Price-Setting with Menu Costs

Matthew Rognlie
(based on Auclert, Rigato, Rognlie, Straub 2022)

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Time dependent vs. state dependent pricing

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(TD) **Time dependent:** *Pr*(price change) depends on time since last adjustment

- tractable, e.g. for Calvo with constant probability get **Phillips curve**

$$\pi_t = \kappa \widehat{mc}_t + \beta \mathbb{E}_t \pi_{t+1} \tag{NK-PC}$$

- $\kappa =$ slope of the Phillips curve, rises with probability
- $\widehat{mc}_t =$ arbitrary real marginal cost $\sim$ output gap $\to$ easy to embed in DSGE

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(SD) **State dependent:** *Pr*(price change) depends on a state, eg price gap $p_{it} - p^*_{it}$

- better micro fit (e.g. menu cost), but hard to simulate $\rightarrow$ no NK-PC!
- simpler experiments: e.g. permanent nominal MC shocks
- key result: "selection effect", price level more flexible than Calvo

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This paper characterizes the **analogue of the NK-PC** for **menu cost models**

The Phillips curve for menu cost models: 3 main results

- Introduce **generalized Phillips curve** (GPC): linear map from $\{\widehat{\text{mc}}_t\}$ to $\{\pi_t\}$, represented as matrix $\mathbf{K}$ in the space of $MA(\infty)$ coefficients:

$$\boldsymbol{\pi} = \mathbf{K} \cdot \widehat{\mathbf{mc}} \tag{GPC}$$

  - here, $\boldsymbol{\pi}$, $\widehat{\mathbf{mc}}$ are coefficients of MA(∞) representation, stacked in vector
  - first order + certainty equivalence $\Rightarrow$ can think of $\widehat{\mathbf{mc}}$ as small MIT shock
  - $\mathbf{K}$ exists for any pricing model, including menu cost models
  - Calvo NK-PC is a special case of GPC for some $\mathbf{K}$

The Phillips curve for menu cost models: 3 main results

- Introduce **generalized Phillips curve** (GPC)

(1) **Menu cost GPC** $=$ GPC of a mixture of **two TD models**

- gives exact sense in which SD and TD are "the same" for small shocks
- TD's depend on steady state moments $\rightarrow$ "exact sufficient statistics" for $\mathbf{K}$

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- Introduce **generalized Phillips curve** (GPC)

(1) **Menu cost GPC** $=$ GPC of a mixture of **two TD models**

(2) **Menu cost GPC** $\approx$ **Calvo NK-PC**: for some κ

$$\pi_t \approx \kappa \widehat{mc}_t + \beta \mathbb{E}_t \pi_{t+1}$$

- holds for all shocks $\widehat{mc}_t \rightarrow \kappa$ is "approximate sufficient statistic" for **K**
- new models, same old Phillips curve (just a higher κ)
- extends Gertler-Leahy result to much larger set of models

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(3) Measuring **K**, κ directly from the data

  - can measure sufficient statistics for **K** straight from cross-sectional data on price changes; no need to simulate the menu cost model

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(2) For quantitative macro literature, approximate equivalence result rationalizes the Calvo New Keynesian Phillips curve with better microfoundations

(3) For literature trying to match both micro and macro, both optimism and caution

- **Optimism**, because micro-based menu cost models can be taken to the macro data using the generalized Phillips curve
- **Caution**, because these seem so close to the Calvo model that they suffer from the same macro deficiencies, like lack of internal persistence and extreme forward-lookingness

Implications

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(2) For quantitative macro literature, approximate equivalence result rationalizes the Calvo New Keynesian Phillips curve with better microfoundations

(3) For literature trying to match both micro and macro, both optimism and caution

(4) **Limitation** : following Phillips curve literature, aggregate analysis is mostly first-order

Pricing models and GPC

Canonical menu cost model

- Discrete time, quadratic approximation to firm's objective function
- Firm i chooses **price gap** $x_{it} = p_{it} - p^*_{it}$:
    - log price p_{it} net of idiosyncratic optimum $p^*_{it} = p^*_{it-1} + \epsilon_{it}$, $\epsilon_{it} \sim f(\epsilon)$ iid
    - if p_{it} is unchanged, x_{it} inherits random walk, $x_{it} = x_{it-1} - \epsilon_{it}$
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$$\min_{\{x_{it}\}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{1}{2} (x_{it} - \log MC_t)^2 + \xi_{it} \cdot 1_{\{x_{it} \neq x_{it-1} - \epsilon_{it}\}} \right]$$

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- Price index and inflation: $\log P_t = \int x_{it} di$, $\pi_t = \log P_t - \log P_{t-1}$

Solution to menu cost model

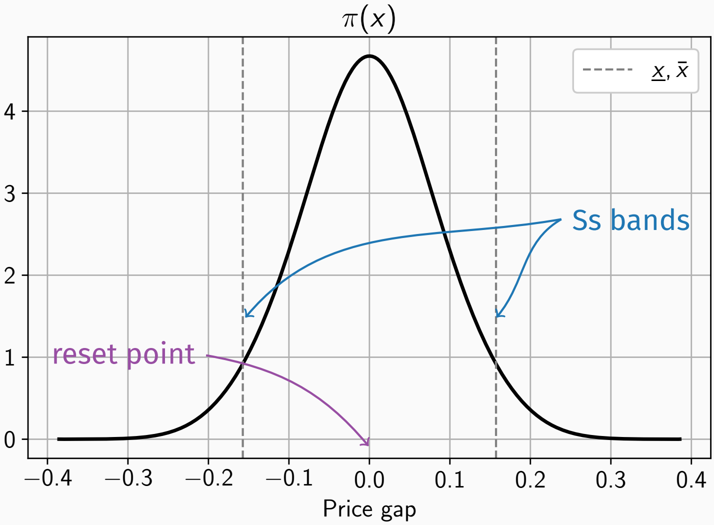
- Optimal pricing policy consists of three objects: $(\underline{x}_t, \overline{x}_t, x_t^*)$
  - $[\underline{x}_t, \overline{x}_t]$ = Ss band, x_t^* = reset point
- Law of motion based on these policies:

  x_{it} follows random walk (no adjustment)

  ... until it leaves $[\underline{x}_t, \overline{x}_t]$ or free adjustment is drawn

  ... then price gap jumps to x_t^*
- Steady state: $\underline{x} = -\overline{x}$, $x^* = MC_{ss} = 0$. Distribution: $\pi(x)$ before adjustment.

Ss bands and steady state price gap distribution



General time dependent model

- Exogenous probability of adjusting after s periods without adjustment

[Whelan, Sheedy, Carvalho-Schwartzman, Alvarez-Borovičková-Shimer]

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- Parametrize with survival function Φ_s: Prob. that price survives for s periods
- When resetting at t, firm i solves

$$\min_{\{x_{it}\}} \mathbb{E}_t \sum_{s=0}^{\infty} \beta^s \left[\frac{1}{2} \Phi_s \left(x_{it+s} - \log MC_{t+s} \right)^2 \right]$$

- **Calvo:** $\Phi_s = (1-\lambda)^s$ (constant adjustment hazard λ)
- Hazard rate can have any shape: increasing (e.g. Taylor model), decreasing...

