Menu Costs, Multi-Product Firms, and Aggregate Fluctuations[†]

Virgiliu Midrigan[*]

New York University and NBER

August 2008

Abstract

This paper uses scanner price data collected in retail stores to document that (i) although the average magnitude of price changes is large, a substantial number of price changes are small in absolute value and (ii) the distribution of non-zero price changes has fat tails. I present an extension of the standard menu-cost model to a multi-product setting in which firms face economies of scope in the technology of adjusting prices. In contrast to earlier studies (Caplin and Spulber (1987), Golosov and Lucas (2007)), this model, because of its ability to replicate this additional set of micro-economic facts, can generate aggregate fluctuations that are 80% as large as those in time-dependent economies.

JEL classifications: E31, E32.
Keywords: state-dependent pricing, multi-product firms.

[†]I am indebted to George Alessandria, Bill Dupor, Paul Evans, Patrick Kehoe and Mario Miranda for valuable advice and support, as well as Ariel Burstein, Michael Dotsey, Mark Gertler, Narayana Kocherlakota, Ellen McGrattan, Martin Schneider, Ivan Werning, two referees and the editor, Harald Uhlig, for comments and suggestions. I acknowledge the James M. Kilts Center, GSB, University of Chicago, for making the data used in this study available. Any errors are my own.

[*]Department of Economics, New York University, 19 W 4th St., 6th Floor, New York, NY, 10012, virgiliu.midrigan@nyu.edu. (212) 992 8081

1. Introduction

New Keynesian Business Cycle models have received widespread attention in the macroeconomics of the last two decades, both as a tool for business cycle accounting, and as a laboratory that underlies monetary policy discussions. At the heart of these models lies the assumption that individual goods prices are sticky. In theory nominal price stickiness is typically motivated by physical (menu) costs of changing prices. In practice, however, the source of nominal price stickiness is rarely explicitly modeled. Rather, researchers postulate an exogenous pattern of price changes, one in which the likelihood of a price change is independent of the state of the world. Although their micro-foundations are incomplete[1], these, so-called time-dependent, models continue to be widely studied, partly because of their computational simplicity and partly because of the conjecture that they are a good reduced-form approximation to models in which price stickiness arises endogenously from physical adjustment costs[2].

Whether this conjecture is indeed true is still an open question. The predictions of models in which price stickiness arises endogenously, due to menu costs, range from stark monetary neutrality[3] to cases in which the economy is virtually indistinguishable from time-dependent setups[4]. Golosov and Lucas (2007) study the properties of a model with firm-level disturbances capable of matching the fact that the average size of price changes is large in the data. They find that the model produces very little output volatility from monetary shocks. Klenow and Kryvtsov (2005) reach the opposite conclusion. They document that there is little evidence of across-firm

[1]See Bonomo and Carvalho (2005) and the references therein for models of endogenous time-dependent pricing.

[2]Seminal contributions include Barro (1972) and Sheshinski and Weiss (1977, 1983).

[3]Caplin and Spulber (1987), Caballero and Engel (1993), Golosov and Lucas (2007), Gertler and Leahy (2006).

[4]Klenow and Kryvtsov (2005), a version of the model in Gertler and Leahy (2006). See also Burstein (2006), Dotsey, King and Wolman (1999), Danziger (1999), Caplin and Leahy (1991) for studies that explore the consequences of fixed costs of resetting prices.

synchronization in the US price data, contrary to what standard menu cost models predict. A model with time-varying costs of price adjustment as in Dotsey, King, Wolman (1999) that can replicate this feature of the data behaves identically to a time-dependent sticky price model and produces output variability from monetary disturbances similar to that in time-dependent models..

This paper revisits the question of whether menu costs of price adjustment can, in fact, generate a monetary transmission mechanism. I start by documenting several salient micro-economic features that characterize firm pricing behavior using a set of scanner price data collected in grocery stores. In addition to the large magnitude of price changes documented by Klenow and Kryvtsov (2008), I document two additional features of the data. First, a large number of non-zero price changes are small in absolute value. Second, the distribution of price changes, conditional on adjustment, exhibits excess kurtosis.

These facts together imply that there is substantial dispersion in the size of price changes. I show that little of this dispersion is accounted for by permanent differences across products, stores, or time periods in, say, menu costs or the volatility of shocks. Rather, most of this dispersion is evidence that a particular product within a store experiences both small and large price changes, a feature that appears inconsistent with simple menu cost models. Firms that face fixed costs of adjustment only reprice when the losses from not doing so are large, and thus tend to do so by a large amount. As Lach and Tsiddon (2007) argue, however, extensions of the menu-cost model to a multi-product setting in which firms face interactions in the costs of price adjustment of various goods can explain the large number of small price changes. Consider the extreme example of a restaurant whose prices are quoted on a single menu. If a single item on the menu is subject to a idyosincratic disturbance and needs repricing, the restaurant might find it optimal to pay the fixed cost and reprint the menu. Conditional on having paid this fixed cost, changing any other price on the menu is costless: the restaurant will then reprice all its other items, even for products that need small price changes. Indeed, I present evidence that the within-store synchronization observed in the data is at least partly accounted for by economies of scope in the technology of price adjustment.

I next study the properties of a model in which a two-product firm faces a fixed cost of changing its entire menu of prices, but, conditional on paying this cost, zero marginal cost of resetting any given price on the menu. I calibrate the distribution of idiosyncratic marginal cost shocks, the size of the fixed costs of price adjustment, as well as the persistence of the marginal cost processes by requiring the model to accord with the features of the data enumerated above. I find that the model, because of its ability to replicate this additional set of micro-economic facts, can generate aggregate fluctuations from monetary shocks that are 80% as large as in time-dependent economies.

The reason simple menu-cost models generate smaller real effects of money than time-dependent setups is the fact that the identity of adjusters in models with menu costs varies endogenously in response to aggregate disturbances. Most firms that adjust in times of, say, a monetary expansion, are firms whose incentive to increase prices arising from the aggregate shock is reinforced by an idiosyncratic disturbance that triggers a desired price change in the same direction. The money shock thus affects the aggregate price level through two channels: by increasing the desired price change of the adjusting firms, but also by changing the mix of adjusters towards firms whose idyosincratic shocks call for larger price increases. This selection effect is absent in time-dependent models. In menu cost models its strength depends, however, on the mass of firms whose desired price changes lie in the neighborhood of the adjustment thresholds and whose adjustment decision depends on the money shock. I show that accounting for the higher-order moments of the distribution of price changes in the data dampens the strength of this effect considerably.

I proceed as follows. Section 2 discusses the data used in the empirical work, and documents its salient features. Section 3 presents the model economy. Section 4 quantitatively evaluates its performance. Section 5 considers additional variations of the model to evaluate the robustness of my results. Section 6 concludes.

2. Data

I use two sources of publicly available sets of scanner price data, maintained by the Kilts Center for Marketing at the University of Chicago Graduate School of Business[5]. The first dataset was assembled by AC Nielsen and consists of daily observations on the purchasing practices of a panel of households in Sioux Falls (South Dakota) and Springfield (Missouri). I use this household level data to construct a panel of weekly price series spanning almost two years (January 1985 to March 1987), 31 stores and more than 700 products in six different product categories (ketchup, tuna, margarine, peanut butter, sugar, and toilet tissue).

The second source of data is a by-product of a randomized pricing experiment conducted by the Dominick's Finer Foods retail chain in cooperation with the Chicago GSB. Nine years (1989 to 1997) of weekly store level data on the prices of more than 9000 products for 86 stores in the Chicago area are available. The products available in this database range from non-perishable food products (frozen and canned food, cookies, crackers, juices, sodas, beer), to various household supplies (detergents, softeners, bathroom tissue), as well as pharmaceutical and hygienic products.

I discuss in a data appendix several aspects regarding the construction of price series. In particular, I aggregate weekly data into monthly observations in order to calculate statistics that can be used to evaluate the performance of a model economy in which the length of the period is a month. For the Dominick's data, I only use the price of one single store (store 122) that has the largest number of available

[5]The data is available online at http://research.chicagogsb.edu/marketing/databases/index.aspx

observations and was not part of a treatment group during the Dominick's pricing experiment. I report two sets of statistics for the data: for the original price data, as well as for the price changes that are not associated with temporary price discounts (sales).

A. The size and frequency of price changes

Figure 1 presents histograms of the distribution of non-zero price changes, $\log\left(\frac{p_t}{p_{t-1}}\right)$, for the two sets of data. I report these separately for the Dominick's and AC Nielsen data, as well as for all price changes and non-sale price changes. I truncate these distributions, by eliminating those price changes that are greater than 100% in absolute value, in order to ensure that results are not driven by outliers. A price change is defined as any change in the price that is greater or equal to 1 cent (in absolute value). This figure, as well as all the statistics reported below, weigh each product (upc) by its revenue share. Superimposed on each histogram is the density of a Gaussian distribution with the same mean and variance as that of the distribution of price changes. Table 1 reports moments of these distributions, again computed using the truncated sample of observations. Several facts emerge in the data.

Fact 1: A large number of price changes are small in absolute value.

Consistent with the evidence presented by Klenow and Kryvtsov (2008), the average size of price changes is large, although less so if one filters out temporary discounts[6]: stores in the AC Nielsen data adjust prices by 19% on average (15% for regular price changes), while those in Dominick's sample do so by 17% (9% for regular price changes). Notice however, in Figure 1, that a large number of price changes are close to zero. I compute two statistics that capture the fraction of small price changes: the fraction of price changes that are less than half (a quarter) of the mean size of price changes. Roughly 30%-40% of price changes in both datasets are below

[6]The volatility of individual goods' prices has also been documented for countries other than the US. See Dhyne et. al (2005) for a survey of findings from studies of European micro-price data.

half the mean. Similarly, 12-24% of price changes are smaller than a quarter of the mean. For example, in the AC Nielsen data, 12% of regular price changes are less than 3.75% (1/4 of 15%) in absolute value and 34% of price changes are less than 7.5% (1/2 of 15%) in absolute value.

Fact 2: The distribution of price changes exhibits excess kurtosis.

Notice in Figure 1, that the number of price changes in the vicinity of zero is greater than that predicted by a normal distribution, while the tails are somewhat fatter. As Table 1 indicates, the kurtosis of the distribution of price changes ranges from 4 to 8, depending on the dataset and on whether sales are filtered, and thus larger than that of a Gaussian distribution[7].

Facts 1 and 2 together imply that there is much dispersion in the size of price changes. In fact, as Table 1 reports, the standard deviation of the absolute value of log price changes, $|\Delta p|$ is roughly equal to the mean size of price changes. The 25th percentile of this distribution ranges from 3% (non-sale price changes in the Dominick's data) to 8% (all price changes in AC Nielsen data), while the 75th percentile is much larger and ranges from 11% (non-sale, Dominick's) to 26% (all price changes, AC Nielsen).

I next establish that little of this dispersion in the size of price changes is accounted for by permanent differences across products, stores or time-periods. To do so, I use variance decompositions in which I gauge the importance of month, product[8], and store-specific effects in explaining the variability of the magnitude and frequency of price changes reported above. Specifically, I estimate

$$y_{it}^s = c + d_i + d_s + d_t + e_{it}^s$$

[7] Kurtosis is defined as the ratio of the fourth central moment to the square of the variance. The kurtosis of the Gaussian according to the convention I employ is then equal to 3.

[8] The number of non-zero price changes for a given product is small in Dominick's data in which I use only one store's observations. I therefore estimate product-category×manufacturer, as opposed to individual good effects for this dataset.

where d_i, d_s, d_t are good, store, and month-specific effects and y_{it}^s is the size of price changes, $|\Delta \log(p_{ist})|$ As Table 2a indicates, month or store-specific heterogeneity accounts for less than 10% of the variation in the size of price changes in the data. Good-specific effects are somewhat more volatile, but nevertheless responsible for less than 15% of the variation in the sample. This evidence suggests that models with permanent differences across products or stores in menu costs, the volatility of shocks, etc., will not be able to entirely match the dispersion in the size of price changes in the data[9].

