Prices and Market Shares in a Menu Cost Model*

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Abstract

Pricing complementarities play a key role in determining the propagation of monetary disturbances in sticky price models. We propose a procedure to infer the degree of firm-level pricing complementarities in the context of a menu cost model of price adjustment using product-level data on prices and market shares. We then apply this procedure by calibrating our model (in which pricing complementarities are based on decreasing returns to scale at the product level) to one particular super-market scanner data set. Although our data supports moderately strong levels of firm-level pricing complementarities, they appear to be too weak to generate much larger aggregate real effects from nominal shocks than a model without these pricing complementarities.

1 Introduction

A central question in monetary business cycle theories is whether models based on nominal rigidities can generate large and persistent delays in price adjustment in response to aggregate shocks to nominal spending and demand. This is complicated by the fact that at the individual firm or product level, prices appear to be anything but sticky. For example, Bils and Klenow (2005) report that the prices of individual products that are used by the BLS to construct the CPI change on average every 4 to 5 months; moreover, when prices change, they usually change by large amounts of up to 10% on average, and they may either increase or decrease.

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One possible source of amplification from the small extent of nominal rigidities at the product level into larger adjustment delays in the aggregate is the introduction of real rigidities or pricing complementarities, which reduce any individual firm's willingness to respond to a nominal shock if it expects that some other firms don't respond right away (Ball and Romer 1990). We define the degree of pricing complementarities by the elasticity of a firm's ideal price with respect to the aggregate price; the closer this elasticity is to one, the stronger are the pricing complementarities. Such pricing complementarities can result from various features of the environment; leading examples are decreasing returns to scale, demand elasticities that vary with scale, firm-specific, local or regional input markets, aggregate input-output linkages across sectors, or real wage rigidities.

From a theoretical perspective, pricing complementarities can amplify arbitrarily small degrees of nominal stickiness at the micro level into large aggregate adjustment delays. Whether they are large enough to provide much amplification is therefore mainly a quantitative question.

In this paper, we propose a procedure to infer the quantitative significance of certain types of pricing complementarities in the context of a menu cost model of price adjustment, using product-level data on prices and market shares.[1] Our main focus is on pricing complementarities that result at the firm level, in particular, decreasing returns to scale, or the presence of firm-specific inputs that lead to upward-sloping marginal costs. The parameters determining firm-level pricing complementarities also determine how a firm's optimal pricing decisions interact with the firm's idiosyncratic shocks, implying that they also have implications for moments on prices and market shares at the product level, so that at least in principle they can be inferred from micro data.

We then apply this procedure by calibrating our menu cost model to one particular data set on prices and market shares, a scanner data from a large chain of supermarkets in the Chicago area (Dominick's), to assess the quantitative importance of pricing complementarities. We conclude from our calibration that, although this data support moderately strong levels of pricing complementarities, these remain too weak to generate by themselves a strong amplification of nominal shocks at a business cycle frequency.

In section 2, we describe our model, which introduces pricing complementarities into an otherwise standard menu cost model, by allowing for decreasing returns to scale. We also allow for idiosyncratic demand shocks in addition to the cost shocks assumed by the existing literature (e.g. Golosov and Lucas 2006, Midrigan 2006).[2] This enables us to match observed fluctuations in prices

[1] We focus on market shares, as opposed to physical quantities, as a simple way to isolate product-level from sectorial fluctuations.

[2] We do not provide a structural interpretation of these shocks, but we just back them out to account for the

and market shares.

In section 3, we discuss how we can infer the degree of pricing complementarities, using data on prices and quantities. For reasons that we discuss below, we cannot focus directly on the pricing complementarity parameter. This leads us to the well-known identification problem of jointly inferring the elasticity of demand and marginal cost.

Our inference exploits properties of the menu cost model, and thus complements solutions to this identification problem that try to instrument for variation in costs and demand. Specifically, we rely on three observations. First, existing measures of the resources firms spend on price changes place an upper bound on the magnitude of the menu cost. Since the demand elasticity and returns to scale affect how frequently, and by what magnitudes firms want to adjust their prices, we can then use the frequency of price changes to determine these parameters.

Second, the menu cost model has some distinct implications for the patterns of price and quantity movements in the data. Firm profits are more sensitive to mispricing when prices are too low rather than too high. This implies that price increases in the model are more frequent than price decreases, but they are also of smaller magnitude. Moreover, this asymmetry becomes larger as we raise the demand elasticity and lower the returns to scale. We can then determine these two parameters if we calibrate our model to match the frequencies and magnitudes of both price increases and decreases.

Finally, the model also has the implication that firms are more willing to adjust their prices when current market shares are above the median. If cost shocks are the main source of idiosyncratic fluctuations, this occurs when prices are relatively low. If instead demand shocks are important, this occurs when prices are relatively high, compared to long-run averages. By comparing whether price changes are more or less likely when current prices are high as opposed to low, we can thus infer the relative importance of cost and demand shocks. This is important, because the relative magnitude of cost and demand shocks affects the inferred degree of pricing complementarities.

Together with the basic properties of frequency, magnitude, variability and correlation of price and share changes, these insights provide enough discipline to infer all relevant model parameters.

In sections 4-7, we apply these insights in a calibration using a particular data set. Ideally one would want to have this data for a comprehensive set of products in the overall economy, but this information is hard to obtain. Instead, we use scanner data from a large chain of supermarkets in the Chicago area. While limited in scope due to its narrow geographic coverage and particular set of grocery products, this dataset has the advantage of providing high frequency information on

magnitude and comovement of price and shares in our dataset.

both prices and quantities for many items within narrowly defined product categories.

In section 4, we report the empirical moments of the data to which our model is calibrated. The reported frequencies and magnitudes of price changes are similar to the ones documented by previous studies for a broader set of goods and services (Bils and Klenow, 2005; Klenow and Kryvtsov, 2005). We complement this with moments on market share fluctuations, and with measures of the asymmetries between price increases and decreases, and between the frequency of price changes when prices and/or market shares are above or below their median levels. The following observations are particularly relevant for our purposes: (i) the magnitude and variability of market share fluctuations is fairly large, (ii) fluctuations in prices and market shares are slightly negatively correlated, (iii) well over half of price changes are increases, but they are on average smaller than price decreases, and (iv) prices are significantly more likely to change when market shares are above as opposed to below their median levels, but the frequency of price adjustment is roughly equal when prices are below or above their median.

In section 5, we calibrate our model to match these moments in steady state. A model with a demand elasticity of roughly 4, and a returns to scale parameter of 0.55 provides the best fit, given the targeted moments. This implies a moderately strong degree of firm-level pricing complementarities, equal to 0.6. To put this number in perspective, Rotemberg and Woodford (1997) estimate a Calvo model using aggregate data, and argue that pricing complementarities must be around 0.85 to generate a sufficiently large propagation of monetary shocks at the business cycle frequency.

In section 6, we simulate the impulse response of our economy to a one-time increase in the growth rate of nominal spending. In our preferred calibration, pricing complementarities double output effects of a nominal shock relative to a model without complementarities, but these effects nevertheless remain small. Allowing for additional aggregate pricing complementarities leads to slightly larger effects, but they still remain smaller than those of a Calvo model without pricing complementarities. Moreover, these aggregate complementarities cannot be directly inferred from product-level fluctuations in prices and quantities.

In section 7, we perform some robustness checks. First, we examine the sensitivity of our conclusions to changes in targets and other parameter changes. Although stronger pricing complementarities are sustainable if one accepts smaller targets for the magnitude of price and/or market share fluctuations, these fluctuations would have to be substantially smaller to sustain much larger pricing complementarities, and much smaller than what our data suggests. Second, we re-calibrate our model targetting only patterns in price changes to explore the role played by the data on quantity fluctuations. Although we can no longer infer all parameters, our main conclusion that pricing complementarities are at best moderate can be established just by looking at prices. Finally, following Midrigan (2006), we re-calibrate our model using fat-tailed distributions of idiosyncratic cost and demand shocks to explore the role of the distributional assumptions for our inference. This does not have a large effect on our results.

In summary, a menu cost model with complementarities based purely on firm-level decreasing returns is unable to generate quantitatively large aggregate amplification effects from nominal rigidities. Our super-market data reject stronger complementarities mainly for two reasons. First, the fact that observed price changes are fairly large when they occur suggests that the fluctuations in marginal costs that trigger these changes must also be large. However, all else equal, stronger complementarities give firms an incentive to respond even to small changes in marginal costs by changing the price. Thus, the only way stronger complementarities can be consistent with the data on observed price changes is if menu costs become larger, but that would require much larger menu costs than what is suggested by existing measures. Second, stronger pricing complementarities would lead to more asymmetry between increases and decreases than what is observed in the data.

Our analysis relates to several literatures. Golosov and Lucas (2006) and Midrigan (2006) calibrate menu cost models to match empirical facts about price changes at the micro level, and then examine the resulting aggregate implications of a nominal shock. Klenow and Willis (2006) introduce pricing complementarities into the Golosov-Lucas model by allowing for scale-dependent mark-ups. They show that such a model would lead to implausible pricing implications at the micro level, and would require implausibly large cost shocks and very large menu costs to match the data. As in our model, firms have a desire to respond to the idiosyncratic cost shocks by adjusting their price frequently, and by small magnitudes.

In contrast to these papers, we calibrate our model to match facts on both prices and market shares, and we augment the model with idiosyncratic demand shocks in order to account for the observed fluctuations in prices and market shares. For our inference results, it is important that we correctly account for the relative importance of cost and demand shocks. With decreasing returns to scale, the observed large variability of quantities may by itself be a source of large fluctuations in marginal costs and prices. Therefore, strongly decreasing returns to scale are more easily consistent with a model with demand shocks than a model with only cost shocks, and ignoring the potential role of either cost or demand shocks may bias the inference in one direction or the other.

Gertler and Leahy (2005) and Nakamura and Steinsson (2006a) consider menu cost models with pricing complementarities at the sector or aggregate level. Gertler and Leahy provide a theoretical foundation for a New Keynesian Phillips Curve based on a model with pricing complementarities arising from sector-specific input markets. Nakamura and Steinsson calibrate a model with pricing complementarities resulting from input-output linkages across sectors.

There is also a large literature embedding pricing complementing complementarities into other models of aggregate price adjustment to generate persistent delays of price adjustment (e.g., Altig, Christiano, Eichenbaum and Linde, 2005; Bergin and Feenstra, 2001; Chari, Kehoe and McGrattan, 2000: Eichenbaum and Fisher, 2004; Dotsey and King, 2006; Kimball, 1995, Rotemberg and Woodford, 1997, among many others). These studies all consider the plausibility of amplication channels that are based on pricing complementarities by calibrating or estimating richer macroeconomic models to aggregate data, with sometimes conflicting conclusions. We complement these studies by calibrating pricing complementarities using micro data.

Finally, our model abstracts form various richer characteristics of the micro data, such as inventories and stock-outs, price promotions, a richer market structure and demand systems, and interactions between whole-salers and retailers. While we view these as important considerations to understand our supermarket data on prices and quantities, our goal is to quantify the monetary transmission mechanism in macro models with nominal rigidities.[3]

2 The Model

We interpret our menu cost model as that of a single sector or product category. Time is discrete and infinite. There is a continuum of varieties, indexed by $i \in [0, 1]$, and uniformly distributed over the unit interval. Each variety is produced by a single monopolistic firm. These varieties are purchased by a representative household in whose preferences they enter through a Dixit-Stiglitz index of consumption. The representative household, in turn sells labor services to the firms, who use labor as the unique input into production.

Demand structure: The demand for each variety i is given by

$$y_{it} = a_{it} Y_t \left(\frac{p_{it}}{P_t} \right)^{-\theta}$$

where Y_t denotes the aggregate (sector-level) real demand in period t, $P_t = \left[\int_0^1 a_{it} p_{it}^{1-\theta} di \right]^{\frac{1}{1-\theta}}$ is the Dixit-Stiglitz price index, p_{it} denotes the price of variety i, a_{it} is an idiosyncratic preference shock for variety i in period t, and $\theta > 1$ is the demand elasticity parameter.

[3]Goldberg and Hellerstein (2006) and Nakamura (2006) consider menu costs in a richer structural IO model, but abstract from the monetary transmission mechanism.

Technologies: Each variety is produced by a single monopolist, using labor l_{it} as unique input, according to the following technology:

$$y_{it} = z_{it} l_{it}^{\alpha}$$

where z_{it} is an idiosyncratic, labor-augmenting technology shock for variety i in period t. The parameter $\alpha \leq 1$ determines the returns to scale in production, which corresponds to the presence of a firm-specific factor that is costly to adjust at short horizons.[4] The firms' nominal profits in period t, exclusive of menu costs are then characterized as

$$\pi_{it} = p_{it} y_{it} - W_t \left(\frac{y_{it}}{z_{it}} \right)^{1/\alpha},$$

where W_t denotes the aggregate nominal wage in period t.

Price adjustment: In each period, firms must decide whether or not to adjust their prices. A firm must hire $F > 0$ units of labor to change its price. At the beginning of each period, firms observe their draw of demand and cost shocks $s_{it} = (a_{it}, z_{it})$ and then decide whether or not to adjust their nominal price, or keep it constant.[5]

The firms maximize the expected net present value of nominal profits, discounted at nominal interest rates:

$$\max_{\{p_{it}\}} \mathbb{E}_0 \sum_{t=0}^{\infty} \prod_{s=0}^{t-1} \left(\frac{1}{1+i_s} \right) \left[\pi_{it} - W_t F \mathbb{I}_{p_{it} \neq p_{it-1}} \right],$$

where $\mathbb{I}_{p_{it} \neq p_{it-1}}$ is an indicator variable that takes on the value 1, if $p_{it} \neq p_{it-1}$ and 0 otherwise.

