Selection Effects in Producer-Price Setting

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Banque de France, December 2015

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Introduction / Motivation

- Key simplifying assumption in the canonical New Keynesian model for monetary policy analysis: The pricing decision is only about the *magnitude* of the price change - Time Dependent Pricing.
- Treating the *timing* and the *magnitude* of price changes as a choice - State Dependent Pricing - can have a dramatic effect on the degree of monetary non neutrality: Caplin and Spulber (1987), Dotsey, King and Wolman (1999), Golosov and Lucas (2007), Midrigan (2011) & Karadi and Reiff (2014).

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- Main driver: Firms that change price in SD models are those that have the most to gain from it - Self selection mechanism.
  - Increases the effect on the price level from a monetary shock relative to a TD-model, and reduce the degree of monetary non-neutrality.
- Also, modeling pricing as TD or SD affect other properties of the model, such as determinacy under a specific policy rule: Dotsey and King (2005).

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- The Idea:
  - Use Swedish matched firm-level data on product prices and unit labor cost ($\propto$ marginal cost under standard assumptions) to evaluate the empirical importance of this self-selection mechanism in pricing directly at the firm level.

  - Importantly, Carlsson and Nordström Skans (2012) showed that current and expected unit labor cost drives the magnitude of price changes in this data.

  Coefficients of 0.56^{**} (s.e. 0.17) and 0.36^{*} (s.e. 0.15).

Introduction / Motivation

- Macro Relevance:
  - Here the focus is directly on the micro-level selection effects - Necessary condition for this mechanism to take a bite out of monetary non-neutrality.

  - For the overall macro effect of self selection the interaction of the measure of marginal firms who lies close to the adjustment threshold and the size of the of the adjustment needs is key (Karadi and Reiff, 2014).

Related Literature

- Small set of papers using data down-streams in the supply chain - relating retail prices to costs (wholesale/spot prices or replacement cost for the vended product); see e.g. Levy, Dutta and Bergen (2002), Davis and Hamilton (2004) and Eichenbaum, Jaimovic and Rebelo (2011).
- Here, as in Carlsson and Nordström Skans (2012), we use up-streams data for a broad sample of industrial firms where we can link quantitative price data on the product level to information on the producing firm's costs.

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Data

Annual data from Statistics Sweden for Industrial firms 1990 – 2002

- Firm/Product specific unit producer prices from the Industrins Varuproduktion Survey
  - Calculated from values and quantities at the 8/9-digits level of the HS/CN.
  -Actual transaction prices and not list prices.
  -Level of detail: Product code 84181010, refers to "*A combined freezer and cooler with separate exterior doors with a volume exceeding 340 liters intended for use in civilian aircrafts*".
- ULC, from the Industristatistiken Survey (use a PPI based on unit value prices to deflate nominal output).

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Data

- Focus on continuing single-plant firms and perform standard data cleaning.
- Everything matched together we have (as in Carlsson and Nordström Skans, 2012):

  $17,282$ Price observations (price spells of ≥ 2 years).
  702 Firms.
  $3,510$ Unique product/firm identities.
  $1,610$ Unique $8/9$ digits product codes.
  The average firm has 65 employees.

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Data

Log price and unit labor cost change distributions

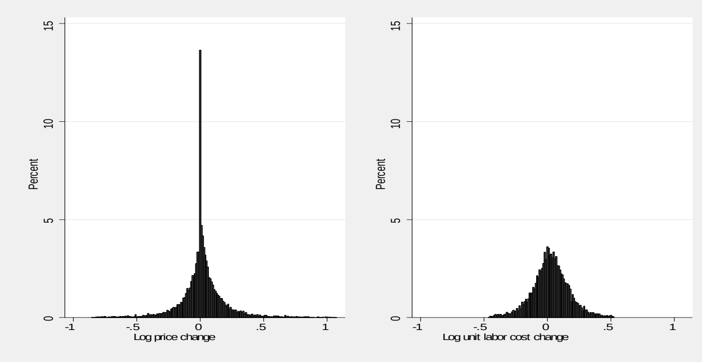

Figure 1: Histograms of data. The left-hand panel describes the distribution of log price changes across 13, 772 observations (for 1, 610 different products across 702 firms). The right-hand panel describes the distribution of log unit labor cost changes across 8, 424 observations (for 702 firms). Bin size 0.01.

