Asymmetries of the Exchange Rate Pass-through to Domestic Prices in Costa Rica during the Exchange Rate Flexibility Period

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Abstract

This article analyses the exchange rate pass-through to domestic prices in Costa Rica during the current exchange rate flexibility period and tests whether there is evidence of asymmetry. To this end, we estimate structural distributed lag models that encompass symmetric and asymmetric data generating process in line with Kilian and Vigfusson (2011). We found evidence of sign asymmetry in the bivariate relationship between inflation and exchange rate and when controlling for interest rate differential and output gap.

Keywords: pass-through asymmetry, exchange rate, exchange rate flexibility.

JEL *classification: E31, E37, E58.*

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1. INTRODUCTION

An environment of free capital movement under an inflation targeting regime demands the monetary authority adopt exchange rate flexibility. Together with inflation commitments, said regime requires appropriate knowledge of the magnitude and time with which exchange rate (ER) movements are transmitted to domestic prices, i. e., the exchange rate pass-through (ERPT). Properly understanding ERPT requires determining whether it exhibits sign or magnitude asymmetries. Abstracting this type of nonlinearities can result in the estimation of pass-through levels different from those actually occurring.

This article analyzes ERPT to prices in Costa Rica from March 2006 to April 2017 and tests the hypothesis that it presents asymmetries. We estimate structural distributed lag models that encompass symmetric and asymmetric data generating process in line with Kilian and Vigfusson (2011), employing data exclusively for the exchange rate flexibility period.

The importance of knowing the magnitude of the ERPT to prices lies in the predictive capacity of such changes and the time it takes the economy to transmit them to domestic prices. Besides determining the magnitude and lag with which they appear, it is important to establish the presence of sign and magnitude asymmetries in said phenomenon. Positive asymmetry means domestic prices react more to domestic currency depreciations, while negative asymmetry would imply a stronger response to appreciations. On the other hand, if the ERPT shows magnitude asymmetries, the response of domestic prices to ER shocks would depend on the size of such shocks.

The amount of ERPT can be related to many factors, including an economy's level of openness, the organizational structure of import sectors, the level and volatility of inflation, the level of flexibility in the exchange rate regime, etc. The exchange rate regime in Costa Rica varied significantly towards the end of 2006 when the fixed rate regime (crawling peg exchange rate) was replaced by increasingly more flexible regimes. In light of the fact that the aforementioned factors upon which the magnitude of the ERPT could depend are not fixed over time, it is reasonable to propose a hypothesis that there are asymmetries in said phenomenon.

Although the ERPT in Costa Rica has been studied previously, in most cases the models employed have assumed that the magnitude of the ERPT is constant over time. Moreover, the data samples employed always include observations from two very different exchange rate regimes. Hence, quantifying and verifying the presence of asymmetries only using data extracted from the exchange rate flexibility period (last 11 years) is relevant given that it could provide estimates for the phenomenon more in line with the current economic situation. Furthermore, before 2006, when the period of exchange rate flexibility began, the exchange rate regime in force (crawling peg) fostered very few episodes of nominal appreciation, meaning the data were not optimal for studying sign asymmetries in the ERPT. Since the end of 2006 there has been a larger degree of freedom in exchange rate movements, there is a relatively greater number of appreciation periods and, therefore, more data for studying asymmetries.

The paper is organized as follows: after this introduction, Section 2 describes the most important background literature and the evolution of methodologies employed in its analysis. Section 3 details the conceptual framework of the methodological approximating used for testing the proposed hypothesis. Next, Section 4 examines methodological aspects, the data and the econometric approach used. Section 5 presents the main results and, finally, Section 6 lists the most important conclusions.

2. BACKGROUND

Empirical literature on the ERPT generally presents more evidence of symmetry for industrialized countries (see Taylor, 2000; Goldfang and Werlang, 2000; Choudhri and Hakamura, 2001; and Engel, 2002), while for emerging economies the linearity assumption does not seem appropriate [see Winkelried (2003), Wang and Guo (2016) and Mendoza (2012)].

Among recent studies that make flexible the linearity assumption, Przystupa and Wróbel (2011) analyze the case of Poland. The authors observe that pass-through varies according to the stage of the business cycle, identifying it as smaller during contractionary periods and larger during expansions. Moreover, for ER fluctuations below a certain magnitude (2%), the pass-through differs from the other observations. They also find that the ERPT is greater during periods of low volatility (understood as a standard deviation of the daily variation below 4.32%).

Pérez and Vega (2016), meanwhile, find evidence for sign asymmetry in the ERPT of Peru. The authors also provide evidence of a different behavior for each exchange rate regime in the period studied.

Lariau, El Said and Takebe (2016) review evidence for the cases of Angola and Nigeria. They find that the ERPT is higher over the long term for the less diversified more import-dependent economy (Angola). They also demonstrate that dedollarization in Angola led to a decline in the ERPT. Furthermore, over the short term the ERPT is not statistically different from zero, which according to the authors reveals distortions caused by protectionism afforded to certain industries. For Nigeria, they show that the food and drinks component of the CPI is not affected by changes on the ER given the large share of domestic production in that index grouping. The research reflects the importance of countries' domestic consumption structure for determining the ERPT. Angola and Nigeria are similar countries with regard to their dependence on crude oil exports and they also implement similar actions to offset possible price shocks in that commodity; despite this, the results reveal different ERPTs.

The Banco Central de Costa Rica has made significant research efforts to improve understanding of the ERPT. Such endeavors span from the fledgling estimations of León, Morera, and Ramos (2001) and León, Laverde, and Durán (2002), up to more recent papers such as those of Rodríguez (2009), Esquivel and Gómez (2010) and Orane (2016). Most of those studies employ the implicit assumption of linearity in the ERPT, estimating it with VAR models. The exception is Esquivel and Gómez (2010), who address the matter using an alternative methodology (LSTVAR) that considers the possibility of some variables inducing sign or magnitude asymmetries in the pass-through. The authors find that the lagged variation of oil prices is the variable most likely to induce asymmetries. Nevertheless, they conclude that there is little evidence of statistically significant sign or magnitude asymmetries.

Meanwhile, Esquivel and Gómez (2010) use a data sample between January 1991 and June 2009. In Costa Rica, the fixed exchange rate regime (crawling peg) was substituted in October 2006 by a flexible regime (exchange rate band), which was subsequently replaced by a managed float regime in February 2015. In view of this, there are at least three events to justify and make important a new study on the ERPT and its possible asymmetries.

First, the observations used in Esquivel and Gómez (2010) combine some (the majority) extracted from the period of fixed ER with others from the flexible phase. It should be taken into account that the crawling peg regime implied a systematic bias towards positive variations in the nominal ER (colones per US dollar). Only 15% of the observations used in that study are not affected by said bias. At present, the abundance of observations for the period after adoption of the flexible ER regime allows for considering estimations of the pass-through and statistical tests for asymmetry that use a sample with observations exclusively from the flexible regime.

Second, there is a large body of documented evidence that the series of variation of the CPI in Costa Rica underwent a structural change during 2009. It is possible that said structural change has influenced the magnitude and characteristics of the ERPT. The data set used in the paper of 2010 evidently does not allow for capturing said phenomenon.

Finally, to provide additional robustness to the test for asymmetries in the ERPT, it is wise to apply alternative estimation methodologies. A traditional approach for measuring asymmetries uses censored VAR models. Applied to the topic of ERPT, the aforementioned method would imply estimating a VAR model where ER variations with a negative sign are censored from the sample and another where positive variations are censored. Subsequently, the impulse response (IR) functions of both models would be compared in order to conclude whether they are statistically different or not.

It is well documented in the literature on static models that censoring explanatory variables causes ordinary least square estimators to be biased, as described in Rigobon and Stoker (2009) or Greene (2003).