One other way to show that permanent differences in the size of price changes account for little of these results is to compute, in the spirit of Klenow and Kryvtsov (2008), moments of the "standardized" distribution of price changes. In particular, I rescale each price change by each upc's mean size of (non-zero) price changes (across time-periods, and stores in case of the AC Nielsen data) $\overline{\Delta p_{ist}} = \frac{\Delta p_{ist}}{mean_i(|\Delta p_{ist}|)}$. By construction, this data is free of good-specific differences in the average size of price changes. Nevertheless, as Table 2b shows, the distribution of "standardized" price changes exhibits kurtosis (ranging from 3 to 4.5, i.e. somewhat less than the distribution of raw price changes), dispersion (the coefficient of variation ranges from .68 to .84, again slightly lower than for raw prices), and small price changes (24% to 34% of price changes are less than half the mean in absolute value, 10%-17% are less than a quarter of the mean). I will use these moments, rather than those in Table 1, as targets for the model of the next section that will abstract from permanent heterogeneity in the size of price changes across products.

Table 3 presents an additional set of facts on the frequency and serial correlation of price changes. It has been widely documented[10] that prices in retail stores adjust frequently. The two datasets I employ here are no exception. The frequency

[9] Klenow and Kryvtsov (2008) reach a similar conclusion in their study of the BLS data.
[10] Kackmeister (2005), Dutta, Bergen and Levy (2002).

of price changes is 0.36 per month in the AC Nielsen data and 0.23 in the Dominick's data. These numbers imply that on average prices change every 2.8 and 2.2 months, respectively. The frequency of regular price changes is somewhat lower, once every 4 (4.4) months. Table 3 also reports the serial correlation of (log) prices in a) all adjacent periods with available price data and b) only in those periods in which prices do change[11]. I report the average (and standard deviation in parantheses) of these autocorrelations across products. Although nominal rigidities do impart some serial correlation unconditionally, the autocorrelation in prices in adjusting periods only is much smaller, in the neighborhood of 0 for all price changes, and 0.05 to 0.32 for regular price changes.

B. Discussion

I have documented two features of the distribution of price changes that, I will argue, are important for understanding the real effects of money implied by menu-cost models: (i) a large number of price changes are small, and (ii) the distribution of price changes is leptokurtic. None of these features of the data I study are unique to grocery stores.

Klenow and Kryvtsov (2008) report that 40% of price changes are less than 5% in absolute value in their dataset of BLS-collected price data covering all goods and services used in the construction of the CPI, a dataset in which prices change by 9.5% on average. They also show that heterogeneity in the size of price changes across sectors is, alone, insufficient to account for this large number of small price changes. Kashyap (1995) uses a dataset of prices for products sold in retail catalogues and also documents that many price changes are small: 44% of price changes in his dataset are less than 5% in absolute value. The kurtosis of price changes, conditional on adjustment, is 15.7 in the data. Kackmeister (2005) reports that one-third of price

[11] I report the serial correlation of the series p_τ where τ are the dates at which the price changes.

changes are less than 10% in absolute value in an environment where the average magnitude of price changes is 20% in a study of prices in retail stores.

The large dispersion in the size of price changes documented above, and especially the large number of small price changes, appears difficult to reconcile with the menu-cost explanation for price stickiness. With menu costs of price adjustment, firms only reprice when the need for a price change is sufficiently large to warrant paying the menu cost. This implies that price changes are typically large in absolute value and concentrated near the firms' adjustment thresholds, the (s,S) bands.

Several remedies are available to bring the menu cost model's predictions closer in line with the large number of small price changes in the data. One might assume time-varying adjustment costs as in Caballero and Engel (1999) and Dotsey, King and Wolman (1999). Alternatively, as Kashyap (1995) has suggested, one might allow fluctuations in the degree of market power possessed by firms, arising from variation in consumer search costs over time[12]. A more recent paper by Woodford (2008) stresses the role of costs of acquiring and processing information as the reason why price setters may choose to undertake small price changes even in the presence of physical adjustment costs.

The mechanism I focus on in this paper is one of economies of scope in the price adjustment technology of multi-product firms. Lach and Tsiddon (2007)[13] have recently argued and presented evidence that economies of scope may account for the fact that some individual price changes are small. Levy et. al (1997) present direct evidence of economies of scope in price adjustment in grocery stores. Appendix 2 presents additional evidence to document the presence of economies of scope. I show that price changes in narrow product categories within a store are synchronized. Moreover, although most price changes in a given period tend to be of the same

[12]See also Benabou (1992).

[13]See also Sheshinski and Weiss (1992), who study the properties of multi-product price setters with interactions in the technology of price adjustment.

sign, the average price change of the bundle of goods that experience adjustment is significantly smaller than the average price change of individual products. Finally, I present direct empirical support for the key implication of models with economies of scope. Namely, I show that the hazard of a good's price change depends not only on that good's desired price change (proxied by changes in costs and the deviation of the good's price from that of its competitors), but also on the desired price change of other goods within a store. It is this dependence of a good's price adjustment decision on the desired price change of other goods that the model of the next section will capture. By explicitly modeling the source of the small price changes, as opposed to relying on the more popular alternative of time-varying random menu costs to account for them, I impose an extra degree of discipline on the model in order to quantify the strength of the selection effect. Clearly this effect is smaller and the real effects of money are greater, if the menu cost is purely random.

3. The Model

A. Model Economy

Throughout, let s_t denote the event realized at time t, $s^t = \{s_0, s_1, ..., s_t\}$ the history of events up to this period and $\Pr(s^t)$ the probability of a particular history as of time 0. The economy is populated by a continuum of consumers and a continuum of monopolistically competitive firms, both of mass 1. Consumers are identical, while firms (indexed by z) differ according to their productivity level. Each firm sells two products, indexed by $i = 1, 2$. I discuss the problem of the representative consumer, that of the firm, and then define an equilibrium for this economy.

Consumers

Consumers' preferences are defined over leisure and a continuum of imperfectly substitutable goods. The consumer sells part of her time endowment to the labor market and invests her wealth in one-period shares in firms. In equilibrium, identical consumers own equal shares of all the economy's firms. The representative consumer's problem is to choose, given prices, how to allocate her income across the different goods available for consumption and how much to work:

$$\max_{\{c^1(z;s^t),c^2(z;s^t)\},n(s^t)} \sum_{t=0}^{\infty} \beta^t \sum_{s^t} \Pr(s^t) U(c(s^t), n(s^t)),$$

subject to

$$\int_0^1 [P^1(z,s^t)c^1(z,s^t) + P^2(z,s^t)c^2(z,s^t)]\, dz = W(s^t)n(s^t) + \Pi(s^t),$$

where

$$c(s^t) = \left(\int_0^1 \left(\tfrac{1}{2} c^1(z,s^t)^{\frac{\gamma-1}{\gamma}} + \tfrac{1}{2} c^2(z,s^t)^{\frac{\gamma-1}{\gamma}} \right)^{\frac{\gamma}{\gamma-1}\frac{\theta-1}{\theta}} dz \right)^{\frac{\theta}{\theta-1}}$$

is an aggregator over the different varieties of goods that the household consumes, $n(s^t)$ is the supply of labor, $W(s^t)$ the nominal wage rate, $\Pi(s^t)$ the profits the consumer receives from her ownership of firms, $P^1(z,s^t)$ and $P^2(z,s^t)$ are the prices of each good. I assume that the elasticity of substitution across goods produced by the same firm, γ, is higher than the elasticity of substitution across firms, θ.

Firms

Firms produce output using a technology linear in labor:

$$y^i(z,s^t) = a^i(z,s^t) l^i(z,s^t),\ i = 1,2,$$

where the firm's technology, $a^i(z,s^t)$, evolves according to

$$\log a^i(z,s^t) = \rho_a \log a^i(z,s^{t-1}) + \varepsilon^i(z,s^t),\ i = 1,2,$$

and $\varepsilon^i(z,s^t) \in [\varepsilon_{\min}, \varepsilon_{\max}]$ is a random variable, uncorrelated across firms and time-periods, but correlated across goods produced by a given firm, as described below. Firms operate along their consumers' demand schedules, derived as solutions to the consumer's problem discussed above:

$$c^i(z,s^t) = \left(\frac{P^i(z,s^t)}{P(z,s^t)}\right)^{-\gamma} \left(\frac{P(z,s^t)}{P(s^t)}\right)^{-\theta} c(s^t),$$

where $P(s^t)$ is the price index in this economy, defined as a consumption-weighted average of the prices of all firm in this economy:

$$P(s^t) = \left(\int_0^1 P(z,s^t)^{1-\theta} dz \right)^{\frac{1}{1-\theta}}, \ P(z,s^t) = \left[\tfrac{1}{2} P^1(z,s^t)^{1-\gamma} + \tfrac{1}{2} P^2(z,s^t)^{1-\gamma} \right]^{\frac{1}{1-\gamma}}$$

I assume that firms face fixed menu costs of resetting prices. Any time at least one of the two prices change, the firm must hire κ additional units of labor. I assume economies of scope in price adjustment by letting this fixed cost be independent of the number of prices that the firm changes. This assumption makes it optimal for the firm to adjust its prices simultaneously and is the key dimension along which this model differs from earlier studies of menu-cost models. Let $q(s^t) = \beta^t \frac{U_c(c(s^t),n(s^t))}{U_c(c(s^0),n(s^0))}$, where U_c is the marginal utility of consumption, denote the t-period stochastic discount factor. The firm's problem is to maximize

$$\sum_{t=0}^{\infty} \sum_{s^t} \Pr(s^t) q(s^t) \pi(z,s^t),$$

where

$$\pi(z,s^t) = \sum_{i=1,2} \left(\frac{P^i(z,s^t)}{P(z,s^t)} \right)^{-\gamma} \left(\frac{P(z,s^t)}{P(s^t)} \right)^{-\theta} \left(\frac{P^i(z,s^t)}{P(s^t)} - \frac{W(s^t)}{a^i(z,s^t)P(s^t)} \right) c(s^t)$$
$$-\kappa \frac{W(s^t)}{P(s^t)} \mathcal{I}_{P^1(z,s^t) \neq P^1(z,s^{t-1}) \ or \ P^2(z,s^t) \neq P^2(z,s^{t-1})},$$

and $\mathcal{I}$ is an indicator function. The last term of this expression is the increase in the firm's wage bill if it decides to adjust any of its two prices. Notice that in the frictionless economy with $\kappa = 0$ the non-separability of the two firm prices in the profit function has no effect on the optimal pricing rule. The optimal frictionless price for one good is $P^i(z,s^t) = \frac{\theta}{\theta-1} \frac{W(s^t)}{a^i(z,s^t)}$ and independent of the technology with which the firm produces the second good or the elasticity of substitution across the two goods, γ. [14]

[14]In the dynamic economy with menu costs, the envelope condition used to derive this optimal price schedule no longer holds and a good's optimal price increases in the deviation of the second good's price from its optimum as long as $\gamma > \theta$.

B. Equilibrium

I introduce money by assuming that nominal spending must be equal to the money stock:

$$\int_0^1 \sum_{i=1,2} P^i(z,s^t)c^i(z,s^t)dz = M(s^t)$$

The money supply growth rate $\mu(s^t) = \frac{M(s^t)}{M(s^{t-1})}$ evolves over time according to an AR(1) process:

$$\log \mu(s^t) = \bar{\mu} + \rho_\mu \log \mu(s^{t-1}) + \eta(s^t),$$

where η is an iid $N(0,\sigma_\eta^2)$ disturbance. The equilibrium is a collection of prices and allocations: $P^i(z,s^t), W(s^t), P(s^t), c^i(z,s^t), c(s^t), n(s^t), l^i(z,s^t), y^i(z,s^t)$ such that, taking prices as given, consumer and firm allocations as well as firm prices solve the consumer and firm problems, respectively, and the labor, goods, and money markets clear.