Nominal spending, wages, and interest rates: We summarize the considerations of general equilibrium by a simple quantity equation that determines aggregate nominal spending, a household Euler Equation that determines nominal interest rates, and an equation relating aggregate nominal spending, wages and prices. Aggregate nominal spending $M_t = Y_t P_t$ is assumed to grow exogenously at a constant rate μ in a non-stochastic steady state. Interest rates are determined by $u'(Y_t)/P_t = \beta (1+i_t) u'(Y_{t+1})/P_{t+1}$, where $u(\cdot)$ is the household's per period utility function, and $\beta \in (0,1)$ the discount factor. In steady-state, Y is constant, and the nominal interest rate equals $1 + i_t = (1+\mu)/\beta$. Nominal wages W_t are determined as an average of nominal spending and nominal prices, $W_t = M_t^{1-\gamma} P_t^{\gamma}$, where $\gamma \in [0,1)$. Although this formulation is reduced form, it allows us to capture several interesting special cases: If $\gamma = 0$, nominal wages move one for one with nominal

[4] This is also isomorphic to the presence of a firm-specific input whose market price is increasing in firm scale (e.g. Woodford 2003).

[5] An alternative specification where firms choose prices after observing their demand shock has similar qualitative implications to our benchmark model when demand shocks are sufficiently persistent.

spending, (or equivalently, real wages move one for one with real output). This case is the one considered in Golosov and Lucas (2006), and can be sustained as a general equilibrium outcome when preferences are log in consumption and linear in labor; we will refer to it as the flexible wage case. Alternatively, in the limit as γ converges to 1, nominal wages become less and less responsive to changes in nominal spending, or equivalently, real wages move less and less with real output. We will refer to this alternative limiting case as the case with rigid real wages. The wage adjustment parameter γ thus indicates the degree of aggregate pricing complementarities.[6]

In a steady-state equilibrium with no aggregate uncertainty, M_t, W_t and P_t all grow at the same rate μ, and the parameter γ has no bearing on our identification of other parameters for price adjustment. However, it will be important for subsequently quantifying the effects of nominal shocks and adjustment out of steady-state.

Shocks: Demand and productivity shocks each follow an AR1 process,

$$\begin{aligned} \ln a_{it} &= \rho_a \ln a_{it-1} + \varepsilon_{it}^a \\ \ln z_{it} &= \rho_z \ln z_{it-1} + \varepsilon_{it}^z \end{aligned}$$

where $\varepsilon_{it}^a \sim \mathcal{N}\left(0, \sigma_a^2\right)$ and $\varepsilon_{it}^z \sim \mathcal{N}\left(0, \sigma_z^2\right)$ are iid across varieties and over time. We let $\Psi\left(s'|s\right)$ denote the transition probability function associated with the idiosyncratic shocks, where $s = (a, z)$.

Optimal pricing decisions and steady-state equilibrium: To characterize optimal pricing strategies, we normalize all nominal variables by M_t, and we let $\hat{P}_t = P_t/M_t$ and $\hat{p}_{it} = p_{it}/M_t$ denote the normalized variables. In a steady-state equilibrium, $\hat{P}_t = \hat{P}$ and $Y_t = \hat{P}^{-1}$ are constant over time, and nominal interest rates are constant and given by $1+i = (1+\mu)/\beta$. Let $V(\hat{p}; s)$ denote the present value of profits for a firm that sets its own normalized price $\hat{p}_{it} = \hat{p}$, with an idiosyncratic state s. This value function is characterized by the following Bellman equation:

$$V(\hat{p}; s) = \hat{\pi}(\hat{p}; s) + \beta \int_{s'} \max\left\{V^*\left(s'\right) - F, V\left(\frac{\hat{p}}{1+\mu}; s'\right)\right\} d\Psi\left(s'|s\right)$$

where $V^*(s) = \max_{\hat{p}} V(\hat{p}; s)$ and $\hat{\pi}(\hat{p}; s)$ denotes the firm's normalized per period profits. Substituting in the definition of the nominal wage, this is defined as

$$\hat{\pi}(\hat{p}; s) = \frac{\pi_{it}}{M_t} = a\left(\frac{\hat{p}}{\hat{P}}\right)^{1-\theta} - \left(\frac{a}{z}\right)^{1/\alpha} \hat{P}^{\gamma - 1/\alpha}\left(\frac{\hat{p}}{\hat{P}}\right)^{-\theta/\alpha}.$$

Moreover, let $p^*(s) = \arg\max_{\hat{p}} V(\hat{p}; s)$ denote the firms' optimal decision rule, conditional on adjusting. Coming into period t with price $\hat{p}_{-1}$, the firms' optimal decision rule $\tilde{p}(\hat{p}_{-1}; s)$ equals

[6] The case with $\gamma > 0$ also results from a model where firms use the final good as an intermediate input in production (as in Basu 1995, or more recently, Nakamura and Steinsson 2006a).

$\hat{p}_{-1}/(1+\mu)$ if the firm does not adjust its price, and $\tilde{p}(\hat{p}_{-1};s) = p^*(s)$ if it adjusts. We conjecture that the value function $V(\hat{p};s)$ is strictly concave in $\hat{p}$, and is unbounded below. A firm then keeps its nominal price constant, as long as its current normalized price is inside an interval $\left[\underline{p}(s);\bar{p}(s)\right]$ around the optimal price $p^*(s)$, and $\tilde{p}(\hat{p}_{-1};s)$ is characterized by $p^*(s)$, $\underline{p}(s)$ and $\bar{p}(s)$, such that $\tilde{p}(\hat{p}_{-1};s) = \hat{p}_{-1}/(1+\mu)$ iff $\hat{p}_{-1} \in \left[\underline{p}(s);\bar{p}(s)\right]$, and $\tilde{p}(\hat{p}_{-1};s) = p^*(s)$ otherwise. These bounds must satisfy $V\left(\underline{p}(s);s\right) = V(\bar{p}(s);s) = V^*(s) - F$. As is well-known, this is a common property of models with fixed adjustment costs, and we will verify numerically that the same property also applies to our model.

At each date, each firm is characterized by its idiosyncratic state s and its previous price $\hat{p}_{-1}$. The aggregate state is then characterized by the cross-sectional distribution Φ over price-state pairs $(s,\hat{p}_{-1})$. A *non-stochastic steady-state equilibrium* of the menu cost economy is characterized by a cross-sectional distribution Φ, a decision rule $\tilde{p}(\hat{p}_{-1};s)$, and a normalized price level $\hat{P}$ such that (i) the decision rule $\tilde{p}(\hat{p}_{-1};s)$ solves the firms' optimization problem, and (ii) Φ is stationary under the Law of Motion induced by the decision rule $\tilde{p}(\hat{p}_{-1};s)$, and $\hat{P}$ satisfies $\hat{P} = \left(\int a\hat{p}^{1-\theta}d\Phi(\hat{p};s)\right)^{1/(1-\theta)}$, for all t. We can compute steady-state equilibria by first solving the firms' pricing problem for a fixed price level $\tilde{P}$, to find the steady-state rule for price adjustment $\tilde{p}(\hat{p}_{-1};s)$. From there, we characterize the Law of Motion for the distribution of prices and determine its fixed point. Finally, we check whether this fixed point is consistent with the initial guess of $\tilde{P}$.

The role of complementarities for aggregate price adjustment: With flexible prices, the firm's normalized ideal price $\hat{p}^f\left(s;\hat{P}\right)$ solves the first-order condition $\pi_p(\hat{p};s) = 0$, which implies

$$\log \hat{p}^f\left(s;\hat{P}\right) = k_0 + k\log\hat{P} - \frac{1}{\alpha+\theta(1-\alpha)}(\log z - (1-\alpha)\log a).$$

Here, $k_0 = \frac{1}{1+\theta/\alpha-\theta}\log\left(\frac{\theta/\alpha}{\theta-1}\right)$ measures the logarithm of the firm's mark-up over marginal cost, and $k = 1 - \frac{1-\alpha\gamma}{\alpha+\theta-\alpha\theta}$ measures the elasticity of a firm's ideal price w.r.t. a change in the aggregate price index.

This is our formal definition of pricing complementarities, which captures the interaction between the firm's ideal prices and the aggregate price level $\hat{P}$. $\hat{P}$ affects the firms' marginal costs through two channels. On the one hand, an increase in $\hat{P}$ lowers a firm's relative price, thus increasing demand and marginal cost if marginal cost is upward-sloping ($\alpha < 1$). On the other hand, if $\gamma > 0$, an increase in $\hat{P}$ raises nominal wages. We refer to the first as firm-level pricing complementarities and the second as aggregate pricing complementarities. Our model abstracts from interactions between the aggregate price and the firms' ideal mark-up.

The parameter k is a function of the wage adjustment parameter γ, the returns to scale parameter α, and the demand elasticity θ. With constant returns to scale ($\alpha = 1$), $k = \gamma$, i.e. individual firms' pricing decisions interact only because the aggregate level of prices affects wages. In contrast, with $\alpha < 1$, k is increasing in θ and in γ. In addition, k is decreasing in α, if and only if $1 - \gamma > 1/\theta$, i.e. when decreasing returns to scale are relatively more important for overall pricing complementarities than real wage rigidities.[7]

When price adjustment is costly, the degree of pricing complementarities k also determines, how fast and by how much prices respond to aggregate shocks. Hence, this is a key parameter in determining the real effects of a monetary disturbance.

Some of the parameters determining k also affect the response of product-level prices and quantities to idiosyncratic demand and cost shocks. In particular, θ and α determine along standard lines, how shifts in demand and marginal cost affect ideal prices and quantities. For example, a lower α implies that demand shocks have a larger impact on prices, and a smaller impact on quantities, while cost shocks have a smaller impact on both quantities and prices. We can therefore attempt to infer these two parameters using observed variation in product-level prices and quantities. This then provides some information towards inferring k, measuring the importance of decreasing returns to scale for overall pricing complementarities.

On the other hand, information on variation in product-level prices and quantities do not shed any light on the value of γ in a steady-state with constant inflation, since it only affects the dynamics of prices and quantities out of steady-state.

3 Inferring Pricing Complementarities

In this section, we discuss what features of the menu cost model enable us to infer the key parameters of the model using moments of the micro data on prices and quantities (or equivalently, expenditure shares) at the product level. While the substitution elasticity θ and the returns to scale α are the parameters of most immediate interest, the model has eight other parameters that we need to consider: the menu cost F, the growth rate of nominal spending μ, the discount rate β, and the wage elasticity parameter γ, and the parameters (ρ_a, σ_a) and (ρ_z, σ_z) that govern the stochastic processes of the productivity and demand shocks. Among the eight parameters, μ will be set equal to the steady-state rate of inflation, and β to match the steady-state real interest rate. Moreover

[7] If γ is sufficiently high, k is increasing in α. For example, if $\gamma = 1$, prices will increase in response to an increase in nominal spending when $\alpha < 1$ but not when $\alpha = 1$.

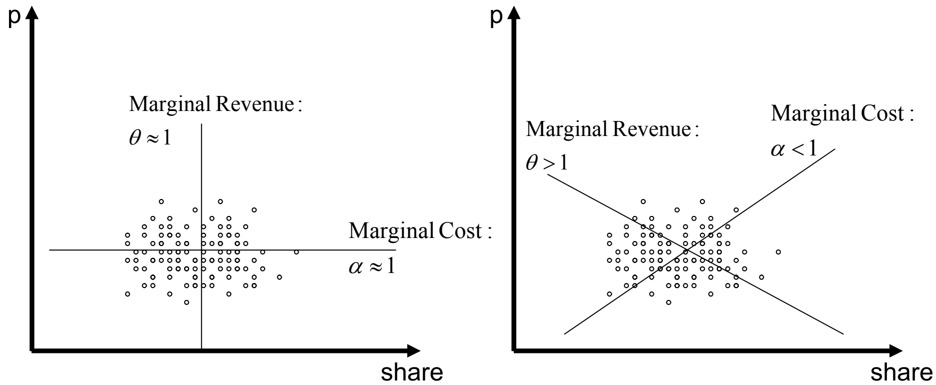

Figure 1: The identification problem

in a steady-state equilibrium with constant wage and price inflation, γ remains unidentified, and doesn't affect our calibration of the other parameters. To simplify our discussion, we focus on the 5 parameters $(F, \sigma_a, \sigma_z, \theta, \alpha)$.

The micro data on prices and market shares gives us information on (*i*) the frequency of price adjustment, (*ii*) the average magnitude of price changes, (*iii*) the variability of month to month changes in market shares, and (*iv*) the correlation of changes in prices and shares. With these four moments, we are still unable to identify the 5 parameters. If we leave aside the fixed cost F and the frequency of price adjustment, this amounts to the well-known problem of separately identifying the elasticity of demand and marginal cost, and the magnitude of cost and demand shocks from observed prices and quantities.

In Figure 1, we illustrate this problem by showing how the same data on prices and shares may be the result of different parameter pairs (θ, α). In the left panel, this is done with a demand elasticity close to 1, and near constant returns; with $\gamma = 0$, this results in $k \approx 0$, i.e. very weak pricing complementarities. In the right panel, the same observations are fitted by a more elastic demand schedule, and decreasing returns to scale, and hence a higher degree of pricing complementarities. More generally, there is a continuum of values of θ and α that can fit the same data, by requiring θ (and hence k) to increase, as α decreases.

