Accounting for persistence and volatility of good-level real exchange rates: the role of sticky information

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Speed of adjustment to LOP = Calvo parameter

Motivation: Law-of-One-Price (LOP) deviation

 Like PPP, the speed of adjustment toward a long-run LOP level is measured by estimating α_i of

$$\boldsymbol{q}_t^j = \boldsymbol{\alpha}_j \boldsymbol{q}_{t-1}^j + \boldsymbol{\nu}_t^j.$$

q_t^j : (log) real exchange rate for good *j*

Kehoe and Midrigan (2007, KM) proved that the Calvo sticky price model implies

$$q_t^j = \lambda_j q_{t-1}^j + \nu_t^j,$$

where λ_j : the probability of no price change (Calvo parameter, degree of price stickiness)

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Persistence and volatility puzzles

KM's findings on persistence and volatility

- Using recent micro studies, λ_j is observable.
 KM find the following two puzzles:
- 1. If the model is correct, $\alpha_j = \lambda_j$. However,

 $\hat{\alpha}_j \gg \lambda_j$ (Persistence puzzle)

2. If the model is correct, it will fully explain volatility. However,

 $\hat{std}(q_t^{j,data}) \gg std(q_t^{j,model})$ (Volatility puzzle)

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1. Confirm KM's findings with highly disaggregated panel data

- Crucini and Shintani's (2007) data
- Highly disaggregated data with 165 goods. (KM: 66 goods)
- Panel data of good-level RER between cities in US and Canada. (KM: time series)

2. Propose a model to solve the two puzzles.

- Integrate sticky information with the standard Calvo sticky price model
- Add sticky information by Mankiw and Reis (2002)
- We call the model 'dual stickiness' model.

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Good-level Real Exchange Rates

- Contribution of our paper

Intuition

Intuition: Why can dual stickiness model solve the puzzles?

- 1. Persistence Puzzle
 - Even if price adjustment is very fast, good-price adjustment can be slow due to information stickiness (ω_i ↑).
 - ► Persistence ↑.

2. Volatility Puzzle

- ► Even if price adjustment is very fast, good-prices can be almost unaltered due to information stickiness ($\omega_j \uparrow$).
- ▶ RER keeps track of volatile nominal exchange rate.
- Volatility ↑.

- Contribution of our paper

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-Model & Data

-Overview of the model

Overview of the model: Two-country general equilibrium model

- Households
 - $U(c_t, n_t) = \log c_t \chi n_t$ with cash-in-advance constraint.

Firms producing good j

- sell goods in monopolistically competitive domestic and foreign local markets.
- set price for good *j* in each local market (local currency pricing)
- face two constraints:
- 1. cannot change price with prob. λ_j .
- 2. cannot update info. with prob. ω_j .

Governments

control money growth rates. AR(1)

-Model & Data

-Overview of the model

Sketch of dual stickiness model (Calvo model with info. delay)

- Dual stickiness model has two nominal rigidities. (price & information)
- Under sticky prices, the domestic optimal price is

$$\begin{split} \hat{P}_{H,t}^{j} &= (1 - \beta \lambda_{j}) \sum_{h=0}^{\infty} (\beta \lambda_{j})^{h} \mathbb{E}_{t}(\hat{W}_{t+h}) \\ \hat{P}_{F,t}^{j} &= (1 - \beta \lambda_{j}) \sum_{h=0}^{\infty} (\beta \lambda_{j})^{h} \mathbb{E}_{t}(\hat{S}_{t+h} + \hat{W}_{t+h}^{*}) \end{split}$$

 $\hat{W}_t(\hat{W}_t^*)$: nominal wages in the home (foreign) country. S_t : nominal exchange rate.

