Economica LSE
Economica (2016) **83**, 443–472
doi:10.1111/ecca.12191

Real Rigidities and Nominal Price Changes

By Peter J. Klenow† and Jonathan L. Willis‡
†*Department of Economics, Stanford University, SIEPR and NBER*
‡*Federal Reserve Bank of Kansas City*

Final version received 16 February 2016.

Real rigidities can help to generate persistent effects of monetary policy shocks. We analyse an industry equilibrium model with two types of real rigidities: a 'micro' real rigidity from a kinked demand curve, and a 'macro' real rigidity due to sticky intermediate prices. We estimate key model parameters using micro data from the US CPI, which features big movements in relative prices within and across sectors. The micro real rigidity necessitates large idiosyncratic shocks to productivity. The macro real rigidity does not entail such large idiosyncratic shocks, and is consistent with the volatility of sectoral TFP growth.

Introduction

Many studies estimate that monetary policy shocks have persistent effects on real output —effects lasting well beyond a year.[1] In terms of microfoundations, one way of obtaining real effects of nominal shocks is, of course, nominal price rigidity. In quantitative treatments, however, the real effects of nominal price stickiness do not last much longer than the average duration of a price.[2] The recent micro empirical literature, meanwhile, finds that nominal prices typically change at least once per year.[3]

Combining the micro evidence and quantitative theory, nominal rigidities by themselves appear unable to generate the persistent non-neutrality seen in the aggregate data. This failure has rekindled interest in combining nominal rigidities with 'real rigidities', that is, ingredients that makes firms reluctant to change their prices by big amounts even conditional on changing their prices. Ball and Romer (1990) emphasize the need for such real rigidities on top of nominal rigidities, and separate 'micro' real rigidities from 'macro' real rigidities. Micro real rigidities include the Kimball (1995) kinked demand curve (see the survey by Gopinath and Itskhoki (2011) for uses of it) and firm-specific inputs suggested by Rotemberg (1996).[4] Examples of macro real rigidities are sticky intermediate prices as in Basu (1995), and real wage rigidities modelled by Blanchard and Galí (2007) and many others.

The critical distinction between micro and macro real rigidities is this: micro real rigidities make it costly for firms to move their relative prices, whereas macro real rigidities lend a common sticky component to costs but do not penalize firms who move their relative prices for other reasons (such as idiosyncratic productivity).

In this paper we focus on two particular real rigidities, one micro and one macro: the Kimball-style preferences and sticky intermediate prices. Under Kimball preferences, the elasticity of substitution between a given variety and others is decreasing in the relative quantity consumed of the variety. Thus sellers face a price elasticity of demand that is increasing in their good's relative price. In contrast to the Dixit–Stiglitz world of a constant elasticity and a constant desired mark-up of price over marginal cost, in Kimball's world the desired mark-up is decreasing in one's relative price. When a re-pricing firm faces a higher marginal cost, say due to higher wages in the wake of monetary stimulus, the firm will temper its price increase because of the endogenous drop in its desired mark-up. The lack of coordination is critical in this story, as it means that a re-pricing seller will be raising its relative price. Each round of re-pricing is more tentative under Kimball preferences, so it takes longer for a monetary shock to fully pass through to the average price level.

As Dotsey and King (2005) and Basu (2005) discuss, Kimball's specification creates a smoothed version of a 'kink' in the demand curve facing a given firm. Consumers flee from individual items with high relative prices, but do not flock to individual items with low relative prices. The result is that profits decline more steeply around a relative price of one. This is what creates 'rigidity' in the relative price that a firm wants. Kimball's real rigidity has become a workhorse ingredient to generate persistent real effects of nominal shocks.[5]

Sticky intermediate prices are comparatively straightforward. Intermediate inputs (materials, fuel and services) are important to virtually every industry, and their prices are sticky.[6] As shown by Basu (1995), sticky intermediate prices slow down the pass-through of nominal shocks into aggregate prices. Price setters see their input costs respond slowly, so that it requires more rounds of price setting to fully adjust to a monetary impulse. Cagliarini et al. (2011) demonstrate that sticky intermediate prices can reduce the reliance of dynamic stochastic general equilibrium models on (unrealistic) price indexation. Nakamura and Steinsson (2010) show that, when combined with sticky intermediate prices, heterogeneity of price-setting across sectors can serve as a powerful real rigidity; the more flexible sectors effectively wait for the stickier sectors.

We investigate the compatibility of Kimball's real rigidity and Basu's sticky intermediate prices with patterns of nominal and relative price changes in the microdata collected by the US Bureau of Labor Statistics (BLS) for the Consumer Price Index (CPI). In these data, nominal price changes are much larger than needed to keep up with overall inflation, as stressed by Golosov and Lucas (2007). Given little synchronization, these large changes in nominal prices translate into big movements in relative prices, suggesting that firms face important idiosyncratic shocks to their marginal cost and/or desired mark-up.

Embedding Kimball's real rigidity in an industry equilibrium model, we assess how large the idiosyncratic shocks must be in order to rationalize the observed changes in relative prices. Given the degree of real rigidity suggested by Kimball (1995) and used by Eichenbaum and Fisher (2007) and Linde et al. (2015), we find that the model requires large idiosyncratic shocks (on the order of 28% per month to item-specific productivity). On average for a given item, the model predicts that demand is eclipsed (and production shuts down) once every seven months.

In contrast, Basu's sticky intermediate prices do not require such large idiosyncratic productivity shocks and do not have extreme predictions for quantities. We find that an intermediate share of 72% implies that price stickiness can generate highly persistent effects on real variables at the sectoral level, while being consistent with both micro facts on price adjustment and sectoral facts on the volatility of inflation and productivity growth.

State-dependent pricing is a key feature of our investigation. Recent evidence for state-dependence includes Eichenbaum et al. (2011), Gagnon et al. (2012), Campbell and Eden (2014), and Alvarez et al. (2015). Our use of state-dependent pricing is in contrast to much of the literature incorporating real rigidities, which has assumed exogenously time-dependent pricing. Both types of real rigidities that we incorporate affect the frequency, size and persistence of price changes in our analysis.

The rest of the paper is organized as follows. In Section I we write down an industry equilibrium model that combines Kimball preferences and intermediate inputs with firm pricing decisions in the face of fixed menu costs. In Section II we briefly describe the CPI microdata. In Section III we estimate the model's parameters—in particular, the required volatility of shocks—under different assumed levels of Kimball's superelasticity (the elasticity of the elasticity of demand itself) and under different shares for intermediate goods in production. Section IV concludes.

I. Model

The model is a variant of the standard monopolistic competition model, and it describes optimal pricing behaviour within a particular sector of the economy.[7] To explore the role of real rigidities, we adapt the standard model to include a flexible variety aggregator à la Kimball (1995), and to include intermediate goods as a factor of production along with labour.

These two additions to the standard model serve to illustrate the main channels by which real rigidities can impact pricing dynamics. As described by Ball and Romer (1990), real rigidities can result from two sources. 'Micro' real rigidities stem from a high degree of concavity in the firm's profit function with respect to its relative price. We use the Kimball variety aggregator to control the concavity of the profit function. 'Macro' real rigidities limit the impact of sectoral and aggregate shocks on the firm's marginal cost. We use sticky-priced intermediate goods as a factor of production to serve this purpose.

Consumers

A representative agent consumes goods and provides labour for production. The economy has S sectors, with each sector containing n_s producers. The representative agent chooses consumption of goods across all sectors and all producers, $\{\{C_{si}\}_{i=1}^{n_s}\}_{s=1}^{S}$. The agent derives utility from consumption of sectoral composite goods that are created by the costless aggregation of goods within each sector.

Each sectoral composite good C_s is created using the following Kimball preferences:

$$\frac{1}{n_s}\sum_{i=1}^{n_s}\Upsilon\left(\frac{n_s C_{si}}{C_s}\right)=1, \tag{1}$$

where $\Upsilon(1) = 1$, $\Upsilon' > 0$ and $\Upsilon'' < 0$. The Kimball formulation features an elasticity of substitution decreasing in x, the relative quantity consumed of the item. Constant elasticity of substitution (CES) preferences, which are used in the standard model of monopolistic competition, are nested within this specification.[8] More generally, C_s may be defined only implicitly by equation (1).

The representative agent chooses C_{si} and labour (L) to maximize utility

$$U=\max_{L,\{\{C_{si}\}_{i=1}^{n_s}\}_{s=1}^{S}}\frac{1}{1-\sigma}\left(\prod_{s=1}^{S}\left(\frac{C_s}{\alpha_s}\right)^{\alpha_s}\right)^{1-\sigma}+v\cdot(1-L) \tag{2}$$

subject to equation (1) and the budget constraint

$$\sum_{s=1}^{S}\sum_{i=1}^{n_s}P_{si}C_{si}=wL+\Pi,$$

where α_s is the Cobb–Douglas preference parameter for the composite good of sector s, w is the nominal wage rate, and Π is the agent's profits from producers.[9] The sectoral shares sum to 1: $\sum_{s=1}^{S} \alpha_s = 1$. The assumption of costless aggregation of composite goods from each sector provides an additional constraint relating the cost of the sectoral composite to the cost of individual goods within that sector:

$$P_s C_s = \sum_{i=1}^{n_s} P_{si} C_{si},$$

where P_s is the price of the sector's composite good.

Since there is no saving in this economy, all income is spent on the purchase of goods. Based on first-order conditions for consumption, the representative agent will spend a constant nominal share on goods from sector s:

$$\alpha_s = \frac{P_s C_s}{PC}.$$

The relative demand for good j in sector s is derived from the first-order conditions from the consumer's optimization problem in equation (2):

$$\frac{n_s C_{sj}}{C_s} = (\Upsilon')^{-1}\left(\frac{P_{sj}}{P_s}\sum_{i=1}^{n_s}\frac{C_{si}}{C_s}\Upsilon'\left(\frac{n_s C_{si}}{C_s}\right)\right).$$

To simplify notation, we define

$$\varphi(x) \equiv (\Upsilon')^{-1}(x), \tag{3}$$

$$D_s \equiv \sum_{i=1}^{n_s}\frac{C_{si}}{C_s}\Upsilon'\left(\frac{n_s C_{si}}{C_s}\right). \tag{4}$$

Using these definitions, the relative demand function for good C_{sj} is expressed as

$$\frac{n_s C_{sj}}{C_s} = \varphi\left(\frac{P_{sj}}{P_s} D_s\right). \tag{5}$$

Producers

Each firm in sector s produces a differentiated good and is monopolistically competitive. The differentiated goods in sector s are combined into a sectoral consumption good and a sectoral intermediate input for production of all goods in sector s.[10] Firms set a price for their good in each period and are assumed to meet all demand at that price, implying that $Y_{si} = C_{si} + M_{si}$, where C_{si} is the demand for the consumption good and M_{si} is the demand for the intermediate input. Given the demand function for their goods, firms set prices to maximize profits. To implement a price change, firms must pay a labour cost $\widetilde{\Phi}$.

Demand from intermediate goods producers within sector

Similar to the consumption composite good C_s, an intermediate composite good $\widetilde{M}_s$ will be created in sector s for use as an intermediate input in the production process. This good is created using the same Kimball preferences:

$$\frac{1}{n_s}\sum_{i=1}^{n_s}\Upsilon\left(\frac{n_s M_{si}}{\widetilde{M}_s}\right) = 1,$$

where $\Upsilon(1)=1$, $\Upsilon' > 0$ and $\Upsilon'' < 0$.

Following a similar optimization problem as solved by the households, the intermediate goods producers will have the following relative demand function, M_{sj}, for a specific good j within sector s:

$$\frac{n_s M_{sj}}{\widetilde{M}_s} = (\Upsilon')^{-1}\left(\frac{P_{sj}}{P_s}\sum_{i=1}^{n_s}\frac{M_{si}}{\widetilde{M}_s}\Upsilon'\left(\frac{n_s M_{si}}{\widetilde{M}_s}\right)\right).$$

To ease notation, define

$$\varphi(x) = (\Upsilon')^{-1}(x),$$
$$E_s = \sum_{i=1}^{n_s}\frac{M_{si}}{\widetilde{M}_s}\Upsilon'\left(\frac{n_s M_{si}}{\widetilde{M}_s}\right),$$

which leads to the following demand function for M_{sj}:

$$\frac{n_s M_{sj}}{\widetilde{M}_s} = \varphi\left(\frac{P_{sj}}{P_s}E_s\right). \tag{6}$$

Production of intermediate good within sector

Firms maximize profits through their choices of prices and inputs of labour and intermediate goods. Contemporaneous profits, excluding the menu costs of any price change, are

$$\widetilde{\Pi}_{si} = P_{si}Y_{si} - wL_{si} - P_s\widetilde{M}_{s,i},$$

where $\widetilde{\Pi}_{si}$ is the nominal profit for firm i in sector s, L_{si} is labour, $\widetilde{M}_{s,i}$ is the composite good in sector s used as an intermediate input by firm i.

