Prices and Market Shares in a Menu Cost Model*

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Abstract

We propose a procedure to infer the quantitative significance 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 data set of super-market scanner data, to explore the quantitative importance of pricing complementarities for the propagation of nominal disturbances at business cycle frequencies. Although our data supports moderately strong levels of pricing complementarities, they appear to be too weak to generate much larger aggregate real effects from nominal shocks than a model without 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 so-called 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.

At a theoretical level, pricing complementarities can amplify arbitrarily small degrees of nominal stickiness at the micro level into arbitrarily large adjustment delays in the aggregate. Whether pricing complementarities 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 (such as decreasing returns to scale, firm-specific input markets, or scale-dependent demand elasticities). 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.[2]

As a key theoretical insight that drives our inference strategy, we discuss how firm-level pricing complementarities also give rise to asymmetries between price increases and decreases, and differences in pricing behavior, depending on whether current market shares and/or prices are high or low relative to their time-series average. Together with empirical measures (or reasonable upper bounds) on the magnitude of menu costs, we can use these asymmetries as additional moment restrictions to guide the choice of the model's parameters.

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

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

[2] We also explore the role of aggregate pricing complementarities, such as real wage rigidities. The strength of these complementarities, however, is not easily inferred from micro data, and requires either some estimates based on aggregate data, or some other outside estimates/calibrations.

(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 much weaker than what would be required to provide, purely on the basis of these firm-level pricing complementarities, 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. To match observed fluctuations in prices and market shares, 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).

In section 3, we then discuss how we can discipline the model's key parameters. In our model, the pricing complementarity depends on the returns to scale and on the elasticity of demand, which we need to infer using the micro data on prices and quantities. This leads to the well known identification problem of inferring the elasticities of demand and marginal cost using data on prices and quantities. Moreover, for reasons that we will discuss below, we need to infer these two parameters separately, and cannot just focus directly on the pricing complementarity to reduce the inference problem.

Our approach exploits key properties of the model for inference purposes, 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, we can place an upper bound on the magnitude of the menu cost using existing measures of the firms' costs of price adjustment. 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.

Alternatively, the menu cost model has some distinct implications for the data on prices and quantities that we can use to discipline model parameters even without taking a stand on the size of menu costs. 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, and we can thus determine these two parameters by calibrating our model to separately match the frequencies and magnitudes of 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 relatively high. 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 in turn provides information on pricing complementarities, since, in order to account for the observed magnitude of price changes, the latter must be stronger, the more important are the demand shocks.

These insights provide some guide, in addition to the basic properties of frequency, magnitude, variability and correlation of price and share changes, to discipline the degree of firm level pricing complementarities.

In sections 4-7, we then apply these insights in a calibration using one 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, in this paper we use a particular 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 both prices and market shares for many items within narrowly defined product categories.

In section 4, we discuss how we measure the empirical moments of the data to which our model is calibrated. The frequencies and magnitudes of price changes that we report are similar to the ones documented by Bils and Klenow (2005) and Klenow and Kryvtsov (2005) for the BLS data on the Consumer Price Index, and by Midrigan (2006) for the same data that we are using. 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 average. 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 average (as opposed to below average), but the frequency of price adjustment is only marginally higher when prices are below, as opposed to above average.

In section 5, we calibrate our model so that it matches these moments in steady state. We conclude that a model with a moderately strong degree of pricing complementarities of 0.6 provides the best fit, given the targeted moments. To put this number in perspective, Rotemberg and Woodford (1997) estimate pricing complementarities in a Calvo model using aggregate data, and argue that in order to generate a large propagation of a monetary disturbance at the business cycle frequency, the pricing complementarities must be much closer to 1, around 0.9.

In section 6, we explore the aggregate implications of our estimate of pricing complementarities. Formally, we simulate the impulse response of our economy to a one-time increase in nominal spending. Our preferred calibration generates only small delays in the response of prices, relative to a model without pricing complementarities, so that nearly half of the nominal shock is absorbed by prices on impact. Along similar lines as Caballero and Engel (2007), we then use a decomposition of the response of prices that isolates the role of pricing complementarities, to conduct some simple counterfactual experiments. We conclude from these that, in order to generate quantitatively significant amplification for aggregate nominal shocks, we would need overall pricing complementarities to be substantially stronger. With our preferred calibration, the firm-level pricing complementarities appear to have only small effects for the model's aggregate implications.[3]

In section 7, we examine how sensitive our conclusions are to changes in the targets and other parameter changes. In particular, we discuss how the results depend on whether we filter out price promotions in computing the targets. 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.

In summary, we conclude that a menu cost model purely with firm-level complementarities is unlikely to generate quantitatively large aggregate amplification effects from nominal rigidities. What is the basic explanation for this finding? The data suggest that changes in prices and quantities are highly variable and fairly large. Stronger firm-level pricing complementarities instead give firms an incentive to change prices more frequently, but by smaller magnitudes. Maintaining the same frequency and magnitude of price changes then requires much larger menu costs than what is consistent with the data. It also generates a much larger asymmetry between price increases and decreases.

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. Most closely related to our analysis, Klenow and Willis (2006) introduce pricing complementarities into the Golosov-Lucas model by allowing for scale-dependent mark-ups. As in our model, firms have a desire to respond to the idiosyncratic cost shocks by adjusting their price frequently, and by small magnitudes. Their

[3] Allowing for aggregate channels of pricing complementarities lead to stronger aggregate effects overall, but this also reduces the role of firm-level complementarities for aggregate amplification.

main conclusion is therefore that such a model would require 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.

In contrast to these papers, we calibrate our model to match facts on both prices and market shares. In the process, we also need to augment the model with idiosyncratic demand shocks in order to account for the observed fluctuations in prices and market shares.[4] Both are crucially important for inferring the degree of pricing complementarities: since the price response to demand fluctuations may increase with stronger decreasing returns, the observed large variability of quantities (which leads to big fluctuations in marginal costs) may by itself be an important source of big price changes - as a consequence, the magnitude of shocks and menu costs in our model no longer seems implausible, given the data.

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 instead calibrate a model with sector-level pricing complementarities resulting from input-output linkages across sectors.

Our model also relates to various aggregate models that embed pricing complementarities to generate persistent delays of price adjustment. Key examples are 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), or Rotemberg and Woodford (1997). All these papers seek to evaluate the plausibility of amplification channels 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 also 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, a question that is not usually the main focus in the IO context.[5]

[4] We do not provide a structural interpretation of these shocks, but we just back them out to account for the magnitude and comovement of price and shares in our dataset.

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

2 The Model

We write down our menu cost model as an equilibrium model of a single sector or product category. For simplicity, we summarize the considerations of general equilibrium by a simple quantity equation that determines aggregate nominal spending and an equation relating aggregate nominal spending, wages and prices.

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.

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 α determines the degree of decreasing returns to scale in production, which correspond to the presence of a firm-specific factor that is costly to adjust at short horizons.[6] 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

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

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.[7]

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: 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. We assume that 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 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. Given this discussion, the parameter γ indicates the degree of aggregate pricing complementarities.[8]

As we will discuss below, 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.

