

# An Endogenous Regime Switching Model for the Exchange Rate Pass-Through Effect in Costa Rica

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## Abstract

Understanding the pass-through effect (PTE) is crucial for policy makers of a small open economy such as Costa Rica. In this paper, we propose an endogenous regime switching vector autoregression (RS-VAR) model to study the exchange rate pass-through effect in Costa Rica. We identify two regimes: High PTE and Low PTE. This model allows for the transition probabilities to be influenced by endogenous variables such as inflation, oil prices and the exchange rate. We find that : i) the PTE is 4.5% in the low regime and 60% in the high regime, ii) a low PTE results from periods of high exchange rate volatility and, iii) a surprise inflation shock increases the probability of low pass-through. Given the evidence we recommend to consider the PTE oscillating between periods of high and low magnitude instead of one single value.

JEL CLASSIFICATION: C32, E52

KEY WORDS: Pass-through effect, inflation, exchange-rate, endogenous regime-switching

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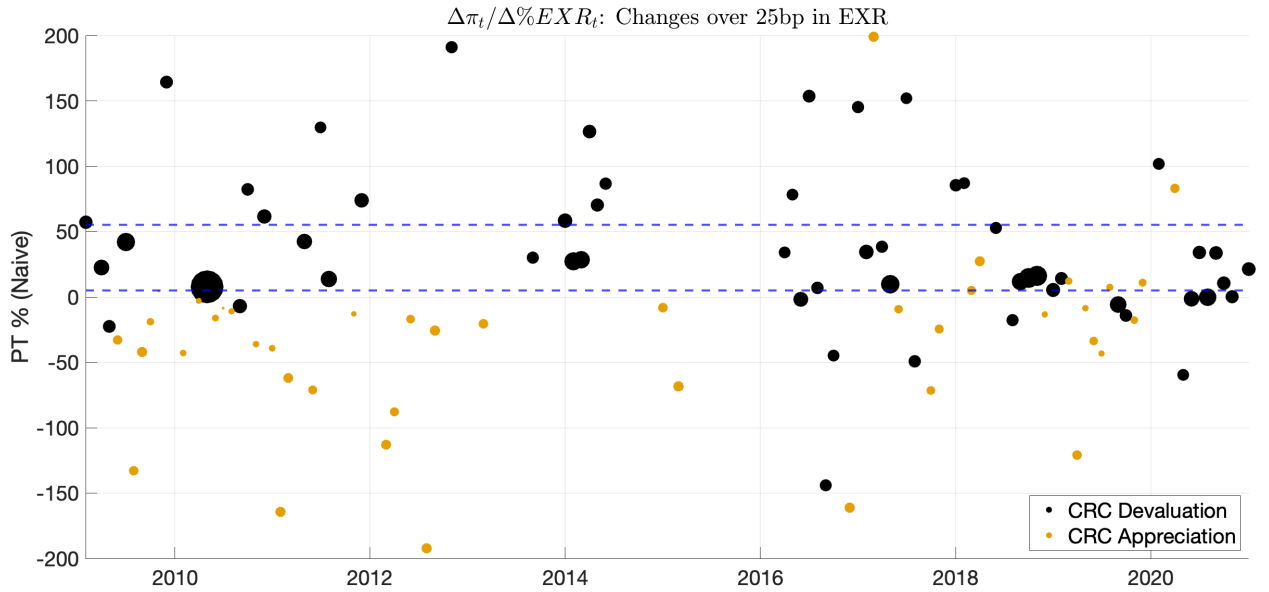
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# 1 Introduction

For a small open economy, such as Costa Rica, it is critical to understand the effects of the US dollar exchange rate dynamics on local inflation. The pass-through effect (PTE) is, *ceteris paribus*, the response of domestic prices to variations in the USD exchange rate.

In Figure 1, we show the ratio between changes in the USD exchange rate and changes in monthly inflation, or as we call it, a “naive” calculation of the pass-through effect. From this overly simplified exercise, we are motivated to question PTE asymmetries: i) do large devaluations (large dots) imply higher or rather lower PTE?, and ii) is there a sign asymmetry between devaluations (black) vs. appreciations (orange)?



**Figure 1:** Ratio of contemporaneous changes in inflation  $\Delta\pi$  and changes in exchange rate  $\Delta\%EXR_t$ . The color of the the dot represents positive (black) or negative (orange) changes in exchange rate. The size of the dot represent the absolute size of the exchange rate variation. The blue lines represent the range of previous estimations of PTE. Sample: 02.2009 - 10.2021. **Source:** Own elaboration.

Previous literature has estimated the PTE between 5% (lower dashed line in Figure 1) and 55% (higher dashed line in Figure 1). In other words, for a 1% variation in the USD exchange rate (about ₡6.20 during 2021), monthly inflation varies between 5 to 55 basis points in the same direction (or sign). Nevertheless, evidence suggests that the pass-through effect in Costa Rica is asymmetric (i.e. the response is not always in the same proportion).

In this paper, we argue that the PTE in Costa Rica has two regimes (*high* and *low*) and that the transition probabilities between regimes are endogenous. Here, endogenous

means that the main variables can influence the dynamics between regimes in the model. Endogeneity is the critical contribution of the present work and distinguishes it from the conventional Markov switching models ([Hamilton \(1989\)](#), [Krolzig \(1997\)](#)).

An attractive feature of this model is that it does not require a previous stance on when the model is in a high or low regime. This characteristic is contrasted to previous efforts to understand the asymmetries of the exchange rate pass-through effect in Costa Rica ([Esquivel and Gomez-Rodriguez \(2010\)](#), [Brenes and Esquivel \(2017\)](#)).

The baseline model we propose here is a structural vector autoregression (SVAR) ([Guillermo Peón and Rodríguez Brindis \(2014\)](#), [Forbes, Hjortsoe and Nenova \(2018\)](#)). This type of model considers the interaction between the variables to extract *structural shocks*. These shocks are considered “surprise” changes uncorrelated to other variables, for instance, changes in the exchange rate independent of changes in oil prices.

Our model is a regime switching vector auto-regression (RS-SVAR) with endogenous feedback, a generalization of the univariate model proposed by [Chang, Choi and Park \(2017\)](#). The products of the model are: i) a representation of the dynamics of the variables, ii) historic regime probabilities, and iii) the expected value of an unobserved latent variable that determines the regime of PTE.

We find that : i) the PTE is 4.5% in the *low regime* and 60% in the *high regime*, ii) a low PTE results from periods when the exchange rate is highly volatile, iii) a surprise inflation shock increases the probability of low pass-through effect which we explain by the fact that these shocks coincide with periods of high volatility in the USD exchange rate.

Contrary to the popular first conception, PTE is not high when we observe large devaluations of the Costa-Rican *colón*. On the contrary, the absolute response of inflation in both regimes is comparable, and it is the large or small changes of the exchange rate that leads to high and low pass-through effects.

We recommend looking at how the economic activity behaves during the low regime of the PTE. The combination of large devaluations and relatively small price changes worsens the local producers’ production factors depending on the USD exchange rate decreasing economic activity.

