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

Virgiliu Midrigan[*]

New York University and NBER

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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 study an extension of the simple 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, produces aggregate fluctuations from monetary shocks that are 80% as large as those in time-dependent economies.

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[*] 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

A widely held view in macroeconomics is that menu costs of price adjustment give rise to aggregate price inertia and thus provide a mechanism through which changes in monetary policy have real effects. This view lies at the heart of New Keynesian analysis which often cites menu costs as the microfoundation for the assumptions on price setting it makes.

Golosov and Lucas (2007) have recently challenged this view. They study an economy in which price changes require a fixed (menu) cost and calibrate it to salient features of the US micro price data[1]. A key feature of the data is that the magnitude of price changes is large: prices change on average by about 10 percent. Golosov and Lucas introduce an idiosyncratic shock to rationalize this magnitude of price changes and find that in this environment money is nearly neutral. Price stickiness at the micro level leads to little stickiness in the aggregate, thus providing a serious challenge to the microfoundations of New Keynesian Business Cycle analysis.

This paper revisits the Golosov and Lucas analysis. I show that their near-neutrality result stems from their model's failure to account for the dispersion in the size of price changes in the data. In particular, a variation of their model consistent with this feature of the data does predict real effects of money that are comparable to those in a Calvo sticky price model, popular in New Keynesian analysis[2], in which adjustment hazards are constant and micro-level stickiness translates one-for-one into macro-level stickiness. Dispersion in the size of price changes in the data is thus evidence against the mechanism that generates monetary neutrality in the Golosov and Lucas setup.

The source of the near-neutrality of money in the menu cost economy studied

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[1] Bils and Klenow (2004) and Klenow and Kryvtsov (2005).

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

by Golosov and Lucas and of the earlier neutrality result of Caplin and Spulber (1987)[3] is a strong *selection effect:* changes in monetary policy alter the mix of adjusting firms. A monetary expansion 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 idiosyncratic cost shocks call for larger price increases. This selection effect is absent in Calvo-type models. In menu cost models its strength depends, however, on the measure of marginal firms whose desired price changes lie in the neighborhood of the adjustment thresholds and whose price change decision thus depends on the money shock.

I show that the strength of the selection effect is tightly related to the dispersion in the size of price changes the model predicts. If the selection effect is strong, the distribution of actual (as opposed to desired) price changes is bimodal with little size dispersion: most price changes are near the adjustment threshold(s). Conversely, if this effect is weak, most price adjusters are dispersed away from their adjustment thresholds, and hence the distribution of the size of price changes shows large dispersion. Accounting for the dispersion of the size of price changes is thus key to studying the aggregate implications of menu costs economies.

To document the pricing facts I use two sets of scanner price data collected in a number of grocery stores over a twelve-year period. I choose to focus on a relatively narrow sector of the economy primarily because this dataset is one of the few publicly available, not because of interest in grocery stores per se. As I discuss below, however, none of the facts I document are specific to grocery stores. I document two salient features of the data. First, a large number of price changes are small in absolute value. For example, while the mean size of a regular price change in one of the datasets (Dominick's) I use is 9 percent, 40% of regular price changes are less than

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[3] Seminal contributions in the menu cost literature are Barro (1972) and Sheshinski and Weiss (1977, 1983). More recent developments appear in Caplin and Leahy (1991), Caballero and Engel (1993), Dotsey, King and Wolman (1999), Danziger (1999) and Burstein (2006).

4.5 percent and 20% are less than 2.25 percent. Second, the distribution of price changes, conditional on adjustment, exhibits excess kurtosis or fat-tails. In other words, a substantial proportion of price changes are also very large in absolute value.

I show that little of this dispersion in the size of price changes in the data is accounted for by permanent differences across products, stores, or time periods. Rather, most of this dispersion is evidence that a particular product within a store experiences both small and large price changes over time, a feature that appears inconsistent with simple menu cost models of the type studied by Golosov and Lucas or variations of their model that allow for heterogeneity in menu costs, volatility of shocks, demand elasticities, etc. across firms.