Finally, we assume that interest rates are determined by the household's Euler Equation

$$\frac{u'(Y_t)}{P_t} = \beta (1 + i_t) \frac{u'(Y_{t+1})}{P_{t+1}}$$

where $u(\cdot)$ is the household's per period utility function, and $\beta \in (0, 1)$ the household's discount factor. In steady-state, Y is constant, and the nominal interest rate therefore satisfies $1 + i_t = (1 + \mu) / \beta$.

[7] 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.

[8] The case with $\gamma < 1$ 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).

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

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

where $\varepsilon^a_{it} \sim \mathcal{N}\left(0,\sigma^2_a\right)$ and $\varepsilon^z_{it} \sim \mathcal{N}\left(0,\sigma^2_z\right)$ 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 $\hat{p}_{-1}/(1+\mu)$ 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 $\hat{P} = \left[\int a\hat{p}^{1-\theta} d\Phi(\hat{p}; s)\right]^{\frac{1}{1-\theta}}$, 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: With flexible prices, the firm's (normalized) optimal price $\hat{p}^f\left(s; \hat{P}\right)$ solves the first-order condition $\pi_p(\hat{p}; s) = 0$, which implies

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

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

In time-dependent pricing models, the rate at which prices adjust in response to aggregate shocks depends on the frequency of price adjustment, and the degree of pricing complementarities k. This parameter in turn depends on the demand elasticity θ, the return to scale parameter α, and the aggregate complementarity parameter γ. With constant returns to scale, $\alpha = 1$ and $k = \gamma$, in which case the overall pricing complementarities are uniquely determined by the aggregate pricing complementarities.

In contrast, with decreasing returns to scale, the firm's demand elasticity and returns to scale also affect the degree of pricing complementarity. In particular, for $\alpha < 1$, k is increasing in θ (implying more pricing complementarities as demand becomes more elastic) and decreasing in α, if and only if $1-\gamma > 1/\theta$; otherwise k is increasing in α. In addition, k is increasing in γ (implying more pricing complementarities overall, when there are stronger aggregate complementarities). With decreasing returns, variations in aggregate prices feed into the firm's production scale, and hence its marginal costs, making optimal pricing decisions interdependent.

Finally, notice that the idiosyncratic variation in $\hat{p}^f\left(s; \hat{P}\right)$ is scaled by a factor that depends on θ and α only, but not on γ. When we calibrate our model to a steady-state equilibrium with constant wage and price inflation, the product level variation in prices and quantities therefore only allows us to identify the pricing complementarity parameters relevant at the firm level, i.e. θ and α, but γ remains unidentified. Nevertheless, both are important for determining overall pricing complementarities k, and we must therefore make additional assumptions or use aggregate measures to determine aggregate pricing complementarities.

3 Inferring Pricing Complementarities

In this section, we discuss our strategy for inferring the key parameters of our model, using moments of the micro data on prices and quantities (or equivalently, expenditure shares) at the product level. Our model has ten parameters: (ρ_a,σ_a) and (ρ_z,σ_z) govern the stochastic processes of the productivity and demand shocks. The substitution elasticity and the returns to scale parameters θ and α determine, respectively the elasticity of demand and the elasticity of marginal cost to output. In addition, there is the menu cost F, the growth rate of nominal spending, μ, the discount rate β, and the wage elasticity parameter γ. To simplify our discussion, let's abstract from ρ_z and ρ_a, set μ equal to the steady-state rate of inflation, and β to match the steady-state real interest rate. Moreover, in a steady-state equilibrium, in which nominal wages and prices grow at the same rate μ, the wage elasticity parameter γ remains unidentified. This still leaves us with 5 parameters to determine: (F,σ_a,σ_z,θ,α).

On the other hand, the micro data on prices and market shares gives us four moments that we can match using these parameters: (*i*) the frequency of price adjustment, (*ii*) the average magnitude of month to month price changes, (*iii*) the variability of month to month changes in market shares, and (*iv*) the correlation of changes in prices and shares. Given these 4 moments, we still have an under-identification problem. Let us abstract for a moment from the fixed cost F, and the frequency of price adjustment. Then, with the remaining three moments and four parameters, the identification problem that we are facing is well-known: Given data on prices and quantities only, we need to separately identify the elasticity of demand and marginal cost, or θ and α in our case, and the magnitude of shocks to cost and demand. The problem is illustrated in figure 1, which shows that the same data on prices and shares may be the result of different parameter pairs (θ,α):

Moreover, these different parameter values of α and θ may have vastly different implications for k: In the figure above, we see that as we decrease the supply elasticity (i.e. reduce the returns to scale parameter α), we need to increase demand elasticity θ to continue to match the same raw moments of prices and shares. If γ is sufficiently low, k is increasing in θ and decreasing in α, and hence, these shifts both contribute to increasing the pricing complementarity. Therefore, the two panels above, which are based on the same set of micro observations, might be consistent with two different levels of pricing complementarities, depending on which parameters of α and θ one admits.

In most earlier calibrations of menu cost models, this issue did not arise, since α was set equal to 1, and θ primarily affected quantities, while the model was calibrated to match data on prices

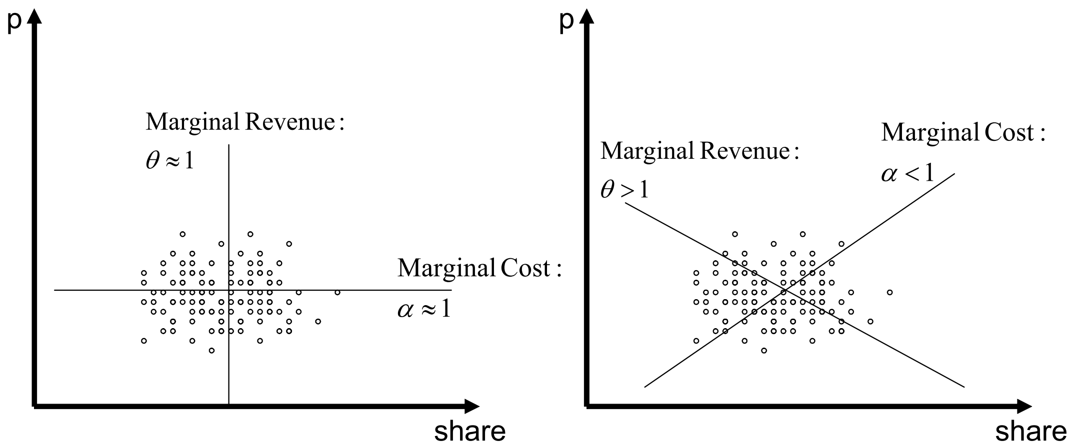

Figure 1: The identification problem

only. For us, the identification issue is central, since θ and α jointly determine the extent of pricing complementarities, i.e. the key parameter for identifying the degree of pricing complementarities.

Outside measures of parameters: A first possible solution to this inference problem is to measure key model parameters directly. For example, θ and α also determine the firm's profit rates, and it might therefore seem tempting to also try to match measures of mark-ups or profits. Such an approach, however, would require assumptions about 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 that are near 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.