Although the bias observed in those procedures is clear when the data generating process (DGP) is symmetric, asymptotic bias continues even when the DGP is asymmetric. Just as stated by Kilian and Vigfusson (2011), only when the DGP is such that it does not exercise an impact on the dependent variable when the explanatory variable decreases can one guarantee that the censored linear model is not biased. In their study, those authors demonstrate that censored VAR models generate asymptotic biases and propose a structural model to prevent them. Their model encompasses symmetric and asymmetric data generating processes as special cases. Combined with the proposal of Lee, Ni and Ratti (1995), in which shocks should be rescaled by a volatility measure before performing an estimation of the pass-through, it is not only possible to diagnose the presence of sign and magnitude asymmetries, but also to determine whether the pass-through is smaller in periods of high volatility. Álvarez and Esquivel (2016) apply this method to assess the presence of asymmetries in the pass-through of commodity prices to domestic prices in Costa Rica.

In the original work of Kilian and Vigfusson (2011), the authors estimate the impact of energy price shocks on economic growth, proposing two statistical tests for applying to the hypothesis of symmetry in the response of growth. One of them is conducted on regression coefficients and is a variation of that proposed by Mork (1989) but with higher statistical power. The other is applied directly to the IR functions. The latter is based on the fact that, as postulated in Koop, Pesaran and Potter (1996), in nonlinear VAR models the magnitude of shocks can influence the dynamic response of the variables. Moreover, under this same context, the dynamic response of a variable can exhibit asymmetries even if the coefficients do not exhibit departures from symmetry.

In addition to this problem, traditional empirical literature on censored VAR models also has the disadvantage of ignoring that, by being nonlinear models, IR functions depend on the history of observations [see Koop, Pesaran, and Potter (1996), and Gallant, Rossi, and Tauchen (1993)]. IR functions in this type of models require a Monte Carlo simulation in order to include possible data histories and different sizes of shocks.

3. CONCEPTUAL FRAMEWORK

Kilian and Vigfusson (2011) show that when the DGP is not symmetric it cannot be represented as a bivariate VAR model for x_t^+ and y_t. A DGP where only positive shocks to x_t have an impact on y_t can be denoted with the following system:

1
$$\begin{aligned} x_t &= a_1 + \rho x_{t-1} + e_{1t}, \\ y_t &= a_2 + \gamma x_t^+ + e_{2t}. \end{aligned}$$

The contemporaneous effect on y_t of a positive shock to x_t in System 1 is given by γ. The impact in the subsequent period would be $\rho\gamma$, and then $\rho^2\gamma$, and so on successively thereafter. Thus, estimation of coefficients γ and ρ of Model 1 would be unbiased. By using a censored VAR model such as Model 2, estimation of ρ would be asymptotically biased despite the fact that the estimation of γ would be unbiased. This would be reflected in the IR function.

2
$$x_t^+ = a_1 + \rho x_{t-1}^+ + \epsilon_{1t},$$
$$y_t = a_2 + \gamma x_{t-1}^+ + \epsilon_{2t}.$$

The problem with System 2 is that it is not a true representation of the DGP. Use of a full structural model would avoid that drawback. Kilian and Vigfusson (2011) propose the following model:

3
$$x_t = a_1 x_{t-1} + a_2 y_{t-1} + \ldots + \epsilon_{1t},$$
$$y_t = \beta_1 x_t^+ + \beta_2 x_{t-1}^+ + \beta_3 y_{t-1} + \ldots + \epsilon_{2t}.$$

System 3 is a structural model where, unlike Model 2, negative shocks to x_t can affect the future path of y_t if such shocks eventually lead to positive shocks in the future path of x_t.

System 4 is the reduced form of 3. The IR functions of a structural model such as 3 cannot be identified from a Cholesky decomposition of the variance-covariance matrix and its reduced version because such a composition does not discriminate between positive and negative shocks. Hence, applying Cholesky in 4 to $Var\left[\epsilon_{1t}, u_{2t}\right]$ is not appropriate given that u_{2t} should only reflect positive shocks.

4
$$x_t = a_1 x_{t-1} + a_2 y_{t-1} + \ldots + \epsilon_{1t},$$
$$y_t = \beta_1 x_{t-1}^+ + \beta_2 y_{t-1} + \ldots + u_{2t},$$

where $u_{2t} = \beta_1 \epsilon_{1t} + \epsilon_{2t}$.

Additional technical details on the conceptual proposal and tests for the absence of asymptotic bias in Model 3 can be consulted in the paper referred to (Kilian and Vigfusson, 2011). The points summarized here motivate the use of the methodology proposed by those authors to verify the presence of asymmetries in the exchange rate pass-through.

4. METHODOLOGY

4.1 Estimation of Impulse Response Functions in Asymmetric Structural Models

We propose a structural model where the endogenous variables in an equation system are used to allow exchange rate shocks to have a varied impact on prices in an economy depending on whether the currency is appreciating or depreciating.

In an initial approach using a bivariate model, the structure would be written as follows:

5
$$\begin{aligned} x_t &= a_1 x_{t-1} + a_2 y_{t-1} + \ldots + \epsilon_{1t}, \\ y_t &= \beta_1 x_t^+ + \beta_2 x_{t-1}^+ + \beta_3 y_{t-1} + \ldots + \epsilon_{2t}, \end{aligned}$$

where

- x_t is the level or variation of the ER in period t.
- y_t is the level or variation of the CPI in period t.
- $x_t^+ = \begin{cases} x_t, \text{ si } x_t > 0 \\ 0, \text{ si } x_t \leq 0 \end{cases}.$

In contrast to a censored VAR, in which the endogenous variables correspond to x_t^+ and y_t, in the proposed Model 5 negative shocks to x_t can affect the future path of y_t if they eventually lead to positive shocks in the future path of x_t. The authors of the reference study demonstrate that the estimators of this model are asymptotically unbiased, unlike those obtained using censored VAR models, regardless of whether the DGP is symmetric or not.

According to different studies (see Gallant, Rossi, and Tauchen, 1993; and Koop, Pesaran, and Potter, 1996), in nonlinear models such as 5, the dynamic response of y_t could be magnified or reduced by the accumulated effect of previous shocks. Hence, IR functions should be estimated as an average of the impulse responses generated based on a data set that is both diverse and representative of initial conditions. We estimate IR functions following the sequence of steps shown below:

1) Random selection of a *history* $\left(\Omega_i\right)$ composed of consecutive p values of x_t and y_t.[1]

2) Given Ω_i, simulate two-time paths for H data after the last observation available for x and y. That is, for x we generate $\left[x_{t+1}, x_{t+2}, \ldots, x_{t+H}\right]$ and $\left[x^*_{t+1}, x^*_{t+2}, \ldots, x^*_{t+H}\right]$, while for y we generate $\left[y_{t+1}, y_{t+2}, \ldots, y_{t+H}\right]$ and $\left[y^*_{t+1}, y^*_{t+2}, \ldots, y^*_{t+H}\right]$. For the first paths of de x and y, as well as the second of y, stochastic disturbances $\left[\epsilon_{1t}, \epsilon_{1t+1}, \ldots, \epsilon_{1t+H}\right]$ and $\left[\epsilon_{2t}, \epsilon_{2t+1}, \ldots, \epsilon_{2t+H}\right]$ are randomly selected from their respective marginal empirical distributions. Furthermore, for the second sequence of x, the value $\left(\delta\right)$ is assigned to the first component of the sequence of disturbances, $\left(\epsilon_{1t} = \delta\right)$, while the rest of the sequence is randomly extracted from its marginal empirical distribution.

3) Random sequences of ϵ_{1t} and ϵ_{2t} can be treated as independent given that they are obtained from the marginal distribution generated by estimated structural Model 5.

4) We proceed to obtain the difference between two paths of y for $t=1, 2,\ldots, H$, defining each difference as y_i^δ, where $i=1, 2,\ldots, H$.

