Nonlinear Pass-Through of Exchange Rate Shocks on Inflation: A Bayesian Smooth Transition VAR Approach

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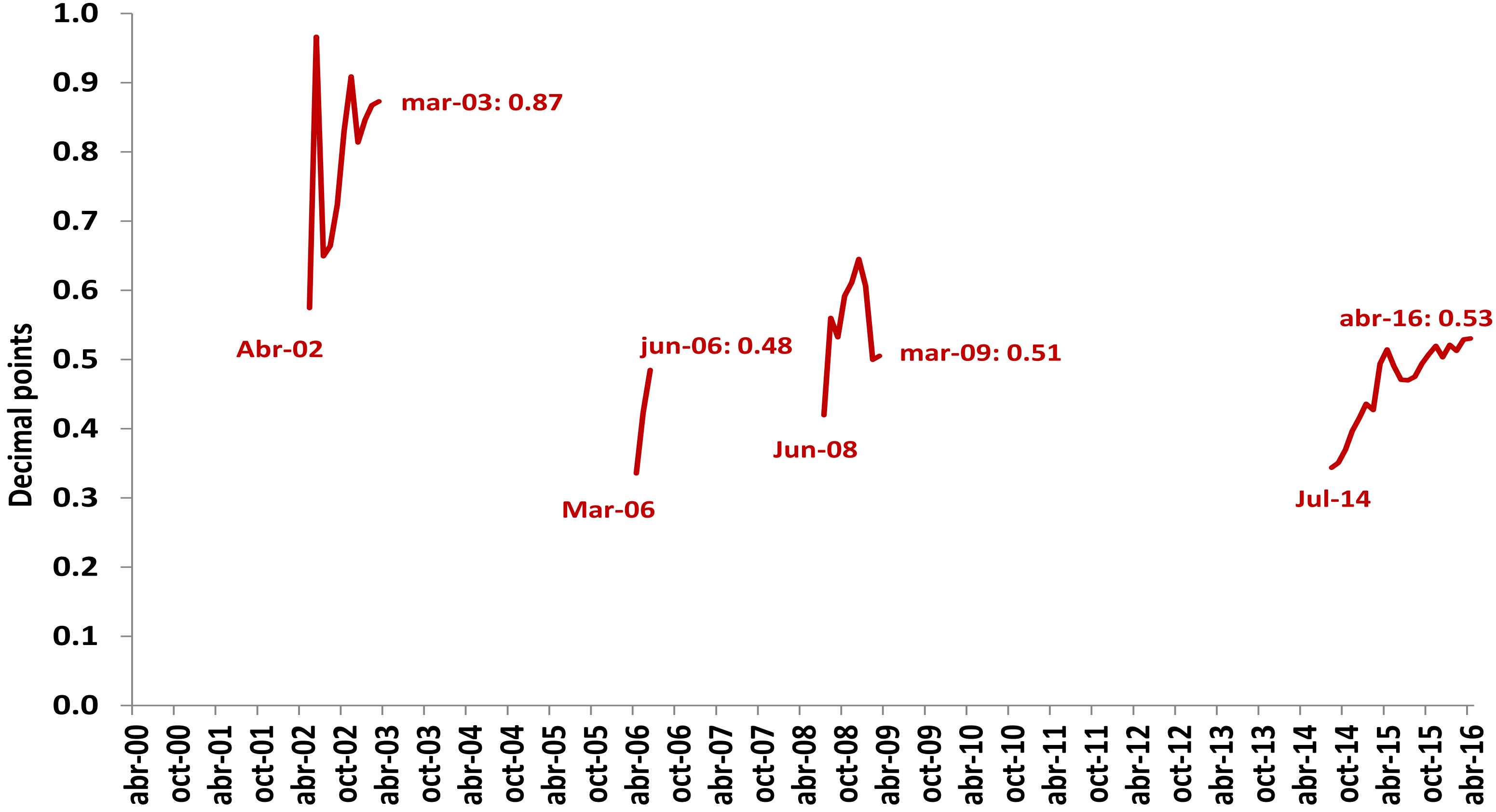
*The points of view expressed in this presentation are the authors' and they do not represent those of Banco de la República or its Board of Directors. The authors are responsible for any errors found.

Motivation

"[C]urrency movements have critical implications for inflation and the appropriate stance of monetary policy… [However], limited understanding of how exchange rate movements affect inflation is – to be candid – quite frustrating for those of us tasked to set monetary policy" (Kristin Forbes, External MPC member at Bank of England and MIT's Professor, September 2015).

Elasticity

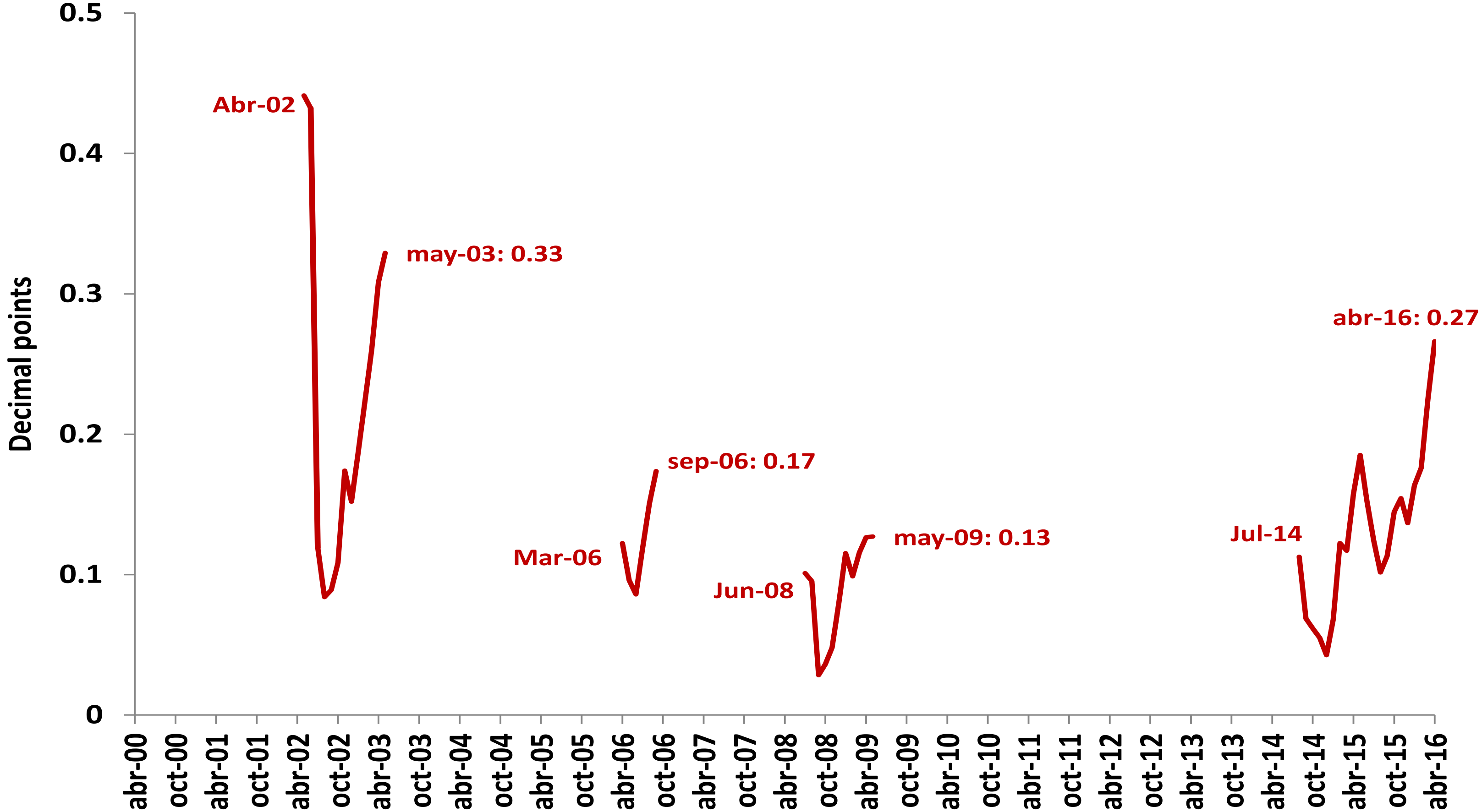
(Accumulated variation of import prices /Accumulated variation of nominal exchange rate)



Source: Department of Inflation and Forecasting, Banco de la República.