-Overview of the model

Sketch of dual stickiness model (2)

- Sticky information: a fraction of firms cannot have the newest information
 - ▶ Prob. ω_j : use info. set they last updated $\Rightarrow \mathbb{E}_{t-k} \hat{P}^j_{H,t}$, $\mathbb{E}_{t-k} \hat{P}^j_{F,t}$
 - Prob. 1 ω_j : use the newest info. set $\Rightarrow \hat{P}^j_{H,t}, \hat{P}^j_{F,t}$
 - The index for newly set prices \hat{X}_t^j collects these prices.
- Due to Calvo assumption,

$$\hat{P}_t^j = \lambda_j \hat{P}_{t-1}^j + (1 - \lambda_j) \hat{X}_t^j$$

• Good-level RER is given by $q_t^j = \hat{S}_t + \hat{P}_t^{j*} - \hat{P}_t^j$.

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Good-level Real Exchange Rates

-Model & Data

-Overview of Data

Overview of Data: Worldwide Cost of Living Survey

- Prices from 13 US × 4 CAN cities:
- Total of 52 cross-border city pairs
- # of goods = 165. Annual data over 1990-2005.



Persistence Puzzle

1. KM's benchmark case ($\omega_j = 0$)

Calvo model without info. delay

2. Our dual stickiness model ($\omega_j \ge 0$)

Calvo model with info. delay

Calvo model's predictions (No information delay)

- We estimate the model with the annual data.
- We have λ_j: monthly infrequency of price change from micro studies.
- Panel version of KM's benchmark case (i.i.d. money growth)

AR(1)
$$q_{i,t}^{j} = \lambda_{j}^{12}q_{i,t-1}^{j} + u'\tilde{D}_{t} + \zeta_{i}^{j} + \nu_{i,t}^{j}$$

- i: cross-border city pair (e.g., NY and Tronto)
- If the Calvo model is correct,
- our estimate of AR(1) coef. $\hat{\alpha}_j = \lambda_j^{12}$ with annual data

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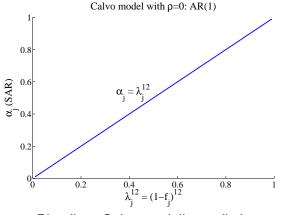
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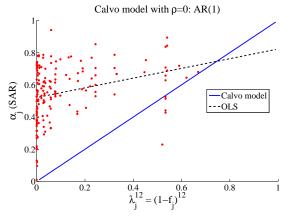
Persistence Puzzle: KM's benchmark case



Blue line: Calvo model's prediction

-Calvo model

Persistence Puzzle: KM's benchmark case



Black dashed line: OLS line from red points.

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- Dual Stickness model

Dual stickiness model's prediction ($\omega_j > 0$)

 Panel version of good-level RER under dual stickiness model

AR(4)
$$q_{i,t}^{j} = \sum_{r=1}^{4} \Psi_{r} q_{i,t-r} + u' \tilde{D}_{t} + \zeta_{i}^{j} + \nu_{i,t}^{j}$$

- In a general AR(p) model, a persistence measure is the sum of autoregressive coefficients (SAR).
- If dual stickiness model is correct, $\alpha_j = \sum_{r=1}^4 \Psi_r$ must be

$$\hat{\alpha}_j = 1 - (1 - \lambda_j^{12})(1 - \rho^{12})(1 - \omega_j^{12})(1 - \omega_j^{12}\rho^{12}).$$

So, $\omega_j \uparrow \Rightarrow$ persistence $\uparrow !!$

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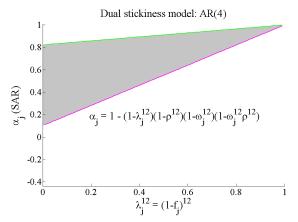
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Persistence Puzzle: dual stickiness model

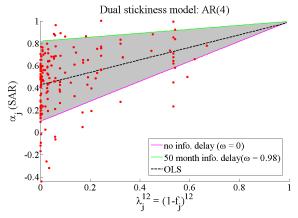


Purple line: No info. delay, Green line: 50 month info. delay

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- Dual Stickness model

Persistence Puzzle: dual stickiness model



Black dashed line: OLS line from red points.

- Dual Stickness model

How much should be information stickiness needed to explain persistence?