5) Steps 2 and 4 are repeated $\left(n_{boot}\right)$ times.

6) Steps 1 to 5 are repeated 1 to 5 $\left(n_{hist}\right)$ times. We, therefore, obtain a number $n_{hist} * n_{hist}$ for different series y_i^δ that are then averaged.

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[1] p corresponds to the number of lags used for each model estimated.

The result obtained from steps 2 to 5 is the response of y to a shock of size δ, over a horizon of H periods and conditional on Ω_i. Following the same nomenclature of Kilian and Vigfusson (2011), we can define this response as $I_y(\delta, H, \Omega_i)$. Repeating the exercise for all possible histories and averaging the responses, we obtain the response of y unconditional on Ω_i, that is, $I_y(\delta, H)$.

To more clearly differentiate the proposal of Kilian and Vigfusson (2011) regarding the traditional way of obtaining the IR functions, we define the response of y conditional on the historical paths of x and y (that is $x_{t-i} = y_{t-i} = 0$ for i=1, 2,...) as follows:

$$I_y(\delta, H, \underline{0}). \tag{6}$$

Relaxing the assumption of $x_{t-i} = y_{t-i} = 0$ and allowing a history (Ω_i) for x and y, besides inducing a shock of magnitude δ in the t-th observation of disturbance term ϵ_1, we can alternatively define the response:

$$I_y^*(\delta, H, \Omega_i) = E\left\{y_{t+h} \mid \Omega_i, \epsilon_{1t} = \delta, \left[\epsilon_{1t+j}\right]_{j=1}^{h}, \left[\epsilon_{2t+j}\right]_{j=0}^{h}\right\} - \\ -E\left\{y_{t+h} \mid \Omega_i, \left[\epsilon_{1t+j}\right]_{j=0}^{h}, \left[\epsilon_{2t+j}\right]_{j=0}^{h}\right\}. \tag{7}$$

As mentioned previously, by averaging 7 for all possible histories, we obtain the unconditional response in Ω_i, which corresponds to $I_y^*(\delta, H)$. The impulse response normally obtained in the literature corresponds to $I_y^*(\delta, H, \underline{0})$. This IR does not allow future shock dynamics (at least in disturbances) and does not condition history. In linear systems, this type of configuration for the calculations does not present any drawbacks. However, they do present them when computing IR in nonlinear systems: The response may not converge to zero even when the DGP is stationary (see Koop, Pesaran, and Potter, 1996). Moreover, Potter (2000) opts for considering future shocks as random rather than fixing them at zero when estimating nonlinear IRs. Finally, due to the lack of realism in conditioning an IR estimation at zero, this is not very useful.

In reduced-form VAR equations the errors are correlated. Based on this we use a method for orthogonalizing the impulses. The usual approach is to employ an inverse Cholesky factorization of the variance-covariance matrix of the estimation residuals. A structural model such as 5 used in this research becomes more attractive for estimating IR functions given that in $I_y(\delta,H,\Omega_i)$ and $I_y(\delta,H)$ calculations, an exchange rate shock (x_t) is orthogonal to other shocks.

Kilian and Vigfusson (2011) show that, for small shocks, the difference between the IR estimated considering possible histories as well as the behavior of errors $\left[I_y^*(\delta,H)\right]$, and that estimated without considering those two items $\left[\bar{I}_y^*(\delta,H,\underline{0})\right]$, is substantial. Nonetheless, this difference declines as the size of the shock increases, i. e., the authors demonstrate that

8 $$\lim_{n\to\infty}\frac{1}{n}I_y(n\delta,H)=I_y^*(\delta,H,\underline{0}).$$

For exchange rate shocks of a sufficiently large magnitude, we would expect that the importance of Ω_i and the randomness of ϵ_{1t} decrease until reaching the point at which the IR estimated using the traditional VAR approach is a good approximation to correct estimation. This is, therefore, the explanation of how the traditional VAR method can generate estimations for the response of domestic prices to exchange rate shocks that are very different from those correctly estimated through a nonlinear specification.

This inverse relationship between the size of shocks and the estimated response of domestic prices is important given that, for series where the variation (in this case of the exchange rate) exhibits a small standard deviation, the advantage of using $I_y(n\delta,H)$, in terms of reducing asymptotic bias in IR function measurement, is greater.

4.2 Symmetry Tests

Despite solving the problem of asymptotic bias with respect to a censured VAR, structural model 5 is asymptotically inefficient compared to a VAR when the DGP is symmetric. Hence, efficient ERPT estimation requires a prior statistical test to evaluate the hypothesis of symmetry in the DGP.

Those defined below as tests of symmetry in parameters assess the equality of the magnitude of coefficients associated with appreciations and depreciations.

Kilian and Vigfusson (2011) show that these tests are useful for reduced-form models to identify asymmetries in parameter responses. Nonetheless, they are not useful for identifying asymmetries in the IR functions of asymmetric structural models. This is due to the fact that they could obtain parameters associated with appreciations and depreciations that are not statistically different, while the IRs are indeed so. The latter because IR functions can be a nonlinear function of both the slope parameters and the variance of the innovations.

In light of this problem, Eldstein and Kilian (2007) suggest an alternative approximation based on the IR functions obtained according to the method explained in Section 4.1 to test the symmetry hypothesis. We refer to this second group of tests as tests of symmetry in the IRs.

4.2.1 Tests of Symmetry in Parameters

Tests for symmetry in parameters, or slope-based symmetry tests, are attractive given their simplicity and because they do not require the computation of IR functions. According to this method, after estimating the regression of y_t on its own lags as well as those on x_t^+ and x_t^-, we test the equality of the coefficients by means of Wald test statistics that, under the null hypothesis of symmetry, have distribution Ji^2 [see Mork (1989)].

Kilian and Vigfusson (2011) show that this approximation does not exploit all the restrictions implied by the null hypothesis of symmetry. They demonstrate that, by working with a reduced model, Mork (1989) omits the equality restriction of the contemporaneous terms of x_t^+ and x_t^-. The authors, therefore, propose, in terms of Model 5, working with the null hypothesis

$$H_0\colon \beta_1 = \beta_2 = 0.$$

The same authors argue that this hypothesis has higher statistical power than that of Mork (1989). They test this hypothesis in a model such as 5, and by means of parameter exclusion Wald tests seek to determine whether the fit of the model improves with the inclusion of regressors $x_t^+,\ x_{t-1}^+,\ldots,x_{t-p}^+$.

4.2.2 Tests of Symmetry in IR Functions

The proposal of Kilian and Vigfusson (2011), adapted for testing sign symmetry in IR functions for prices in the presence of exchange rate shocks to *h* over different horizons can be summarized in the following steps:

1) Estimate structural Model 5.

2) Calculate IR *h* periods ahead (in this case it was performed with a horizon of 24 periods) for both positive and negative shocks. That is, calculate $I_y^*\left(\delta,h\right)$ and $-I_y^*\left(-\delta,h\right)$.

3) Construct a Wald test of the joint null hypothesis of symmetry in positive and negative IRs up to a horizon of *h* periods in the future. The statistic, therefore, takes the form: $W=\sum_{i=0}^{h}\left[I_y^*\left(\delta,i\right)+I_y^*\left(-\delta,i\right)\right]^2=0.$

4) Estimate the variance-covariance matrix of the vector sum of response coefficients by bootstrap simulation.

The *W* statistic, therefore, has distribution Ji^{2}_{h+1} given the asymptotic normality of the parameter estimators of the model.

4.3 Data

The database employed in the estimations corresponds to series published by the Banco Central de Costa Rica on its official online data portal.[2] Basic exchange rate data sets have a daily frequency, but a monthly series was constructed by taking the average between the purchase and sale references on every business day each month. Meanwhile, the series for the CPI are originally monthly.