Elasticity

(Accumulated variation of CPI /Accumulated variation of exchange rate)



Source: Department of Inflation and Forecasting, Banco de la República.

Content

I. Introducción

Why is important to study the impact of exchange rate shocks on inflation?

- Central banks…

✓ To learn about the exchange rate ability of being a short term macroeconomic adjustment mechanism (expenditure-switching mechanism).

✓ To know their inflationary impact and implications for making monetary policy decisions.

- Domestic producers…

➢ They change the domestic price of imported inputs, so they impact their production costs and expectations about their future behavior.

- Domestic consumers…

➢ They change their consumption decisions, whenever the final good prices in local currency are modified.

- **Objective**

To examine the short-and long-term impacts of exchange rate shocks on a small open economy's (Colombia) prices along the distribution chain (Pass-through, PT), in the presence of endogeneity, nonlinearity and asymmetry.

Contributions

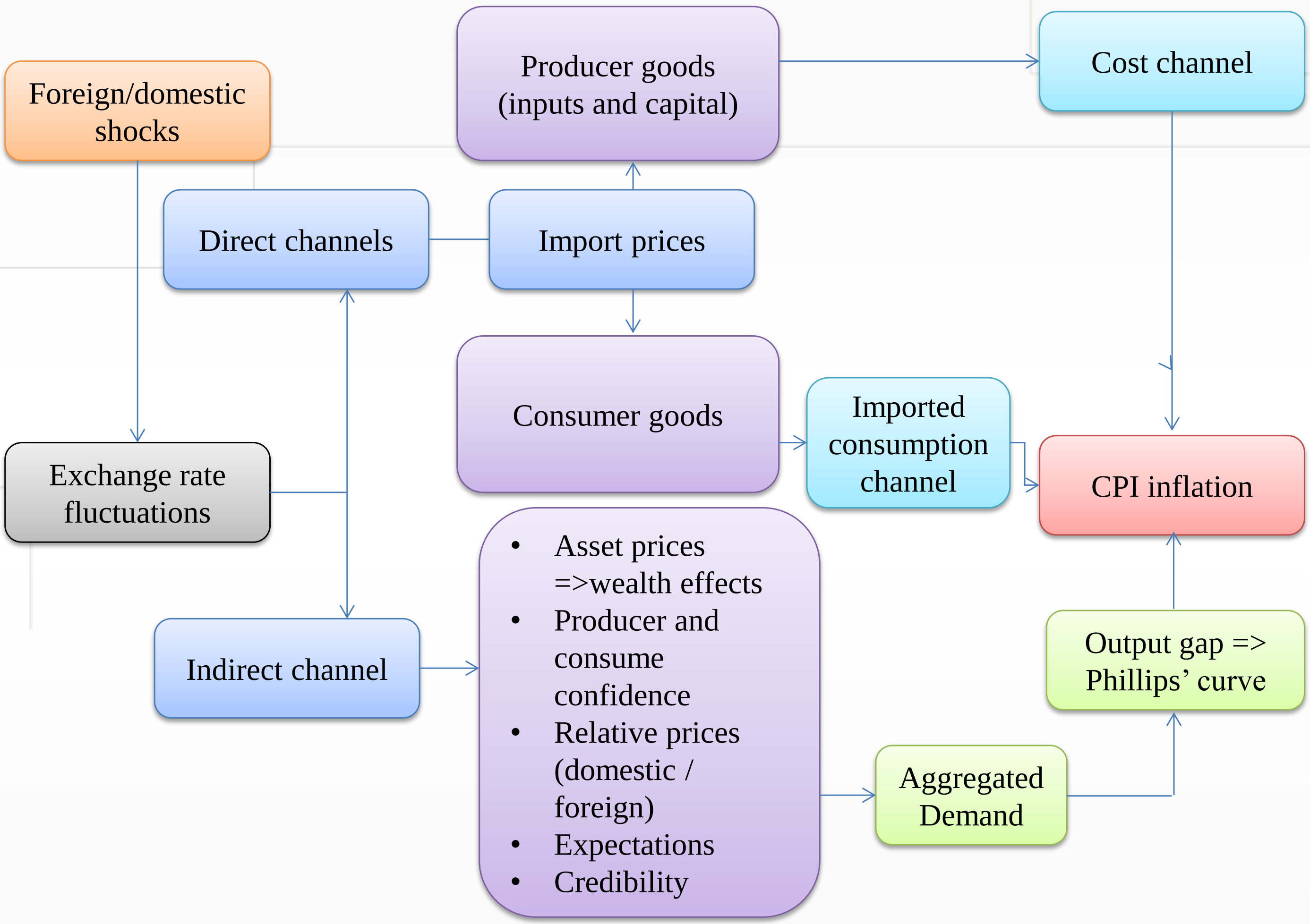
- ✓ Model and evaluate empirically the endogenous, nonlinear and asymmetric nature of PT (Dornbusch, 1987; Taylor, 2000; Devereux and Yetman, 2003; Corsetti et al., 2005).

- ✓ Implement a Bayesian approach for estimation and inference, which surmounts issues of "frequentist" approaches such as,

  - Too rich in their parameters [integrates out nuisance];
  - Optimization algorithms of the likelihood functions are unstable [joint estimation avoiding grid-search];
  - Inference is based on asymptotic properties [inference does not depend on sample size considerations];
  - Sensitive to model specification [allows model selection and measurements based on model-averaging].

- ✓ Obtain a historical decomposition of shocks, which is novel in LST-VAR models.

II. Transmission channels



Source: Authors' construction, based on Miller (2003) and own deductions.

III. Analytical framework

Model: Pricing model along the distribution chain (adjusted and augmented version of McCarthy's (2007)).

⇒Price variations at a specific distribution stage (import, producer, imported consumer and total consumer) in period *t* has different components:

1) Expected inflation at the respective stage based on all information available at period t-1;

2) Foreign marginal cost shock at that stage;

3) Exchange rate shock at a particular stage;
4) Domestic demand and supply shocks at a particular stage;
5) Inflation shocks of the other goods at the previous stages;
6) Respective inflation shock at period t.