Data

- Substantial spike in price-change distribution:
  - Zero bin ($\pm 0.5\%$) contains 13.6 percent of the observations.
  - Average price change close to comparable producer price inflation rate (1.8/1.7).
- No spike in unit labor cost change distribution:

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A Baseline Menu-Cost Model

- Need a benchmark for what micro-level selection effects to expect in the empirical work.
- Stay close to the previous literature - Rely on a partial equilibrium menu-cost model where price changes are driven by marginal cost variation along the lines of Nakamura and Steinsson (2008) and many others.

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A Baseline Menu-Cost Model

- Allow for fat-tailed marginal cost shocks (Laplace), akin to Karadi and Reiff (2014) and Midrigan (2011), to better match the log unit labor cost change distribution.
- Handle time aggregation - Calibrate a monthly model and then aggregate simulated data to annual frequency consistently with how the observed data is constructed.

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A Baseline Menu-Cost Model

- Calibration of monthly marginal cost process parameters and menu cost so to match (i) the persistence of annual log real marginal cost (ii) the standard deviation of the log real marginal cost change distribution and (iii) the size of the zero bin in the log price change distribution.

A Baseline Menu-Cost Model

- Rounding/Measurement Errors:
  - Prices calculated from reported values and volumes of sold products. Since, e.g., survey respondents are asked to state the value of sold products in thousands of SEK gives rounding errors in calculated prices and thus small erroneous price changes in the data.
- No measurement errors in the synthetic data from the model.
- Difference motivates calibrating the model to match the zero bin rather than to the share of exactly zero change observations.
  - If measurement error are confined within the zero bin, misclassification does not matter for the moment-matching exercise.

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Simulation Results - Monthly Data

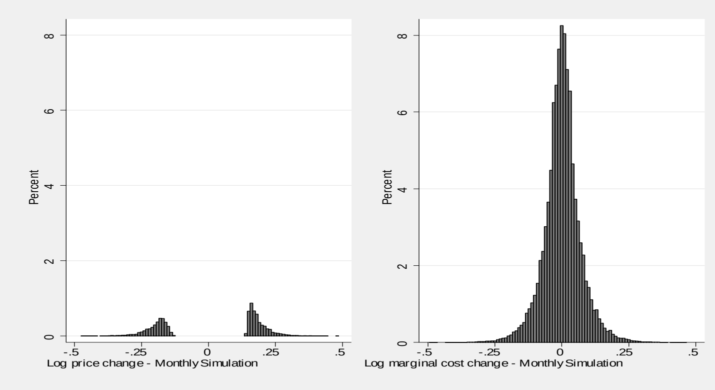

Figure 2: Histograms of simulated monthly data from the menu-cost model. The log price change distribution (left panel) omits the zero bin.

- Large menu cost (23 percent of the average monthly real gross profits) needed to match annual moments. Zero spike - 92%

A Baseline Menu-Cost Model
Simulation Results - Annual Data

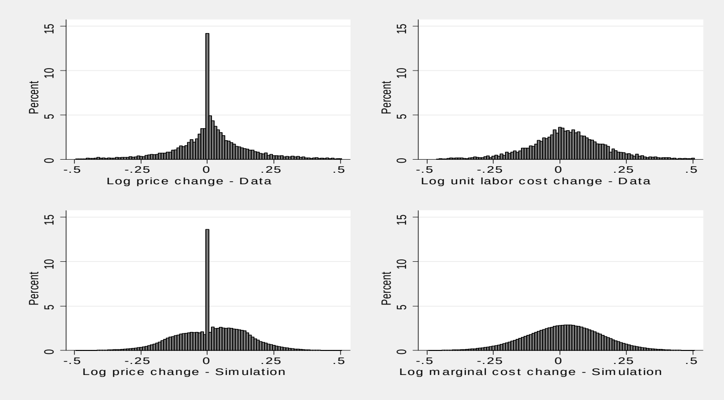

Figure 3: Histograms of actual (top panel) and simulated data from the menu-cost model (bottom panel). Bin size 0.01.