As controls in the estimations, we included indicators on output gap and interest rate differentials. The base information for the output gap is the seasonally adjusted series of the monthly economic activity index (IMAE). We applied a Hodrick-Prescott filter to this with smoothing parameter $\lambda = 23.000$ in line with Segura and Vásquez (2011).

Finally, the series for interest rate differentials considers the United States Treasury federal funds effective rate[3] and the monetary policy rate of the Banco Central de Costa Rica. The sample period spans from January 2006 to March 2017.

5. RESULTS

5.1 Evaluation of Stationary Properties

The stationary properties of the series employed are determined in order to define the type of econometric method with which to perform the prior analysis. The results of the unit root tests applied are displayed in Table 1. It can be seen that both under the Dickey-Fuller (DF) test and that of Phillips-Perron (PP), it is not possible to reject the null hypothesis of a unit root for all the series at levels, except for the IMAE gap. In the case of the first difference, the null hypothesis of a unit root is

[2] <https://www.bccr.fi.cr/seccion-indicadores-economicos/indicadores-econ%C3%B3micos>.

[3] <https://fred.stlouisfed.org/series/FEDFUNDS>.

Table 1

P VALUES IN UNIT ROOT TESTS (H_0: X_T HAS UNIT ROOT)

			Variable			
Variable in:	*Type of test*	*Specification*	*CPI*	*ER*	*Interest rate differential*	*IMAE gap*
Levels	ADF	Const	0.99	0.27	0.72	0.00
		Const and trend	0.99	0.55	0.91	0.00
	PP	Const	0.98	0.31	0.47	0.00
		Const and trend	1.00	0.60	0.77	0.00
First difference	ADF	Const	0.00	0.00	0.00	0.00
		Const and trend	0.00	0.00	0.00	0.00
	PP	Const	0.00	0.00	0.00	0.00
		Const and trend	0.00	0.00	0.00	0.00

Source: Authors' calculations.

rejected for all the series. Based on these results, all the variables in the estimations were used in first differences, except the IMAE gap, which was kept at levels.

5.2 Lag Order

We proceeded to determine the most appropriate lag order for estimating Model 5 in two ways. Firstly, based on VAR model lag selection criteria and secondly using goodness-of-fit criteria for the equation of y_t (price equation in the application of this paper) in asymmetric structural Model 5. The selection was made for three different model specifications: one bivariate model (consisting of the first difference of the CPI and the exchange rate); two models of three variables constructed based on the bivariate model adding the IMAE gap and interest rate differential, respectively. Table 2 displays the results for those models under five different criteria.

Table 2

OPTIMAL NUMBER OF LAGS ACCORDING TO DIFFERENT CRITERIA

		Model		
Specification	*Criteria*	*Bivariate*	*Bivariate + interest rate differentials*	*Bivariate + IMAE gap*
	LR	5	1	3
	FPE	1	1	1
VAR	AIC	1	1	1
	SC	1	1	1
	HQ	1	1	1
Asymmetric prices equation	AIC	5	5	5
	SC	1	1	1

Note: LR stands for likelihood ratio, FPE to final prediction error, AIC to Akaike information criterion, SC to Shwarz's criterion, and HQ to that of Hannan-Quinn.
Source: Authors' calculations.

In general, the specification that includes only one lag tends to dominate both in the criteria for the VAR model and for the equation of y_t in the asymmetric structural model, regardless of whether the model is bivariate or incorporates interest rate differentials or the IMAE gap. It should be emphasized, however, that based on the AIC, the model with five lags dominates all the cases for the equation of y_t in the asymmetric structural model.

The results presented here are useful for assessing the evidence on asymmetric effects shown in the following section, where tests of symmetry in parameters and in IR functions for models with up to 12 lags are revealed. Furthermore, the IR functions presented below for measuring the exchange rate pass-through correspond precisely to the specifications with lag order selection based on the evidence in Table 2.

Table 3

P VALUE IN TEST OF PARAMETER SYMMETRY
(H_0: SYMMETRIC PASS-THROUGH)

	Type of model		
Lags	*Bivariate*	*Trivariate with interest rate differentials*	*Trivariate with IMAE gap*
1	0.29	0.43	0.19
2	0.64	0.85	0.46
3	0.48	0.71	0.44
4	0.71	0.87	0.58
5	0.55	0.61	0.38
6	0.58	0.56	0.41
7	0.33	0.28	0.39
8	0.24	0.25	0.23
9	**0.07**	0.13	0.15
10	**0.07**	0.11	0.10
11	**0.10**	0.20	**0.08**
12	0.11	0.32	**0.07**

Note: Cases with the rejection of the H_0 at 10% are highlighted in bold.
Source: Authors' calculations.

5.3 Symmetry Tests

5.3.1 Test of Symmetry in Parameters

The results of the test of symmetry in the parameters, explained in Section 4.2.1, are shown in Table 3. As mentioned previously, they include the models that consider from 1 up to 12 lags. As can be seen, for models identified as having better goodness-of-fit (with 1 and 5 lags) there is not sufficient evidence to reject the null hypothesis of symmetric pass-through either in the bivariate case or trivariate ones. Nonetheless, it is interesting to see that the inclusión of additional lags (above 9) tends to increase the evidence against the hypothesis of symmetry, at least for the bivariate and trivariate models that include IMAE gap.

5.3.2 Test of Symmetry in Impulse Response Functions

The results from applying the test of symmetry on IR functions, the methodology for which was described in Section 4.2, can be seen in Table 4. The results were obtained by simulating 40,000 forecasts of structural Model 5 with a horizon of up to 24 months.[4] It is worth remembering that the variables involved are, alternatively, the first difference of the CPI and the first difference of the nominal ER (bivariate case), adding IMAE gap and interest rate differentials for the models denominated trivariate. In view of the fact that the nonlinearity of IR functions may appear on any horizon, the table contains p values for each forecasting horizon from 1 up to 24 months.

In general, the results do not lead to very different conclusions than those obtained from the tests of symmetry in parameters. For the models with better goodness-of-fit (those that include 1 and 5 lags), the evidence against the symmetry hypothesis is scarce in all models and for all horizons. Table 4 also displays the results for the model with most evidence against the symmetry hypothesis (the version that includes up to 12 lags). In this case, and at 10% significance, the bivariate model at horizons of between four and six months, and the trivariate model with interest rate differentials for horizons above ten months, exhibit some evidence in favor of the alternative hypothesis of an asymmetric response in domestic prices to exchange rate shocks. Nevertheless, it should be emphasized that goodness-of-fit criteria do not favor this specification.

The fact that the greatest evidence of asymmetric pass-through is found when the model estimated includes 12 lags (trivariate model with interest rates differentials) might be because the estimations do not take into account seasonal factors.

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[4] See procedure explained in Section 4.1.

