Price Rigidity: Microeconomic Evidence and Macroeconomic Implications

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WHY CARE ABOUT PRICE RIGIDITY IN MACRO?

Diverse evidence that demand shocks affect output:

Monetary shocks: Friedman-Schwartz 63, Eichengreen-Sacks 85, Mussa 86, Christiano-Eichenbaum-Evans 99, Romer-Romer 04, Gertler-Karadi 15, Nakamura-Steinsson 15

Fiscal shocks: Blanchard-Perotti 02, Ramey 11, Barro-Redlick 11, Nakamura-Steinsson 14

Household deleveraging shocks: Mian-Sufi 12

Major challenge: How to explain this empirical finding?

In RBC type models, demand shocks have small effects on output

Leading explanation: Prices adjust sluggishly to shocks
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Same logic implies muted response of real rates to other shocks such as: deleveraging shocks, financial panics, increased uncertainty, “animal spirits”
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Could Price Rigidities Cause Major Recessions? 

Many people’s first reaction is that this is not plausible. But many shocks call for sharp movements in the real interest rate. 

Deleveraging shocks: (Eggertsson-Krugman 12 and Guerrieri-Lorenzoni 15)

- Sharp increase in desire to save
- Sharp drop in “natural” rate of interest

But if prices are sticky and nominal rate constrained by ZLB ... Real rate stuck at too high a level, output stuck at too low a level.

Financial disruptions and investment hang-overs have similar effects.
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Nominal price stickiness not the whole story!
**Price Rigidity and Coordination Failure**

- Nominal price stickiness not the whole story!
- Usually combined with coordination failures among price setters
  - Staggered price setting
  - Strategic complementarity among price setters
    (firm A’s optimal price increasing in firm B’s price)

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Can price rigidity create long-lived effects on output?
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What matters for the business cycle is the extent to which micro price rigidity lead to a sluggish response of the aggregate price level.
Micro Price Rigidity and the Business Cycles

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What matters for the business cycle is the extent to which micro price rigidity lead to a sluggish response of the aggregate price level. This depends on the nature of the micro price rigidity. Stark comparison: Calvo model vs. Caplin-Spulber model.
Calvo Model

- Each firm adjusts with probability $1 - \alpha$ each period

$$p_t = (1 - \alpha)p^*_t + \alpha p_{t-1}$$
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CES demand:

$$p^*_t = (1 - \alpha \beta) \sum_{j=0}^{\infty} (\alpha \beta)^j E_t m c_{t+j}$$
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- CES demand:

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- MP targets nominal output: \( m_t = y_t + p_t \)

- Simple utility and production function: \( mc_t = m_t \)

- Random walk nominal output (no drift): \( E_tmc_{t+j} = m_t \)

\[ p_t = (1 - \alpha)m_t + \alpha p_{t-1} \]
This illustrates that as the frequency of price change approaches one, the degree of monetary non-neutrality goes to zero, while monetary non-neutrality can be large and persistent if the amount of time between price changes is large. A simple measure of the amount of monetary non-neutrality in this model is the cumulative impulse response (CIR) of output—the sum of the response of output in all future periods (the area under the real output curve in Figure 1). In this simple model, the CIR of output is $1/(1/C_0a)$, and the CIR is proportional to the variance of real output. Another closely related measure is the half-life of the output response, $\frac{\log 2}{\log a}$. Using these measures, one can see that it will matter a great deal for the degree of monetary non-neutrality in this model whether the frequency of price change is 10% per month or 20% per month.

In this simple model, there is a clear link between the frequency of price change and the degree of sluggishness of the aggregate price level following a monetary shock. An analogous argument can be made for other demand shocks. The link between price rigidity and the aggregate economy’s response to various shocks explains macroeconomists’ persistent interest in the frequency of price adjustment. In the following sections, we discuss how changing some of the critical assumptions of this simple model regarding the nature of price adjustment (e.g., allowing for temporary sales, cross-sectional heterogeneity, and endogenous timing of price changes) affects the speed of adjustment of the aggregate price level and, in turn, the response of output to various economic disturbances.

4. TEMPORARY SALES

Figure 2 plots a typical price series for a grocery product in the United States. This figure illustrates a central issue in thinking about price rigidity for consumer prices: Does this product have an essentially flexible price, or is its price highly rigid? On the one hand, the posted price for this product changes quite frequently. There are 117 changes in the posted price in 365 weeks. The posted price thus changes on average more than once a month. On the other hand, there are only nine regular price changes over a roughly seven-year period. Which of these summary measures of...
MP targets nominal output: $m_t = y_t + p_t$

- $m_t$ is increasing (i.e., high inflation)
- $p_t^* \propto m_t$
**Caplin-Spulber Model**

- MP targets nominal output: $m_t = y_t + \rho_t$
- $m_t$ is increasing (i.e., high inflation)
- $p^*_t \propto m_t$
- Fixed cost of changing prices
- When real price falls to $s$, firms raise it to $S$
- Initial distribution of real prices uniform on $(s, S)$
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$p_{it} - p^*_t$ falls by $\Delta m$ for all firms

Firms with initial real price below $s + \Delta m$ fall below $s$
and raise their price $tp$ $S$ (think of this occurring in continuous time)
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Conclusion: Money is neutral no matter how sticky prices are!!
Caplin-Spulber vs. Calvo

Calvo model:
- Timing of price changes random
- Random assortment of firms that change prices
- Some don’t really need to change
- Aggregate price level responds modestly

Caplin-Spulber model:
- Timing of price changes chosen optimally
- Firms with biggest “pent-up” desire to change price do
- Aggregate price level responds a great deal
  
Golosov-Lucas call this “selection effect”
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Fig. 6.—Price adjustment in menu cost and Calvo models. a, Price adjustment before aggregate shock. b, Price adjustment after aggregate shock.