C. Computing the Equilibrium

I normalize all nominal variables by the money stock in the economy, e.g., $p(s^t) = \frac{P(s^t)}{M(s^t)}$, in order to render the state-space of this problem bounded. Let $p^i_{-1}(z,s^t) = \frac{P^i(z,s^{t-1})}{M(s^t)} \in \mathcal{P}$ be a firm's (normalized) old price and $\mathcal{A} = [\frac{\varepsilon_{\min}}{1-\rho_a}, \frac{\varepsilon_{\max}}{1-\rho_a}]$ the support of the distribution of technology levels in the economy. The aggregate state of this economy is an infinite-dimensional object, consisting of the growth rate of money $\mu(s^t)$, and the endogenously varying joint distribution of last period's firm prices and technology levels. Let $\boldsymbol{\phi}$: $\mathcal{P}^2 \times \mathcal{A}^2 \rightarrow [0,1]$ denote this distribution and $\mathbf{\Gamma}$ it's law of motion: $\boldsymbol{\phi}' = \mathbf{\Gamma}(\mu,\boldsymbol{\phi})$. Finally, let $\mathbf{a} = (a^1, a^2)$ be a vector of a firm's technology levels and $\mathbf{p}_{-1} = \left(p^1_{-1}, p^2_{-1}\right)$ collect the firm's last period's (normalized) nominal prices. Let $V^a(\mathbf{a};\mu,\boldsymbol{\phi})$ and $V^n(\mathbf{p}_{-1},\mathbf{a};\mu,\boldsymbol{\phi})$ denote a firm's value of adjusting and not adjusting its nominal prices, as a function of its old prices and current technology, as well as the aggregate state of the economy. These two functions satisfy the following system of functional equations:

$$V^a(\mathbf{a};\mu,\boldsymbol{\phi}) = \max_{\mathbf{p}} \left(\pi(\mathbf{p};\mu,\boldsymbol{\phi}) - \kappa\frac{w}{p} + \beta \int \frac{U_c\prime}{U_c} V(\mathbf{p}'_{-1},\mathbf{a}';\mu\prime,\boldsymbol{\phi}\prime) dF(\varepsilon^1,\varepsilon^2,\eta) \right)$$

$$V^n(\mathbf{p}_{-1},\mathbf{a};\mu,\boldsymbol{\phi}) = \pi(\mathbf{p}_{-1};\mu,\boldsymbol{\phi}) + \beta \int \frac{U_c\prime}{U_c} V(\mathbf{p}'_{-1},\mathbf{a}';\mu\prime,\boldsymbol{\phi}\prime) dF(\varepsilon^1,\varepsilon^2,\eta),$$

where $\pi(\mathbf{p};\mu,\boldsymbol{\phi})$ denotes firm's (real) profits, gross of the adjustment cost, $V = \max(V^a, V^n)$ is the firm's value function and $\mathbf{p}$ is a vector of nominal prices the firm chooses every time it adjusts. The laws of motion for the state variables are:

$$\boldsymbol{\phi}\prime = \boldsymbol{\Gamma}(\mu,\boldsymbol{\phi}), a^{i\prime} = a^{i\rho_a}\exp\left(\varepsilon^i\right), \mu\prime = \mu^{\rho_\mu}\exp(\eta), p^{i\prime}_{-1} = \begin{cases} \frac{p^i}{\mu'} \text{ if adjust} \\ \frac{p^i_{-1}}{\mu'} \text{ otherwise} \end{cases}$$

The unknowns in this problem are the following functions: $V^a()$, $V^n()$, $c()$, $w()$, $p()$, $\boldsymbol{\Gamma}()$. To solve this system of functional equations, I follow an approach developed by Krusell and Smith (1998).[15] That is, I restrict the aggregate-state space to μ, the growth rate of the money stock, and ϕ_1, the mean of (log) past prices (normalized by the current stock of money and technology level), $\phi_1 = mean_{i,z}\left(\log(p^i_{-1}a^i)\right)$. Intuitively, ϕ_1 measure the average deviation of firm prices from their frictionless optimum. Aggregate variables are assumed to be log-linear functions of these two state variables, e.g., $\log(p) = \varsigma_0 + \varsigma_1 \log\mu + \varsigma_2\,\phi$.

Given a guess for the coefficients in these log-linear functions, I solve the firm's problem using projection methods[16]. I then simulate firm decision rules and use the simulated data to re-estimate the coefficients in the postulated aggregate functions. These updated coefficients are used to recompute firm decision rules. Once these coefficients converge the distance between actual (in simulations) and predicted (by

[15] See also Klenow and Willis (2006) and Khan and Thomas (2007) for applications of this approach to models with non-convexities.

[16] See Miranda and Fackler (2002) for a detailed description of these methods as well as a toolkit of routines that greatly facilitate their implementation.

the coefficients in the aggregate functions) aggregate time-series is insignificant: (the out-of-sample forecasts have an R^2 in excess of 99%), suggesting that higher-order moments of $\boldsymbol{\phi}$ would add little precision.

The existence and continuity of V^a, V^n and V can be established using standard theorems (Stokey and Lucas (1989)). Although these value functions are not concave, it can be shown that they satisfy $\kappa-$concavity, a property introduced by Scarf (1959), which guarantees uniqueness of the optimal price functions. Aguirregabiria (1999) proves $\kappa-$concavity in the context of a model similar to the one presented here in which the two control variables are each subject to a fixed cost of adjustment. Sheshinski and Weiss (1992) study a special case of the economy presented here and also prove uniqueness of the optimal decision rules.

4. Quantitative Results

A. Calibration and Parametrization

I parameterize the utility function as

$$U(c,n) = \log(c) - \psi n.$$

This specification follows Hansen (1985) by assuming indivisible labor decisions implemented with lotteries. I set the length of the period to one month, and therefore choose a discount factor $\beta = .997$. I choose ψ to ensure that in the absence of aggregate shocks households supply 1/3 of their time to the labor markets. I choose $\theta = 3$, a number in the range of estimates of demand elasticities available in the retail industry[17]. I set $\gamma = 11.5$, a number from Broda and Weinstein (2007) who estimate within-brand elasticities using scanner price data.

As for the process characterizing the evolution of the money stock, I follow Chari Kehoe and McGrattan (2002) and postulate an AR(1) process for the growth rate of money, $\log \mu(s^t) = \bar{\mu} + \rho_\mu \log \mu(s^{t-1}) + \eta(s^t)$. I allow for persistence in the

[17] Nevo (1997), Barsky et. al. (2000), Chevalier, Kashyap and Rossi (2003).

growth rate of money given that most applied work assumes persistence in monetary policy[18]. I calibrate the coefficients in the money growth rule by first projecting the growth rate of M1 on current and 24 lagged measures of monetary policy shocks[19] I then fit an AR(1) process for the fitted values in this regression and obtain an autoregressive coefficient of $\rho_\mu = 0.61$ and standard deviation of residuals of $\sigma_\eta = 0.0018$. I relax the assumption of inertia in the money growth rule in the robustness section below.

The rest of the parameters are calibrated to allow the model to match the micro-price facts documented in the earlier section. I assume that the firm draws a pair of productivity shocks $\tilde{\varepsilon}_t^i$ that are drawn from the following mixture:

$$\tilde{\varepsilon}_t^i = \begin{cases} -b_t^i \sigma_\varepsilon, & \text{with} \quad \text{prob} = \frac{1}{2} \\ b_t^i \sigma_\varepsilon, & \text{with} \quad \text{prob} = \frac{1}{2} \end{cases}$$

where b_t is an iid random variable drawn from a Beta distribution with parameters α_1 and α_2. The distribution of technology shocks is thus symmetric around zero, and flexible enough to enable the model to reproduce the distributional features of the data. Given that the support of the Beta distribution is 0 to 1, σ_ε is an upper bound on the technology shock the firm can draw. To allow for correlation across the two productivity shocks within a given firm, I assume that the actual productivity shocks of the firm, ε_t^i, depend on the underlying draws as follows: $\varepsilon_t^i = \tilde{\varepsilon}_t^i + \chi mean(\tilde{\varepsilon}_t^1, \tilde{\varepsilon}_t^2)$, where χ is a parameter that governs the correlation of productivity shocks across the two goods.

[18]Christiano, Eichenbaum and Evans (2005) report that the growth rate of money increases persistently in response to an (identified) exogenous monetary policy shock and postulate a process for μ_t that is well approximated by an AR(1) with a (quarterly) persistence coefficient of 0.5. Alternatively, Smets and Wouters (2007) assume an interest rate rule and also find evidence of inertia: their estimate of the coefficient on lagged interest rates in the interest rate rule is 0.8.

[19]The results reported below use a new measure of shocks due to Romer and Romer (2004) available for 1969-1996. I have also used the measure used by Christiano, Eichenbaum and Evans (2005) and find very similar results. I thank Oleksiy Kryvtsov for sharing the CEE (2005) data with me.

The seven parameters that I calibrate are $\bar{\mu}$ - the parameter governing the mean growth rate of money, κ – the size of the fixed costs incurred by the firm when it changes its menu of prices, ρ_a – the parameter that governs the persistence of marginal cost shocks, χ– the parameter governing the correlation of productivity shocks across goods within a firm, α_1 and α_2 – the two parameters governing the shape of the Beta distribution, as well as σ_ε – the parameter governing the volatility of idiosyncratic productivity shocks.

I choose these parameters in order to match the salient properties of the micro-price data discussed in Section 2. In particular, the criterion function is the sum of the squared % deviation of eight moments in the model from the data. To compute moments in the data, I take a simple average of the moments calculated for the two datasets, Dominick's and AC Nielsen, which are reported in the left column of Table 4. I choose to target the moments of the sale-unrelated price changes (the columns to the right in Tables 1-3) for comparison with earlier work that filters out sales from the definition of price changes. I return to the issues of sales in the next section.

To summarize, I target a frequency of price changes of 0.24 per month, a mean price change of 0.1%, a mean size of price changes of 12%, serial correlation of prices of 0.65, standard deviation of price changes of 9%, fraction of price changes smaller (in absolute value) than half the mean of 0.28, fraction of price changes less than 1/4 the mean of 0.12, and a kurtosis of 4. The last four moments are those of the "standardized" distribution of price changes in the data that I have reported in Table 2b.

B. Results

Benchmark Model

Table 5 reports the calibrated parameter values used in the model (column I, Benchmark). Table 4 reports the moments in the model (column I, Benchmark) and the data (left-most column). The additional columns in these tables refer to additional experiments I discuss below. Table 4 shows that the Benchmark model is fairly successful at matching the targets in the data. In particular, the model generates the dispersion in the size of price changes, including the fraction of small price changes and the kurtosis of the distribution of price changes.

The growth rate of money is slightly positive, $\bar{\mu} = 0.024\%$. The price adjustment cost, κ, is equal to 1.11% of a firm's steady-state revenues. This number is close to that reported by Levy et. al. (1997) in a study of the price adjustment costs of five large supermarkets. Productivity shocks are fairly transitory: $\rho_a = 0.47$ and strongly correlated across the two goods: $\chi = 1.131$. This number implies a correlation of productivity shocks within a firm of 2/3. As in the data I discuss in the Appendix, stores tend to change their prices in the same direction: the fraction of times the two price changes within a store have the same sign is 91%. Intuitively, the model requires fairly correlated cost shocks to simultaneously account for all 4 measures of dispersion I target, including the kurtosis and fraction of small price changes. Too little correlation across products would generate too many small price changes for a given level of kurtosis. Finally, and most crucially, the distribution of raw technology shocks, $\tilde{\varepsilon}_t^i$ is highly leptokurtic and very dispersed ($\alpha_1 = 0.046$, $\alpha_2 = 1.057$, $\sigma_a = 0.298$). The implied kurtosis of actual technology shocks, ε_t^i, is around 19.

I next turn to the model's aggregate implications. My measures of real effects of money are the volatility and persistence of Hodrick and Prescott (1997) (HP)-filtered output. For comparison, I also report results from a Calvo-type time-dependent model, identical in all respects to the original model, in which firms adjust with constant probability λ, chosen to match the frequency of price changes in the data. In the (log-linearized approximation to the) Calvo model the distribution of idiosyncratic cost shocks plays no role[20] and the law of motion for aggregate consumption is:

$$\log c_t = \lambda \log c_{t-1} + \lambda \frac{(1-\beta\rho_\mu)}{(1-\lambda\beta\rho_\mu)} \log \mu_t$$

Table 6 (Calvo and Benchmark (I) column) report the results. The menu-cost model generates business cycle fluctuations from monetary disturbances that are 4/5 as large as of those in the Calvo setup: 0.17% vs. 0.21%. Business cycles are equally persistent in the two models: the autocorrelation of output is equal to 0.90 and 0.88 respectively. Thus, in contrast to the findings of Caplin and Spulber (1987), Caballero and Engel (1993), Dotsey, King and Wolman (1999) and Golosov and Lucas (2007), the implications regarding the behavior of output in my menu cost economy are not too dissimilar from those of Calvo (1983).