Table 4

P VALUE IN TEST OF SYMMETRY IN IMPULSE RESPONSE FUNCTIONS
(H_0: SYMMETRIC PASS-THROUGH)

	Model Specification								
	Bivariate			*Bivariate with interest rate differentials*			*Bivariate with IMAE gap*		
Horizon	*1 lags*	*5 lags*	*12 lags*	*1 lags*	*5 lags*	*12 lags*	*1 lags*	*5 lags*	*12 lags*
1	0.19	0.10	0.16	1.00	0.95	0.35	0.97	0.97	0.96
2	0.35	0.16	**0.10**	1.00	0.98	0.12	1.00	1.00	0.98
3	0.55	0.29	0.17	1.00	1.00	**0.07**	1.00	1.00	1.00
4	0.68	0.30	**0.04**	1.00	1.00	0.12	1.00	1.00	1.00
5	0.78	0.41	**0.03**	1.00	1.00	0.20	1.00	1.00	1.00
6	0.86	0.47	**0.05**	1.00	1.00	0.25	1.00	1.00	1.00
7	0.92	0.57	**0.08**	1.00	1.00	0.34	1.00	1.00	1.00
8	0.96	0.68	0.12	1.00	1.00	0.30	1.00	1.00	1.00
9	0.98	0.76	0.12	1.00	1.00	0.38	1.00	1.00	1.00
10	0.98	0.83	0.10	1.00	1.00	0.11	1.00	1.00	1.00

11	0.99	0.89	0.12	1.00	1.00	0.07	1.00	1.00	1.00
12	1.00	0.93	0.16	1.00	1.00	0.05	1.00	1.00	1.00
13	1.00	0.95	0.20	1.00	1.00	0.05	1.00	1.00	1.00
14	1.00	0.97	0.25	1.00	1.00	**0.07**	1.00	1.00	1.00
15	1.00	0.98	0.29	1.00	1.00	**0.08**	1.00	1.00	1.00
16	1.00	0.99	0.35	1.00	1.00	**0.08**	1.00	1.00	1.00
17	1.00	0.99	0.42	1.00	1.00	**0.04**	1.00	1.00	1.00
18	1.00	1.00	0.48	1.00	1.00	**0.05**	1.00	1.00	1.00
19	1.00	1.00	0.55	1.00	1.00	**0.02**	1.00	1.00	1.00
20	1.00	1.00	0.40	1.00	1.00	**0.03**	1.00	1.00	1.00
21	1.00	1.00	0.46	1.00	1.00	**0.01**	1.00	1.00	1.00
22	1.00	1.00	0.52	1.00	1.00	**0.01**	1.00	1.00	1.00
23	1.00	1.00	0.54	1.00	1.00	**0.02**	1.00	1.00	1.00
24	1.00	1.00	0.60	1.00	1.00	**0.02**	1.00	1.00	1.00

Note: Cases with rejection of the H_0 at 10% are highlighted in bold.
Source: Authors' calculations.

Nonetheless, visual examination of the correlograms, as well as simple tests in which the variables analyzed are regressed in fictitious seasonal variables, do not suggest the presence of this type of effects (see Figure A.1 and Table A.1 in the Annex).

5.4 Quantification of Exchange Rate Pass-through to Prices

In this section, we quantify the ERPT estimated using structural Model 5. For each model (bivariate and the two model variations with three endogenous) IR function estimations were performed following the procedure described in Section 4.1, fixing $n_{boot} = n_{hist} = 200$, i. e., averaging 40,000 estimations at each horizon from 1 up to 24 months. The magnitude of these functions is shown as a proportion of the size of the original shock. Moreover, those corresponding to negative exchange rate shocks are shown multiplied by –1 to allow their magnitude to be easily compared with those corresponding to positive shocks. The confidence bands shown are empirical and correspond to percentiles 5 and 95 of the distribution of the 40,000 forecast simulations performed for each horizon and for each model specification.

They also display IR functions for four different sizes of ER shock (1, 2, 4 and 10 standard deviations), in order to analyze whether sign asymmetry could be associated to the size of the shocks, a matter that would not be evident in the tables presented in the previous section.

Figure 1 displays the IR functions obtained from the bivariate model that includes only one lag. The first point that should be mentioned is that the proportional magnitude of the pass-through during positive shocks (appreciations) ends up being between 22% and 35%, which is consistent with the most recent estimations based on linear methods.[5] However,

[5] See Orane (2016).

the pass-through in negative shocks is estimated to be around 15% for small shocks and close to 0% for larger shocks.

Meanwhile, with respect to matters of asymmetry, it can be seen that, for the case of small shocks (one standard deviation), the evidence is consistent with that shown in Table 4 in the sense that the dynamic response of prices is not statistically different in positive or negative ER shocks. Furthermore, in accordance with the size of the shock confidence bands for the estimations cease to overlap. Thus, for mid-sized and large shocks the response of prices does appear statistically different.

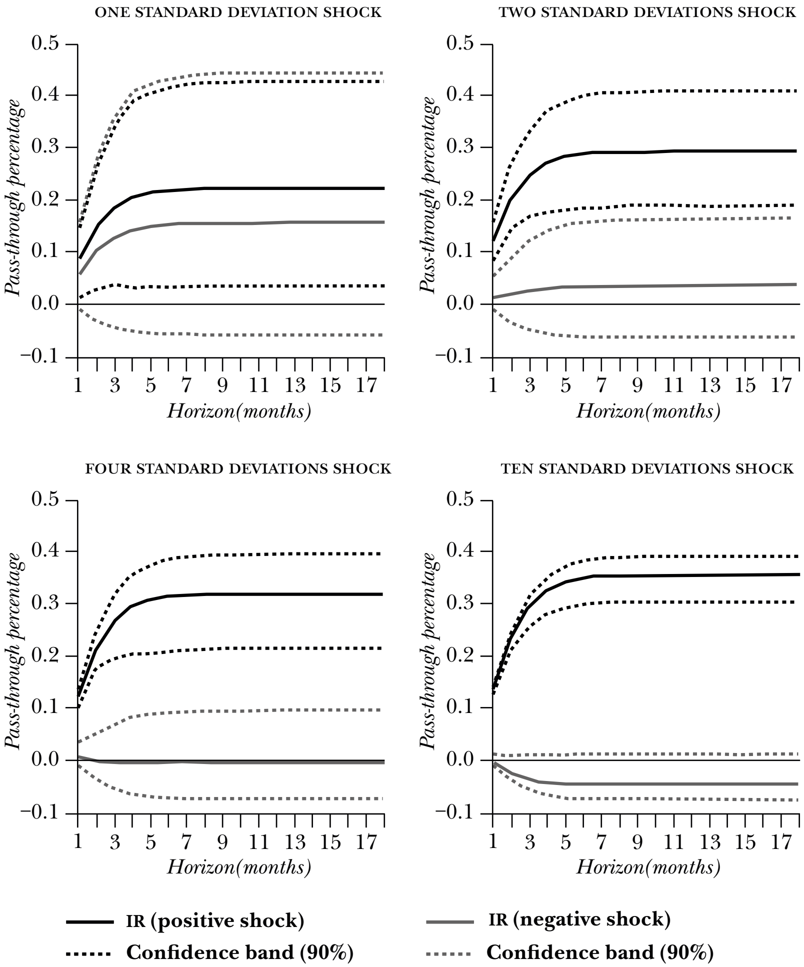
Figure 2 shows the IR functions obtained when the additional variable is incorporated into the model, specifically interest rate differentials. In terms of the proportional magnitude of the long-term pass-through we estimate, there is not much difference from the bivariate case. The pass-through is between 20% and 30% in depreciations, and between 0% (large shocks) and 15% (small shocks) in the case of appreciations.

Just as in the bivariate case, when the ER shock is small (one standard deviation), there is no significant difference in the dynamic response of domestic prices. Nonetheless, for larger shocks (four and ten standard deviations) the spaces between the confidence bands move apart during positive and negative shocks, indicating sign asymmetry in the response.