We thus need to find additional moments that will enable us to resolve the problem of inferring θ and α. In the remainder of this section, we discuss some key properties of the menu cost model that will enable us to do.[8][9]

Observation 1: *Holding constant the four benchmark moments, the inferred magnitude of menu costs is increasing in the degree of pricing complementarities (increasing in θ and decreasing in α).*

In the model, firm profits become more concave in $\hat{p}$, as we lower α and increase θ. Firms thus become more sensitive to mispricing, which tightens the Ss-bands and provides an incentive to adjust prices more frequently. Therefore, maintaining the same frequency of price changes will require larger menu costs. We can therefore infer α and θ by targeting existing empirical measures of the size of menu costs, together with the other four benchmark moments.

The next observation provides an alternative that enables us infer α and θ directly from product-level variation in prices and market shares.

Observation 2: *Price changes become increasingly asymmetric, as pricing complementarities become stronger: Price increases become more frequent, but smaller in size relative to decreases.*

In the model, having a price that is too low lowers the mark-up and reduces the profit margin until profits eventually become negative. Having a price that is too high instead reduces the quantity sold, but profit margins are actually even higher than at the optimum. Profits are therefore much less sensitive to price, when price is above the optimum, than when it is below. This asymmetry carries over to the firm's value function, and hence its Ss bands, which are asymmetric around the ideal price p^*: the lower Ss band is closer to the optimal price than the upper Ss band. This is illustrated in figure 2, where, for a particular realization of s, we plot the firm's value function, and in figure 3, where we plot the Ss bands - in the latter figure, we project pairs $\left(a, z^{-1}\right)$ into a single dimension on the horizontal axis.

The asymmetry in the Ss bands in turn has implications for the frequency and magnitude of price increases and decreases. With no inflation, the firm will hit its lower sS band more frequently

[8] In earlier calibrations of menu cost models, this issue does not arise, since α was set equal to 1, and θ primarily affects quantities, while the model was calibrated to match data on prices only. For us, however, it is the key to identifying the degree of pricing complementarities.

[9] Another alternative would be to directly look for more direct information regarding some parameters. For example, θ and α also determine the firm's profit rates and mark-ups, and it might therefore seem tempting to calibrate our model to match measures of mark-ups or profits. Such an approach, however, would require us to take an explicit stand on the interpretation of what the unmodelled fixed factors of production are, how they compensated, and how they are accounted for in any measure of profit rates. Nevertheless, estimates of θ close to 1 or of α near 0 would lead to the implication that the implied profit rates and mark-ups over average costs are near infinite, which, even after accounting for fixed factors, seems implausible.

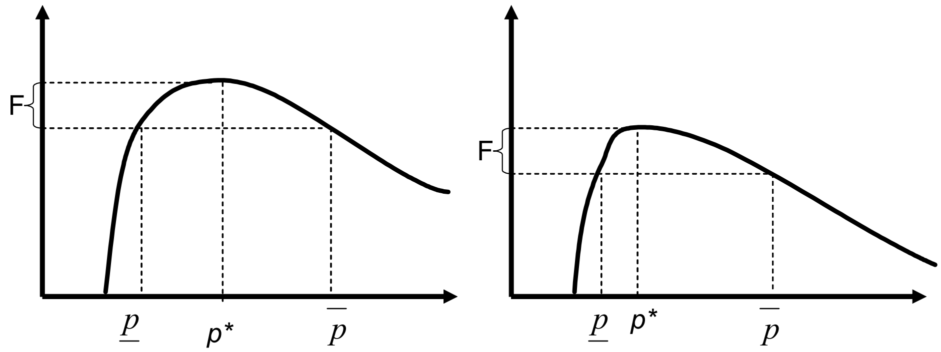

Figure 2: Asymmetry in value function and Ss-bands

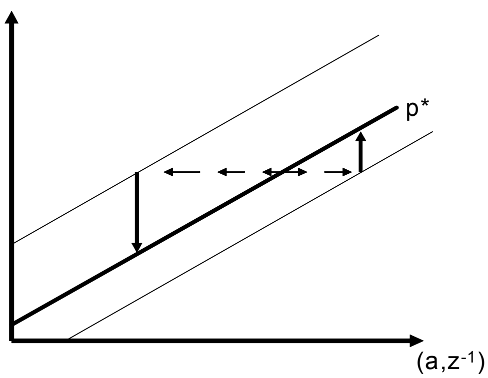

Figure 3: Asymmetry between price increases and decreases

than its upper Ss band, implying that it is going to raise its price more often than lower it. On the other hand, when price increases occur, they tend to be by a smaller magnitude.[10]

Now, how does this asymmetry depend on θ and α? The lower is α, the more marginal costs respond to quantities, and the higher is θ, the more the firm's mispricing affects its quantity. If prices are too low, the profit margin is then further reduced by the increased quantity (and hence the rise in marginal costs), whereas if prices are too high, the reduction in profits resulting from the lower quantity is mitigated by the fact that marginal costs are also reduced. Therefore, with higher θ and lower α, the asymmetry in the profit function and the Ss bands becomes even more pronounced, which implies that the asymmetry between price increases and decreases also grows, with increases becoming relatively more frequent but smaller in size than decreases.

We can therefore infer θ and α by calibrating our model to match these asymmetries between

[10] See Burstein (2006), Devereux and Siu (2005) and Ellingsen, Friberg and Hassler (2006) for a related discussion of pricing asymmetries in state dependent sticky price models.

price increases and decreases. Trend inflation affects the magnitude of these asymmetries, in particular the fraction of price changes that are increases, but not the fact that they become more pronounced as k increases (θ increases, α decreases).

Related to the problem of inferring pricing complementarities is the problem of isolating the relative importance of cost and demand shocks. Contrary to a model in which cost shocks are the only source of product level variation, a model with demand shocks will generate large fluctuations in prices only if there are sufficiently strong decreasing returns to scale. The observed magnitude of price changes will therefore be consistent with more strongly decreasing returns to scale in a model that allows for demand shocks than in a model with idiosyncratic cost shocks only.

Our inference of pricing complementarities would therefore be biased, if we followed existing calibrations by just focusing on one source of idiosyncratic shocks. Instead, it is important that we consider a model with both cost and demand shocks, and try to isolate how much of the price and share fluctuations are driven by each. We do this by calibrating the model to all four benchmark moments, in particular the ones relating to fluctuations in expenditure shares.

Our third observation provides an alternative for inferring whether price changes are mainly driven by cost or demand shocks, without directly relying on the data on market shares.

Observation 3: *Price changes are more likely to occur in periods with large sales (market shares). If cost shocks are important this occurs when the original price is low. If demand shocks are important, this occurs when the original price is high.*

Ceteris paribus, profits are more sensitive to mispricing, when a good is in high demand. This in turn leads to narrower Ss bands, and a higher frequency of price changes, than when demand is low. Now, if price changes are driven mostly by cost shocks, a product is in high demand when its price is low. In contrast, if price changes are driven mostly by demand shocks, a product that is in high demand also tends to have a high price.

As plotted by figure 4, this suggests a difference in the width of the Ss-bands, depending on whether idiosyncratic shocks are to demand or to technology: in a cost shock model, price changes should be more frequent, when the original price is relatively low. In a demand shock model, price changes instead should be more frequent, when the original price is relatively high. A model that combines both shocks will fall somewhere in between, but knowing how the likelihood of a price change depends on the original price can still inform us about the relative importance of cost vs. demand shocks.

This argument is based on the premise that price changes are indeed more likely when demand

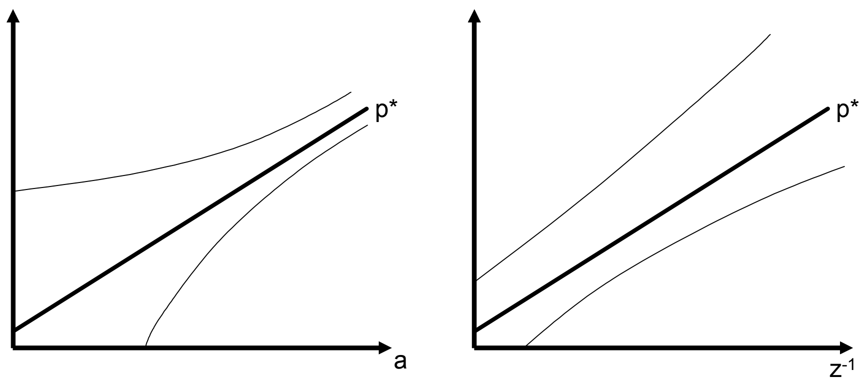

Figure 4: Asymmetry between high and low relative prices

is high. Therefore, we will also need to look at how the likelihood of price adjustment depends on the current level of demand (or the current market share).

In summary, the first two observations allow us to infer θ and α, and therefore measure the strength of pricing complementarities. All else equal, stronger pricing complementarities require higher menu costs and generate more asymmetries between price increases and decreases. To correctly infer these pricing complementarities, we also need to infer the relative importance of cost and demand shocks. We can infer this either from the benchmark moments (in particular, the fluctuations in market shares), or using our third observation, that price changes are more likely to occur in periods with high demand, which occurs at low prices when cost shocks are important, and at high prices when demand shocks are important.

4 Data on prices and market shares

We now apply the ideas described above, designed to discipline the model's parameters, using a specific dataset. This dataset measures retail sales by Dominick's Finer Food, a large supermarket chain with 86 stores in the Chicago area, and was prepared by the University of Chicago's Graduate School of Business in cooperation with Dominick's. The products included in this dataset include non-perishable food products (e.g. crackers), household supplies (e.g. detergents), and hygienic products (e.g.: shampoo). While limited in scope due to its narrow geographic coverage and particular set of grocery products, this dataset has the advantage of providing high frequency information on both prices and quantities for many items within narrowly defined product categories.

It is a weekly store-level scanner data by universal product code (UPC), ranging between 1989 and 1997. For each UPC it includes weekly sales and retail prices. The dataset includes 29 product categories (e.g.: beer, bottled juice, toothpaste, dish detergent) and more than 4500 UPCs (e.g.: Crest mint 8.2 oz., Tropicana mango 46 oz). We conduct our analysis of pricing at the chain level. Dominick's follows a chain-wide pricing strategy, with some discretion given to individual stores which results in prices not perfectly correlated across locations. Stores are divided into high, medium, and low pricing zones, depending on the extent of local competition. We only consider stores that are included in the middle-level pricing zone, which contains the largest number of stores. We focus on fluctuations in market shares, as opposed to fluctuations in physical quantities, to isolate fluctuations that are due to idiosyncratic, as opposed to sectoral shocks to aggregate quantities of a product category.

We index weeks by w, product categories by i, UPC's by j, and stores by k. We construct market shares, s_{kw}^{ij}, as the ratio of sales of UPC (i, j) in store k and week w, to total sales across all UPCs within product category i in store k and week w. Similarly, we construct relative prices p_{kw}^{ij} as the ratio of the nominal price P_{kw}^{ij} of UPC (i, j) in store k in week w to the aggregate price P_{kw}^{i} of product category i in store k in week w (product category prices P_{kw}^{i} are averages of individual price levels using store k, week w market shares as weights). We also construct an indicator variable x_{kw}^{ij} of temporary price mark-downs, defined as a price reduction that is reversed to its original value in no more than 6 weeks. That is, $x_{kw}^{ij} = 1$ if $P_{kw}^{ij} < P_{kw'}^{ij} = P_{kw''}^{ij}$, $w' < w$, $w'' > w$, for at least one pair $\{w', w''\}$ such that $w'' - w' \in \{2, 3, 4, 5, 6\}$, and $x_{kw}^{ij} = 0$ otherwise.[11]

We aggregate the data across weeks and stores, as follows. We define time periods as $T-$week intervals, and we index periods by t. That is, period $t = 1$ includes weeks $w = 1, ..., T$, period $t = 2$ includes weeks $w = T + 1, ..., 2T$, and so forth. We aggregate the data on relative prices and market shares by taking simple averages across stores and weeks within a T week time period, for UPC's with at least 8 consecutive time periods of data. The resulting relative prices and shares are denoted by p_t^{ij} and s_t^{ij} – note that these measures exclude store index k and week index w. We report moments of the data that include or exclude temporary price markdowns, where the latter are computed using only observations with $x_{kw}^{ij} = 0$. We also report the moments of the data if we use weighted averages instead of simple averages, if we only focus on data for one store (the one with the lowest number of missing observations), and if we compute our statistics for price

[11] The V pattern that we use to construct a sales indicator is closely related to the definition of "filter B" in Nakamura and Steinsson (2006). It is more restrictive than that in Midrigan (2006), who does not impose price reductions to return to their original level when defining a sale.

and market share changes across all individual stores for each UPC (rather than constructing one chain-level price and market share for each UPC).

For our statistics on changes in chain-wide price levels, we do not calculate an average price across weeks and stores – this would deliver artificially high price flexibility as simple price averages would reflect changes in only a subset of (some) individual store/week prices. Instead, we measure the median price set by Dominick's across stores (within the medium pricing zone) for each UPC in a given time period. If there is more than one price observation per time period (say because a time period includes multiple weeks), then we use the price observation corresponding to the first available week. In the calculations that abstract from temporary price mark-downs, we exclude those price observations with $x_{kw}^{ij} = 1$ when computing the median price for each UPC/period.

Our baseline statistics are constructed using 4 week time periods ($T = 4$) — the time length of a period in the calibration of our model, and abstracting from UPC/periods with market shares that are sufficiently small (i.e. 0.1%). Below we discuss how the results change if the moments of the data that we focus on are constructed in alternative ways. We compute the statistics described below for each UPC, and then compute a weighted average of the value of these statistics across all UPC's within each product category (using as weights the fraction of sales of each UPCs in total sales of its product category during the total time span). We report each statistics for the median product category. We then perform the same calculations using data generated by our model.