Aggregate dynamics: pass-through matrix

- Start in steady state, consider MIT shock to nominal cost $\{MC_s\}_{s\geq 0}$
- Both models boil down to functions $\mathcal{P}_t$ such that

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- Define the **pass-through matrix** Ψ as sequence-space Jacobian with elements $\Psi_{t,s} \equiv \frac{\partial \log P_t}{\partial \log MC_s}$. Then:

$$\hat{\mathbf{P}} = \Psi \cdot \widehat{\mathbf{MC}}$$

where $\hat{\mathbf{P}} \equiv \left(\hat{P}_0, \hat{P}_1, \hat{P}_2, \ldots\right)'$, $\widehat{\mathbf{MC}} \equiv \left(\widehat{MC}_0, \widehat{MC}_1, \ldots\right)'$

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  - column s = IRF of price level to small aggregate nominal cost shock at date s
  - IRF to permanent shock: $\hat{\mathbf{P}} = \Psi \cdot \mathbf{1}$ [Golosov-Lucas, Alvarez-Le Bihan-Lippi, ...]
  - flexible prices $\Leftrightarrow$ $\Psi = \mathbf{I}$

- For TD model with survival curve $\{\Phi_s\}$, optimal reset point at t:

$$x_t^* = \frac{\sum_{s \geq 0} \beta^s \Phi_s \widehat{MC}_{t+s}}{\sum_{s \geq 0} \beta^s \Phi_s} \qquad \text{(Policy equation)}$$

Pass-through matrix for TD model

Examples: Calvo and Taylor

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Implies **rank-one fake news matrix**:

$$\mathbf{F}^{\Phi} \equiv \frac{1}{\left(\sum_{s\geq 0} \Phi_s\right)\left(\sum_{s\geq 0} \beta^s \Phi_s\right)} \begin{pmatrix} \Phi_0 \\ \Phi_1 \\ \Phi_2 \\ \vdots \end{pmatrix} \begin{pmatrix} \Phi_0 & \beta\Phi_1 & \beta^2\Phi_2 & \cdots \end{pmatrix}$$

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Can read off $\{\Phi_s\}$ from IRF to permanent shock: $\left(\Psi^{\Phi} \cdot \mathbf{1}\right)_t = \sum_{s=0}^{t} \Phi_s / \sum_{s=0}^{\infty} \Phi_s$

General equilibrium aggregate dynamics: GPC

▸ Relation to Alvarez-Lippi-Souganidis

- In simple GE models, $\widehat{\mathbf{P}} = \Psi \cdot \mathbf{1}$ gives IRF of price level to money shock
- In std NK models, want response of π_t to *real* marginal cost $\widehat{mc}_t = \widehat{MC}_t - \hat{P}_t$

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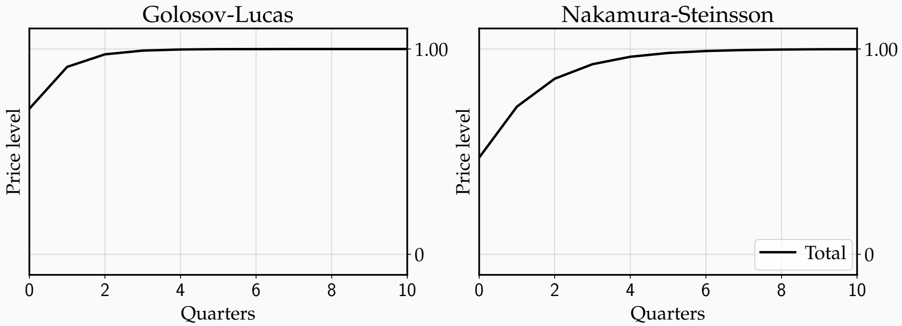
- Models with the **same** Ψ also have the **same** $\mathbf{K}$.

Exact equivalence: Menu cost model $= 2 \times$ TD

Are menu cost and TD models exactly the same?

▸ Calibration

- Permanent nominal shock: $(\underline{x}, \bar{x}, x^*)$ all shift up by 1 (infinitesimal unit)



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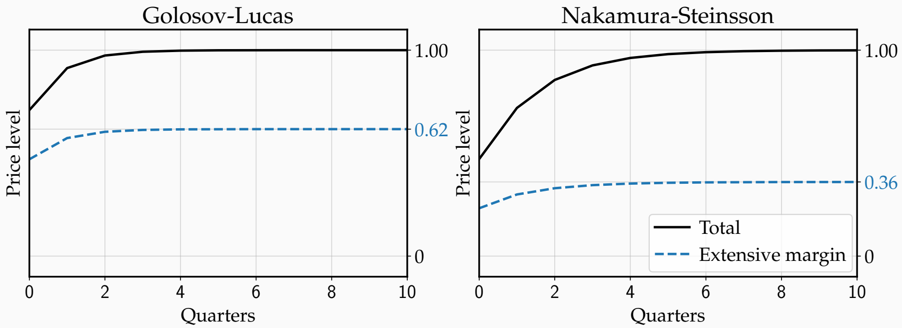

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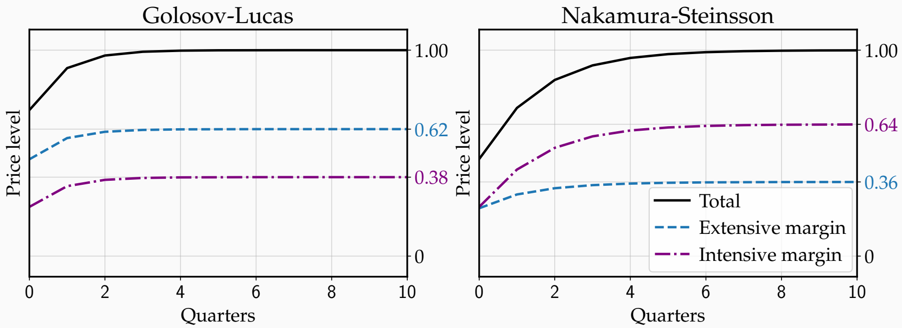

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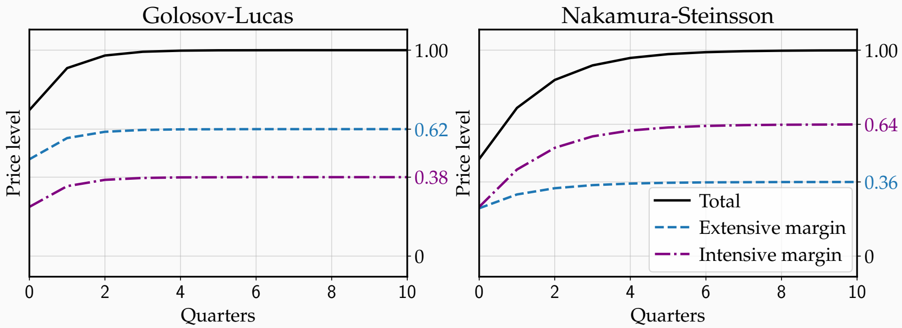

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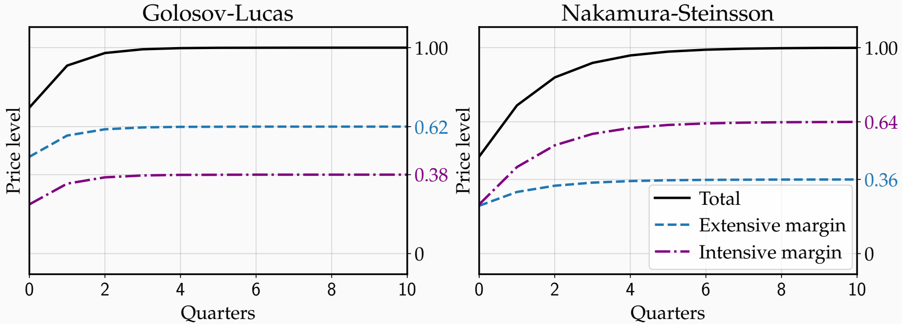