A number of 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: time-varying adjustment costs[4], fluctuations in the degree of market power of the firms[5], informational frictions[6] or costs of price adjustment that increase in the size of the price change[7]. I choose to illustrate the importance of accounting for the distribution of the size of price changes in a menu-cost model by employing a mechanism for generating small price changes that has been recently suggested by Lach and Tsiddon (2007). These researchers[8] present evidence that economies of scope in price setting may account for the fact that some price changes are small. The idea is that it is possible to simultaneously generate both small and infrequent price changes if the average cost of changing the price of a bundle of goods is high (infrequent price changes), but the marginal cost of any given product's price change is small (small individual price changes for some goods).

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[4] Caballero and Engel (1999) and Dotsey, King and Wolman (1999).

[5] Benabou (1992), Kashyap (1995).

[6] Woodford (2008).

[7] Rotemberg (2009).

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

I choose to focus on this mechanism because of recent evidence that economies of scope are indeed a feature of the price setting technology in retail stores. In addition to the evidence of Lach and Tsiddon, Levy et. al. (1997) present direct evidence of economies of scope in price adjustment by measuring the steps undertaken in the price adjustment process. I present, in Appendix 2 of this paper, additional evidence to document the presence of economies of scope. 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. I emphasize however that multi-product economies of scope are not critical to my findings. I illustrate this point in a robustness section in which I assume instead time-varying adjustment costs.

The model I study is closely related to that of Golosov and Lucas (2007). I extend their analysis along two dimensions: I assume two-product firms that face a fixed cost of changing the entire menu of prices, but, conditional on paying this cost, a zero marginal cost of resetting any given price on the menu. In addition, I depart from their assumption of Gaussian idiosyncratic shocks and allow instead for a more flexible family of distributions that is calibrated to match the salient features of the micro-price data. I find that the distribution of idiosyncratic shocks must have extremely fat tails in order for the model to account for the kurtosis of price changes in the micro data. I then show that the model, because of its ability to replicate this additional set of micro-economic facts, generates aggregate fluctuations from monetary shocks that are 80% as large as in time-dependent economies. This result is robust to introducing i) a motive for temporary price discounts (sales), ii) strategic complementarities in price setting, or iii) alternative specifications of monetary policy and the distribution governing idiosyncratic shocks. Although sales and strategic complementarities have been argued important in recent work, I choose to study them in an extension of the model in order to isolate and study the role of the selection effect and how it is shaped by the distribution of the size of price changes.

This paper is closely related to recent work by Klenow and Kryvtsov (2005) and Gertler and Leahy (2006). Both of this papers present parameterizations of economies in which menu costs generate aggregate price inertia almost as large as in Calvo-type models. In Klenow and Kryvtsov the selection effect is weak because of the assumption of time-varying adjustment costs: most price changes occur in periods in which the realization of the adjustment cost is low. The economy studied by Gertler and Leahy is also characterized by a weak selection effect because of the assumption of a Poisson process for idiosyncratic shocks. The economy I study here shares elements of both of these approaches and, importantly, provides empirical evidence for the mechanism that underlies these results.

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. Appendices discuss the dataset I use, the computational algorithm employed, as well as evidence of economies of scope in price setting.

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[9]. 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),

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

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 the price series. In particular, I use data at the monthly frequency 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 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[10]: 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 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[11].

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.

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[10] 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.

[11] 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.

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[12], and store-specific effects in explaining the variability of the magnitude and frequency of price changes reported above. Specifically, I estimate

$$|\Delta \log (p_{ist})| = c + d_i + d_s + d_t + e_{it}^s$$

where $d_i, d_s,\ d_t$ are good, store, and month-specific effects and $|\Delta \log (p_{ist})|$ is the size of price changes. 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., are not able to account for the dispersion in the size of price changes in the data[13].

An alternative 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

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[12] 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.

[13] Klenow and Kryvtsov (2008) reach a similar conclusion in their study of the BLS data.

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[14] that prices in retail stores adjust frequently. Consistent with this evidence, the frequency 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[15]. I report the average (and standard deviation in parentheses) 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. Evidence from other studies

I have documented two features of the distribution of price changes that, I will argue, are critical in determining 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

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[14] Kackmeister (2005), Dutta, Bergen and Levy (2002).

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

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 using 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 is 15.7 in his data. Kackmeister (2005) reports that one-third of price 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.