Likewise, one might resort to existing measures of menu costs. The basic premise of menu cost models is that such costs can be small, yet have significant aggregate effects. 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 small compared to the overall costs and revenues of a firm's activities.

If we fix the menu cost to match these empirical measures, we can then use the other four moments to match the other four parameters. As we lower α and increase θ, the firms' profits become more sensitive to mispricing, which creates incentives for more frequent, but smaller magnitude price changes, all else equal. To correct for this, we would need to raise both the magnitude

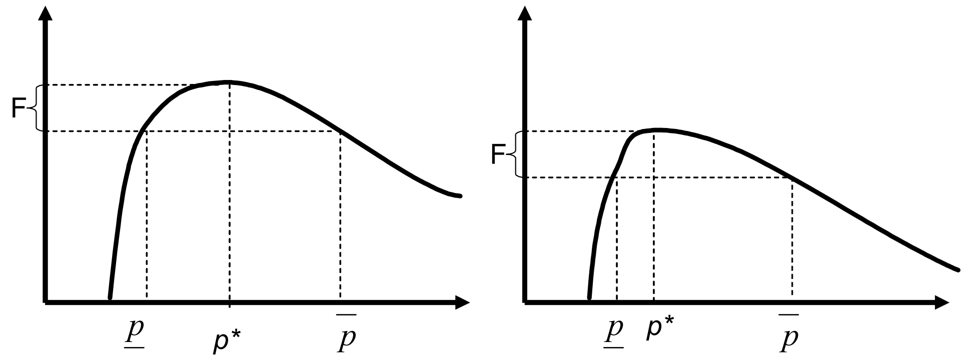

Figure 2: Asymmetry in value function and Ss-bands

of menu costs and the magnitude of the shocks. However, the menu cost is fixed to match the empirical measures, so the frequency of price changes then effectively pins down α and θ.

Alternatively, we can resort to additional moments regarding the data on prices and market shares to identify our model. In particular, we focus on the asymmetries the model generates between price increases and decreases, and show how these can be used to infer the returns to scale. In addition, the model also implies an asymmetry between high and low relative prices (as well as high and low market shares), which we can use to identify the relative importance of cost and demand shocks. We now discuss how these asymmetries can inform us about the underlying structural parameters.

Asymmetry between price increases and decreases: The idea behind matching separately the average frequencies and magnitudes of price increases and decreases is the following. Suppose for a moment that $\mu = 0$, i.e. that there is no inflation. The firms' value function, and hence its Ss bands, are asymmetric around the ideal price p^*. 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 bounds - in the latter figure, we project pairs $\left(a,z^{-1}\right)$ into a single dimension on the horizontal axis. The shapes in these figures are explained as follows: when prices are away from their optimum, both prices and quantities change. Having a price that is too low lowers the mark-up over marginal cost and increases the quantity sold; with decreasing returns to scale, increasing the quantity raises the marginal cost, thus further lowering mark-up. If the mispricing is sufficiently large, it may even be the case that profits are negative. On the other hand, when prices are too high, this increases the mark-up, but lowers the quantity sold, and as a result, profits can never be negative. This already puts a bound on the firm's potential losses, when prices are set too high.

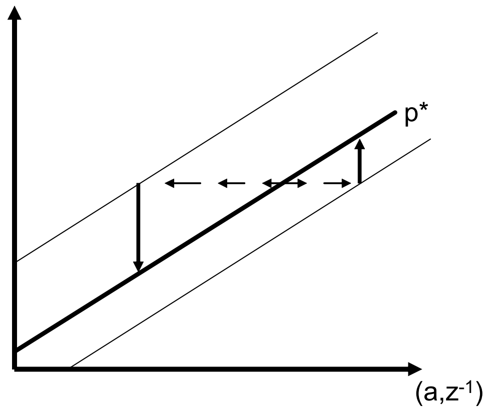

Figure 3: Asymmetry between price increases and decreases

Overall, this suggests that the firm's profits decline more rapidly when prices are too low than when they are too high. This in turn implies that firms are on average more likely to reach their lower sS band and increase their price than the upper sS band and decrease their price; i.e. the frequency of price increases should be larger than the frequency of price decreases. On the other hand, price decreases are on average larger in absolute magnitude than increases.[9]

Now, how does this asymmetry depend on θ and α? The parameters θ and α determine the extent to which firms' marginal costs responds to a departure from the ideal price; the higher is θ and the lower is α, the more marginal costs respond to quantities. 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, the higher is θ and the lower is α, the larger should be the difference in frequency between increases and decreases, and the larger should be the difference in magnitudes between increases and decreases.

So far, this discussion relied on a zero steady-state inflation rate. If we introduce positive inflation rates, this is going to have an effect on the magnitudes of these asymmetries, but the general feature remains the same. To match both the asymmetries in frequencies and in magnitudes of price changes, it is therefore important that we account for steady-state inflation.

Asymmetry between high and low relative prices: The menu cost model suggests a related argument for identification that is based on the difference between high and low relative

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

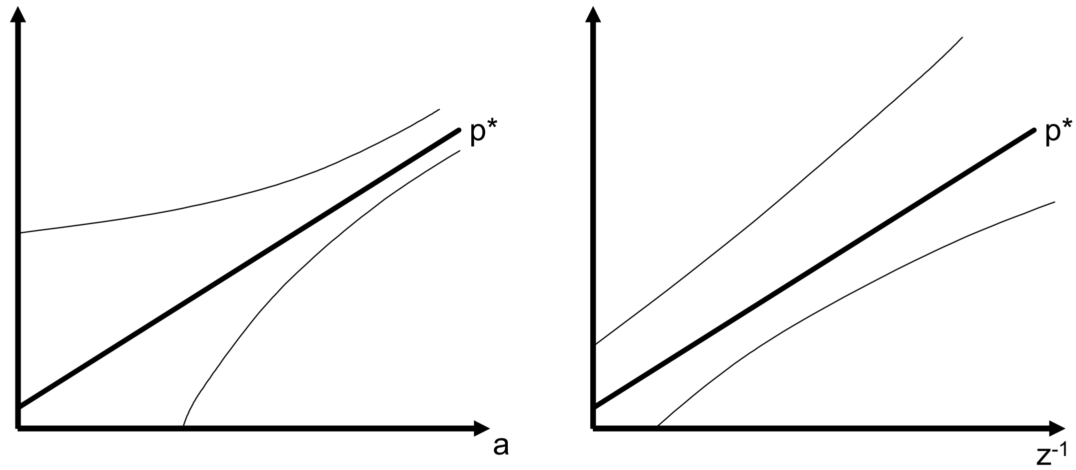

Figure 4: Asymmetry between high and low relative prices

prices, which enables us to identify the respective roles of cost and demand shocks. Ceteris paribus, profits are more sensitive to mispricing, when a good is in high demand. This in turn should lead to narrower sS bands, and a higher frequency of price changes, than when demand is low. Now, a model, in which price changes are driven mostly by cost shocks, demand is high, when the prices are low, i.e. when there is a favorable technology shock (high z). In contrast, in a model, in which price changes are driven mostly by demand shocks, demand is high when there is a large demand shock (high a), which in turn also implies a high price, on average.