Source: Golosov and Lucas (2007)
Both models extreme cases

- **Calvo**: Aggregate conditions have no effect on which firms or how many firms change prices

- **Caplin-Spulber model**: Aggregate shocks only determinant of which firms and how many firms change prices
  (+ other special assumption that matter for result)
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Subsequent literature explores intermediate cases and uses empirical evidence on characteristics of micro price adjustment to choose between models
Literature Gets Revitalized

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  - Only so much you can do analytically
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  - Lack of data to discipline models
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  - Only so much you can do analytically
    (computers not yet good enough to simulate realistic models)
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- Both things changed after 2000:
  - Computers became powerful enough to simulate realistic models
  - Bils and Klenow (2004) introduced massive new source of data
Basic Facts: How Often Do Prices Change?

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- Spawned a large subsequent literature
**ADDITIONAL FACTS ABOUT PRICES**

- BLS micro data allowed researchers to document additional facts about price adjustment

Klenow and Kryvtsov (05,08):
- Average absolute size of price changes large: about 10%

Golosov-Lucas 07:
- 2.5% annual inflation
- 20% of prices changing every month
- Average absolute size of price change: 10%

How can this be?
- Evidence for large, transitory idiosyncratic shocks that drive price adjustment
- Quantitatively assess monetary non-neutrality in menu cost model in light of these facts
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Households maximize:

$$E_0 \sum_{t=0}^{\infty} \beta^t [\log C_t - \omega L_t]$$

where

$$C_t = \left[ \int_0^1 c_t(z) \frac{\theta}{\theta - 1} \, dz \right]^\theta \theta - 1$$

subject to:

$$P_tC_t + Q_{t,t+1}B_{t+1} \leq B_t + W_tL_t + \int_0^1 \Pi_t(z) \, dz$$

and natural borrowing limits
Cost minimization implies

\[ c_t(z) = C_t \left( \frac{p_t(z)}{P_t} \right)^{-\theta} \]
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Labor-leisure optimization yields:

\[ W_t = \omega P_t C_t \]

So, nominal wages are proportional to nominal output
Define nominal aggregate demand as:

\[ S_t = P_t C_t \]

Suppose central banks varies interest rate / money supply in such a way that log nominal aggregate demand follows a random walk:

\[ \log S_t = \mu \log S_{t-1} + \eta_t \]

where \( \eta_t \sim N(0, \sigma^2_\eta) \).

This is aggregate source of uncertainty in the model.
Firm’s Problem

Linear production function

\[ y_t(z) = A_t(z)L_t(z) \]

This implies that marginal cost of production is \( W_t/A_t(z) \)
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Idiosyncratic productivity follows an AR(1) in logs:

\[ \log A_t(z) = \rho \log A_{t-1}(z) + \epsilon_t(z) \]

where \( \epsilon_t(z) \sim N(0, \sigma_{\epsilon}^2) \)
Firm’s Problem

Firm maximizes value of expected profits

\[ E_t \sum_{\tau=0}^{\infty} D_{t,t+\tau} \Pi_{t+\tau}(z) \]

where profits are

\[ \Pi_t(z) = p_t(z)y_t(z) - W_tL_t(z) - \chi_j W_tI_t(z) - P_tU \]

- Firm must hire \( \chi_j \) units of labor to change price
- \( U \) fixed cost of operation
  (helpful to reconcile large markups with small profits)
- \( D_{t,t+\tau} \) is household’s stochastic discount factor
How to Solve Firm’s Problem

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- Need to use dynamic programming, i.e., set up a Bellman equation

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V(Z_t) = \max_{p_t} [\Pi_t^R(z) + E[D_{t,t+1}^R V(Z_{t+1})]]
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\Pi_t^R(z) = C_t \left( \frac{p_t(z)}{P_t} \right)^{-\theta} \left( \frac{p_t(z)}{P_t} - \frac{1}{A_t(z) P_t} W_t \right) - \chi_j \frac{W_t}{P_t} I_t(z) - U
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- \(Z_t\) denotes vector of state variables
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- Key question: What is the state?
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  - Entire joint distribution of \((p_{t-1}(z)/P_t, A_t(z))\)
HOW TO SOLVE FIRM’S PROBLEM

Krusell-Smith (1998):

- Assume firms are slightly boundedly rational
- Firms perceive price level as being a function of a small number of moments of the joint distribution of \( p_t(z)/P_t, A_t(z) \)
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  - Conjecture path for endogenous aggregates
  - Solve household problem conditional on this by backward induction
  - Simulate and update conjecture
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- Reiter (2009) method

- Continuous time methods (Ahn et al. 17, Achdou et al. 15)
  More generally, see Ben Moll’s website.
Menu costs and Phillips curves

Fig. 1.—Pricing bounds for 0.64 percent quarterly inflation. Solid lines: upper and lower bounds $U(v)$ and $L(v)$. Dotted line: $g(v)$.

Source: Golosov and Lucas (2007)
Figure 3.—Fraction of prices changed each month

The United States is also shown. This pair lies very close to the upper curve, reflecting the fact that we used the Klenow-Kryvtsov data to calibrate our model. The model so calibrated fits the international evidence well, too, in spite of the fact that these studies are based on quite different samples of individual prices and differ in many other details. Our model and the Sheshinski-Weiss model both make the correct, qualitative prediction that the repricing frequency should increase as the rate of inflation increases, but ours gets the magnitude about right at both high and low inflation rates. Since we used only low-inflation data to calibrate the model, this is a genuine out-of-sample test of the theory.