**Related Literature.** [León, Morera and Ramos \(2001\)](#) used an ordinary least squares regression to estimate the pass-through effect in Costa Rica in the period 1991-2001. Their results indicate a PTE of 16% after two months and up-to 55% in the long-run. In 2007, [Castrillo and Laverde \(2007\)](#) re-estimated the same model and report a PTE of 6% after four

months and up-to 33% in the long run. [Rodríguez \(2009\)](#) estimates the pass-through effect to be 5% in the short run and 36% in the long-run. Additionally, he finds evidence of a negative correlation between the exchange rate volatility and the pass-through coefficient. Based on the conclusions of previous studies that the PTE is asymmetric, [Esquivel and Gomez-Rodriguez \(2010\)](#) use a logistic smooth transitions vector auto-regression (LSTVAR) to determine high and low regimes for the pass-through. They found that when the effect is high it reaches 47% in the long-run, while in the low regime the portion of a given shock on the exchange rate that is passed to domestic prices is about 24,7%. Most recently, [Brenes and Esquivel \(2017\)](#) estimate the PTE to be between 20% and 35% for depreciations of the Costa Rican *Colón* and 0% to 15% for appreciations.

**Outline.** Section two describes the baseline econometric model. The discussions includes the baseline structural model and the implementation of the endogenous regime switching model. It ends with a description of the data used to estimate the model. The three section shows the results of the estimation and the implied impulse responses. Section five presents policy recommendations derived from our results and conclusions.

## 2 The Econometric Model

Our starting point is a conventional vector auto-regression model

$$y_t = c + \sum_{i=1}^p \Phi_i y_{t-i} + u_t \quad (1)$$

where  $y_t$  is a  $d$ -dimensional vector. Among the  $d$  variables our model most include inflation and exchange rate. The vector  $c$  is the intercept and  $\Phi_i$  autocovariance matrices of  $y_t$ . New information in time  $t$  enters the system through the reduce form residuals  $u_t$  for which we assume that  $u_t \sim \mathcal{N}(0, \Sigma)$ <sup>1</sup>.

There are many factors causing exchange rate changes. Our goal is to generate a “surprise” or “unpredicted” variation in the exchange rate and observe the reaction of inflation to measure PTE. Using an SVAR model allows us to disentangle “pure” exchange rate changes from those caused by other factors. We want to avoid considering co-movements of exchange rate and inflation as they respond to a third variable in calculating the pass-through. This

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<sup>1</sup>typically it is not necessary to assume  $u_t$  is multivariate normal, but eventually the regime switching model is estimated using maximum likelihood approach for which a specific distribution is necessary.

requirement is to make sure we look at inflation as it responds to exchange rate variations and not to a third variable. Using SVAR models to determine the PTE is common in the literature (*inter alia* [Guillermo Peón and Rodríguez Brindis \(2014\)](#) and [Forbes, Hjortsoe and Nenova \(2018\)](#) ).

A structural VAR consists in focusing on a factorization of the reduced form residuals as follows

$$u_t = B\varepsilon_t \quad \text{s.t.} \quad \Sigma = BB' \quad (2)$$

where  $\varepsilon_t$  are the so-called structural shocks. Note that  $\varepsilon_t$  is a vector of serially uncorrelated innovations which are also uncorrelated among themselves.

$$\begin{aligned} \text{Corr}(\varepsilon_{i,t}, \varepsilon_{i,(t-s)}) &= 0 \text{ for all } s > 0 \\ \text{Corr}(\varepsilon_{i,t}, \varepsilon_{j,t}) &= 0 \text{ for all } i \neq j \in \{1, 2, \dots, d\} \end{aligned}$$

The *identification problem* is that the matrix  $B$  is not unique. For any orthogonal<sup>2</sup> matrix  $H$ , if  $B$  holds (2) then  $(BH)$  also holds the condition<sup>3</sup>. The simplest of all possible solutions to this problem is to assume that  $B$  is lower triangular. This is called recursive identification. The reason for the name will become clear shortly.

Once we have identified  $B$ , each column of the matrix  $B$  describes how the  $d$  variables in the system responds to different structural shocks. For this reason, the matrix  $B$  is crucial for the estimation of the PTE as it contains the response of inflation to an USD exchange rate shock.

Say, for example, that the third out of four variables in the model is exchange rate and the fourth one is inflation. Now, the third column of  $B$  is given by  $B_{\cdot 3} = (b_{13} \ b_{23} \ b_{33} \ b_{43})'$ . The value of  $b_{33}$  is how exchange rate responds to a one standard deviation exchange rate shock. Similarly,  $b_{43}$  is how inflation responds to the same exchange rate shock. The PTE at impact is given by the ratio  $b_{43}/b_{33}$ .

For a model with different regimes we want to consider two different matrices  $B(0)$  and  $B(1)$ . So, there will be two possible PTEs  $b_{43}^{(0)}/b_{33}^{(0)}$  and  $b_{43}^{(1)}/b_{33}^{(1)}$ .

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<sup>2</sup>An orthogonal matrix  $H$  is given by the following defining property  $H \cdot H' = I$

<sup>3</sup>If  $BB' = \Sigma$  then,  $BB' = BIB' = BHH'B' = BH(BH)' = \Sigma$

## 2.1 Regime Switching SVAR

To model the asymmetries of the PTE, we substitute the time invariant matrix of responses-at-impact  $B$  for a time-varying matrix  $B_t$

$$B_t = B(s_t)$$

where the stochastic process  $s_t$  takes as many values as the number of regimes in the model. Here, we consider **two** regimes: *high* PTE and *low* PTE.

$$y_t = c + \sum_{i=1}^p \Phi_i y_{t-i} + u_t \quad (3)$$

$$u_t \sim \mathcal{N}(0, \Sigma(s_t)) \quad (4)$$

where  $s_t$  is a binary process  $s_t \in \{0, 1\}$  indicating the regime in time  $t$ . We define  $s_t = 0$  for the *low* regime and  $s_t = 1$  for the *high* regime.

Imposing recursive identification we obtain the following descriptions of the matrices  $B(0)$  and  $B(1)$

$$u_t = B(0)\epsilon_t = \begin{bmatrix} + & 0 & 0 & 0 \\ * & + & 0 & 0 \\ * & * & \boxed{+} & 0 \\ * & * & \boxed{x} & + \\ & & \text{(low)} & \end{bmatrix} \epsilon_t \quad u_t = B(1)\epsilon_t = \begin{bmatrix} + & 0 & 0 & 0 \\ * & + & 0 & 0 \\ * & * & \boxed{+} & 0 \\ * & * & \boxed{X} & + \\ & & \text{(high)} & \end{bmatrix} \epsilon_t \quad (5)$$

where  $*$  stands for unrestricted parameters,  $+$  for positive restricted values. In the illustrated case by (5), we assume that exchange rate is the third variable and inflation the fourth one. The third column represents how each variable responds to an exchange rate shock. So the pass-through effect at-impact is the ratio between the response at-impact of inflation to an exchange rate shock (represented by  $x$  and  $X$ ) and the response at-impact of exchange rate to an exchange rate shock.

**Regime dynamics.** The model uses a latent variable  $w_t$  to determine the regime. We assume that  $w_t$  is autoregressive process of order one. or AR(1)

$$w_t = \alpha w_{t-1} + \eta_t \quad (6)$$

the model is in the low regime ( $s_t = 0$ ) when  $w_t < \tau$  and in high regime ( $s_t = 1$ ) when  $w_t \geq \tau$ . The parameter  $\tau$  is the threshold parameter. In the appendix we show how several combinations of values of  $\alpha$  and  $\tau$  can achieve different regime dynamics.