Goods are produced via a Cobb–Douglas production function that is constant returns to scale in labour and intermediates:

$$Y_{si} = Z_s A_{si} L_{si}^{1-\eta}\widetilde{M}_{s,i}^{\eta}, \tag{7}$$

where Z_s is a sectoral productivity index, A_{si} is an idiosyncratic productivity index, and η is the production elasticity for intermediates. Total output of good Y_{si} is the sum of goods used for consumption C_{si}, and for the sectoral intermediate input for production M_{si}. The producer faces demand for C_{si} and M_{si} given by equations (5) and (6).

Taking as given the prices of labour and the sectoral intermediate good, firms select the mix of inputs to minimize the cost of producing Y_{si}:

$$\widetilde{M}_{s,i} = \frac{w}{P_s}\frac{\eta}{1-\eta}L_{si}. \tag{8}$$

Firm profits are normalized by the portion of (smoothly-growing) nominal aggregate consumption demand going to firms in sector s per firm in the sector, where

$$\Pi_{si} \equiv \frac{\widetilde{\Pi}_{si}}{\alpha_s PC/n_s}.$$

Using equations (5), (6), (7) and (8) along with the assumption that the composite consumption good and composite intermediate good, respectively, are aggregated in the same manner ($D_s = E_s$), the normalized profit function can be expressed as

$$\widetilde{\Pi}_{si} = \frac{Y_s}{C_s}\varphi\left(\frac{P_{si}}{P_s}D_s\right)\left(\frac{P_{si}}{P_s} - \frac{1}{1-\eta}\left(\frac{\eta}{1-\eta}\right)^{-\eta}A_{si}^{-1}\zeta_s\right),$$

where

$$\zeta_s = \left(\frac{w}{P_s}\frac{1}{Z_s^{1/(1-\eta)}}\right)^{1-\eta}.$$

ζ_s is the component of real marginal cost common to all firms in sector s, and it will be endogenously determined by firms' responses to shocks in the dynamic optimization problem. The ratio of sector output to sector consumption, Y_s/C_s, is determined by the amount of intermediate goods needed for production, $\widetilde{M}_s$ and the relationship $Y_s = C_s + \widetilde{M}_s$. We approximate the value of intermediate production in the sector by averaging out the idiosyncratic shocks to arrive at

$$\widetilde{M}_s = \left(\frac{w}{P_s}\right)^{1-\eta}\left(\frac{\eta}{1-\eta}\right)^{1-\eta}\frac{1}{Z_s}Y_s.$$

With this relationship, the sectoral output-consumption ratio is

$$\frac{Y_s}{C_s} = \left(1 - \left(\frac{\eta}{1-\eta}\right)^{1-\eta}\zeta_s\right)^{-1}.$$

Menu costs

Firms choosing to change their price in a given period will be faced with a menu cost. To implement a price change, a firm in sector s must hire $\widetilde{\Phi}_s$ units of labour at the going wage w. Expressed relative to nominal consumption per firm in sector s, this adjustment cost is

$$\Phi_s \equiv \frac{n_s w}{\alpha_s PC} \widetilde{\Phi}_s.$$

Normalized profits, net of menu costs, are therefore

$$\Pi_{si} = \frac{Y_s}{C_s} \varphi\left(\frac{P_{si}}{P_s} D_s\right)\left(\frac{P_{si}}{P_s} - \frac{1}{1-\eta}\left(\frac{\eta}{1-\eta}\right)^{-\eta} A_{si}^{-1} \zeta_s\right) - \Phi_s.$$

Note that these normalized profits will be stationary because they involve only relative prices and quantities, the idiosyncratic productivity process will be stationary, and the menu cost is expressed relative to average firm revenue in the sector.

Dynamic optimization

Given the menu cost of a price change, the firm solves a dynamic optimization problem to maximize profits. In each period, the firm decides whether or not to adjust its price. If it decides to adjust, it pays a menu cost and resets its price. If it does not adjust, then its nominal price remains fixed, and its relative price $p_{si} = P_{si}/P_s$ decreases at the rate of sectoral inflation. As noted, we assume that the nominal consumption of the economy, PC, is growing at a constant rate. Sectoral inflation rates, however, will be buffeted by shocks to the sectoral technology index Z_s.

The state variables for the firm's optimization problem are the firm's relative price at the end of the previous period ($p_{si,-1}$), the growth rate of the sectoral technology index (g_{Z_s}), the sectoral inflation rate (π_s), sectoral real marginal cost (ζ_s), the idiosyncratic productivity index (A_{si}), and the information set Ω used to form future expectations.

Given these state variables $S = \{p_{si,-1}, g_{Z_s}, \pi_s, \zeta_s, A_{si}, \Omega\}$, the firm maximizes the value function

$$V(S) = \max(V^C(S), V^{NC}(S)), \tag{9}$$

where $V^C(S)$ represents the firm's value if it changes its price, and $V^{NC}(S)$ represents its value if it does not change its price. These value functions, in turn, are

$$V^C(S) = \max_{p_{si}} \left\{ \frac{Y_s}{C_s} \varphi(p_{si} D_s)\left(p_{si} - \frac{1}{1-\eta}\left(\frac{\eta}{1-\eta}\right)^{-\eta} A_{si}^{-1}\zeta_s\right) - \Phi_s + E_{S'|S}[\beta V(S')] \right\},$$

with

$$S' = \{p_{si}, g'_{Z_s}, \pi'_s, \zeta'_s, A'_{si}, \Omega'\},$$

and

$$V^{NC}(S) = \frac{Y_s}{C_s} \varphi\left(\frac{p_{si,-1}}{1+\pi_s} D_s\right)\left(\frac{p_{si,-1}}{1+\pi_s} - \frac{1}{1-\eta}\left(\frac{\eta}{1-\eta}\right)^{-\eta} A_{si}^{-1}\zeta_s\right) + E_{S'|S}[\beta V(S')],$$

with

$$S' = \left\{ \frac{p_{si,-1}}{1+\pi_s}, g'_{Z_s}, \pi'_s, \zeta'_s, A'_{si}, \Omega' \right\}.$$

The parameter β is the discount factor.

In order to solve this optimization problem, each firm must be able to form expectations over the state variables in the subsequent period. Based on the consumer's optimization problem, each sector's nominal consumption share is constant: $\alpha_s = P_s C_s / PC$. We assume that $\sigma = 1$ so that nominal consumption grows at the same constant rate as nominal wages, $g_{PC} = g_w$. Since all firms know this constant growth rate, they need to compute a forecast of only one of the sectoral aggregates (inflation or real sectoral marginal cost), and then they can back out the implied forecast of the other. Here we will describe forecasts of inflation.

In the spirit of Krusell and Smith (1998), and similar to the pricing analysis of Midrigan (2011), we assume that each firm forecasts next period's inflation using the linear forecasting rule

$$\pi^f_{s,t+1} = a_0 + a_1 \pi_{s,t} + a_2 \log \zeta_{s,t} + a_3 g_{Z_s,t} + \varepsilon_{\pi_s,t}, \quad \varepsilon_{\pi_s} \sim N(0, \sigma^2_{\varepsilon_{\pi_s}}), \tag{10}$$

where the residual is assumed to be orthogonal to the other right-hand-side variables. The 'regressors' are all state variables in firms' information sets at time t. A firm's idiosyncratic shock is not included because the price setting behaviour of a single firm should not affect the sectoral inflation rate. Because of the error term, firms are not simply using a point forecast for next period's inflation, but rather are taking into account the distribution of next period's inflation conditional on this period's observables.

Given their forecasts for next period's inflation rate and the sectoral technology shock combined with the assumption of constant growth of nominal wages, firms can derive expectations for the sectoral real marginal cost

$$\zeta_{s,t+1} = \left(\frac{w}{P_{s,t+1}} \frac{1}{Z^{1/(1-\eta)}_{s,t+1}} \right)^{1-\eta}$$

as

$$\log \zeta^f_{s,t+1} = \log \zeta_{s,t} + (1-\eta)(g_{PC} - \pi^f_{s,t+1}) - g^f_{Z_s,t+1}. \tag{11}$$

Regarding the exogenous processes, we assume that the idiosyncratic productivity index follows a log-normal autoregressive process:

$$\log A_{si,t+1} = \rho_A \log A_{si,t} + \varepsilon_{A,t+1}, \quad \varepsilon_A \sim N(0, \sigma^2_A).$$

We specify a stationary process because studies such as Midrigan (2011) have found that item relative prices within product categories exhibit mean reversion. In contrast, sectoral prices exhibit differential trends—see Bils and Klenow (2004), for example. We therefore assume serial correlation of the *growth* rate of the sectoral technology index, with sector-specific mean growth:

$$g_{Z_s,t+1} = \mu_{g_{Z_s}} + \rho_{g_{Z_s}} g_{Z_s,t} + \varepsilon_{g_{Z_s},t+1}, \quad \varepsilon_{g_{Z_s}} \sim N(0, \sigma^2_{g_{Z_s}}). \tag{12}$$

Expectations of sectoral inflation and real marginal cost

In order to compute expectations of sectoral inflation and real marginal cost, we will set up a three-variable VAR(1) using the sectoral state variables

$$\begin{bmatrix} \pi^f_{s,t+1} \\ \log \zeta^f_{s,t+1} \\ g_{Z_s,t+1} \end{bmatrix} = A_0 + A_1 \begin{bmatrix} \pi_{s,t} \\ \log \zeta_{s,t} \\ g_{Z_s,t} \end{bmatrix} + \xi_{t+1}.$$

We assume that ξ_{t+1} is not known until after all pricing decisions are made in period t.

With a little manipulation, we can convert (10), (11) and (12) into the following VAR system:

$$\begin{aligned} \pi^f_{s,t+1} &= a_0 + a_1 \pi_{s,t} + a_2 \log \zeta_{s,t} + a_3 g_{Z_s,t} + \varepsilon_{\pi,t+1}, \\ \log \zeta^f_{s,t+1} &= (1-\eta)(g_{PY} - a_0) - \mu_{g_{Z_s}} - (1-\eta) a_1 \pi_{s,t} \\ &\quad + \big(1 - (1-\eta) a_2\big) \log \zeta_{s,t} - \big(\rho_{g_{Z_s}} + (1-\eta) a_3\big) g_{Z_s,t} \\ &\quad - (1-\eta)\varepsilon_{\pi,t+1} - \varepsilon_{g_{Z_s},t+1}, \\ g_{Z_s,t+1} &= \mu_{g_{Z_s}} + \rho_{g_{Z_s}} g_{Z_s,t} + \varepsilon_{g_{Z_s},t+1}, \end{aligned}$$

where

$$a_0 = (1 - a_1)\pi_{ss} - a_2 \log \zeta_{SS} - a_3 \frac{\mu_{g_{Z_s}}}{1 - \rho_{g_{Z_s}}}$$

with

$$\log \zeta_{SS} = \left(\frac{\theta - 1}{\theta}\right) \eta^{\eta} (1-\eta)^{1-\eta}.$$

Kimball aggregator

In order to explore the role of real rigidities, we have selected a flexible function for the aggregator $\Upsilon(x)$. Recall that x is the relative quantity consumed of an individual variety. Our function is parsimoniously governed by two parameters, $\overline{\theta}$ and ε:

$$\Upsilon(x) = 1 + (\overline{\theta} - 1) \exp\left(\frac{1}{\varepsilon}\right) \varepsilon^{(\overline{\theta}/\varepsilon)-1} \left(\Gamma\left(\frac{\overline{\theta}}{\varepsilon}, \frac{1}{\varepsilon}\right) - \Gamma\left(\frac{\overline{\theta}}{\varepsilon}, \frac{x^{\varepsilon/\overline{\theta}}}{\varepsilon}\right)\right),$$

where $\Gamma(u,z)$ is the incomplete gamma function

$$\Gamma(u, z) \equiv \int_z^{\infty} s^{u-1} e^{-s} \mathrm{d}s.$$

This function is a generalization of the CES aggregator Υ^{CES}. In the limit as $\varepsilon \to 0$, we have $\Upsilon \to \Upsilon^{CES}$.