C. Economies of scope

The mechanism I will use to generate small price changes in the model of the next section is one of economies of scope in price adjustment. Although this modeling choice is not critical to my results (as shown in a robustness section), I make this assumption because of the recent evidence in Lach and Tsiddon (2007) and Levy et. al (1997) in favor of this mechanism. In this paper I present additional evidence of interactions in the price adjustment technology in grocery stores, which, because of space considerations, I relegate to Appendix 2. Here I briefly summarize this evidence.

Appendix 2 establishes four additional features of the data. 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 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.

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 representative consumer and a unit measure of of monopolistically competitive firms, indexed by z. 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. 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:

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

subject to

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

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 productivity, $a^i(z,s^t)$, 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:

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

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.

In a 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 a given good is $P^i(z, s^t) = \frac{\theta}{\theta-1} \frac{W(s^t)}{a^i(z,s^t)}$ and independent of the productivity with which the firm produces the second good or the elasticity of substitution across the two goods, γ. [16]

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.

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[16] 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 $\gamma > \theta$.

An equilibrium is a collection of prices and allocations: $P^i(z,s^t), W(s^t), P(s^t), c^i(z,s^t), c(s^t)$, $n(s^t), l^i\left(z,s^t\right), y^i(z,s^t)$ 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 productivity in the economy. The aggregate state of this economy is summarized by the growth rate of money μ, and the joint distribution of last period's firm prices and productivity levels. Let $\boldsymbol{\phi}$: $\mathcal{P}^2 \times \mathcal{A}^2 \rightarrow [0,1]$ denote this distribution and $\mathbf{\Gamma}$ its 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 productivity 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 Bellman equations:

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

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

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 when it adjusts. The laws of motion for the state variables are:

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

Solving for the equilibrium in this economy requires characterize the following objects: $V^a()$, $V^n()$, $c()$, $w()$, $p()$, $\mathbf{\Gamma}()$. To solve this system of functional equations, I follow an approach developed by Krusell and Smith (1998).[17] 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), $\phi_1 = mean_{i,z}\left(\log(p_{-1}^i a^i)\right)$. 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., $\log(p) = \varsigma_0 + \varsigma_1 \log\mu + \varsigma_2\ \phi_1$.

Given a guess for the coefficients in these log-linear functions, I solve the firm's problem using projection methods[18]. 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 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[19].

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

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

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

[19] Notice that this does not contradict my argument that higher-order moments of the distribution of desired price changes determine the economy's aggregate implications. The precision of the simple pricing rules reflects the fact that monetary disturbances induce little variation in these higher-order moments in the time-series (or that this variation covaries strongly with μ and ϕ_1).

(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[20]. 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 growth rate of money given that most applied work assumes persistence in monetary policy[21]. 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[22]

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

[21] 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.

[22] 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.

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^i 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. Here σ_ε is the 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.

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 deviations 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. To gauge the robustness of my results to this choice, I return to the issues of sales in the next section where I allow explicitly a motive for sales in the model.

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[23] 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

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[23] 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.

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 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 parameterizations 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 simplified example[24]. 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 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:

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

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 mon-

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

etary 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 $(h(x+\Delta m) - h(x))\,x$ 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 $f(x)\,(h(x+\Delta m) - h(x))$ 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 $\Delta m \to 0$, the response of the aggregate price leve to a money shock is

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

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 output 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[25].

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 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

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

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, 4) an economy with intermediate inputs that features strategic complementarities and thus a lower responsiveness of real marginal cost to output, and 5) an economy with random menu costs of price adjustment. 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[26], 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

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

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.

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:

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

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

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

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 $p^T \leq p^R_{-1}$ 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[27].

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[27] 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%.

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 familiar 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 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 rigidities.[28] 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 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

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

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.

E. Random Menu Costs

I finally show that economies of scope in price adjustment are not necessary to generate the large number of small price changes in the data. To this end, I maintain the assumption of single-product firms, but assume that firms occasionally have the chance to adjust their prices for free. This assumption follows the spirit of the economy studied by Dotsey, King, and Wolman (1996), and is a simple, yet mechanical way of introducing small price change. Table A5.III report the fit of this variation of the model. With fat-tailed shocks, the model once again accounts for the distribution of price changes in the data: the fit is as good as in the Benchmark economy with multi-product firms. Table 7e reports that the aggregate fluctuations in this economy are 85% as large as those in the Calvo model, and slightly higher (standard deviation of HP-filtered output is 0.18) than in the Benchmark model (0.17).

