Sticky Information and Inflation Persistence

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Introduction
- The model
- Other estimations of the SIPC

The estimation
- Econometric strategy
- Results

More
- Structural breaks
- Alternative Model: the Hybrid SIPC

The Sticky Information Phillips Curve

1. proposed by Mankiw and Reis (QJE, 2002) as structural theory of inflation
2. Assumptions
   - Monopolistic competitive market, continuum of producers, no nominal rigidities
   - ! Each firm has $\lambda \in (0, 1]$ probability to update information in period t, regardless of how long it has been since its last update
3. Result: in each period A fraction λ of firms make new price plans that stays in place for an average duration of $\frac{1}{\lambda}$ periods
4. The symmetric equilibrium solution of firms' profits maximization problem gives:

$$\pi_t = \frac{\alpha\lambda}{1-\lambda} y_t + \lambda \sum_{j=0}^{\infty} (1-\lambda)^j E\left[\pi_t + \alpha\Delta y_t \mid \Omega_{t-1-j}\right] \qquad (1)$$

Why the focus on Inflation Persistence?

- Originally the main call of SIPC was to explain persistence in inflation dynamics
- Intuition of the mechanism
  - t A Shock occurs. A fraction λ of firms set $p*_t$ accordingly $\rightarrow$ shock affects inflation in t
  - t+1 A fraction $(1-\lambda)$ of firms get aware of the shock and set $p*_{t+1}$ accordingly $\rightarrow$ shock affects inflation in t+1
  - ... and so on $\rightarrow$ a shock in t is correlated with all future inflation rates

Empirical evidences

- Original model calibration $\lambda = 0.25$.
- The value of λ is crucial to assess whether SIPC model is relevant to explain inflation persistence [1]
- Is this calibration correct? Are there empirical evidences supporting it?
- This paper tests this calibration using US post-war data
- Other papers did it
  - Limited-Information estimators $\longrightarrow \lambda_T \in [0.15, 0.35]$
    Khan and Zhu (2002, 2006); Dopke et al. (2006); Coibion (2006)
  - Full-Information estimators $\longrightarrow \lambda_T \in [0.7, 0.85]$
    Laforte (2005); Mankiw and Reis (2006)
- Why such substantial difference in the estimates of λ_T?

[1] In the SIPC model there is an *inverse* relationship between λ and inflation persistence.

Write the model as function of exog. shocks

Lemma

Let $\{Z_t\}_{t=0}^{\infty}$ *be a covariance stationary* $(n \times 1)$ *vector process s.t.* $\{\pi_t, \Delta y_t\} \subset Z_t$. *Then SIPC (1) implies:*

$$\frac{\alpha\lambda}{1-\lambda} y_t + \alpha \Delta y_t = \sum_{i=0}^{\infty} (1-\lambda)^i \, \delta A_i \varepsilon_{t-i} \qquad (2)$$

where the $(n \times n)$ *matrices* A_i *are the dynamic multipliers of the* Z_t *process, and* ε_t *is a* $(n \times 1)$ *vector of exogenous shocks.* δ *is a* $(1 \times n)$ *row vector that picks up* $(\pi_t + \alpha \Delta y_t)$ *within* Z_t.

Orthogonality Conditions

Using lemma 1 it is possible to derive a set of O.C.
In particular, assuming ϵ_t *i.i.d.* I obtain

$$E\left[\left(\frac{\alpha\lambda}{1-\lambda}y_t+\alpha\Delta y_t\right)(\delta\varepsilon_{t-i})'\right] = (1-\lambda)^i\,\delta A_i\Sigma\delta' \qquad (3)$$
$$\text{for} \quad i = 0,\ldots,l$$

where A_i and ε_t are defined as in lemma 1, and Σ is the VCV matrix of ε_t.

Intuition: for $i=0$ RHS of (3) is the conditional variance of δZ_t.
For $i>0$ RHS of (3) is a linear combination of IRFs of inflation and output to shocks.