Figure 3 also confirms the necessity of including idiosyncratic shocks if the model is to fit the evidence from low-inflation economies. As inflation rates are reduced, a lot of “price stickiness” remains in the data. Of course, this evidence does not bear on our interpretation of the idiosyncratic shocks as productivity differences, as opposed to shifts in preferences, responses to inventory buildups, or other factors.

Source: Golosov and Lucas (2007)
Sample path without idiosyncratic shocks. Small price changes. No price decreases.
Sample path with idiosyncratic shocks.
Fig. 5.—Output responses in menu cost and Calvo models

The impulse responses are much more transient than a standard time-dependent model would predict. The two heavy curves in figure 5 compare the output response to the monetary shock described in figure 4 to the output response that would occur in a Calvo (1983) type model, otherwise identical to ours, in which a firm is permitted to reprice in any period with a fixed probability that is independent of its own state and the state of the economy. (The two light, “fixed-factor,” curves are discussed below.) In both simulations we set this fixed repricing probability equal to .23 per month, the frequency predicted by our model. The two curves are very different. The initial response is much larger with “time-dependent” repricing, as compared to our “state-dependent” pricing. Time-dependent pricing also implies a much more persistent effect.

Figure 6 compares before and after distributions of individual prices to illustrate the reason for these different responses. Figure 6 shows repricing behavior in the absence of any aggregate shock. Firms in the menu cost model reprice when idiosyncratic shocks are large enough, and then they reprice to \( p^* \). The average size of these price adjustments is

Source: Golosov and Lucas (2007)
GOLOSOV AND LUCAS 07

- Very strong selection effect
- 6 times less monetary non-neutrality than in Calvo model
Golosov and Lucas 07

- Very strong selection effect
- 6 times less monetary non-neutrality than in Calvo model
- Bottom line: Realistic menu cost model yields monetary non-neutrality that is “small and transient”
Assault on Keynesian Economics


- Prices change every 4-5 months
Assault on Keynesian Economics

- Prices change every 4-5 months

Golosov and Lucas (2007)
- Monetary non-neutrality is “small and transient”
Perhaps Golosov-Lucas model not sufficiently realistic to yield credible policy conclusions
Perhaps Golosov-Lucas model not sufficiently realistic to yield credible policy conclusions

Empirical Issues:
- How should we treat temporary sales?
Perhaps Golosov-Lucas model not sufficiently realistic to yield credible policy conclusions

Empirical Issues:
- How should we treat temporary sales?
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- Are all price changes selected?
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Empirical Issues:
- How should we treat temporary sales?
- How does heterogeneity in price rigidity matter?
- Are all price changes selected?
- What is a realistic distribution of idiosyncratic shocks?
price rigidity is more informative? Which should we use if we wish to calibrate the frequency of price change in the model in Section 3?

One view is simply that a price change is a price change; in other words, all price changes should be counted equally. However, Figure 2 also illustrates that sales have very different empirical characteristics than regular price changes do. Whereas regular price changes are in most cases highly persistent, sales are highly transient. In fact, in most cases, the posted price returns to its original value following a sale.

Table 2 reports results from Nakamura & Steinsson (2008) on the fraction of prices that return to the original regular price after one-period temporary sales in the four product categories of the BLS CPI data for which temporary sales are most prevalent. This fraction ranges from 60% to 86.

Clearance sales are not included in these statistics because a new regular price is not observed after such sales. Nakamura & Steinsson (2008, supplementary material) argue that clearance sales, like other types of sales, yield highly transient price changes.

Sales are identified either by direct measures such as sales flags (as in the BLS data) or by sale filters that identify certain price patterns (such as V-shaped temporary discounts) as sales. Although it is often said that by looking at a price series, one can easily identify the regular price and the timing of sales, constructing a mechanical algorithm to do this is more challenging. Nakamura & Steinsson (2008), Kehoe & Midrigan (2010), and Chahrour (2011) consider different complex sale filter algorithms that allow, for example, for a regular price change over the course of a sale and for the price to go to a new regular price after a sale. Such algorithms are used both by academics and by commercial data collectors such as IRI and ACNielsen to identify temporary sales.

It is noticeable that the fraction of prices that return to the original price after a sale is negatively correlated with the frequency of regular price change across these categories. In fact, Table 2 shows that the probability that the price returns to its previous regular price can be explained with a frequency of regular price change over this period that is similar to the frequency of regular price change at other times (the third data column). In addition, higher-frequency data sets indicate that many sales are shorter than one month. This suggests that the estimates in Table 2 for the fraction of sales that return to the original price are downward biased.

Source: Nakamura and Steinsson (2013)
Two features stand out:

- Change in “regular” price is infrequent and “lumpy”
  - Only 9 “regular price” changes in a 7 year period
Two features stand out:

1. Change in “regular” price is infrequent and “lumpy”
   - Only 9 “regular price” changes in a 7 year period
2. Frequent temporary discounts (sales)
   - 117 price changes in 365 weeks
Two features stand out:

1. Change in “regular” price is infrequent and “lumpy”
   - Only 9 “regular price” changes in a 7 year period

2. Frequent temporary discounts (sales)
   - 117 price changes in 365 weeks

Does this product have essentially flexible prices?