6. Conclusion

This paper shows that simple state-dependent pricing models fail to account for 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. 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[29] or consumer level[30], time-varying demand elasticities[31], or adjustment costs[32] 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 manufacturer-specific. Nevertheless, 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[33], inventory management[34], intertemporal price discrimination[35], to name a few, as a potential for a more structural modeling 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.

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[29] Woodford (2008).

[30] Chen et. al (2008)

[31] Benabou (1992), Kashyap (1995).

[32] Dotsey, King and Wolman (1999). Caballero-Engel (1999).

[33] Varian (1980)

[34] Aguirregabiria (1999), Khan and Thomas (2008), Kryvtsov and Midrigan (2008),

[35] Conlisk, Gerstner and Sobel (1984)

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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 ($\lvert\Delta p\rvert$)	0.12	0.12	0.12	0.12	0.12
ser. corr. p	0.65	0.68	0.65	0.73	0.69
std ($\lvert\Delta p\rvert$)	0.09	0.10	0.03	0.07	0.09
fraction changes < 1/2 mean	0.28	0.30	0.00	0.23	0.30
fraction changes < 1/4 mean	0.12	0.11	0.00	0.11	0.00
kurtosis(Δp)	4	3.74	1.40	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
σ(y), %	0.21	0.17	0.05	0.10	0.14
ρ(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		
σ(y) with flat hazard (Calvo adjustment) (relative to original model)	1	1.37	6.55	2.38	1.86
σ(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)	0.88	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

Table 7e: Aggregate Statistics, economy with random menu cost

	Calvo	Random menu cost Fat-tailed shocks	No random menu cost Gaussian shocks
σ(y)	0.21	0.18	0.05
ρ(y)	0.88	0.91	0.62