	$median(lpha_{i}^{theory}/lpha_{i}^{data})$				
ω	0	0.5	0.9	0.95	0.98
Bils and Klenow's data	0.31	0.32	0.79	1.21	1.53

- Our model can explain 100% of the median of persistence if
- $\omega = 0.93$ with Bils and Klenow's data
- ($\omega = 0.89$ with Nakamura and Steinsson's data)
- Avg. duration btwn info. updates is 14 and 9.5 months, resp.

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Volatility Puzzle

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Calvo model without info. delay

2. Our dual stickiness model ($\omega_j \ge 0$)

Calvo model with info. delay

Calvo model

Calvo model's predictions (No information delay)

We compute std ratio of the theory to the data in terms of a time varying component.

$$median\left[\frac{std(q_{i,t}^{j,theory})}{std(q_{i,t}^{j,data})}\right] = 0.13 \quad \text{from Bils \& Klenow}$$

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- Conclusion

Conclusion

- 1. The Kehoe and Midrigan's findings are robust to the use of highly disaggregate panel data.
 - Calvo model fails to explain perisistence and volatility of good-level RER.
- 2. One possible explanation is the dual stickiness model.
 - The dual stickiness model solves persistence and volatility puzzles.
 - Implied durations between info. updates are comparable to estimates of previous studies.

- Reconciling monthly models with annual data

Reconciling monthly models with annual data

e.g., the monthly Calvo model with iid money growth:

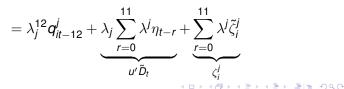
$$\boldsymbol{q}_{it}^{j} = \lambda_{j} \boldsymbol{q}_{it-1}^{j} + \lambda_{j} \eta_{t} + \tilde{\zeta}_{i}^{j}.$$

where η_t : difference between money growth rates of two countries.

Annual transformation

. . .

$$q_{it}^{j} = \lambda_{j}q_{it-1}^{j} + \lambda_{j}\eta_{t} + \tilde{\zeta}_{i}^{j}$$
$$= \lambda_{j}^{2}q_{it-2}^{j} + \lambda_{j}\eta_{t} + \lambda_{j}^{2}\eta_{t-1} + (1+\lambda_{j})\tilde{\zeta}_{i}^{j}$$

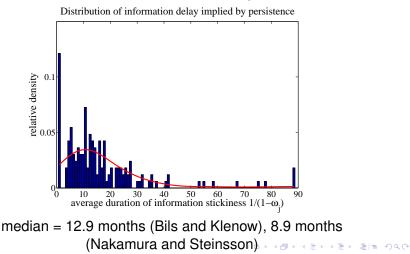


Good-level Real Exchange Rates

- How much should be information stickiness needed?

- Persistence

How much should be information stickiness needed to explain persistence?Good-specific ω_j rather than ω

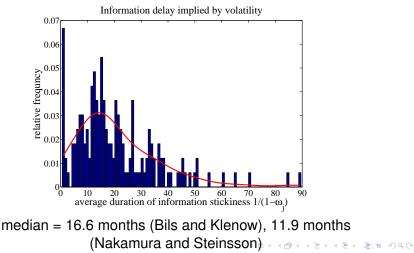


Good-level Real Exchange Rates

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Strategic complementarities

KM find pricing complementarities do not help for solving puzzles

- ► KM also consider pricing complementarities.
- Production function of firms

$$y = m^a n^{1-a}, \quad m = \left(\int m_j^{\frac{\theta-1}{\theta}} dj\right)^{\frac{\theta}{\theta-1}}, \quad m_j = \left(\int m_{j,z}^{\frac{\theta-1}{\theta}} dz\right)^{\frac{\theta}{\theta-1}}$$

- Input costs of firms in all good j move together.
- They set an extreme value of a = 0.99. They find....
- The persistence can be explained somewhat better than otherwise.
- The volatility cannot be explained by pricing complementarities.