… If the conditional expectations in the model are replaced by own projections of the lags of the variables ⇒ equations of the model can be expressed as a VAR system given by the vector of endogenous variables,

$$Y_t = \begin{bmatrix} \Delta mgc_t^* \\ \Delta e_t \\ \pi_t^m \\ D_t \\ S_t \\ \pi_t^w \\ \pi_t^{mc} \\ \pi_t^{cpi} \end{bmatrix} \qquad (9)$$

… and a vector of structural shocks given by,

$$\boldsymbol{\varepsilon}_t = \begin{bmatrix} \varepsilon_t^{\Delta mgc^*} \\ \varepsilon_t^{\Delta e} \\ \varepsilon_t^{\pi^m} \\ \varepsilon_t^{D} \\ \varepsilon_t^{S} \\ \varepsilon_t^{\pi^w} \\ \varepsilon_t^{\pi^{mc}} \\ \varepsilon_t^{\pi^{cpi}} \end{bmatrix} \tag{10}$$

IV. Regression model and data

- **Regression model**: A logistic smooth transition LST-VAR model (Luukkonen, Saikkonen and Terasvirta, 1988; Granger and Teräsvirta, 1993; Terasvirta, 1994; He et al., 2009),

$$(11) Y_t = \begin{bmatrix} \Delta mgc_t^* \\ \Delta e_t \\ \pi_t^m \\ D_t \\ S_t \\ \pi_t^w \\ \pi_t^{mc} \\ \pi_t^{cpi} \end{bmatrix} = A(L)Y_{t-1} + F(V_{t-d}; \gamma, c)B(L)Y_{t-1} + \boldsymbol{\mu}_t$$

- $A(L)$ and $B(L)$ are p-order polynomial matrixes; L being the lag operator

- $F(V_{t-d}; \gamma, c)$ is a diagonal matrix whose elements f_j are transition functions, with $f_j(\cdot) = \{1 + \exp[-\gamma(V_t - c)]\}^{-1}$ representing the cumulative function of logistical probability for the j-th transition variable;

- V_j : j-th variable de transición;

- γ: smoothing parameter (γ>0). When $\gamma \rightarrow 0 \Rightarrow$ equation (11) becomes a VAR. When $\gamma \rightarrow \infty \Rightarrow$ becomes an indicator function $I(V_t > c)$.

- c: Localization parameter; $\boldsymbol{\mu}$: vector of white noise processes.

PT coefficient: Accumulated response of prices to a shock to the exchange rate, relative to the accumulated response of the exchange rate to the same shock (Goldfajn and Werlang, 2000; Winkelried, 2003; Mendoza, 2004; González, Rincón and Rodríguez, 2010):

$$PT_\tau = \frac{\sum_{j=0}^{\tau} \frac{\partial \pi_{t+j}^{n}}{\partial \varepsilon_t^{\Delta e}}}{\sum_{j=0}^{\tau} \frac{\partial \Delta e_{t+j}}{\partial \varepsilon_t^{\Delta e}}}, n = m, w, mc, cpi \quad (12)$$

- The structural shocks in equation (11) are identified by using the Cholesky decomposition, but PT estimates are constructed using GIRFs (invariant to the ordering of the variables in the VAR system).

- The regression model is estimated by Bayesian methods (similar to Gefang and Strachan, 2010; Gefang, 2012).

➢ Data:

- ❖ Period: 2002 – 2015 (floating and inflation targeting regimes)
- ❖ Frequency: monthly
- ❖ Time series:

- Import, producer, imported consumer and total consumer price indexes.
- Nominal effective exchange rate index (pesos/USD). It is weighted using imports from the Colombian's main trading partners.
- Measurements of aggregate supply and demand.
- Trade weighted measure of foreign countries' marginal costs.

Data –Transition variables

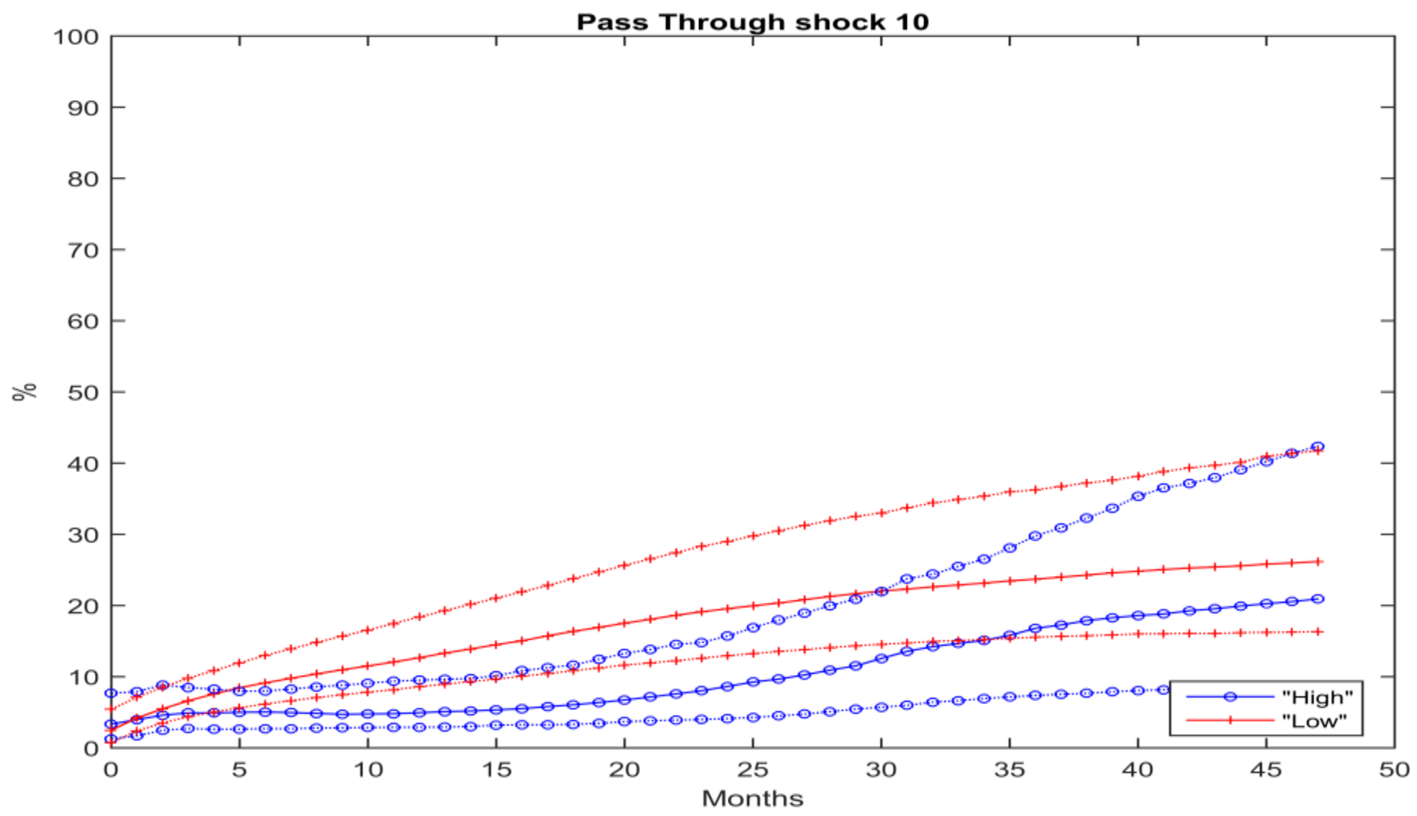
- Variation of the CPI inflation ($\Delta\pi^{cpi}$)
- Volatility of inflation ($V(\pi^{cpi})$)
- Deviation of CPI inflation from the central bank target ($D\pi$)
- Variation of the exchange rate change ($\Delta(\Delta e)$)
- Volatility of the exchange rate ($V(\Delta e)$)
- Misalignment of the real exchange rate (Dq)
- Output gap (Gy)
- Degree of economic openness ($Opennes$)
- Variation of a commodity price ($\Delta Pcomm$)
- Interbank interest rate (IBR): operative instrument of monetary policy
- Time ($Trend$)

V. Results

… Show the dynamic of the cumulated PT coefficients on CPI of a positive 10% shock to the exchange rate, conditional on the two regimes of three (out of eleven) of the transition variables, only…

PT estimates on CPI (percentage points)...