- Time aggregation fills up the gap!

A Baseline Menu-Cost Model

Simulation Results - Annual Data

- Price distribution: No regions of inaction in the time aggregated synthetic data

  Cf. other mechanisms for "filling the gap": Economies of scope suggested by Lach and Tsidon, 2007, Midrigan, 2011, Alvarez and Lippi, 2014, Stochastic menu costs as in Caballero and Engel, 1999, Dotsey, King and Wolman, 1999, Incomplete information regarding the optimal price change Woodford, 2009, Gertler and Leahy, 2006 or Trembling-hand price setters Costain and Nakov, 2015.

Probability Regressions

- To compare the relative strength of the selection mechanism in the Menu-Cost model vs. the data, we run probability regressions as in Cecchetti (1986), Loupias and Sevestre (2013) and others.
- Define an indicator for price changes (outside the zero bin) as

$$I_{gt}^{OZB} = \begin{cases} 1 \text{ if } \left(\left|d\ln P_{g,t}\right| > 0.005\right) \\ 0 \text{ otherwise} \end{cases}$$

where $P_{g,t}$ denote the price of good g (produced by firm j) at time t.

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Probability Regressions

- Linear probability models

1) Absolute value of log marginal cost change

$$I_{gt}^{OZB} = \gamma_0 + \gamma_1 \left| d \ln MC_{j,t} \right| + \eta_{gt}$$

2) Absolute value of accumulated log marginal cost change since last price change

$$I_{gt}^{OZB} = \gamma_0 + \gamma_1 \left| d^S \ln MC_{j,t} \right| + \eta_{gt}$$

cluster standard errors on the firm-level.

Probability Regressions

- Again, looking at a small band around zero in the price change distribution is useful:
  - Renders potential misclassification of small price changes a non-issue when comparing results between model and data.
  - Increases the variation in the dependent variable.
- This estimate is likely to be an upward biased estimate of the true selection effects. Small price changes (within the zero bin) are associated with small marginal cost changes also in a purely TD model. Exercises in the paper evaluating this bias.

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Probability Regressions

Table 3: Estimation and Simulation Results

	(1)	(2)	(3)
		Data	
$\lvert d^s \ln MC_{jt} \rvert$	0.071		
	(0.050)		
$\lvert d \ln MC_{jt} \rvert$		0.129*	0.114*
		(0.053)	(0.053)
$\lvert d \ln MC_{jt-1} \rvert$			−0.014
			(0.072)
		Simulation - Menu-Cost Model	
$\lvert d^s \ln MC_{jt} \rvert$	0.959		
	[0.032]		
$\lvert d \ln MC_{jt} \rvert$		1.076	1.067
		[0.031]	[0.033]
$\lvert d \ln MC_{jt-1} \rvert$			0.308
			[0.035]

Notes: Dependent variable takes on a value of one if the price change is outside the zero bin and zero otherwise. Data panel: Superscript * denotes estimates significantly different from zero at the five-percent level. Robust standard error clustered on the firm level is inside the parenthesis. The number of observations (by columns) is 9,694, 13,772 and 12,292, respectively. Simulation panel: The coefficent denotes the average across 200 panel simulations. The standard deviation of the point estimate across 200 panels is inside the square bracket.