One pattern that can be extracted from the IR functions in Figure 1 and Figure 2 is that when ER shocks are small, the response of domestic prices is no different in the presence of appreciations or depreciations. However, when the shocks are mid-sized and large, the response during appreciations tends to decrease in proportional magnitude, eventually differing from the response during depreciations. One possible explanation for this behavior is that economic agents may interpret large appreciations as temporary phenomena that do not merit price adjustments. This could be caused by the historical trend (which has reverted during recent years) of inflation in Costa Rica being higher than in the country's main trading partners. The aforementioned meant the public became accustomed to

Figure 1

IMPULSE RESPONSE FUNCTIONS OF PRICES TO EXCHANGE RATE BY SHOCK SIZE
Bivariate model with a lag

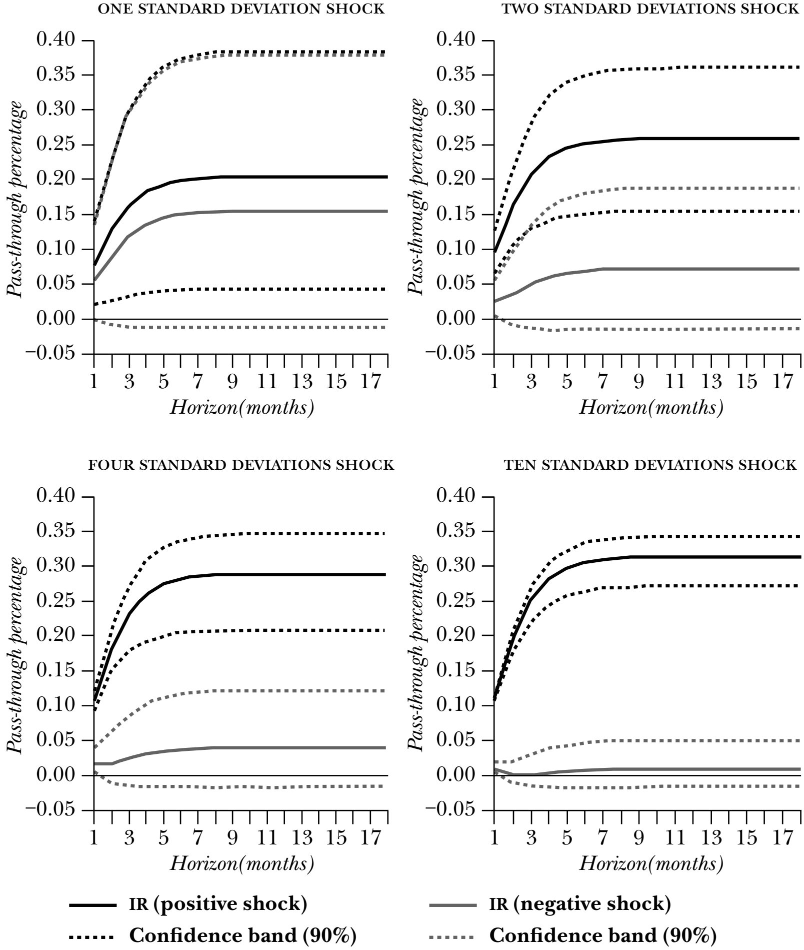


Source: Authors' calculations.

Figure 2

IMPULSE RESPONSE FUNCTIONS OF PRICES TO EXCHANGE RATE BY SHOCK SIZE

Trivariate model (rates differential) with a lag



Source: Authors' calculations.

increases in the nominal ER, and episodes of appreciations, particularly very large ones, tend to be seen as exceptions to the trend and therefore temporary.

Figures A.2 and A.3 in the Annex display the IR functions for the case of bivariate and trivariate models (with interest rate differentials) with five lags. Except for being necessary a horizon of over 18 months to illustrate convergence, the dynamic response pattern is similar to that observed in the figures mentioned here.

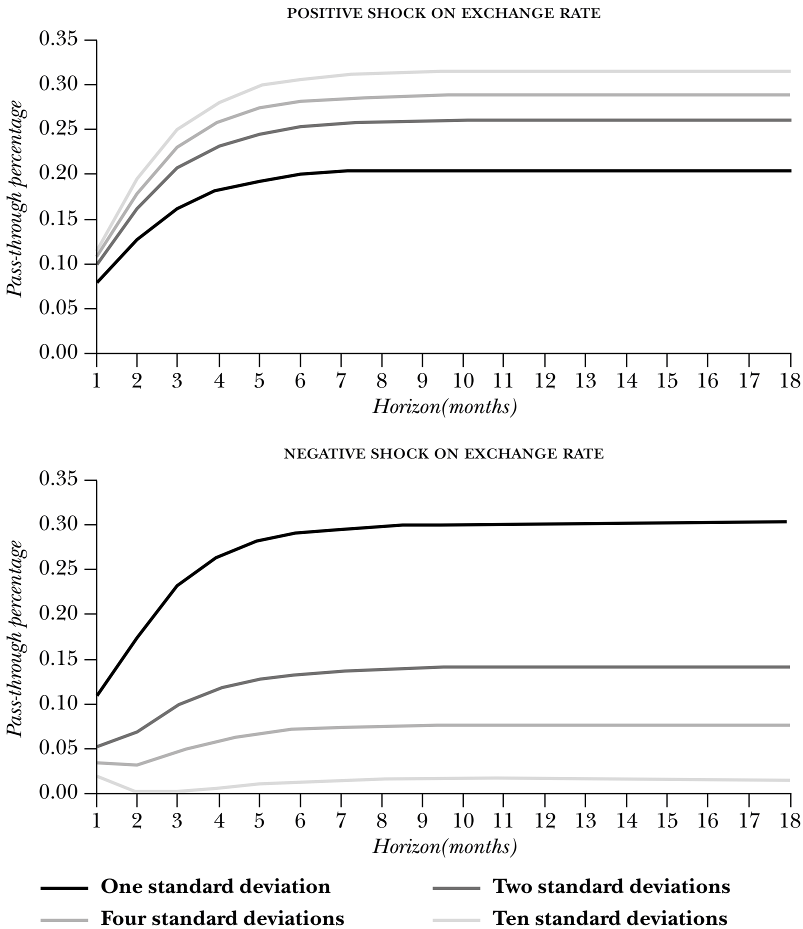
One item that can be extracted from the estimations performed, but that is not easily appreciable in Figure 1 or Figure 2, is that the magnitude of the pass-through is a growing function of the shocks when they are depreciations, but a decreasing function if they are appreciations. This is illustrated in Figure 3 corresponding to estimations using the trivariate model that includes interest rate differentials (the trend is the same in the case of the bivariate model). Note that for positive exchange rate shocks (upper panel of the figure) the dynamic response of domestic prices is larger than for smaller shocks. On the other hand, for negative shocks (lower panel of the figure), the smaller the shock, the larger the proportional response (in absolute value).[6]

As mentioned, this phenomenon could be explained by economic agents' expectations being rooted in considering episodes of appreciation in the domestic currency as unusual. If this were the case, negative exchange rate shocks, especially the largest ones, would be considered temporary and, possibly due to items such as menu costs, would not generate downward adjustments in prices in domestic currency.

[6] As shown, IR functions appear multiplied by −1 in the presence of appreciations.

Figure 3

IMPULSE RESPONSE FUNCTIONS OF PRICES TO EXCHANGE RATE BY SHOCK SIZE
Trivariate model (rates differential) with a lag



Source: Author's calculations.

6. CONCLUSIONS

In general, the magnitude of exchange rate pass-through to prices is calculated to be between 20% and 35% in the case of depreciations. This estimation is similar in size to the most recent ones obtained by the Banco Central de Costa Rica employing linear methods. Nevertheless, those linear methods assume sign symmetry in the estimation. In this paper, we calculate that in the case of appreciations the magnitude of the pass-through is between 0% and 15 percent.

The dynamic response of the CPI to exchange rate shocks exhibits evidence of sign asymmetry only when the shocks are mid-sized or large.

For more common unexpected appreciations or depreciations (of one standard deviation), tests for asymmetry in parameters and in IR functions do not find sufficient evidence to reject the hypothesis of symmetry. Meanwhile, the empirical confidence bands for IR functions indicate that when the size of the appreciation or depreciation is mid-sized or large (four or more standard deviations), the response of domestic prices is greater (in absolute value) during a depreciation. Hence, it is not correct to assume a response of similar magnitude in domestic prices to appreciations than to deprecations when these are relatively large.

The size of the shock influences the proportional magnitude of the pass-through

When it comes to unexpected depreciations in the domestic currency, those of greatest magnitude are transmitted to a larger extent than smaller ones. Moreover, during unexpected appreciations, the largest ones are transmitted less to domestic prices.