The solution to the model derived above depends on the derivative and the inverse of the derivative of Υ:

$$\Upsilon'(x) = \frac{\overline{\theta}-1}{\overline{\theta}} \exp\left(\frac{1-x^{\varepsilon/\overline{\theta}}}{\varepsilon}\right), \quad \varphi(x) \equiv (\Upsilon')^{-1}(x) = \left(1+\varepsilon \ln\left(\frac{\overline{\theta}-1}{\overline{\theta}x}\right)\right)^{\overline{\theta}/\varepsilon}.$$

With our functional form for Υ, the price elasticity of demand for a given variety can vary with the variety's relative price. The elasticity is

$$\theta(x) \equiv -\frac{\Upsilon'(x)}{x\Upsilon''(x)} = \overline{\theta}x^{-\overline{\varepsilon}/\overline{\theta}},$$

where

$$x = \frac{n_s Y_{si}}{Y_s} = \varphi\left(\frac{P_{si}}{P_s} D_s\right).$$

Recall that

$$D_s = \sum_{i=1}^{n_s} \Upsilon'\left(\frac{n_s Y_{si}}{Y_s}\right)\frac{Y_{si}}{Y_s}.$$

In the Dixit–Stiglitz case ($\varepsilon \to 0$), the elasticity is constant and equal to $\overline{\theta}$.

This functional form also produces variation in the superelasticity, or the rate of change of the elasticity. The superelasticity is expressed as

$$\varepsilon(x) \equiv 1 - \frac{\Upsilon'(x)}{x\Upsilon''(x)} - \frac{\Upsilon'(x)\Upsilon'''(x)}{\Upsilon''(x)^2} = \varepsilon x^{-\varepsilon/\overline{\theta}},$$

where, again,

$$x = \frac{nY_{si}}{Y_s} = \varphi\left(\frac{P_{si}}{P_s} D_s\right).$$

Depending on the value of ε, the superelasticity can provide a strong incentive for a firm to keeps its price close to the average sectoral price. Note that $\overline{\theta}$ and ε are the values of the elasticity and the superelasticity at any symmetric equilibrium, that is, whenever $nY_{si}/Y_s = 1$ for all i.

The effects of the superelasticity on demand for a given variety are illustrated in Figure 1. Compared to the Dixit–Stiglitz case of $\varepsilon = 0$, the demand curve is less convex with $\varepsilon > 0$. When $\varepsilon = 5$, the demand curve is approximately linear, and with $\varepsilon = 10$ it is ostensibly concave. Kimball's preferences create a smoothed version of a kinked demand curve, although for different reasons than in the traditional use of the term (other prices are held fixed here, so it does not hinge on asymmetric responses of competitor prices). As a firm's relative price rises above 1, its demand is choked off more quickly than with CES . And as its relative price declines below 1, its demand rises less rapidly than it does under CES. Unlike CES preferences, with concavity there is a finite 'choke price' at

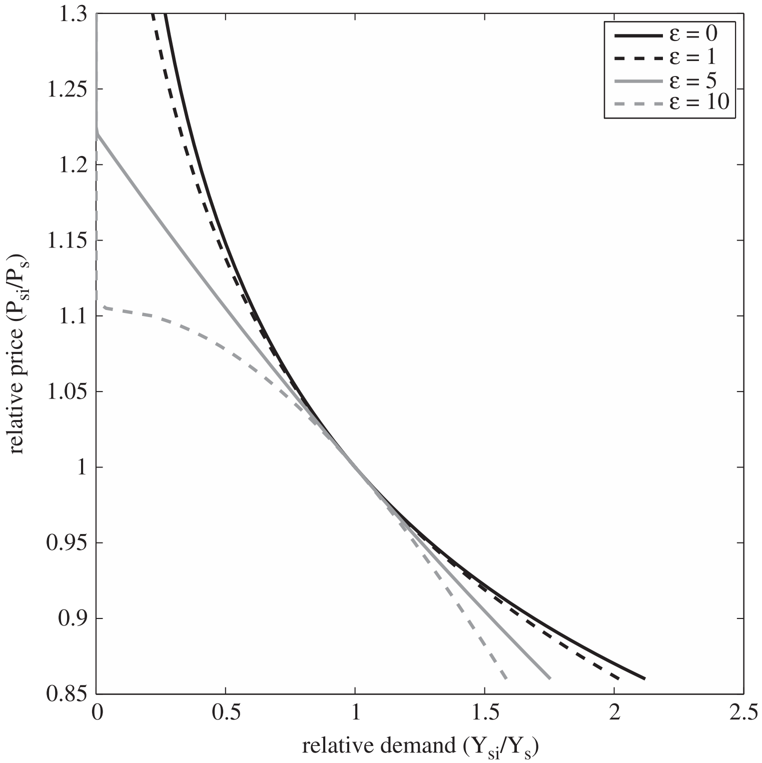

FIGURE 1. Demand function with real rigidities
Notes: Each line represents the contemporaneous demand function for a value of the Kimball micro real rigidity ε

which demand is zero. This will play an important role in our simulations, because it effectively offers a firm the option of selling no output if it should so desire in the face of comparatively low idiosyncratic productivity.

Figure 2 plots a firm's profits as its price moves away from the symmetric point, assuming common productivity and labour as the sole input ($\eta = 0$). The higher the superelasticity, the more concave the profit function. Profits decline more steeply away from 1 because price increases are penalized by plummeting demand, and price decreases are not rewarded by soaring demand. As in Figure 1, the prices at which demand disappears entirely are clearly visible. The greater concavity drives home the 'real rigidity' induced by Kimball's preferences. When idiosyncratic productivity shocks hit, firms will be less aggressive in passing these marginal cost shocks on to their relative prices. And when common sectoral shocks hit, firm price responses will not be synchronized because of the idiosyncratic shocks. As a result, the 'Kimball kink' will slow down the response to common shocks as well—how much so, we will see in Section III.[11] In the interim we will briefly describe the solution to the model and the data used to discipline the model's predictions.

Model solution

Due to the presence of a discrete-choice decision in the optimization problem expressed in (9), the model is solved numerically using value function iteration. In this solution, all

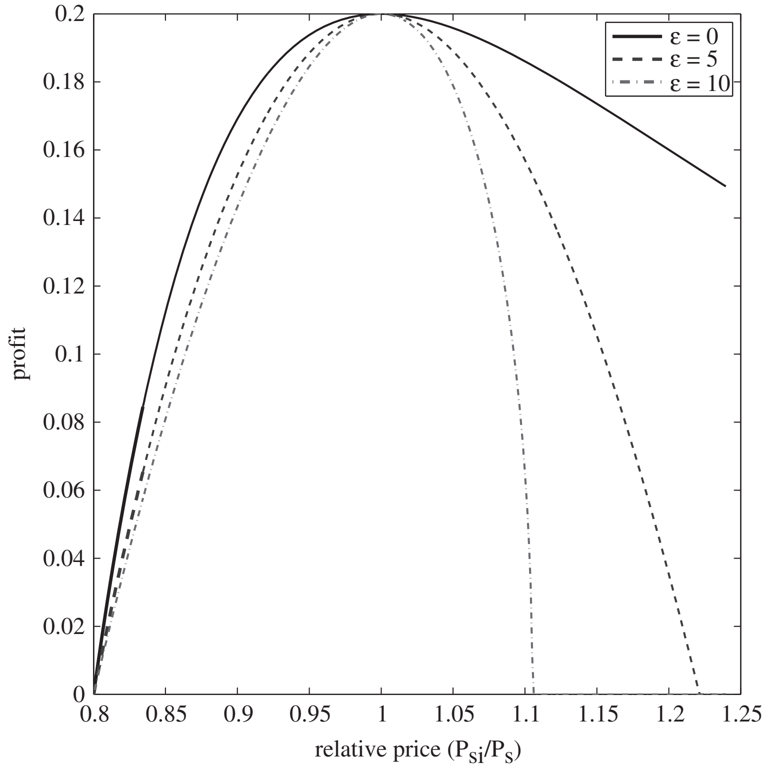

FIGURE 2. Profit function.

Notes: Each line represents contemporaneous profit as a function of the relative price for a value of the Kimball micro real rigidity ε

state variables are placed on discrete grids. The bounds of the relative price state are set wide enough to include all optimal pricing decisions, and prices are placed on the grid in increments of 0.5%. The autoregressive process for idiosyncratic productivity is transformed into a discrete-valued Markov chain following Tauchen (1986).[12] The three-variable VAR for sectoral inflation, the sectoral real marginal cost and the sectoral technology growth are similarly converted into a first-order Markov chain.[13] This conversion results in a transition matrix expressing the probability of observing any realization of future sectoral-level state variables as a function of the current state variables.

In addition to the parameters that we will estimate, we set several parameters based on the literature, US data or the steady-state solution of the model. The growth rate g_{PC} of nominal consumption for the economy is set at 0.5% per month, which reflects average nominal personal consumption expenditures consumption growth of 6% in the USA over 1988–2004. The monthly discount rate β is set at 0.996.

Following Willis (2000), the inflation forecasting equation in (10) is used to compute a rational expectations equilibrium of the model. For a given specification of the structural parameters of the model along with the inflation forecasting parameters $\Theta = \{a_1, a_2, a_3\}$, the model is solved and the policy function is generated. A panel of 320 firms over 240 months is then simulated using the policy functions.[14]

Simulating data from the model requires an updating process to determine the evolution of the endogenous sectoral-level state variables. For tractability, we assume that the sectoral variable D_s, which is a function of relative output levels of firms within the sector, is held constant at its average value. The steady-state value of this variable when $\varepsilon = 0$ is $D_s = (\overline{\theta} - 1)/\overline{\theta}$. More generally, D_s is concave in the dispersion of relative output, and decreasing in ε. Since no closed-form solution is available for D_s, its value is set equal to the average value of D_s computed using simulated data and equation (4).

The sectoral inflation rate and the sectoral real marginal cost ($\log \zeta_s$) are determined by the collective actions of firms in the simulation. When setting prices in the current period, firms are assumed to know the current value of inflation and $\log \zeta_s$. In the simulation, the current period inflation rate and $\log \zeta_s$ are selected by choosing the grid point in their respective discretized state spaces that most closely match the following two conditions from the model:[15]

$$1 = \frac{1}{n_s}\sum_{i=1}^{n_s} \Upsilon\left(\varphi\left(\frac{P_{si}}{P_s}D_s\right)\right), \quad 1 = \frac{1}{n_s}\sum_{i=1}^{n_s} \frac{P_{si}}{P_s}\varphi\left(\frac{P_{si}}{P_s}D_s\right).$$

As a reminder, the first equation is the Kimball flexible variety aggregator. The second equation is the implicit definition of D_s given in (4) after substituting the demand function given in (5).

After simulating a panel of firm–months, we evaluate the forecasting rule used to form expectations for future inflation. Adding in the exogenous sectoral productivity growth shock g_{Z_s}, an OLS regression of the linear forecasting rule in (10) is executed on the simulated data. The initial assumed values of the forecast parameters, Θ_0, are then compared to the OLS estimates, Θ_1. If these values differ, then the forecast parameters are updated based on Θ_1, and a new solution for the model is derived. This updating process continues until a fixed point is reached. This fixed-point solution represents a rational expectations equilibrium where the inflation forecasting rule assumed by firms matches up with the behaviour of the simulated data.

II. CPI DATA

In its Commodities and Services Survey, the US Bureau of Labor Statistics checks the prices of around 85,000 items per month in order to tabulate the US CPI. An individual item refers to a product or service with specific attributes sold by a particular outlet in a given location. The survey covers all goods and services other than shelter, or about 70% of the CPI based on BLS consumer expenditure weights. The CPI Research Database, maintained by the BLS Division of Price and Index Number Research, contains all prices in the Commodities and Services Survey from January 1988 to the present.[16] We base our statistics on data to December 2004 for the three largest areas—New York, Los Angeles and Chicago—for which all items are surveyed every month (as opposed to bimonthly for most items in other areas). This subsample consists of about 14,000 prices per month.