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- Let α be the long-run price level in the extensive margin experiment

Equivalence result

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Proposition

The pass-through matrix Ψ of the canonical menu cost model with any λ, ξ and any symmetric f is the weighted average of the two TD pass-through matrices

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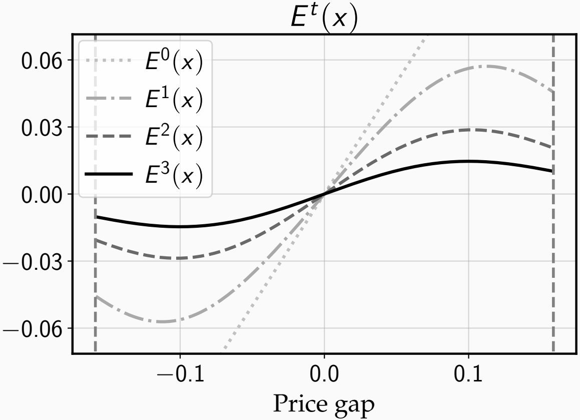
- Menu cost model = $2 \times$ TD model. Also: Menu cost GPC = GPC of $2 \times$ TD
- Next: Proof idea + what Φ^e and Φ^i look like

Expected price gaps

▸ Relation to Gertler-Leahy

- Key objects in the proof: **expected price gaps**
- $E^t(x) \equiv \mathbb{E}[x_t | x_0 = x]$ is the expected price gap in t periods starting from any x



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$$\log P_t = \int_{\underline{x}_0}^{\bar{x}_0} E^t(x)\,\pi(x)\,dx + \underbrace{\left(1 - \int_{\underline{x}_0}^{\bar{x}_0} \pi(x)\right)}_{\text{freq}} \underbrace{E^t(0)}_{0}$$

Given **steady state policies**, transition dynamics are governed by $E^t(x)$

[Alvarez-Le Bihan-Lippi, Alvarez-Lippi]

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$$\log P_t = \int_{\underline{x}_0}^{\overline{x}_0} E^t(x)\,\pi(x)\,dx + \underbrace{\left(1 - \int_{\underline{x}_0}^{\overline{x}_0} \pi(x)\right)}_{\text{freq}} \underbrace{E^t(0)}_{0}$$

Given **steady state policies**, transition dynamics are governed by $E^t(x)$

[Alvarez-Le Bihan-Lippi, Alvarez-Lippi]

- For a small shock, using symmetry

$$d\log P_t = \pi(\overline{x})\left(d\underline{x}_0 + d\overline{x}_0\right) E^t(\overline{x})$$

Why does the extensive margin behave like a TD model?

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- With many changes at dates $t-s$, get law of motion:

$$d\log P_t = \pi(\overline{x})\sum_{s\geq 0} E^s\left(\overline{x}\right)\cdot\left(d\underline{x}_{t-s} + d\overline{x}_{t-s}\right)$$

Proof

- How are $d\bar{x}_t$, $d\underline{x}_t$ optimally determined? (Policy equation?)

Extensive margin policies and summary

▸ Proof

- How are $d\bar{x}_t$, $d\underline{x}_t$ optimally determined? (Policy equation?)
- Using envelope theorem, can show:

$$d\underline{x}_t = d\bar{x}_t = \frac{\sum_{s\geq 0} \beta^s E^s(\bar{x}) \cdot \widehat{MC}_{t+s}}{\sum_{u\geq 0} \beta^u E^u(\bar{x})}$$

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  The *same* "virtual survival rate" matters as for l.o.m., just with extra β

- Use to rewrite law of motion as

$$d\log P_t = \underbrace{2\pi(\bar{x}) \sum_{s\geq 0} E^s(\bar{x})}_{\alpha} \frac{\sum_{s\geq 0} E^s(\bar{x}) \cdot d\bar{x}_t}{\sum_{s\geq 0} E^s(\bar{x})}$$

- Extensive margin acts like a TD model, scaled by α, with $\Phi_t^e \equiv E^t(\bar{x})/\bar{x}$.

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- With many changes at dates $s \leq t$, get TD law of motion

$$d\log P_t = \text{freq} \cdot \sum_{s \geq 0} (E^s)'(0)\,dx_{t-s}^* = (1-\alpha)\frac{\sum_{s\geq 0}(E^s)'(0)\cdot dx_{t-s}^*}{\sum_{s\geq 0}(E^s)'(0)}$$

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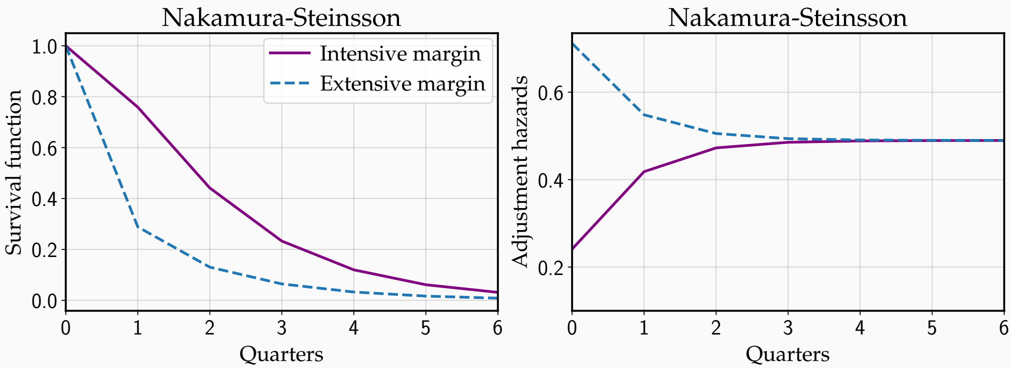
  Meanwhile, envelope theorem shows policy is

$$dx_t^* = \frac{\sum_{s \ge 0} \beta^s (E^s)'(0) \cdot \widehat{MC}_{t+s}}{\sum_{u \ge 0} \beta^u (E^u)'(0)}$$

- Intensive margin acts like a TD model, scaled down by $(1 - \alpha)$, $\Phi_t^i \equiv (E^t)'(0)$.

Properties of the recovered mixture

▸ Golosov-Lucas ▸ Gertler-Leahy



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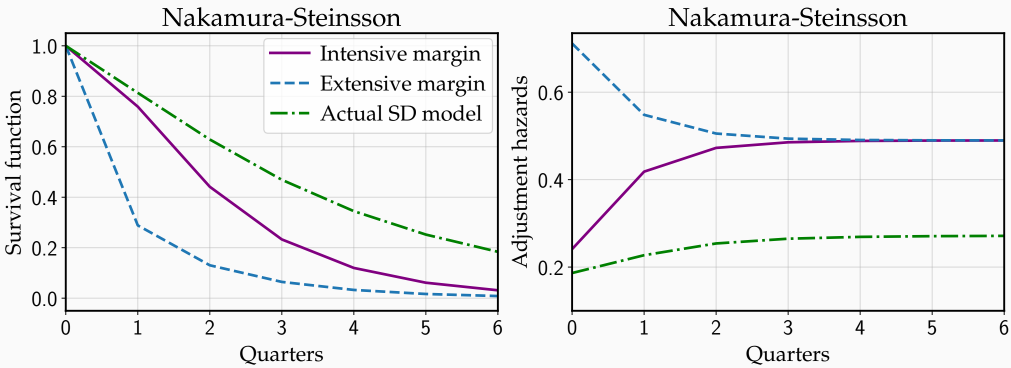