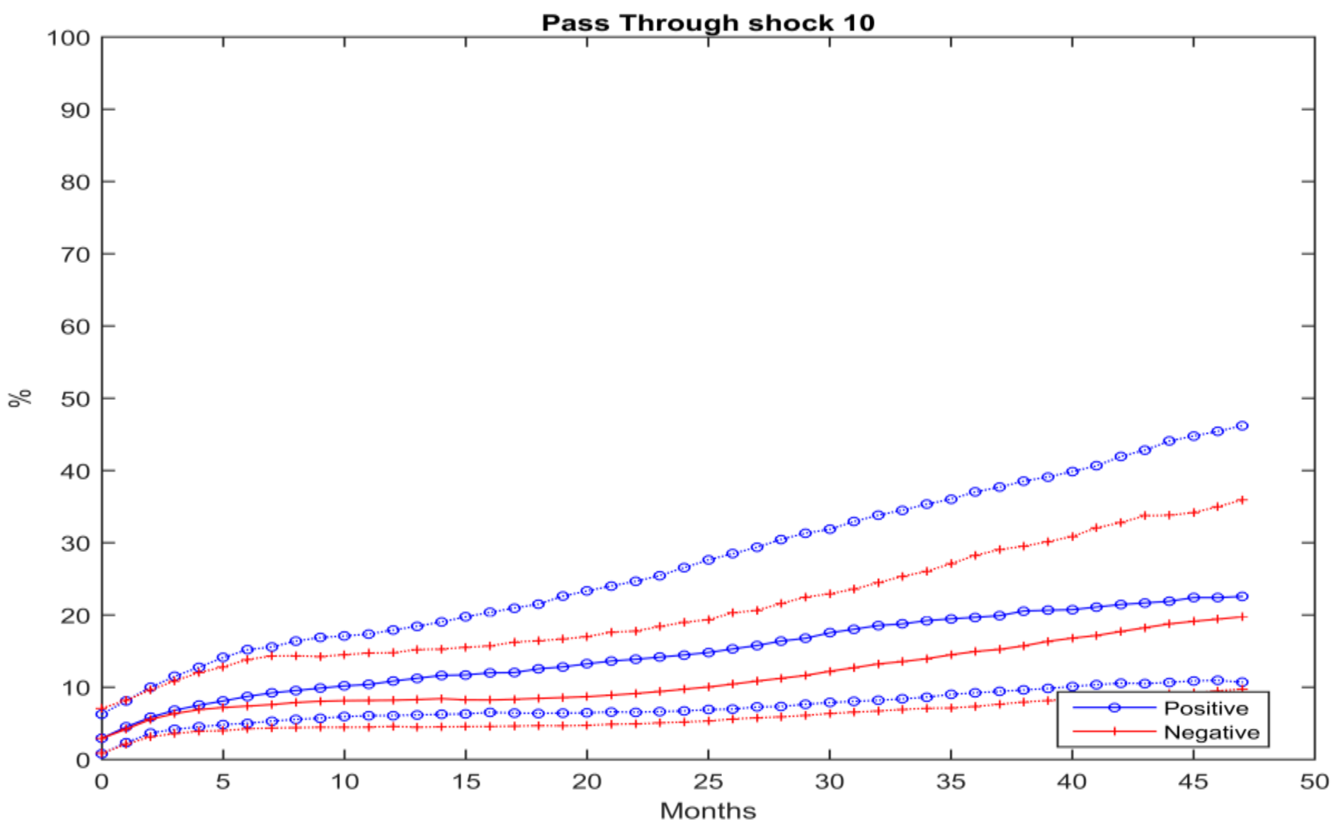
➢ **Transition variable: Interbank interest rate (IBR)**



Source: Authors' calculations.

PT estimates on CPI (percentage points)...

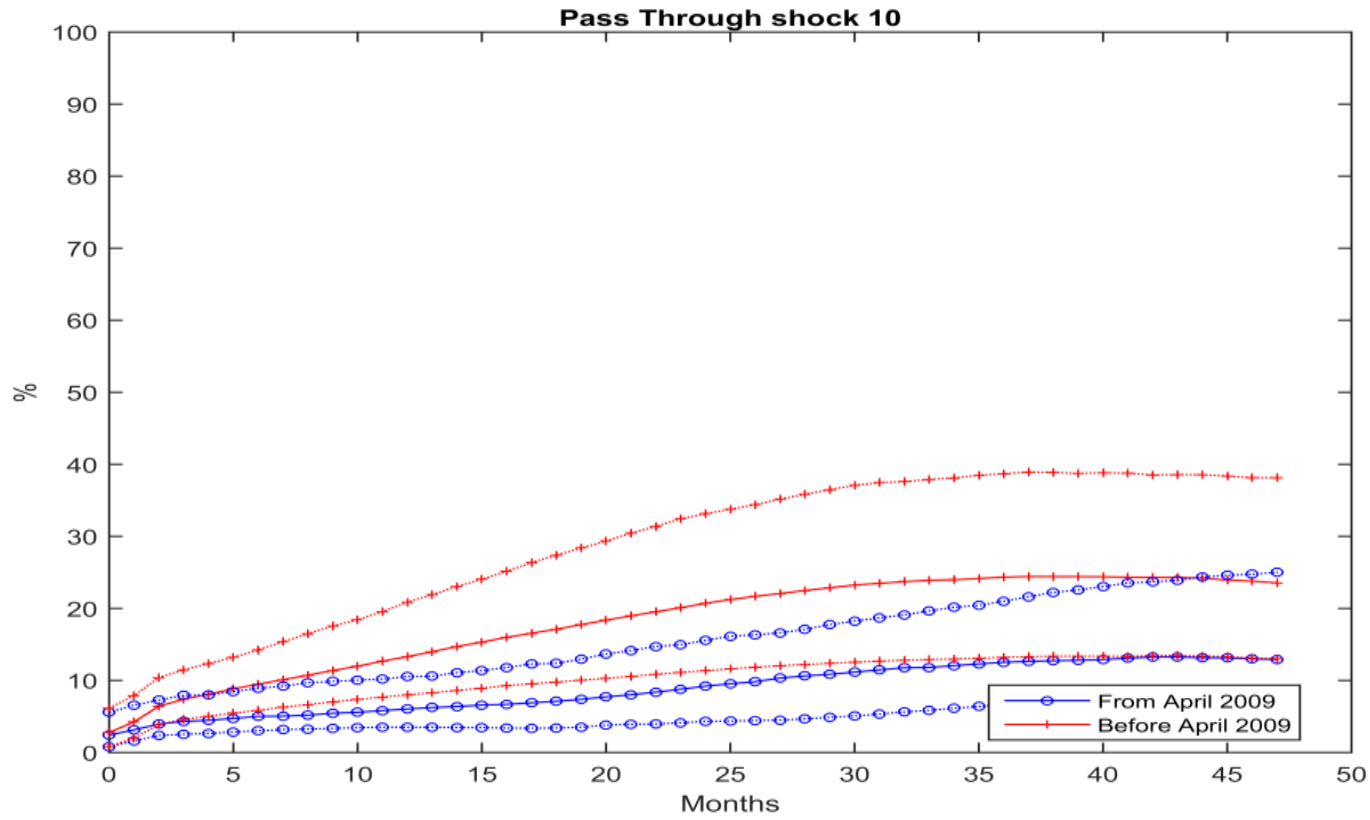
➤ **Transition variable: Output gap (Gy)**



Source: Authors' calculations.