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

Figure 1: Distribution of non-zero price changes

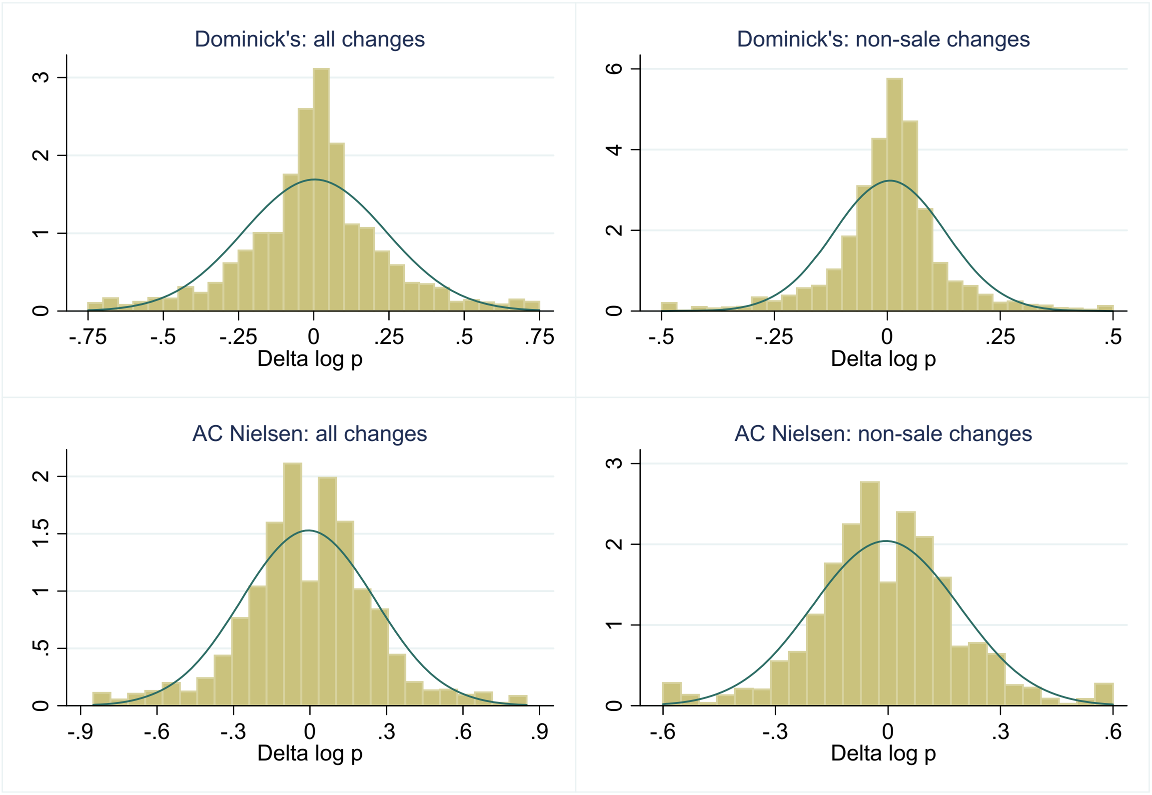

Figure 2: Distribution of price changes, conditional on adjustment

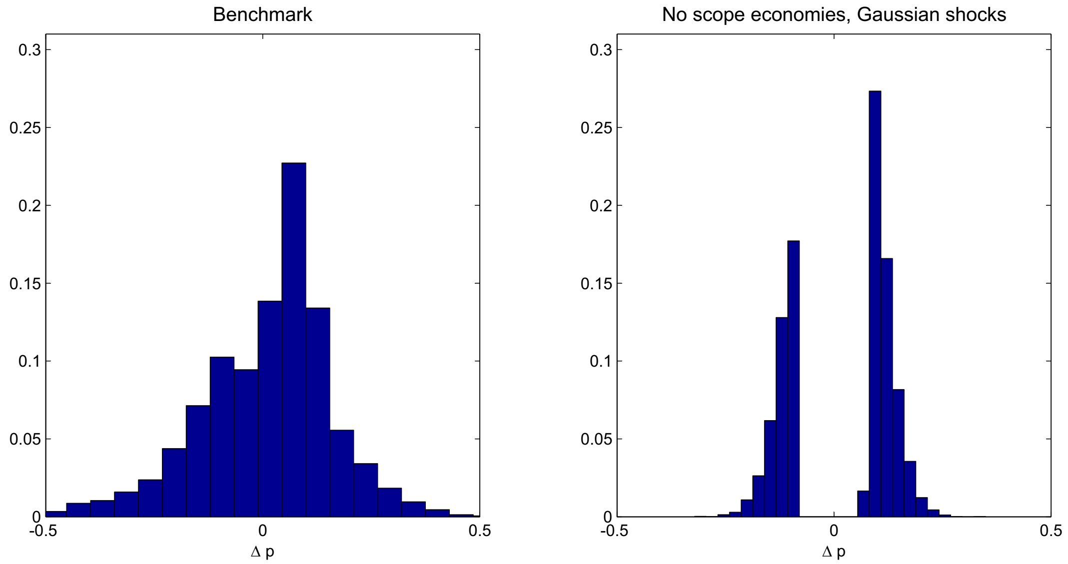