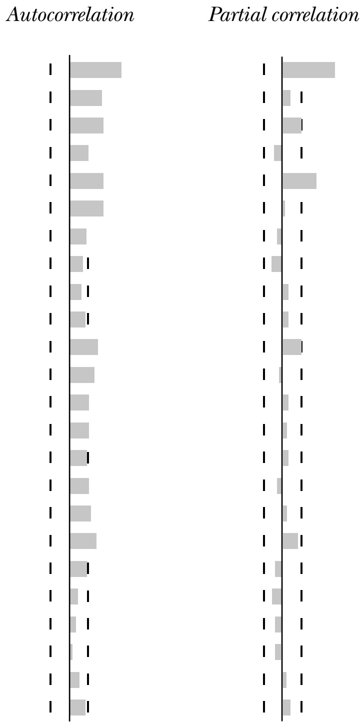
The evidence found in this research indicates that considering a constant pass-through regardless of the direction or magnitude of exchange rate shocks possibly leads to erroneous estimates for the impact of exchange rate variations on domestic prices.

ANNEX

Figure A.1

CORRELOGRAM AND PARTIAL CORRELOGRAM OF LOGARITHMIC FIRST DIFFERENCE OF THE CPI

Sample: 2006M1-2017M4
Observations: 13



	AC	*PAC*	*Q statistic*	*Prob.*
1	0.493	0.493	33.504	0.000
2	0.300	0.076	46.029	0.000
3	0.312	0.183	59.655	0.000
4	0.174	−0.071	63.926	0.000
5	0.332	0.312	79.605	0.000
6	0.316	0.020	93.880	0.000
7	0.167	−0.045	97.929	0.000
8	0.116	0.094	99.882	0.000
9	0.102	0.057	101.41	0.000
10	0.147	0.054	104.59	0.000
11	0.277	0.184	116.01	0.000
12	0.230	−0.014	123.95	0.000
13	0.172	0.050	128.45	0.000
14	0.180	0.026	133.40	0.000
15	0.156	0.044	137.16	0.000
16	0.174	−0.041	141.86	0.000
17	0.198	0.027	147.98	0.000
18	0.252	0.151	158.02	0.000
19	0.164	−0.058	162.33	0.000
20	0.074	−0.084	163.21	0.000
21	0.065	−0.056	163.89	0.000
22	0.023	−0.051	163.97	0.000
23	0.088	0.029	165.26	0.000
24	0.155	0.076	169.27	0.000

Source: Author's calculations.

Table A.1

STATIONARITY TEST WITH DICHOTOMOUS VARIABLES

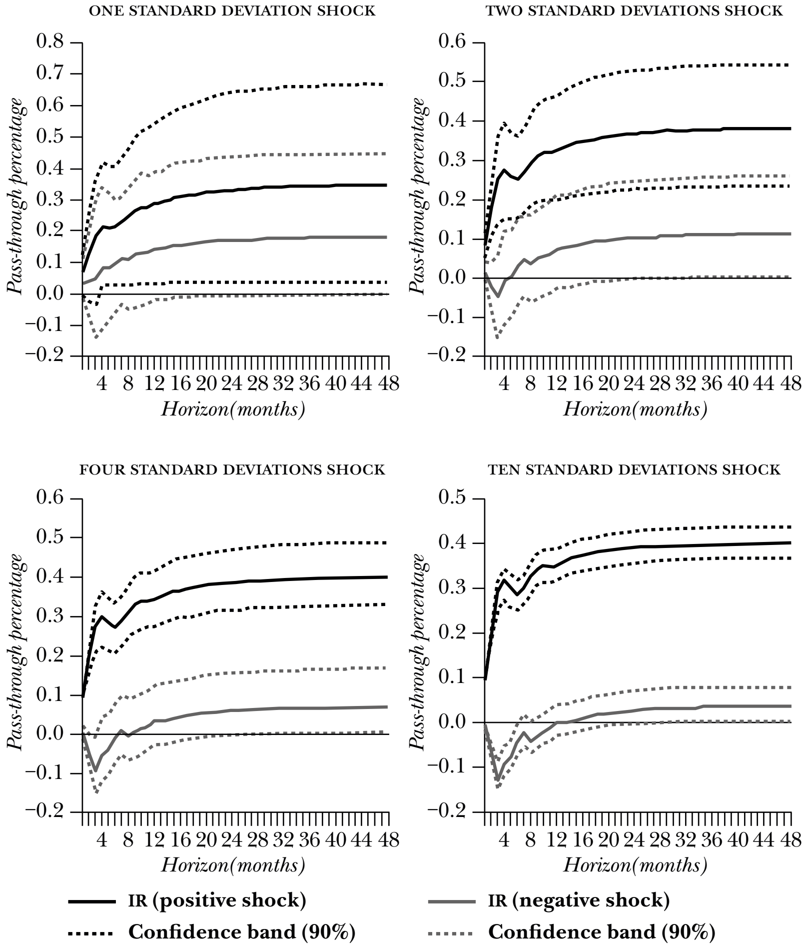
Dependent variable: DLOGIPC
Method: least squares
Sample (adjusted): 2006M2-2017M4
Included observations: 135, after adjustments

Variable	*Coefficient*	*Standard error*	*Statistical probability* t	*Probability*
C	0.5911	0.1250	4.7305	0.0000
DUMCE	0.6718	0.0818	8.2114	0.0000
@SEAS(2)	−0.2532	0.1718	−1.4732	0.1433
@SEAS(3)	−0.6152	0.1718	−3.5801	0.0005
@SEAS(4)	−0.3096	0.1718	−1.8018	0.0740
@SEAS(5)	−0.1398	0.1756	−0.7959	0.4276
@SEAS(6)	−0.3344	0.1756	−1.9041	0.0592
@SEAS(7)	−0.1404	0.1756	−0.7994	0.4256
@SEAS(8)	−0.2920	0.1756	−1.6627	0.0989
@SEAS(9)	−0.7188	0.1756	−4.0935	0.0001
@SEAS(10)	−0.6174	0.1756	−3.5159	0.0006
@SEAS(11)	−0.2678	0.1756	−1.5249	0.1299
@SEAS(12)	−0.1626	0.1755	−0.9267	0.3559
R^2		0.4498	Mean of the dependent variable	0.4377
Adjusted R^2		0.3956	Standard deviation of the dependent variable	0.5293
Standard error of the regression		0.4115	Akaike criteria	1.1532
Residual sum of squares		20.6554	Schwarz criteria	1.4329
Log likelihood		−64.8392	Hannan-Quinn criteria	1.2669
Statistical measure of F		8.3102	Durbin-Watson statistic	1.3304
Probability (statistical measure of F)		0.0000		

Source: Authors' calculations.

