

Asymmetries and Non-linearities in the Exchange Rate Pass-Through to Inflation – Evidence for Peru*

Fernando J. Pérez Forero[†]

February 28, 2026

Abstract

This paper examines the impact of exchange rate variations on the consumer price inflation in Peru, i.e. the exchange rate pass-through effect to prices (ERPT), emphasizing the inherent non-linearities of this process, such as the differences between depreciations and appreciations, and also exploring the differences associated with the magnitude of the shocks. The ERPT is not necessarily constant over time, so it is necessary to identify the source of the temporal variation. This leads to the consideration of different models: i) A Linear Bayesian Structural VAR, ii) A non-linear censored SVAR, iii) A time varying coefficients SVAR with Stochastic Volatility, and iv) A Threshold Bayesian SVAR with volatility feedback. In all the models mentioned, an exchange rate shock is identified, and the dynamic effect that this has on measures of total inflation is examined. We find strong evidence of asymmetries and non-linearities in the ERPT, with a time varying effect that fluctuates between 0.1 and 0.3 over 12 months, but can be potentially higher in more uncertain and volatile episodes.

JEL Classification: C32, E31, F31

Key words: Exchange Rate Pass-Through, Inflation, Asymmetric effects, Non-linearities

*I would like to thank seminar participants at the BCRP for their helpful comments and suggestions. The views expressed are those of the author and do not necessarily reflect those of the Central Reserve Bank of Peru. All remaining errors are mine.

[†]Deputy Manager of Monetary Policy Design, Central Reserve Bank of Peru (BCRP), Jr. Santa Rosa 441, Lima 1, Perú; Email address: fernando.perez@bcrp.gob.pefernando.perez@bcrp.gob.pe

1 Introduction

The exchange rate pass-through effect to prices (ERPT) has always played a relevant role in the study of inflation dynamics, especially in emerging economies such as Peru, where there is a significant contribution from the prices of imported goods (imported inflation), particularly inputs for production. Thus, the evolution of the exchange rate over time is a crucial concern for economic agents (such as producer or retailer firms) that have the task of setting the price of finished products in soles (especially those with some market power), which will then be faced by final good consumers. The fluctuations in the exchange rate, measured as the price of the US dollar expressed in soles (S/ per USD), are positive (depreciation of the Peruvian sol) or negative (appreciation), and these can be of a small or large magnitude.

This paper examines the impact of exchange rate variations on the aforementioned prices, measured through changes in the consumer price index (inflation), emphasizing the inherent non-linearities of this process, such as the differences between depreciations and appreciations, and also exploring the differences associated with the magnitude of the shocks. Although there is empirical evidence of a small pass-through effect (ERPT) to prices in countries with floating exchange rate regimes, given the reduction of this effect over the last thirty years, it remains statistically significant in most cases.

Previous evidence (Peru): [Winkelried \(2003\)](#), [Miller \(2003\)](#), [Maertens Odría *et al.* \(2012\)](#), [Winkelried \(2013\)](#), [Pérez Forero and Vega \(2016\)](#), [Rodríguez *et al.* \(2024\)](#) among others. Evidence from advanced and other emerging economies: [Cheikh \(2012\)](#), [Delatte and López-Villavicencio \(2012\)](#), [Shintani *et al.* \(2013\)](#), [Caselli and Roitman \(2019\)](#), [Jaramillo Rodríguez *et al.* \(2019\)](#), [Carrière-Swallow *et al.* \(2025\)](#) among others.

Indeed, the ERPT is not necessarily constant over time, so it is necessary to identify the source of the temporal variation. This leads to the consideration of different non-linear models, with the aim of identifying and capturing the mechanisms mentioned above. For that reason, this paper explores the presence of different sources of non-linearities in the ERPT using four models for the sample is 1993-2025:

- Model 1: A Linear Bayesian Structural VAR.
- Model 2: A non-linear censored SVAR used in [Pérez Forero and Vega \(2016\)](#).
- Model 3: A time varying coefficients SVAR with Stochastic Volatility ([Cogley and Sargent, 2005](#); [Primiceri, 2005](#)) using the version of [Canova and Pérez Forero \(2015\)](#).
- Model 4: A Threshold Bayesian SVAR with volatility feedback ([Alessandri and Mumtaz, 2019](#)) using the version of [Canova and Perez Forero \(2024\)](#).

The specified models allow exploring different non-linearities, such as permanent changes in parameters, and where it is also possible to differentiate between positive and negative shocks, and between small and large shocks. Furthermore, to complete the empirical exercise, a linear model is considered as a basis for comparison. In all the models mentioned, an exchange rate shock is identified, and the dynamic effect that this has on measures of total inflation is examined, particularly after 3, 6, 12 and 24 months after this shock occurred. We find strong evidence of asymmetries and non-linearities in the ERPT, with a time varying effect that fluctuates between 0.1 and 0.3 over 12 months, but can be potentially higher in more uncertain and volatile episodes.

The document is organized as follows: section 2 presents the models used in the empirical analysis, section 3 describes the data used for each model and the experiment design, section 4 discusses the main results, and section 5 concludes.

2 The Models used in the Empirical Analysis

2.1 Model 1 (M1) : A Linear Bayesian Vector Autorregressive (BVAR) Model

The first model to consider is a standard Bayesian Vector Autorregressive (BVAR) model with $p \geq 1$ lags:

$$y_t = c + \sum_{k=1}^p B_k y_{t-k} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \Omega) \quad (1)$$

where y_t is a $N \times 1$ vector of macroeconomic and financial variables properly detrended, and we have data for $t = 1, \dots, T$ periods. The error term ε_t is normally distributed with zero mean and covariance matrix Ω that is $N \times N$. In addition, c is a $N \times 1$ column vector and B_k are $N \times N$ matrices.