Or is its price highly rigid?
<table>
<thead>
<tr>
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<tr>
<td>Processed Food</td>
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<td>10.5</td>
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<td>Unprocessed Food</td>
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<tr>
<td>Apparel</td>
<td>6.5</td>
<td>3.6</td>
<td>31.0</td>
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<td>87.1</td>
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<td>31.3</td>
<td>31.3</td>
<td></td>
<td>8.0</td>
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<tr>
<td>Recreation Goods</td>
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<td>6.0</td>
<td>11.9</td>
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<td>49.1</td>
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<tr>
<td>Vehicle Fuel</td>
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<td>Travel</td>
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<td>Services (excl. Travel)</td>
<td>38.5</td>
<td>6.1</td>
<td>6.6</td>
<td></td>
<td>3.1</td>
</tr>
</tbody>
</table>

Source: Nakamura and Steinsson (2008)
Source: Nakamura-Steinsson-Sun-Villar (2016)
The results in Table 1 illustrate two important issues that arise when assessing price rigidity. First, the extent of price rigidity is highly sensitive to the treatment of temporary price discounts or sales. For posted prices, the median implied duration is roughly 1.5 quarters, whereas for regular prices, it is roughly three quarters depending on the sample period and the treatment of sub-
stitutions.

But why is it interesting to consider the frequency of price change excluding sales? Isn’t a price change just a price change? The sensitivity of summary measures of price rigidity to the treatment of sales implies that these are first-order questions, and recent work has shed a great deal of light on them. This work has developed several arguments, based on the special empirical characteristics of sales price changes, for why macro models aiming to characterize how sluggishly the overall price level responds to aggregate shocks should be calibrated to a frequency of price change substantially lower than that for posted prices. We discuss this work in Section 4.

A second important issue that is illustrated by the results reported in Table 1 is the distinction between the mean and the median frequencies of price change. For example, in Nakamura & Steinsson’s (2008) results on the frequency of regular price changes including substitutions for the sample period 1998–2005, the median monthly frequency of regular price change is 11.8%, whereas

Table 1 Frequency of price change in consumer prices

<table>
<thead>
<tr>
<th></th>
<th>Median</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Frequency</td>
<td>Implied duration</td>
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<tr>
<td>Nakamura &amp; Steinsson (2008)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Regular prices (excluding substitutions 1988–1997)</td>
<td>11.9</td>
<td>7.9</td>
</tr>
<tr>
<td>Regular prices (excluding substitutions 1998–2005)</td>
<td>9.9</td>
<td>9.6</td>
</tr>
<tr>
<td>Regular prices (including substitutions 1988–1997)</td>
<td>13.0</td>
<td>7.2</td>
</tr>
<tr>
<td>Regular prices (including substitutions 1998–2005)</td>
<td>11.8</td>
<td>8.0</td>
</tr>
<tr>
<td>Posted prices (including substitutions 1998–2005)</td>
<td>20.5</td>
<td>4.4</td>
</tr>
<tr>
<td>Klenow &amp; Kryvtsov (2008)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Regular prices (including substitutions 1988–2005)</td>
<td>13.9</td>
<td>7.2</td>
</tr>
<tr>
<td>Posted prices (including substitutions 1988–2005)</td>
<td>27.3</td>
<td>3.7</td>
</tr>
</tbody>
</table>

Source: Nakamura and Steinsson (2013)
Temporary sales have very special empirical characteristics
  
  - They are highly transient
  - They very often return to the original price
  - Strongly suggests that firms are not reoptimizing
This evidence strongly suggests that firms are not reoptimizing their prices based on all available new information when sales end. Furthermore, the empirical characteristics of sales price changes do not accord well with the simple model developed in Section 3. This model and most other standard macroeconomics models do not yield sale-like price changes in which large price decreases are quickly reversed.

To answer the question of how to treat sales in arriving at a summary measure of price rigidity, it is essential to understand how the distinct empirical characteristics of sales affect their macroeconomic implications. Several recent papers have attempted to develop more sophisticated models to capture the dynamics of prices displayed in Figure 2 and Table 2 and investigate their implications for the rate of adjustment of the aggregate price level, and the extent of monetary non-neutrality. These authors have also investigated the extent to which simpler models—such as the one presented in Section 3—generate approximately correct rates of price adjustment when they are calibrated to the frequency of price change including or excluding sales.

Kehoe & Midrigan (2010) build a menu cost model in which firms can either change their prices permanently (i.e., change their regular price) or, at a lower cost, change their prices temporarily (i.e., have a sale). They choose the parameters of their model to match moments such as the size and frequency of price changes, and the probability of return to the original price in the BLS CPI data. In their model, sales are simply temporary price changes, motivated by firms' desire to change their prices temporarily. The timing and magnitude of sales are fully responsive to the state of the economy, and a large fraction of quantity sold is sold at sales prices. Nevertheless, sales price changes contribute little to the response of aggregate prices to monetary shocks. In their model, thus, the degree of monetary non-neutrality is similar to that in the case where sales price changes are completely absent. The key intuition is that because sales price changes are so transitory, they have a much smaller long-run impact on the aggregate price level per price change than do regular price changes.

Guimaraes & Sheedy (2011) develop the idea that firms use sales to price discriminate between low– and high–price elasticity consumers into a macroeconomic business cycle model. The sample period is 1998–2005. The first data column gives the median fraction of prices that return to their original level after one-period sales. The second is the median frequency of price changes excluding sales. The third lists the median monthly frequency of regular price change during sales that past one month. The monthly frequency is calculated as $1 - (1 - f)^{0.5}$, where $f$ is the fraction of prices that return to their original levels after one-period sales. The fourth data column gives the weighted average duration of sale periods in months. Data taken from Nakamura & Steinsson (2008).