For our benchmark calibration, we focus on the moments excluding temporary mark-downs. In the sensitivity analysis in section 7, we discuss how our results change if we instead used the moments that included mark-downs.

A. Frequency of price adjustment: The frequency of price adjustment for each UPC is defined as the fraction of observations with price changes, and the price duration is defined as the inverse of the frequency. Table 1, Row 1, shows that, for the median product category, the price of the average UPC changes every roughly 4 four-week periods (this is equal to 1/0.25) excluding temporary price markdowns, and 2.5 four-week periods including temporary price markdowns. In the model calibration, we target an average duration of 4.5 periods, in order to make the results comparable to Golosov and Lucas (2006) and Midrigan (2006).

B. Magnitude of Price Changes: We focus on measures of the size of changes in prices over time (and changes over time in the logarithm of market shares in the following subsections), and we do not focus on differences in price levels (or levels of market shares) across goods at a point in time, because our model abstracts from permanent differences across goods in quality, size, characteristics, etc. that explain some of the price (and market share) differences across goods observed in the data.

Table 1, Rows 2-4, reports three measures to document large changes in UPC prices. Row 2 displays the average magnitude of non-zero price changes. It is roughly 10% if we exclude temporary price markdowns, and 13% otherwise. Row 3 displays the standard deviation of non-zero price changes, roughly 15% excluding temporary price discounts and 19% if we include them. Row 4 displays the standard deviation of relative prices p (the nominal price of the UPC divided by the nominal price of the product category). Note that here we do not exclude zero price level changes, as even in those cases the relative price might change if the aggregate product level price changes. The standard deviation of relative price changes is 7% if we exclude temporary price markups and 9% if we include them.

The magnitude of price changes (as well as the magnitude of price increases relative to price decreases described in F) that we observe in the Dominick's supermarket dataset is very similar to that reported in Klenow and Kryvtsov (2005) and Nakamura and Steinsson (2006) for the overall CPI in the US, and in Dhyne et. al. (2006) for the overall CPI in the Euro Area.

In our calibration, we target a 4-week average magnitude of prices changes equal to 10%.

C. Magnitude of Share Changes: Table 1, Rows 5-7 reports the magnitudes and standard deviations of changes in log-market shares (note that this is different from the standard deviation of percentage point changes in market shares). The average magnitude of changes in log market shares is 17%, and the standard deviation is roughly 25%. Row 7 indicates that fluctuations in market shares are significant even if we focus on periods with no price change. If we include temporary price markdowns, log market shares are roughly 5% more volatile.

In the benchmark calibration of our model, we target a 4-week standard deviation of changes in market shares equal to 25%.

D. Comovement of Prices and Share Changes: Table 1, Rows 8-11 report four statistics that summarize the comovement between changes in prices and changes in market shares. Recall that a model with only idiosyncratic cost shocks would imply a strongly negative correlation between price and market share changes, and a model with only idiosyncratic demand shocks would imply a strongly positive correlation, in the presence of decreasing returns to scale.

Row 8 displays the fraction of price changes in which price and market shares are of the same sign. Note that the model with only idiosyncratic cost shocks would imply that all price changes are accompanied with share changes in the opposite signs (provided that prices are set along the elastic part of the demand schedule). For the median product category, this ratio is roughly 45% if we exclude temporary price markdowns, and 40% if we include them.

Row 9 and 10 display the correlation between changes in price levels and market share changes (row 10 conditions on observations with non-zero price changes). The correlations are roughly -0.1 if we exclude temporary price markdowns and -0.2 if we include them.

Row 12 displays the correlation between changes in relative prices and market shares (including zero price change observations). This correlation, which is computed aggregating the data across all stores, is roughly -0.2 if we exclude temporary price markdowns, and -0.35 if we include them. These correlations are only slighly closer to zero if we condition on nominal price adjustment.[12][13]

The fact that correlations between prices and market shares are far from -1 and that prices and market shares frequently move in the same direction suggests that idiosyncratic demand-like shocks are partly responsible for movements in prices and quantities. In our benchmark calibration we target a correlation of price and share changes, conditional on nominal price adjustment, of -0.20.[14]

E. Menu Costs: Our dataset does not contain information on the costs of changing prices, either by Dominik's or its suppliers. Levy et al. (1999) and Zbaracki et al. (2004) report that firms devote between 0.4% and 0.7% of their revenues on average to price changes. Although these numbers are based on a small number of firms and on time-use survey data, they are consistent with the common sense notion that costs of price changes are very small compared to the overall costs and revenues of a firm's activities. In our benchmark calibration, we target average spending on menu costs that are not larger than 1% of steady-state revenues.

F. Price Increases vs. Decreases: Rows 13-14 reports the likelihood and size of price increases relative to price decreases. Row 13 shows that for the median product category, roughly 60% of prices changes, exclusive of temporary price markdowns, are price increases. Including price promotions, the fraction of price increases is roughly 54%. Row 14 shows that the size of price increases is only slightly smaller than the size of price decreases (the ratio of the average magnitude

[12] We also compute an alternative relative price (market share) measure, defined as the ratio of the current price (market share) of a UPC to the average price (market share) across periods for that UPC. The standard deviation and correlation of these alternative measure of relative prices and market shares is very similar to those that we report in Table 1.

[13] We also compute these statistics using physical quantities for each UPC, instead of using market shares. We find that quantities are slightly more volatile than market shares, and the correlation between prices and quantities is slightly more negative than the correlation between prices and market shares.

[14] Note that increases in relative prices driven by temporary price markdowns of a firm's competitor, if associated to a rise in the quantity sold, would generate a negative comovement between relative prices and market shares. Hence, accounting for the observed comovement between relative prices and market shares, which is far from -1, requires additional sources of demand fluctuation.

of price increases relative to price decreases is roughly 0.85 if we exclude sales and 0.90 if we include them).

In pure accounting terms, the steady state inflation rate can be decomposed into the frequencies and magnitudes of price increases and decreases. With the right steady state inflation rate, matching one of these two moments automatically implies that we also match the other one. In our model, the steady state inflation rate primarily impacts the fraction of price increases versus decreases, with only minimal effects on the relative magnitudes.[15] In order for our results to be robust to small variations in the steady state rate of inflation, we decide to target the relative size of price increases and decreases, rather than the relative frequencies.

G. High vs. Low Prices: Row 15 reports the frequency of price changes conditioning on whether the price level is higher or lower than the median price for each individual UPC. We first compute the median price for each UPC. We then compute the frequency of price change separately for periods in which prices that are higher or lower than the median price. We then average each frequency across UPC's, and take the ratio of the high-price frequency to the low-price frequency. We report the median ratio across product categories.

Row 15 shows that, excluding price promotions, the frequency of prices changes is roughly independent on whether pre-change prices are low or high (the ratio of frequencies conditional on prices being high versus low is roughly 0.95). If we include price promotions, prices are slightly less likely to change if the initial price levels is high.

H. High vs. Low Market Shares: Row 16 redoes the calculations in F, now conditioning on high versus low initial market shares (instead of conditioning on high versus low price levels). We follow the same steps as before, computing the median market share for each UPC, and separately computing the frequency of price changes for periods in which the market share of a UPC is above or below the median. The results in Row 16 suggest the that prices are more likely to change in periods when the market share is high (the ratio of frequencies is roughly 1.2).

Table 2 reports the statistics when we depart from the baseline calculations reported in Table 1 along five different dimensions: (1) construct one-week time-periods ($T = 1$) instead of four-week time periods ($T = 4$), (2) compute weighted averages of relative prices and market shares, instead of simple averages, across stores and weeks, (3) exclude from the calculation of the statistics UPCs/time periods with average market shares lower than 1% (instead of 0.1% in the benchmark

[15] Gagnon (2006) reports, using CPI data for Mexico, that changes in inflation have a large effect on the relative frequencies of price increases and decreases, but not on the relative magnitudes.

case), (4) use data for only one store per product category (the one with the lowest number of missing observations for each product category), and (5) construct the statistics on price and market share changes using all individual store observations (as opposed to computing a single chain-wide price and market share for each UPC). Overall, in terms of the basic moments of the data, these perturbations from the baseline computations generate slightly lower frequencies of price adjustment, slighly larger price changes, more volatile market shares, and correlations between prices and market shares that are closer to zero. Also, there are only small changes in the magnitude of the asymmetries (both the size of positive relative to negative price changes, and frequency of price adjustment conditional on high and low relative prices). In Section 7, we perform sensitivity analysis in our model and argue that small changes in the calibration targets in the direction suggested by these robustness checks have only a minor impact on the inferred level of firm-level pricing complementarities. Moreover, the choice of targets (especially the relatively small size of price and market share fluctuations) biases our inference toward finding higher levels of firm-level pricing complementarities.[16]

5 Calibration Results: Steady-State

In this section, we report our steady-state calibration results. As in the data, we consider a period to be 4 weeks. We set $\beta = 0.995$ to match an annual real interest rate of 6%, and $\mu = 0.0017$ to match an annual inflation rate of 2.2%, which is the sector-level price inflation that we measure in the Dominick's data, for the median sector. Finally, we set the persistence parameters $\rho_z = \rho_a = 1/2$. In section 7, we present some sensitivity analysis regarding the persistence parameters.

To determine the remaining five parameters $\left(\theta, \alpha; F, \sigma_a^2, \sigma_z^2\right)$, we fix α at various levels between 0 and 1, and calibrate the other four parameters to match our four benchmark moments. We then compare how well these different calibrations match our secondary targets to determine what values of α and θ are plausible. Before going to the full calibration, we present results for menu cost models with exclusively cost and demand shocks, setting $\sigma_\alpha = 0$ or $\sigma_z = 0$. This preliminary step illustrates the previous observations that underlie our main calibration results.

Single Shock Model: In Table 3, Columns 1-5, we report results for the model with cost shocks only. Without demand shocks, the correlation between prices and market shares must be

[16] In related work, Dossche, Heylen and Dirk Van den Poel (2006) infer a relatively small degree of demand-based pricing complementarities using a large scanner dataset of a European retailer. Their data, which covers a wide variety of products such as clothing, equipment, and leisure goods, reveals a very high volatility of quantity changes, as well as comovements between relative prices and quantitites that are significantly larger than -1.

-1 by assumption (Row 10). For different values of α, we then calibrate the other parameters to match the remaining three benchmark moments (Rows 7-9). F and σ_z are adjusted to jointly match the frequency and magnitude of price changes. The demand elasticity is then adjusted to match the variability of share changes. The case with $\alpha = 0.99$ (Column 1) roughly replicates the calibration results of Golosov and Lucas (2006), with near constant returns to scale.

Table 3, Columns 6–9 report similar results for a model with demand shocks only. With fully flexible prices, such a model would imply that prices and shares are perfectly, positively correlated. With menu costs, the correlation between prices and market shares need not be perfect, but remains large and positive (Row 10). As before, we therefore fix α at different levels, and adjust the remaining parameters to match all the benchmark moments except the correlation (Rows 7-9). In the demand shock model, we are no longer able to match the magnitude and frequency of price increases with near constant returns to scale (Column 6). Since prices respond then very little to demand shocks, shocks must become very large to match the frequency and magnitudes of price changes. But that in turn would generate implausibly large changes in market shares. We will therefore exclude Column 6 from our discussion.

The results illustrate our three observations from the previous section. First, with more strongly decreasing returns, both menu costs and idiosyncratic shocks become larger. In the model with cost shocks only and $\alpha = 0.35$, the average menu cost represents as much as 5% of firm revenues (Row 5), and cost shocks become as large as 25% month-to-month (Row 3). In the demand shock model, the effect is less pronounced, with the magnitude of idiosyncratic demand shocks rising from 24% to 30% as α falls from 0.75 to 0.35 (Row 4), and the magnitude of menu costs rising to 2.5% of revenues (Row 5).

Second, lower α generate larger asymmetries between price increases and decreases. In the cost shock model, the relative magnitude of price increases drops from 90% to 78% of the magnitude of decreases, as α drops to 0.35 (Row 11). In the demand shock model, increases and decreases tend to be less asymmetric overall, but the same pattern emerges, with the magnitude of increases relative to decreases dropping from 95% to 80% as we lower α all the way to $\alpha = 0.35$. To maintain the same steady-state inflation, price increases become more frequent relative to decreases.

Third, the repricing probability depends positively on the level of demand and current prices. In the cost shock model, price changes are only about 60% as likely to occur when relative prices are high, than when they are low (Row 12), and they are 1.6 times as likely to occur when market shares are high (Row 13) rather than low. In the demand shock model, price changes are about 1.3 times as likely to occur when prices are high as opposed to when they are low (Row 12), and

1.25 times as likely when shares are large as opposed to small (Row 13).

Finally, the comparison between the cost shock and the demand shock model reveals how a model with demand shocks may be more easy to reconcile with strongly decreasing returns to scale, and hence how our inference may be invalid, if one doesn't correctly account for the relative importance of cost and demand shocks. In the model with cost shocks, a model with at best moderate returns to scale ($\alpha \geq 0.75$; $\theta \approx 6$) seems to do the best, matching a size of menu costs that is no larger than 1.3% of revenues and an asymmetry between increases and decreases of 0.88, meaning that increases are on average 12% smaller than decreases. In the demand shock model, instead, the model fits the additional targets best when decreasing returns are more substantial ($\alpha \leq 0.55$; $\theta \approx 3$), generating menu costs of at least 0.6% and increases that are at least 11% smaller than decreases. Both of these extremes completely miss out on the correlation between price and share movements (Row 10) and on the sensitivity of the repricing frequency to the level of prices and demand (Rows 11 and 12), suggesting that some intermediate case will be most consistent with the data.