2.2 Model 2: A Non-Linear Censored Vector Autorregressive Model

In this case we estimate the expression following [Pérez Forero and Vega \(2016\)](#)

$$y_t = c + B_1^F \mathbf{F}(y_{t-1}) B_2^F \mathbf{F}(y_{t-2}) + \dots + B_p^F \mathbf{F}(y_{t-p}) + \varepsilon_t \quad (2)$$

where c is a $N \times 1$ column vector and B_k^F are $N \times N$ matrices. Naturally, the exclusion of the linear terms generates a potential source for the omitted variable bias. On the other hand, the cost in terms of degrees of freedom implies that the estimation of the complete model might be either unfeasible or highly unstable. Furthermore, consider the nonlinear function

$$\mathbf{F}(y_t) = \begin{cases} y_t, & \text{if } \Delta ER_t > 0 \\ y_t^* & \text{otherwise} \end{cases} \quad (3)$$

where y_t^* has $\Delta ER_t = 0$ (the YoY variation in the exchange rate) and keeps the other elements of y_t unchanged. That is, we include a censored variable in our VAR model. The use of censored variables in VAR models is not new, it comes from the oil-prices-shocks literature, see [Hamilton \(2010\)](#) and [Kilian and Vigfusson \(2011\)](#). We take this lead and present the estimation results below. However, we consider separately the cases of positive ($\Delta ER_t > 0$) and negative ($\Delta ER_t \leq 0$) changes in the exchange rate (depreciation and appreciation, respectively), but we include the same information for the remaining variables.

2.3 Model 3: A Time-Varying Parameter BVAR Model with Stochastic Volatility

Consider now the extended BVAR model named the Time-Varying Bayesian VAR(p) model with Stochastic Volatility (TVP-BVAR-SV):

$$y_t = c_t + B_{1,t}y_{t-1} + \dots + B_{p,t}y_{t-p} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \Omega_t) \quad (4)$$

where the vector y_t is the same as before, c_t a $N \times 1$ is a vector of time varying intercepts, $B_{i,t}$ are $N \times N$ matrices of time varying parameters for each lag $i = 1, \dots, p$. The error term ε_t is a normally distributed vector with zero mean and a time varying covariance matrix Ω_t such that $\Omega_t = A_t^{-1}\Sigma_t^2(A_t^{-1})'$.

Orthogonalized structural shocks are given by $u_t \sim N(0, I_N)$ such that:

$$\varepsilon_t = P_t u_t = A_t^{-1} \Sigma_t u_t \quad (5)$$

which means that P_t is a time-varying identification matrix, and also the diagonal matrix of structural variances is given by $\Sigma_t = \text{diag}(\sigma_t)$, where σ_t is a column vector containing the time-varying standard deviations of structural shocks. Time variation in parameter blocks is *a priori* assumed to be as random walks, so that:

$$\beta_t = \beta_{t-1} + v_t \quad (6)$$

$$\alpha_t = \alpha_{t-1} + \zeta_t \quad (7)$$

$$\log(\sigma_t) = \log(\sigma_{t-1}) + \eta_t \quad (8)$$

with

$$V = \text{Var} \left(\begin{bmatrix} \varepsilon_t \\ v_t \\ \zeta_t \\ \eta_t \end{bmatrix} \right) = \begin{bmatrix} I & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & W \end{bmatrix} \quad (9)$$

All matrices Q , S and W are positive definite. Bayesian Time varying parameter estimation and the identification of structural shocks is performed in line with the recent literature (see

(Cogley and Sargent (2005), Primiceri (2005), Canova and Pérez Forero (2015)), among others. That is, the parameter set Θ contains $\Theta = \{\beta^T, \alpha^T, \sigma^T, V\}$, where the time-varying parameters $\{\beta^T, \alpha^T\}$ are estimated through the Kalman Filter-Smoother following Carter and Kohn (1994), and the stochastic volatility component σ^T is estimated following Kim *et al.* (1998). Finally, V follows an Inverse-Wishart distribution. Given the estimated parameters, we can now compute the time varying impulse responses according to:

$$\frac{\partial y_{t+h}}{\partial u_t} = \Phi_{h,t} = \Psi_{h,t} P_t, \quad h = 0, 1, \dots, \bar{H} \quad (10)$$

2.4 Model 4: A Threshold BVAR with volatility feedback

Consider the extended version of the BVAR presented in the previous subsection. In this opportunity we specify the following two-regime Vector Autoregressive model (Threshold-BVAR), which closely follows Alessandri and Mumtaz (2019):

$$y_t = \left(c_1 + \sum_{j=1}^p \beta_{1,j} y_{t-j} + \sum_{j=0}^J \gamma_{1,j} \lambda_{t-j} + \Omega_{1t}^{1/2} \varepsilon_t \right) \tilde{S}_t + \left(c_2 + \sum_{j=1}^p \beta_{2,j} y_{t-j} + \sum_{j=0}^J \gamma_{2,j} \lambda_{t-j} + \Omega_{2t}^{1/2} \varepsilon_t \right) (1 - \tilde{S}_t) \quad (11)$$

where the vector of variables y_t is the same as in the previous models, and where the shocks are normally distributed, i.e. $e_t \sim i.i.d.N(0, I_{dim(y)})$.

The binary regime indicator \tilde{S}_t is defined by

$$\tilde{S}_t = 1 \iff \Delta ER_{t-d} \leq Z^* \quad (12)$$

and where both the delay d (which follows a discrete distribution $d = 1, \dots, d^*$) and the threshold Z^* are unknown parameters that need to be estimated.