Probability Regressions

- Data: Estimated marginal effect is 0.07 $\Rightarrow$ Very small effect - A standard deviation change in $\left|d^S \ln MC_{jt}\right|$ implies only a 1 percent higher probability of price change.
- Simulated Data from Menu-Cost Model: Average estimated marginal effect (across 200 simulated panels) is 0.96 $\Rightarrow$ Much larger effect - A standard deviation change in $\left|d^S \ln MC_{jt}\right|$ implies a 13.2 percent higher probability of price change.
- Similar result using $\left|d \ln MC_{jt}\right|$ - Lag comes in significantly in model (0.31) but not in data (-0.01).
- Results robust to: Single-Product Firms, Probit/Logit estimators, Time and Firm-fixed effects.

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Structural Evaluation
CalvoPlus Model

- Much too strong selection effect in the Menu-Cost model.
- Next: Fit a price-setting model that nests TD and SD elements to structurally quantify the regression results.
- The CalvoPlus model of Nakamura and Steinsson (2010):
  - Probability to change price at a low cost or a high cost
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- Keep calibration of monthly marginal-cost process. Calibrate high/low menu cost and the probability by matching annual probability regression estimates and zero spike.
- The data wants a menu-cost setup that is in line with the standard Calvo (1983) model
  - Very high menu cost in the high cost state (14 months of average monthly real gross profits).
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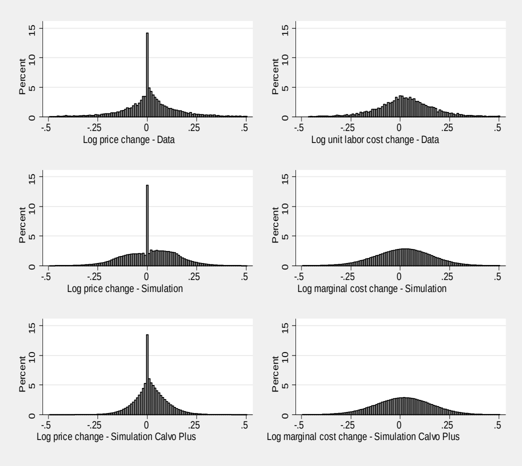

Figure 4: Histograms of actual (top panel), simulated data from the menu-cost model (middle panel) and simulated data from the CalvoPlus model. Bin size 0.01.

Structural Evaluation
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- Compared to the price dispersion generated by the Menu-Cost model (s.d. of 0.13), the simulated log price-change distribution (s.d. of 0.08) is actually further away from the observed dispersion (s.d. of 0.19).
- CalvoPlus model is better at capturing the high kurtosis observed in the data (8.62) and the overall shape of the log price change distribution. The kurtosis of the log price change distribution of the CalvoPlus model is 4.71 as compared to 3.39 from the Menu Cost model - Still some way to go.

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Conclusions

- A canonical Menu-Cost model + Time aggregation gives mileage in replicating the observed price change distribution, but predicts much too strong selection effects as compared to the data.
- Fitted CalvoPlus model + Regression exercises points away from selection effects being an important feature of up-streams micro data.
- Eichenbaum, Jaimovic and Rebelo (2011) also link a measure of marginal cost, i.e. the replacement cost of the vended product, to the price set in data drawn from a large US food and drug retailer and documents a high degree of selection effects in pricing $\Rightarrow$ Considerable differences in pricing behavior along the supply chain. Difference in market conditions?

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Conclusions

- A simple supply chain model, where the price set by the upstreams firm represent marginal cost for the downstream firm, does not need price-setting frictions throughout the whole supply chain in order to generate significant monetary non-neutrality$\Rightarrow$

  - Frictions found in the down-stream sectors can only add to monetary non-neutrality and given the results presented here, they are not instrumental for the existence of sizable monetary non-neutrality.

Extra

A Baseline Menu-Cost Model

- Firm j's product demand

$$Y_{jt} = Cp_{jt}^{-\theta}$$

where C is (constant) aggregate demand and $p_{jt} = P_{jt}/P_t$.