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 the extent of this asymmetry can still inform us about the relative importance of cost vs. demand shocks.

Therefore, by examining how the frequency of price adjustment depends on the current price level, we can learn something about the relative importance of cost and demand shocks. To validate this argument, we also need to look at how the frequency of price adjustment depends on the current level of demand (or the current market share) - after all, the above argument is empirically relevant only if price changes are indeed more likely when demand is high. In our calibration, we will therefore attempt to match how the frequency of price adjustment depends on the current level of both prices and market shares.

In summary, we can thus use the magnitude of menu costs, and the asymmetries between price increases and decreases, and high and low prices and market shares to gain three additional moment targets for our menu cost model. Since strictly speaking we only need one additional restriction to infer the parameters, we have two additional moment targets that can be used to assess the overall fit of the model.

4 Data on prices and market shares

We now apply the procedure 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.[10]

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 also report moments of the data that exclude temporary price markdowns, computed as simple averages across 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 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

[10] 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.

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.

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 (footnote: In calculating the frequency, we exclude temporary price markdowns from the numerator and the denominator). 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.

In calibrating our model, we target a 4-week average magnitude of prices changes equal to 10%. This figure is very close to the targets used in Golosov and Lucas (2006) and Midrigan (2006).

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.[11][12]

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 could be partly driving the movements in prices and quantities. In our benchmark calibration we target a correlation of price and share changes, conditional on nominal price adjustment, equal to -0.20.[13]

[11] 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.

[12] 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.

[13] 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.

E. 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%. These figures are very similar to those reported in Klenow and Kryvtsov (2005) and Nakamura and Steinsson (2006). Row 14 shows that the size of price increases is slightly smaller than the size of price decreases (the ratio of the average magnitude of price increases relative to price decreases is roughly 0.85 if we exclude sales and 0.90 if we include them).

In our calibration, we will just focus on the relative magnitudes and abstract from the fraction of price increases. 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. Since there are measurement issues with the inflation rate, and since in the model the inflation rate primarily impacts the fraction of price increases versus decreases with only minimal effects on the relative magnitudes, we decide to target the latter. This is also in line with results by Gagnon (2006), who reports that changes in inflation have a large effect on the relative frequencies of price increases and decreases, but not on the relative magnitudes.

F. High vs. Low Relative Prices: Row 15 reports the frequency and size of price changes conditioning on whether the initial price level is high or low. We first compute the average price of each UPC using the available observations in the data sample. For each UPC, we then compute the frequency and magnitude of price changes separately for pre-change prices that are higher or lower than the average price. We then average the ratio of high to low frequencies and magnitude of price changes across UPCs, and report the average ratio for the median product category.

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.

G. 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 price levels). We follow the same steps as before, computing the average market share for each UPC, and separately computing the frequency and magnitude of price changes for periods in which the market share of a UPC is above or below average. 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 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.[14]

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 the persistence parameters $\rho_z = \rho_a = 1/2$ as a first pass (in section 7, we present some sensitivity analysis regarding the persistence of idiosyncratic shocks. In subsequent work, we plan to calibrate these parameters more rigorously). Finally, we set $\beta = 0.995$ to match a steady-state real interest rate of 6%, and $\mu = 0.0017$ to match a steady-state inflation rate of 2.2% annually, which is the sector-level price inflation that we measure in the Dominick's data, for the median sector.

This leaves us with five parameters, $\left(\theta, \alpha\,; F, \sigma_a^2, \sigma_z^2\right)$. To calibrate these parameters, we first

[14] 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.

fix α at various levels between 0 and 1, and calibrate the other four parameters to match the four benchmark moments we identified from the micro data. We then compare the calibrations for different values of α in terms of how well they match our secondary targets, in order to assess what values of α and θ appear plausible, and hence determine the resulting pricing complementarities.

Before going to the full calibration, we present some results for menu cost models with exclusively cost and demand shocks, setting $\sigma_\alpha = 0$ or $\sigma_z = 0$. This preliminary step clarifies the results in the existing literature (in terms of calibration successes and failures), and it provides some illustration of the identification underlying our main calibration results.

Cost Shock Model: In Table 3, Columns 1-4, we report results for model with cost shocks only. Since the demand curve is fixed in this case, the correlation between prices and market shares must be -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).

In the first column, the case with constant returns to scale ($\alpha = 1$) roughly replicates the calibration results of Golosov and Lucas (2006). F and σ_z are adjusted to jointly match the frequency and magnitude of price changes: lower F implies more frequent, smaller price changes, while higher σ_z implies more frequent, larger price changes, ceteris paribus. The demand elasticity, which has only small effects on price changes, is then adjusted to match the variability of share changes.

Columns 2-5 consider the cases with $\alpha = 0.95$, $\alpha = 0.75$, $\alpha = 0.55$, and $\alpha = 0.35$, in which there are positive pricing complementarities. As α is lowered, the implied magnitude of cost shocks that is required to match the magnitude of price changes explodes to levels of 25% month-to-month (row 3), and the fixed cost of price changes explodes to a magnitude of 5%, much higher than the existing estimates (row 5). With complementarities, firms have an incentive to make very frequent, small price changes. To reduce this frequency, yet have price changes that are as big as in the data, the menu costs and the shocks must both become large. This finding is similar to Klenow and Willis (2006), who consider a model with idiosyncratic cost shocks and pricing complementarities resulting from a scale-dependent demand elasticity.

The cost shock model also illustrates the idea underlying the identification derived from the asymmetries: Row 11 shows that, as α becomes smaller, price increases become relatively smaller in size compared to price decreases (their relative magnitude drops from 0.88 to 0.78). To compensate while maintaining the same steady-state inflation, price increases become more frequent relative to decreases.

Finally, notice the asymmetry between high and low relative prices: As expected from our earlier discussion, 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. On both accounts, the model misses the data by a large margin.

Overall, if we were to disregard the fact that the model completely misses out on (i) the price-share correlation, and (ii) the asymmetry between high and low relative prices and high and low market shares, we would conclude that a cost shock model without pricing complementarities does remarkably well in matching the other targets, matching an average menu cost of 0.7% of revenues, and a relative magnitude of increases to decreases of about 0.88. Any introduction of decreasing returns only worsens the calibration results, generating larger menu costs, and much stronger asymmetries between increases and decreases.

Demand shock model: Table 3, Columns 6–9 report similar results for a model with demand shocks only. If prices were perfectly flexible, such a model would imply that prices and shares are perfectly, positively correlated. With positive 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).

When α is near 1, we are no longer able to match the magnitude and frequency of price increases: with near constant returns to scale, demand 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 therefore abstract from the first column with $\alpha = 0.95$.