The covariance matrix for the error term $\Omega_{it}^{1/2} e_t$ for each regime $i = 1, 2$ are as follows:

$$\Omega_{1t} = A_1^{-1} \Sigma_t A_1^{-1'} \quad (13)$$

$$\Omega_{2t} = A_2^{-1} \Sigma_t A_2^{-1'} \quad (14)$$

with A_i as a lower triangular matrix and Σ_t as a matrix defined by:

$$\Sigma_t = \exp(\lambda_t) \times S \quad (15)$$

with S being a diagonal matrix that captures the constant heteroskedasticity:

$$S = \begin{bmatrix} s_1 & 0 & \dots & 0 \\ 0 & s_2 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & s_{\dim(y)} \end{bmatrix} \quad (16)$$

with $s_j > 0$ for $j = 1, \dots, \dim(y)$. The matrix A_i is lower triangular with the main diagonal governed by ones and free parameters below the main diagonal, i.e.

$$A_i = \begin{bmatrix} 1 & 0 & \dots & 0 \\ \alpha_{1,i} & 1 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ \alpha_{k,i} & \alpha_{k+1,i} & \dots & 1 \end{bmatrix}. \quad (17)$$

In this context, recall also that $\text{vec}(A_i) = S_A \alpha_i + s_A$ (Amisano and Giannini, 1997), with S_A and s_A are matrices governed by 0s and 1s. The latter is a useful transformation in order to sample the full parameter vector α (Canova and Pérez Forero, 2015).

Finally, log-volatility λ_t enters both in mean (with lags) and also in the covariance matrix Ω_{it} . The log-volatility component can be represented as a stationary $AR(1)$ process with drift:

$$\lambda_t = \mu + F(\lambda_{t-1} - \mu) + \eta_t \quad (18)$$

with $0 < F < 1$ and $\eta_t \sim i.i.d.N(0, Q)$.

In this case the parameter space Θ is such that $\Theta = \{\beta, \gamma, \alpha, \lambda^T, S, \mu, F, Q\}$ plus the variances of the transition equations.

For the case of this model, in order to capture the asymmetries and non-linearities, impulse response functions should be computed as the difference of two forecasts such that:

$$\frac{\partial y_{t+h}}{\partial u_t} = E(y_{t+h} | \Theta, \delta) - E(y_{t+h} | \Theta), \quad h = 0, 1, \dots, \bar{H} \quad (19)$$

Notice that in the threshold model the shock could cause a regime switch. Therefore, in this case is even more important to consider these two forecasts instead of a static power matrix formula. In this context, we consider the year-to-year depreciation rate as the threshold variable, so that it is important to also take a look to its historical distribution for the period under analysis. The histogram is depicted in Figure 1, which reflects an asymmetric distribution, suggests that there is room for differences between positive and negative shocks, and also for studying differences between small and large shocks. Moreover, although the modal value is around zero, the threshold parameter Z^* needs to be estimated in order to quantify the mentioned non-linearities.

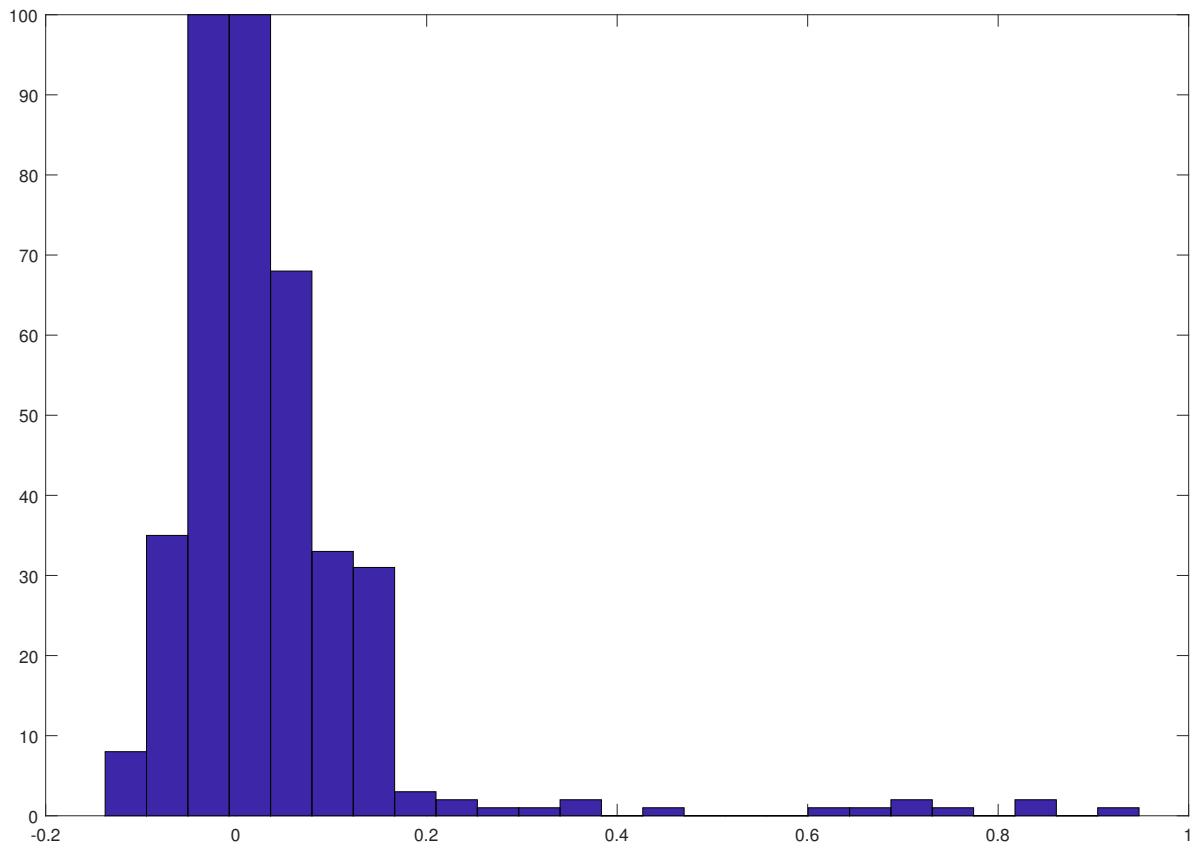


Figure 1: **Peru**: Year-to-Year PEN Depreciation Histogram (1993-2025)

3 Data description and Experiment Design

Data is taken from the website of the Central Reserve Bank of Peru (BCRP) and from the National Institute of Statistics (INEI) for the period of January 1993 to September 2025. All variables were expressed in year-to-year percent changes (see Figure 2). These variables are: i) The Real Exchange Rate Depreciation, ii) The Gross Domestic Product Growth, iii) The Nominal Exchange Rate (PEN per USD) Depreciation, iv) The Inflation of Imported Goods, v) The Producer Prices Inflation, and vi) The Consumer Prices Inflation. All these variables were obtained from the BCRP's Website (BCRPData).