The BLS identifies each collected price as either a ‘regular’ price or a ‘sale’ price (i.e. a temporarily low price that is labelled so in some way). Although going to and from sale prices may require menu costs, we focus on regular prices because they exhibit smaller relative price changes. As we will report shortly, this will be a conservative approach. We also exclude all price changes coinciding with a change in the item surveyed, seasonal changeovers and temporary stockouts. To minimize the importance of measurement error, we drop price changes that exceed ten natural log points in absolute value. These price jumps constitute less than 0.1% of all price changes. Using a lower threshold, such as five log points, has almost no effect on our tabulations.

In order to estimate the parameters in our model, we calculate five statistics from the CPI data. Several of these are related to statistics calculated by Klenow and Kryvtsov (2008) using earlier vintages of the CPI Research Database. Golosov and Lucas (2007) and Nakamura and Steinsson (2010) use similar statistics for their analysis.

The first moment that we calculate is the average sectoral inflation rate over time. Let P_{sit} denote the price of item i in sector s in month t, and let ω_{sit} denote the BLS weight on item i within category s in month t. The weights in sector s sum to ω_s^{93} in every month, that is, the BLS consumption expenditure weights of category s in 1993 (which themselves sum to 1). We define the sectoral inflation rate in month t as

$$\pi_{st} = \sum_i \frac{\omega_{sit}[\log(P_{sit}) - \log(P_{sit-1})]}{\omega_s^{93}}.$$

For each of 67 sectors ('expenditure classes') in the BLS data, we calculate the mean of inflation across the 203 months from February 1988 to December 2004, or $\pi_s = \sum_{t=1}^{203} \pi_{st}/203$. We then take the weighted average of these across sectors to arrive at 0.153% per month:

$$\overline{\pi} = \sum_s \omega_s^{93} \pi_s = 0.00153.$$

In a similar fashion we calculate our second moment, the cross-sector average of the standard deviation of sectoral inflation. We first compute the standard deviation of inflation across months for each sector, and then calculate the weighted mean of these sectoral standard deviations to be 1.02%:

$$\sigma_\pi = \sum_s \omega_s^{93} \sqrt{\sum_{t=1}^{203} (\pi_{st} - \pi_s)^2/202} = 0.0102.$$

Our third moment is the average fraction of items changing price from one month to the next. Let $I(\Delta P_{sit} \neq 0)$ be a price-change indicator for item i in sector s in month t. It takes on the value 1 if the item changed price from month $t-1$ to month t, and 0 otherwise. Weighting items and sectors appropriately, this indicator averages 21.5% across items, sectors and time:

$$\overline{I(\Delta P \neq 0)} = \sum_s \omega_s^{93} \left[\sum_{t=1}^{203} \left(\sum_i \omega_{sit} I(\Delta P_{sit} \neq 0)/\omega_s^{93} \right) /203 \right] = 0.215.$$

Our fourth and fifth moments are the serial correlation and standard deviation of an item's price relative to a sectoral price index. We construct the sectoral price index as

$$\overline{P}_{st} = \exp\left(\sum_{k=2}^{t} \pi_{sk} \right).$$

The index is 1 at t=1 in each sector, and cumulates inflation going forward. We let p_{sit} denote the ratio of the price of item i to the sectoral price index, that is, $p_{sit} = P_{sit}/\overline{P}_{st}$. This is the relative price of item i within sector s at time t. For each sector, we calculated the serial correlation and standard deviation of $\log(p_{sit})$ across months with price changes. We took out item-specific means to deal with any discrepancy in units (e.g. sizes of cereal boxes). We then took the weighted mean of sector statistics to obtain a serial correlation of 0.318 and a standard deviation of 13.9%, again across new prices:

$$\rho_p = \sum_s \omega_s^{93} \sqrt{\sum_i \omega_{si} \sum_{I_{sit}=1} (\log p_{sit} - \overline{\log p_{sit}})(\log p_{sit-\tau_{sit}} - \overline{\log p_{sit}})} = 0.318,$$

$$\sigma_p = \sum_s \omega_s^{93} \sqrt{\sum_i \omega_{si} \sum_{I_{sit}=1} (\log p_{sit} - \overline{\log p_{sit}})^2} = 0.139.$$

Here I_{sit} is shorthand for $I(\Delta P_{sit} \neq 0)$, and τ_{sit} is the age (duration) of the price at the time of its 'death' in month t. Separately, note that the sectoral price index that we defined above is *not* the same as that implied by the Kimball aggregator. We do not observe all of the prices in the market, and hence do not construct this ideal price index. When we simulate the model below, we will construct a simulation counterpart to what we calculated in the data.

In Table 1, we provide these moments. We compute bootstrapped standard errors by drawing 'quotelines' (strings of prices for a given item) with replacement. As shown, the moments are estimated with great precision—not surprising given the 2.8 million microdata points on prices underlying them. If we had looked at posted prices rather than regular prices (i.e. omitted temporary price discounts), then the main difference would be a higher standard deviation of new relative prices over time (19% rather than 14%). Including price changes involving product turnover, seasonal changeovers or temporary stockouts would also have boosted the standard deviation. Finally, with more disaggregate BLS sectors, specifically 250 instead of 67, the standard deviation was virtually identical. Our estimates in Table 1 are consistent with recent surveys by Klenow and Malin (2010), and Nakamura and Steinsson (2013).

Table 1
BLS CPI Moments

$\overline{\pi}$	σ_π	$\overline{I(\Delta P \neq 0)}$	ρ_p	σ_p
0.00153	0.0102	0.215	0.318	0.139
(0.00001)	(0.0002)	(0.001)	(0.012)	(0.002)

Notes
Standard errors are in parentheses. Source: author calculations from the *CPI Research Database*, January 1988 to December 2004, prices in New York, Los Angeles and Chicago.

III. Model Estimation and Simulation

We selected the statistics in Table 1 from many possible statistics because we think that they represent key features of the data that a model should be able to mimic. We now use the statistics in Table 1 to estimate some of the structural parameters of the model. The parameters that we will estimate are the standard deviation of innovations to sectoral productivity growth (σ_{g_Z}), the autocorrelation coefficient for the idiosyncratic technology process (ρ_A), the standard deviation of innovations to the idiosyncratic technology component (σ_A), and the magnitude of the menu cost (Φ).[17] We assume that sectoral technology growth follows an independent and identically distributed process ($\rho_{g_{Z_s}} = 0$), in line with evidence in Bils and Klenow (2004). With this assumption, the mean growth rate of sectoral productivity is calibrated directly using the mean sectoral inflation rate from BLS data ($\overline{\pi} = 0.00153$), the growth rate of nominal consumption ($g_{PC} = 0.005$), and the steady-state relationship for $\log \zeta_s$: $\mu_{g_{Z_s}} = (1-\eta)(g_{PC} - \overline{\pi})$.

Although the four parameters to be estimated do not map one-to-one to data statistics, we have strong intuition for how they relate to each other. More volatile sectoral productivity growth, *ceteris paribus*, should boost the volatility of sectoral inflation and the frequency of price changes. Higher serial correlation of the idiosyncratic productivity term should increase the serial correlation and standard deviation of relative price movements. A bigger standard deviation of idiosyncratic innovations should increase the frequency of price changes and the size of relative price movements. Finally, a higher menu cost should, *ceteris paribus*, reduce the frequency of price changes.

We use the Simulated Method of Moments procedure to estimate these parameters. The BLS moments $\Psi_{\text{BLS}} = \{\sigma_\pi, \overline{I(\Delta P \neq 0)}, \rho_p, \sigma_p\}$ are matched up against the same moments computed from simulated data, $\Psi_{\text{sim}}(\Lambda)$. The moments from the simulated data are functions of the structural parameters, $\Lambda = \{\sigma_{g_Z}, \rho_A, \sigma_A, \phi\}$. The estimation involves finding the vector Λ of structural parameters that minimizes the weighted distance between BLS moments and simulated moments:

$$\min_{\Lambda} \left(\Psi_{\text{BLS}} - \Psi_{\text{sim}}(\Lambda)\right) W \left(\Psi_{BLS} - \Psi_{\text{sim}}(\Lambda)\right)'.$$

Note that W represents the weighting matrix constructed as the inverse of the variance-covariance matrix of the BLS moments.[18]

Before each round of estimation, we fix the values of three parameters. First, we set the elasticity of demand (evaluated at a relative price of 1) to $\overline{\theta} = 5$, which implies a mark-up of 25% in the case with no real rigidities. This is at the high end of most estimates in the industrial organization literature, but lower than the value of 11 (10% mark-up) typically used in the macro literature.

Second, we set the value of the superelasticity at the symmetric point ε. Initially, we consider $\varepsilon = 0$, the Dixit–Stiglitz case of a constant elasticity. Then we contrast this with the case of $\varepsilon = 10$. This is the value used by Smets and Wouters (2007) and the low value entertained by Eichenbaum and Fisher (2007), who also considered the value of 33 suggested by Kimball (1995).

Third, we choose the intermediate share in production η. We start with $\eta = 0$, so that production is linear in labour. Then we experiment with $\eta = 0.5$, a value considered by Nakamura and Steinsson (2010) and close to the share of intermediates (relative to labour) across US industries.[19]

Our final experiments explore two changes in the estimation procedure. First, we explore the implications of a lower frequency of price change of 9% that is closer to the median value across the 67 CPI sectors. And second, we estimate, instead of calibrate, the value of the intermediate share in production η.

To recap, we set some parameters based on the previous literature (the value for the elasticity of demand and the random walk process for sectoral). We then either impose no real rigidities or add real rigidities based on parametrizations in the literature. For each model, we then estimate the volatility of sectoral shocks, the volatility and persistence of idiosyncratic costs, and the menu cost. Finally, we compare the resulting estimates to limited outside evidence on the size of idiosyncratic and sectoral shocks and the size of menu costs.

In Table 2 we present estimates of the four model parameters for the case when we impose $\varepsilon = 0$ and $\eta = 0$. In this baseline case, the model features nominal rigidities but no real rigidities. Note that the idiosyncratic shock must be sizeable (innovation standard deviation of around 12%) and somewhat persistent (serial correlation around 0.68) in order to match the persistence and volatility of item relative prices (across newly set prices). Also worth noting is the menu cost, which amounts to around 6.6% of average firm revenue *when spent*. The menu cost must be multiplied by the frequency of price changes to obtain the average expenditures on menu costs relative to average firm revenue. Expended menu costs are 1.33%, in the neighbourhood of estimates by Levy et al. (1997) and Zbaracki et al. (2004) and 0.7% and 1.22%, respectively. A comparison of the first two rows of Table 3 illustrates that the simulated method of moments estimation is able to very closely match moments from the baseline model with moments from the BLS data.

Figure 3 plots the model response of the sectoral price index to a negative shock to sectoral productivity.[20] Impulse responses are computed by introducing a shock to sectoral productivity growth relative to the baseline simulation. The shock is applied iteratively to each possible period in the simulation, creating a series of impulse responses. Each impulse response is based on a one-period deviation in the sectoral productivity growth rate relative to baseline that generates an eventual 1% increase in the sectoral price index. The variation across the responses arises from the model's

TABLE 2
ESTIMATION WITH $\varepsilon = 0$

Structural parameters				Inflation forecast coefficients				Expended menu costs mean (Φ/Revenue)
σ_{g_Z}	ρ_A	σ_A	Φ	π_s	$\log \zeta$	g_{Z_s}	R^2	
0.0160 (0.0013)	0.684 (0.015)	0.117 (0.004)	0.0642 (0.0041)	−0.02	0.30	−0.04	0.15	0.0133

Notes
The share of intermediates in production is η=0. Standard errors are in parentheses. Expended menu costs are calculated as the average expenditures on menu costs relative to average firm revenue across all months.