Three observations stand out: first, as α decreases, the increase in idiosyncratic shocks that is required to match the magnitude of price changes is much less dramatic than in the cost shock model, going from 24% to 30%, as α falls from 0.75 to 0.35 (Row 4). Second, the required menu costs are much smaller than in the cost shock model, although at a level of 2.5% of revenues, they are still larger than existing estimates at high levels of pricing complementarity (Row 5). Third, as in the cost shock model, lower values of α lead to stronger asymmetries between price increases and decreases, to the extent that price increases are eventually substantially smaller than decreases (the ratio of magnitudes drops from 0.95 to 0.80, Row 11). Likewise, 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). This is again in line with our earlier discussion which suggested that price changes are more likely in a menu cost model, when demand is high. Notice also that these relative frequencies are a lot more in line with the data than they are in the cost shock model.

Overall, the model with demand shocks appears to be fairly successful at matching all moments, except the correlation and the asymmetry regarding high vs. low prices and shares, if $\alpha \approx 0.55$. In particular, this gives a pretty reasonable measure of menu costs, and matches the asymmetry between increases and decreases almost exactly.

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 correlation 0, by setting θ close to 1: if $\alpha = 1$, prices only respond to productivity shocks, and with $\theta = 1$, these price changes have no impact on shares, and prices and share changes are therefore 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 very large mark-ups.

As we lower α, the firms optimal prices begin to respond also to demand shocks, which, ceteris paribus should lead to a positive correlation between prices and shares. To compensate for this, θ increases (a higher demand elasticity reduces the correlation between prices and shares). The firms' profits then become more sensitive to prices, and firms have an incentive to have more frequent and smaller price adjustments. This in turn requires that holding the duration fixed requires a larger value of F, and σ_a and σ_z also increase to maintain the same magnitudes of price and share changes (Rows 2-5).

However, in contrast to the pure cost shock model, the magnitudes of the shocks do not appear to be implausible, 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.[15] Our measure of the magnitude of demand shocks is a bit larger, but this is to be expected given the fairly large variability in market shares.

In line with our inference strategy, the relative magnitude of price increases goes from 1 to 0.8, as α decreases (Row 11). Moreover, the adjustment probability when prices are high is also gradually increasing as we lower α (from a value of 0.87 for $\alpha = 0.99$ to a value of 0.99 for $\alpha = 0.25$ - Row 11), a sign that demand shocks become more important as we move to stronger decreasing returns. In addition, throughout, the adjustment probability when market shares is roughly 1.2

[15] The data report the cost of acquisition of the current inventory, not the current replacement costs. 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.

times the probability of adjustment when market shares are low - right on target.

How well do these different calibrations do in terms of matching our secondary targets? If we consider the size of the menu costs, it appears that a value of α in the range of 0.55 to 0.75 is in line with the existing empirical menu cost measures. It turns out that the same values of α also do fairly well in matching the asymmetry between price increases and price decreases. A value of $\alpha \approx 0.55$ also matches the asymmetry between price increases and decreases almost exactly, and comes very close to matching the asymmetry between high and low relative prices.

In contrast, lower values of α require significantly larger menu costs, and imply that price increases become much smaller, relative to decreases. Higher values of α in turns are problematic, because they would generate price increases that are too large in comparison to the price decreases, relative to what is observed in the data, and they would generate too much asymmetry in adjustment frequency between high and low relative prices. They also would imply implausibly low demand elasticity and very large mark-ups and profit margins.

The degree of pricing complementarity that is implied by these values of α and θ depends on the value of aggregate pricing complementarities γ. For example, if $\gamma = 0$ (flexible wages), a point estimate of $\alpha = 0.65$ and $\theta = 4.2$, which matches the asymmetries almost exactly and implies a menu cost of 0.86% of steady-state revenues, leads to a pricing complementarity coefficient $k \approx 0.53$. As a range estimate for $\alpha \in [0.55, 0.75]$, we find that with flexible wages, the corresponding values of k are between 0.41 and 0.60. 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) which suggest that a value of $k \approx 0.85$ to 0.9 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 range estimate of k goes to $k \approx 0.82$ to 0.85, so that significantly stronger pricing complementarities can be sustained, i.e. we find ourselves 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.

6 Aggregate impulse responses

We now turn from the steady-state calibration to the aggregate impulse response to a one-time increase in M. Starting from the steady-state distribution of normalized prices Φ, we consider the effects of a one-time increase in M by a factor Δ (following by continued growth of M at a steady-state rate μ) on the subsequent dynamics of P. This experiment is equivalent to computing the transition path of this economy, starting from an initial distribution of relative prices Φ_0, where $\Phi_0(\hat{p}; s) = \Phi(\hat{p}/(1+\Delta); s)$.

In principle, this requires resolving the associated non-stationary optimization problem, in which the firms take into account the entire future path of prices $\hat{P}^{\infty} = \left\{\hat{P}_t\right\}_{t=0}^{\infty}$ in forming their decisions, and the resulting sequence of state-price distributions $\Phi^{\infty} = \{\Phi_t\}_{t=0}^{\infty}$ is consistent with the Law of Motion induced by the resulting sequence of pricing strategies, and generates the sequence of prices $\hat{P}^{\infty}$.

As a first pass, we will approximate the solution to this complicated dynamic equilibrium problem using the steady-state Ss-bands and pricing strategies for each idiosyncratic state. 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 then approximate dynamics out of steady-state by holding the size of the Ss-bands $\bar{K}(s)$, $\underline{K}(s)$ and front-loading factor $\rho^*(s)$ constant, in which case variation in pricing decisions enters through the effect of $\hat{P}_t$ on the ideal flexible price $\hat{p}^f\left(s; \hat{P}_t\right)$:

$$\begin{aligned}
\ln p_t^*(s) &\approx \rho^*(s) + \ln \hat{p}^f\left(s; \hat{P}_t\right) \\
\ln \bar{p}_t(s) &\approx \bar{K}(s) + \ln p_t^*(s) \\
\ln \underline{p}_t(s) &\approx \underline{K}(s) + \ln p_t^*(s)
\end{aligned}$$

In the future, we also plan to present exact solutions for the complete transition path to a one-time shock.

Besides computational tractability, this approximation has the additional advantage that it leads to a useful decomposition of the aggregate impulse response that allows us to separate the effects of pricing complementarities from the role of distributional assumptions, i.e. the selection effect that is emphasized in Golosov and Lucas (2006) and Midrigan (2006). This decomposition is a special case of the one proposed in a recent paper by Caballero and Engel (2007).