PT estimates on CPI (percentage points)…

➢ Transition variable: Trend



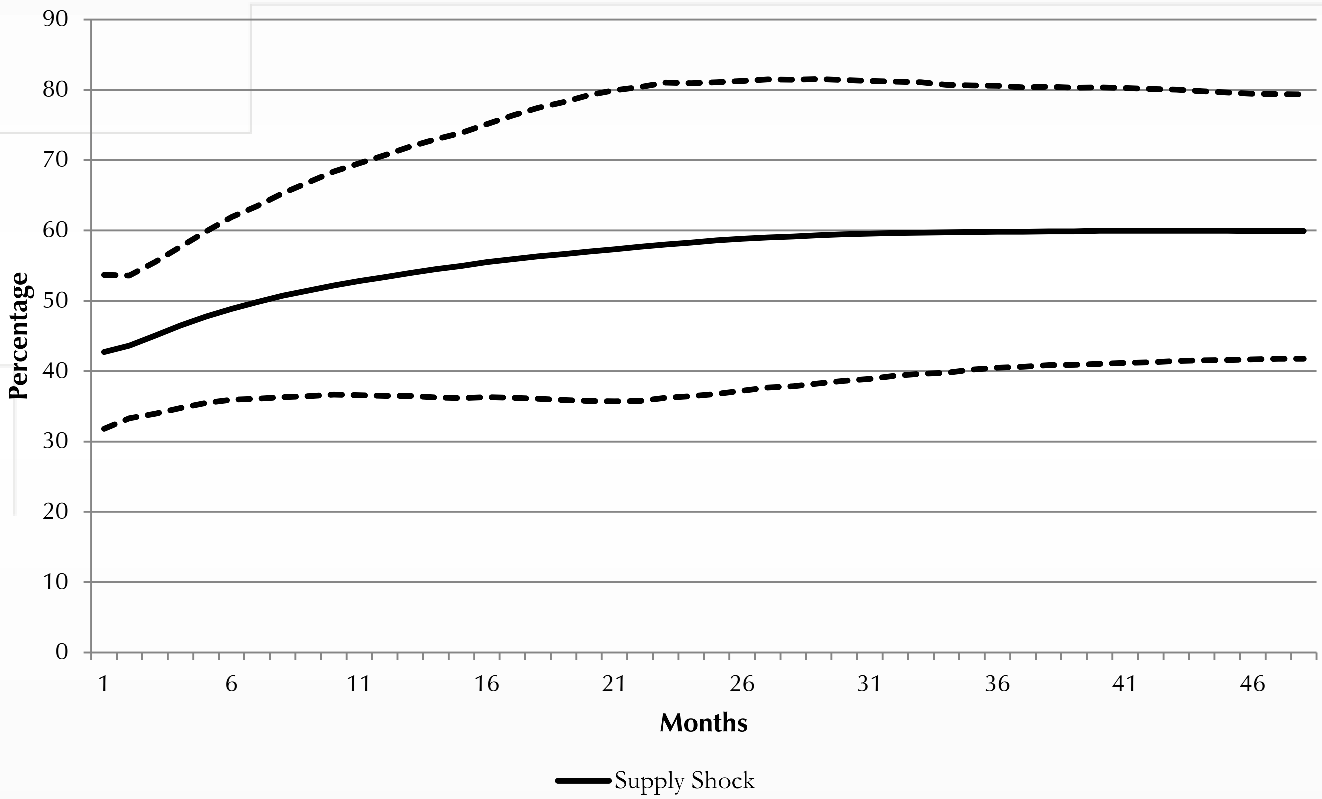
Source: Authors' calculations.

… **A digression**: Estimation of the "Pass-through (PT)" (Shambaugh, 2008)

$$"PT_{\tau}" = \frac{\sum_{j=0}^{\tau} \frac{\partial \pi_{t+j}^{cpi}}{\partial \varepsilon_t^i}}{\sum_{j=0}^{\tau} \frac{\partial \Delta e_{t+j}}{\partial \varepsilon_t^i}}, \; i = \varepsilon^S$$

"PT" estimates on the CPI (percentage points)...

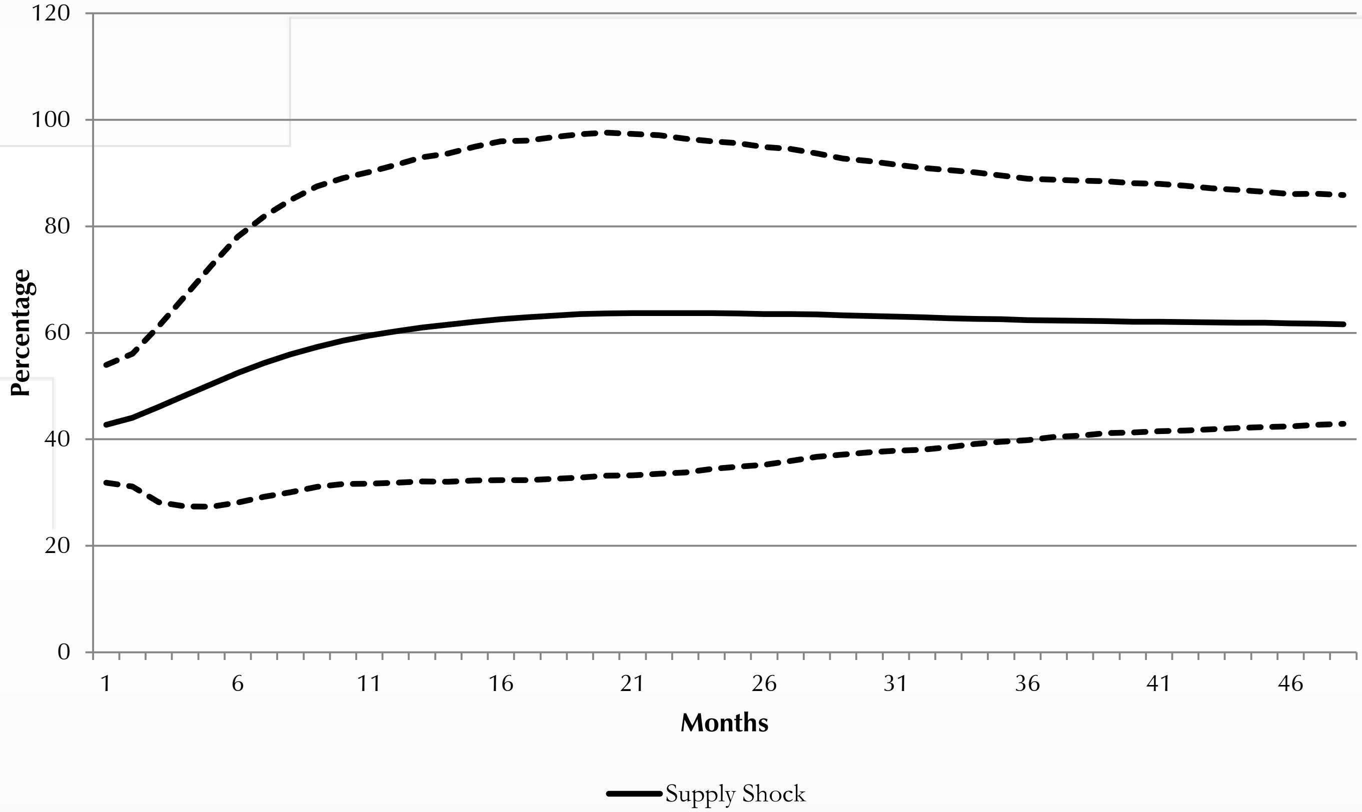
➢ **Transition variable: CPI inflation increases**



Source: Authors' calculations.