Figure 3: Impulse response to a money shock

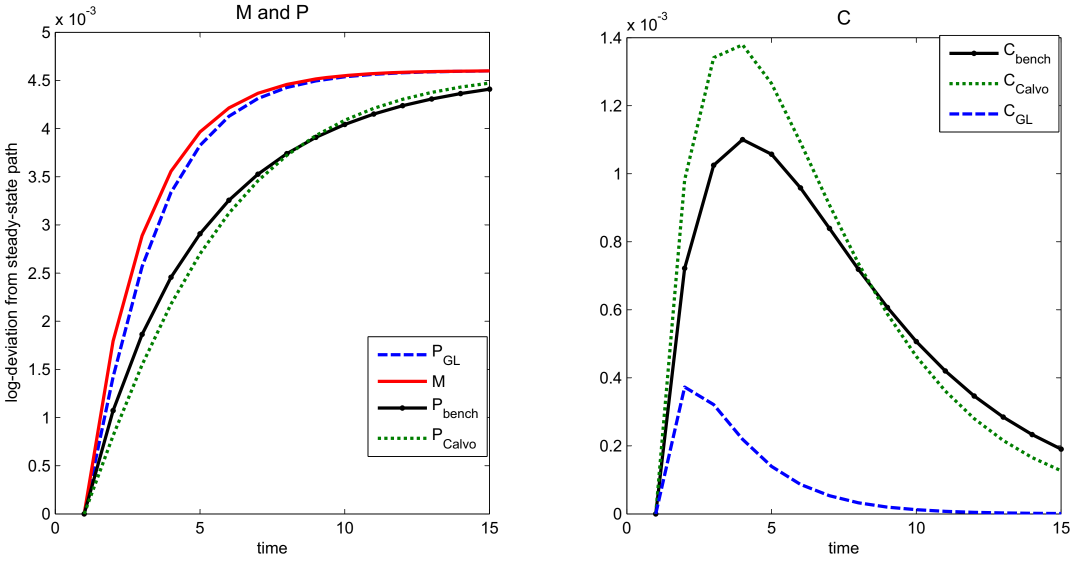

Figure 4: Adjustment hazard and distribution of desired price changes

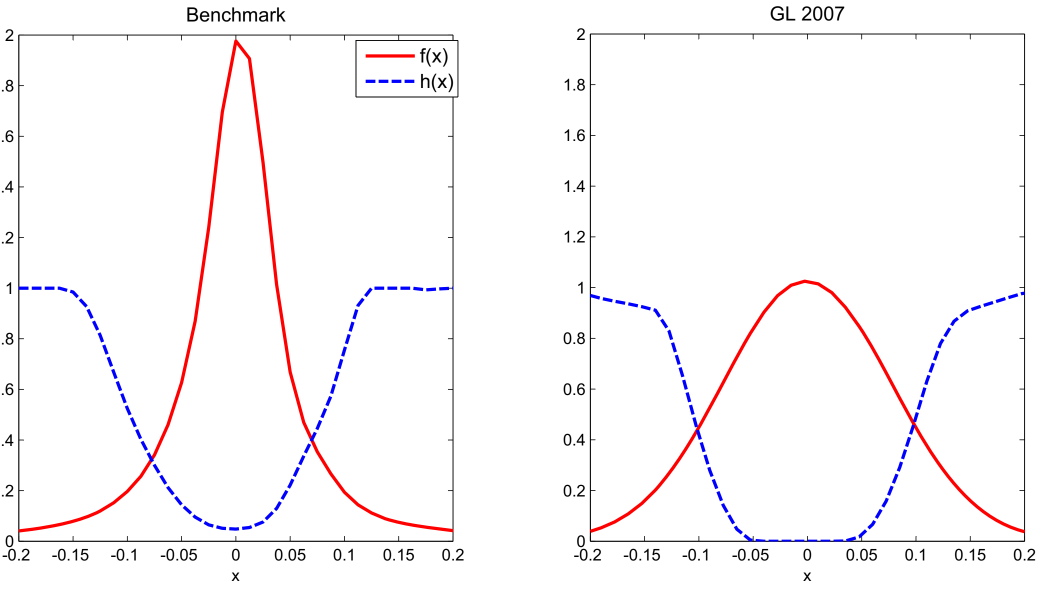