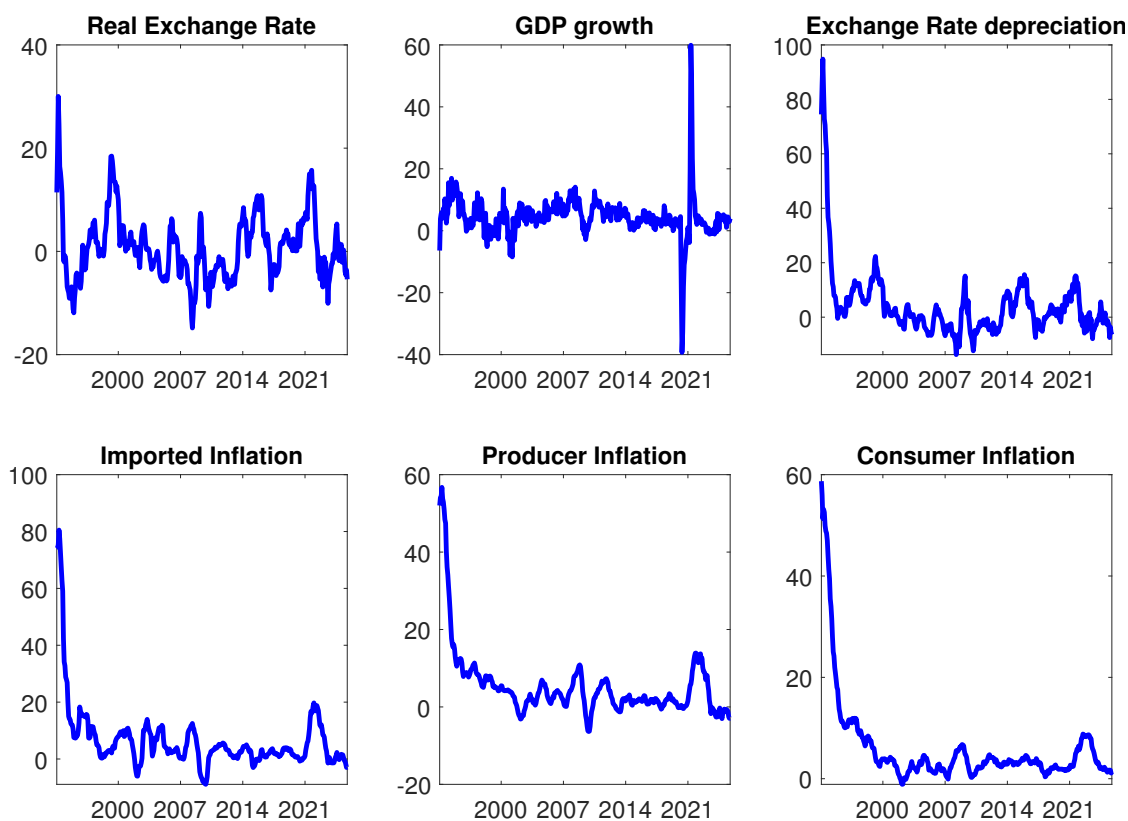


Figure 2: Peruvian Macroeconomic Data - 1993-2025

For comparison purposes, we use the same data set depicted in Figure 2 for each of the presented models. In each case we also compute the impulse responses after an orthogonalized exchange rate shock using the Cholesky factorization and the same ordering where the three inflation rates react contemporaneously to the shock. That is, orthogonalized structural shocks are given

by $u_t \sim N(0, I_N)$, and can be obtained through a matrix P such that $\varepsilon_t = Pu_t$ and $\Omega = PP'$. Given the identified structural shocks u_t and the estimated parameters Θ , then it is possible to simulate the posterior distribution of the dynamic multipliers, i.e. the well known impulse response functions, such that:

$$\frac{\partial y_{t+h}}{\partial u_t} = \Phi_h = \Psi_h P, \quad h = 0, 1, \dots, \bar{H} \quad (20)$$

Notice that in models M2, M3 and M4 both matrices P and Φ_h are not constant over time. After that, the pass-through effect of shock k to variable l after h periods is defined as ([Winkelried, 2013](#)):

$$PT_{l,k,h} = \frac{\mathbf{e}'_l \bar{\Psi}_h \mathbf{e}_k}{\mathbf{e}'_k \bar{\Psi}_h \mathbf{e}_k} \quad (21)$$

where $\bar{\Psi}_h = \sum_{j=0}^h \Phi_j$ is the cumulative impulse responses matrix, and \mathbf{e}_k is a N -dimensional column vector full of zeros with the exception of the entry k .

4 Results

Model 1: First, the linear model estimates that the pass-through effect of the exchange rate to prices, measured as the ratio between the cumulative impulse response functions of total inflation and the exchange rate after the shock, is 0.12, 0.16, 0.22 and 0.30 for the 3, 6, 12 and 24 month horizons, respectively. These values represent the average effect across the sample considered, between 1993 and 2025, which is statistically significant. However, if different types of nonlinearities are considered, these results may vary depending on the state variable to which this dynamic effect is conditioned.