### Table 2 Transience of temporary sales

<table>
<thead>
<tr>
<th></th>
<th>Fraction return after one-period sales</th>
<th>Frequency of regular price change</th>
<th>Frequency of price change during one-period sales</th>
<th>Average duration of sales</th>
</tr>
</thead>
<tbody>
<tr>
<td>Processed food</td>
<td>78.5</td>
<td>10.5</td>
<td>11.4</td>
<td>2.0</td>
</tr>
<tr>
<td>Unprocessed food</td>
<td>60.0</td>
<td>25.0</td>
<td>22.5</td>
<td>1.8</td>
</tr>
<tr>
<td>Household furnishings</td>
<td>78.2</td>
<td>6.0</td>
<td>11.6</td>
<td>2.3</td>
</tr>
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<td>Apparel</td>
<td>86.3</td>
<td>3.6</td>
<td>7.1</td>
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**Source:** Nakamura and Steinsson (2013)
Temporary sales have very special empirical characteristics
  - They are highly transient
  - They very often return to the original price
  - Strongly suggests that firms are not reoptimizing

How do these empirical characteristics affect degree to which temporary sales enhance the flexibility of the aggregate price level?
Menu cost model (also consider Calvo model)

- Firms can change prices for one period at lower cost
  - Change regular price permanently ("buy" a new price)
  - Temporary sale ("rent" a new price)
Menu cost model (also consider Calvo model)

Firms can change prices for one period at lower cost
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Timing of sales chosen optimally and responds to macro shocks
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  - Temporary sale (“rent” a new price)

- Timing of sales chosen optimally and responds to macro shocks

Nevertheless, sales generate very little aggregate price flexibility

- Results on monetary non-neutrality close to those if sales had been excluded
Two Views of Sales:

- Intertemporal price discrimination (e.g., Varian, 1980)
- Inventory Management (e.g., Lazear, 1986)
  - Due to unpredictable shifts in taste (fashion)?
Nakamura and Steinsson (2008): No sales in PPI

- Sales not responding to shocks at manufacturer level?
Sales Orthogonal to Macro Shocks?

- Nakamura and Steinsson (2008): No sales in PPI
  - Sales not responding to shocks at manufacturer level?
- Nakamura (2008): Sales not synchronized across outlets or similar products
  - Sales not responding to cost or demand shocks at retail or manufacturer level?
SALES ORTHOGONAL TO MACRO SHOCKS?

- Nakamura and Steinsson (2008): No sales in PPI
  - Sales not responding to shocks at manufacturer level?
- Nakamura (2008): Sales not synchronized across outlets or similar products
  - Sales not responding to cost or demand shocks at retail or manufacturer level?
- Andersen, et al. (2016):
  - Regular prices respond to macro shocks but sales don’t
  - Sales not used to respond to wholesale price change
  - Temporary sales follow sticky plans due to logistical complexity
Empirical Issues

- How should we treat temporary sales?
- How does heterogeneity in price rigidity matter?
- Are all price changes selected?
- What is a realistic distribution of idiosyncratic shocks?
The results in Table 1 illustrate two important issues that arise when assessing price rigidity. First, the extent of price rigidity is highly sensitive to the treatment of temporary price discounts or sales. For posted prices, the median implied duration is roughly 1.5 quarters, whereas for regular prices, it is roughly three quarters depending on the sample period and the treatment of substitutions.

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Source: Nakamura and Steinsson (2013)
5. HETEROGENEITY IN THE FREQUENCY OF PRICE CHANGE

There is a huge amount of heterogeneity in the frequency of price change across sectors of the US economy.

Figure 3 illustrates this in a histogram of the frequency of regular price change across different CPI product categories from Nakamura & Steinsson (2008). Whereas many service sectors have a frequency of price change below 5% per month, prices in some sectors, such as gasoline, change several times a month. A key feature of this distribution is that it is strongly right-skewed. It has a large mass at frequencies between 5% and 15% per month, but then it has a long right tail, with some products having a frequency of price change above 50% and a few close to 100%. As a consequence, the expenditure-weighted median frequency of regular price change across industries is about half the mean frequency of regular price change (see Table 1).

The simple model in Section 3 assumes a common frequency of price adjustment for all firms in the economy. The huge amount of heterogeneity and skewness in the frequency of price change across products begs the question, how does this heterogeneity affect the speed at which the aggregate price level responds to shocks? In other words, will the price level respond more sluggishly to shocks in an economy in which half the prices adjust all the time (e.g., gasoline) and half hardly ever adjust (e.g., haircuts) or one in which all prices adjust half of the time? A related question is, if one wishes to approximate the behavior of the US economy using a model with homogeneous firms, should one calibrate the frequency of price change to the mean or median frequency of price change?

Source: Nakamura and Steinsson (2013)
Heterogeneity in Price Rigidity

- Distribution is skewed: long right tail
  - Many products with low frequency
  - Some products with very high frequency

Questions:
- Does this heterogeneity matter for aggregate monetary non-neutrality?
- What statistic should single sector models be calibrated to?
HETEROGENEITY IN PRICE RIGIDITY

- Distribution is skewed: long right tail
  - Many products with low frequency
  - Some products with very high frequency
- Different summary statistics give impressions:
  - Excl. sales: Mean freq: 23%, median freq: 11%
HETEROGENEITY IN PRICE RIGIDITY

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Heterogeneity matters a lot!

No model free answer for calibrating a single sector model
Heterogeneity matters a lot!