Model with demand and cost shocks: In Table 4, we report our results for the model with demand and cost shocks. As before, we fix α at different levels, and then determine the other four parameters to match our four moments, including the price-share correlation.

For example, beginning with $\alpha = 1$, we can match a slightly negative correlation by setting θ fairly close 1: if $\alpha = 1$, prices only respond to productivity shocks; $\theta \approx 1$ in turn implies that price and share changes are completely orthogonal to each other. The parameters F, σ_z and σ_a are then set to match, respectively, the average duration and average magnitude of price changes, and the variability of share changes. This parametrization, however, would imply fairly large mark-ups.

As we lower α, the firms' optimal prices begin to respond also to demand shocks, which, ceteris paribus makes the correlation between prices and shares less negative. Moreover, firm profits become more sensitive to mispricing, which generates an incentive to have more frequent, but smaller price adjustments. To compensate for this, we need to raise θ to reduce the correlation between prices and shares, and F, σ_a and σ_z need to increase to maintain the same frequency and magnitude of price and share changes (Rows 2-5).

In contrast to the pure cost shock model, the shocks no longer appear to be implausibly large given the fluctuations we observe in the data. The 10% magnitude of cost shocks is similar to the values used in other calibrations. In addition, this value is similar to the magnitudes of changes in whole-sale prices in the Dominick's data.[17] Our measure of the magnitude of demand shocks is a

[17] The Dominick's data report the cost of acquisition of the current inventory, not the current replacement costs.

bit larger, but this is to be expected given the fairly large variability in market shares.

How well do the different calibrations do in terms of matching our secondary targets? It appears from Row 5 that a model with α in the range of 0.55 to 0.75 and θ in the range of 3.8 to 4.3 requires menu costs that are in line with existing empirical measures; lower values of α lead to significantly larger menu costs of up to almost 4% of revenue at $\alpha = 0.25$, while higher values of α generate menu costs that are even smaller than the existing estimates of 0.4% to 0.7% of revenue. Moreover, a higher value of α would also implausibly low demand elasticities, and extremely high profit rates and mark-ups.

The same values of α also match the asymmetry between price increases and price decreases fairly well: at $\alpha \approx 0.55$, increases are about 13% larger than decreases (Row 11). A lower α would lead to asymmetries between increases and decreases that are too large, with price increases that are up to 25% smaller than decreases, while higher values of α generate asymmetries that are too small, with price increases that are almost the same magnitude as price decreases.

Finally, throughout all calibrations, the adjustment probability when market shares are high is roughly 20% larger than the probability of adjustment when market shares are low (Row 13), and when prices are high, they are roughly 5% less likely to change as when they are low (Row 12). Both of these values are close to the target, which confirms that our calibration successfully matches the relative importance of cost and demand shocks. However, since they are pretty much constant throughout all the calibrations, they do not add anything to the inference of pricing complementarities.

The degree of pricing complementarity that is implied by these values of α and θ depends on the assumed value of aggregate pricing complementarities γ. With $\gamma = 0$ (flexible wages), our range estimate of $\alpha \in [0.55, 0.75]$ and $\theta \in [3.8, 4.3]$ leads to a pricing complementarity coefficient of k between 0.4 and 0.6. Since these values are bigger than 0, there exist moderate levels of pricing complementarities, but these are much less strong than the macro estimates by Rotemberg and Woodford (1997), who suggest that a value of $k \approx 0.85$ is needed to match the aggregate persistence of nominal shocks in the context of a Calvo model. On the other hand, if $\gamma \to 1$ (rigid wages), our estimate of k is roughly 0.85, which gets us much closer to the range suggested by Rotemberg and Woodford. Aggregate channels for pricing complementarities thus appear to be essential for reconciling these macro estimates of pricing complementarities with our calibration to micro data.

Whole-sale prices therefore provide a reliable proxy for costs only for items that have a fast turn-over rate, such as certain refrigerated food items.

Why don't the data support stronger firm-level pricing complementarities? First, fluctuations in prices and quantities are both fairly large, and the price-share correlation suggests that a significant component of these fluctuations is driven by demand shocks. With more strongly decreasing returns, these demand fluctuations would lead to sizeable fluctuations in the firm's marginal costs, and hence would give the firm a motive to change prices much more frequently and hence spend much more resources on changing prices. This however would lead to much larger menu cost than is observed in the data. Second, a model with stronger pricing complementarities would generate much more asymmetry between price increases and decreases than the moderate degree of asymmetry that we observe in the data.

6 Aggregate impulse responses

We now consider the aggregate impulse response of a one-time spending shock. Starting from the steady-state distribution of normalized prices Φ, we consider the dynamic effects on prices and output of a one-time increase in M by 0.5%, followed by a return to steady-state growth rate μ. This experiment is equivalent to computing the transition path of the distribution of prices $\Phi^\infty = \{\Phi_t\}_{t=0}^\infty$ and the resulting price levels $\hat{P}^\infty = \left\{\hat{P}_t\right\}_{t=0}^\infty$ to the steady state distribution Φ and price level $\hat{P}$, starting from an initial distribution Φ_0, where $\Phi_0(\hat{p}; s) = \Phi(\hat{p}/(1+\Delta); s)$, where $\Delta = 0.5\%$ denotes the size of the shock.

In Table 5, we report our results regarding the aggregate effects of a nominal shock.[18] Each row corresponds to a different calibration, with α being the value that is reported in Column 1, and the values of $(\theta, F, \sigma_a, \sigma_z)$ corresponding to the calibrated parameter values from Table 4. Column 2 reports the assumed value of γ that we use to compute impulse responses, and Column 3 the resulting degree of pricing complementarities. Our preferred calibration is highlighted in bold.

We consider two different measures to evaluate the effects on output to the nominal spending shock. In Column 4, we report the response of aggregate output Y *on impact*. By ignoring the dynamic effects of the shock after the first period, this measure only provides a very incomplete picture of the overall effects, but it has the advantage that it is easy to interpret within the context of the menu cost model. In Column 5, we report the Cumulative Impulse Response (CIR), which sums the impulse response of aggregate output over all months. This measure summarizes the cumulative impact of the nominal spending shock on output at different horizons and therefore provides a more complete picture of the real effects (see also Nakamura and Steinsson, 2006a, who

[18] In the table, all impulse responses are normalized by the size of the shock.

use and discuss this measure).[19] For example, if a shock increases output one-for-one on impact ($\Delta \ln Y / \Delta \ln M = 1$), and dies out at a linearly declining rate over a period of 24 months, the CIR would be equal to 12.

Table 5: Response to Nominal Shock				
α	γ	k	$\frac{\Delta \ln Y}{\Delta \ln M}$	CIR
0.95	0	0.06	0.32	0.41
0.55	**0**	**0.60**	**0.54**	**1.23**
0.25	0	0.73	0.64	1.95
0.95	0.85	0.82	0.72	2.23
0.55	**0.85**	**0.79**	**0.69**	**2.34**
0.25	0.85	0.79	0.70	2.42

Two observations stand out from the table:

Result 1: *Without aggregate pricing complementarities ($\gamma = 0$), the inferred pricing complementarities k increase the output effects of a nominal shock, but their overall effect remains small.*

With constant returns to scale, over two thirds of the nominal shock is absorbed by prices on impact. Going to our preferred calibration of $\alpha = 0.55$ slightly reduces this, but still nearly half the effect is absorbed on impact. Even substantially more decreasing returns ($\alpha = 0.25$) only raise the impact effect on output to 64%, meaning that more than a third of the shock is absorbed on impact. The cumulative output effect goes from 0.4 with constant returns to 1.2 in our preferred calibration, and 1.9 with $\alpha = 0.25$.

To assess the overall magnitude of these effects, we compare these values to the impulse responses for a benchmark Calvo model with an exogenous monthly adjustment probability of 1/4.5, and a degree of pricing complementarity of 0.8, which is close to the aggregate estimates of Rotemberg and Woodford (1997). This model implies a CIR of roughly 13. Even though our preferred calibration triples the CIR relative to the model with constant returns, the overall real effects remain smaller by a factor of 10 than in the alternative Calvo model.

Result 2: *Adding aggregate pricing complementarities does not lead to much stronger output*

[19] We do not consider the full dynamic reponse of the model economy to a monetary policy shock in relation to the estimates from a VAR analysis such as Christiano, Eichenbaum and Evans (2005), because we are abstracting from a richer macroeconomic model that would be required to account for the response of various other aggregates.

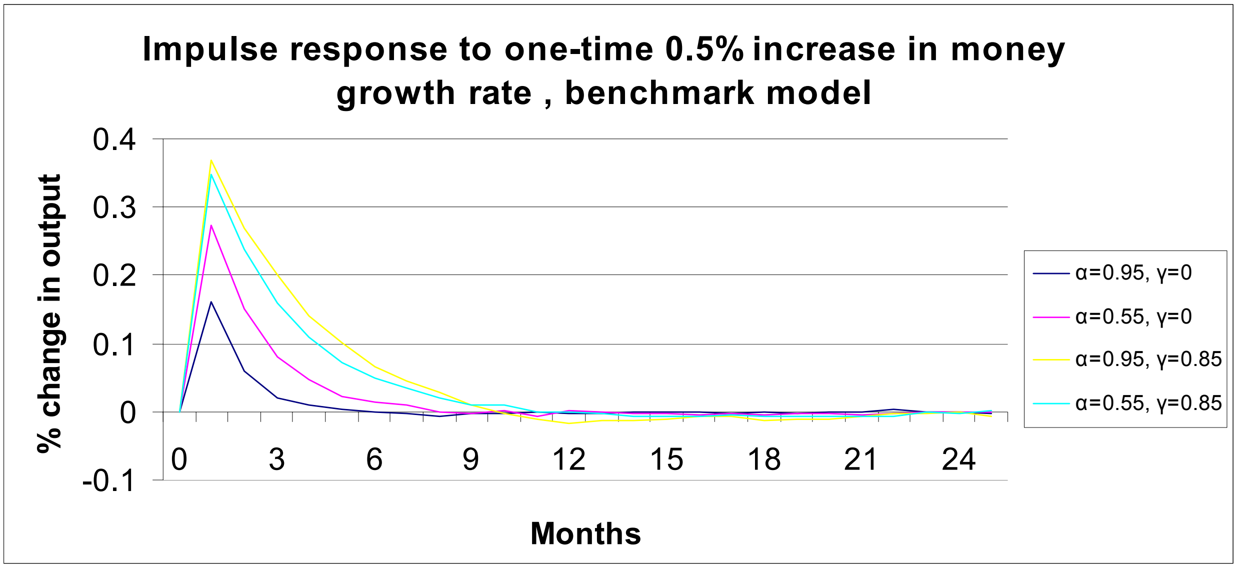

Figure 5: Impulse response to a 0.5% nominal shock

effects for $\alpha = 0.55$.

Increasing γ from 0 to 0.85 further raises pricing complementarities from 0.6 to 0.8, but it has only a relatively small additional effect on output, increasing the response of output on impact to roughly 70% in our preferred calibration, and increasing the CIR from 1.2 under $\gamma = 0$ to 2.3 under $\gamma = 0.85$. Adding strong aggregate pricing complementarities almost doubles the output effects, but these are still only one fifth of those in a Calvo model with comparable pricing complementarities.

Note also that with $\gamma = 0.85$, α plays a very minor role in determining aggregate effects. If γ was even higher, a lower α would actually weaken pricing complementarities and real output effects. Therefore, to assess the effects of aggregate pricing complementarities it is important to take into account the possibility of decreasing returns to scale; ignoring them would over-state the role of aggregate pricing complementarities, and for γ sufficiently high, also the output effects of nominal shocks.

Both results are also transparent from Figure 5, which plots the impulse responses of output to a 0.5% increase in nominal spending for the calibrations that we reported in the previous table. The time it takes for the shock to be completely absorbed into prices is proportional to the response on impact, and the CIR reported in the table above. In all cases, however, the shock is pretty much completely absorbed after 9 months. In the case with constant returns to scale and no aggregate pricing complementarities, the impact is much shorter, with almost complete adjustment taking place in 3-4 months.