No scope economies and Gaussian shocks (Golosov-Lucas 2007)

I next illustrate that these results are accounted for by the ability of the benchmark model to account for the dispersion in the size of price changes. To do so, I solve a version of the economy with menu costs similar to that studied in Golosov and Lucas (2007). This economy differs from the one I describe above along two dimensions. First, I assume no economies of scope in price adjustment: firms sell one good each and pay a fixed cost κ for each price change. Second, I assume that technology shocks are drawn from a Gaussian distribution with standard deviation σ_ε. To illustrate the role of the higher-order moments I document, I choose the four parameters in this economy (menu cost, persistence of technology shocks, mean growth rate of money, standard deviation of technology shocks) to match only four targets in the data: the

[20] I have checked the accuracy of the log-linear approximation by solving the firm's problem using non-linear spline approximations to the firm's value. The results I obtain using the two different approximationt techniques are very similar.

mean price change, the mean size of a price change, the serial correlation of prices, and the frequency of price changes. These are reported in Table 4 and 5, respectively, in column II.

Notice in Table 4 that this economy does a poor job at matching the untargeted higher-order moments. It generates no small price changes, too little kurtosis (1.4 vs. 4 in the data) and too little dispersion in the size of price changes (0.03 vs. 0.09 in the data). In Figure 2 I plot a histogram of the distribution of price changes, conditional on adjustment, for the Benchmark model and the model with no scope economies and Gaussian shocks. Clearly, the Benchmark model mimics the pattern in the data in Figure 1 much more closely.

Table 6 (column II) reports the two measures of real effects of money I use for this parameterization of the menu cost model. The standard deviation of output is equal to 0.05 in this economy, that is, roughly 1/4 of that predicted by Calvo. Given that in all these economies a quantity-theory equation, $M = Pc$, holds, the lack of output variability is a direct consequence of the responsiveness of the aggregate level, P, to a monetary shock. Figure 3 plots impulse responses of prices and aggregate consumption in the three different economies (Calvo, Benchmark and the economy with no scope economies and Gaussian shocks, referred to as GL). In the Golosov-Lucas (2007) –type calibration, the aggregate price level responds almost one-for-one to the change in the money growth rate and hence the consumption response is small. In contrast, in the Benchmark model the price response is not too dissimilar from that of the Calvo model and the consumption response is substantially larger than in the GL case.

C. Discussion

I trace the finding that the benchmark economy produces real effects of money similar to those of Calvo to two differences between the economy studied here and those in earlier studies that find opposite results. First, the economy I study features little synchronization of price changes in response to monetary shocks. To see this, I compute a statistic due to Klenow and Kryvtsov (2008), $IM = \frac{var(dp_t)\overline{fr}^2}{var(\pi_t)}$ that quantifies the importance of the Intensive Margin (variation in dp_t, the mean price change conditional on adjustment, as opposed to fr_t, the fraction of price changes) in accounting for the variability of inflation, $\pi_t = dp_t \times fr_t$. This statistic, reported in Table 6, is equal to 0.99 in the benchmark calibration (0.91 as reported by Klenow and Kryvtsov (2008) in the US data), suggesting little variation in the fraction of price changes in the economy I study. Although the fraction of price changes does co-move with inflation, (the correlation between fr_t and π_t is 0.36 in the model, vs. 0.25 in the data), it moves too little to contribute much to the flexibility of the aggregate price level. Notice that the Golosov and Lucas (2007)-type economy also features little synchronization ($IM = 0.99$ and the correlation of the fraction of price changes with inflation is 0.44). In both of these economies idiosyncratic shocks are large and adjustment decisions are driven mostly by idiosyncratic, rather than aggregate shocks.

A second difference between my economy and earlier studies of state-dependent pricing is the smaller role played by what Golosov and Lucas (2007) refer to as the *selection effect* and Caballero and Engel (2007) refer to as the *extensive margin effect.* The endogenous timing of price changes implies that the mix of adjusters varies with the aggregate shock in menu costs models: in times of a monetary expansion adjusters are mostly firms whose idiosyncratic state is such that they need to raise prices. The strength of this effect critically depends on the shape of the distribution of desired price changes and on the shape of the adjustment hazard.

To see this, consider the following heuristic example[21]. Let $f(x)$ be the distribution of desired price changes of firms in the economy: $x = \log\left(\frac{p^*}{p_{-1}}\right)$, absent a money shock in the current period, and $h(x)$ be the adjustment hazard of firms of

[21] This discussion closely follows Caballero and Engel (2007) as well as Burstein and Hellwig (2008).

type x. Assume, for simplicity, that a money shock has a one-for-one effect on the firm's desired price (more on this below). A firm's desired price change, given the money shock, is therefore $x + \Delta m$, where Δm is the monetary disturbance. Given that the money shock shifts the adjustment hazard to $h(x + \Delta m)$, the effect Δm has on the price level in this economy is:

$$\Delta p = \int_x f(x) \left(h(x + \Delta m) - h(x)\right) x dx + \Delta m \int_x f(x) h(x + \Delta m) dx \qquad (1)$$

The second term in this expression is the intensive margin through which the money shock affects the price level: the fraction of adjusting firms times the size of the monetary disturbance. The first term captures the selection effect. A positive monetary shock, $\Delta m > 0$ shifts the adjustment hazard: firms that need price increases ($x > 0$) are now more likely to adjust as the total desired price change is higher. Firms that need price decreases are less likely to adjust. This positive correlation between the change in hazard and the initial desired price change magnifies thus the effect the money shock has on Δp. Clearly, the selection effect is stronger the more mass there is in the region in which $\left(h(x + \Delta m) - h(x)\right) x$ is largest.

Figure 4 plots the adjustment hazard and the ergodic distribution of desired price changes in the Benchmark model (left panel), as well as in the GL-type calibration (right panel). The more fat-tailed ergodic distribution in the Benchmark calibration has less mass in the region of sharply rising hazard. Moreover, the absolute value of x is lower in the Benchmark model in the region in which $f(x) \left(h(x + \Delta m) - h(x)\right)$ is largest. Figure 5 plots the distribution of price changes conditional on adjustment, $h(x)f(x)$, in an economy with no money shock (upper panels) and in an economy with positive monetary disturbance (lower panel). The Figure shows that the monetary shock has a disproportionately large effect on the distribution of price changes in the Golosov and Lucas (2007)-type calibration.

Caballero and Engel (2007) suggest the following measure of the strength of the selection effect. Taking the limit of (1) as $\Delta m \rightarrow 0$, the response of the aggregate price leve to a money shock is

$$\frac{\Delta p}{\Delta m} = \int_x f(x)h'(x)xdx + \int_x f(x)h(x)dx$$

The second term in this expression, the fraction of price changes, is equal to 0.24 in the two calibrations. As for the first term, measuring the selection effect, it is equal to 0.22 in the Benchmark model, and 0.46 in the GL-type calibration. Thus, although selection acts to double the flexibility of the aggregate price level in the Benchmark setup, it triples it in the model with no scope economies and Gaussian shocks.

These numbers, although instructive, do not accurately measure the role of selection as they are computed from the ergodic distribution of desired price changes and ignore dynamic considerations. For example, notice in Figure 3 that the elasticity of the aggregate price level to the money shock is not too dissimilar in the Benchmark and GL-type calibrations in the first period of the shock; the largest discrepancy is in future periods after the distribution of desired price changes has shifted. The numbers above are thus, although informative about the instantaneous response of the price level to a money shock, more difficult to map into the effect of selection on the inertia of the price level.

To gauge the role of selection in the model, I therefore resort to the following two counterfactual experiments In the first experiment, I use policy rules optimal in the Benchmark model but assume that the adjustment hazard is independent of the firm's state and constant over time. This counterfactual most closely corresponds to the Calvo setup, but differs from Calvo in that it uses the policy rules that are optimal in the original menu cost economy. In the second exercise I maintain the assumption of a hazard independent of x, but allow the fraction of adjusters to vary as in the original simulations of the menu-cost model. The two bottom rows of Table 6 report the standard deviation of HP-filtered output in these two experiments. These experiments show that using a flat adjustment hazard raises the standard deviation of ouput by about 40% in the Benchmark setup. In contrast, the standard deviation of output rises by about 550% in the GL setup. Fluctuations in the fraction of adjusting firms play, as noted earlier, little role.

The role of selection is not the sole difference between the Calvo and the menu-cost models: the two economies also differ in the optimal response of adjusting firms to a given monetary shock. Given inertia in monetary policy, firms front-load expected future increase in the money stock by raising it above their frictionless optimum. As Figure 6 shows, Calvo firms do so more strongly than firms in the benchmark model. Unlike a firm in a menu-cost setup, a Calvo-type firm has no control over the timing of its price changes: its losses from having its price deviate from the optimum increase faster with the price deviation. These price differences account for the smaller gap between the real effects of money predicted by the model with menu costs and Calvo than suggested by the counterfactual exercises. [22].

To conclude, I have shown above that the aggregate implications of economies with menu costs are sensitive to the shape of the distribution of price changes in the economy. If the distribution of price changes fluctuates excessively from periods of high inflation to periods of low inflation, as in the GL-type calibration, the few firms that do adjust prices impart considerable flexibility to the aggregate price level. In Figure 7 I plot the distribution of non-zero price changes in periods of positive and negative inflation in the scanner price data. Clearly, these figures are more in line

[22]Dotsey, King and Wolman (1999) also point out this difference in the optimal price functions of time- and state-dependent firms.

with those in the Benchmark model.

D. Fat-tailed shocks or economies of scope?

I next ask, can fat-tailed shocks and economies of scope, on their own account for the dispersion in the size of price changes in the data, as well as the other higher-order moments? What are the aggregate implications of each of these two mechanisms in isolation? To this end I eliminate each of these two individual features, one at a time, and recalibrate the model to match the moments in the micro-data.

Scope economies, Gaussian shocks

Here I assume multi-product firms but Gaussian shocks to productivity. I calibrate the 5 parameter values in this economy (all those in the Benchmark economy, except the 2 parameters characterizing the Beta distribution) to match the same 8 moments that were targeted in the Benchmark economy. Tables 4 and 5 (column III) present the parameter values and fit of the model. Matching the same set of moments as earlier requires a) much larger menu costs, b) somewhat less persistent productivity shocks, and c) substantially less correlation (0.24 vs. 0.66 earlier) in productivity shocks across the two goods produced by a given firm. As expected, the kurtosis of price changes is now much smaller in this economy than in the data (1.91 vs. 4 in the data). Nevertheless, the model does fairly well at matching the dispersion in the size of price changes (0.07 vs. 0.09 in the data).

In Table 6 I report the measures of real effects of money in this model. The standard deviation of output is now 0.10, double that in the Golosov-Lucas (2007) type calibration without scope economies, but half that of the Calvo model. Moreover, fluctuations in output are somewhat less persistent. As the counterfactual experiments described above indicate, the selection effect is now weaker than in the GL setup: in its absence output fluctuations would be only 2.4 times more volatile.

No scope economies, Fat-tailed shocks

Here I assume single-product firms, but maintain the assumption of flexible shocks drawn from the mixture of Betas. As above, I calibrate the relevant parameter values to match the 8 moments in the data. This model misses the fraction of very small price changes (no price changes are less than 3% in absolute value (1/4 of the mean)), but matches all other moments as well as the Benchmark model, by imposing a very small cost of price adjustment (0.26% of revenue, or 1/4 of that in the Benchmark setup). Given that productivity shocks are extremely fat-tailed, with most mass near 0, and also because money shocks are very small (as I target the VAR-based innovations), large menu costs are not needed in this model to prevent firms from adjusting infrequently.

Table 6 reports the real effects of money predicted by this version of the menu-cost model. The standard deviation of output is slightly smaller than in the Benchmark calibration (0.14% vs. 0.17%), an artifact of a somewhat stronger selection effect.