No model free answer for calibrating a single sector model

In Taylor model: Bils-Klenow (2002) use median frequency

In Calvo model: Carvalho (2007) use mean implied duration (NOT = inverse of mean frequency)

In menu cost model: Nakamura and Steinsson (2010) say use median frequency for US data (no general theorem)

Intuition: Extra price change not as useful in high frequency sector since everyone has already changed
Heterogeneity matters a lot!

No model free answer for calibrating a single sector model

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HETEROGENEITY AND MONETARY NON-NEUTRALITY

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- Intuition: Extra price change not as useful in high frequency sector since everyone has already changed
Figure: Variance of Output vs. Frequency of Price Change

Variance of Output

\(10^{-4}\)

\(\text{Frequency}\)

- Blue line: \(\pi = 0.002, \sigma_{\epsilon} = 0.0425\)
- Red line: \(\pi = 0.01, \sigma_{\epsilon} = 0.01\)

Source: Nakamura and Steinsson (2010)
Empirical Issues

- How should we treat temporary sales?
- How does heterogeneity in price rigidity matter?
- Are all price changes selected?
- What is a realistic distribution of idiosyncratic shocks?
Source: Nakamura and Steinsson (2008)
Nakamura and Steinsson 10:

- Consider version of model in which substitutions are not selected (i.e., substitutions are like Calvo price changes, while other price changes are selected)
- Non-selected price changes matter very little
VI. SEASONALITY OF PRICE CHANGES

The synchronization or staggering of price change is an important determinant of the size and persistence of business cycles in models with price rigidity. One form of synchronization of price change is seasonality. We find a substantial seasonal component of price changes for the U.S. economy, for both consumer and producer goods.

Figure V presents the weighted median frequency of price increases and decreases by month for consumer prices excluding sales over the period 1988–2005. Three results emerge. First, the frequency of regular price change declines monotonically over the four quarters. It is 11.1% in the first quarter, 10.0% in the second quarter, 9.8% in the third quarter, and only 8.4% in the fourth quarter. Second, in all four quarters, the frequency of price change is largest in the first month of the quarter and declines...
The figure plots the weighted median frequency of price increase and decrease by month.

Source: Nakamura and Steinsson (2008 Supplement)
Empirical Issues

- How should we treat temporary sales?
- How does heterogeneity in price rigidity matter?
- Are all price changes selected?
- What is a realistic distribution of idiosyncratic shocks?
Midrigan (2011)

- Strength of selection effect highly sensitive to assumptions about distribution of idiosyncratic shocks
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Golosov-Lucas 07 assume normal shocks
Midrigan (2011)

- Strength of selection effect highly sensitive to assumptions about distribution of idiosyncratic shocks
- Golosov-Lucas 07 assume normal shocks
- Suppose we instead assume shocks are either tiny or huge, i.e., that they have huge kurtosis
Strength of selection effect highly sensitive to assumptions about distribution of idiosyncratic shocks

Golosov-Lucas 07 assume normal shocks

Suppose we instead assume shocks are either tiny or huge i.e., that they have huge kurtosis

In the limit, model becomes much like Calvo
Midrigan (2011)

- Strength of selection effect highly sensitive to assumptions about distribution of idiosyncratic shocks
- Golosov-Lucas 07 assume normal shocks
- Suppose we instead assume shocks are either tiny or huge i.e., that they have huge kurtosis
- In the limit, model becomes much like Calvo
- Midrigan evidence:
  - Size of price changes dispersed
  - Many small price changes
  - Coordination of timing of price changes within category
Distribution of $p$ changes: Data vs. GL model

Source: Midrigan (2011)
Two changes to Golosov-Lucas model:

- Leptokurtic distribution of idiosyncratic shocks
- Returns to scale in price adjustment
Two changes to Golosov-Lucas model:

- Leptokurtic distribution of idiosyncratic shocks
- Returns to scale in price adjustment

- Selection effect much smaller.
- Model yields similar conclusions as Calvo model
**Sufficient Statistic for Real Effects**

Alvarez-Le Bihan-Lippi 15:

- In a wide class of models ...
  (Calvo, Taylor, Golosov-Lucas, Reis, Midrigan, etc.)
- Cumulative output effect of money shock:
  \[
  M = \frac{\delta}{6\epsilon} \frac{\text{Kur}(\Delta p_i)}{N(\Delta p_i)}
  \]

  - \(\delta\) size of monetary shock
  - \(1/\epsilon - 1\) Frisch elasticity of labor supply
  - Kur(\(\Delta p_i\)) kurtosis of size distribution of price changes
  - N(\(\Delta p_i\)) frequency of price change

Obviously, there are some simplifying assumptions (e.g., unit root shock, no inflation, no strategic complementarity, etc.)
Sufficient Statistic for Real Effects

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- \( \delta \) size of monetary shock
- \( 1/\epsilon - 1 \) Frisch elasticity of labor supply
- \( \text{Kur}(\Delta p_i) \) kurtosis of size distribution of price changes
- \( N(\Delta p_i) \) frequency of price change

- Obviously, there are some simplifying assumptions
  (e.g., unit root shock, no inflation, no strategic complementarity, etc.)
Kurtosis is Key

\[ M = \frac{\delta \text{Kur}(\Delta p_i)}{6\epsilon \text{N}(\Delta p_i)} \]

- Kurtosis in Calvo model is 6
- Kurtosis in Golosov-Lucas model is 1
Kurtosis is hard to measure!!
Kurtosis is hard to measure!!