TABLE 3
MOMENTS WITH AND WITHOUT THE MICRO REAL RIGIDITY

	σ_π	$\overline{I(\Delta P \neq 0)}$	ρ_p	σ_p
BLS	0.0102	0.215	0.318	0.139
$\varepsilon = 0$	0.0102	0.215	0.318	0.139
$\varepsilon = 10$	0.0050	0.089	0.158	0.040

Notes
The first row displays moments computed using BLS micro price data. The second and third rows present simulated moments from the baseline model under two settings for the micro real rigidity ε. The share of intermediates in production is η=0 for both model specifications.

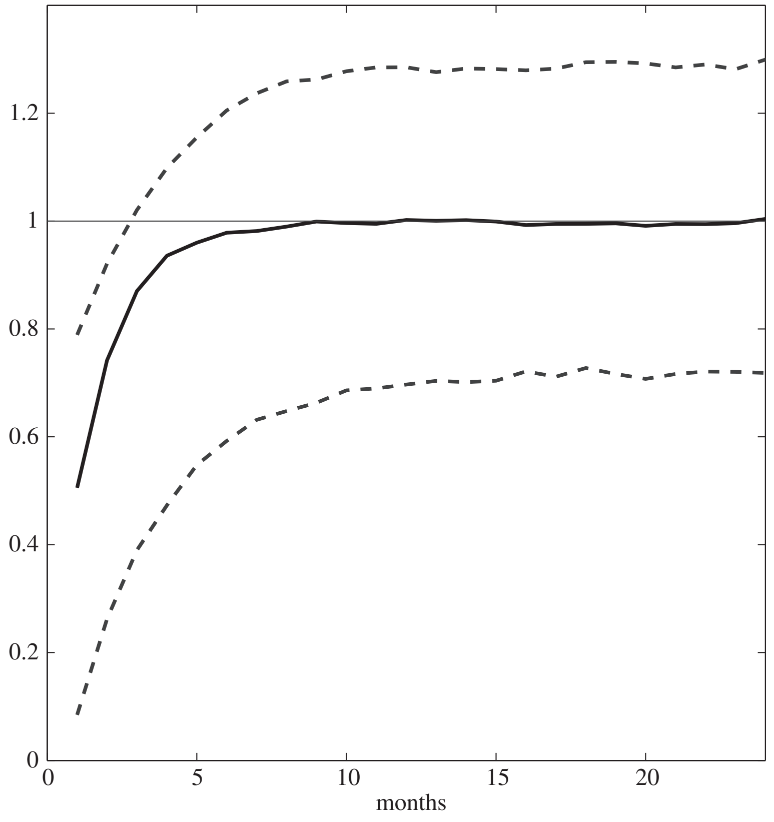

FIGURE 3. Sectoral price response to a permanent sectoral productivity drop in baseline specification
Notes: Impulse responses are computed by introducing a shock to sectoral productivity growth relative to the baseline that generates an eventual 1% increase in the sectoral price index. The solid line in the middle is the *average* response across simulations, and the two dashed lines represent the boundaries for the region that contains the middle 68% of the impulse responses.

non-linearity. In a linear model, the response is the same regardless of the starting distribution of relative prices.

In Figure 3, the solid line in the middle is the *average* response across simulations. The two dashed lines represent the boundaries for the region that contains the middle 68% of the impulse responses, which approximates one standard deviation. The width of the bands illustrates that the underlying distribution plays a large role in the response to sectoral shocks.

By construction, prices ultimately rise about 1% in response to the shock. Our focus is on how long it takes to get there. The longer it takes, the greater the real output response in the meantime. In the absence of the real rigidity and in the presence of modest nominal rigidity (over 20% of items changing prices per month), the response is swift. The half-life is about one month, and prices almost fully respond after six months. Clearly, the baseline model does not generate as much persistence as sought to match structural VAR evidence of effects lasting several years.

We next consider the micro and macro real rigidities sequentially.

Micro real rigidity

We next simulate a model with micro real rigidities ($\varepsilon = 10$) using the same structural parameters as estimated above. The results, in Table 3, are intuitive. Adding a real rigidity à la Kimball (1995) makes firms more reluctant to change prices (10% of the time, down from 23%), and makes relative prices more stable (serial correlation of 0.18 down from 0.31, and standard deviation of 4% down from 15%). With the Kimball kink, firms do not pass marginal cost shocks as fully onto their prices.

Adding the real rigidity does prolong the response to a sectoral shock. Figure 4 contains impulse responses from the two versions of the baseline estimation model. The addition of real rigidities ($\varepsilon = 10$) to the baseline model (dark dashed line) increases the half-life of the response from less than 1 month to 4 months, and it now takes about 20 months for the full effect to be realized.

As shown in Table 3, however, adding the real rigidity pushes the model moments away from the data moments. We therefore re-estimate the model subject to $\varepsilon = 10$. The resulting parameter estimates are given in Table 4, where the fit between data and model moments (not shown) is as precise as in the baseline model estimation comparison in

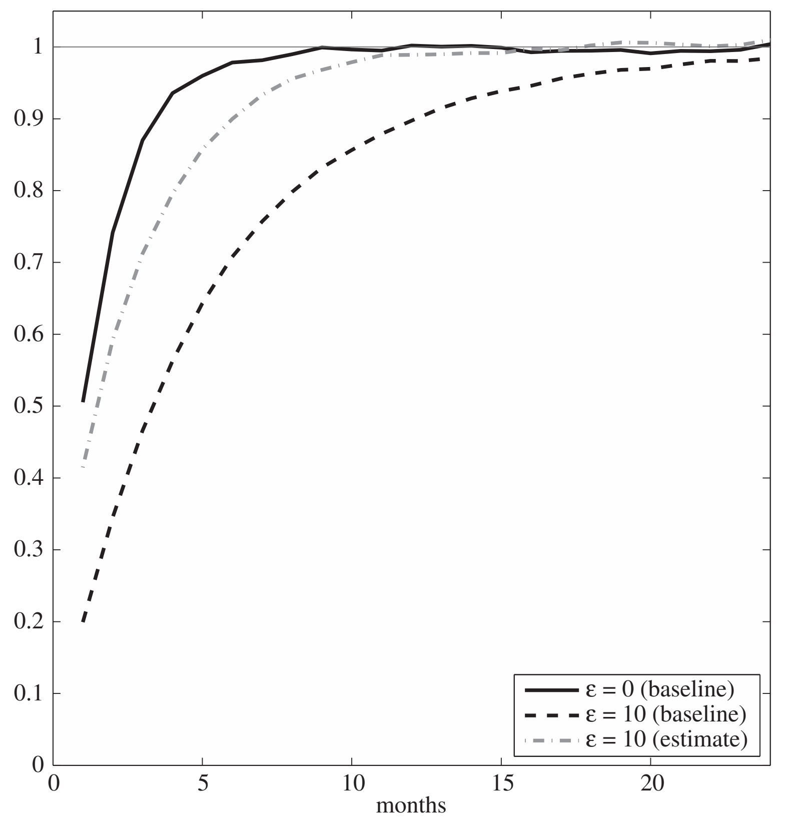

FIGURE 4. Impact of micro real rigidity on sectoral price response to a permanent sectoral productivity drop
Notes: Impulse responses are computed by introducing a shock to sectoral productivity growth relative to the baseline that generates an eventual 1% increase in the sectoral price index. Each line represents the *average* response across simulations for each specification. The first two responses are generated using the baseline model parameter estimates, while the third response uses parameter estimates from the specification with micro real rigidities ($\varepsilon = 10$).

TABLE 4
PARAMETER ESTIMATES WITH ε = 10

Structural parameters				Inflation forecast coefficients				Expended menu costs mean
σ_{g_Z}	ρ_A	σ_A	Φ	π_s	$\log \zeta$	g_{Z_s}	R^2	(Φ/Revenue)
0.0181 (0.0005)	0.725 (0.020)	0.281 (0.013)	0.0963 (0.0052)	−0.10	0.25	−0.05	0.13	0.0205

Notes
The share of intermediates in production is η=0. Standard errors are in parentheses. Expended menu costs are calculated as the average expenditures on menu costs relative to average firm revenue across all months.

Table 3. The light dashed line in Figure 4 shows that when the structural parameters are re-estimated with ε = 10, the price response is more rapid than shown by the baseline specification with ε = 10 (dark dashed line), but still more persistent than the baseline model with no real rigidities (ε = 0).

Comparing the parameter estimates in Tables 2 and 4, two differences are evident. First, in the presence of a micro real rigidity, the idiosyncratic shock innovation must be very large—about 28%, compared to 12% without the real rigidity. This is the standard deviation of the *monthly* innovation to firm productivity. Such big shocks are necessary because in the presence of the micro real rigidity, firms must face very large marginal cost shocks in order to change their relative prices as much as we observe in the CPI data. The second notable change is to the size of menu costs. Taking into account the frequency of price changes, menu costs absorb 2.1% of average firm revenue. This is about double the size of menu costs estimated by the papers using direct evidence (around 1%).

The models with and without the micro real rigidity also differ markedly in their implications for quantity movements. For the model with $\bar{\varepsilon}$ = 0, Panel A of Figure 5 plots simulated prices and quantities for 100 months for a single item/firm under the baseline specification. Both prices and quantities are relative to the industry aggregates. Given that supply (productivity) shocks drive price movements in the model, the price and quantity movements are in opposite directions. And given that demand is elastic ($\bar{\theta}$ = 5≫1), the quantities move significantly more, in percentage terms, than the prices do.

Panel B of Figure 5 plots simulated prices and quantities when ε = 10. Compared to when ε = 0, quantities do not reach the same highs with ε = 10. The real rigidity dampens the rise in quantity demanded when the price falls; relative quantities do not reach even twice the symmetric value, compared to over three times the symmetric value with no real rigidity. The flip side is that quantities fall more sharply with the real rigidity in response to relative price increases. Whereas quantities bottom out at half the symmetric level without the real rigidity, they frequently fall to zero in the presence of the real rigidity. Strong real rigidity induces concavity in the demand curve, as shown in Figure 1. So quantities hit zero at finite relative prices. Figure 5 demonstrates that this is not just a possibility, but a regular occurrence. Across many simulations, 'total eclipse of demand' occurs in about 15% of months. We find this implication implausible, but it needs to be verified with data on quantities (e.g. from scanner data).

We next look at the histogram of relative prices and relative quantities in the absence and presence of the Kimball real rigidity, respectively. Panels A and B of Figure 6 display histograms of relative prices (pooled across firm–months). With ε = 10, relative prices are

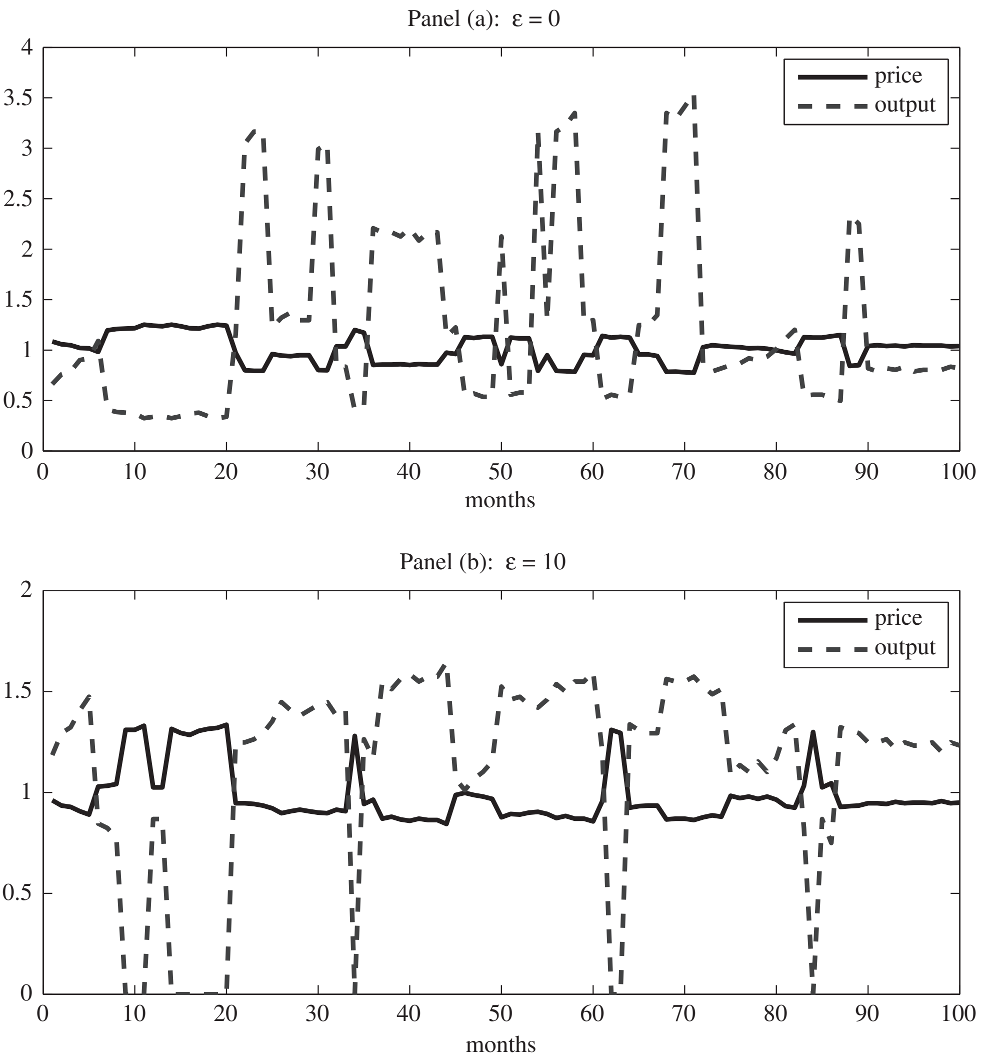

FIGURE 5. Simulation of firm-level prices and output

Notes: Each panel shows a simulation of relative prices and relative quantities (output) for a single firm in the simulated dataset. The top panel is generated using the baseline model parameter estimates, while the lower panel is generated using parameter estimates from the specification with micro real rigidities (ε = 10).