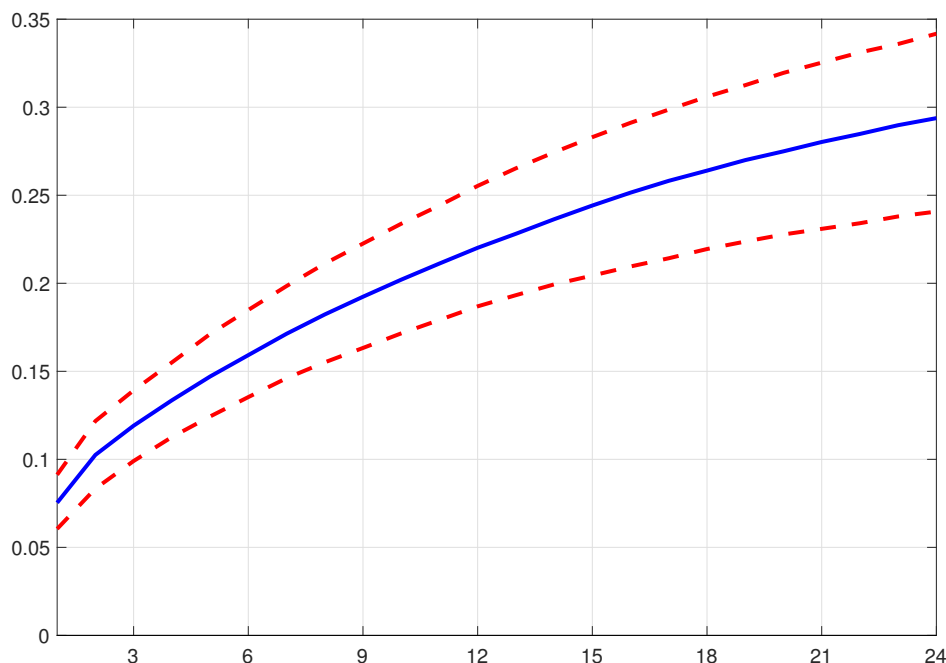


Figure 3: ERPT - Linear Model (M1), median value and 68% bands

Model 2: The results of model 2, which differentiates between positive shocks (depreciation) and negative shocks (appreciation), show that the effect on total inflation is only significant in the case of a depreciation, with an approximate value of 0.23 over the one-year horizon. In other words, in the case of an appreciation, it is not possible to rule out a zero (null) effect of the exchange rate on inflation. This is an initial indication or piece of evidence that points to the existence of asymmetric and non-linear effects. As explored by [Pérez Forero and Vega \(2016\)](#),

this asymmetry would be associated with the market power of price-setting firms, which adjust prices upward when their costs rise, but do not do the same when those costs fall.

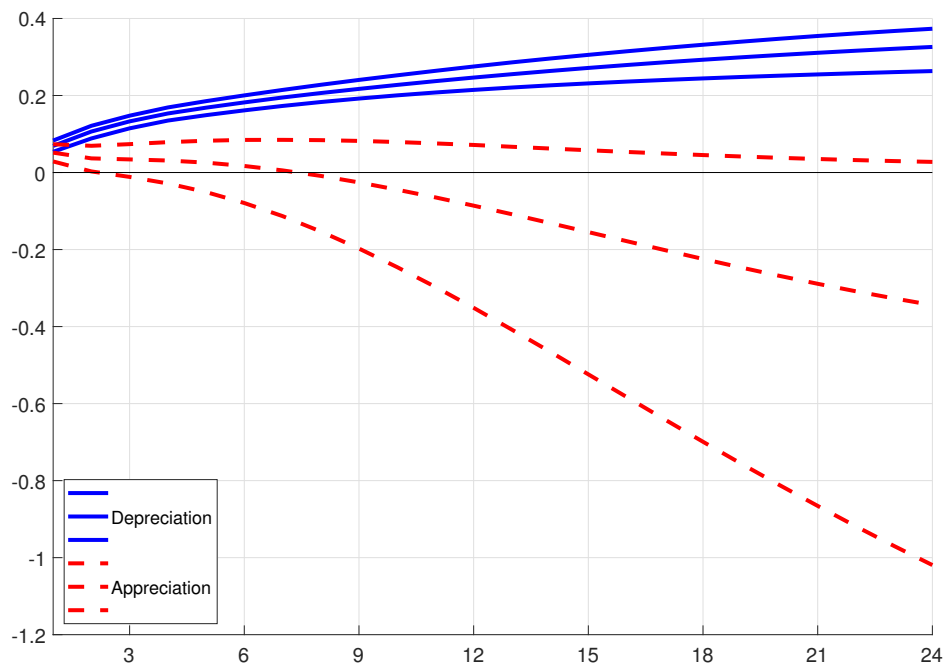


Figure 4: ERPT - Non-Linear Censored Model (M2), median value and 68% bands

Model 3: In the case of model 3, which allows us to observe the continuous evolution of this effect over time, it can be seen in Figure 5 that for total inflation, this effect was much greater in the 1990s decade (even greater than 0.3 over 12 months), and the latter occurred when the economy had a high degree of dollarization (above 80%). This effect decreased sharply in the following two decades (during which greater appreciation was recorded, especially during the commodities boom), reaching a value of around 0.1. However, after the episode of global inflation between 2021 and 2023, with greater domestic political uncertainty from 2021 onwards, which was accompanied by a rise in the exchange rate (depreciation), this effect raised sharply, thus settling again at around 0.2 over 12 months. The documented changes are statistically significant according to the error bands for each horizon¹.

¹See the evolution over 1993-2025 for every horizon in Figure A.7.