- Heterogeneity:
  - Mixture of distributions with different variances but same kurtosis will have higher kurtosis
  - Authors divide by standard deviation at category level

- Measurement errors:
  - Standard to drop large observations. Kurtosis very sensitive to this!!
  - Authors drop largest 1% of price changes
  - Spurious small price changes also a problem (product not held constant, coupons)
  - Authors drop price changes that are smaller than 1 cent or 0.1%
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MEASURING KURTOSIS

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The figures use the elementary CPI data from France (2003-2011), and the Dominick’s data set. Price changes are the log difference in price per unit, standardized by good category (272) and outlet type (11) and pooled. Price changes equal to zero are discarded. The panel with French CPI uses about 1.5 million data points, the panel with Dominick’s about 0.3 million.

Estimates of Kurtosis

- French CPI (standardized): kurtosis of 8
  (8.9 excluding sales)
- Likely upward biased due to heterogeneity within category
- In Dominick's data:
  - 4.0 standardized at UPC level
  - 4.9 standardized at category level
- CPI data also include heterogeneity due to multiple outlet types
- Trimming small price changes at 1% reduces kurtosis to 7
- Match subset of CPI with data from BPP.
- Kurtosis in BPP data about half of that in CPI
- Conclude that French CPI kurtosis is 4.0
- Measure kurtosis of 4.0 in Dominick's data
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Table 1: Overview of estimates of kurtosis

<table>
<thead>
<tr>
<th>Source</th>
<th>US</th>
<th>Other countries</th>
</tr>
</thead>
<tbody>
<tr>
<td>Source: M11 NS08 V13 CR15</td>
<td>KR14 W10 CR15</td>
<td></td>
</tr>
<tr>
<td>Kurtosis: 4.0 5.1 4.9 4.1</td>
<td>3.98 5.7–8.1 4.0</td>
<td></td>
</tr>
</tbody>
</table>


Distinction between time-dependent and state-dependent pricing models important for key questions:

- Degree of monetary non-neutrality
- Costs of inflation
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- Degree of monetary non-neutrality
- Costs of inflation

Which class of models does the evidence favor?
Calvo versus Menu Costs

- Calvo model implies that frequency of price change doesn’t change as inflation changes
- Menu cost model implies that frequency increases
**Calvo versus Menu Costs**

- Calvo model implies that frequency of price change doesn’t change as inflation changes
- Menu cost model implies that frequency increases

- Empirical Strategy: Measure how frequency changes as inflation changes
Calvo model implies that frequency of price change doesn’t change as inflation changes

Menu cost model implies that frequency increases

Empirical Strategy: Measure how frequency changes as inflation changes

- Gagnon 09: Mexico 1994-2002 (Tequila crisis)
- Nakamura-Steinsson-Sun-Villar 16: U.S. 1978-2014 (Great Inflation/Volcker disinflation)
My data set captures considerably more variation in inflation than do other studies of consumer prices with comparable product coverage. As Figure I indicates, inflation was low and stable in the United States and the euro area relative to Mexico throughout the periods covered by the related studies. For high-inflation economies, the evidence is limited mainly to food products in Israel (Lach and Tsiddon 1992; Eden 2001; Baharad and Eden 2004) and Poland (Konieczny and Skrzypacz 2005) and to supermarket products in Argentina (Burstein, Eichenbaum, and Rebelo 2005). My paper differs from these studies because my data set is representative of a much larger set of goods and services in the CPI.

The monthly frequency of price changes varied extensively over my sample period. It rose from an average of 22.1% in 1994.
FIGURE IV
Scatterplot of the Monthly Frequency and Average Magnitude of Price Changes and Inflation (Nonregulated Goods)

Each panel contains a scatter plot of the annualized monthly inflation rate, on the x-axis, and the associated monthly frequency or average magnitude statistics, on the y-axis. All statistics were computed using all nonregulated goods in the sample. The frequency and average magnitude were regressed on linear, quadratic, and cubic inflation terms, as well as a full set of year dummies. The dashed lines show the relationships predicted using all monthly observations in the regressions, conditional on the mean year dummy, and the solid lines show the same relationships when observations associated with negative monthly inflation outcomes and the April 1995 value-added tax change are excluded.

Source: Gagnon (2009)
The lines in the panels display the model's predicted frequency (left-hand panels) and average magnitude (right-hand panels) of price changes, increases, and decreases at various levels of annual inflation. The first, second, and third rows of panels show separate model calibrations using all items in the sample, all goods, and all services, respectively. For each calendar year in each subsample, the diamonds, squares, and triangles show the corresponding sample annual averages for price changes, increases, and decreases, respectively.

Figure 12: Frequency of Price Changes in U.S. Data

Note: To construct the frequency series plotted in this figure, we first calculate the mean frequency of price changes in each ELI for each year. We then take the weighted median across ELI’s.

we plot the 12 month average frequency of price change at a quarterly frequency to see a bit more detail. The most striking feature of this figure is that it is the frequency of price increases that varies with the inflation rate, while the frequency of price decreases is unresponsive. Nakamura and Steinsson (2008) show that this asymmetry arises naturally in the menu cost model when prices are drifting upward due to a positive average inflation rate. In this case, prices tend to “bunch” toward the bottom of their inaction region. Because of this bunching, when there is an aggregate shock that changes desired prices, there is a large response of the frequency of price increases (reflecting the relatively large mass at the bottom of the band), but a much smaller response of the frequency of price decreases. This is the same argument as the one described by Foote (1998) for why job destruction will be more volatile than job creation in declining industries.