bimodal. Firms keep their relative price close to 1 unless their marginal cost is so high that it is not profitable to sell, in which case they price themselves out of the market.[21]

Panels A and B of Figure 7 display histograms of relative quantities (again, pooled across firm–months). Quantities are more tightly distributed in the presence of the real rigidity. But the left tail of zeros representing zero quantity sold stands out relative to what happens without the real rigidity.

Macro real rigidity

We next explore the impact of a macro real rigidity in the form of sticky intermediate prices. In Table 5 we present structural parameter estimates when the intermediate share

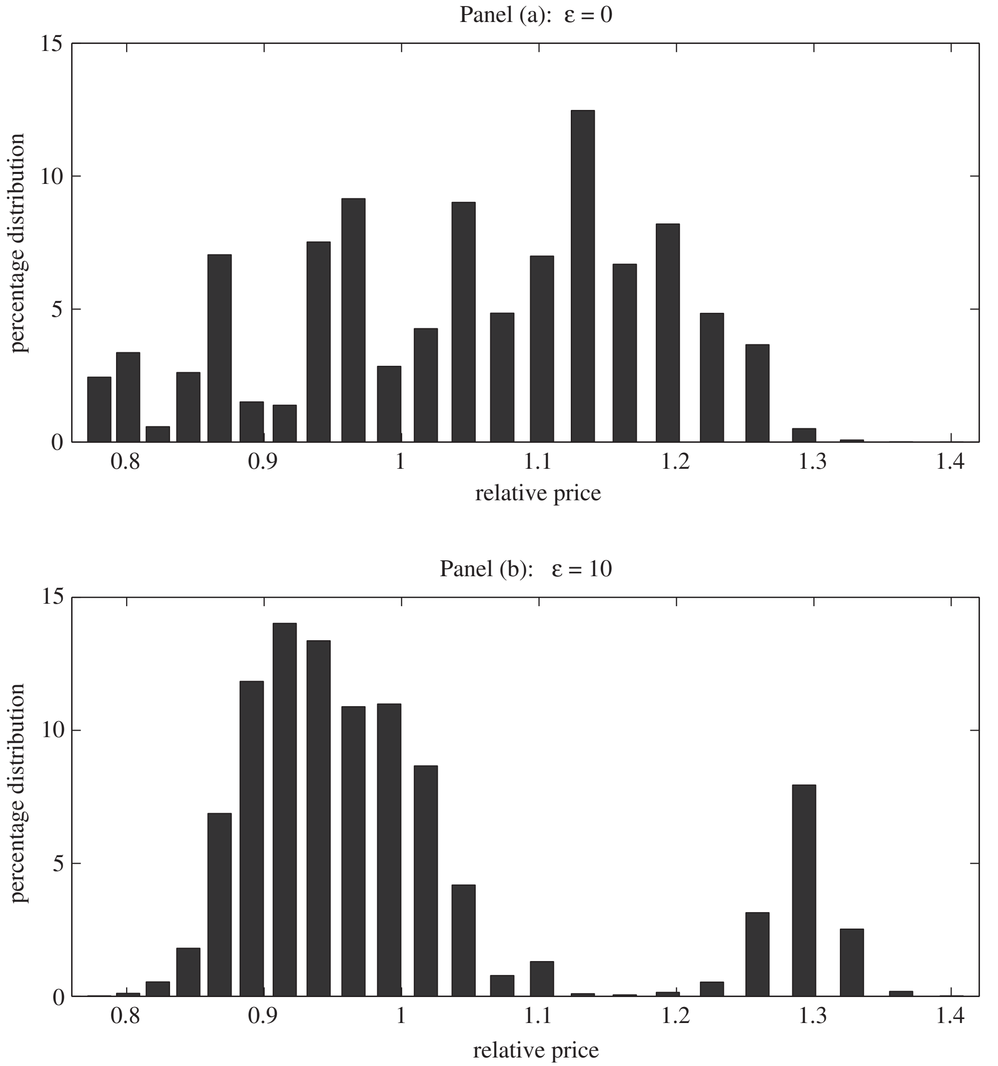

FIGURE 6. Histogram of relative prices

Notes: Each panel shows a histogram of relative prices generated using all price observations in the simulated dataset. The top panel is generated using the baseline model parameter estimates, while the lower panel is generated using parameter estimates from the specification with micro real rigidities ($\varepsilon = 10$).

in production is $\eta = 0.5$. The volatility of the sectoral productivity shock is cut in half, as a given productivity change has twice ($1/\eta$) the impact on the long-run sectoral price once it feeds through the intermediate price. The parameters of the idiosyncratic productivity process (ρ_A and σ_A) are very similar to the baseline estimates. And while the estimate of the menu cost (Φ) is almost double that of the baseline estimation, the size of expended menu costs as a share of average revenues is approximately the same as in the baseline model. The closeness of fit of the moments between actual and simulated data (not shown) is as precise as in the baseline estimate comparison in Table 3.

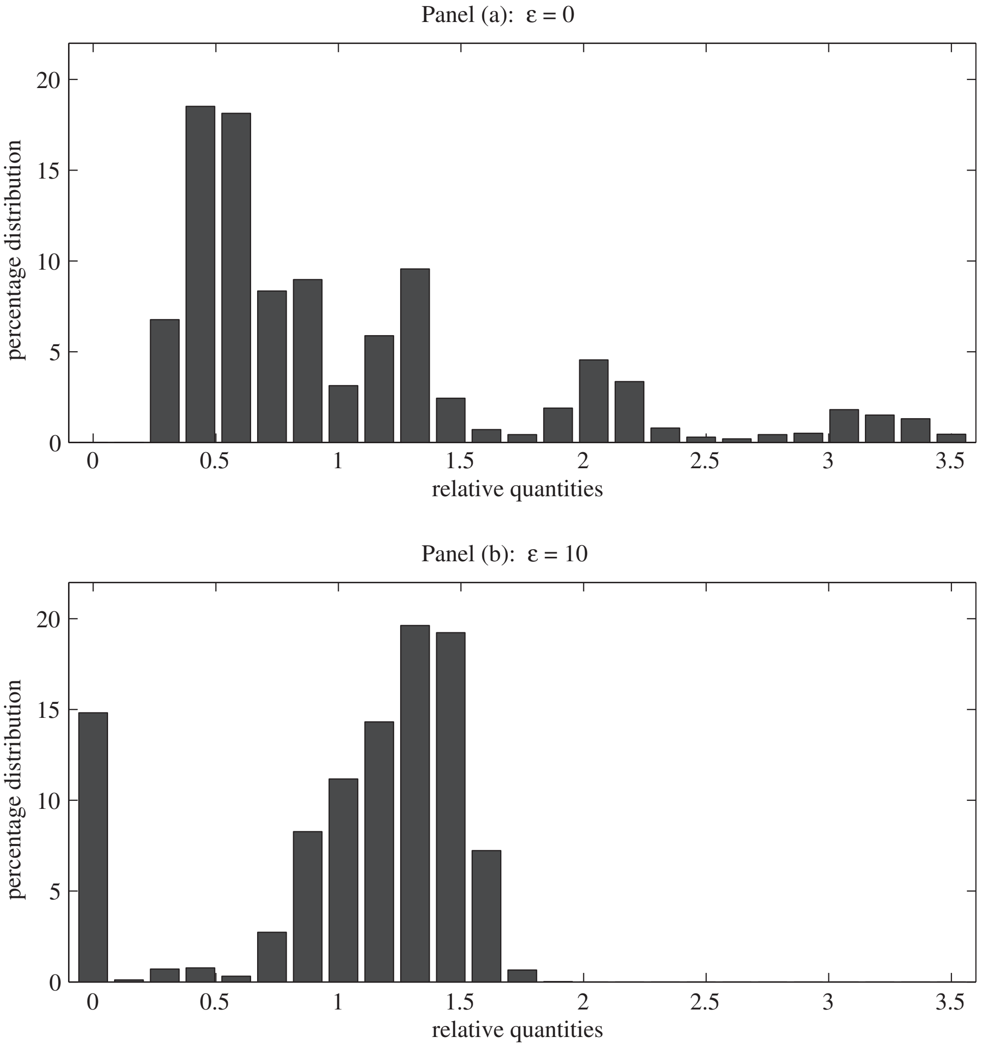

FIGURE 7. Histogram of relative quantities

Notes: Each panel shows a histogram of relative quantities generated using all price observations in the simulated dataset. The top panel is generated using the baseline model parameter estimates, while the lower panel is generated using parameter estimates from the specification with micro real rigidities ($\varepsilon = 10$).

TABLE 5
ESTIMATION WITH $\eta = 0.5$

Structural parameters				Inflation forecast coefficients				Expended menu costs mean (Φ/Revenue)
σ_{g_Z}	ρ_A	σ_A	Φ	π_s	$\log \zeta$	g_{Z_s}	R^2	
0.0098 (0.0003)	0.686 (0.025)	0.118 (0.005)	0.107 (0.0050)	0.00	0.56	−0.04	0.20	0.0135

Notes The Kimball superelasticity is ε=0. Standard errors are in parentheses. Expended menu costs are calculated as the average expenditures on menu costs relative to average firm revenue across all months.

Figure 8 shows surprisingly rapid pass-through compared to the literature. The half-life is a mere 2–3 months, and the full effect is realized within 1 year. The reason is that the frequency of price change is 21% *per month*, much higher than the values considered by Basu (1995) and Nakamura and Steinsson (2010). When prices change quickly, intermediates are also less sticky.

We therefore entertain a much lower frequency of price change of 9% per month. This is close to the median value across the 67 CPI sectors. Nakamura and Steinsson (2010) argue that heterogeneity in the frequency of price changes across sectors interacts with intermediate inputs to serve as a powerful mechanism for slowing down pass-through. They advocate using the median frequency across sectors for calibrating a one-sector model, to mimic the effects of heterogeneity across sectors. See also Carvalho (2006).