"PT" estimates on the CPI (percentage points)...

➢ **Transition variable: Output gap (positive)**



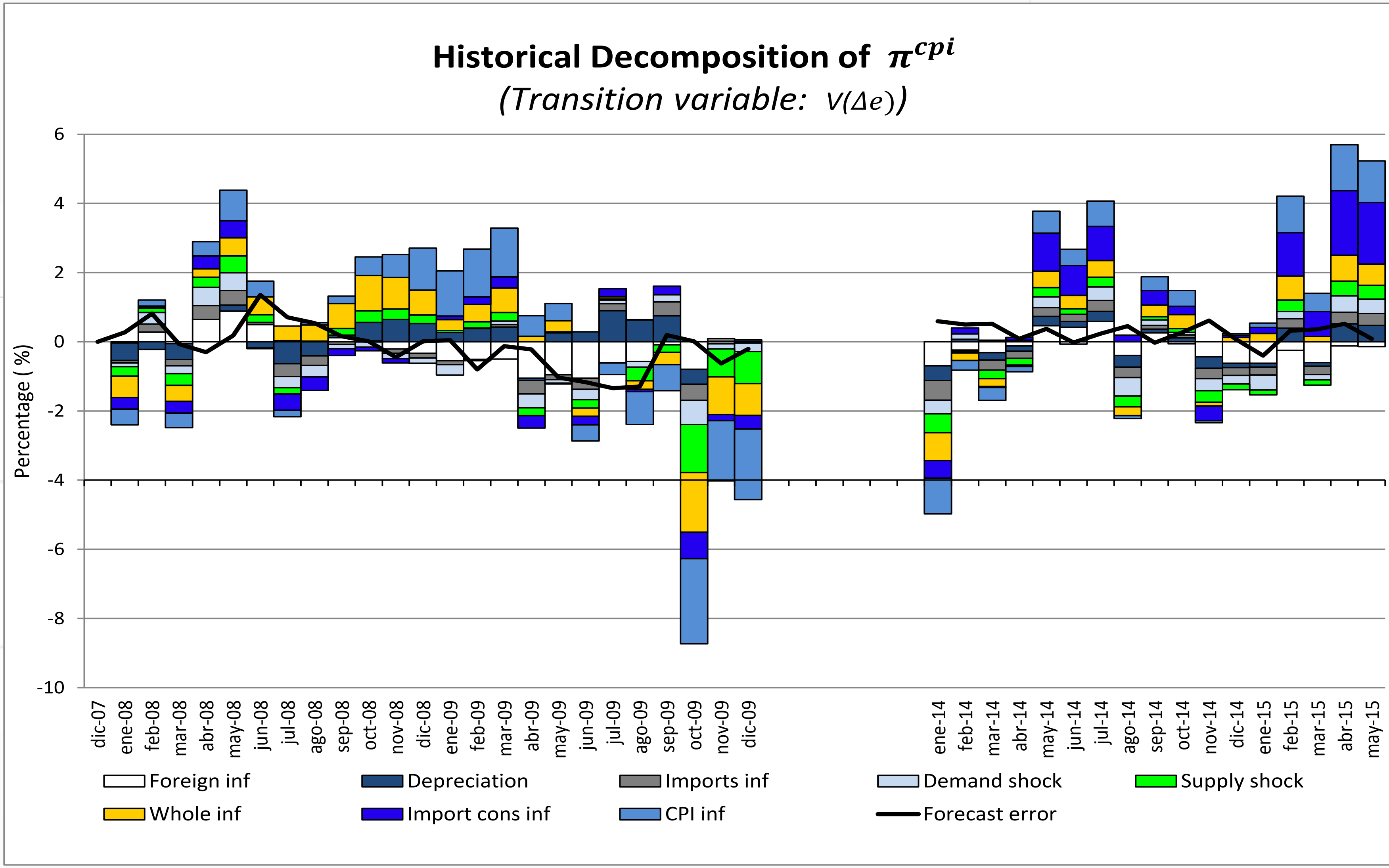
Source: Authors' calculations.

Finally, the historical decomposition (HD) of shocks…

Hint:

HD allows to approximate the magnitude of the contribution of each shock to the unpredicted value of each endogenous variable at each period of time.

⇒ Permits to differentiate which of the shocks were the main determinants of the behavior of the endogenous variables in each time period; in our case, of the different inflations along the distribution chain…



Source: Authors' calculations.

VI. Conclusions and policy implications

- The degree of PT is incomplete, even for import prices, in the short and long terms.
- PT is endogenous to the state of the economy and to shocks, which causes it changes over time $\Rightarrow$ PT is state-dependent and shock-dependent.
- PT is nonlinear to the size and sign of the exchange rate shock.
- HD reveal that the final impact of exchange rate shocks is endogenous to other shocks the economy and the exchange rate itself are facing.

- **Policy implications:**

  - Models used in central banks for policy making need to be adjusted to the incomplete, endogenous, nonlinear and asymmetric nature of PT.

  - There should not exist a specific rule on PT on prices for policy making, even in the short term.

- Transmission of movements in the exchange rate on prices vanishes along the distribution chain, as expected, and this behavior seems independent from any market behavior by firms, the state of the economy or shocks.

- Uncertainty about PT estimates increases rapidly across time after the shock.

Thanks!

III. Analytical framework

Model: Pricing model along the distribution chain (adjusted and augmented version of McCarthy's (2007)).

⇒Price variations at a specific distribution stage (import, producer, imported consumer and total consumer) in period *t* has different components:

1) Expected inflation at the respective stage based on all information available at period t-1;

2) Foreign marginal cost shock at that stage;

3) Exchange rate shock at a particular stage;

4) Domestic demand and supply shocks at a particular stage;

5) Inflation shocks of the other goods at the previous stages;

6) Respective inflation shock at period t.

That is…

… Inflation rates in period t at each of the stages – import (m), producer (w), imported consumer (mc) and total consumer (cpi) goods – can be written as,

(1) Foreign marginal cost: $\Delta mc_t^* = E_{t-1}(\Delta r_t^*) + \varepsilon_t^{\Delta mgc^*}$

(2) Exchange rate: $\Delta e_t = E_{t-1}(\Delta e_t) + \alpha_1 \varepsilon_t^{\Delta mgc^*} + \varepsilon_t^{\Delta e}$

(3) Inflation of import prices: $\pi_t^m = E_{t-1}(\pi_t^m) + \beta_1 \varepsilon_t^{\Delta mgc^*} + \beta_2 \varepsilon_t^{\Delta e} + \varepsilon_t^{\pi^m}$

(4) Domestic demand: $D_t = E_{t-1}(D_t) + \gamma_1 \varepsilon_t^{\Delta mgc^*} + \gamma_2 \varepsilon_t^{\Delta e} + \gamma_3 \varepsilon_t^m + \varepsilon_t^D$