Underlying both of these results is the fact that there is a strong extensive margin of price adjustment in the menu cost model that is not present in a Calvo model (the so-called 'selection effect' that is emphasized in Golosov and Lucas, 2006, and Midrigan, 2006). In our model, we can see this extensive margin by considering the following approximation of the response of prices on impact, which is similar to the one in Caballero and Engel (2007). Let $\underline{K}(s) = \ln \underline{p}(s) - \ln p^*(s)$ and $\bar{K}(s) = \ln \bar{p}(s) - \ln p^*(s)$ denote the steady-state Ss-bands in terms of their deviation from the target price $p^*(s)$, and let $\rho^*(s) = \ln p^*(s) - \ln \hat{p}^f\left(s; \hat{P}^{SS}\right)$ denote the steady-state "front-loading factor", by which firms who adjust their prices depart from the ideal price which maximizes current profits. We approximate equilibrium pricing strategies out-of-steady state by $\ln p_t^*(s) \approx \rho^*(s) + \ln \hat{p}^f\left(s; \hat{P}_t\right)$, $\ln \bar{p}_t(s) \approx \bar{K}(s) + \ln p_t^*(s)$ and $\ln \underline{p}_t(s) \approx \underline{K}(s) + \ln p_t^*(s)$, holding constant the size of the Ss-bands $\bar{K}(s)$, $\underline{K}(s)$ and front-loading factor $\rho^*(s)$. In the appendix, we show that under these assumptions, the response of prices on impact is approximated by

$$\frac{\Delta \log P}{\Delta \log M} \approx \frac{(1-k)(f+S)}{1-k(f+S)}$$

where f denotes the frequency of price adjustment, and S the selection effect. The frequency f captures or the the intensive margin of price adjustment, or the fact that all the firms that do adjust slightly increase their new target price after the shock has occurred. The selection effect S captures the extensive margin, or the fact that after the shock, some firms that would have kept their price constant now prefer to raise it (first term in S), and some other firms that would have reduced their price prefer now prefer to keep it constant (second term in S). Formally, these are defined as

$$\begin{aligned} f &= \int_{s'} \int_{-\infty}^{\underline{p}(s')} \hat{\phi}(p; s')\, dp ds' + \int_{s'} \int_{\bar{p}(s')}^{\infty} \hat{\phi}(p; s')\, dp ds' \\ S &= \int_{s'} \bar{K}(s')\, \hat{\phi}(\bar{p}(s'); s')\, ds' - \int_{s'} \underline{K}(s')\, \hat{\phi}(\underline{p}(s'); s')\, ds' \end{aligned}$$

where $\hat{\phi}(p; s') = \psi(s'|s)\, \phi(p; s) / \int_s \psi(s'|s)\, d\Phi(p; s)$ is the pdf of the distribution of prices and idiosyncratic states $(p; s')$ after the new idiosyncratic shock s' has hit, and before prices are adjusted. Since S and f are a function of the steady-state distribution of prices, and k is a function of the model parameters, we can compare the decomposition to the actual output response on impact, and find that in almost all cases this gives an accurate approximation. Throughout all our calibrations, the measured S is roughly constant at 0.45 in the menu cost model, and equal to 0 in the Calvo model. With a frequency of price adjustment targetted to 22%, this implies that on impact, our menu cost model has similar aggregate implications as a Calvo model in which 67% of all firms change their prices every period.

To illustrate the importance of this selection effect, we can use the decomposition for some simple counter-factuals, which are summarized in Table 6.

Table 6: Counter-Factuals

k	0	0.6	0.80	0.97
$\frac{\Delta Y}{\Delta M}$ $(S = 0.45)$	0.33	0.55	0.71	0.95
$\frac{\Delta Y}{\Delta M}$ $(S = 0.22)$	0.56	0.76	0.86	0.98
$\frac{\Delta Y}{\Delta M}$ $(S = 0)$	0.78	0.90	0.95	> 0.99

Without complementarities ($k = 0$), the Calvo model would predict an output response on impact of 78%, whereas the menu cost model predicts a response of 33% - two thirds of the shock is absorbed on impact. For the moderate firm-level complementarities that we identify in the data ($k = 0.6$), the selection effect reduces the output response from 90% to 55% on impact. Even for much stronger pricing complementarities, the selection effect substantially reduces output effects: In the context of a Calvo model, with $S = 0$ our inferred level of firm-level combined with $\gamma = 0.85$ ($k = 0.8$) would imply an output response of 95%. A selection effect of $S = 0.45$ reduces this number to 71%. To obtain an output response of 95% on impact with a selection effect of $S = 0.45$, one would need an extremely strong complementarity of $k = 0.97$.

We conclude from this discussion that a menu cost model can hope to obtain substantial output effects only if (i) there is a very large degree of pricing complementarities, and/or (ii) the selection effect is much smaller than what is suggested by our calibration. Moreover, the complementarity appears to have only a secondary role: if $f + S$ is sufficiently large, then even large values of k will imply a sizeable response of prices on impact. Pricing complementarities that are purely driven by product-level decreasing returns appear to be unable to quantitatively account for large output effects. While allowing for large aggregate complementarities increases k closer to the Rotemberg-Woodford range, the total output response of nominal shock remains small in the presence of a strong selection effect.

7 Extensions

In this section, we discuss a few extensions to our model, to explore the robustness of our results. In principle, their is an infinite number of alternative modeling assumptions and robustness checks that one might consider. Here, we restrict ourselves to a few for which one can make a plausible argument that they might significantly alter the results of our inference on pricing complementarities.

Sensitivity Analysis: First, we performed some rather simple sensitivity checks, recalibrating our model with different parameters or targets, to explore how sensitive our conclusions are to the targets that we picked for our calibration. We give a brief summary here; complete results are available on request.

As a first check, we varied the steady-state inflation rate over a range between 0 and 4% of annual inflation. This mainly affected the fraction of price changes that are increases, with little effects on the other moments. This confirms our earlier argument for focusing on the relative magnitudes as the relevant target to match.

We then considered the effects of different targets for the frequency of price changes (Nakamura and Steinsson 2006b for example, argue for a significantly longer duration of prices). When we raise the average duration of prices in the model to 8 months, our inference remains roughly the same: a longer duration leads to a higher menu cost, conditional on changing the price, but since price changes occur less frequently, the average menu cost remains roughly the same magnitude.

We also considered changes in the calibration targets for the magnitudes of price changes, the variability and magnitude of share changes, and the correlation between price and share changes. In Table 7, we report a summary of calibration results when we change some of the model targets, in a way that roughly cover the spectrum of targets that one could possibly support using a different measurement of the moments in the data, as reported for example in Table 2. The correlation between prices and shares turns out to have little effect on the resulting inference for pricing complementarities, but the magnitudes of price changes and of share changes do: lowering the average magnitude of price changes to 5% may increase the inferred k as far as 0.78, but requires a magnitude of price changes that are much lower than any existing micro estimates. Along the same lines, raising the volatility of shares lowers pricing complementarities, and lowering this volatility would increase them, but such a change does not appear to be supported by the data moments. Product-level pricing complementarities that are much stronger than $k \approx 0.6$ therefore seem to be difficult to support based on our our data.

These results also suggest that if we had instead targetted the moments of the data that do not exclude temporary price markups (reported in Tables 1 and 2), our inferred firm-level pricing complementarities would be even smaller, since prices and quantities are more volatile, if we include sales.By filtering out sales, we thus also err on the side of caution with regards to our conclusion that firm level complementarities appear to be relatively weak.

Finally, we conducted some sensitivity analysis with regards to the persistence parameters ρ. The findings of this are summarized in Table 8, where it can be seen that changing the persistence of shocks has little effect on our inference for complementarities.

The role of quantity data: Next, we explored the role of the data on quantities for our inference strategy and results. This is an important issue, since the pricing facts are much better studied, and have been observed over much more varied data sets (such as the CPI data, which includes a much broader range of products), whereas the facts about quantities are based on this particular data set.

In Table 9, we recalibrated our benchmark model, but only using data from prices. We fixed $\alpha \in (0, 1)$ at different levels, and calibrated the other parameters to match the frequency and magnitude of price changes (as before), the relative magnitude of increases vs. decreases, and the relative frequency of changes, conditional on the current price being above or below the mean. We then compared how well the different calibrations matched the remaining moments, so as to examine which of our conclusions rely on information about shares.

For $\alpha \leq 0.75$, the inferred magnitude of the menu cost is roughly constant near 1.1%, which is slightly higher than our target. This suggests that the information about menu costs may not be sufficient to differentiate between these different values of α. However, we also notice that over the same set of calibrations, the inferred degree of pricing complementarity remains roughly constant, at $k \in (0.55, 0.6)$. Therefore, although the exact values of α and θ cannot be inferred on the basis of price data and the magnitude of the menu cost alone alone, the calibration results nevertheless suggest 0.6 as an upper bound for firm-level pricing complementarities.

The quantity moments then help us fully identify the parameters. Market shares are much more variable, and the effect of share levels on the probability of price changes much larger, when α is closer to 1. As in the main calibration, a value of $\alpha \approx 0.55$ exactly matches these two moments; higher values of α imply share movements that are too large, and generate too much asymmetry between high and low shares, whereas lower values of α generate share movements that are too small, with too little asymmetry. The price-share correlation is only slightly higher than our target of -0.2, which suggests that by calibrating to the asymmetry between high and low prices, we account reasonably well for the relative importance of cost and demand shocks.

In summary, our general conclusion that 0.6 represents an upper bound for firm-level pricing complementarities does not seem to rely heavily on our use of quantity data; our inference of the exact parameter values for α and θ, however, does.

Modelling small price changes: Midrigan (2006) observes that almost 30% of all price changes are small in magnitude, i.e. by less than 50% of the median absolute price change. He rationalizes this observation by the idea that some firms may change more than one price at once, which essentially allows them to change some prices 'for free', and hence by small amounts, when they decide to undertake other, more important price changes.

We can embed a simple version of this mechanism in our model by assuming that in each period, there is a probability q that firms get to change their price for free. When we reformulate our model to take this possibility into account, we find that our inference of pricing complementarities remains roughly the same, although they are now the result of a slightly lower demand elasticity and slightly more strongly decreasing returns to scale (Table 10, Columns 1-4). The inferred selection effect, however, falls to $S \approx .22$, and S is approximated by

$$S = (1-q)\left[\int_{s'} \bar{K}\left(s'\right)\hat{\phi}\left(\bar{p}\left(s'\right);s'\right)ds' - \int_{s'} \underline{K}\left(s'\right)\hat{\phi}\left(\underline{p}\left(s'\right);s'\right)ds'\right]$$

Also, the model is no longer able to replicate the asymmetry between price increases and decreases. The reason is that this alternative formulation of menu cost begins to resemble more closely a Calvo model (in the extreme case, where F becomes infinite, the model is exactly like a Calvo model, since price changes will occur only when they are free). In a Calvo model, however, price increases tend to be larger on average than price decreases, since the firms want to front-load prices to preempt the risk of being committed to a price that is far too low after long periods without price adjustment and positive steady-state inflation.

Alternative shock distributions: Next, we explored the role of distributional assumptions regarding the shocks. Midrigan (2006) also emphasizes that the distribution of price changes has fat tails, which isn't consistent with the assumption of normally distributed shocks. In a model with cost shocks that allow for fat tails, the selection effect becomes much smaller, and aggregate adjustment delays become larger than in the model with normal shocks. It is therefore only natural to ask whether the distribution of idiosyncratic shocks also affects our inference of pricing complementarities.[20]

In our model, pricing complementarities give firms an incentive to respond to the idiosyncratic shocks they face by frequently adjusting their prices by small amounts. A model with stronger complementarities thus requires much larger menu costs, and larger shocks to account for the magnitude of price and share fluctuations observed in the data. Relative to a normal distribution, a fat-tailed distribution leads to a bigger mass of near-zero shocks (where the firms would not adjust

[20] Notice, however, that for given complementarities and selection effect, the aggregate implications are still summarized by the approximation formula.

unless returns to scale were really small, and a larger mass of really big shocks (where the firms would always adjust), but fewer mid-sized shocks, where the returns to scale have their strongest impact on the firms' desire to change prices. One might therefore conjecture that stronger pricing complementarities might be sustainable with fat-tailed distributions of idiosyncratic shocks, since this reduces the extent to which changes in returns to scale affect the frequency of price changes, all else equal.[21]

To explore this conjecture, we recalibrated our model assuming that the cost and the demand shocks were both AR1 processes whose innovations were drawn from a beta distribution, following Midrigan (2006):

$$\ln a_{it} = \rho_a \ln a_{it-1} + \begin{cases} +\sigma_a \varepsilon_{it}^a \text{ with probability } 1/2 \\ -\sigma_a \varepsilon_{it}^a \text{ with probability } 1/2 \end{cases}$$

$$\ln z_{it} = \rho_z \ln z_{it-1} + \begin{cases} +\sigma_z \varepsilon_{it}^z \text{ with probability } 1/2 \\ -\sigma_z \varepsilon_{it}^z \text{ with probability } 1/2 \end{cases}$$

where ε_{it}^z and ε_{it}^a are both independent over time and across products, and are both drawn from a $\beta\,(0.05; 1.3)$ distribution, and σ_a and σ_z are scaling parameters that are calibrated to target our benchmark moments. The parameters of the beta distribution are the same as those used by Midrigan (2006). They imply a higher kurtosis of price changes, consistent with the Dominick's data.

Table 10, Columns 5-8 report our results, which suggest that changing the distribution of shocks has only a minor influence on our inference results. As before, we fix α, and calibrate the other four parameters F, θ, σ_a and σ_z to match the four benchmark moments. For a given value of α, the calibration supports a somewhat higher demand elasticity, and hence somewhat higher value of k. For our preferred value of $\alpha \approx 0.55$, this leads to a value of $k \approx 0.7$. But while this is consistent with a similar magnitude of menu costs as in the benchmark model, it generates a substantially larger asymmetry between price increases and decreases, which contradicts any stronger pricing complementarities. Furthermore, this calibration implies that fluctuations in market shares as measured by the average magnitude (as opposed to the standard deviation) of share changes are substantially smaller than in the data, and in our previous calibrations. If we were to target the average magnitude of expenditure share changes, our results would reject bigger pricing complementarities even more strongly than they did before.

[21] To illustrate this point with an example, imagine that the idiosyncratic shocks are Poisson, i.e. are zero with high probability and non-zero, but with a wide distribution otherwise. Then, price changes occur only if non-zero shocks occur, irrespective of the pricing complementarities.