Using the lower frequency of price change, the first two rows of Table 6 show structural parameter estimates for the baseline model ($\eta = 0$) and the model with an intermediate share of $\eta = 0.5$. In order to generate a lower frequency of price change while continuing to match the other three moments, both models require less volatility in the idiosyncratic shock process but greater volatility of the sectoral productivity shock

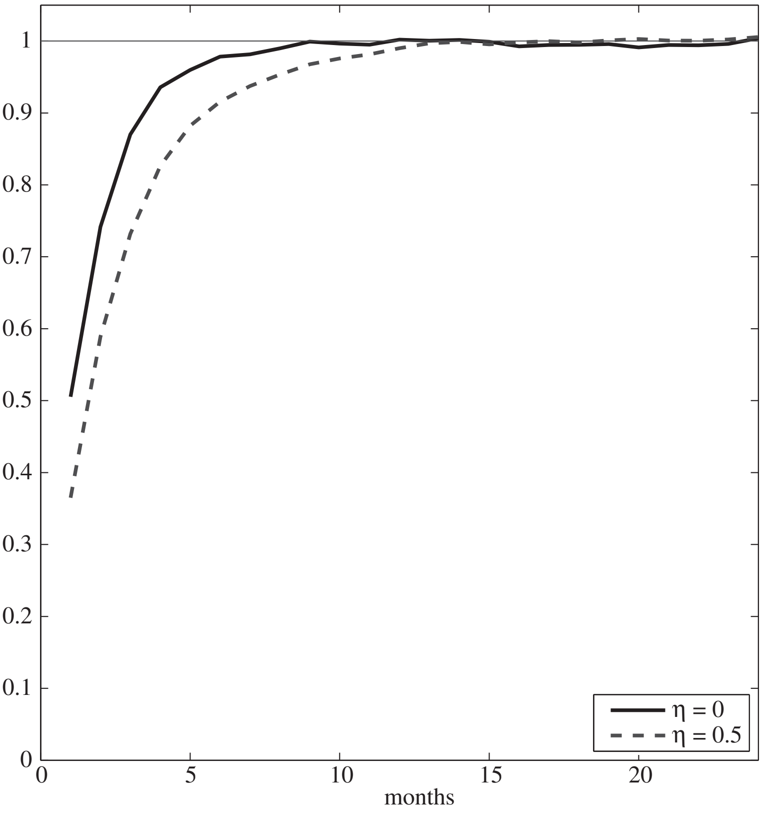

FIGURE 8. Impact of macro real rigidity on sectoral price response to a permanent sectoral productivity drop
Notes: Impulse responses are computed by introducing a shock to sectoral productivity growth relative to the baseline that generates an eventual 1% increase in the sectoral price index. Each line represents the *average* response across simulations for each specification. The first response is generated using the baseline model parameter estimates, while the second response uses parameter estimates from the specification with macro real rigidities ($\eta = 0.5$).

TABLE 6
ESTIMATION WITH MEDIAN PRICE CHANGE FREQUENCY OF 9%

Case		Structural parameters				Inflation forecast coefficients				Expended menu costs mean
ε	η	σ_{g_Z}	ρ_A	σ_A	Φ	π_s	$\log\zeta$	g_{Z_s}	R^2	(Φ/Revenue)
0	0	0.0241 (0.0006)	0.862 (0.014)	0.0829 (0.0051)	0.163 (0.009)	0.00	0.30	−0.04	0.28	0.0141
0	0.5	0.0153 (0.0006)	0.867 (0.007)	0.0809 (0.0022)	0.265 (0.012)	0.06	0.30	−0.05	0.35	0.0141
10	0	0.0318 (0.0029)	0.895 (0.009)	0.176 (0.009)	0.237 (0.028)	−0.03	0.18	−0.02	0.33	0.0212

Notes
The first two columns display the settings for the real rigidities parameters in each estimation. Standard errors are in parentheses. Expended menu costs are calculated as the average expenditures on menu costs relative to average firm revenue across all months.

relative to estimates with a higher frequency of price change. As expected, a higher menu cost Φ is necessary to lower the frequency of price change. Factoring in the lower frequency of paying the menu cost, the expended menu cost as a share of average revenue is only slightly higher (1.4%) in these specifications relative to the baseline specification (1.3%) where the price change frequency is 21%.

The final row of Table 6 reports parameter estimates from the model with micro real rigidities. As in the estimates with a higher frequency of price change, this model requires larger sectoral and idiosyncratic shock volatility to achieve the same frequency of price change as models without the Kimball micro real rigidity. The expended menu cost remains higher as well. Table 7 reports the corresponding moments all three estimation exercises, demonstrating a very close fit between data and model moments.

Given the importance of the sectoral technology shock for this particular macro real rigidity, we can further discipline this model by drawing evidence from industry data. In the BLS Multifactor Productivity Database, the weighted mean standard deviation of sectoral productivity growth is 3.36% at an annual frequency. Converting this to a monthly frequency under our assumption of an independent and identically distributed process for sectoral productivity growth, the standard deviation of sectoral technology shocks is 1.02%.

TABLE 7
DATA AND MODEL MOMENTS CORRESPONDING TO ESTIMATIONS WITH MEDIAN PRICE CHANGE FREQUENCY OF 9%

	σ_π	$\overline{I(\Delta P \neq 0)}$	ρ_p	σ_p
BLS data	0.0102	0.090	0.318	0.139
ε=0 η=0	0.0102	0.090	0.317	0.139
ε=0 η=0.5	0.0102	0.090	0.318	0.139
ε=10 η=0	0.0102	0.090	0.318	0.139

Notes
The first row displays moments computed using BLS micro price data with the exception of the price-change frequency moment, which has been lowered to 9% for this experiment. The other rows present simulated moments using the estimated parameters in Table 6 under various settings for the real rigidities ε and η.

We next shift our approach to estimate (instead of calibrate) the intermediate share in production. For this final estimation, we set the parameter for the standard deviation of the sectoral technology shock, σ_{g_Z}, to match the data estimate of 1.02%. This frees up a degree of freedom to estimate the intermediate share as one of the four structural parameters in the simulated method of moments procedure. Table 8 shows the results of this estimation, where the fit of the moments (not shown) is as precise as displayed in Table 7 for the prior estimations. The intermediate share is estimated to be $\eta = 0.72$. This is higher than our calibrated value of 0.5, but in line with values considered by Basu (1995) and Nakamura and Steinsson (2010). Relative to the estimated models in Table 7 with lower intermediate shares, the model with $\eta = 0.72$ has a larger menu cost Φ, but the expended menu cost is little changed.

Figure 9 displays the impulse response functions for the macro real rigidity models from Tables 6 and 8. The re-estimation to match a lower frequency of price change results in delayed adjustment of sectoral prices, as expected. The impulse response with $\eta = 0$ has a half-life of 2 months, and full pass-through occurs in about a year. When the intermediate share is raised to $\eta = 0.5$, the half-life rises to 3 months, and full pass-through takes place after about 20 months. In the final model, where the sectoral technology shock is set to match industry data and η is estimated at 0.72, the half-life of the impulse response function increases to nearly 5 months, and full pass-through takes longer than 2 years to achieve. The latter case illustrates that a model with sticky intermediates can generate highly persistent effects on real variables at the sectoral level, while being consistent with micro facts on price adjustment and sectoral facts on the volatility of inflation and productivity growth.

IV. Conclusion

Research on monetary policy shocks seeks a model in which these shocks have real effects lasting several years. Promising ingredients include real rigidities coupled with nominal rigidities. In this paper we explored the implications of Kimball's concave demand curve and sticky intermediate prices. The Kimball kink makes firms averse to changing their relative prices, so that it takes a long time for aggregate shocks to fully work themselves into prices. Sticky intermediate prices make price changers slow to fully incorporate nominal shocks, since their input prices have not adjusted. With roundabout production this slows down marginal cost adjustments for future price changers.

Table 8

Estimation of Intermediates Share (η) with Median Price Change Frequency of 9%

Structural parameters				Inflation forecast coefficients				Average menu cost mean
η	ρ_A	σ_A	Φ	π_s	$\log \zeta$	g_{Z_s}	R^2	(Φ/Revenue)
0.721 (0.007)	0.865 (0.008)	0.0826 (0.004)	0.395 (0.019)	0.09	0.53	−0.05	0.40	0.0144

Notes The Kimball superelasticity is set to ε=0 for this estimation. Standard errors are in parentheses. The standard deviation of the sectoral technology shock is set to 0.0102 to match evidence from the BLS Multifactor Productivity Database.

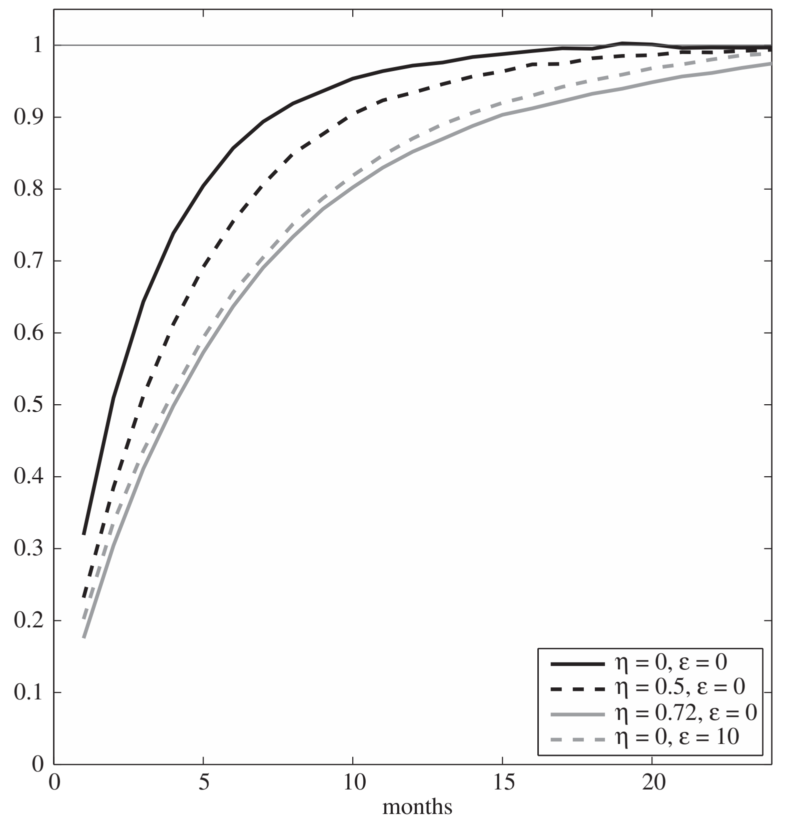

FIGURE 9. Impact of macro real rigidity on sectoral price response to a permanent sectoral productivity drop when price change frequency is 9%.

Notes: Impulse responses are computed by introducing a shock to sectoral productivity growth relative to the baseline that generates an eventual 1% increase in the sectoral price index. Each line represents the *average* response across simulations for each specification. All responses are based on parameter estimates that match a price change frequency of 9% (see Tables 6 and 8). The first three responses are generated from specifications with different intermediate shares in production, and the final response is generated from the specification with the Kimball micro real rigidity ($\varepsilon = 10$).

The micro evidence from the US CPI displays large changes in relative prices across items in narrow sectors—the standard deviation of monthly innovations is around 14%. Reconciling this micro fact with the Kimball real rigidity required large shocks to firm productivity (around 28% per month). Firms would need to be hit with big shocks to explain why they would change their relative prices so much when facing a kinked demand curve.

Our result is consistent with recent (negative) findings obtained by other studies. Dossche et al. (2010) estimate a kinked demand curve using price and quantity data from a large Euro Area retailer. Beck and Lein (2015) do so using a homescanner dataset covering 280 goods in Belgium, Germany and the Netherlands. Both papers find that the elasticity of demand is increasing in an item's relative price, but not nearly as much as assumed in the macro literature—a superelasticity closer to 2 than to 10.

Sticky intermediate prices, in contrast, do not require such large idiosyncratic productivity shocks. They are also consistent with the observed modest volatility of sectoral inflation and sectoral productivity growth (both about 1% standard deviation across months). We conclude that macro real rigidities such as sticky intermediate prices and sticky wages are the more promising microfoundations for persistent aggregate real effects of nominal shocks.

We think that the logic of our results would extend to other micro vs. macro real rigidities. Firm-specific inputs imply sharply diminishing return to variable inputs, making firms reluctant to move their relative prices. Sticky wages serve as a common sticky input that allows pass-through of idiosyncratic shocks, just like sticky intermediate prices do. We conclude that macro real rigidities provide a more realistic microfoundation than micro real rigidities for the persistent real aggregate effects of nominal shocks.

ACKNOWLEDGMENTS

The authors are grateful to the Division of Price and Index Number Research at the US Bureau of Labor Statistics for comments and access to the CPI Research Database. Adam Cagliarini and Romans Pancs provided excellent research assistance. The article incorporates many helpful comments from seminar participants, two referees, and Étienne Gagnon.

The views expressed herein are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Kansas City.