(5) Domestic supply: $S_t = E_{t-1}(S_t) + \delta_1 \varepsilon_t^{\Delta mgc^*} + \delta_2 \varepsilon_t^{\Delta e} + \delta_3 \varepsilon_t^{m} + \delta_4 \varepsilon_t^{D} + \varepsilon_t^{S}$

(6) Inflation of producer goods: $\pi_t^{w} = E_{t-1}(\pi_t^{w}) + \theta_1 \varepsilon_t^{\Delta mgc^*} + \theta_2 \varepsilon_t^{\Delta e} + \theta_3 \varepsilon_t^{m} + \theta_4 \varepsilon_t^{D}{}_2 + \theta_5 \varepsilon_t^{S} + \varepsilon_t^{\pi^w}$

(7) Inflation of imported consumer goods: $\pi_t^{mc} = E_{t-1}(\pi_t^{w}) + \vartheta_1 \varepsilon_t^{\Delta mgc^*} + \vartheta_2 \varepsilon_t^{\Delta e} + \vartheta_3 \varepsilon_t^{m} + \vartheta_4 \varepsilon_t^{D} + \vartheta_5 \varepsilon_t^{S} + \vartheta_6 \varepsilon_t^{w} + \varepsilon_t^{\pi^{mc}}$

(8) Inflation of total consumer goods: $\pi_t^{cpi} = E_{t-1}(\pi_t^{cpi}) + \varphi_1 \varepsilon_t^{\Delta mgc^*} + \varphi_2 \varepsilon_t^{\Delta e} + \varphi_3 \varepsilon_t^{m} + \varphi_4 \varepsilon_t^{D} + \varphi_5 \varepsilon_t^{w} + \varphi_6 \varepsilon_t^{mc} + \varepsilon_t^{\pi^{cpi}}$

V. Results

Linear or nonlinear regression model?..

Model	Transition variable	*p*-lag	*d*-lag	Ln(BF)
VAR	$\Delta(\pi^{cpi})$	3	NA	-1220.2
LST-VAR	$\Delta(\pi^{cpi})$	3	2	-20101.2
VAR	$V(\pi^{cpi})$	3	NA	-2002.7
LST-VAR	$V(\pi^{cpi})$	3	1	-19237.8
VAR	$D\pi$	3	NA	-1015.8
LST-VAR	$D\pi$	3	1	-20179.8
VAR	$\Delta(\Delta e)$	3	NA	-1888.3
LST-VAR	$\Delta(\Delta e)$	3	2	-19540.5
VAR	$V(\Delta e)$	4	NA	-2901.7
LST-VAR	$V(\Delta e)$	4	2	-19429.2
VAR	Mq	3	NA	-1098.3
LST-VAR	Mq	3	1	-20350.9
VAR	Gy	3	NA	-2916.1
LST-VAR	Gy	3	1	-20000.0
VAR	*Openness*	3	NA	-4315.4
LST-VAR	*Openness*	3	2	-21615.7
VAR	$\Delta(Pcomm)$	3	NA	-1170.3
LST-VAR	$\Delta(Pcomm)$	3	1	-20731.3
VAR	*IBR*	3	NA	-1586.6
LST-VAR	*IBR*	3	2	-20764.2
VAR	*Trend*	3	NA	-6254.1
LST-VAR	*Trend*	3	2	-22065.7

Source: Authors' calculations. "BF" means 'Bayes factor', Ln: natural logarithm, and "NA" means 'Not Apply'.

⇒ Data validate an endogenous and nonlinear PT.

Hint: Bayes factor...

Posterior odds of the null hypothesis, that is the degree to which we favor a null hypothesis (constant model) over an alternative (linearity or nonlinearity) after observing the data, given the prior probabilities on the null and alternative.

$\Rightarrow$ the more negative "Ln(BF)" is, the better specification is obtained.

Parameter estimates of the LST-VAR…

Transition variable	Estimated parameters		# obs. per regime		Threshold	p-lag	d-lag
	γ	c	Low	High			
$\Delta(\pi^{cpi})$	32.11	-12.67	78	74	0.07	3	2
$V(\pi^{cpi})$	1.10	0.44	99	53	0.53	3	1
$D\pi$	6.76	-1.92	87	65	0.29	3	1
$\Delta(\Delta e)$	5.03	-120.69	85	67	0.0	3	2
$V(\Delta e)$	6.92	3.34	86	65	5.72	4	2
Mq	2.23	-11.38	87	65	0.00	3	1
Gy	2.30	-1.35	81	71	0.00	3	1
Openness	5.69	26.37	79	73	36.31	3	2
Δ(Pcomm)	2.10	-30.65	72	80	5.75	3	1
IBR	1.13	4.31	78	74	5.80	3	2
Trend	4.27	225.10	76	76	275.50	3	2

Source: Authors' calculations.

⇒ The estimated c is fairly located at the center of the distribution of the j − th transition variable

VI. Conclusions and policy implications

- The degree of PT is incomplete, even for import prices, in the short and long terms.

⇒ Evidence against a complete exchange rate transmission such as that predicted by PPP.

⇒ Limited ability of the nominal exchange rate to produce a full automatic adjustment in the price of tradable goods and then in the current account… ¿Does it require an additional instrument?

- PT is endogenous to the state of the economy and to shocks, which causes it changes over time.

- Thirdly, we found that PT is nonlinear and responds differently to the size and sign of shocks

  ⇒ PT is nonlinear and asymmetric.

- HD show that the impact of shocks on inflation depends very much on the state of the economy

- … Also, HD reveal that the final impact of exchange rate shocks on inflation is determined by or is endogenous to other shocks the economy and the exchange rate itself are facing.

Why a Bayesian approach?

"Frequentist" approaches	vs.	Bayesian approach
- Too rich in their parameters		- Integrates out nuisance parameters
- Optimization algorithms of the likelihood functions are unstable		- Permits for joint estimation of all model parameters avoiding grid-search type of procedures, which may generate unstable estimations
- Inference depends on sample size considerations		- Inference does not depend on sample size considerations because is based on model-averaged measures
- Inference is very sensitive to model specification		- Inference is based on model-averaged measures
- Prediction and understanding dynamics depends on asymptotically justified methods such as the bootstrap		- Prediction and dynamics does not rely upon asymptotic methods but on the different models and the observed sample

Sources: Koop and Potter (1999) and Koop (2003).

Bayesian estimation

(Koop, 2003; Gefang and Strachan, 2010; Gefan; 2012)

Step 1: Build the likelihood function of the model…

Write model (11) in a compact form as

(A3.1.1) $$Y = X^{\theta}B + E.$$

where $B = (A_0, A_1, \dots, A_p, B_0, B_1, \dots, B_p)'$. But model (A3.1.1) can be vectored and transformed into,

(A3.1.2) $$y = x^{\theta}b + e,$$

where $y = vec(Y)$, $b = vec(B)$, $x^{\theta} = I_n \otimes X^{\theta}, X^{\theta} = \left[x_1^{\theta\prime}, \dots, x_T^{\theta\prime}\right]'$, with $x_t^{\theta} = [x_t \;\; F(z_{t-d})x_t]$, $\theta = (\gamma, c)'$, and $e = vec(E)$. Given that errors terms are assumed to be white noise processes, the likelihood function of the model can be expressed as

(A3.1.3) $$L(b, \Sigma, \gamma, c) \propto |\Sigma|^{-T/2} exp\left\{-\frac{1}{2}e'(\Sigma^{-1} \otimes I_T)e\right\}.$$

Now notice that the term in the exponent of (A3.1.3) can be rewritten as

$$e'(\Sigma^{-1} \otimes I_T)e = s^2 + (b - \hat{b})'V^{-1}(b - \hat{b}) \qquad \text{(A3.1.4)}$$

where $s^2 = y'M_V y$, $M_V = \Sigma^{-1} \otimes (I_T - X^{\theta}(X^{\theta\prime}X^{\theta})^{-1}X^{\theta\prime})$,
$\hat{b} = vec((X^{\theta\prime}X^{\theta})^{-1}X^{\theta\prime}Y$ and

$V = \Sigma \otimes (X^{\theta\prime}X^{\theta})^{-1}$.