To obtain this decomposition, notice that the approximated Ss-bands and the target price (in logs) each change by the same magnitude δ in response to a small monetary injection of size Δ. Then, define $\hat{\Phi}(p; s')$ as the distribution of prices and idiosyncratic states $(p; s')$ after the new idiosyncratic shock has hit, and before prices are adjusted:

$$\hat{\Phi}(p; s') = \int_s \psi(s'|s)\, d\Phi(p; s),$$

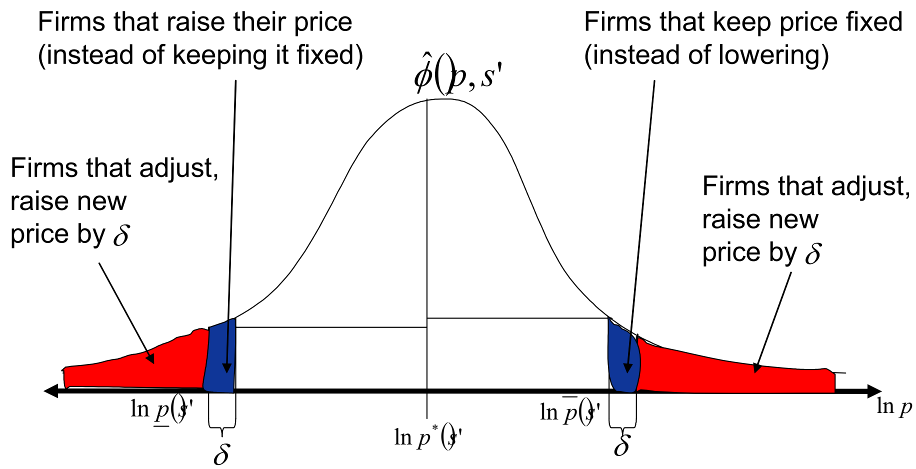

Figure 5: Price adjustment after shock

and let $\hat{\phi}(p; s')$ denote the associated pdf. The aggregate response of prices (net of trend inflation, and in logs) is then approximated by:

$$\begin{aligned} \Delta \log P \approx\ & \delta \left[\int_{s'} \int_{-\infty}^{\underline{p}(s')} \hat{\phi}(p; s')\, dpds' + \int_{s'} \int_{\bar{p}(s')}^{\infty} \hat{\phi}(p; s')\, dpds' \right] \\ & + \delta \int_{s'} \left[\log \bar{p}(s') - \log p^*(s') \right] \hat{\phi}(\bar{p}(s'); s')\, ds' \\ & - \delta \int_{s'} \left[\log \underline{p}(s') - \log p^*(s') \right] \hat{\phi}(\underline{p}(s'); s')\, ds' \end{aligned}$$

The logic behind this expression is illustrated in Figure 5, which plots the density $\hat{\phi}(\cdot; s')$, for some realization of the shock s'. The first line measures the intensive margin: all firms that originally changed their price now raise it by an additional amount δ. The second and third terms measure the extensive margin of adjustment: some firms that prior to the shock decided to lower their price now prefer to keep it constant (second 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 on average by an amount $\log \bar{p}(s') - \log p^*(s')$. By the same logic, the third term captures all the firms who originally chose to keep their price fixed, but now decide to increase it by an amount $\log \underline{p}(s') - \log p^*(s')$.

We rewrite this decomposition as

$$\Delta \log P \approx \delta [f + S],$$

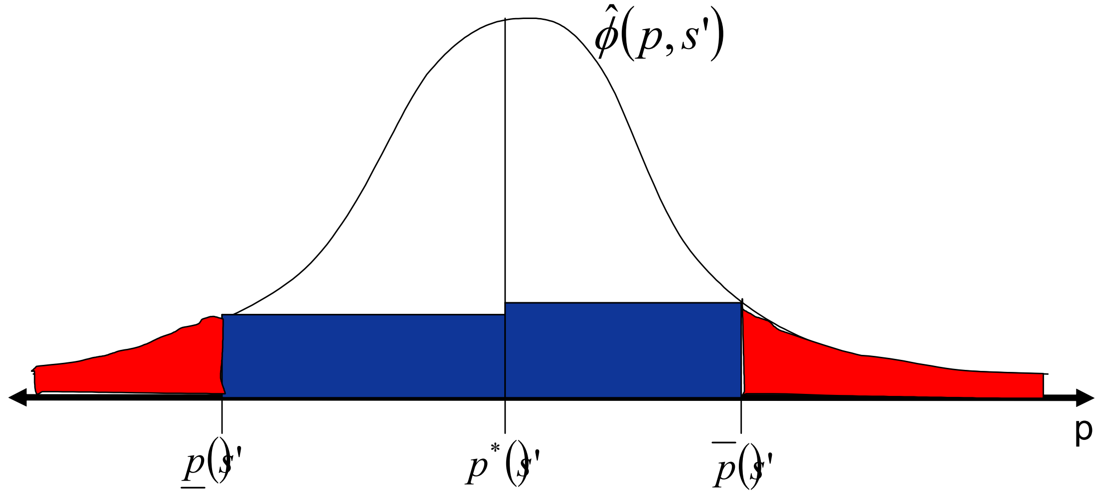

Figure 6: Frequency and selection effect

where

$$f = \int_{s'} \int_{-\infty}^{\underline{p}(s')} \hat{\phi}\left(p; s'\right) dp ds' + \int_{s'} \int_{\bar{p}(s')}^{\infty} \hat{\phi}\left(p; s'\right) dp ds'$$

is the steady-state frequency of price adjustment, and S measures the "selection effect", defined as

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

Figure 6 illustrates the frequency and selection effects, if δ is small. The red areas in the tails measure the intensive margin, due to the fact that all firms that adjust in state s' increase their new price by δ, relative to before the occurrence of the shock. The blue rectangles measure the extensive margin, or the selection effect. At $\bar{p}\left(s'\right)$, a density $\hat{\phi}\left(\bar{p}\left(s'\right); s'\right)$ of firms that initially would have lowered their price by $\log \bar{K}\left(s'\right)$ now prefer to keep it fixed. Likewise, a measure $\hat{\phi}\left(\underline{p}\left(s'\right); s'\right)$ of firms at $\underline{p}\left(s'\right)$ now prefer to increase their price by an amount $\log \underline{K}\left(s'\right)$, instead of keeping it constant. To find the overall effect of a shock on impact we then simply integrate over all states s'. The white area, integrated over all s', then measures the residual, which corresponds to the real effect of the shock on impact.

This figure also illustrates some of the key findings of the recent and not so recent literature on menu cost models. For example, this formulation also recovers the well-known neutrality result by Caplin and Spulber (1987) as a special case: in the case where $\hat{\phi}\left(p; s'\right)$ is a uniform density w.r.t. p, for each s', over an interval that strictly includes $\left[p\left(s'\right), \bar{p}\left(s'\right)\right]$, we can immediately see from the picture that the white area disappears, so that the nominal shock has no real effects.[16] More

[16] This can also be derived using our decomposition: if $\hat{\phi}\left(p; s'\right)$ is a uniform density w.r.t. p, for each s', over an

generally, this figure illustrates the important point made by Midrigan (2006), that distributional assumptions determine the magnitude of the selection effect and hence matter a great deal for the aggregate effects of nominal shocks. Midrigan shows that in a model with fat-tailed distributions of the shocks, the density $\hat{\phi}$ inherits the fat tails, and the model's calibration leads to a much smaller selection effect.