We also reconsidered the aggregate effects of nominal shocks in the model with fat-tailed idiosyncratic shocks. Irrespective of the strength of complementarities, the response of output on impact was only slightly larger than with normally distributed shocks, but the effects are a lot more persistent, so that the Cumulative Impulse Response increases roughly by a factor of 4. In the case where $\alpha = 0.55$ and $\gamma = 0.85$, the CIR is 8.57, which is still well below our Calvo benchmark of 13.

8 Conclusion

In sticky price models, pricing complementarities play an important role in determining the real effects of a monetary disturbance. In this paper, we have sought to infer the quantitative importance of one type of pricing complementarities, based on upwards-sloping marginal costs, by calibrating a menu cost model to data on price and quantity fluctuations at the product level. Our results suggest that pricing complementarities at the firm level are at best moderate, and thus seem unlikely, on their own, to generate large aggregate real effects. The presence of other complementarities at the aggregate level might lead to a bigger response of output to nominal shocks, but these complementarities cannot be directly inferred from idiosyncratic fluctuations in prices and quantities.

In addition to the robustness checks and extensions that we have already discussed above, there are at least three important caveats to our approach and our results. First, we abstracted from sector-level or aggregate shocks in the model. Our data however suggest that these shocks may be fairly large and induce important fluctuations in sectorial price and spending levels. To the extent that sectoral shocks add to the firms' desire to change prices, we conjecture that they would only reinforce our conclusions, since our calibration would then require larger menu costs and imply weaker pricing complementarities to match the data moments on prices and shares.[22]

Second, we had to rely on price-quantity data from a very small and highly specific set of goods to draw inference on important aggregate questions. This raises the obvious question of how representative our data is of the aggregate economy. While an adequate answer to this question requires similar data sources from other sectors, the calibration that matches only the pricing facts (Table 9) lends some support to our main conclusion rejecting stronger pricing complementarities. To us this is reassuring, since the pricing facts are observed across a much wider set of data (including the BLS data for the consumer price index), and can therefore be expected to be much

[22] In addition, aggregate fluctuations in prices and spending may also be useful for more direct ways of inferring pricing complementarities, which would complement the approach we have explored in this paper.

more representative of the aggregate economy.

Finally, we have focused on one specific form of pricing complementarities at the firm level, based on increasing marginal costs at the product level. There are, however, other forms of pricing complementarities at the firm level, based on variation in desired mark-ups, as originally studied in Kimball (1995) and more recently in Klenow and Willis (2006). We believe that some of our insights also apply to those types of complementarities, but it remains an open question whether they will significantly change our quantitative results.

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9 Appendix: Approximation Formula

Here, we derive and briefly discuss the approximation formula for the response of prices on impact that we used in section 6. We approximate optimal pricing strategies as in the text by $\log p_t^*(s) \approx \rho^*(s) + \log p^f\left(s; \hat{P}_t\right)$, $\log \bar{p}_t(s) \approx \bar{K}(s) + \log p_t^*(s)$, and $\log \underline{p}_t(s) \approx \underline{K}(s) + \log p_t^*(s)$, where $\rho^*(s) =$

$\log p^*(s) - \log \hat{p}^f\left(s; \hat{P}^{SS}\right)$ denotes the steady-state front-loading factor, and $\phi(p/(1+\mu); s) = \log \underline{p}(s) - \log p^*(s)$ and $\bar{K}(s) = \log \bar{p}(s) - \log p^*(s)$ denote the steady-state Ss-bands, in terms of deviation from the target. In the initial period of impact of a shock of size Δ to the log of nominal spending, the ideal flexible price $\log p^f\left(s; \hat{P}\right)$, and the approximated target price $\log p_t^*(s)$ and Ss-bands $\log \bar{p}_t(s)$ and $\log \underline{p}_t(s)$ all increase by the same magnitude δ. If $\Delta \log P$ denotes the response of the average price in the period of impact, δ satisfies $\delta = k(\Delta \log P - \mu) + (1-k)\Delta$.

We next compute the response of prices on impact $\Delta \log P$ as a function of δ, using our approximation of the pricing rule out of steady-state. Let

$$\hat{\phi}(p; s') = \psi(s'|s)\,\phi(p/(1+\mu); s) \Big/ \int_s \psi(s'|s)\,\phi(p/(1+\mu); s)\, ds'$$

denote the pdf of the steady-state distribution of prices and idiosyncratic states $(p; s')$ after the new idiosyncratic shock has hit, and before prices are adjusted. The aggregate response of prices (in logs) is then approximated by:

$$\Delta \log P_t \approx \int_{s'} \int_{p \le \underline{p}_t(s')} \left(\log p_t^*(s') - \log p\right) \hat{\phi}(p; s')\, dpds' + \int_{s'} \int_{p \ge \bar{p}_t(s')} \left(\log p_t^*(s') - \log p\right) \hat{\phi}(p; s')\, dpds'$$

where $\underline{p}_t(s')$, $\bar{p}_t(s')$, and $p_t^*(s')$ are approximated as above. Using the fact that

$$0 \approx \int_{s'} \int_{p \le \underline{p}(s')} \left(\log p^*(s') - \log p\right) \hat{\phi}(p; s')\, dpds' + \int_{s'} \int_{p \ge \bar{p}(s')} \left(\log p^*(s') - \log p\right) \hat{\phi}(p; s')\, dpds'$$

we can rearrange the above expression to that for a small δ, the response of prices on impact (in logs, and net of steady-state inflation) is approximated by

$$\Delta \log P \approx \delta(f + S)$$

$$\begin{aligned} \text{where } f &= 1 - \int_{s'} \int_{\underline{p}(s')}^{\bar{p}(s')} \hat{\phi}(p; s')\, dpds' \\ \text{and } S &= \int_{s'} \bar{K}(s)\,\hat{\phi}(\bar{p}(s'); s')\, ds' - \int_{s'} \underline{K}(s)\,\hat{\phi}(\underline{p}(s'); s')\, ds' \end{aligned}$$

f is the frequency of adjustment, which measures the intensive margin: all firms that would have change their price prior to the shock raise their new price by an amount δ. S measures the extensive margin: some firms that prior to the shock decided to lower their price now prefer to keep it constant (first term), their density is given by the steady-state density $\hat{\phi}(\bar{p}(s'); s')$, times the magnitude of the shift in the upper Ss band, δ, and these firms would have lowered their price by an amount $\bar{K}(s)$. By the same logic, the second term captures all the firms who originally chose

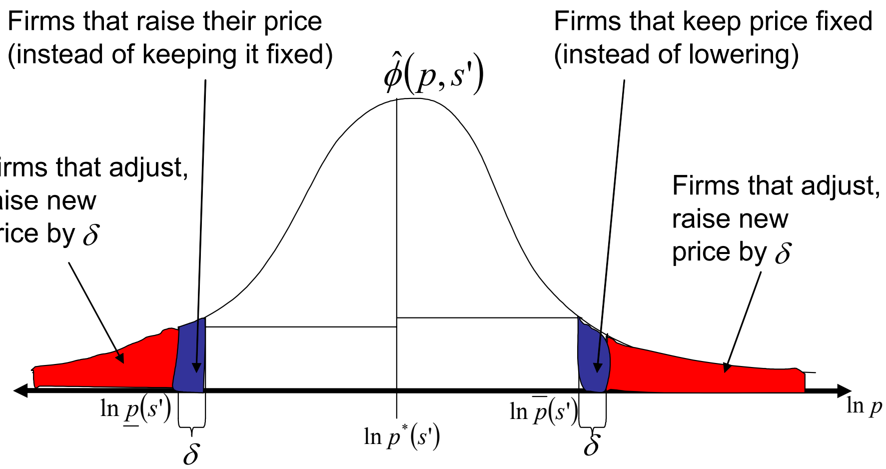

Figure 6: Price adjustment after shock

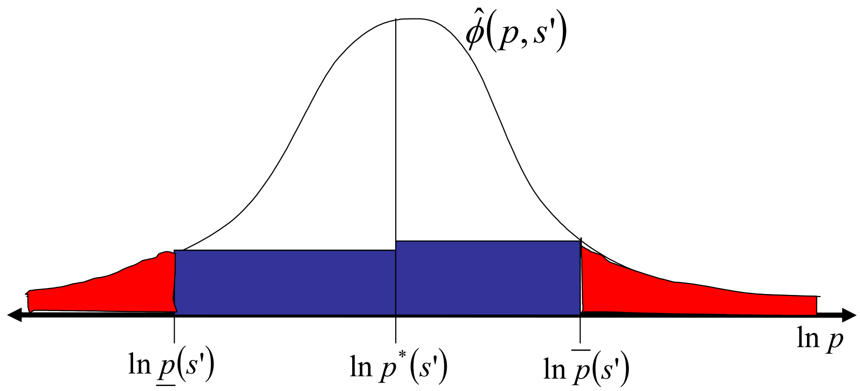

Figure 7: Frequency and Selection effect

to keep their price fixed, but now prefer to increase it. On average, they raise their price by an amount $\underline{K}(s)$. This is illustrated in Figure 6.

Figure 7 illustrates the frequency and selection effects for small δ. Integrating over all s', the red areas in the tails measures the frequency or intensive margin, and the blue rectangles measure the selection effect or extensive margin. The white area, integrated over all s', measures the residual, which corresponds to the real effect of the shock on impact.

This figure illustrates Midrigan's (2006) observation, how distributional assumptions determine the magnitude of the selection effect and hence matter a great deal for the aggregate effects of nominal shocks. If the density $\hat{\phi}$ has fat tails, a given frequency of price adjustment f will require a lower density at the Ss-bands $\underline{p}(s')$ and $\bar{p}(s')$, and a given average magnitude of price changes will require that the Ss-bands are closer to the target price $p^*(s')$. This however, reduces the size of the blue rectangles, implying a smaller selection effect, and a larger effect on output. As an extreme case, we also recover the neutrality example Caplin and Spulber (1987). If the density $\hat{\phi}(p; s')$ is a uniform density w.r.t. $\log p$, for each s', over an interval that strictly includes $\left[\underline{p}(s'), \bar{p}(s')\right]$, we can immediately see from the picture that the white area disappears, so that the nominal shock has no real effects.[23]

Finally, combining $\Delta \log P = \delta (f + S)$ with $\delta = (1 - k)\Delta + k\Delta \log P$ leads to the decomposition in the text.

[23] This can also be derived from our decomposition: in this case, f and S satisfy $f = 1 - \int_{s'} \hat{\phi} \int_{\log \underline{p}(s')}^{\log \bar{p}(s')} dp ds' = 1 - \int_{s'} \left[\log \bar{p}(s') - \log \underline{p}(s')\right] \hat{\phi} ds'$ and $S = \int_{s'} \left[\log \bar{K}(s') - \log \underline{K}(s')\right] \hat{\phi} ds' = \int_{s'} \left[\log \bar{p}(s') - \log \underline{p}(s')\right] \hat{\phi} ds'$.

Table 1: Prices and market shares, Dominiks data, Baseline Statistics

		4 week periods (T=4)	
		Excluding markdowns	**Including markdowns**
	A - Frequency of price adjustment		
1	Frequency	0.26	0.41
	B - Magnitude of price changes		
2	Mean absolute value	0.11	0.13
3	Standard deviation of non-zero changes	0.15	0.19
4	Standard deviation of relative price changes	0.07	0.09
	C - Magnitude of share changes		
5	Mean absolute value of log share changes	0.17	0.23
6	Standard deviation of log share changes	0.24	0.31
7	Standard deviation of log share changes for zero-price changes	0.22	0.29
	D - Comovement of price and share changes		
8	Fraction of prices and log share changes of equal sign	0.45	0.40
9	Correlation of price and log share changes	-0.08	-0.17
10	Correlation of price and log share changes for non-zero price changes	-0.11	-0.22
11	Correlation of relative price and log share changes	-0.23	-0.36
12	Correlation of relative price and log share changes for non-zero price changes	-0.20	-0.33
	E - Price Increases vs. Decreases		
13	Fraction of price increases	0.60	0.54
14	Size of price increases relative to decreases	0.86	0.92
	F - High vs. Low Relative Prices		
15	Frequency of high relative to low prices	0.97	0.90
	G - High vs. Low Shares		
16	Frequency of high relative to low shares	1.22	1.17

Table 2: Prices and market shares, Dominiks data, Robustness

		1 week periods (T=1)		One Store (least missing obs.)		Minimum share = 1%		Weighted averages		Compute stats across stores	
		Excluding markdowns	Including markdowns	Excluding markdowns	Including markdowns	Excluding markdowns	Including markdowns	Excluding markdowns	Including markdowns	Excluding markdowns	Including markdowns
	A - Frequency of price adjustment										
1	Frequency	0.13	0.24	0.18	0.38	0.28	0.43	0.24	0.41	0.16	0.43
	B - Magnitude of price changes										
2	Mean absolute value	0.12	0.15	0.08	0.12	0.11	0.14	0.11	0.13	0.09	0.14
3	Standard deviation of non-zero changes	0.16	0.21	0.10	0.17	0.16	0.20	0.15	0.19	0.12	0.18
4	Standard deviation of relative price changes	0.10	0.12	0.07	0.08	0.07	0.09	0.10	0.13	0.09	0.10
	C - Magnitude of share changes										
5	Mean absolute value of log share changes	0.23	0.26	0.33	0.35	0.16	0.23	0.39	0.28	0.35	0.39
6	Standard deviation of log share changes	0.35	0.38	0.43	0.45	0.23	0.30	0.53	0.39	0.46	0.50
7	Standard deviation of log share changes for zero-price changes	0.28	0.27	0.41	0.44	0.21	0.27	0.49	0.36	0.45	0.49
	D - Comovement of price and share changes										
8	Fraction of prices and log share changes of equal sign	0.42	0.27	0.47	0.41	0.44	0.39	0.59	0.39	0.47	0.42
9	Correlation of price and log share changes	-0.13	-0.35	-0.05	-0.14	-0.12	-0.18	0.11	-0.17	-0.04	-0.15
10	Correlation of price and log share changes for non-zero price changes	-0.21	-0.44	-0.10	-0.21	-0.17	-0.23	0.18	-0.24	-0.10	-0.20
11	Correlation of relative price and log share changes	-0.25	-0.45	-0.12	-0.27	-0.25	-0.37	-0.03	-0.40	-0.10	-0.25
12	Correlation of relative price and log share changes for non-zero price changes	-0.29	-0.47	-0.13	-0.28	-0.23					
	E - Price Increases vs. Decreases										
13	Fraction of price increases	0.55	0.53	0.62	0.53	0.59	0.54	0.61	0.55	0.65	0.54
14	Size of price increases relative to decreases	0.88	0.94	0.84	0.92	0.86	0.95	0.85	0.92	0.80	0.92
	F - High vs. Low Relative Prices										
15	Frequency of high relative to low prices	0.86	0.95	0.87	0.86	0.99	0.93	0.98	0.88	0.93	0.92
	G - High vs. Low Shares										
16	Frequency of high relative to low shares	1.36	1.54	1.18	1.14	1.21	1.13	0.81	1.18	1.13	1.15