- ”virtual” survival functions Φ_t^e, Φ_t^i + implied hazards $\neq$ *actual* ones!
  The difference is the **“selection effect”**

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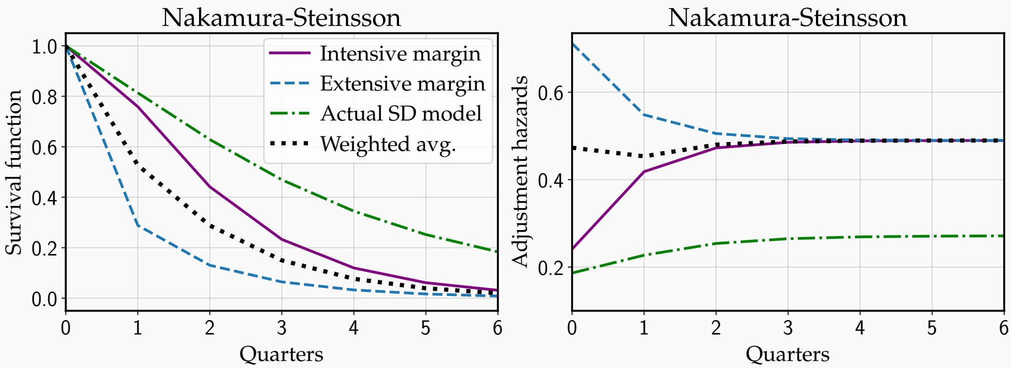


- ”virtual” survival functions Φ_t^e, Φ_t^i + implied hazards $\neq$ *actual* ones! The difference is the **“selection effect”**
- **Average survival function** $\alpha\Phi_t^e + (1-\alpha)\,\Phi_t^i$ is close to exponential in practice

Numerical equivalence: Menu cost model $\approx$ Calvo

Calvo

- Ultimately interested in the menu cost GPC $\mathbf{K} = (\mathbf{I} - \mathbf{L})(\mathbf{I} - \Psi)^{-1}\Psi$

- Ultimately interested in the menu cost GPC $\mathbf{K} = (\mathbf{I} - \mathbf{L})(\mathbf{I} - \Psi)^{-1}\Psi$
- To compare, consider Calvo NK-PC:

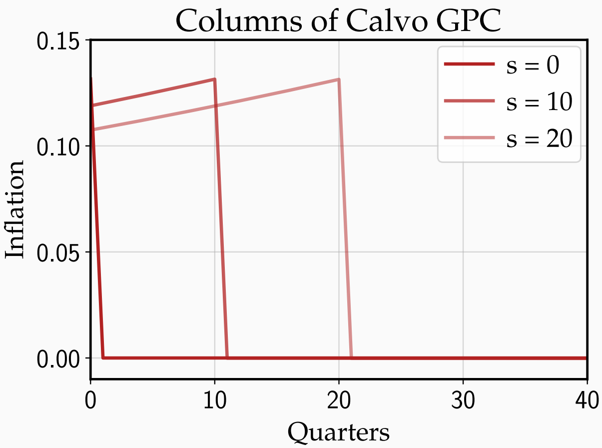
$$\pi_t = \kappa \widehat{mc}_t + \beta \mathbb{E}_t \pi_{t+1} = \sum_{s=0}^{\infty} \kappa \beta^s \mathbb{E}_t \widehat{mc}_{t+s}$$

which gives the GPC

$$\mathbf{K}^{Calvo}(\kappa) = \left(\frac{\partial \pi_t}{\partial \widehat{mc}_{t+s}}\right)_{t,s} = \begin{pmatrix} \kappa & \kappa\beta & \kappa\beta^2 & \cdots \\ 0 & \kappa & \kappa\beta & \cdots \\ 0 & 0 & \kappa & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{pmatrix}$$

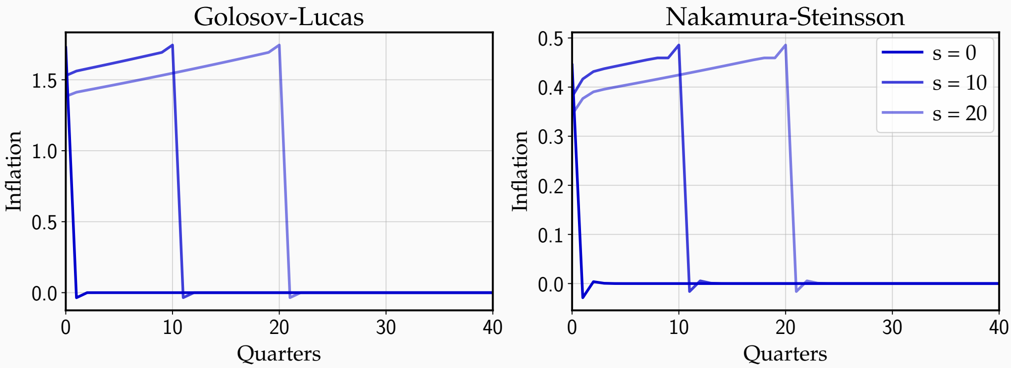
$\rightarrow$ inflation is purely & strongly forward looking, no “intrinsic” persistence

Visualizing GPC for Calvo model



- **Q**: how “far” are our menu cost models from a simple Calvo in practice?

GPC in our two calibrated menu cost models



- Menu cost GPCs “look” very similar to Calvo with different slope parameters!

Finding closest-distance Calvo model

- Let's look for κ that minimizes

$$\text{dist} = \min_{\kappa} |||\mathbf{K} - \mathbf{K}^{Calvo}(\kappa)|||_2 \, / \, |||\mathbf{K}|||_2$$

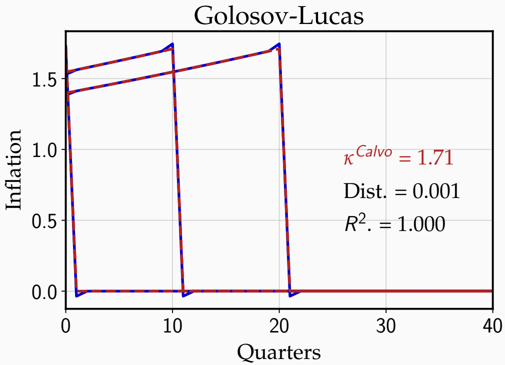
  - if $\mathbf{K} = \mathbf{K}^{Calvo}(\tilde{\kappa})$, then dist $= (\tilde{\kappa} - \kappa)/\tilde{\kappa}$

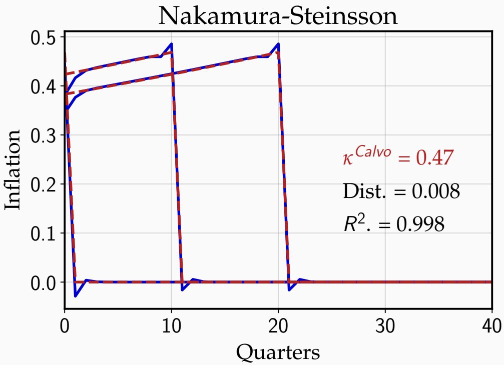
- Recall that two models that share the exact same $\mathbf{K}$ also share the same:
  - pass-through matrix Ψ
  - IRF to any shock to MC or mc
  - IRF to any fundamental shock once integrated in a broader macro model

(so, they are also indistinguishable in estimation based on macro data)