With the latent variable we can calculate transition probabilities as follows

$$\begin{aligned} \mathbb{P}(s_t = 0 | s_{t-1} = 0) &= \mathbb{P}(w_t < \tau | w_{t-1} < \tau) & \mathbb{P}(s_t = 1 | s_{t-1} = 0) &= \mathbb{P}(w_t \geq \tau | w_{t-1} < \tau) \\ \mathbb{P}(s_t = 0 | s_{t-1} = 1) &= \mathbb{P}(w_t < \tau | w_{t-1} \geq \tau) & \mathbb{P}(s_t = 1 | s_{t-1} = 1) &= \mathbb{P}(w_t \geq \tau | w_{t-1} \geq \tau) \end{aligned}$$

**Endogeneity.** So far, the process  $w_t$  is exogenous to the model described by (3) and (4). To model endogenous regime dynamics we assume that there is a vector of correlations  $\rho$  such that  $\rho = \text{Corr}(\eta_t, \varepsilon_{t-1})$ . The correlation vector  $\rho$  represents how changes in the variables  $y_t$  influence the transition probabilities. The vector  $\rho$  is called *endogenous feedback*.

The entire RS-SVAR model is the collection of equations (3), (4) and (6) together with the parameters  $\rho$  and  $\tau$ . The estimation of the models consists in obtaining the parameters  $c, \Phi_1, \dots, \Phi_p, B(0), B(1), \alpha, \tau$  and  $\rho$ . Using the filter proposed by [Chang, Choi and Park \(2017\)](#) adjusted to the multivariate case we estimate the parameters of the model. The filter extracts the regime probabilities and delivers a likelihood function which we optimize to obtain the parameters.

**Determining the baseline model.** To obtain the specification of our baseline model we can consider we used a several combinations of variables and lags. We choose the one which consistently (across samples and horizon) perform better at out-of-sample prediction of inflation and exchange rate. For different combinations of samples and horizons we evaluated the sum of the forecast square error

$$(y_{t+h} - \hat{y}_{t+h}^{(i)})^2$$

where  $\hat{y}_{t+h}$  is predicted value given by model  $i$ .

The chosen model was one with oil price, the average yield on Costa Rican sovereign debt, USD-CRC exchange rate and inflation with two lags. For robustness of results in the

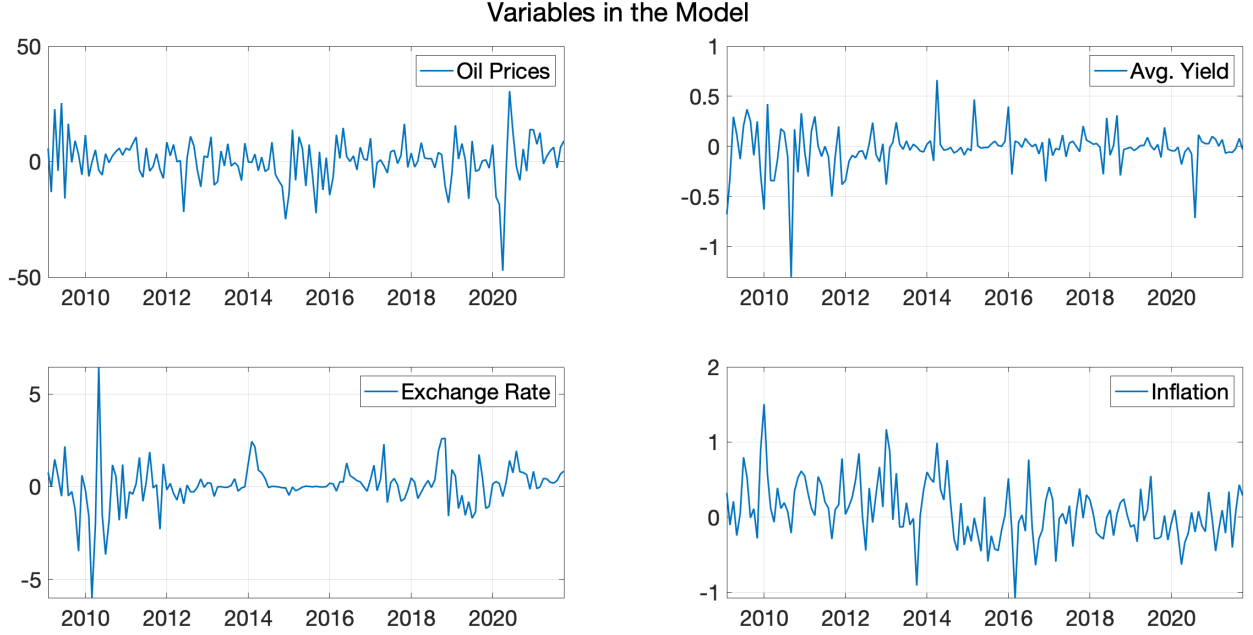
appendix we report the estimation for several different combinations of variables.

## 2.2 Data and Identification

As mentioned, the benchmark model considered here is given by the following variables

$$y_t = (p_t \quad z_t \quad x_t \quad \pi_t)' \quad (7)$$

where  $p_t$  stands for percentage changes of oil price regulated locally,  $z_t$  stands for the average yield on Costa Rica sovereign debt hold by foreigners,  $x_t$  monthly exchange rate variation in percent and  $\pi$  for monthly changes in the price level in percent. The sample we used monthly from February 2009 to October 2021<sup>4</sup> (see Figure 2).



**Figure 2:** Top-left: monthly exchange rate. Top-right: Percentage change in oil prices. Bottom-left: percentage change in USD exchange rate. Bottom-right: monthly inflation. **Source:** BCCR web-page

As discussed before the order of the variables in the model also determine the identification of shocks (therefore the name *recursive identification*). In our model we identified the following shocks:

1. **Oil Price Shock** is the shock to the most exogenous variable in the model. This shock is the only shock for which all other variables respond *ipso facto*. Note that this shock

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<sup>4</sup>An additional robustness check we made was to cut the sample before the pandemic.



causes variations in both exchange rate and inflation. Nonetheless, we don't consider this shock in our calculation as this type of variation of inflation is caused by changes in the price of oil and not exchange rate. Reads the first columns of  $B(0)$  and  $B(1)$ .

2. **Average Yield Shock** is orthogonal to the oil price shock. It represents changes in the average yield of sovereign debt not caused by surprised changes in oil prices. The variable oil prices does not respond contemporaneously to this shock. Again, this shock is assume to modify both exchange rate and inflation, but given the cause of the change is not considered in the calculation of PTE. Reads the second columns of  $B(0)$  and  $B(1)$ .
3. **Exchange Rate Shock** changes exchange rate but is orthogonal to the previous two shocks. This shock cannot be anticipated from oil prices changes or variations in the average yield of Costa Rican debt. We consider this shock a *surprise exchange rate shock*. This is the main shock in for our study. The response of inflation to this shock is what we use to calculate PTE. Reads the third columns of  $B(0)$  and  $B(1)$ .
4. **Surprise Inflation Shock** This shock is not caused either by oil price changes nor exchange rate. With this shock, inflation varies but non of the other variables in the model respond contemporaneously. Note that this shock represents variation in inflation not caused by oil prices, sovereign debt nor exchange rate. Reads the fourth columns of  $B(0)$  and  $B(1)$ .

By considering an endogenous model we allow for all these shocks to influence the transition probabilities in the model. This is more realistic that conventional Markov Switching models where the probability of switching from one regime to another is time-invariant. As we will discuss in the next section, our estimates show, for instance, that a positive surprise inflation shock increases the probability of switching to a low PTE regime. We explain this by the fact that surprise inflation causes a devaluation of the Costa-Rican *colón* which follows with an increase in the exchange rate that may lead to a low PTE as we discuss in the next section.

### 3 Results

In this section, we begin by showing the results of the linear estimation, that is, without regime-switching. That will be our comparison point for the regime-dependent results. We

find that the symmetric PTE is 5%, which vanishes quickly. Then, we proceed to regime-dependent results. We find that PTE is about 65% in the high regime and 4.5% in the low regime. Additionally, we discuss the different inflation and exchange rate responses to an exchange rate shock. We learned that the low PTE is low for the combination of two results: i) because the inflation change is relatively similar across regimes, and ii) the exchange rate response, the denominator of PTE, is up to eight times more extensive during the low regime. We corroborate with the inferred regime probabilities that historical episodes of significant exchange rate variations show a high likelihood of a low PTE regime.