5. Additional Experiments

I next perform an additional set of experiments to gauge the sensitivity of the results above to several modifications to the model. In particular, I study 1) a calibration with no persistence in the growth rate of money that matches the relatively low serial correlation of food price inflation, 2) a version of the economy in Kehoe and Midrigan (2008) in which I allow for temporary price cuts that frequently revert to their pre-existing level, 3) an economy in which I replace the fat-tailed shocks with uniformly distributed shocks that arrive infrequently, according to a Poisson process, and 4) an economy with intermediate inputs that features strategic complementarities and thus a lower responsiveness of real marginal cost to output. All these economies are re-calibrated to match the same set of micro moments I targeted earlier. To conserve on space, I report the fit of these models and the parameter values used in the online appendix in Tables A5 and A6.

A. No monetary policy inertia

Here I assume a serially uncorrelated process for the growth rate of the money supply. In particular, I attempted to match the serial correlation of price inflation in the food retail sector[23], of 0.31, and its standard deviation of 0.26%. It turns out that the menu-cost model cannot deliver this low degree of serial correlation of inflation even with a serial correlation of money growth shocks of 0. I thus set $\rho_\mu = 0$ and choose the volatility of money shocks ($\sigma_\eta = 0.52\%$), together with all other parameters in the model, to match the micro-moments, together with the standard deviation of inflation in the food retail sector. The implied serial correlation of inflation in this economy is 0.36, slightly higher than the 0.31 in the data. Table 7a shows that in this case the Calvo model generates output fluctuations that are 1.6 times larger than those in the Benchmark model and 3.3 times more volatile than those in the GL-type setup. This increase in the gap between the predictions of the Calvo and Benchmark model reflects the absence of differences in the price functions of the two types of firms as it is no longer optimal to front-load. Moreover, the extensive margin is now more volatile (as aggregate shocks are larger): the variation of inflation due to the intensive margin is 0.96 (0.99 earlier). Finally, notice also that the selection effect is somewhat stronger now in the Benchmark setup and weaker in the Golosov-Lucas-type calibration. These numbers are now much more in line with the Caballero-Engel (2007) measures of the role of the extensive margin described above.

[23] Table 2AUI, line 60, in the BEA Underlying Detail Sector.

B. Sales

Here I use a variant of the economy studied in Kehoe and Midrigan (2007, 2008) that allows the model to match the large number of sale-related price changes in the data. For simplicity I abstract now from economies of scope in price adjustment: as shown above this omission is not crucial for matching most of the microeconomic pricing facts nor for the economy's aggregate predictions. The technology for changing prices is as follows. The firm enters the period, taking as given its current regular price, p_{t-1}^R. The firm has the option to sell at this price in period t at no extra cost. Alternatively, the firm can pay a menu cost, κ^R, to change its regular price to p_t^R. This is also the price the firm will inherit next period. Finally, the firm has the option of a temporary price change. A temporary price change costs κ^T units of labor and entitles the firm to charge a price, p_t^T, that is different from its current regular price, p_{t-1}^R. This is a temporary price change in that paying κ^T does not alter the firm's regular price. Absent any additional intervention, the firm's price reverts from p_t^T to p_{t-1}^R next period. Although mechanical, these assumptions on the technology of price adjustment allow the model to replicate the frequent returns of temporary price changes to their pre-existing level.

Formally, the firm's problem is now:

$$V^r(p_{-1}^R, a; \mu, \boldsymbol{\phi}) = \max_{p^R} \left(\pi(p^R; \mu, \boldsymbol{\phi}) - \kappa^R \frac{w}{p} + \beta \int \frac{U_{c'}}{U_c} V(p_{-1}^{R\prime}, a'; \mu\prime, \boldsymbol{\phi}\prime) dF(\varepsilon, \eta) \right)$$

$$V^t(p_{-1}^R, a; \mu, \boldsymbol{\phi}) = \max_{p^T \le p_{-1}^R} \pi(p^T; \mu, \boldsymbol{\phi}) - \kappa^T \frac{w}{p} + \beta \int \frac{U_{c'}}{U_c} V(p_{-1}^{R\prime}, a'; \mu\prime, \boldsymbol{\phi}\prime) dF(\varepsilon, \eta),$$

$$V^n(p_{-1}^R, a; \mu, \boldsymbol{\phi}) = \pi(p_{-1}^R; \mu, \boldsymbol{\phi}) + \beta \int \frac{U_{c'}}{U_c} V(p_{-1}^{R\prime}, a'; \mu\prime, \boldsymbol{\phi}\prime) dF(\varepsilon, \eta),$$

where $V = \max(V^r, V^t, V^n)$ is the firm's value, V^r is the value of exercising the option to have a regular price change, V^t the value of a temporary price change, and

V^n the value of inaction. The laws of motion for exogenous states are specified as earlier. The law of motion for the regular price is $p_{-1}^{R\prime} = p^R/\mu'$ if the firm exercises the option to adjust its regular price, and $p_{-1}^{R\prime} = p_{-1}^R/\mu'$ if the firm exercise the inaction option or if it has a temporary price change. Also, note above that the firm is only allowed to charge a temporary price that is lower than its pre-existing regular price, p_{-1}^R. Again, this is a mechanical feature introduced to match the pattern of price changes in the data. Kehoe and Midrigan (2008) relax this assumption. Inspecting the problem above, it is clear, that conditional on exercising the option of a temporary price change, the firm charges its static optimum, $p^T = \frac{\theta}{\theta-1}\frac{w}{a}$, as long as this does not violate the $p^T \leq p_{-1}^R$ constraint.

The workings of this economy are discussed in detail in Kehoe and Midrigan (2007). In particular, the firm chooses to exercises its option of a temporary price change if it expects the deviation of its pre-existing regular price from the optimum to be temporary (as when this deviation is caused by a temporary increase in productivity). In contrast, the firm exercises the option of a regular price change when it expects the deviation to be more permanent (as if triggered by a series of monetary policy shocks). In this latter case the firm is better off paying a one-time cost κ^R to change its regular price, than a series of κ^T costs to cover the deviation using a series of temporary price changes. Because of the $p^T \leq p_{-1}^R$ constraint, the firm must use a regular price change to respond to a negative productivity shock that triggers a desired price increase.

I choose to calibrate this economy to match the same set of facts as earlier, but now target the moments of the distribution of all (standardized) price changes, including sales (the first columns of Table 1 and Table 2b). In particular, the mean size of price changes is now higher (18% vs. 12% earlier), and so is its standard deviation (14% vs. 9% earlier). All other moments are fairly similar. In addition, I calibrate this economy to match the frequency of all price changes (40% per month), the frequency of regular price changes (24%), as well as two additional moments that Kehoe and Midrigan (2008) emphasize: the fraction of times a sale returns to the pre-existing price (64%) and the likelihood a sale ends next period conditional on there being a sale today (75%). These moments, in the model and the data, are presented in A5.II. In Table A6.II I report the parameters of the model that best match these moments. Again, with fat-tailed shocks alone menu costs need to be fairly small in order to match the micro facts. Note also that the cost of a regular price change is twice as large as that of a temporary price change.

I compare the standard deviation predicted by this setup to that of a GL-type calibration in which I match all moments listed above, excluding the higher-order moments of the distribution of price changes. I also compare the predictions of this economy to those of a Calvo version of the economy with sales in which with probability α_R a firm is allowed a regular price change, and with probability α_T the firm is allowed a temporary price change (after which, absent additional events, i.e., with probability $(1 - \alpha_T - \alpha_R)$, it reverts to its old regular price, $p_{R,t-1}$). I choose α_R and α_T to match the frequency of regular price changes and temporary price cuts in the menu-cost model. The details of the Calvo-type economy with sales are described in Kehoe and Midrigan (2008). Here I simply note that in this environment aggregate consumption evolves according to

$$c_t = -\alpha_R A \left(\mu_t - \alpha_T \mu_{t-1}\right) + (1 - \alpha_R - \alpha_T)\mu_t + (1 - \alpha_R)\, c_{t-1}$$

where $A = \frac{(1-\alpha_T-\alpha_R)\beta}{1-\alpha_T\beta}\frac{\rho_\mu}{1-(1-\alpha_R)\beta\rho_\mu}$. Ignoring front-loading considerations (captured by a non-zero ρ_μ and therefore A), this equation says that the persistence of c_t is governed by the frequency of regular price changes, α_R, while the instantaneous effect of a money shock on output is governed by the frequency of both regular and temporary changes, as both types of changes allow the firm respond to the money shock.

In Table 7b I report the aggregate implications of these economies. These are clearly not too dissimilar from those in the setup that abstracts from sales and is calibrated to the frequency of regular price changes. Whereas the real effects of money are somewhat smaller when sales are explicitly accounted for, the relative magnitudes of real effects in the three economies are similar. The intuition for these results comes from Kehoe and Midrigan (2008). Sales-related price changes are special because they typically revert to their pre-existing level. Thus, even though a price cut does respond to the change in monetary policy, it does so only for a short period as the initial response is offset the next time the price returns to its pre-existing value[24].

C. Poisson arrival of idiosyncratic shocks

The distribution of idiosyncratic shocks used above to match the microeconomic features of the data is non-standard. The large mass in the neighborhood of 0 and rapid decline away from 0 suggests that this distribution may be well approximated with a more familar one in which firms are subject to a Poisson arrival of shocks.This is the route taken by Gertler and Leahy (2006) who show that the flexibility of the aggregate price level is reduced if only a subset of firms in the economy are subject to idiosyncratic shocks in any given period.

In this exercise I again assume away economies of scope in price adjustment. The process for a firm's productivity is again $\log a_t(z) = \rho_a \log a_{t-1}(z) + \varepsilon_t(z)$. I assume now that $\varepsilon_t(z) = 0$ with probability τ and a random draw from a uniform distribution, $U[-\sigma_\varepsilon, \sigma_\varepsilon]$ with probability $1 - \tau$. I then recalibrate this economy by

[24]Kehoe and Midrigan (2008) show that this intuition holds in a much richer setting that accounts for the frequency of regular and temporary price changes, the duration of temporary price cuts, the frequency with which these return to the pre-existing price, the average size and dispersion of price changes, as well as the fact that sales account for a disproportionately large share (35%) of units sold. In particular, they show that calibrating simple menu-cost models to the frequency of price changes excluding sales overstates the real effects of money by 40%. In contrast, calibrating simple menu-cost models to the frequency of all price changes, including sales, understates the real effects of money by 500%.

choosing τ and σ_ε, in addition to all other parameters, to match the same set of moments targeted in the Benchmark setup earlier.

Table A5.III in the online appendix illustrates that this economy is somewhat less successful at matching the higher-order moments in the data. In particular, it generates a kurtosis of price changes that is smaller than in the data (3.1 vs. 4). Table A6.III shows that τ is equal to 0.905, consistent with the extreme degree of kurtosis needed in the more flexible specification earlier. Finally, Table 7c shows that the real effects of money in this economy are slightly greater than those in the economy with fat-tailed shocks and no scope economies studied earlier: the volatility of output is 0.17% (0.14%) earlier. This is an outcome of the fact that the density of desired price changes decays faster away from 0 and thus has less mass in the region of increasing hazard.

D. Intermediate inputs

The economy studied above lacks many ingredients currently used in monetary models of the business cycle, including capital, variable factor utilization, strategic complementarities in price setting, adjustment costs on factors of production, as well as nominal wage and intermediate input price rigidites.[25] I abstract from these additional factors in order to isolate the role of self-selection and understand the micro-economic properties of menu-cost models calibrated to match the micro-economic features of the price data. I next extend my analysis to include what is arguably a key feature of current monetary models: factors that dampen the elasticity of real (economy-wide) marginal cost to (economy-wide) output. Although measuring this elasticity is difficult in practice and numbers used in recent work range from 0.10-0.15 (Woodford 2003) and 0.33 (Dotsey and King 2002) to 2.25 (Chari Kehoe and McGrattan 2002), it is widely acknowledged that this elasticity is central to the ability

[25] Christiano, Eichenbaum, Evans (2005), Smets and Wouters (2007).

of current New Keynesian monetary models to account for the observed inertia in the effects of monetary policy.