Figure 5: Effect of money shock on distribution of price changes

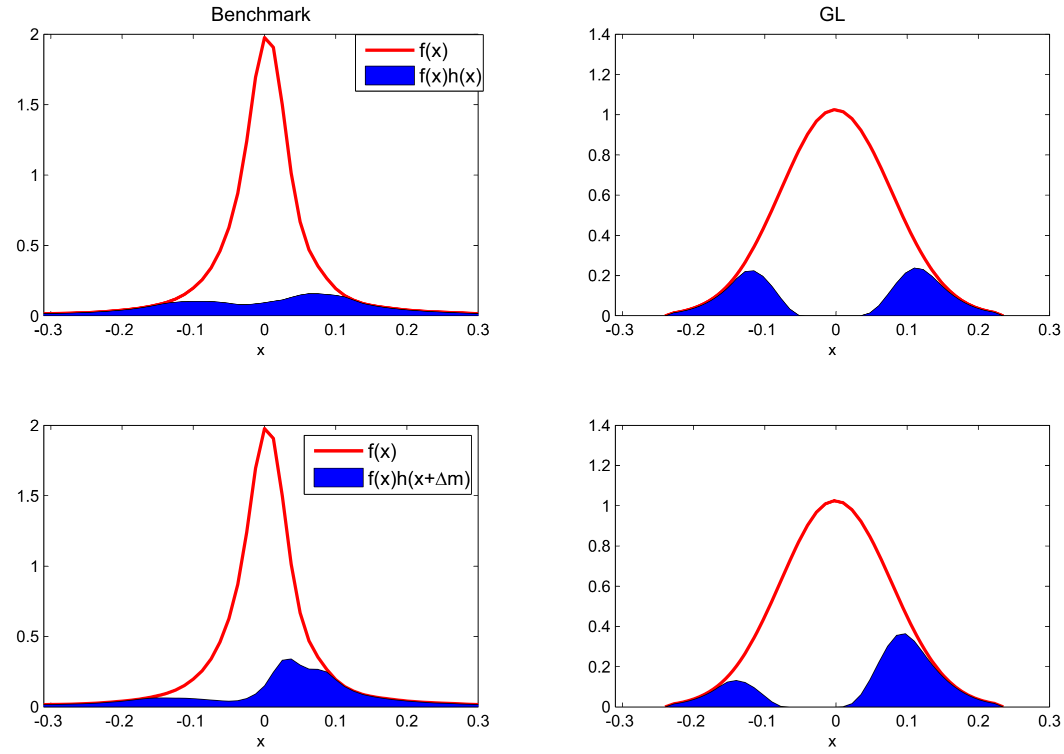

Figure 6: Optimal price response to money shocks, Benchmark vs. Calvo

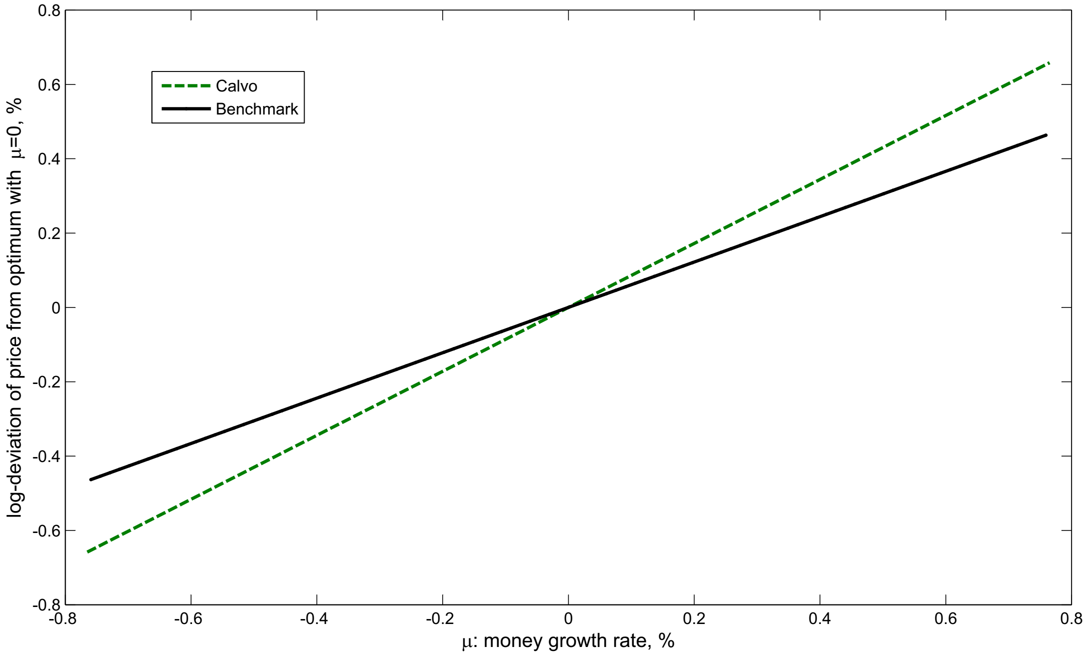

Figure 7: Distribution of price changes vs inflation