GPC vs best fitting Calvo for our two menu cost models

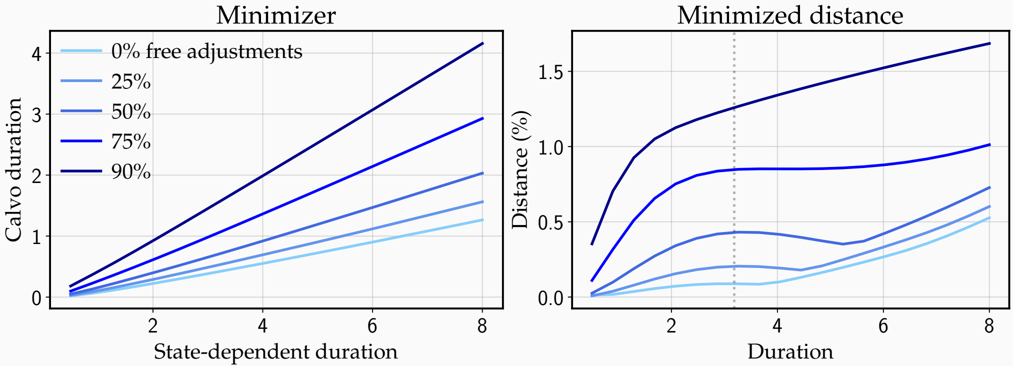
▸ AR shocks ▸ Smets-Wouters





[Reported R^2 from predicting π_t with $\kappa\widehat{mc}_t + \beta\mathbb{E}_t\pi_{t+1}$ on **K** simulated data]

▸ ALL fit


Minimizer
0% free adjustments
25%
50%
75%
90%
Calvo duration
State-dependent duration
0
1
2
3
4
2
4
6
8
Minimized distance
Distance (%)
Duration
0.0
0.5
1.0
1.5
2
4
6
8

Extensions

- Strategic complementarities $\rightarrow$
- Steady state inflation $\rightarrow$
- Infrequent shocks $\rightarrow$
- Multi-product models $\rightarrow$
- Multi-sector models $\rightarrow$
- Large shocks $\rightarrow$

Measuring the GPC directly

Measuring the GPC exactly using $E^t(x)$

- For **K**, we can measure $E^t(x)$ in the data.
- One option: use data on price changes alone + model law of motion
- To do this, first enrich model to allow for general cdf $\xi_{it} \sim G(\cdot)$

  $\rightarrow$ leads to a generalized state-dependent adjustment hazard $\Lambda(x)$

  [Caballero-Engel, Alvarez-Lippi-Oskolkov, Karadi-Schoenle-Wursten]

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- $\Lambda(x)$, $\pi(x)$, σ_ϵ can all be backed out from data on price changes

  $\rightarrow$ recover expected price gaps $E^t(x)$ from this

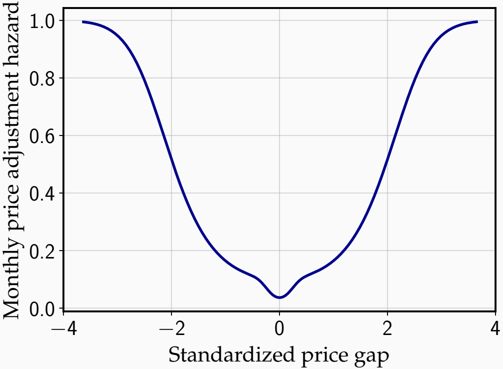
- Plug into generalized decomposition

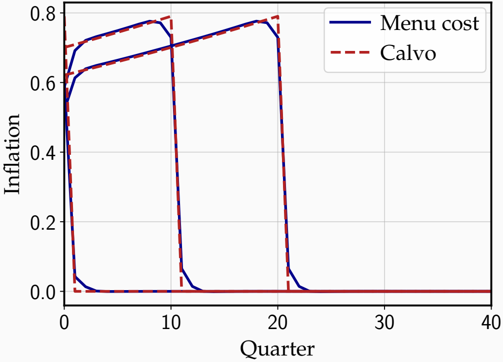
$$\Psi = \alpha \int \frac{\Lambda'(x)\pi(x)G(x)}{\int \Lambda'(\tilde{x})\pi(\tilde{x})G(\tilde{x})d\tilde{x}} \cdot \Psi^{\Phi^e(x)} dx + (1-\alpha) \cdot \Psi^{\Phi^i}$$

where $\Phi^e_t(x) = E^t(x)/x$ and $\Phi^i_t = \left(E^t\right)'(0)$ similar to before

$G(x) \equiv \sum_t E^t(x)$

- Apply this to Israeli price change distribution
  [Bonomo-Carvalho-Kryvtsov-Ribon-Rigato]





Conclusion

- **Calvo:**

$$\pi_t = \kappa^{Calvo} \widehat{mc}_t + \beta \mathbb{E}_t \pi_{t+1}$$

- **Menu cost:**

$$\pi_t = \sum_{s \geq 0} \mathbf{K}_{t,s} \cdot \widehat{mc}_s \approx \kappa \widehat{mc}_t + \beta \mathbb{E}_t \pi_{t+1}, \qquad \kappa > \kappa^{Calvo}$$

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- Sequence-space Jacobians Ψ and **K** give new insights!

$\rightarrow$ Menu cost models suffer from similar shortcomings as Calvo....

... more work needed to get model that matches micro prices **and** macro inflation

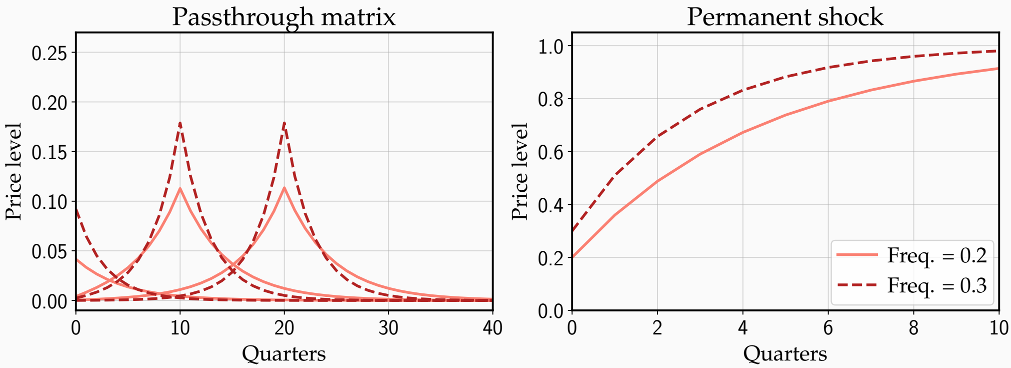
Extra slides

Calibration of random menu cost model

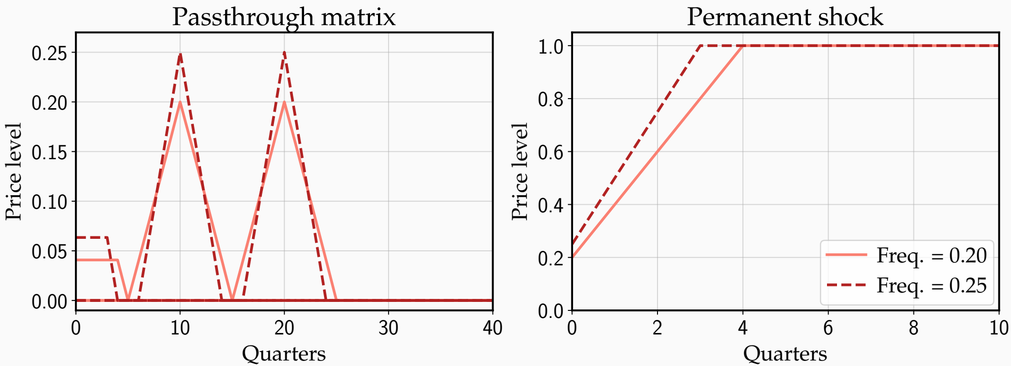
Back

- For calibration, assume idiosyncratic shock distribution is $\phi \sim \mathcal{N}(0, \sigma)$
- Given λ; calibrate ξ, σ to match:
- Average frequency of price change of 23.9% quarterly ("freq")
  - Median price adjustment of 8.5%