Figure A.2

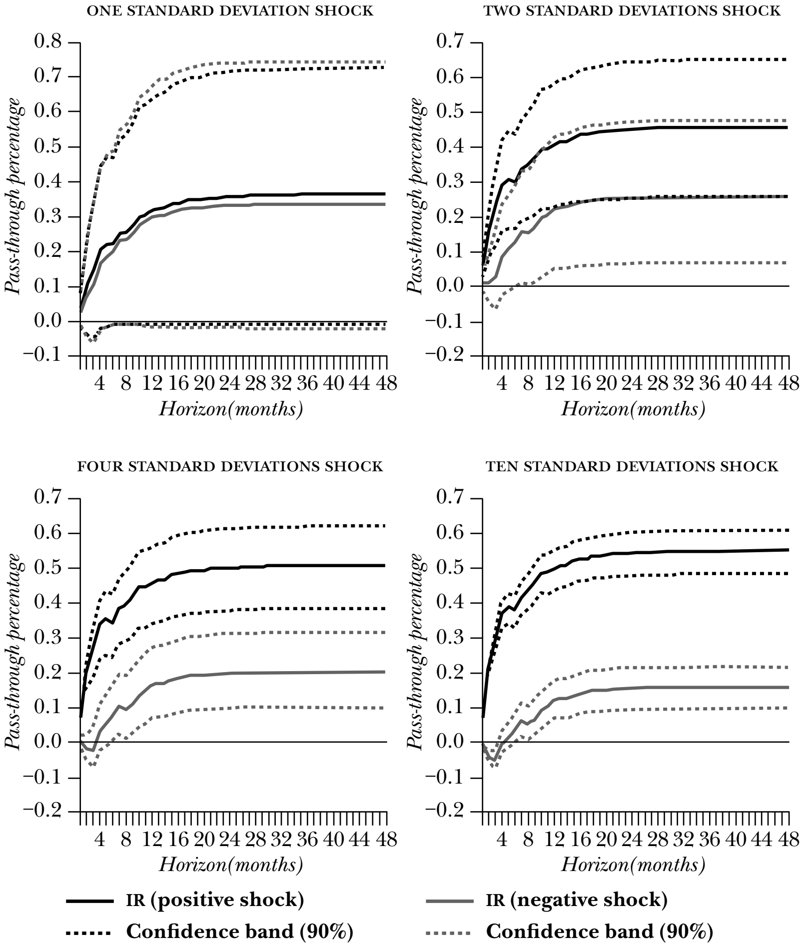
IMPULSE RESPONSE FUNCTIONS OF PRICES TO EXCHANGE RATE BY SHOCK SIZE
Bivariate model with five lag



Source: authors' calculations.

Figure A.3

IMPULSE RESPONSE FUNCTIONS OF PRICES TO EXCHANGE RATE BY SHOCK SIZE
Trivariate model (rates differential) with five lags



Source: Authors' calculations.

References

Álvarez, Cristian, and Manfred Esquivel (2016), *Efecto de cambios de precio en materias primas sobre los precios domésticos en Costa Rica, ¿influye el nivel de competencia en los mercados?,* Documento de Investigación, No. DEC-DIE-06-2016, Banco Central de Costa Rica.

Bernanke, Ben, Mark Gertler, and Mark Watson (1997), *Systematic Monetary Policy and the Effects of Oil Price Shocks*, Brookings Papers on Economic Activity, No. 1, pp. 91-157.

Choudhri, E., and D. Hakamura (2001), *Exchange Rate Pass Through to Domestic Prices: Does the Inflationary Environment Matter?,* FMI Working Paper, No. 01/194.

Eldstein, Paul, and Lutz Kilian (2007), "The Response of Business Fixed Investment to Changes in Energy Prices: A Test of Some Hypotheses About the Transmission of Energy Price Shocks," *The B. E. Journal of Macroeconomics*, Vol. 7, No. 1, pp. 1-41.

Engel, Charles (2002), "Expenditure Switching and Exchange-rate Policy," in M. Gertler y K. Rogo (eds.), *NBER Macroeconomics Annual*, pp. 231-272.

Esquivel, Manfred, and José Fabio Gómez (2010), *Asymmetries of the Exchange Rate Pass Through to Domestic Prices: The Case of Costa Rica*, Documento de Investigación, No. DEC-DIE-043-2010, Banco Central de Costa Rica.

Gallant, Ronald, Peter E. Rossi, and George Tauchen (1993), "Nonlinear Dynamic Structures, "*Econometrica,* vol. 61, núm. 4, pp. 871-907.

Goldfang, I., and S. Werlang (2000*), The Pass-through from Depreciation to Inflation: A Panel Study*, Working Paper, No. 5, Banco Central do Brasil.

Greene, William H. (2003), *Econometric Analisys,* Prentice Hall, Upper Saddle River, N.J.

Hamilton, James D. (1996), *Time Series Analisys,* Princeton University Press, Chichester, United Kingdom.

Kilian, Lutz, and Robert J. Vigfusson (2011), "Are the Responses of the U.S. Economy Asymmetric in Energy Price Increases and Decreases?," *Quantitative Economics*, Vol. 2, pp. 419-453.

Koop, Gary, M. Hashem Pesaran, and Simon M. Potter (1996), "Impulse Response Analysis in Nonlinear Multivariate Models, " *Journal of Econometrics,* Vol. 74, No. 1, pp. 119-147.

Lariau, A., M. El Said, and M. Takebe (2016), *An Assessment of the Exchange Rate Pass-through in Angola and Nigeria*, FMI Working Paper, No. 16/191.

Leduc, Sylvain, and Keith Sill (2004), "A Quantitative Analysis of Oil Price Shocks, Systematic Monetary Policy and Economic Downturns," *Journal of Monetary Economics*, Vol. 51, No. 4, pp. 781-808.

Lee, Kiseok, Shawn Ni, and Ronald A. Ratti (1995), "Oils Shocks and the Macroeconomy: The Role of Price Volatility," *Energy Journal*, Vol. 16, No. 39-56.

León, Jorge, Ana P. Morera, and Welmer Ramos (2001), *El pass through del tipo de cambio: Un análisis para la economía costarricense de 1991 al 2001*, Documento de Investigación, No. DIE-DM-11-2001-DI, Banco Central de Costa Rica.

León, Jorge, Bernal Laverde, and Rodolfo Durán (2002), *El pass through del tipo de cambio en los precios de bienes transables y no transables en Costa Rica*, Documento de Investigación, No. DIE-05-2002-DI, Banco Central de Costa Rica.

Mendoza, Omar (ed.) (2012), *El efecto transferencia (pass-through) del tipo de cambio sobre los precios de Latinoamérica*, Banco Central de Venezuela, Caracas.

Mork, Knut A. (1989), "Oil and the Macroeconomy When Prices Go Up and Down: An Extension of Hamilton's Results," *Journal of Political Economy*, Vol. 97, No. 3.

Orane, Angelo (2016), *Estimación del traspaso del tipo de cambio hacia distintos componentes el índice de precios al consumidor*, Documento de Investigación, No. DI-06-2016, Banco Central de Costa Rica.

Pérez, Fernando J., and Marco Vega (2016), *Asymmetric Exchange Rate Pass-through: Evidence from Nonlinear SVARs*, Working Paper, No. 63, Asociación Económica Peruana.

Potter M., Simon (2000), "Nonlinear Impulse Response Functions," *Journal of Economic Dynamics and Control*, Vol. 24, No. 10, 1425-1446.

Przystupa, J., and E. Wróbel (2011), *Asymmetry of the Exchange Rate Pass-through: An Exercise on the Polish Data*, MPRA Paper, No. 17660, Munich Personal RePEC Archive, pp. 1-29.

Rigobón, Roberto, and Thomas M. Stocker (2009), "Bias from Censored Regressors," *Journal of Business & Economic Statistics*, Vol. 27, No. 3, pp. 340-353.

Rodríguez, Adolfo (2009), *Evaluación del modelo lineal de pass-through para la proyección de inflación dentro del régimen de banda cambiaria,* Documento de Investigación, No. DEC-DIE-DI-07-2009, Banco Central de Costa Rica.

Segura, Carlos, and José Pablo Vásquez (2011), *Estimación del parámetro de suavizamiento del filtro de Hoddrick y Precott para Costa Rica,* Documento de Trabajo, No. DEC-DIE-DT 006-2011, Banco Central de Costa Rica.

Taylor, John B. (2000), "Low Inflation, Pass Through, and the Pricing Power of Firms," *European Economic Review*, Vol. 44, No. 7, pp. 1389-1408.

Wang, Sheng, and Rufei Guo (2016), "Asymmetric Exchange Rate Pass-through and Monetary Policy in Open Economy," *Annals of Economics and Finance*, Vol. 17, No.1, pp. 33-53.

Winkelried, Diego (2003), "¿Es asimétrico el pass-through en el Perú? Un análisis agregado," VIII Reunión de Red de Investigadores de Bancos Centrales del Continente Americano, CEMLA.