- To change the nominal price, P_{jt}, κ units of labor is needed.
- CRS technology + Constant aggregate wage $w = (\theta - 1)/\theta$ (as in Nakamura and Steinsson, 2008) $\Rightarrow$ Firm's real profit

$$\Pi_{jt} = Cp_{jt}^{-\theta}\left(p_{jt} - mc_{jt}\right) - \kappa\left(\frac{\theta - 1}{\theta}\right) I_{jt}$$

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- The log of real marginal cost follows an AR(1) process

$$\log mc_{jt} = \lambda + \rho \log mc_{jt-1} + \epsilon_{jt}$$

where $\lambda = (1-\rho)\log((\theta-1)/\theta) \Rightarrow$ expectation of long-run mc converges to w.
$\epsilon_{jt} \sim Laplace(0, \sigma_\epsilon/\sqrt{2})$, implying a standard deviation of ϵ_{jt} equal to σ_ϵ.

- The log of the price level drifts with the rate μ

$$\log P_t = \mu + \log P_{t-1}$$

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A Baseline Menu-Cost Model

- Denoting the relative price the firm enters the period with as $p_{jt}^{-} = P_{jt-1}/P_t$, the value function of firm j can be written as

$$V(p_{jt}^{-}, mc_{jt}) = \max_{P_{jt}} [\Pi_{jt} + \beta E_t V(p_{jt+1}^{-}, mc_{jt+1})]$$

  where β is the discount factor and E is the expectations operator.

  Solve this problem by value function iterations on a grid and using the method of Tauchen (1986) to approximate AR-processes.

A Baseline Menu-Cost Model
Monthly Calibration

μ: Estimated from monthly data on the Swedish industrial producer-price index.

θ: Use the firm-level estimate for the Swedish manufacturing sector reported in Carlsson, Messina and Nordström Skans (2014).

C: Normalized to unity.

ρ, σ_ϵ and κ: Set to match the annual data in terms of (i) the persistence of log real marginal cost estimated in Carlsson and Nordström Skans (2012) (0.542) (ii) the standard deviation of the log real marginal cost change distribution (0.145) and (iii) the size of the zero bin in the log price change distribution (0.136).

A Baseline Menu-Cost Model
Monthly Calibration

Table 1: Menu-Cost Model Calibration

	Parameter	Value
μ	Inflation Drift	0.00138
β	Discounting	$0.96^{1/12}$
θ	Price elasticity of demand	3
C	Market size	1
ρ	Real marginal cost persistence	0.921
σ_ϵ	S.D. real marginal cost shock	0.0676
$\frac{\kappa(\theta-1)}{\theta}$	Menu Cost	0.0791

Model needs a sizable menu cost (23 percent of the average monthly real gross profits) in order to match annual moments.

A Baseline Menu-Cost Model

Monthly to Annual Frequency

- Time Aggregation:
  - To match annual statistics, we time-aggregate the monthly data using monthly output weights consistently with the annual data we observe. Note that the annual unit price of firm j is constructed as

$$
\begin{aligned}
P_{jt} &= \frac{\textit{Annual Sales}_{jt}}{\textit{Annual Volume}_{jt}} = \frac{\sum_m P_{jt}^m Y_{jt}^m}{\sum_m Y_{jt}^m} = \\
&= P_{jt}^1 \frac{Y_{jt}^1}{\sum_m Y_{jt}^m} + \ldots + P_{jt}^{12} \frac{Y_{jt}^{12}}{\sum_m Y_{jt}^m},
\end{aligned}
$$

  where m denotes month, and similarly for unit labor cost.

A Baseline Menu-Cost Model
Simulation Results - Monthly Data

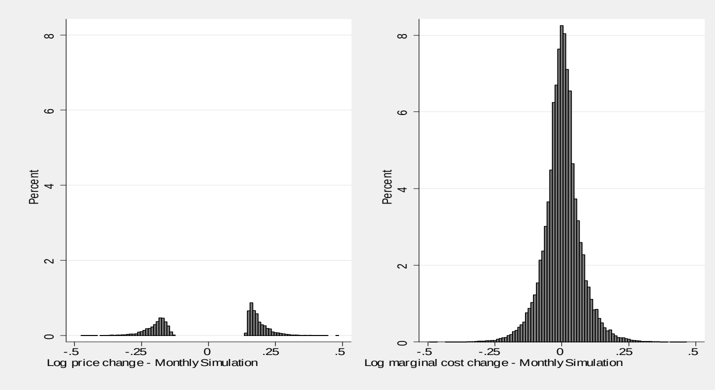

Figure 2: Histograms of simulated monthly data from the menu-cost model. The log price change distribution (left panel) omits the zero bin.