### 3.1 Results of the Linear Model

The estimation of the PTE with our linear model (in Figure 3) shows about 5% response at impact and a quickly decaying response, which becomes statistically insignificant after one month (see Figure 3). This result is similar to the results obtained by [Guillermo Peón and Rodríguez Brindis \(2014\)](#) for the case of Mexico.

This result raises the question if the exchange rate has really such a little effect on the inflation in the case of Costa Rica. Or, instead, if the PTE effect is asymmetric and the results of the linear model show an off-setting combination of high and low PTEs.

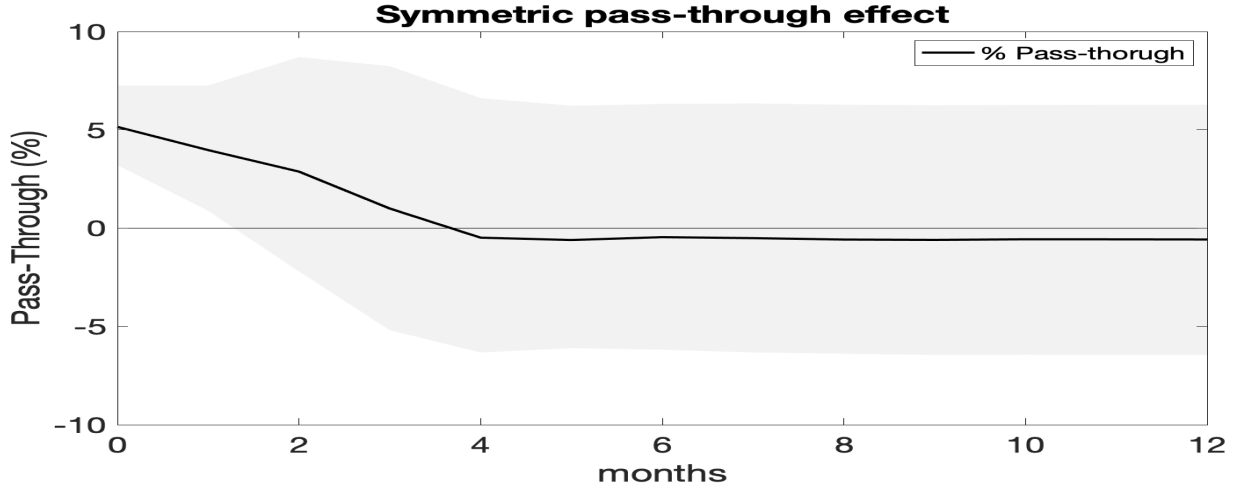
As evidence that the PTE in Costa Rica is asymmetric. We test the hypothesis of a linear PTE by performing a log-likelihood ratio test. We pretend that the linear model estimation is a regime switching model with the condition that the regimes are restricted to be equal. Then, we consider our regime switching estimation an unrestricted estimation. We use the log-likelihood value of each estimation to get the statistic and the  $\chi^2$  distribution to obtain the  $p$  value. The result is striking. With a  $p$ -value of practically zero, we can, with confidence, reject the hypothesis that the PTE is linear.

Now, we can focus on a regime switching PTE. We consider, as already discussed two different regimes. The results of the estimation are presented in the next part of this section.

### 3.2 Results of the Regime Switching Model

The estimation of a PTE with two regimes shows that the PTE in Costa Rica combines periods of large pass-through and periods of small or even negligible pass-through.

As it is shown in Figure 10 we estimate the PTE to be about 65% during the high regime and 80% after three months. The low-regime shows a PTE of 4.5% and becomes insignificant after just one month.



**Figure 3:** Pass-through effect in Costa Rica. Linear estimation with 68% confidence bands estimated using bootstrap methods. **Source:** Own elaboration.

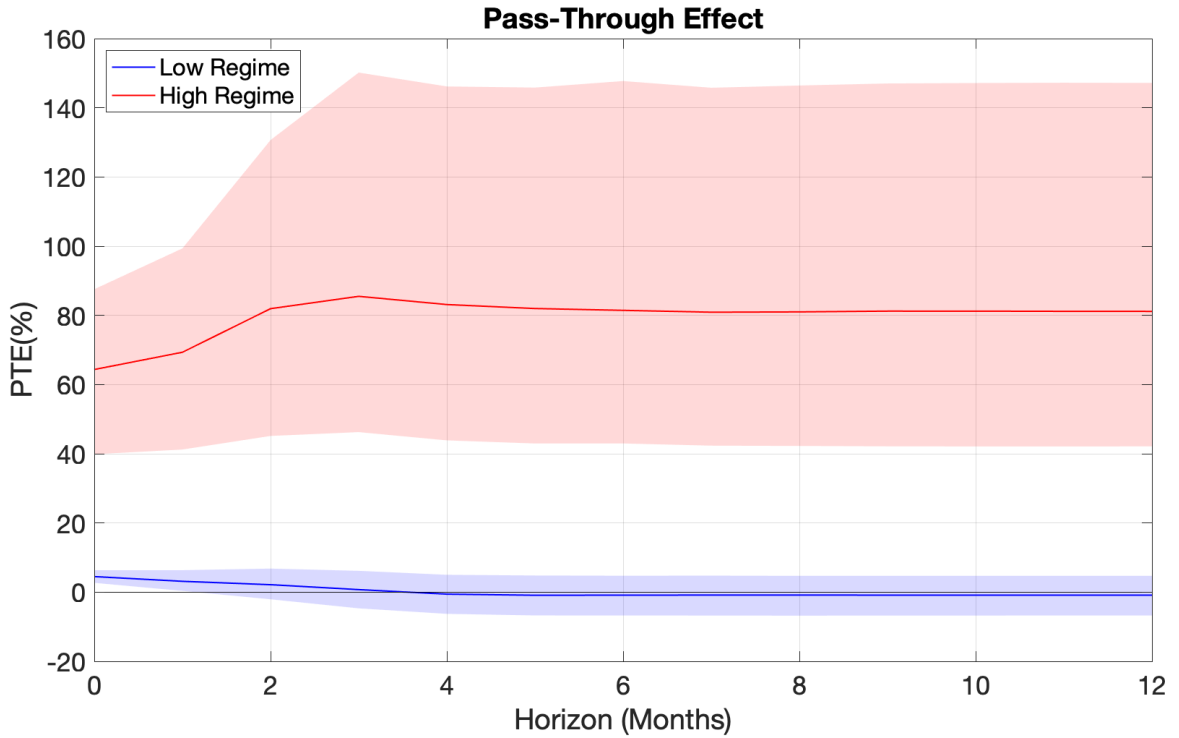
In figure 10, we also observe that the confidence band for the effects in the high regime are large (about 100%). This is a consequence of the fact that during the high PTE regime the variance of the exchange rate is small. Since the PTE is a ratio, when the denominator is small, the variability of PTE is large.

Note that the IRFs represented in the figure assume that the regime does not change for at least 12 months. Later we will see that for the regime persistence implied in the model this is often the case.

This results imply that when exchange rate increases one standard deviation the response of inflation to that shock is 0.045 standard deviations in the low regime and 0.65 standard deviations during the high regime.

The changes for inflation and exchange rate are given in standard deviations because their distribution is regime dependent. For instance, during the high regime a one-standard deviation change in exchange rate is just 0.20% (approx ₡ 1.24 in 2021) and during the low regime, the same one-standard deviation represents 1.60% (approx ₡ 9.92 in 2021).