Now, how does the approximated change in ss-bands and optimal pricing rules, δ, related to the nominal spending shock Δ? Our approximation of the ss-bands and the optimal pricing rule implies that δ corresponds to the change in $\ln \hat{p}^f \left(s; \hat{P}\right)$ on impact, or $\delta \equiv k\Delta \log P + (1-k)\Delta$. Combining this with our decomposition for $\Delta \log P$, we approximate the response of prices on impact as follows:

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

This decomposition enables us to isolate the effects of pricing complementarities and the selection effect in accounting for the response of prices on impact. In the model, we can compute S, f and k from the steady-state calibration (where f is also one of the targeted moments), and therefore compare the approximated response to a shock to the one directly computed from the model. In almost all cases, we find that this is a very accurate approximation.

To provide a simple illustration of the role the selection effect is playing, notice that in a Calvo model, the same approximation would apply, but with $S = 0$. A menu cost model with an adjustment frequency f and a selection effect $S > 0$ thus appears to have similar properties on impact as a Calvo model with a frequency of price adjustment of $f + S$.

Results: Table 5 reports our results regarding the aggregate effects of a nominal shock. To organize the discussion, we simply report the response of the aggregate price index and the CES output index to the nominal spending shock *on impact*, focusing on the case with flexible wages, in which $\gamma = 1$. We also report the values we compute from the model for k and S. Since $f \approx 0.22$ throughout all calibrations, the above approximation enables us to decompose the output effects of the spending shocks.[17]

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interval that strictly includes $[\underline{p}(s'), \bar{p}(s')]$, we have

$$\begin{aligned} f &= 1 - \hat{\phi} \int_{s'} \int_{\log \underline{p}(s')}^{\log \bar{p}(s')} dp ds' = 1 - \hat{\phi} \int_{s'} \left[\log \bar{p}(s') - \log \underline{p}(s')\right] ds' \\ &= 1 - \hat{\phi} \int_{s'} \left[\log \bar{K}(s') - \log \underline{K}(s')\right] ds' = 1 - S, \end{aligned}$$

and therefore $f + S \approx 1$.

[17] 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

Several observations stand out. First, we notice that adding pricing complementarities to the menu cost model does indeed reduce the price adjustment on impact. However, these effects are small overall: whereas in a model with constant returns to scale, almost two thirds of the monetary shock are absorbed by prices on impact, for the range of α we identified as quantitatively the most plausible, prices still absorb roughly half of the shock on impact. Even if we were to go to significantly stronger pricing complementarities, prices still adjust by a large amount on impact, and shocks only have small real effects.

Second, we notice that the cost and the demand shock and the combined models all give roughly similar output implications, for a given level of pricing complementarities. Therefore, there appear to be no major differences in the aggregate implications of models that focus on cost vs. demand shocks as the source of idiosyncratic variation.

Both of these findings can be explained by considering the selection effect. In our model, it is large, and relatively stable across the different specifications, always around 0.45. In practice this means that our menu cost model is comparable to a Calvo model in which over 65% of all prices change every month!

We can further illustrate the importance of this selection effect with different comparisons. Without complementarities ($k = 0$), the Calvo model would predict a response of prices on impact of 22%, whereas the menu cost model predicts a response of prices of 70% - over two thirds of the shock is absorbed on impact. For the moderate complementarities that we identify in the data ($\alpha = 0.65$, $k = 0.53$), the selection effect raises the response of prices on impact from 10% to 49%. Even for much stronger pricing complementarities, in the range of $k = 0.85$ to 0.9 that is suggested by Woodford, our decomposition suggests that a selection effect of $S \approx 0.45$ still raises the response of prices on impact from roughly 4% to 23%.

Alternatively, we can use our decomposition for some simple back-of-the-envelope calculations to determine how much pricing complementarities we would need to get substantial aggregate output responses. Rotemberg and Woodford's estimate is based on a Calvo model, without selection effect. Setting $S = 0$ in our approximation formula, and using an adjustment frequency of 0.22, their estimate is consistent with a response on impact of roughly 4%. To match the same number within our model with a selection effect of $S = 0.45$, we would need a value of $k > 0.97$, which is much higher than the Rotemberg-Woodford estimate, which is itself much higher than our estimates.

We conclude from this discussion that a menu cost model can hope to obtain substantial delays in price adjustment only if (i) there is a very large degree of pricing complementarities, and (ii)

a richer macroeconomic model that would be required to account for the response of various other aggregates.

the selection effect is much smaller than what is suggested by our calibration. Moreover, among these two, the complementarity appears to have only a secondary role: if $f + S$ is sufficiently large, then even with values of k that are close to 1, the model will imply a sizeable response on impact, and a rapid adjustment to the new steady-state. As Midrigan (2006) shows, the latter of course depends on distribution of the underlying idiosyncratic shocks. Pricing complementarities that are purely driven by product-level decreasing returns appear to be unable to quantitatively account for such strong pricing complementarities. Aggregate sources of complementarities appear to be more promising. As discussed before, allowing for large aggregate complementarities lowers pricing complementarities closer to the Rotemberg-Woodford range. In that case, however, product-level decreasing returns appear to play only a secondary role for the resulting aggregate implications.[18]

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: A first important consideration is, how sensitive our conclusions are to the targets that we picked for our calibration. To this end, we performed some rather simple sensitivity checks, recalibrating our model with different parameters or targets. We give a brief summary here; complete results are available on request.

As a first check, we altered the steady-state inflation rate, over a range between 0 and 4% of annual inflation.[19] As predicted, we found that this mainly affects 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

[18] Nakamura and Steinsson (2006a), for example, consider a version of the model with cost-shocks only, in which they calibrate γ to match the share of intermediate inputs used in the production of final goods. In their main calibration, they use $\gamma = 0.75$. In addition, they have constant returns to scale, and set $\theta = 4$. In practice, $\gamma = 0.75$ and $\theta = 4$ implies that $k = \gamma$, i.e. the returns to scale have no effect on the overall pricing complementarity. This is still approximately true for our preferred calibration with $\theta \approx 4.2$ and $\alpha \approx 0.65$.

[19] Based on the model targets, the targeted rate of inflation would have to be 4% (instead of the 2.2% directly measured from the data) to match both the relative magnitudes and the relative frequencies of increases and decreases, along with the overall absolute magnitudes and frequencies of price changes.

and Steinsson, 2006b, for example, argue for a significantly longer duration of prices). When we raise the duration of prices in the model, this turns out to have little to no overall effects on the calibration results: 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, and hence our inference remains roughly the same.

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. These results are summarized in Table 6, in which we report a summary of calibration results when we change some of the model targets. These alternative results 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 k as far as 0.78. This gets us closer to the range estimate of Rotemberg-Woodford, but it does require magnitude of price changes that are much lower than any existing micro estimates. Along the same lines, we also observe that 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. It also worsens the model's fit along some of the dimensions such as how well it can match the asymmetries.

We therefore conclude that based on the measures that our data support, it appears close to impossible to support product-level pricing complementarities that are much stronger than $k \approx 0.6$. Lowering the magnitude of price and share fluctuations would lead to more pricing complementarities, but the target values that would sustain quantitatively important pricing complementarities appear to be implausibly small, given what we observe in our micro data.