    [regular price changes for median sector in US CPI, see Nakamura-Steinsson]
- Two benchmarks: $\lambda = 0$ (GL) and $\lambda = 0.75 \cdot$ freq (NS)
- Notes:
  - only two effective parameters are λ/freq and ξ/σ^2, ξ then determines scale
  - for convenience, we reparameterize by λ/freq and freq (or duration=1/freq)


Passthrough matrix
Price level
0.25
0.20
0.15
0.10
0.05
0.00
0
10
20
30
40
Quarters
Permanent shock
Price level
1.0
0.8
0.6
0.4
0.2
0.0
0
2
4
6
8
10
Quarters
Freq. = 0.2
Freq. = 0.3

Back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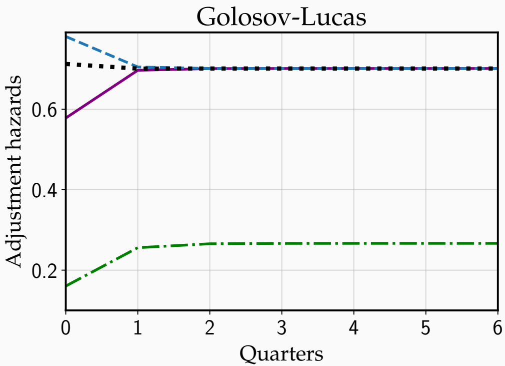
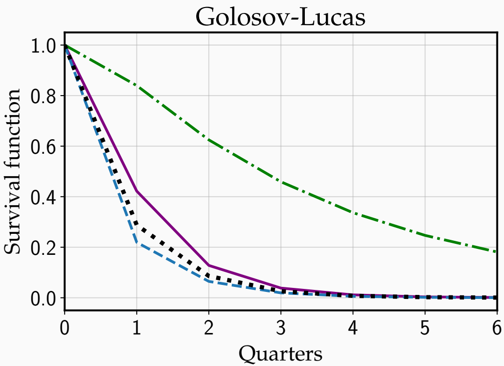
Properties of the recovered mixture (GL)

Back





Alvarez-Lippi-Souganidis

back

- Another use of Ψ : permanent cost shock but strategic complementarities
- As in Alvarez-Lippi-Souganidis (2022): parameterize by θ
  - from either Kimball demand or I-O with common input
- Get $\hat{P}_t$ via fixed point equation

$$\hat{\mathbf{P}} = \Psi \cdot \left(\mathbf{1} + \theta \hat{\mathbf{P}}\right)$$

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- ALS use self-adjointness of Ψ to write with eigenvalues-eigenfunctions
- When $\theta = 1$, we get the GPC $\mathbf{K}$

Back

- Gertler and Leahy (2008 JPE) assume the mixture distribution

$$\phi = (1-\eta) \cdot \mathbf{0} + \eta \cdot \mathcal{U}[-M, M]$$

where M is large

- This implies

$$E^t(x) = (1-\eta)^t x$$

so

$$\Phi_t^e = \frac{E^t(\bar{x})}{\bar{x}} = (1-\eta)^t \qquad \Phi_t^i = \left(E^t\right)'(0) = (1-\eta)^t$$

so pass-through matrix Ψ is a Calvo with reset frequency $1-\eta$

Response of Ss bands

Back

- Reason for shock at s affecting date 0, then sum across s and shift
- Start with upper Ss band. Value matching implies

$$V_0\left(\overline{x_0}\right) = V_0\left(x_0^*\right) + \xi$$

Differentiate and use $V'(0) = dV_0(0) = 0$

$$dV_0\left(\overline{x}\right) + V'\left(\overline{x}\right) d\overline{x_t} = 0$$

- Next, envelope theorem implies

$$V'(x) = \sum_t \beta^t E^t(x)$$

$$dV_0(x) = -\beta^s E^s(x) d\hat{MC}_s$$

- Conclude that

$$d\overline{x_0} = \frac{\beta^s E^s(\bar{x})}{\sum_u \beta^u E^u(\bar{x})} d\hat{MC}_s$$

Back

- For reset point, FOC is

$$V_0'\left(x_0^*\right) = 0$$

Differentiate

$$dV_0'\left(0\right) + V''\left(0\right) dx_0^* = 0$$

- Envelope theorem again

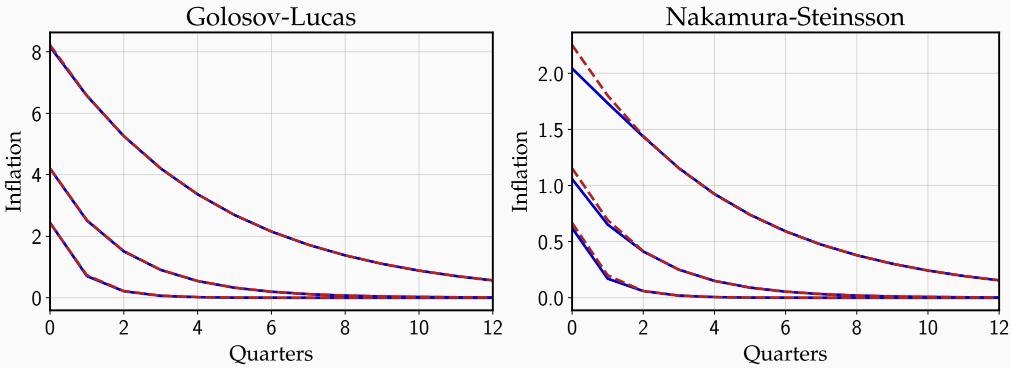
$$V''\left(x\right) = \sum_t \beta^t \left(E^t\right)'\left(x\right)$$

$$dV_0'(x) = -\beta^s \left(E^s\right)'\left(x\right) d\hat{MC}_s$$

- Conclude that

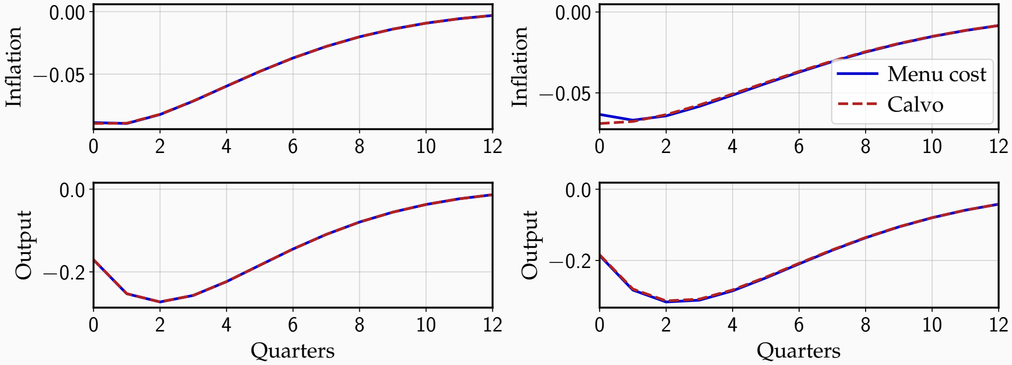
$$dx_0^* = \frac{\beta^s \left(E^s\right)'\left(0\right)}{\sum_u \beta^u \left(E^u\right)'\left(0\right)} d\hat{MC}_s$$