In Figure 5 we observe the difference between the absolute responses of the variables inflation and exchange rate to shock to the latter variable. We appreciate that the main difference between the regimes is the distribution of the exchange rate. During the low regime, exchange rate shows large changes (about 8 time larger) than in the high regime. So, the low PT regime is due the combination of small changes in inflation and large changes in exchange rate while the high regime results from comparable changes inflation (across regimes) but much smaller exchange rate variations.

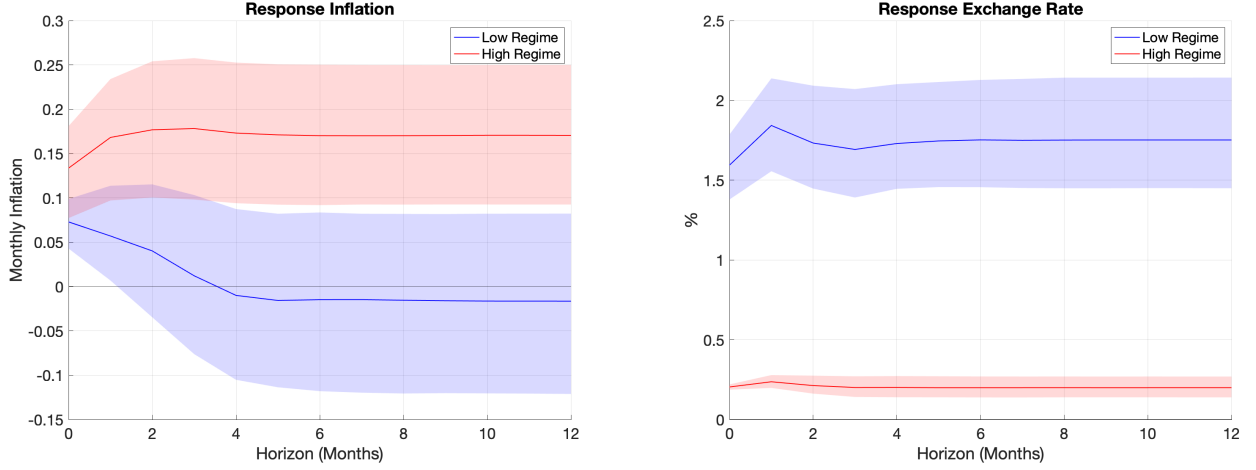


**Figure 4:** Pass-through effect in Costa Rica. The red line represents the PTE during the high-regime and the blue line the PTE during the low-regime. The shaded area represent the 68% confidence bands estimated using bootstrapping methods. **Source:** Own elaboration.

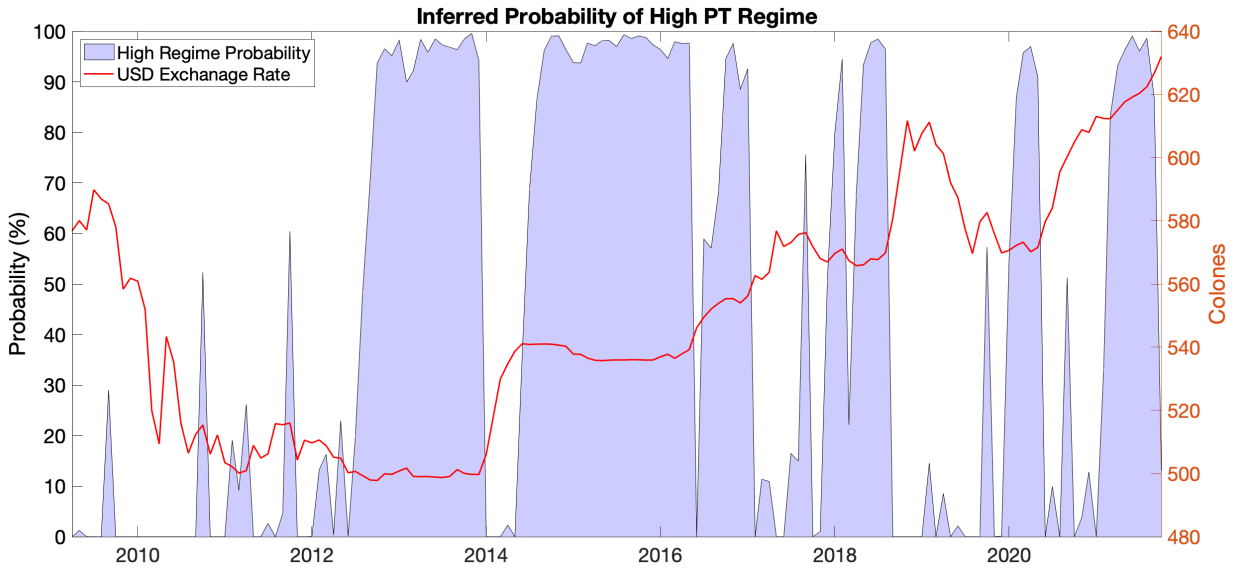
The response of inflation is very similar across regimes (see Figure 5). Nonetheless, the persistence of the response is different. After 4 months the response of inflation to an exchange rate shock is 0.17% (2.06% annual inflation) in the high regime and not significant in the low regime. We can practically say, that in the low regime, inflation does not respond to exchange rate variations.

In Figure 6 we show the regime probabilities during our sample from February 2009 to September 2021. For reference we added the USD-CRC exchange rate. One result that becomes clear is the fact that in periods where the exchange rate is volatile the probability of high regime is low or zero.

**Regime Dynamics** In Table 1 we present the estimation of the regime dynamics parameters. We deduce from the estimate of alpha that the regimes are quite persistent. The slightly (statistically) positive value of  $\tau$  suggest a small imbalance in favor of low regime periods (79 vs. 63). We show the endogenous effects in the norm of the  $\rho$  vector. The significant



**Figure 5:** Regime dependent impulse responses of exchange rate (right panel) and inflation (left panel) to an exchange rate shock. **Source:** Own elaboration.



**Figure 6:** The shaded area represent the probability of Inferred regime probabilities (left y-axis). In red (right y-axis) we have the USD exchange rate. **Source:** Own elaboration.

component of  $\rho$  is the correlation to surprise inflation  $-0.4799$  (increases transition probability to low regime). We explain this correlation by considering that an increase in inflation (not caused either by oil prices, sovereign debt, nor exchange rate) causes a devaluation of the CRC *colón*, consequently, this generate an increase in the exchange rate which causes a higher probability of transitioning to the low regime.