- Omitted zero spike - 92% share.
- Standard SD price-change distribution.

A Baseline Menu-Cost Model

Simulation Results - Annual Data

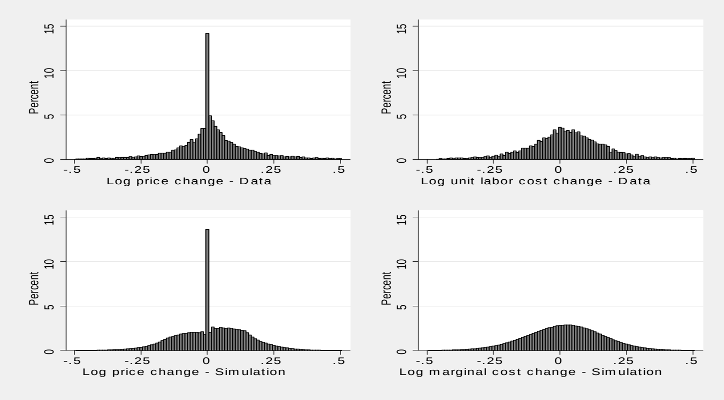

Figure 3: Histograms of actual (top panel) and simulated data from the menu-cost model (bottom panel). Bin size 0.01.

- Time aggregation fills up the gap!

Probability Regressions

Table 2: Summary Statistics of Regression Data

Variable	Obs	Mean	Std. Dev.	Min	Max
I_{gt}^{OZB}	$9,694$	0.884	0.320	0	1
$\lvert d^s \ln MC_{jt} \rvert$	$9,694$	0.104	0.138	0	0.694
I_{gt}^{OZB}	$13,772$	0.864	0.343	0	1
$\lvert d \ln MC_{jt} \rvert$	$13,772$	0.105	0.091	0	0.521

Note: $|d^s \ln MC_{j,t}|$ and $|d \ln MC_{jt}|$ are weighted as in the regressions.

- Mean of I_{gt}^{OZB} in top row is reflecting that 13.6% in the zero bin.
- Less observations for $\left|d^S \ln MC_{jt}\right|$ - Need an initial price change observation before accumulating
- Sizable variation in both $\left|d \ln MC_{jt}\right|$ and $\left|d^S \ln MC_{jt}\right|$.

Probability Regressions

Kernel Regression

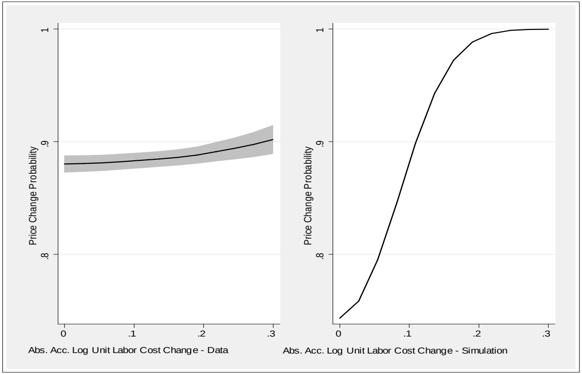

Figure 4: Kernel regressions of price-change dummy on the absolute accumulated change in log marginal cost. The left-hand panel present results from data. Gray area depicts the 95-percent confidence band. The rigth-hand panel presents results from simulated data from the Menu-Cost model.