Notice that in the economy studied earlier my assumptions on preferences ensure an elasticity of real marginal cost $\left(\frac{W}{P}\right)$ to output of unity, given that the labor-leisure choice gives $\frac{W(s^t)}{P(s^t)} = \psi C(s^t)$. I next assume that firms use, in addition to labor, materials as factors of production. This roundabout production structure as in Basu (1995) and more recently Nakamura and Steinsson (2008) generates strategic complementarities in price setting. I assume that firm z produces output using

$$y(z,s^t) = a\left(z,s^t\right) l(z,s^t)^{1-s_m} m\left(z,s^t\right)^{s_m}$$

Here $m(z,s^t)$ denotes a composite of the intermediate goods purchased from all other firms:

$$m(z,s^t) = \left(\int_0^1 m_i(z,s^t)^{\frac{\theta-1}{\theta}} di\right)^{\frac{\theta}{\theta-1}}$$

The resource constraint for output produced by firm z is now:

$$y(z,s^t) = c(z,s^t) + \int_0^1 m_i(z,s^t)di$$

so that part of the firm's output is used in consumption, and part by each individual producer as intermediate goods. Cost minimization implies that the (real) cost of producing $y(z,s^t)$ units of output is

$$(1-s_m)^{s_m-1}\, s_m^{-s_m} \frac{y(z,s^t)}{a(z,s^t)} \left(\frac{W\left(s^t\right)}{P(s^t)}\right)^{1-s_m}$$

I set $s_m = \frac{2}{3}$ so that the elasticity of real marginal cost to output is $\frac{1}{3}$, as in Dotsey and King (2002). Given the markup, this implies a materials share of 44%, in line with the data.

The higher-order moments of the distribution of price changes are little affected by this addition to the model, as it affects the response of prices to monetary shocks, which in my baseline calibration are small. I thus use the same parameter values as those used in the earlier calibration of the economy with no scope economies and fat-tailed shocks in Table 5. Table 7d presents the aggregate implications of this economy. Clearly, adding strategic complementarities raises the implied real effects of money (measured here, as earlier, by the standard deviation of HP-filtered real value added, i.e, aggregate consumption, $c(s^t)$) in all models, but more so in the menu-cost economies. The standard deviation of aggregate consumption in the economy with fat-tailed shocks is now 0.29%, i.e., 85% of that in the Calvo model. This finding mimics that of Gertler and Leahy (2006) who find that adding strategic complementarities in price adjustment bridges the gap between the aggregate implications of the Calvo and menu-cost models. Based on this result I conjecture that adding additional features currently employed in estimated business cycle monetary models would not alter the conclusions obtained in the simple model above about the strength of the selection effect in menu-cost models calibrated to match the higher-order moments of the price data.

6. Conclusion

This paper shows that standard state-dependent pricing models are inconsistent with two features of the microeconomic price data: the large number of small price changes and kurtosis of price changes in the data. An economy with economies of scope in price adjustment and a more flexible specification of the distribution of firm-level uncertainty is shown to be able to account for these higher-order moments of the data. I find that in this economy the flexibility of the aggregate price level to monetary shocks is considerably reduced, an artifact of a smaller role played by endogenous fluctuations in the identity of adjusting firms (the selection effect).

Economies of scope in price adjustment are not the sole mechanism that can bridge the gap between the predictions of menu-cost models and the micro data. Informational frictions at the firm[26] or consumer level[27], time-varying demand elasticities[28], or adjustment costs[29] have been argued to play a role as well. Recent work by Caballero and Engel (2007) and Woodford (2008) suggests however that the results I obtain here are robust in settings in which alternative assumptions generate a distribution of price changes similar to that observed in the data.

An important question that I leave unanswered in this paper is, What are the sources of retail price variation? Nakamura (2008) presents evidence that much of this variation is retail, rather than the manufacturer-specific. Netherveless, she also reports that observed variation in costs and demand at the retail level accounts for little of the variation in prices observed in the data. This leaves room for strategic interactions in price setting[30], inventory management[31], intertemporal price discrimination[32], to name a few, as a potential for a more structural source of the firm-level uncertainty taken as given here and in earlier studies of state-dependent pricing. Studying the role of these additional mechanisms in accounting for the dynamics of prices at the firm and aggregate level remains an exciting area of future research.

[26]Woodford (2008).
[27]Chen et. al (2008)
[28]Benabou (1992), Kashyap (1995).
[29]Dotsey, King and Wolman (1999). Caballero-Engel (1999).
[30]Varian (1980)
[31]Aguirregabiria (1999), Khan and Thomas (2008), Kryvtsov and Midrigan (2008),
[32]Conlisk, Gerstner and Sobel (1984)

References

[1] Aguirregabiria, Victor, 1999, "The Dynamics of Markups and Inventories in Retailing Firms," Review of Economic Studies, 66(2): 275-308

[2] Barro, Robert, 1972, "A Theory of Monopolistic Price Adjustment," Review of Economic Studies, 39(1): 17-26

[3] Barsky, Robert, Mark Bergen, Shantanu Dutta, and Daniel Levy, 2000, "What Can the Price Gap Between Branded and Private Label Products Tell Us About Markups?," mimeo

[4] Basu, Shantanu, 1995, "Intermediate Goods and Business Cycles: Implications for Productivity and Welfare," American Economic Review, 85(3): 512-531

[5] Benabou, Rolland, 1992 "Inflation and Efficiency in Search Markets,"Review of Economic Studies, 59(2): 299-329

[6] Bonomo, Marco and Carlos Viana de Carvalho, 2005, "Endogenous Time-Dependent Rules and Inflation Inertia," forthcoming, Journal of Money, Credit and Banking

[7] Broda, Christian and David Weinstein, 2007, "Product Creation and Destruction," NBER Working Paper 13041

[8] Burstein, Ariel, 2006, "Inflation and Output Dynamics with State-Dependent Pricing Decisions," Journal of Monetary Economics, 53(7): 1235-1257

[9] Burstein, Ariel and Christian Hellwig 2007, "Prices and Market Shares in a Menu Cost Model," mimeo

[10] Caballero, Ricardo and Eduardo Engel, 1993 "Heterogeneity and Output Fluctuations in a Dynamic Menu-Cost Economy," Review of Economic Studies, 60(1): 95-119

[11] Caballero, Ricardo and Eduardo Engel, 1999 "Explaining Investment Dynamics in US Manufacturing: A Generalized (S,s) approach," Econometrica, 67(4): 783-826

[12] Caballero, Ricardo and Eduardo Engel, 2007 "Price Stickiness in Ss models: New Interpretations of Old Results," Journal of Monetary Economics, 54: S100-121

[13] Calvo, Guillermo, 1983, "Staggered Prices in a Utility-Maximizing Framework," Journal of Monetary Economics, 12(3): 383-398

[14] Caplin, Andrew and Daniel Spulber, 1987, "Menu Costs and the Neutrality of Money," Quarterly Journal of Economics, 102(4): 703-725

[15] Caplin, Andrew and John Leahy, 1991, "State-Dependent Pricing and the Dynamics of Money and Output," Quarterly Journal of Economics,106(3): 683-708

[16] Cecchetti, Stephen, 1986, "The Frequency of Price Adjustment: A Study of the Newsstand Prices of Magazines," Journal of Econometrics, 31(3): 255-274

[17] Chari, V.V., Patrick Kehoe and Ellen McGrattan, 2002, "Can Sticky Price Models Generate Volatile and Persistent Real Exchange Rates?" Review of Economic Studies, 69: 533-563

[18] Chen, Haipeng, Daniel Levy, Sourav Ray, Mark Bergen, 2008, "Asymmetric Price Adjustment in the Small," Journal of Monetary Economics, 55: 728-737

[19] Chevalier, Judith, Anil Kashyap and Peter Rossi, 2003, "Why Don't Prices Rise During Periods of Peak Demand? Evidence from Scanner Data," American Economic Review, 93(1): 15-37

[20] Christiano, Lawrence, Martin Eichenbaum and Charles Evans, 2005, "Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy," Journal of Political Economy, 113(1): 1-45

[21] Conlisk, John, Eitan Gerstner, and Joel Sobel, 1984 "Cyclic Pricing by a Durable Goods Monopolist," Quarterly Journal of Economics, 99(3): 489-505

[22] Danziger, Leif, 1999, "A Dynamic Economy with Costly Price Adjustments," American Economic Review, 89(4): 878-901

[23] Dhyne, Emmanuel, et. al., 2005, "Price Setting in the Euro Area. Some Stylized Facts from Individual Consumer Price Data," ECB working paper

[24] Dotsey, Michael and Robert King, 2002, "Pricing, Production and Persistence," NBER Working Paper 8407

[25] Dotsey, Michael, Robert King and Alexander Wolman, 1999, "State-Dependent Pricing and the General Equilibrium Dynamics of Money and Output," Quarterly Journal of Economics, 114(2): 655-690

[26] Dutta, Shantanu, Mark Bergen and Daniel Levy, 2002, "Price flexibility in channels of distribution: Evidence from Scanner Data," Journal of Economic Dynamics and Control

[27] Fisher, Timothy, and Jerzy Konieczny, 2000, "Synchronization of Price Changes by Multi-Product Firms: Evidence from Canadian Newspaper Prices," Economic Letters, 68: 271-277

[28] Gertler, Mark and John Leahy, 2006, "A Phillips Curve with an Ss Foundation," NBER Working Paper 11971

[29] Golosov, Mikhail, and Robert E. Lucas, Jr, 2007, "Menu Costs and Phillips Curves," Journal of Political Economy, 115(2): 171-199

[30] Hansen, Gary, 1985, "Indivisible Labor and the Business Cycle," Journal of Monetary Economics, 16(3): 309-327

[31] Hoch, Stephen, Xavier Dreze and Mary E Purk, 1994, "EDLP, Hi-Lo, and Margin Arithmetic," Journal of Marketing, 58: 16-27

[32] Hodrick, Robert and Edward Prescott, 1997, "Post-War US Business Cycles: An Empirical Investigation," Journal of Money, Credit and Banking, 29(1): 1-16

[33] Hosken, Daniel and David Reiffen, 2004, "Patterns of Retail Price Variation," Rand Journal of Economics, 35(1): 128-146

[34] Kackmeister, Alan, 2005, "Yesterday's Bad Times are Today's Good Old Times: Retail Price Changes in the 1890s Were Smaller, Less Frequent, and More Permanent," Finance and Economics Discussion Series, Federal Reserve Board

[35] Kashyap, Anil, 1995, "Sticky Prices: New Evidence From Retail Catalogues," Quarterly Journal of Economics, February, 245-274

[36] Kehoe, Patrick and Virgiliu Midrigan, 2007, "Sales and the Real Effects of Monetary Policy," mimeo

[37] Kehoe, Patrick and Virgiliu Midrigan, 2008, "Temporary Price Changes and the Real Effects of Monetary Policy," mimeo

[38] Khan, Aubhik and Julia Thomas, 2007, "Inventories and the Business Cycle: An Equilibrium Analysis of (S,s) Policies," American Economic Review, 97(4): 1165-1188

[39] Khan, Aubhik and Julia Thomas, 2008, "(S,s) inventories, State-Dependent Pricing and the Propagation of Nominal Shocks," mimeo

[40] Klenow, Peter and Oleksiy Kryvtsov, 2005, "State-Dependent or Time-Dependent Pricing: Does it Matter for Recent US Inflation?" Bank of Canada Working Paper

[41] Klenow, Peter and Oleksiy Kryvtsov, 2008, "State-Dependent or Time-Dependent Pricing: Does it Matter for Recent US Inflation?" forthcoming, Quarterly Journal of Economics

[42] Klenow, Peter and Jonathan Willis, 2006, "Real Rigidities and Nominal Price Changes," FRB Kansas City Working Paper 06-03

[43] Kryvtsov, Oleksiy and Virgiliu Midrigan, 2008, "Inventories, Markups and Real Rigidities in Menu Cost Models," mimeo

[44] Krusell, Per and Anthony Smith, 1998, "Income and Wealth Heterogeneity in the Macroeconomy", Journal of Political Economy, 106(5): 867-896

[45] Lach, Saul and Daniel Tsiddon, 2007, "Small Price Changes and Menu Costs," Managerial and Decision Economics, 28: 649-656