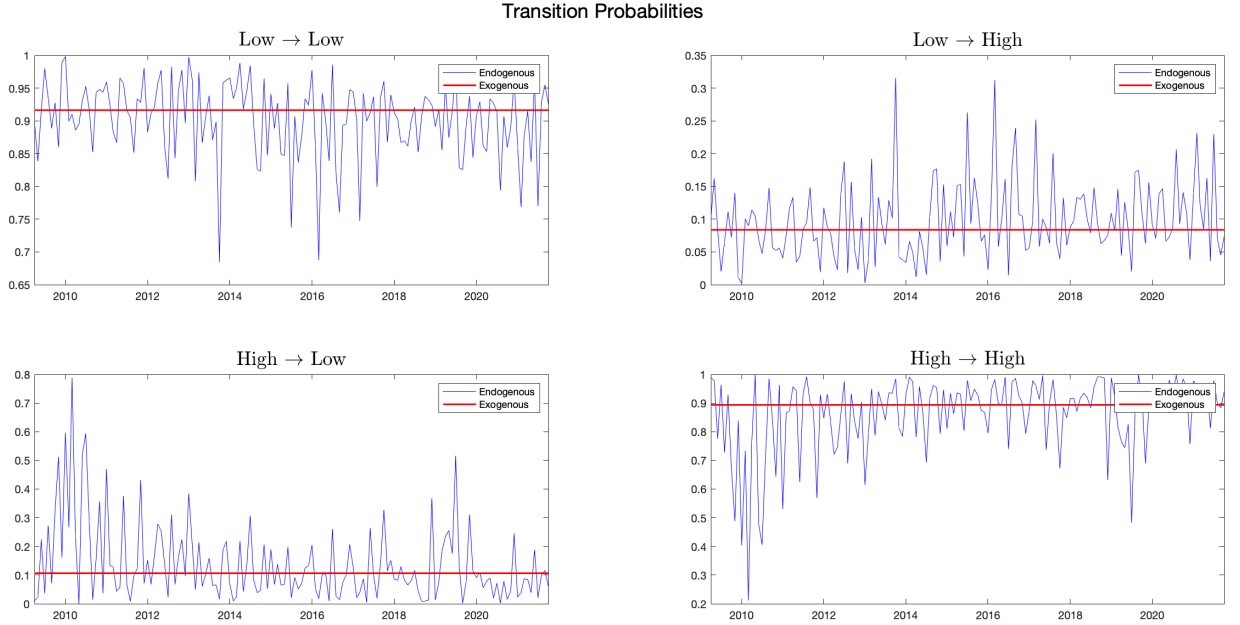
We used a log-likelihood test to determine the significance of the endogenous parameters.

Parameter	$\alpha$	$\tau$	$\ \rho\ $	Low Regime	High Regime
Estimate	.9431 (0.0449)	.3619 (0.9531)	.4799 (0.3024)	79 periods(52.32%)	63 perdios(41.72%)

**Table 1:** Regime dynamics parameters. Standard errors determined using the information matrix of the estimation optimization. **Source:** Own elaboration.

With a  $p$ -value of 8% we may, with moderate confidence reject the hypothesis that the regime dynamics is exogenous to the model.

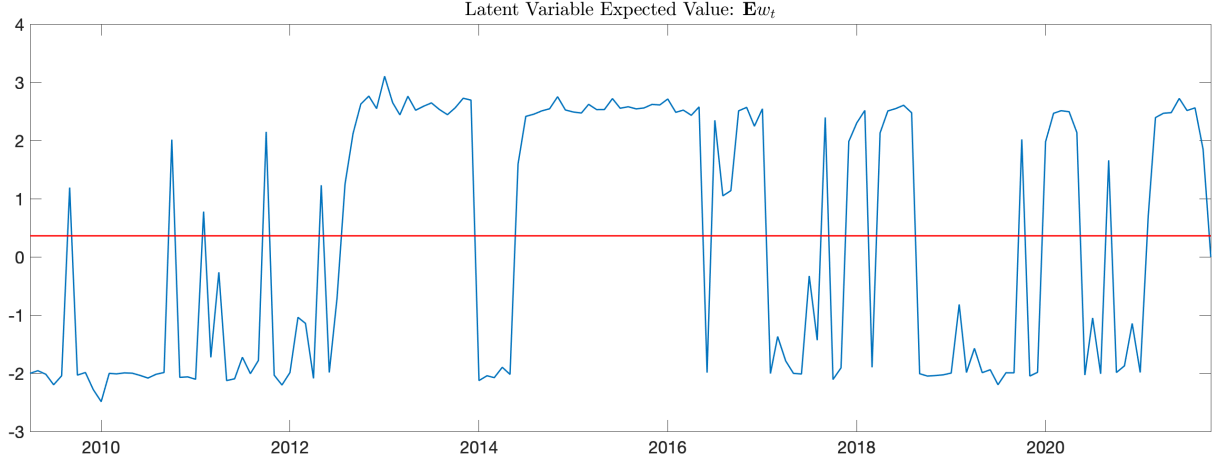
A consequence of the endogenous effects of the model is the fact that the transition probabilities may vary over time.



**Figure 7:** Inferred regime probabilities.

in Figure 7 we observe the comparison between exogenous and endogenous regime probabilities.

An additional interesting by-product of our models is the expected value of the latent variable. Since  $w_t$  is unobserved, by definition, we can obtain its exact value. But given the data, the filter developed by Chang, Choi and Park (2017) also delivers the expected value of the latent variable. This is, given the data an estimate of the possible value of the  $w_t$  during the whole sample.



**Figure 8:** Expected value of the latent variable  $w_t$ . The red line represents the value of  $\tau$  which determine the regime of the model. **Source:** Own elaboration.

**A caveat about the low regime.** It follows from our results that when the exchange rate volatility is above average, inflation seems unresponsive. This fact could be interpreted as a "get free out of jail card" for a policymaker juggling exchange rate and monetary policy during the low regime. We believe this is not the case.

Even though the effects of exchange rate on economic activity are beyond the present work's focus, we look (superficially) into it. We argue that during the low regime, changes in exchange rate manifests into economic activity (instead of prices).

To study this possibility we use the  $\mathbb{E}w_t$  series to estimate the following regressions

$$ea_t = k + \beta_1 x_t + e_t \quad (8)$$

$$ea_t = k + \tilde{\beta}_1 x_t + \tilde{\beta}_2 (x_t \cdot \mathbb{E}w_t) + e_t \quad (9)$$

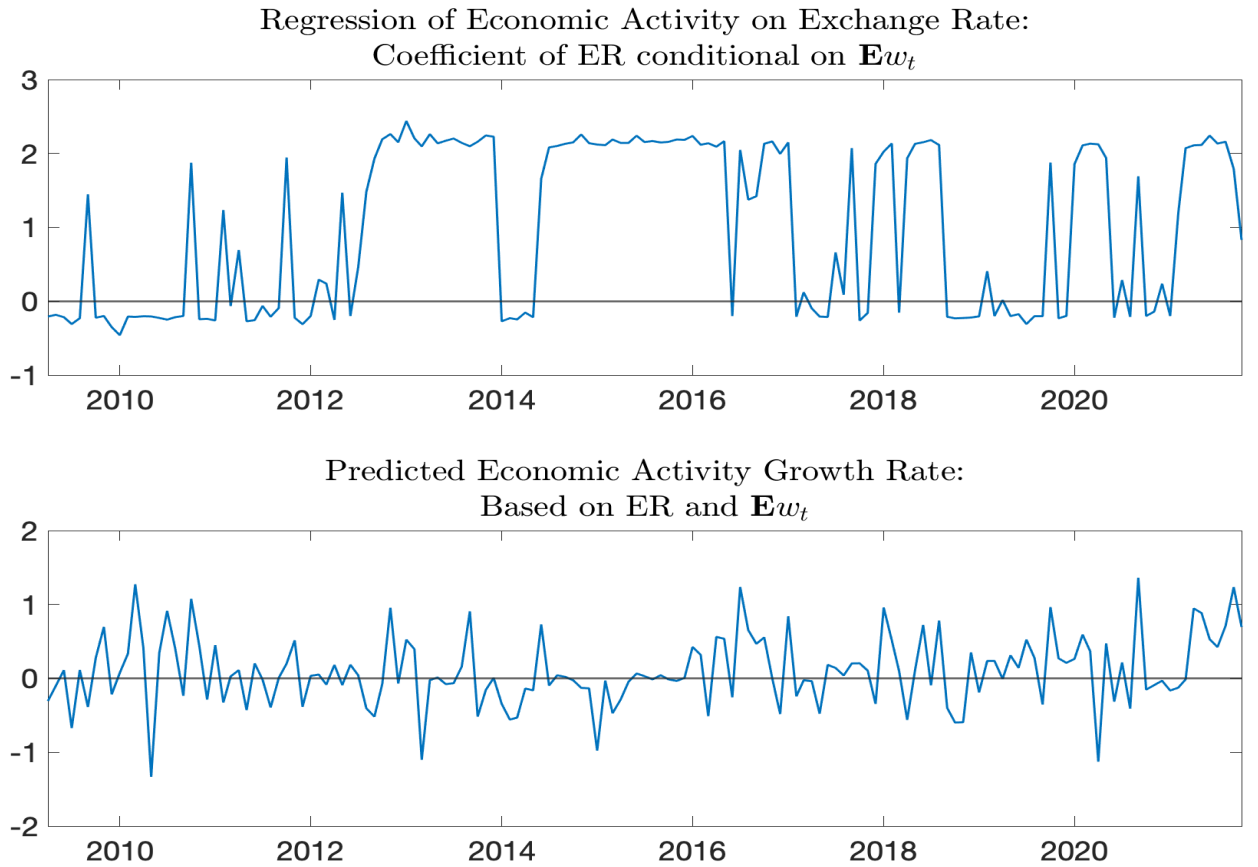
which link economic activity with exchange rate. In the second regression we consider an interaction term to determine how the latent variable could change the relation exchange rate and economic activity.