Impulse responses to real marginal cost shock with $\rho \in \{0.3, 0.6, 0.8\}$ Back

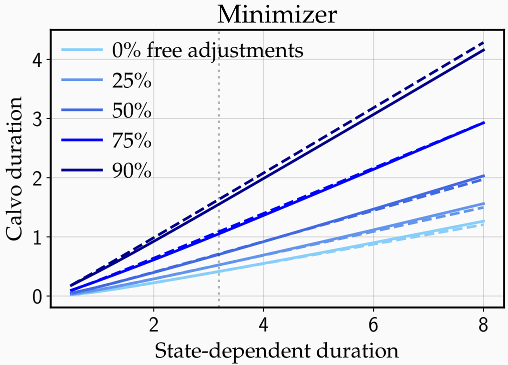


Menu costs in a Smets-Wouters model

Back



Minimizer vs ALL formula across the parameter space



What determines κ? A sufficient statistic approach

◂ back

- Implementing with $\beta = 0.99$, find κ to be: ▸ performance vs model

		Kur (Δp)		
		2	*3*	*4*
Freq (Δp)	*0.2*	0.40	0.17	0.09
	0.3	1.02	0.40	0.22
	0.4	2.26	0.77	0.40

- For reference:
  - In data, quarterly *Freq* $(\Delta p) \simeq 0.2$ to 0.3 (model $= 0.24$)
  - In data: *Kur* (Δp) between 3 and 4

    [Alvarez-Le Bihan-Lippi, Bonomo-Carvalho-Kryvtsov-Ribon-Rigato]
  - In models: *Kur* (Δp) is 1.3 for GL, 2.3 for NS, 2 for Midrigan

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  - In models: *Kur* (Δp) is 1.3 for GL, 2.3 for NS, 2 for Midrigan
- Contrast to recent macro full-sample IV estimate of $\kappa = 0.0031$!

  [Hazell-Herreño-Nakamura-Steinsson, using $\kappa = \frac{\kappa^u}{\sigma+\phi}$ with $\sigma = \phi = 1$]

Strategic complementarities

◂ back

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back

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Proposition

Generalized Phillips Curve scales with ζ:

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back

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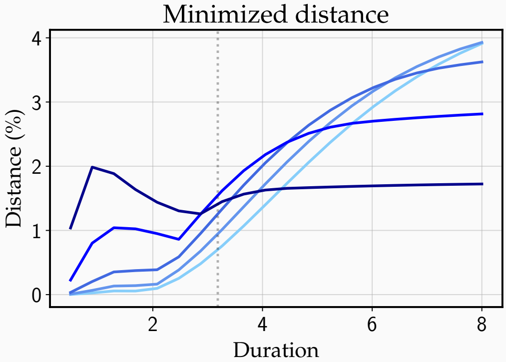
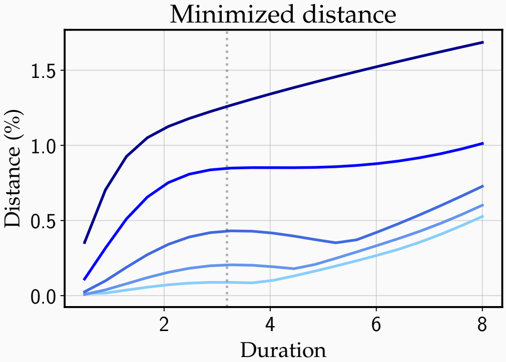
- Note **shape** of Phillips curve is unchanged by ζ, e.g. no more persistence