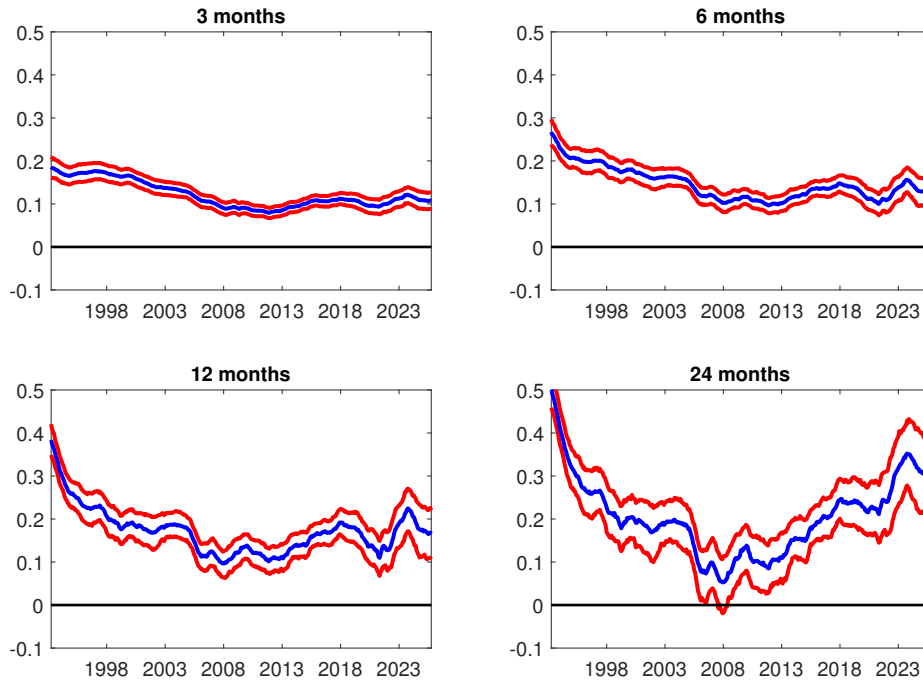


Figure 5: ERPT 1993-2025 - TVC-SVAR-SV Model (M3), median value and 68% bands

Model 4: Finally, model 4 allows us to explore different types of asymmetries in these effects. The model estimates a year-to-year depreciation threshold of around 5.7%, which allows us to differentiate the economic regimes. As a consequence, it is possible to differentiate the effects depending on whether the shock occurred in a low depreciation (or even appreciation) environment, or in a high depreciation environment. Likewise, it is possible to differentiate between a small and a large shocks, and between positive and a negative shocks (appreciation) as in model M2. In particular, according to Figure 6 the greatest differences can be seen in cases of positive and negative shocks, especially for those below the estimated threshold, even for small shocks.

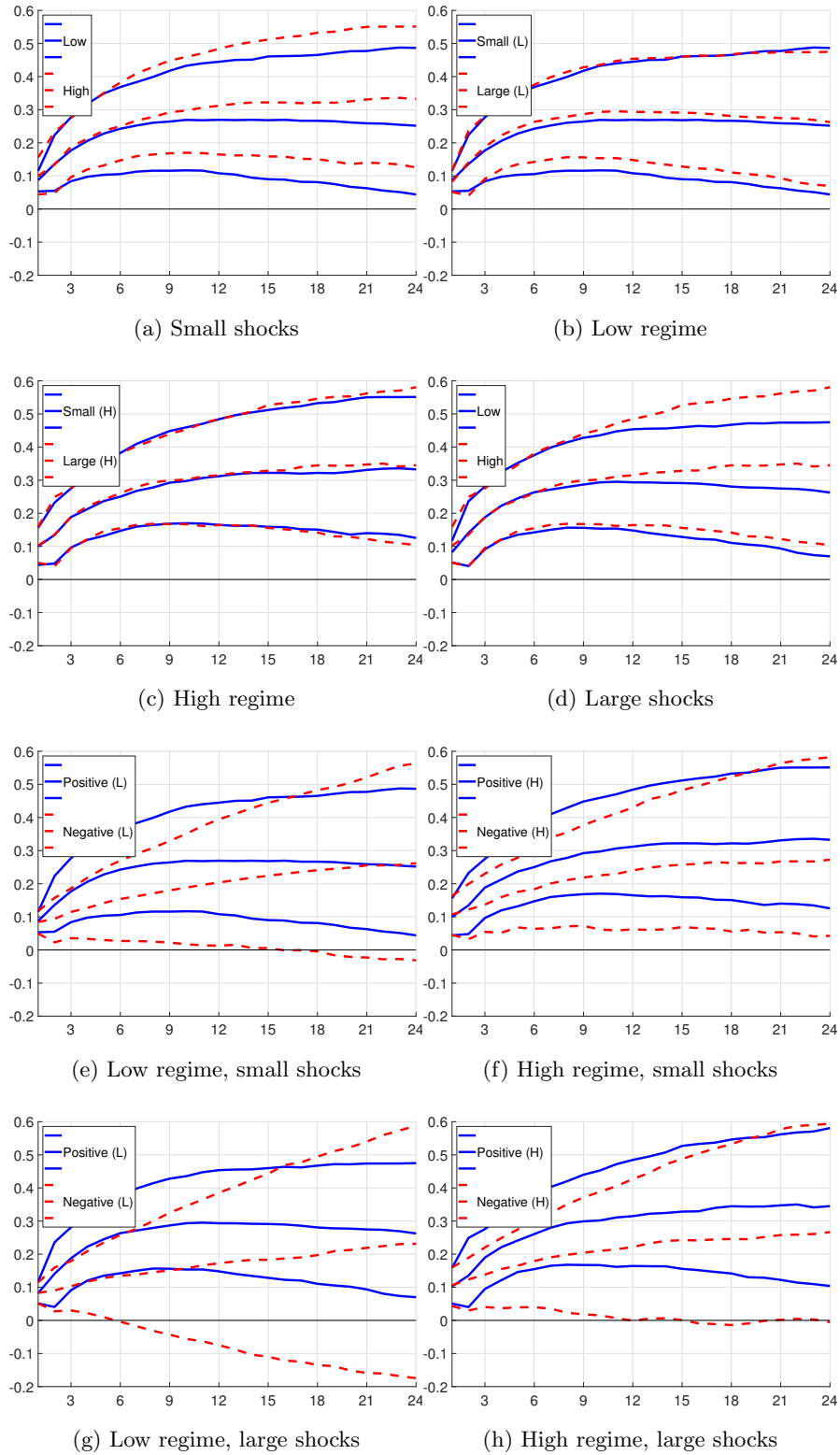


Figure 6: ERPT - Threshold BVAR Model with SV (M4), median value and 68% bands

5 Concluding Remarks

The pass-through effect of the exchange rate to inflation has been re-estimated and documented for the Peruvian economy. The estimated ERPT presents various asymmetries and non-linearities, which continues to be significant today, although it registers a lower magnitude compared to the 1990s. We also found that the ERPT has been lower in episodes of appreciation, corroborating the idea that there exists a considerable asymmetry between depreciation and appreciation shocks. However, in the case of the last episode between 2021 and 2024 it would have recovered its previous level as a result of the large depreciation of the sol against the dollar in those years. There is a large research agenda related with the microfoundations that could explain these asymmetries and non-linearities.