The estimation of the first regression shows that  $\hat{\beta}_1 = -0.16625$  is negative and only mildly significant. This estimation associates an increase in exchange rate with a decrease in economic activity. The  $p$ -value of this coefficient is 0.1987. The  $R^2$  of the regression is 1.14%.

To the contrary, the estimation of the second regression given by  $\hat{\tilde{\beta}}_1 = 0.83013$  and  $\hat{\tilde{\beta}}_2 =$

0.51839 demonstrates that the correlation between exchange rate and inflation can be positive (0.19332) and significant if the latent factor is positive and negative if the latent variable is negative. The  $p$ -value of each of the parameters are 0.03 and 0.008 (both significant at 5%) with an  $R^2$  of 5.84%.

For instance, during the devaluation in February 2014 the negative value the latent variable and the increase in the exchange rate had only a little effect on inflation but meant a reduction of the economic activity.



**Figure 9:** Top: Coefficient of the regression of exchange rate on inflation. Bottom: Predicted economic growth based on exchange rate and the expected value of the latent variable. **Source:** Own elaboration.

The top panel of Figure 9 suggests that during the low regime, an increase (decrease) in exchange rate could be associated with a reduction (growth) of economic activity.

In the bottom panel, we observe the predicted growth in economic activity based on the exchange rate and its interaction with the latent variable of the regime switching model of the PTE.



## 4 Policy Recommendations and Conclusions

Now, we present our policy recommendations based on our results and the conclusions of our study. We start with some of the statistical results and their implication and then we follow with suggestions on how to incorporate the endogenous asymmetric PTE into economic analysis.

### 4.1 Recommendations

Based on our results we have the following recommendations to policy makers:

- 1. Understand the pass-through effect as an asymmetric phenomenon.** The results in this paper indicate that considering the pass-through effect symmetric (or linear) underestimates the PTE. We have statistically shown (with strong confidence) that the PTE is not linear. During the low regime it is 4.5% at impact and vanishes after one month, but during the high regime it is 65% and in the long-run it can be up-to 80%.
- 2. The most significant asymmetry of PTE is the size.** It is the size of the exchange rate variation (volatility) what causes different magnitudes of pass-through effect. Contrary to the popular conception, with high volatility the size of the absolute response of inflation does not increase (in fact, it decreases). With high volatility we observe low PTE.
- 3. Consider that surprise Inflation has endogenous effects on the regime transition probabilities of PTE.** For example, if inflation increases and the variation cannot be attributed to oil prices, the yield on sovereign debt nor exchange rate, the probability of transitioning into the low regime. It could be explained by the fact that the surprise inflation devalues the CRC colón increasing exchange rate volatility and the probability of the low regime.
- 4. Examine the effects in economic activity of the combination of exchange rate variations and small (or absent) inflation response.** As we superficially analyzed in the low regime, when exchange rate is volatile and inflation responds mildly to ER, the effects on economic activity could be negative.

## 4.2 Conclusions

We used a regime switching structural vector auto-regression (RS-VAR) to study the asymmetries of the exchange rate pass-through effect in Costa Rica.

The statistical evidence that the PTE is asymmetric is overwhelming. We found a low (4.5%) and high (65%) pass-through effect.

The low regime is characterized by high exchange rate volatility. The high regime, to the contrary, is present during periods of large variations in the USD price.

Surprise inflation, defined as changes in inflation not caused by oil prices, average yield of sovereign debt nor exchange rate has endogenous effects on the regime transitions probabilities.

For future research we recommend to look into the relationship between the PTE and the real economy.

## References

- BRENES, C. and ESQUIVEL, M. (2017). Asimetrías en el traspaso del tipo de cambio durante el periodo de flexibilidad cambiaria en costa rica.
- CASTRILLO, D. and LAVERDE, B. (2007). Validación y actualización del modelo de pass through del tipo de cambio en costa rica 1991 -2007.
- CHANG, Y., CHOI, Y. and PARK, J. Y. (2017). A new approach to model regime switching. *Journal of Econometrics*, **196** (1), 127 – 143.
- ESQUIVEL, M. and GOMEZ-RODRIGUEZ, F. (2010). Asymmetries of the exchange rate pass through to domestic prices: The case of costa rica.
- FORBES, K., HJORTSOE, I. and NENOVA, T. (2018). The shocks matter: improving our estimates of exchange rate pass-through. *Journal of international economics*, **114**, 255–275.
- GUILLERMO PEÓN, S. B. and RODRÍGUEZ BRINDIS, M. A. (2014). Analyzing the exchange rate pass-through in mexico: Evidence post inflation targeting implementation. *Ensayos sobre Política Económica*, **32** (74), 18–35.
- HAMILTON, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica: Journal of the econometric society*, pp. 357–384.
- KROLZIG, H.-M. (1997). The markov-switching vector autoregressive model. In *Markov-Switching Vector Autoregressions*, Springer, pp. 6–28.
- LEÓN, J., MORERA, A. and RAMOS, W. (2001). El pass through del tipo de cambio: Un análisis para la economía costarricense de 1991 al 2001.
- RODRÍGUEZ, A. (2009). Evaluación del modelo lineal de pass-through para la proyección de inflación dentro del régimen de banda cambiaria.

## A Robustness Checks

### A.1 Variable Selection

We consider several combinations of variables to check the robustness of our results. Across all specifications the low regime pass-through is between 3% and 5%. The high regime pass-through is between 22% and 50%.