Procedure

step1 Replace unknown regressors with consistent estimates coming from a VAR(p) model;

step2 It can be shown that if $\{\widehat{\varepsilon}_t,\ \widehat{A}_i,\ \Sigma_T\}$ converge respectively to $\{\varepsilon_t,\ A_i,\ \Sigma\}$, then the sample analog

$$\frac{1}{T}\sum_{t=1}^{T}\left[\left(\frac{\alpha\lambda}{1-\lambda}y_t+\alpha\Delta y_t\right)(\delta\widehat{\varepsilon}_{t-i})'-(1-\lambda)^i\,\delta\widehat{A}_i\Sigma_T\delta'\right] \tag{4}$$

converges almost sure to the population moment (3).

step3 Estimate (3) with GMM to pin down λ_T

I estimate (3) with $i = 0, ..., l$.
Bad results: we can never accept Hansen J-test of overidentifying restrictions.

The model cannot match the moments all together.

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I try to estimate (3) with $i = 1, ..., 6$.
Those are the covariances between inflation and lagged shocks, i.e. the moments that measure inflation persistence.

Orthogonality Conditions based on lagged covariances

Restricted $\alpha = .2$	Specification	λ_T^{Gmm}	Adjusted std.err.	Null MR cal.	t-stat (p-val)	Null RE	t-stat (p-val)	J-stat (p-val)
					0.71		-4.30	2.22
defl; VAR	(1)	0.35	0.149	0.25	(0.47)	1	(0.00)	(0.81)
$\{\Delta y_t, \pi_t, i_t\}$					2.17		-11.41	1.95
	(2)	0.36	0.055	0.25	(0.03)	1	(0.00)	(0.85)
					1.35		-5.70	2.18
defl; VAR	(1)	0.39	0.106	0.25	(0.17)	1	(0.00)	(0.82)
minRMSE					2.15		-7.81	2.79
	(2)	0.41	0.075	0.25	(0.03)	1	(0.00)	(0.87)
					3.67		-8.44	2.70
cpi; VAR	(1)	0.47	0.061	0.25	(0.00)	1	(0.00)	(0.74)
$\{\Delta y_t, \pi_t, i_t\}$					4.21		-8.85	2.24
	(2)	0.49	0.057	0.25	(0.00)	1	(0.00)	(0.81)
					2.88		-4.48	3.38
cpi; VAR	(1)	0.54	0.101	0.25	(0.00)	1	(0.00)	(0.64)
minRMSE					3.48		-4.47	2.74
	(2)	0.57	0.094	0.25	(0.00)	1	(0.00)	(0.73)

2-step GMM with optimal weighting matrix. US data, sample 1958q4 – 2005q4. HP filter for output gap. Newey-West HAC standard errors adjusted for stochastic regressors. p-values in parenthesis. J statistic is the Hansen test of overidentifying restrictions (6 d.o.f.)

The model does well in matching lagged covariances

Estimates in line with other empirical estimations

Why different results?

The model does well in matching lagged covariances

Estimates in line with other empirical estimations

Why different results?

I estimate (3) with $i = 0$.

That is, we use the model to match the conditional variance of Z_t

NOTE: To exploit more information, the (single) O.C. is multiplied by a vector x_{t-1} of past variables, which are included in the information set at time t.

Orthogonality Conditions based on conditional variance

Restricted $\alpha = .2$	Specification	λ_T^{Gmm}	Adjusted std.err.	Null MR cal.	t-stat (p-val)	Null RE	t-stat (p-val)	J-stat (p-val)
defl; VAR $\{\Delta y_t, \pi_t, i_t\}$	(1)	0.75	0.089	0.25	5.58 (0.00)	1	-2.76 (0.00)	22.21 (0.22)
	(2)	0.86	0.084	0.25	7.24 (0.00)	1	-1.59 (0.11)	15.29 (0.64)
defl; VAR minRMSE	(1)	0.71	0.099	0.25	4.64 (0.00)	1	-2.90 (0.00)	22.62 (0.205)
	(2)	0.84	0.103	0.25	5.70 (0.00)	1	-1.55 (0.12)	15.55 (0.623)
cpi; VAR $\{\Delta y_t, \pi_t, i_t\}$	(1)	0.82	0.073	0.25	7.83 (0.00)	1	-2.43 (0.01)	20.26 (0.318)
	(2)	0.85	0.067	0.25	9.03 (0.00)	1	-2.11 (0.03)	13.97 (0.731)
cpi; VAR minRMSE	(1)	0.80	0.083	0.25	6.61 (0.00)	1	-2.39 (0.01)	22.93 (0.197)
	(2)	0.85	0.079	0.25	7.70 (0.00)	1	-1.79 (0.07)	16.39 (0.565)

2-step GMM with optimal weighting matrix. US data, sample 1958q4 – 2005q4. HP filter for output gap. Newey-West HAC standard errors adjusted for stochastic regressors. p-values in parenthesis. J statistic is the Hansen test of overidentifying restrictions (18 d.o.f.).