A Additional Figures

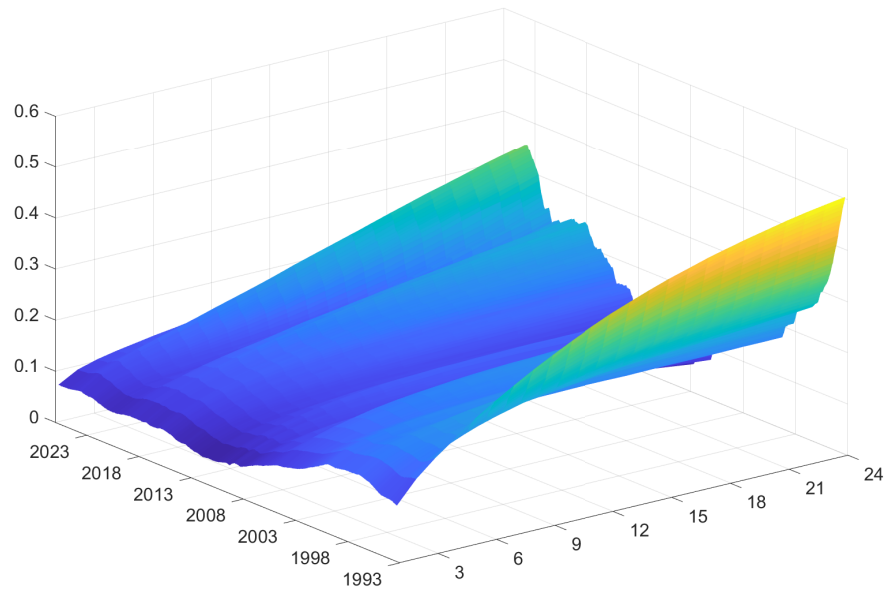


Figure A.7: ERPT 1993-2025 - TVC-SVAR-SV Model (M3) - Median value

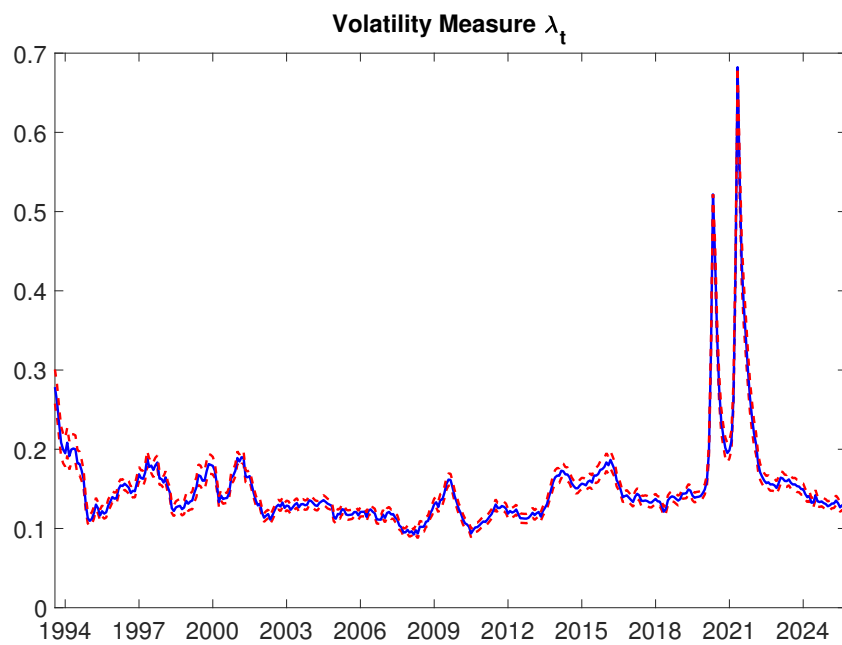


Figure A.8: Estimated volatility (M4)

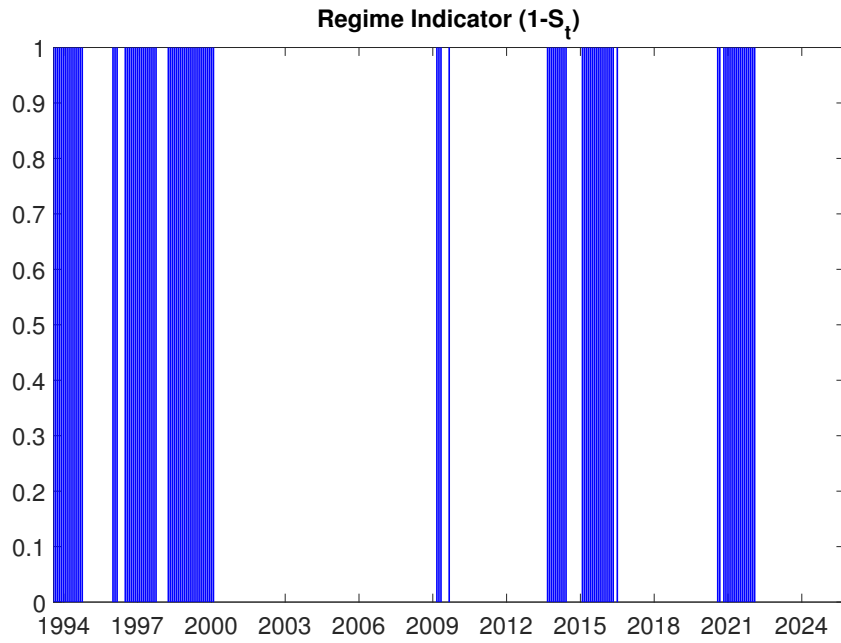


Figure A.9: Estimated regimes (M4)