Arbitrary parameters

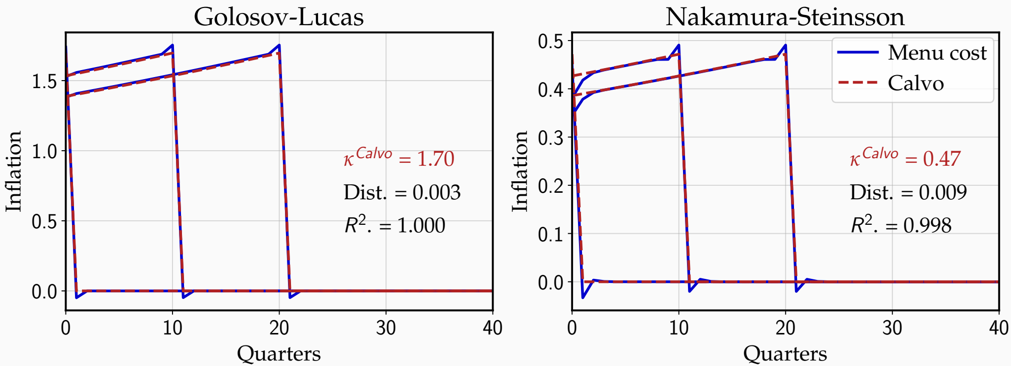
◂ back



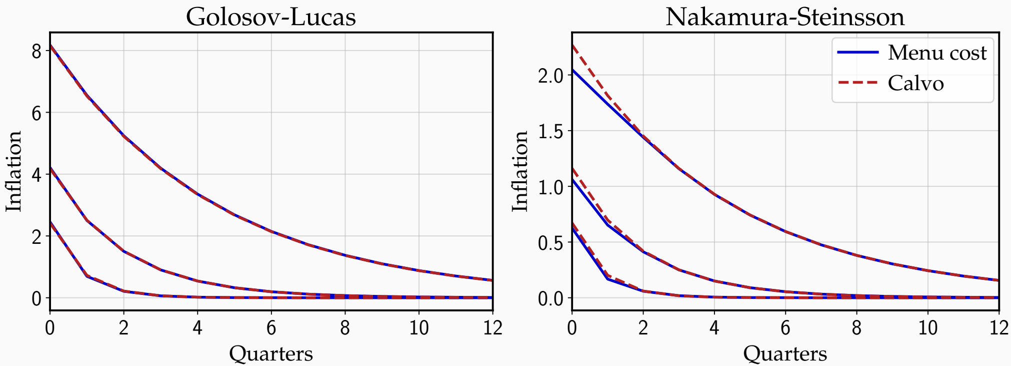


Steady state inflation of 2% - Jacobians

back

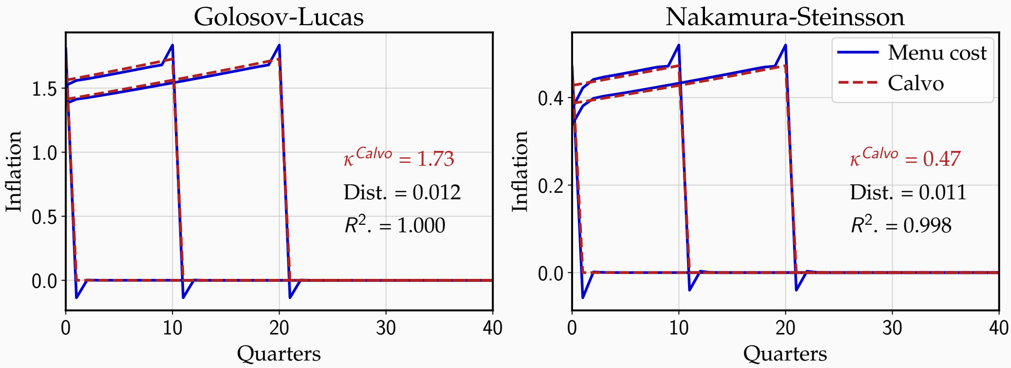


Steady state inflation of 2% - Impulse responses

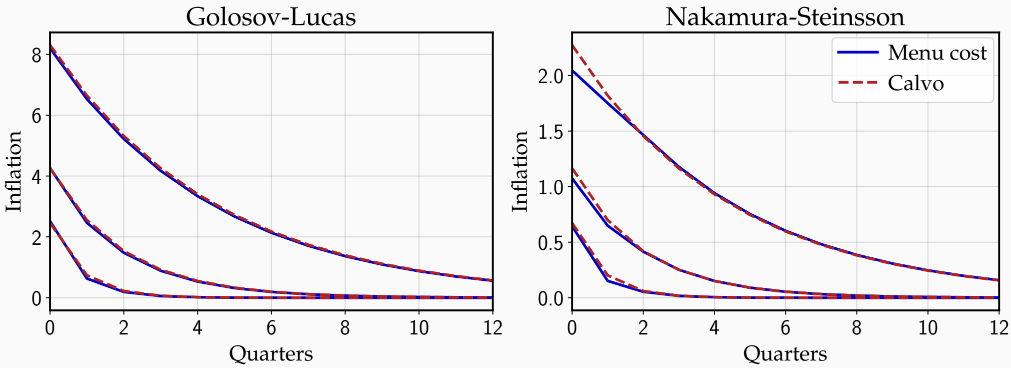


Steady state inflation of 5% - Jacobians

back



Steady state inflation of 5% - Impulse responses



Infrequent shocks

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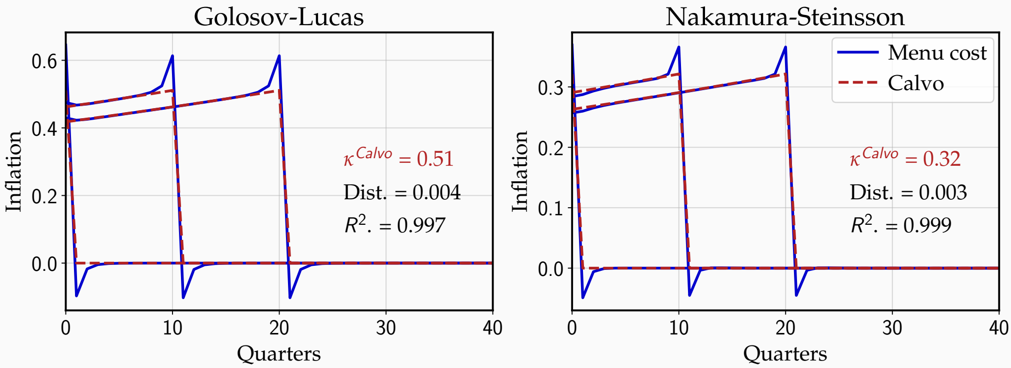

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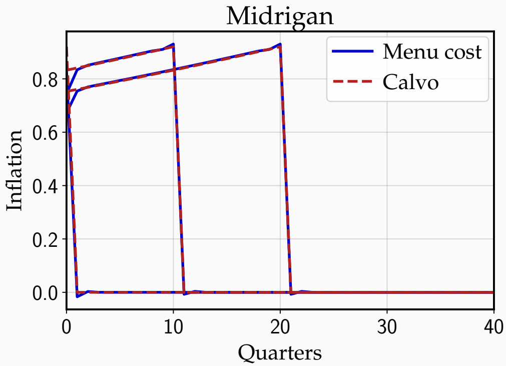
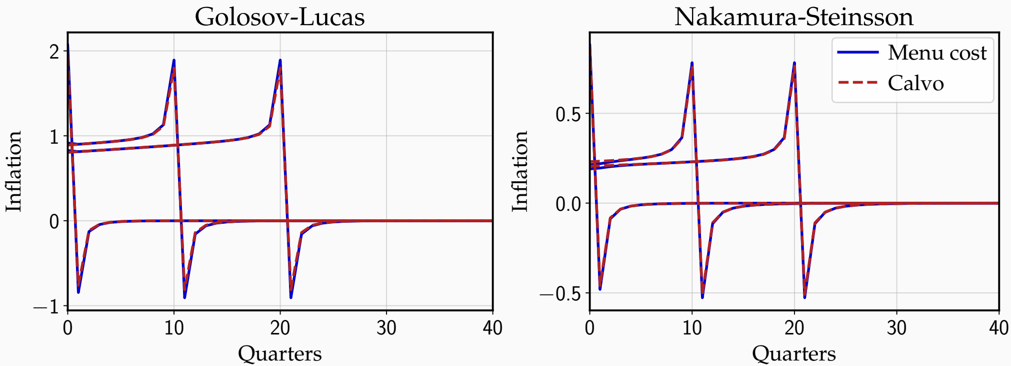


- Midrigan model: 2 products.

Multi-sector models

back



Multi-sector models

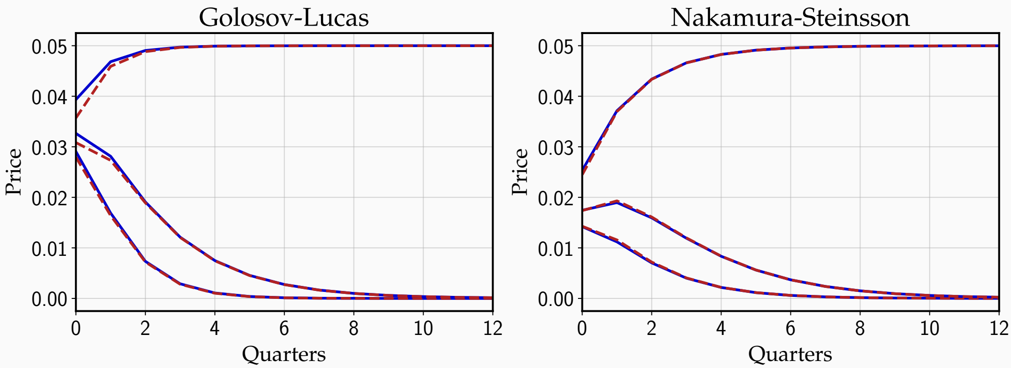
◂ back

Sectors	Golosov-Lucas		Nakamura-Steinsson	
	Real Norm	κ^{Calvo}	Real Norm	κ^{Calvo}
Vehicle fuel, used cars	-	-	-	-
Utilities	0.212	618.8	0.003	98.82
Travel	0.071	294.6	0.001	44.13
Unprocessed food	0.002	23.24	0.003	5.19
Transp. goods	0.001	13.31	0.004	3.27
Services (1)	0.001	14.07	0.004	3.42
Processed food, other	0.001	3.23	0.009	0.90

Sectors	Golosov-Lucas		Nakamura-Steinsson	
	Real Norm	κ^{Calvo}	Real Norm	κ^{Calvo}
Services (2)	0.001	1.60	0.010	0.44
Hh. furnishings	0.002	0.97	0.010	0.26
Services (3)	0.002	0.89	0.010	0.23
Recreation goods	0.002	0.86	0.010	0.23
Services (4)	0.003	0.56	0.010	0.15
Apparel	0.007	0.31	0.012	0.08
Services (5)	0.011	0.20	0.015	0.05

Large nominal cost shock and the price level

back



- 5% shock size with persistence $\in \{0.3, 0.6, 1\}$.