Structural Evaluation
CalvoPlus Model

- Firm's real profit in the CalvoPlus economy

$$\Pi_{jt}^{CP} = Cp_{jt}^{-\theta}\left(p_{jt} - mc_{jt}\right) - \left(\kappa^{L}\left(1 - I_{jt}^{H}\right) + \kappa^{H} I_{jt}^{H}\right)\left(\frac{\theta - 1}{\theta}\right) I_{jt}$$

where I_{jt}^{High} is a (0/1) high-cost indicator.

- Value function

$$V^{CP}(p_{jt}^{-}, mc_{jt}, I_{jt}^{H}) = \max_{P_{jt}}[\Pi_{jt}^{CP} + \beta E_t V^{CP}(p_{jt+1}^{-}, mc_{jt+1}, I_{jt+1}^{H})]$$

where

$$I_{jt+1}^{H} \sim Bernoulli(\alpha)$$

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Structural Evaluation

CalvoPlus Model

- To fit the model, again set $\mu = 0.00138$, $\beta = 0.96^{1/12}$, $\theta = 3$ and normalize C to unity.
- To keep computations feasible we set ρ and σ_ϵ to the same values as for the menu-cost model and set κ_H, κ_L and α so as to minimize the criterion function $\mathbf{M}'\mathbf{M}$ where

$$\mathbf{M} = \begin{bmatrix} (\bar{I}^{IZB}_{Model} - \bar{I}^{IZB}_{Data})/\sigma(\bar{I}^{IZB}_{Data}) \\ (\gamma_{1,Model} - \gamma_{1,Data})/\sigma(\gamma_{1,Data}) \\ (\gamma_{2,Model} - \gamma_{2,Data})/\sigma(\gamma_{2,Data}) \end{bmatrix}$$

$\bar{I}^{IZB}$ is the average of $1 - I^{OZB}_{gt}$.
$\gamma_{1,Data}$ and $\gamma_{2,Data}$ denotes prob. regression coefficients.
σ denotes the s.d. of the observed data moments.

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Structural Evaluation

CalvoPlus Model

Table 4: CalvoPlus Model Calibration

Monthly Calibration

	Parameter	Value
μ	Inflation drift	0.00138
β	Discounting	$0.96^{1/12}$
θ	Price elasticity of demand	3
C	Market size	1
ρ	Real marginal cost persistence	0.921
σ_ϵ	S.D. real marginal cost shock	0.0676
$\frac{\kappa_H(\theta-1)}{\theta}$	Menu cost (High State)	4.733
$\frac{\kappa_L(\theta-1)}{\theta}$	Menu cost (Low State)	0.000153
α	Calvo probability	0.892

Annual Moments Match

Moment	Model	Data (S.E.)
Persistence of log real marginal cost	0.544	0.542 (0.042)
S.D. log real marginal cost change distribution	0.143	0.145 (0.002)
Price spike $\bar{I}^{IZB}$	0.135	0.136 (0.008)
Parameter $\lvert d\ln MC_{jt}\rvert$	0.172	0.114 (0.053)
Parameter $\lvert d\ln MC_{jt-1}\rvert$	0.121	−0.014 (0.072)

Note: Robust standard errors clustered on the firm-level within parenthesis in the moments-match panel.

Selection Effects and Estimation Bias

- The small positive contemporaneous selection effect we find in the regression exercise may be due to the way we define the zero band.
- Note that shrinking the I^{IZB} band in the analysis will have two consequences:
  a) Reclassifies true price changes as price changes in the data $\Rightarrow$ Reduce the positive bias discussed before and drive down the point estimate in the probability regression.

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Selection Effects and Estimation Bias

b) - Reclassifies true non-changing observations (if there is small measurement errors) as price changes in the data $\Rightarrow$

In a TD model this will not bias the point estimate since the probability of being stuck with the old price, as well as, the measurement error in prices are independent of marginal cost.

In a SD model, firms that do not change the price does so because they typically had small changes in marginal costs so downward bias on the point estimate.

- Comparing results (Band/No Band) yields an interval within which the true selection effect lies.