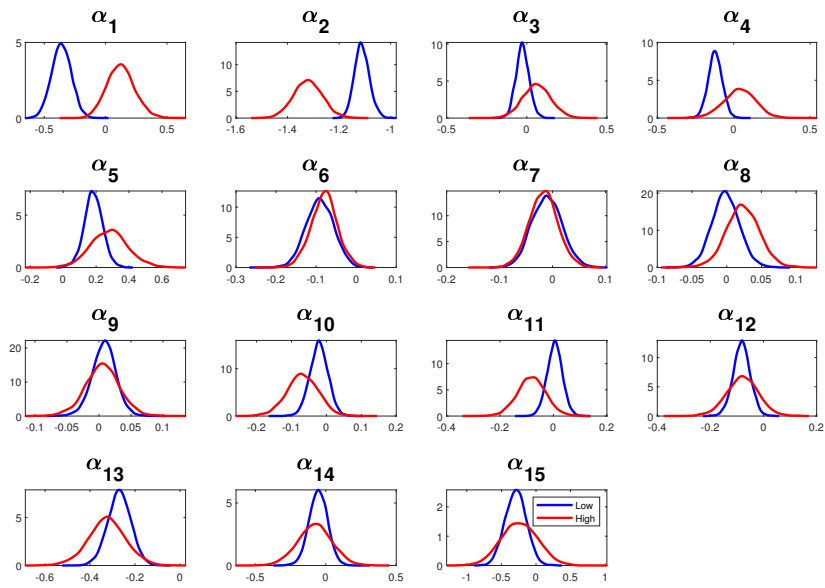


Figure A.10: Contemporaneous Coefficients' Matrix for Two Regimes (M4)

References

- ALESSANDRI, P. and MUMTAZ, H. (2019). Financial regimes and uncertainty shocks. *Journal of Monetary Economics*, **101**, 31–46.
- AMISANO, G. and GIANNINI, C. (1997). *Topics in Structural VAR Econometrics*. Springer, 2nd edn.
- CANOVA, F. and PEREZ FORERO, F. (2024). *Does the Transmission of Monetary Policy Shocks Change when Inflation is High?* CEPR Discussion Papers 18993, C.E.P.R. Discussion Papers.
- and PÉREZ FORERO, F. J. (2015). Estimating overidentified, nonrecursive, time-varying coefficients structural vector autoregressions. *Quantitative Economics*, **6**, 359–384.
- CARRIÈRE-SWALLOW, Y., FIRAT, M., FURCERI, D. and JIMÉNEZ, D. (2025). State-dependent exchange rate pass-through. *Oxford Bulletin of Economics and Statistics*, **87** (3), 539–561.
- CARTER, C. K. and KOHN, R. (1994). On gibbs sampling for state space models. *Biometrika*, **81** (3), 541–553.
- CASELLI, F. G. and ROITMAN, A. (2019). Nonlinear exchange-rate pass-through in emerging markets. *International Finance*, **22** (3), 279–306.
- CHEIKH, N. B. (2012). Non-linearities in exchange rate pass-through: Evidence from smooth transition models. *Economics Bulletin*, **32** (3), 2530–2545.
- COGLEY, T. and SARGENT, T. J. (2005). Drifts and volatilities: Monetary policies and outcomes in the post WWII u.s. *Review of Economic Dynamics*, **8** (2), 262–302.
- DELATTE, A. and LÓPEZ-VILLAVICENCIO, A. (2012). Asymmetric exchange rate pass-through: Evidence from major countries. *Journal of Macroeconomics*, **34** (3), 833–844.
- HAMILTON, J. D. (2010). Nonlinearities and the macroeconomic effects of oil prices, nBER Working Paper 16186.

- JARAMILLO RODRÍGUEZ, J., PECH MORENO, L., RAMÍREZ, C. and SANCHEZ-AMADOR, D. (2019). Nonlinear exchange rate pass-through in Mexico, Banco de México Working Papers No. 2019-16.
- KILIAN, L. and VIGFUSSON, R. J. (2011). Are the responses of the U.S. economy asymmetric in energy price increases and decreases? *Quantitative Economics*, **2**, 419–453.
- KIM, S., SHEPHARD, N. and CHIB, S. (1998). Stochastic volatility: Likelihood inference and comparison with ARCH models. *The Review of Economic Studies*, **65** (3), 361–393.
- MAERTENS ODRÍA, L. R., CASTILLO, P. and RODRÍGUEZ, G. (2012). Does the exchange rate pass-through into prices change when inflation targeting is adopted? The Peruvian case study between 1994 and 2007. *Journal of Macroeconomics*, **34**, 1154–1166.
- MILLER, S. (2003). Estimación del pass-through del tipo de cambio a precios: 1995-2002. *Revista de Estudios Económicos*, **10**.
- PÉREZ FORERO, F. and VEGA, M. (2016). Asymmetric exchange rate pass-through: Evidence from nonlinear SVARs, working Papers 2016-63, Peruvian Economic Association.
- PRIMICERI, G. (2005). Time varying structural vector autoregressions and monetary policy. *Review of Economic Studies*, **72**, 821–852.
- RODRIGUEZ, G., CASTILLO B., P., CALERO, R., SALCEDO CISNEROS, R. and ATATURIMA ARELLANO, M. (2024). Evolution of the exchange rate pass-through into prices in Peru: An empirical application using TVP-VAR-SV models. *Journal of International Money and Finance*, **142**, 103023.
- SHINTANI, M., TERADA-HAGIWARA, A. and YABU, T. (2013). Exchange rate pass-through and inflation: A nonlinear time series analysis. *Journal of International Money and Finance*, **32**, 512–527.
- WINKELRIED, D. (2003). ¿es asimétrico el pass-through en el Perú?: Un análisis agregado. *Revista de Estudios Económicos*, **10**.

— (2013). Exchange rate pass-through and inflation targeting in peru. *Empirical Economics*.