The specification based on the conditional variance of inflation fits the data

But now the model matches it with $\lambda_T \approx 0.75$

The model couldn't match all the moments (3) together because we'd need two significatively different values of λ_T to do that.

Inflation persistence issue:
$\lambda_T \approx 0.75$ implies little persistence in inflation process...
counterfactual

Structural Breaks

- During the 1990's U.S. economy experienced a disinflation accompanied by a fall of inflation persistence.
- Do we find a structural break in the estimates of λ?

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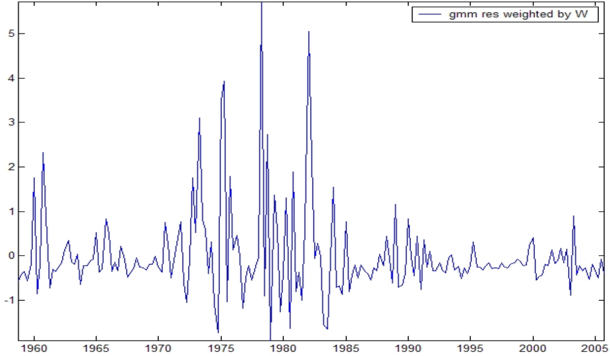
- Do we find a structural break in the estimates of λ?
- I perform Andrews's supLM test to check for breaks during the sample.

Structural breaks H_0 : *no S.B.*		sup LM	Asymptotic critical values 10%	5%	1%
O.C. (3)	$\pi_0 = .2$	1.18***	6.80	8.45	11.69
with $i = 1, ..., 6$					
	$\pi_0 = .1$	1.18***	7.63	9.31	12.69
O.C. (3)	$\pi_0 = .2$	2.08***	6.80	8.45	11.69
with $i = 0$					
	$\pi_0 = .1$	1.89***	7.63	9.31	12.69

Andrews's test accepts the null hypothesis of NO structural breaks over the sample.

GMM residuals

During mid 1970's exogenous increase in inflation volatility. Possibly supLM test captures the spurious effect of oil shock as a structural break in λ_T.



Subsample comparison: 1960's vs 1990's

- I tried an alternative test. Under the null hypothesis that the same model holds throughout the sample, I test whether $\lambda_{60's} = \lambda_{90's}$ in two subsamples.
- This is tested with Wald and LM tests on subsamples estimates

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Structural breaks H_0 : *no S.B.*	λ_{60} (s.e.)	λ_{90} (s.e.)	*Wald* (p-val)	*LM* (p-val)
O.C. (3) with $i = 1, ..., 6$	0.44	0.74	3.83	5.25
	(0.069)	(0.140)	(0.05)**	(0.03)*
O.C. (3) with $i = 0$	0.61	0.95	44.51	1871.1
	(0.049)	(0.025)	(0.00)	(0.00)

Table: Wald statistics H_0 of equal λ's in the two subsamples.

Hybrid SIPC: Derivation

- Can we improve theory in some direction? Let's try first simple things[2]
- Suppose some producers are inattentive as in the SIPC, while some others are adaptive, i.e.

$$p_t^b = \begin{cases} p_{t-1} & \text{(a)} \\ \\ p_{t-1} + \pi_{t-1} & \text{(b)} \end{cases}$$

[2] Cfr. Dupor et al. (2006)

Hybrid SIPC: Derivation

We derive an alternative model, i.e. some Hybrid SIPC in the spirit of the Hybrid NKPC.
Inflation in this "hybrid" model evolves according to:

$$\pi_t = \begin{cases} (1-\varphi)\left[\frac{\alpha\lambda}{1-\lambda} y_t + \lambda \sum_{j=0}^{\infty} (1-\lambda)^j E_{t-j-1}(\pi_t + \alpha \Delta y_t)\right] \\ \qquad + \varphi \pi_{t-1} & \text{(a)} \\ \\ (1-\varphi)\left[\frac{\alpha\lambda}{1-\lambda} y_t + \lambda \sum_{j=0}^{\infty} (1-\lambda)^j E_{t-j-1}(\pi_t + \alpha \Delta y_t)\right] \\ \qquad + \varphi(2\pi_{t-1} - \pi_{t-2}) & \text{(b)} \end{cases}$$