Table 3: Baseline model, Steady State, Cost and Demand shocks only

		Target	1	2	3	4	5	6	7	8	9
			Cost shocks only					Demand shocks only			
	Parameters										
1	Returns to scale , α		**0.99**	**0.95**	**0.75**	**0.55**	**0.35**	**0.95**	**0.75**	**0.55**	**0.35**
2	Elasticity of substitution, θ		6.10	5.85	6.29	6.30	5.90	1.20	1.25	2.90	4.30
3	Standard deviation cost shocks, σ_z		0.06	0.08	0.13	0.19	0.25	0.00	0.00	0.00	0.00
4	Standard deviation demand shocks, σ_a		0.00	0.00	0.00	0.00	0.00	0.22	0.24	0.27	0.30
5	Average menu costs (% SS revenue)	< 1 %	0.45%	0.64%	1.30%	2.52%	5.02%	0.00%	0.03%	0.63%	2.45%
6	*Firm based pricing complementarities k* $(\gamma = 0)$		*0.05*	*0.20*	*0.57*	*0.70*	*0.76*	*0.01*	*0.06*	*0.46*	*0.68*
	Basic steady state implications										
7	Frequency of price adjustment (4 weeks)	0.22	0.22	0.23	0.22	0.22	0.22	0.22	0.21	0.22	0.22
8	Mean absolute price change, non-zero price changes	0.10	0.10	0.11	0.10	0.10	0.10	0.02	0.09	0.11	0.10
9	Standard deviation share change	0.25	0.24	0.26	0.26	0.25	0.25	0.25	0.27	0.25	0.26
10	Correlation of price and share changes, non-zero price changes	-0.2	-1.00	-1.00	-1.00	-1.00	-1.00	0.92	0.93	0.82	0.62
	Other steady state implications										
11	Size of price increases relative to decreases	0.85	0.90	0.88	0.88	0.85	0.78	1.00	0.95	0.88	0.80
12	Frequency of high relative to low prices	0.95	0.58	0.61	0.56	0.58	0.59	0.84	1.46	1.29	1.24
13	Frequency of high relative to low shares	1.2	1.74	1.66	1.80	1.77	1.73	1.07	1.53	1.38	1.32

Table 4: Baseline model, Steady State, Cost and Demand shocks combined

		Target	1	2	3	4	5	6	7
			Cost and demand shocks combined						
	Parameters								
1	Returns to scale , α		**0.99**	**0.95**	**0.75**	**0.65**	**0.55**	**0.35**	**0.25**
2	Elasticity of substitution, θ		1.55	2.18	3.83	4.20	4.30	4.59	4.64
3	Standard deviation cost shocks, σ_z		0.06	0.06	0.08	0.09	0.10	0.11	0.11
4	Standard deviation demand shocks, σ_a		0.21	0.23	0.25	0.25	0.26	0.26	0.25
5	Average menu costs (% SS revenue)	< 1 %	0.05%	0.11%	0.54%	0.86%	1.35%	2.79%	3.91%
6	*Firm based pricing complementarities k* $(\gamma = 0)$		*0.01*	*0.06*	*0.41*	*0.53*	*0.60*	*0.70*	*0.73*
	Basic steady state implications								
7	Frequency of price adjustment (4 weeks)	0.22	0.22	0.22	0.22	0.22	0.23	0.22	0.22
8	Mean absolute price change, non-zero price changes	0.10	0.11	0.10	0.10	0.10	0.11	0.10	0.10
9	Standard deviation share change	0.25	0.24	0.26	0.26	0.25	0.25	0.25	0.23
10	Correlation of price and share changes, non-zero price changes	-0.20	-0.20	-0.20	-0.21	-0.19	-0.22	-0.19	-0.20
	Other steady state implications								
11	Size of price increases relative to decreases	0.85	1.00	0.99	0.91	0.89	0.87	0.80	0.75
12	Frequency of high relative to low prices	0.95	0.87	0.90	0.92	0.92	0.94	0.96	0.99
13	Frequency of high relative to low shares	1.20	1.17	1.20	1.21	1.20	1.20	1.24	1.27

Table 7: Sensitivity Analysis to Model Parameters

	Parameters and steady state implications	Duration = 2 months				Duration = 8 months			
1	Returns to scale , α	0.95	0.75	0.55	0.35	0.95	0.75	0.55	0.35
2	Firm based pricing complementarities k $(\gamma = 0)$	0.05	0.38	0.64	0.71	0.05	0.39	0.60	0.70
3	Average menu costs (% SS revenue)	0.08%	0.38%	1.27%	3.07%	0.10%	0.43%	1.03%	2.45%
4	Size of price increases relative to decreases	0.97	0.96	0.93	0.88	0.95	0.90	0.86	0.79
5	Frequency of high relative to low prices	0.95	0.96	0.96	0.96	0.67	0.74	0.82	0.96
	Parameters and steady state implications	**Correlation of price, share changes = 0**				**Correl. of price, share changes = -0.4**			
6	Returns to scale , α	0.95	0.75	0.55	0.35	0.95	0.75	0.55	0.35
7	Firm based pricing complementarities k $(\gamma = 0)$	0.04	0.36	0.60	0.70	0.07	0.40	0.64	0.72
8	Average menu costs (% SS revenue)	0.07%	0.46%	1.24%	2.75%	0.14%	0.54%	1.53%	3.16%
9	Size of price increases relative to decreases	1.01	0.91	0.87	0.80	1.01	0.91	0.87	0.80
10	Frequency of high relative to low prices	0.94	0.95	0.97	1.02	0.84	0.87	0.90	0.92
	Parameters and steady state implications	**Mean absolute price change = 0.05**				**Mean absolute price change = 0.15**			
11	Returns to scale , α	0.95	0.75	0.55	0.35	0.95	0.75	0.55	0.35
12	Firm based pricing complementarities k $(\gamma = 0)$	0.13	0.60	0.78	0.83	0.03	0.27	0.47	0.63
13	Average menu costs (% SS revenue)	0.09%	0.57%	1.44%	3.29%	0.13%	0.50%	1.28%	3.23%
14	Size of price increases relative to decreases	0.97	0.89	0.85	0.79	1.02	0.91	0.86	0.80
15	Frequency of high relative to low prices	0.82	0.86	0.86	0.92	0.94	0.91	0.95	1.00
	Parameters and steady state implications	**Standard deviation share change = 0.4**							
16	Returns to scale , α	0.99	0.75	0.55	0.35				
17	Firm based pricing complementarities k $(\gamma = 0)$	0.01	0.57	0.75	0.81				
18	Average menu costs (% SS revenue)	0.08%	1.28%	3.39%	6.74%				
19	Size of price increases relative to decreases	1.00	0.85	0.77	0.70				
20	Frequency of high relative to low prices	0.85	0.92	0.97	1.00				

Table 8: Sensitivity Analysis to Model Parameters (Idiosyncratic Shock Autocorrelations)

	Parameters and steady state implications	$\rho_a = 0$, $\rho_z = 0.5$				$\rho_a = 0.5$, $\rho_z = 0$			
1	Returns to scale , α	0.95	0.75	0.55	0.35	0.95	0.75	0.55	0.35
2	Firm based pricing complementarities k $(\gamma = 0)$	0.05	0.36	0.59	0.67	0.05	0.36	0.59	0.72
3	Average menu costs (% SS revenue)	0.10%	0.39%	1.02%	2.21%	0.07%	0.41%	1.22%	2.91%
4	Size of price increases relative to decreases	1.03	0.92	0.87	0.83	0.97	0.89	0.85	0.79
5	Frequency of high relative to low prices	0.88	0.78	0.74	0.79	0.92	0.95	1.02	1.04
	Parameters and steady state implications	$\rho_a = 0.8$, $\rho_z = 0.5$				$\rho_a = 0.5$, $\rho_z = 0.8$			
6	Returns to scale , α	0.95	0.75	0.55	0.35	0.95	0.75	0.55	0.35
7	Firm based pricing complementarities k $(\gamma = 0)$	0.06	0.44	0.63	0.73	0.05	0.39	0.59	0.72
8	Average menu costs (% SS revenue)	0.11%	0.62%	1.61%	3.76%	0.10%	0.52%	1.37%	3.09%
9	Size of price increases relative to decreases	0.99	0.91	0.85	0.76	0.93	0.92	0.86	0.79
10	Frequency of high relative to low prices	1.02	1.13	1.11	1.09	0.90	0.85	0.85	0.86

Table 9: Inferring parameters using only price data

		Target	1	2	3	5	6	7
	Parameters		**Inference using asymmetries**					
1	Returns to scale , α		**0.95**	**0.85**	**0.75**	**0.55**	**0.35**	**0.25**
2	Elasticity of substitution, θ		8.00	6.20	5.90	4.45	3.20	2.50
3	Standard deviation cost shocks, σ_z		0.07	0.08	0.08	0.09	0.08	0.09
4	Standard deviation demand shocks, σ_a		1.10	0.50	0.38	0.26	0.17	0.13
5	Average menu costs (% SS revenue)	< 1 %	0.64%	0.90%	1.04%	1.32%	1.16%	1.13%
6	*Firm based pricing complementarities k* $(\gamma = 0)$		*0.26*	*0.44*	*0.55*	*0.61*	*0.59*	*0.53*
	Basic steady state implications							
7	Frequency of price adjustment (4 weeks)	0.22	0.223	0.217	0.219	0.223	0.218	0.225
8	Mean absolute price change, non-zero price changes	0.10	0.102	0.103	0.095	0.102	0.097	0.104
9	Standard deviation share change	0.25	1.21	0.52	0.38	0.26	0.16	0.13
10	Correlation of price and share changes, non-zero price changes	-0.20	-0.01	-0.08	-0.05	-0.15	-0.05	-0.08
	Other steady state implications							
11	Size of price increases relative to decreases	0.85	0.86	0.85	0.86	0.86	0.86	0.87
12	Frequency of high relative to low prices	0.95	0.94	0.95	0.96	0.95	0.95	0.96
13	Frequency of high relative to low shares	1.20	1.79	1.40	1.29	1.21	1.15	1.13

Table 10: Extended Model with Small Price Changes and Beta distribution

		Target	1	2	3	4	5	6	7	8
			Small price changes				**Beta distribution**			
	Parameters									
1	Returns to scale , α		**0.95**	**0.75**	**0.55**	**0.35**	**0.95**	**0.75**	**0.55**	**0.35**
2	Elasticity of substitution, θ		1.75	2.40	2.90	3.00	2.15	5.19	7.05	8.85
3	Standard deviation cost shocks, σ_z		0.09	0.11	0.13	0.15	0.40	0.55	0.74	0.95
4	Standard deviation demand shocks, σ_a		0.23	0.23	0.24	0.24	1.71	2.07	2.49	3.11
5	Average menu costs (% SS revenue)	< 1 %	0.10%	0.35%	0.89%	1.72%	0.03%	0.40%	1.31%	3.86%
6	Probability of zero menu-cost, **q**		0.14	0.15	0.15	0.15	0.00	0.00	0.00	0.00
	Firm based pricing complementarities k $(\gamma = 0)$		*0.04*	*0.26*	*0.46*	*0.57*	*0.05*	*0.51*	*0.73*	*0.84*
	Basic steady state implications									
7	Frequency of price adjustment (4 weeks)	0.22	0.22	0.22	0.23	0.22	0.22	0.22	0.22	0.22
8	Mean absolute price change, non-zero price changes	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
9	Standard deviation share change	0.25	0.26	0.26	0.26	0.26	0.25	0.25	0.24	0.26
10	Correlation of price and share changes, non-zero price changes	-0.20	-0.20	-0.20	-0.22	-0.20	-0.21	-0.21	-0.22	-0.22
11	Fraction of prices changes smaller than 5%	0.30	0.33	0.34	0.32	0.33	0.16	0.03	0.09	0.18
	Other steady state implications									
12	Size of price increases relative to decreases	0.85	1.02	1.04	1.03	1.05	0.91	0.87	0.80	0.71
13	Frequency of high relative to low prices	0.95	0.94	0.90	0.91	0.88	0.84	0.80	0.73	0.65
14	Frequency of high relative to low shares	1.20	1.11	1.12	1.14	1.17	1.16	1.21	1.22	1.20