[46] Lach, Saul and Daniel Tsiddon, 1996, "Staggering and Synchronization in Price-Setting: Evidence from Multiproduct Firms," American Economic Review, 86(5): 1175-1196

[47] Lazear, Edward, 1986, "Retail Pricing and Clearance Sales," American Economic Review, 76: 14-32

[48] Levy, Daniel, Mark Bergen, Shantanu Dutta, and Robert Venable, 1997, "The Magnitude of Menu Costs: Direct Evidence from Large US Supermarket Chains," Quarterly Journal of Economics, 112(3): 781-826

[49] Miranda, Mario and Paul Fackler, 2002, "Applied Computational Economics and Finance," MIT press

[50] Nakamura, Emi, 2008, "Pass-Through in the Retail and Wholesale," American Economic Review, 98(2), 430-437

[51] Nakamura, Emi and Jon Steinsson, 2008, "Monetary Non-Neutrality in a Multi-Sector Menu Cost Model," mimeo

[52] Nevo, Aviv, 1997, "Measuring Market Power in the Ready-to-Eat Cereal Industry," Econometrica, 69(2): 265-306

[53] Peltzman, Sam, 2000, "Prices Rise Faster Than They Fall," Journal of Political Economy, 108(3): 466-502

[54] Romer, Christina and David Romer, 2004, "A New Measure of Monetary Shocks: Derivation and Implications," American Economic Review, September, 1055-1084

[55] Scarf, Herbert, 1959, "The Optimality of (S,s) Policities in the Dynamic Inventory Problem," in K. Arrow, S. Karlin, and P. Suppes (eds.), Mathematical Methods for the Socials Sciences, 196-202

[56] Sheshinski, Eytan and Yoram Weiss, 1977, "Inflation and Costs of Price Adjustment," Review of Economic Studies, 44(2): 287-303

[57] Sheshinski, Eytan and Yoram Weiss, 1983, "Optimum Pricing Policy Under Stochastic Inflation: the Multi-Product Monopoly Case," Review of Economic Studies, 59: 331-359

[58] Sheshinski, Eytan and Yoram Weiss, 1992, "Staggered and Synchronized Price Policies UnderInflation," Review of Economic Studies, 50(3): 513-529

[59] Stokey, Nancy, and Robert E. Lucas Jr., 1989, "Recursive Methods in Economic Dynamics," Harvard University Press

[60] Smets, Frank and Rafael Wouters, 2007, "Shocks and Frictions in US Business Cycles. A Bayesian DSGE Approach," ECB Working Paper 722

[61] Varian, Hal, 1980, "A Model of Sales," American Economic Review, 70(4): 651-659

[62] Warner, Elizabeth and Rober Barsky, 1995, "The Timing and Magnitude of Retail Store Markdowns: Evidence from Weekends and Holidays," Quarterly Journal of Economics, 110(2): 321-352

[63] Woodford, Michael, 2003, "Interest and Prices: Foundations of a Theory of Monetary Policy," Princeton University Press

[64] Woodford, Michael, 2008, "Information-Constrained State-Dependent Pricing," mimeo

[65] Zbaracki, Mark, Mark Ritson, Daniel Levy, Shantanu Dutta, and Mark Bergen, 2004 "Managerial and Customer Costs of Price Adjustment: Direct Evidence from Industrial Markets," Review of Economics and Statistics, 86(2): 514-533

Table 1: Distribution of price changes conditional on adjustment

	AC Nielsen		Dominick's	
Δp	all Δp	non-sale Δp	all Δp	non-sale Δp
mean	-0.008	-0.005	0.003	0.007
std. dev.	0.25	0.20	0.24	0.13
kurtosis	4.14	5.37	4.8	8.5
|Δp|				
mean	0.19	0.15	0.17	0.09
std. dev.	0.16	0.13	0.17	0.10
25% prctile	0.08	0.06	0.04	0.03
75% prctile	0.26	0.19	0.24	0.11
fraction changes <1/2 mean	0.34	0.34	0.42	0.41
fraction changes <1/4 mean	0.12	0.12	0.24	0.19
# obs.	23976	16325	128513	50591

Notes:
1. p is the natural logarithm of a store's price
2. Statistics are weighted by revenue share of each upc, excluding obs. with |Δp|>100%

Table 2a: Fraction of variance accounted for by ex-ante heterogeneity

	AC Nielsen		Dominick's	
Size of price changes	all Δp	non-sale Δp	all Δp	non-sale Δp
store	0.07	0.10	-	-
product	0.15	0.14	0.15	0.13
month	0.02	0.02	0.02	0.04

Table 2b: Distribution of "standardized" price changes conditional on adjustment

	AC Nielsen		Dominick's	
Size of price changes	all Δp	non-sale Δp	all Δp	non-sale Δp
std(|Δp|)/mean(|Dp|)	0.68	0.72	0.84	0.81
kurtosis(Δp)	3.0	3.6	4.1	4.5
fraction changes <1/2 mean	0.24	0.25	0.34	0.31
fraction changes <1/4 mean	0.10	0.10	0.17	0.14

Notes: Fraction of variance attributed to store/product/month fixed effects reported.
Observations weighted by revenue share of each product
Product category x manufacturer, as opposed to upc-specific effects used in anova analysis in Dominick's data

Table 3: Frequency of price adjustment and persistence

	AC Nielsen		Dominick's	
	all Δp	non-sale Δp	all p	regular p
fraction of price changes	0.36	0.25	0.45	0.23
duration of price spells, months	2.8	4.0	2.2	4.4
Serial correlation of prices				
unconditional	0.45	0.61	0.45	0.73
(std. dev.)	(0.34)	(0.31)	(0.34)	(0.26)
conditional on price change	-0.07	0.04	0.07	0.32
(std. dev.)	(0.38)	(0.41)	(0.41)	(0.42)

Notes:

All statistics are weighted by revenue share of each upc.

Correlations computed separately for each upc with at least 5 observations available. Mean (std. dev.) across upcs reported

Table 4: Calibration targets

	Data	Model			
		I	II	III	IV
		Benchmark	No scope economies Gaussian shocks (GL 2007)	Scope economies Gaussian shocks	No scope economies Fat-tailed shocks
frequency of price changes	0.24	0.25	0.24	0.24	0.24
mean(Δp)	0.001	0.001	0.001	0.001	0.001
mean (|Δp|)	0.12	0.12	0.12	0.12	0.12
ser. corr. p	0.65	0.68	0.65	0.73	0.69
std (|Δp|)	0.09	0.10	<u>0.03</u>	0.07	0.09
fraction changes < 1/2 mean	0.28	0.30	<u>0.00</u>	0.23	0.30
fraction changes < 1/4 mean	0.12	0.11	<u>0.00</u>	0.11	0.00
kurtosis(Δp)	4	3.74	<u>1.40</u>	1.91	3.75

Note: In Model II the underlined entries are moments that are not targeted in calibration.

Table 5: Parameter Values

		I	II	III	IV
		Benchmark	No scope economies Gaussian shocks (GL 2007)	Scope economies Gaussian shocks	No scope economies Fat-tailed shocks
Assigned parameters					
β	discount factor	0.997	0.997	0.997	0.997
ψ	marginal disutility from work	2.0	2.0	2.0	2.0
θ	elasticity of substitution across stores	3	3	3	3
γ	elasticity of substitution across goods within store	11.5	-	11.5	-
σ_η	std. dev. of money shocks	0.0018	0.0018	0.0018	0.0018
ρ_μ	persistence of money shocks	0.61	0.61	0.61	0.61
Calibrated parameters					
μ	mean growth rate of money, %	0.024	0.024	0.024	0.024
κ	menu cost, % of SS revenue	1.109	0.980	2.998	0.260
ρ_a	persistence of technology shocks	0.473	0.490	0.330	0.487
χ	correlation of techn. shocks within store	1.131	-	0.263	-
α_1	Beta(α_1,α_2)	0.046	-	-	0.045
α_2	Beta(α_1,α_2)	1.057	-	-	1.0424
σ_ε	volatility of technology shocks	0.298	0.065	0.078	0.459

Table 6: Aggregate Statistics

		I	II	III	IV
	Calvo	Benchmark	No scope economies Gaussian shocks (GL 2007)	Scope economies Gaussian shocks	No scope economies Fat-tailed shocks
$\sigma(y)$, %	0.21	0.17	0.05	0.10	0.14
$\rho(y)$	0.88	0.90	0.62	0.79	0.91
var(π) due to intensive margin	1	0.99	0.99		
corr(π, frac. adj.)	-	0.36	0.44		
			Counterfactual Experiments		
$\sigma(y)$ with flat hazard (Calvo adjustment) (relative to original model)	1	1.37	6.55	2.38	1.86
$\sigma(y)$ with time-varying fraction of adjusters (relative to original model)	1	1.36	6.51	2.37	1.79

Note: output data detrended using an HP(14400) filter

Table 7a: Aggregate Statistics, no inertia in monetary policy

	Calvo	Scope economies Fat-tailed shocks Benchmark	No scope economies Gaussian shocks (GL 2007)
σ(y)	0.46	0.29	0.14
ρ(y)	0.64	0.59	0.21
var(π) due to intensive margin	1	0.96	0.99
corr(π, frac. adj.)	-	0.28	0.42
		Counterfactual Experiments	
σ(y) with Calvo timing (relative to original model)	-	1.62	3.29
σ(y) with no self-selection (relative to original model)	-	1.59	3.29

Note: output data detrended using an HP(14400) filter

Table 7b: Aggregate Statistics, economy with sales

	Calvo	No scope economies Fat-tailed shocks	No scope economies Gaussian shocks
σ(y)	0.20	0.13	0.04
ρ(y)	0.89	0.88	0.49

Table 7c: Aggregate Statistics, economy with Poisson shocks

	Calvo	No scope economies Poisson shocks	No scope economies Gaussian shocks
σ(y)	0.21	0.17	0.05
ρ(y)	0.89	0.91	0.62

Table 7d: Aggregate Statistics, economy with intermediate inputs

	Calvo	No scope economies Fat-tailed shocks	No scope economies Gaussian shocks
σ(y)	0.35	0.29	0.10
ρ(y)	0.92	0.90	0.76