Selection Effects and Estimation Bias

Table 7: Estimation and Simulation Results - Band Size

	(1)	(2)	(3)	(4)	(5)	(6)
Band Size:	Base	Zero	Base	Zero	Base	Zero
	Data		Menu Cost		CalvoPlus	
$\lvert d^s \ln MC_{jt} \rvert$	0.071	−0.020	0.959	0.831	0.143	−0.031
	(0.050)	(0.025)	[0.032]	[0.031]	[0.034]	[0.030]
$\lvert d \ln MC_{jt} \rvert$	0.114*	−0.001	1.067	0.948	0.173	0.009
	(0.053)	(0.035)	[0.033]	[0.031]	[0.033]	[0.026]
$\lvert d \ln MC_{jt-1} \rvert$	−0.014	−0.060	0.308	0.334	0.122	0.017
	(0.072)	(0.071)	[0.035]	[0.031]	[0.036]	[0.030]

Notes: The dependent variable takes on a value of one if the price change is outside the zero band defined in the first row above and zero otherwise. Data panels: Superscript * denotes estimates significantly different from zero at the five-percent level. The number of observations is 9,694 (top) and 12,292 (bottom), respectively. Robust standard error clustered on the firm level insiden the parenthesis. Simulation panel: The coefficent denotes the average across 200 panel simulations. Standard deviation of the point estimate across 200 panels is inside the square bracket.

Selection Effects and Estimation Bias

- Estimated effect shrink to zero as band narrows - Drop of 0.091
- Standard errors also shrink - no problem with precision Also, robust to using Probit/Logit estimators.
- Models behave as expected - Time aggregation does not affect the basic intuition for the mechanisms at work.

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Selection Effects and Estimation Bias

- Synthetic data - drop of 0.128 in SD model and 0.174 in TD model. No measurement errors in the models $\Rightarrow$ Provides a measure of the size of the positive bias from using the baseline zero-bin definition.
- Drop in data is actually smaller than in the models $\Rightarrow$ Points away from that the estimate when only relying on exactly zero observation is downward biased due to misclassification + state dependence.
- Also, the results from fitting the Calvo Plus model, which indicate very little state dependence, suggest that the estimate when only relying on exactly zero observation is more or less an unbiased estimate of the true selection effect.
- Similar results with non-accumulated mc changes

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Data

- Cleaning:
  - Focus on continuing single plant firms and perform standard data cleaning.
  - Split the individual product price series (new identifier) whenever a large change in the growth rate appears in the raw data.
  - Use the full raw data distribution of price changes (all price changes that can be matched to the firms in the data) and determine the cut-off levels as given by the 1.5/98.5 percentiles of this distribution.
  - Similarly for ULC - keep firms which have growth rates of ULC within the 1.5 and 98.5 percentiles of the raw data distribution all years.
  - Keep the ULC computation consistent between steps (i.e. the calculation of the firm-level PPI).

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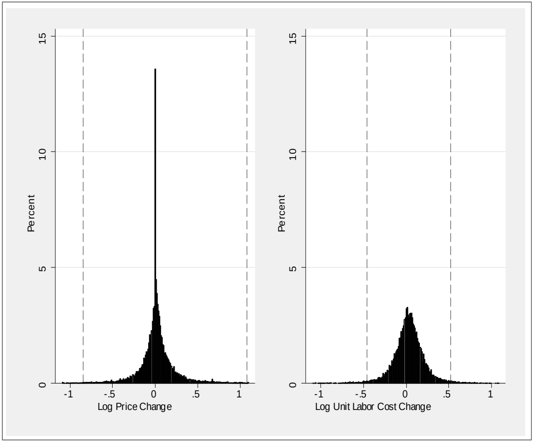

Figure 5: Histograms of raw data of log changes truncated at ± 1.1. The left-hand panel describes the distribution of log price changes across 18,878 observations (for 2,463 different products across 943 firms). The right-hand panel describes the distribution of log unit labor cost changes across 17,760 observations (for 1,480 firms). Dashed lines indicate truncation limits. Bin size 0.01.