These results also suggest that if we had instead targetted the monents 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 sales are generally associated with above average magnitude price and share movements, and with no asymmetry between price decreases and the subsequent increases. 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 also conducted some sensitivity analysis with regards to the persistence parameters ρ. The findings of this are summarized in Table 7, where it can be seen that changing the persistence of shocks has little effect on our inference for complementarities - the only thing that is affected by the persistence parameters is the asymmetry between high and low relative prices.

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 8). The inferred selection effect, however, is lowered more significantly; S is now approximated by

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

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: Another important consideration in our calibration is the role played by the distribution of idiosyncratic shocks. Midrigan (2006) emphasizes that the distribution of price changes has fat tails, which isn't consistent with our or Golosov and Lucas' assumption of normally distributed shocks. When he recalibrates the Golosov-Lucas model with cost shocks to allow for fat tails, the selection effect becomes much smaller, and adjustment delays become larger.

However, the shape of the distribution may also be important for our identification of pricing complementarities. Many of our findings are driven by the observation that 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.

Notice that the shape of the distribution is directly relevant for the strength of this argument. Relative to a normal distribution, Midrigan's fat-tailed beta distribution leads to a much bigger mass of near-zero shocks, and a larger number of really big shocks, but fewer mid-sized shocks, relative to a normal distribution. By exposing the firms to fewer medium-size shocks, where the returns to scale have their strongest impact on the firms' desire to change prices at the margin, and more very small shocks (where the firms would not adjust in any case) or very large shocks (where the firms would always adjust), the range of shocks in which decreasing returns to scale give the firms an incentive to respond to the idiosyncratic shocks with frequent small price changes becomes less important.[20]

The fat-tailed distributions of shocks proposed by Midrigan might therefore provide a plausible argument not only why the selection effect ought to be smaller than what is suggested by our calibration results, but also provide an avenue for why pricing complementarities may be stronger than the ones we inferred here. In a future version of our paper, we will present results discussing how the assumption of fat-tailed shocks alters not only the measured selection effect, but also the inferred degree of pricing complementarities.

Alternative Demand Structures: In future drafts, we will also investigate the role of firm-level pricing complementarities based on variation in desired markups due to scale-dependent elasticities of demand, as originally studied in Kimball (1995) and more recently in Klenow and Willis (2006). In the presence of demand elasticities that are declining in market shares, a positive idiosyncratic cost shock leads to incomplete pass-through to prices, as desired markups fall. Moreover, in response to a positive idiosyncratic demand shock, desired markups and thus prices increase. Given these considerations, we expect that our main insights on the inference of firm level pricing complementarities will still hold. However, we think that our price and quantity data will not enable us to distinguish the different sources of firm level pricing complementarities.

8 Conclusion

In this paper, we have calibrated a menu cost model with pricing complementarities using micro data. As our central innovation, we have sought to directly identify the pricing complementarities

[20] 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 and their magnitude is driven essentially by the magnitude of the shocks, irrespective of the pricing complementarities.

using micro data, and we have calibrated our model to match facts not only regarding prices, but also regarding quantities at the product level. In the process, we have developed some ideas about how a menu cost model with pricing complementarities may be used to resolve the central identification problem of jointly inferring the elasticity of demand and marginal cost using micro data on prices and quantities.

At present, our results suggest that pricing complementarities at the micro level are at best moderate, and thus seem unlikely to generate large amplification effects for nominal business cycles in the aggregate. This conclusion, however, is based on several explicit and implicit modelling assumptions, and we therefore view it more like a first attempt at answering the question of how important pricing complementarities are, rather than as a definite final answer.

In addition to the robustness checks and possible extensions that we have already discussed above, there are at least two important caveats to 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. 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. Whether or not our conclusions apply to the aggregate economy thus depends on how representative our data is. This question, however cannot be answered without similar data sources from other sectors.

Future work will have to resolve how robust our conclusions are to reasonable departures from our baseline model or alternative calibrations. Throughout the paper, we have sought to give a clear discussion of what we regard as the limitations of our approach, and what one might have to consider, if one were to confirm or disprove our main quantitative results.

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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

			1	2	3	4	5	6	7	8	9
		Target			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	-0.25	-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 5: Baseline model, Aggregate Response to one-time Small Money growth increase

		Cost shocks only				Demand shocks only			
1	Returns to scale parameter , α	**0.99**	**0.75**	**0.55**	**0.35**	**0.95**	**0.75**	**0.55**	**0.35**
2	Firm based pricing complementarities k $(\gamma = 0)$	0.05	0.57	0.70	0.76	0.01	0.06	0.46	0.68
3	$\Delta \log P / \Delta \log M$	0.64	0.46	0.37	0.32	0.66	0.62	0.51	0.40
4	$\Delta \log Y / \Delta \log M$	0.36	0.54	0.63	0.68	0.34	0.38	0.50	0.60
5	Selection effect, s	0.43	0.43	0.43	0.43	0.42	0.43	0.44	0.44

		Cost and demand shocks combined						
6	Returns to scale parameter , α	**0.99**	**0.95**	**0.75**	**0.65**	**0.55**	**0.35**	**0.25**
7	Firm based pricing complementarities k $(\gamma = 0)$	0.01	0.06	0.41	0.53	0.60	0.70	0.73
8	$\Delta \log P / \Delta \log M$	0.71	0.66	0.55	0.49	0.46	0.39	0.36
9	$\Delta \log Y / \Delta \log M$	0.29	0.34	0.45	0.51	0.54	0.61	0.64
10	Selection effect, s	0.46	0.45	0.44	0.45	0.45	0.45	0.45

Table 6: 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 7: 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 8: Extended Model with Small Price Changes

		Target	1	2	3	4
			Cost and demand shocks combined			
	Parameters					
1	Returns to scale , α		**0.95**	**0.75**	**0.55**	**0.35**
2	Elasticity of substitution, θ		1.75	2.40	2.90	3.00
3	Standard deviation cost shocks, σ_z		0.09	0.11	0.13	0.15
4	Standard deviation demand shocks, σ_a		0.23	0.23	0.24	0.24
5	Average menu costs (% SS revenue)	< 1 %	0.10%	0.35%	0.89%	1.72%
6	Probability of zero menu-cost, **q**		0.14	0.15	0.15	0.15
	Firm based pricing complementarities k $(\gamma = 0)$		*0.04*	*0.26*	*0.46*	*0.57*
	Basic steady state implications					
7	Frequency of price adjustment (4 weeks)	0.22	0.22	0.22	0.23	0.22
8	Mean absolute price change, non-zero price changes	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
10	Correlation of price and share changes, non-zero price changes	-0.20	-0.20	-0.20	-0.22	-0.20
11	Fraction of prices changes smaller than 5%	0.30	0.33	0.34	0.32	0.33
	Other steady state implications					
12	Size of price increases relative to decreases	0.85	1.02	1.04	1.03	1.05
13	Frequency of high relative to low prices	0.95	0.94	0.90	0.91	0.88
14	Frequency of high relative to low shares	1.20	1.11	1.12	1.14	1.17
	Aggregate implications					
15	$\Delta \log P / \Delta \log M$		0.47	0.40	0.34	0.26
17	Selection effect, s		0.26	0.23	0.24	0.21