One curious feature of Figure 12 is the spike in the frequency of price changes that occurs in 2008. Looking at Figure 13 and especially the analogous plot for food in Figure A.3 in the appendix, we see however, that inflation was highly volatile in 2008. It first spiked up due to the

Source: Nakamura-Steinsson-Sun-Villar (2016)
Have Prices Become More Flexible?

- Large changes in technology over past 40 years
- Perhaps costs of changing prices have fallen?
- This would make price changes more frequent
Have Prices Become More Flexible?

- Large changes in technology over past 40 years
- Perhaps costs of changing prices have fallen?
- This would make price changes more frequent

- However, evolution of frequency of price (excluding sales) change can be explained by menu cost model with a constant menu cost over entire sample period
- Regular prices have not become more flexible
An alternative (arguably better) measure of price flexibility is the menu cost needed to match the frequency of price change at a particular point in time given the level of inflation at that time. If the menu cost model is able to match the frequency of price change over time with a constant menu cost, this would indicate that prices (excluding sales) have not become more flexible over time.

Figure 14 presents the results of this type of exercise. The broken lines in the figure are the frequency of price increases and decreases in the data. The solid lines are the frequency of price increases and price decreases from a simple menu cost model with a constant menu cost.

Evidently, the frequency of price change in the data tracts the model implies frequency of price change quite well over time as inflation rises and falls. If the costs of price adjustment had trended down over the past four decades, one would expect that our model would systematically underpredict the frequency of price change toward the end of the sample period. This is not the case.

Since our simple menu cost model with a fixed cost of price adjustment can explain the overall...
At zero inflation:

- Derivative of frequency = 0
- Derivative of price dispersion = 0
- Inflation 9/10th due to “extensive margin”

\[ \pi = \lambda^+ \Delta^+ - \lambda^- \Delta^- \]
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\[ \pi = \lambda^+ \Delta^+ - \lambda^- \Delta^- \]

At high inflation:

- Elasticity of frequency with inflation equal to 2/3
- Elasticity of dispersion with inflation equal to 1/3
The "instantaneous" frequency of price changes, which has the dimension of the number of price changes per month.

Later we perform robustness checks by using different methods of aggregation across goods, by considering different treatments for sales, substitutions and missing observations, and by dropping the assumption that price changes follow a Poisson process.

Note: Simple estimator of $\hat{\lambda} = \log(1 + f_t)$, where $f_t$ is the fraction of outlets that changed price in period $t$. $\hat{\lambda}$ is estimated separately for homogeneous goods (bi-weekly sample) and for differentiated goods (monthly sample). Homogeneous goods frequencies are converted to monthly by adding the bi-weekly ones for each month pair. The aggregate number is obtained by averaging with the respective expenditure shares in the Argentine CPI. Inflation is the average of the log-difference of monthly prices multiplied by 1200 and weighted by expenditure shares. Expected inflation is the average inflation rate $1/\hat{\lambda}$ periods ahead.
Figure 6: The Frequency of Price Changes ($\lambda$) and Expected Inflation.

% change in $\lambda$ of increasing $\pi$ from 0 to 1% = 0.04

Elasticity for high inflation = 0.53

Source: Alverez-Beraja-Gonzalez-Rozada-Neumeyer (2016)
What level of inflation should central banks target?

- Pre-crisis policy consensus to target roughly 2% inflation per year
- Academic studies argued for still lower rates
  (Schmitt-Grohe and Uribe, 2011; Coibion et al., 2012)
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- Great Recession has lead to increasing calls for higher inflation targets
  - Blanchard, Dell’Ariccia, Mauro (2010), Ball (2014), Krugman (2014)
  - Blanco (2015)
Price Dispersion and the Costs of Inflation

- Higher inflation will lead to higher price dispersion
  - Prices will drift further from optimum between times of adjustment
  - Distorts allocative role of the price system
Price Dispersion and the Costs of Inflation

- Higher inflation will lead to higher price dispersion
  - Prices will drift further from optimum between times of adjustment
  - Distorts allocative role of the price system
- In standard New Keynesian models, these costs are very large
  - Going from 0% to 12% inflation per year yields a 10% loss of welfare
- Much more costly than business cycle fluctuations in output in these same models
Welfare Loss

- Menu Cost Model $\theta=4$
- Calvo Model $\theta=4$
- Menu Cost Model $\theta=7$
- Calvo Model $\theta=7$
- Calvo Varying $\theta=4$

Nakamura-Steinsson (Columbia)
Measure sensitivity of inefficient price dispersion to changes in inflation
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Challenges:

- Very limited variation in inflation over last 30 years!
Measure sensitivity of inefficient price dispersion to changes in inflation

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  - Extend BLS micro-data on consumer prices back to 1977
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1. Very limited variation in inflation over last 30 years!
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Measure sensitivity of inefficient price dispersion to changes in inflation

Challenges:

1. Very limited variation in inflation over last 30 years!
   - Extend BLS micro-data on consumer prices back to 1977
   - Covers "Great Inflation" and Volcker disinflation

2. Difficulty in interpreting raw price dispersion
   - Heterogeneity in size and quality of products
   - Absolute size of price changes informative about inefficient price dispersion
Mean Absolute Size of Price Changes

- **Menu Cost Model**
- **Calvo Model**
- **Calvo Varying**

Fraction of Original Price

Annual Inflation

Nakamura-Steinsson (Columbia)  Price Rigidity
Absolute Size of Price Changes

- Regular Price Changes
- All Price Changes Including Sales

Nakamura-Steinsson (Columbia)
No evidence that absolute size of price changes rose during Great Inflation

Suggests inefficient price dispersion not any higher during Great Inflation

Costs of inflation emphasized in New Keynesian models elusive