Therefore, the likelihood function of the model is

$$L(b, \Sigma, \gamma, c) \propto |\Sigma|^{-T/2} exp\left\{-\frac{1}{2}[s^2 + (b - \hat{b})'V^{-1}(b - \hat{b})]\right\} \qquad \text{(A3.1.5)}$$

whose kernel, which is depends on *b* and the rest of parameters, has the familiar multivariate Normal form.

Step 2: Define the priors…

- To let data choose between linear and nonlinear models symmetrically, an Inverse-Wishart prior is specified for the variance-covariance matrix Σ.
- Need to calculate posterior model probabilities in order to compare across different models and, as the dimension of b changes across different model specifications, one should not use flat priors for b to avoid meaningless Bayes factors (Koop, 2003)

  ⇒ Use a weakly informative conditional proper prior for b: Normal with zero mean and covariance matrix $\underline{V} = \eta^{-1} I_{nk}$, where η is a shrinkage prior distributed Gamma with mean $\underline{\mu_\eta}$ (equal 5.6) and degrees of freedom $\underline{\nu_\eta}$ (0.25).

- Now, the identification problem when $\gamma = 0$ is tackled by setting its prior distribution as nearly non-informative as possible, then a Gamma distribution with mean $\underline{\mu_\gamma}$ (equal 2) and degree of freedom $\underline{\nu_\gamma}$ (equal 0.1).

- As for c, and to avoid just one regimen with few histories, we elicit the prior of c as uniformly distributed between the upper and lower limits of the middle 68% of the observed transition variables.

➢ Robustness exercises on the priors…

✓ Since the most sensitive one is the prior distribution for b, the parameters $\underline{\mu_\eta}$ and $\underline{\nu_\eta}$ were calibrated so that they yielded suitable acceptance rates of the Metropolis algorithm, as well as that the simulated PTs met the restriction $0 \leq PT_T \leq 100$ in most of the draws.

✓ We assigned $\underline{\nu_\eta}$ values consistent with an uninformative prior distribution, as recommended by Gefang (2012), since results were sensitive to their variations up to the order of 10^{-4}.

✓ The coefficients that characterize the prior distributions of the variance-covariance matrix Σ, the smoothing parameter γ, and the location parameter c fail to have great influence on the acceptance rates or the Pass-through estimates.

Step 3: Compute posterior distributions…

- The combination of equations (A3.1.3) and the priors yields the conditional distribution for Σ as the inverted Wishart with scale matrix $E'E$ and degrees of freedom T and the conditional posterior distribution for the vector b as normal with mean $\bar{b} = \bar{V}V^{-1}\hat{b}$ and variance $\bar{V} = (V^{-1} + \eta I_{nk})^{-1}$. Since no close form is obtained for c and γ, for these parameters we use the Metropolis within Gibbs strategy.

- The Gibbs sampling scheme is used to compute the outputs from the posteriors, as follows

1. Initialize $(b, \Sigma, \gamma, c, \eta) = (b^0, \Sigma^0, \gamma^0, c^0, n^0)$;
2. Draw $\Sigma/b, \gamma, c, \eta$ from $IW(E'E, T)$;
3. Draw $b/\Sigma, \gamma, c, \eta$ from $N(\bar{b}, \bar{V})$;
4. Draw $\gamma/b, \Sigma, c, \eta$ through a Metropolis-Hastings method;
5. Draw $c/b, \Sigma, \gamma, \eta$ from a uniform (c_min, c_max);
6. Draw $\eta/b, \Sigma, \gamma, c$ from $G(\overline{\mu_\eta}, \overline{v_\eta})$;
7. Repeat step 2 to 6 for a suitable number of replications, say B.

- To avoid the draws from Metropolis-Hastings simulator getting stuck in a local mode, we also tried different starting values for the sampler. Convergence diagnostic indicated that 10,000 effective draws were enough to attain convergence, after 1,500 burnings. The hyperparameters $\underline{\mu_\eta}$ and $\underline{\nu_\eta}$ were calibrated per each transition variable in order to get those acceptation rates.

How we estimated PT by Bayesian methods?

(Koop, 2003; González, Rincón y Rodríguez, 2010; Lo and Morley, 2013)

The generalized impulse response function (GIRF) is defined as the expected deviation caused by a shock on the model's predicted values. Formally, if

(A4.1) $$Y_t = A(L)Y_{t-1} + B(L)Y_{t-1}F(V_{t-d}\,;\gamma, c) + \boldsymbol{\mu}_t,$$

in the presence of a shock of magnitude s to the k^{th}-element of the perturbations vector $\boldsymbol{\mu}_t$, the result is:

(A4.2) $$G(j, s, W_{t-1}) = E\left[Y_{t+j}|\mu_{k,t} = s, W_{t-1}\right] - E\left[Y_{t+j}|\mu_{k,t} = 0, W_{t-1}\right],$$

where $W_{t\text{-}1}$ denotes the initial conditions (the history or state of the economy). Thus, $G(.)$ is the expected deviation of expected value of Y_{t+j} caused by a shock s from the expected value of Y_{t+j} conditional on the history at time t, W_{t-1}. Then, the PT on a τ horizon is calculated by means of the following procedure :

1. Choose randomly a point in the sample where the $V_{t\text{-}d} < Threshold$ is met. The number of these points will be written *N_lower*.

2. For this point, forecast the model for T periods ahead through simulation, while considering the respective history for the elements of vector $V_{t\text{-}d}$ and the observed values brought forward. This forecast is built by using the Bayesian estimates on each effective step of the Gibbs sampler. With that forecast we get $E[Y_{t+j}|\mu_{k,t} = 0, W_{t-1}]$ for $j = 0,1,..T$.

3. Simulate the model for T periods ahead considering the same history for the elements of vector $V_{t\text{-}d}$ from step 2, after subjecting the second element of V_t (corresponding to the devaluation) to a shock (add s in $j=0$ period). With that you get for $E[\mathbf{Y}_{t+j} \mid \mu_t = s, W_{t-1}]$ for $j = 0, 1, \ldots, T$. We considered different values of s.

4. Calculate $G(.)$ in accordance with (A4.2).

5. Compute the PT estimates by equation (12).

6. Return to step 1 each time, use the Gibbs sampler (following the steps stated above) and generate a new set of parameters.

⇒ There is a resulting total of *N* trajectories of the PT estimates, considering $V_{t-d} < Threshold$ as initial conditions.

- To study the $V_{t-d} > Threshold$ case, the procedure should be repeated. In the simulations presented, shocks were orthogonalized by the *Cholesky decomposition* method.

⇒ By drawing randomly from histories at each regimen and averaging across them, we obtain an estimate and then the median of the PT, which is conditional upon the current state of the economy.

✓ For each of the inflation series, we present two set of paths for *G*(.) and PT median estimates, that is, whether the transition variable exhibits a "high" or "low" regime.

✓ We report the estimated path of *G*(.) and PT when the shock to the exchange rate was a negative one or ten percent.