Estimation

Hybrid SIPC $i = 0, \ldots, I$ Restr. $\alpha = .2$	Specif.	O.C. from (a) λ_T^{2s} (s.e.)	O.C. from (a) φ_T^{2s} (s.e.)	O.C. from (a) J-stat (p-val)	O.C. from (b) λ_T^{2s} (s.e.)	O.C. from (b) φ_T^{2s} (s.e.)	O.C. from (b) J-stat (p-val)
defl; VAR	(1)	0.41	-1.23*	3.56	0.62	-0.66*	3.08
$\{\Delta y_t, \pi_t, i_t\}$		(0.055)	(0.775)	(0.61)*	(0.101)	(0.476)	(0.68)*
	(2)	0.44	-1.33*	3.18	0.67	-0.81*	2.05
		(0.060)	(0.885)	(0.67)*	(0.101)	(0.664)	(0.84)*
defl; VAR	(1)	0.45	-1.08*	1.85	0.64	-0.54*	1.37
minRMSE		(0.054)	(0.813)	(0.86)*	(0.104)	(0.479)	(0.92)*
	(2)	0.46	-1.14*	1.76	0.66	-0.60*	1.03
		(0.056)	(0.884)	(0.88)*	(0.107)	(0.568)	(0.95)*
cpi; VAR	(1)	0.55	-1.37*	8.05	0.75	-0.66*	4.65
$\{\Delta y_t, \pi_t, i_t\}$		(0.065)	(0.986)	(0.15)*	(0.064)	(0.416)	(0.45)*
	(2)	0.64	-2.40*	6.35	0.77	-0.79*	3.39
		(0.080)	(2.628)	(0.27)*	(0.065)	(0.553)	(0.64)*
cpi; VAR	(1)	0.69	-0.83*	6.18	0.78	-0.34*	3.88
minRMSE		(0.087)	(0.671)	(0.28)*	(0.070)	(0.265)	(0.56)*
	(2)	0.78	-0.97*	4.46	0.80	-0.39*	3.21
		(0.101)	(1.09)	(0.48)*	(0.072)	(0.330)	(0.66)*

Table: Table 3. 2-step GMM with optimal weighting matrix. U.S. data, sample 1958q4 – 2005q4. HP filter for output gap. Newey-West HAC standard errors not adjusted for stochastic regressors. * means that the coefficient is not significatively different from zero. J-statistics is Hansen test of overidentifying restrictions (18 d.o.f.).

Specifications

- I fit two different specifications of the VAR(p) model to obtain the exog. shocks
  - (i) the baseline, which includes inflation, output gap growth and interest rate
  - (ii) the *min RMSE*, which includes 8 variables [Stock and Watson (2003)]
- I use either GDP deflator or CPI as inflation rate
- I estimate two different specifications of (4) to control for GMM small sample bias

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Adjusted standard errors

To compute the correct variance of λ_T^{Gmm}

(i) We build a vector of O.C. pooling together the O.C. (3), and the O.C. from the VAR(p) model that we used to estimate $\widehat{\varepsilon}_t$ and $\widehat{\Sigma}_T$.

(ii) We compute the variance of λ_T in this "pooled" GMM model, which is

$$V(\lambda_T) = \left((TV_{na})^{-1} - E\frac{\partial g'_{1,t}}{\partial \lambda} \Sigma_{g_1}^{-1} E\frac{\partial g_{1,t}}{\partial \beta'} \left(E\frac{\partial g'_{1,t}}{\partial \beta} \Sigma_{g_1}^{-1} E\frac{\partial g_{1,t}}{\partial \beta'} + E\frac{\partial g'_{2,t}}{\partial \beta} \Sigma_{g_2}^{-1} E\frac{\partial g_{2,t}}{\partial \beta'} \right)^{-1} E\frac{\partial g'_{1,t}}{\partial \beta} \Sigma_{g_1}^{-1} E\frac{\partial g_{1,t}}{\partial \lambda} \right)^{-}$$

(iii) Is useful to see that $V(\lambda_T^{Gmm}) \geq V_{na}(\lambda_T^{Gmm})$.

(iv) After the correction the s.e. increases on average around 60% in the baseline specifications, and 40% in the *minRMSE*.

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