NOTES

1. For a sampling of estimates, each using a different identification strategy, see Christiano *et al.* (1999), Romer and Romer (2004), Bernanke *et al.* (2005) and Smets and Wouters (2007).
2. Chari *et al.* (2000) examine time-dependent models in the spirit of Taylor (1980). Golosov and Lucas (2007) characterize a state-dependent model, i.e. a model with fixed 'menu costs' of changing prices and endogenous timing of price changes. Dotsey *et al.* (1999) investigate a hybrid of the Calvo (1983) time-dependent model and a conventional state-dependent model.
3. See Bils and Klenow (2004), Klenow and Kryvtsov (2008), and Nakamura and Steinsson (2008) for US evidence.
4. Firm-specific inputs feature prominently in, for example, Woodford (2003), Gertler and Leahy (2008), and Altig *et al.* (2011).
5. Applications include Dotsey and King (2005), Eichenbaum and Fisher (2007), Gopinath and Itskhoki (2010), Gopinath *et al.* (2010) and Linde *et al.* (2015).
6. See Goldberg and Hellerstein (2011). Nakamura and Steinsson (2008) document a high positive correlation between the frequency of price changes of goods at the final and intermediate stages. Bils and Klenow (2004) report that consumer prices are stickier for goods with a high fraction of intermediate inputs relative to gross output.
7. See Blanchard and Fischer (1994).
8. The Kimball specification reduces to CES preferences if $\Upsilon(x) = x^{(\theta-1)/\theta}$, where θ is the elasticity of substitution between items.
9. Making disutility from work convex rather than linear would add another micro real rigidity. Our focus will be on an industry's dynamics, with labour moving in and out of the industry freely, rather than the elasticity of aggregate labour supply.
10. Firms do not use intermediates produced by other sectors. We limit sectoral interactions in this way for tractability. But input–output matrices do typically feature high weights on own-industry inputs, and upstream–downstream price stickiness is highly correlated—see Nakamura and Steinsson (2008), for example.
11. The precise mechanism by which real rigidities delay price responses to a sectoral technology shock is more involved. A positive sectoral technology shock will lead to a decline in the optimal price, but firms will choose to adjust only if the potential loss in value to the firm from not changing price is greater than the menu cost. When we quantify this loss in a later section, we will find that real rigidities dampen the profit loss from not changing one's price.
12. The discrete grid for idiosyncratic productivity contains seven points.
13. The discrete grids for sectoral inflation, the sectoral real marginal cost and the sectoral technology growth shock contain 11, 7 and 7 points, respectively.
14. The size of the panel was chosen to match the size of the average sector in the BLS dataset.

15. Ideally, we would use these equations to endogenously determine D_s and π_s. However, the assumption of a constant value for D_s does not appear to be too restrictive for the model. The standard deviation of D_s, computed using simulated data and equation (4), is relatively small at 0.002.
16. See Klenow and Kryvtsov (2008) for more detail on the CPI Research Database.
17. The literature on measuring menu costs directly is, in our view, too thin to put on the same plane as the moments in Table 1 when it comes to estimation. We will, however, compare our estimated menu costs to such studies.
18. As discussed in Gourieroux and Monfort (1996), the resulting estimator is consistent. To limit simulation error, we simulate a panel in the estimation procedure that is ten times as long as the BLS dataset. Since there are no permanent differences across firms, this approach is the same as simulating ten panels, each with a different initial distribution, and then taking the average of the moments across the ten panels. We choose the former approach for computational simplicity.
19. We use the Multifactor Productivity Database from the US Bureau of Labor Statistics here: see www.bls.gov/mfp (accessed 22 February 2016). It contains annual data from 1987–2012 and covers 60 industries (18 in manufacturing). We include energy, materials and services as intermediate inputs.
20. We analyse a sectoral productivity shock rather than a monetary shock because solving an industry equilibrium involves fewer state variables than solving for general equilibrium. Looking at industry shocks has the further advantage of obviating the need to specify the monetary policy rule, which can obscure the effect of real rigidities on the price level. We consider negative shocks here, but we have also computed results with positive shocks. Despite the asymmetry of the profit function (Figure 2), the impulse response from positive vs. negative sectoral shocks are surprisingly symmetric.
21. In the model, firms do not have the option of simply stocking out temporarily. This occurs in about 7% of months in the CPI microdata, according to Bils and Klenow (2004). But no data on prices are available in such months. The CPI relative price variability applies to items in stock.

REFERENCES

ALTIG, D., CHRISTIANO, L. J., EICHENBAUM, M. and LINDE, J. (2011). Firm-specific capital, nominal rigidities and the business cycle. *Review of Economic Dynamics*, **14**(2), 225–47.

ALVAREZ, F., BERAJA, M., GONZALEZ-ROZADA, M. and NEUMEYER, A. (2015). From hyperinflation to stable prices: Argentina's evidence on menu cost models. Unpublished paper.

BALL, L. and ROMER, D. (1990). Real rigidities and the non-neutrality of money. *Review of Economic Studies*, **57**(2), 183–204.

BASU, S. (1995). Intermediate goods and business cycles: implications for productivity and welfare. *American Economic Review*, **85**(3), 512–31.

——— (2005). Comment on implications of state-dependent pricing for dynamic macroeconomic models. *Journal of Monetary Economics*, **52**(1), 243–7.

BECK, G. W. and LEIN, S. (2015). Microeconometric evidence on demand-side real rigidity and implications for monetary non-neutrality. WWZ Working Paper no. 2015/13.

BERNANKE, B. S., BOIVIN, J. and ELIASZ, P. (2005). Measuring the effects of monetary policy: a factor-augmented vector autoregressive (FAVAR) approach. *Quarterly Journal of Economics*, **120**(1), 387–422.

BILS, M. and KLENOW, P. J. (2004). Some evidence on the importance of sticky prices. *Journal of Political Economy*, **112**, 947–85.

BLANCHARD, O. and FISCHER, S. (1994). *Lectures on Macroeconomics*. Cambridge, MA: MIT Press.

——— and GALÍ, J. (2007). Real wage rigidities and the new Keynesian model. *Journal of Money, Credit and Banking*, **39**(S1), 35–65.

CAGLIARINI, A., ROBINSON, T. and TRAN, A. (2011). Reconciling microeconomic and macroeconomic estimates of price stickiness. *Journal of Macroeconomics*, **33**(1), 102–20.

CALVO, G. A. (1983). Staggered prices in a utility-maximizing framework. *Journal of Monetary Economics*, **12**, 383–98.

CAMPBELL, J. R. and EDEN, B. (2014). Rigid prices: evidence from US scanner data. *International Economic Review*, **55**(2), 423–42.

CARVALHO, C. (2006). Heterogeneity in price stickiness and the real effects of monetary shocks. *Frontiers in Macroeconomics*, **6**(3).

CHARI, V., KEHOE, P. J. and MCGRATTAN, E. R. (2000). Sticky price models of the business cycle. *Econometrica*, **68**, 1151–80.

CHRISTIANO, L. J., EICHENBAUM, M. and EVANS, C. (1999). Monetary policy shocks: what have we learned and to what end? In J. B. Taylor and M. Woodford (eds), *Handbook of Macroeconomics*. Amsterdam: Elsevier.

DOSSCHE, M., HEYLEN, F. and VAN DEN POEL, D. (2010). The kinked demand curve and price rigidity: evidence from scanner data. *Scandinavian Journal of Economics*, **112**(4), 723–52.

DOTSEY, M. and KING, R. (2005). Implications of state-dependent pricing for dynamic macroeconomic models. *Journal of Monetary Economics*, **52**(1), 213–42.
———, ——— and WOLMAN, A. (1999). State-dependent pricing and the general equilibrium dynamics of money and output. *Quarterly Journal of Economics*, **114**, 655–90.
EICHENBAUM, M. and FISHER, J. D. (2007). Estimating the frequency of price re-optimization in Calvo-style models. *Journal of Monetary Economics 54(7)*, **101**(1), 2032–47.
———, JAIMOVICH, N. and REBELO, S. (2011). Reference prices, costs, and nominal rigidities. *American Economic Review*, 234–62.
GAGNON, E., LÓPEZ-SALIDO, D. and VINCENT, N. (2012). Individual price adjustment along the extensive margin. *NBER Macroeconomics Annual*, **27**(1), 235–81.
GERTLER, M. and LEAHY, J. (2008). A Phillips curve with an SS foundation. *Journal of Political Economy*, **116** (3), 533–72.
GOLDBERG, P. K. and HELLERSTEIN, R. (2011). How rigid are producer prices? Unpublished paper.
GOLOSOV, M. and LUCAS, R. E. (2007). Menu costs and Phillips curves. *Journal of Political Economy*, **115**(2), 171–99.
GOPINATH, G. and ITSKHOKI, O. (2010). Frequency of price adjustment and pass-through. *Quarterly Journal of Economics*, **125**(2), 675–727.
——— and ——— (2011). In search of real rigidities. *NBER Macroeconomics Annual*, **25**(1), 261–310.
———, ——— and RIGOBON, R. (2010). Currency choice and exchange rate pass-through. *American Economic Review*, **100**(1), 304–36.
GOURIEROUX, C. and MONFORT, A. (1996). *Simulation-Based Econometric Methods*. Oxford: Oxford University Press.
KIMBALL, M. (1995). The quantitative analytics of the basic neomonetarist model. *Journal of Money, Credit and Banking*, **27**(4), 1241–77.
KLENOW, P. J. and KRYVTSOV, O. (2008). State dependent or time dependent pricing: does it matter for recent U.S. inflation? *Quarterly Journal of Economics*, **123**, 863–904.
——— and MALIN, B. A. (2010). Microeconomic evidence on price-setting. In B. Friedman and M. Woodford (eds), *Handbook of Monetary Economics*, Vol. **3**. Amsterdam: Elsevier, pp. 231–84.
KRUSELL, P. and SMITH, A. (1998). Income and wealth heterogeneity in the macroeconomy. *Journal of Political Economy*, **106**(5), 867–96.
LEVY, D., BERGEN, M., DUTTA, S. and VENABLE, R. (1997). The magnitude of menu costs: direct evidence from large U.S. supermarket chains. *Quarterly Journal of Economics*, **112**(3), 791–825.
LINDE, J., SMETS, F. and WOUTERS, R. (2015). Challenges for macro models used at central banks. In J. B. Taylor and H. Uhlig (eds), *Handbook of Macroeconomics*. Amsterdam: Elsevier.
MIDRIGAN, V. (2011). Menu costs, multiproduct firms, and aggregate fluctuations. *Econometrica*, **79**(4), 1139–80.
NAKAMURA, E. and STEINSSON, J. (2008). Five facts about prices: a reevaluation of menu cost models. *Quarterly Journal of Economics*, **123**(4), 1415–64.
——— and ——— (2010). Monetary non-neutrality in a multi-sector menu cost model. *Quarterly Journal of Economics*, **125**(3), 961–1013.
——— and ——— (2013). Price rigidity: microeconomic evidence and macroeconomic implications. *Annual Review of Economics*, **5**(1), 133–63.
ROMER, D. H. and ROMER, C. D. (2004). A new measure of monetary shocks: derivation and implications. *American Economic Review*, **94**(4), 1055–84.
ROTEMBERG, J. (1996). Prices, output and hours: an empirical analysis based on a sticky price model. *Journal of Monetary Economics*, **37**, 505–33.
SMETS, F. and WOUTERS, R. (2007). Shocks and frictions in US business cycles: a Bayesian DSGE approach. *American Economic Review*, **97**(3), 586–606.
TAUCHEN, G. (1986). Finite state Markov-chain approximations to univariate and vector autoregressions. *Economics Letters*, **20**, 177–81.
TAYLOR, J. B. (1980). Aggregate dynamics and staggered contracts. *Journal of Political Economy*, **88**, 1–23.
WILLIS, J. (2000). General equilibrium of a monetary model with state-dependent pricing. Unpublished paper.
WOODFORD, M. (2003). *Interest and Prices*. Cambridge: Cambridge University Press.
ZBARACKI, M. J., RITSON, M., LEVY, D., DUTTA, S. and BERGEN, M. (2004). Managerial and customer dimensions of cost of changing prices: direct evidence from industrial markets. *Review of Economics and Statistics*, **86**(2), 514–33.