td>
<td>d_p</td>
<td>_t)$</td>
<td>0.92 (0.01)</td>
</tr>
<tr>
<td>$\text{corr} \ (d_p,</td>
<td>d_p</td>
<td>_t)$</td>
<td>0.99 (0.01)</td>
</tr>
<tr>
<td>$\text{corr} \ (\bar{f}_t,</td>
<td>d_p</td>
<td>_t)$</td>
<td>0.75 (0.05)</td>
</tr>
<tr>
<td><strong>Serial</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\text{corr} \ (\pi_t, \pi_{t-1})$</td>
<td>0.75 (0.07)</td>
<td>0.64 (0.07)</td>
<td>0.20</td>
</tr>
<tr>
<td>$\text{corr} \ (\bar{f}<em>t, \bar{f}</em>{t-1})$</td>
<td>0.68 (0.07)</td>
<td>0.02 (0.08)</td>
<td>0.29</td>
</tr>
<tr>
<td>$\text{corr} \ (d_p, \bar{d}_{t-1})$</td>
<td>0.86 (0.05)</td>
<td>0.70 (0.05)</td>
<td>0.19</td>
</tr>
</tbody>
</table>

**Notes:** For the model economies we report mean values across 100 simulations (and standard deviations across simulations in parentheses). Each simulation consists of equilibrium responses to stochastic disturbances for 183 months. The Top 3 area data spans the 183 months from February 1988 through April of 2003.
Table 9

Simulations of a 1970s DKW Economy

<table>
<thead>
<tr>
<th># of cohorts, J</th>
<th>8</th>
</tr>
</thead>
</table>

*Cumulative Absolute Response Differences*

*after a monetary shock:*

<table>
<thead>
<tr>
<th>Variable</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output</td>
<td>0.4%</td>
</tr>
<tr>
<td>Price</td>
<td>0.5%</td>
</tr>
</tbody>
</table>

*after a productivity shock:*

<table>
<thead>
<tr>
<th>Variable</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output</td>
<td>0.4%</td>
</tr>
<tr>
<td>Price</td>
<td>0.4%</td>
</tr>
</tbody>
</table>

*Variance Decomposition of Inflation:*

<table>
<thead>
<tr>
<th>Component</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>TDP term</td>
<td>96%</td>
</tr>
<tr>
<td>SDP first-order terms</td>
<td>0%</td>
</tr>
<tr>
<td>SDP higher order terms</td>
<td>4%</td>
</tr>
</tbody>
</table>

*Notes:* All parameters are from the Calibrated Monthly DKW economy except for trend and standard deviation of the money growth, which are chosen to match the proportionately higher mean and standard deviation of monthly CPI inflation from January 1970 through December 1979. Means are across 100 simulations (and standard deviations across simulations are in parentheses). Each simulation consists of equilibrium responses to stochastic disturbances for 120 months.
References