Note: output data detrended using an HP(14400) filter

Figure 1: Distribution of non-zero price changes

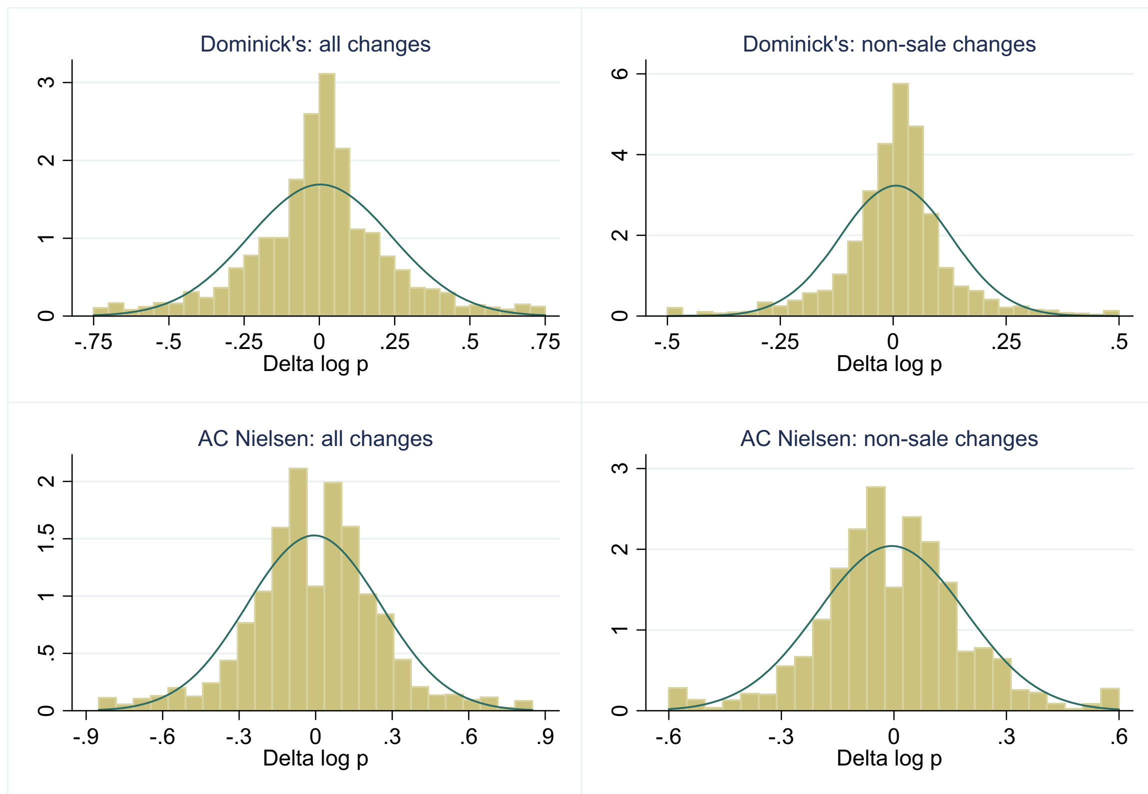

Figure 2: Distribution of price changes, conditional on adjustment

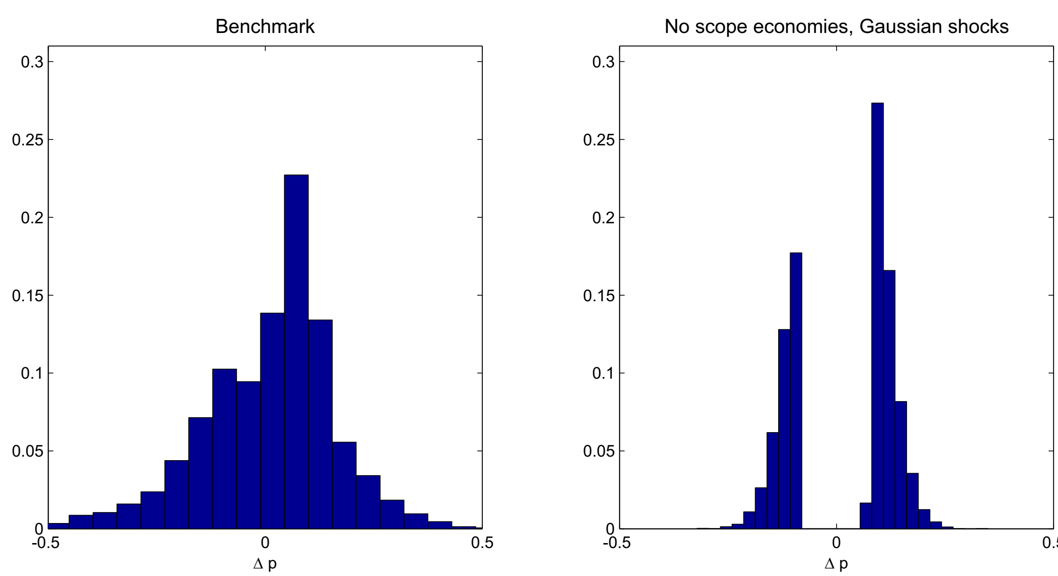

Figure 3: Impulse response to a money shock

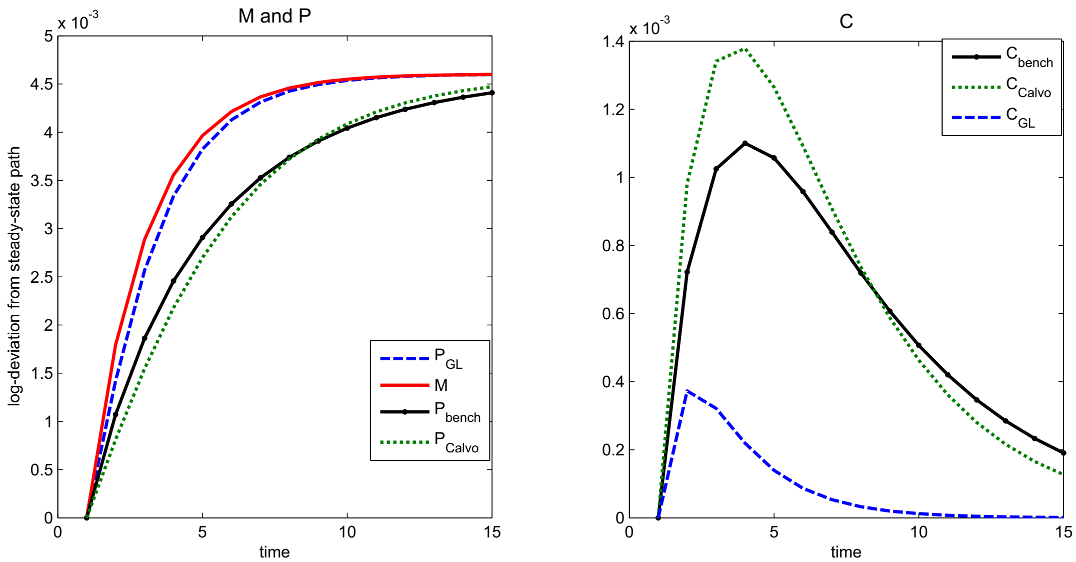

Figure 4: Adjustment hazard and distribution of desired price changes

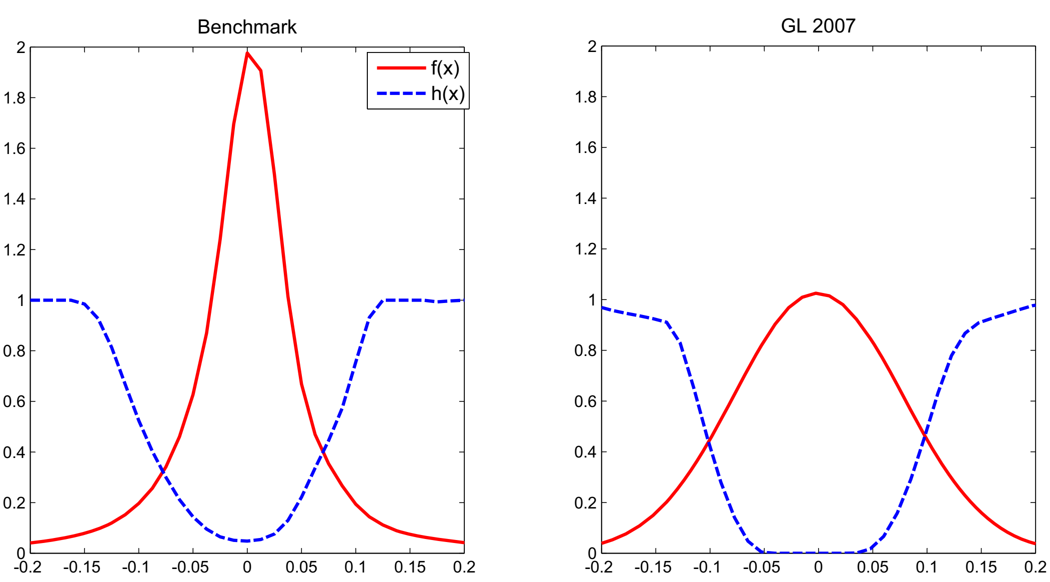

Figure 5: Effect of money shock on distribution of price changes

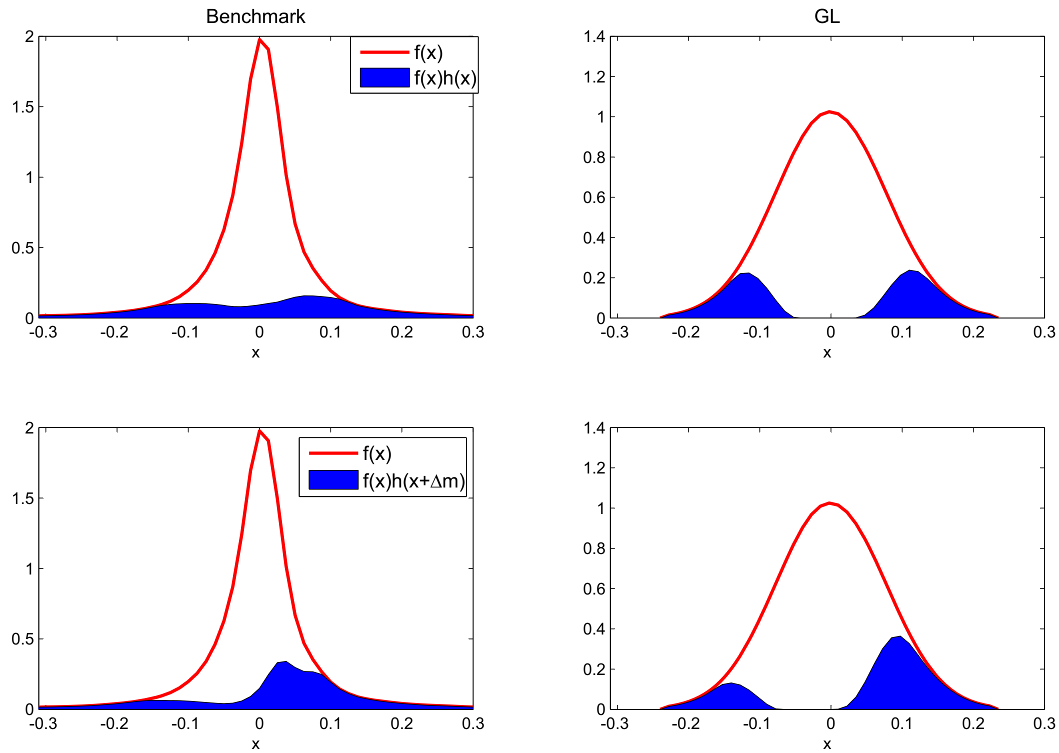

Figure 6: Optimal price response to money shocks, Benchmark vs. Calvo

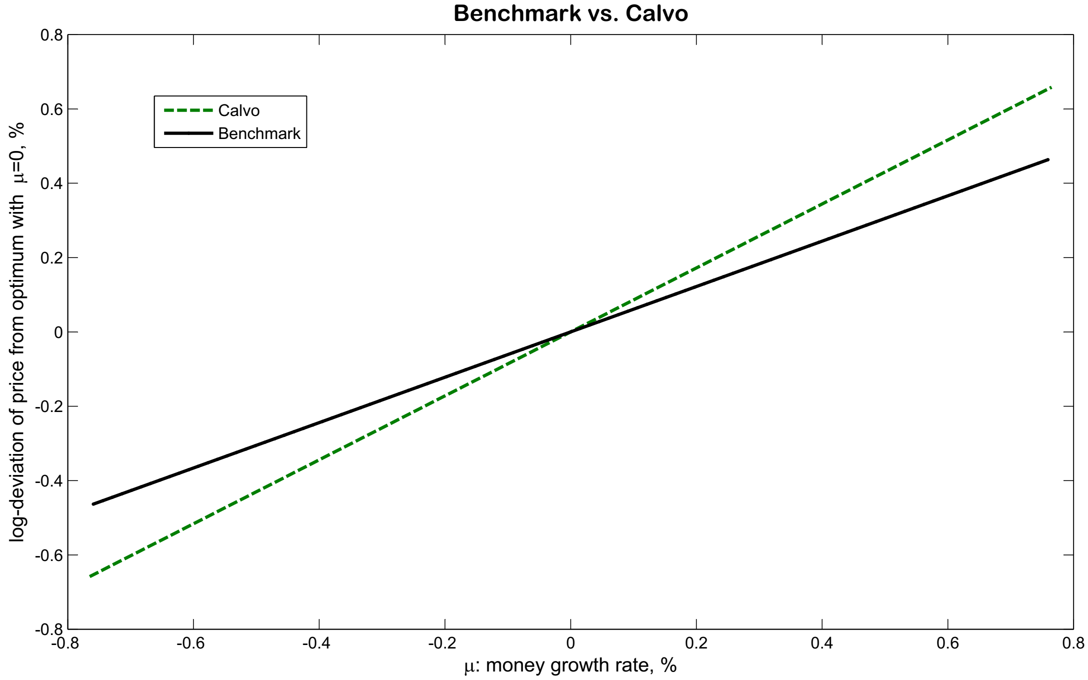

Figure 7: Distribution of price changes vs inflation