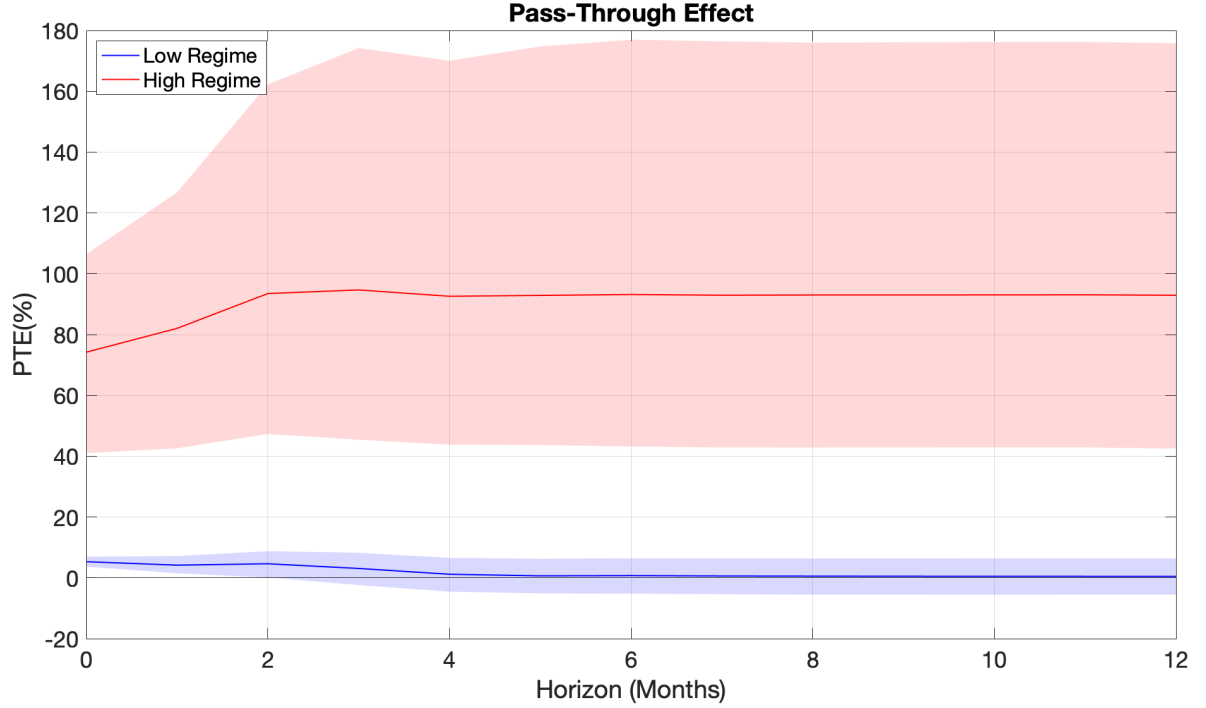
	Model						
Variable	Alternative 1	Alternative 2	Alternative 3	Alternative 4	Alternative 5	Benchmark	Alternative 6
Inflation	4 <sup>th</sup>	4 <sup>th</sup>	4 <sup>th</sup>	4 <sup>th</sup>	4 <sup>th</sup>	4 <sup>th</sup>	5 <sup>th</sup>
Exchange Rate	3 <sup>rd</sup>	3 <sup>rd</sup>	3 <sup>rd</sup>	3 <sup>rd</sup>	3 <sup>rd</sup>	3 <sup>rd</sup>	4 <sup>th</sup>
Gap Economic Activity	2 <sup>nd</sup>	2 <sup>nd</sup>	2 <sup>nd</sup>	2 <sup>nd</sup>	2 <sup>nd</sup>		2 <sup>nd</sup>
Oil Prices	1 <sup>st</sup>	1 <sup>st</sup>	1 <sup>st</sup>	1 <sup>st</sup>		1 <sup>st</sup>	1 <sup>st</sup>
Yield (hold by foreigners)					1 <sup>st</sup>	2 <sup>nd</sup>	3 <sup>rd</sup>
Sample	01.2009-02.2021	11.2006-03.2021	01.1991-03.2021	01.1991-12.2001	01.2009-02.2021	01.2009-02.2021	01.2009-02.2021
	Pass-Through Effect						
Lineal (0M)	4.95% [0.91%,6.69%]	3.47% [0.82%,6.22%]	4.87% [1.98%,7.79%]	12.71% [1.24%,29.95%]	5.23% [3.36%,7.05%]	4.72% [2.93%,6.60%]	4.84% [2.85%,6.62%]
Lineal (12M)	5.00% [0.13%,9.37%]	7.89% [2.66%,12.79%]	10.82% [5.61%,16.44%]	26.60% [10.92%,46.81%]	4.63% [-0.01%,9.42%]	4.11% [-0.48%,8.71%]	3.91% [-0.82%,8.80%]
Low (0M)	4.39% [2.71%,6.42%]	2.96% [1.11%,5.40%]	3.97% [2.20%,5.88%]	unbalanced	8.42% [5.48%,11.85%]	4.23% [2.32%,7.13%]	4.30% [2.52%,6.51%]
Low (12M)	4.44% [-0.34%,8.85%]	6.98% [11.03%,3.41%]	10.04% [8.97%,10.94%]	unbalanced	11.30% [3.73%,19.97%]	3.23% [-1.36%,9.21%]	2.57% [-2.21%,7.21%]
High (0M)	26.59% [6.84%,55.81%]	38.68% [16.97%,71.67%]	48.13% [19.40%,126.70%]	unbalanced	40.62% [18.16%,76.83%]	27.05% [13.15%,51.46%]	22.36% [8.81%,58.89%]
High (12M)	31.93% [6.72%,69.23%]	48.42% [21.84%,93.82%]	17.60% [31.11%,12.74%]	unbalanced	60.63% [25.37%,119.18%]	34.48% [15.64%,72.06%]	27.01% [8.56%,72.79%]

**Table 2:** Summary of alternative Models. The order of the variables describes the most exogenous variable.

### A.2 Pre-pandemic Results

To check for the robustness of our results to the pandemic period we estimated the same model using a sample ending in December 2019. We estimate the pre-pandemic regime dependent pass-through effect to be 5.3% in the low regime and 74.2% for the high PT regime.

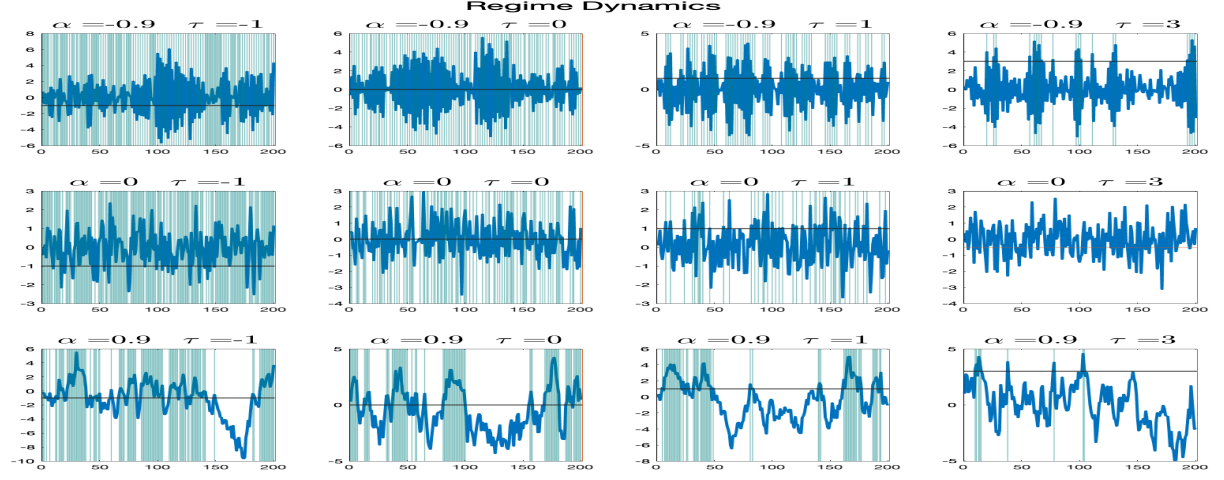
The pass-through effect is higher than the full-sample estimation but in both cases inside the confidence bands. Based on our estimation in the main text we determined that the most probable regime during the pandemic is a high PTE. The difference, nonetheless, is that in this period the USD exchange rate has increased more than in other high regime periods. This explain the increase in inflation we have observed in the last couple of months.



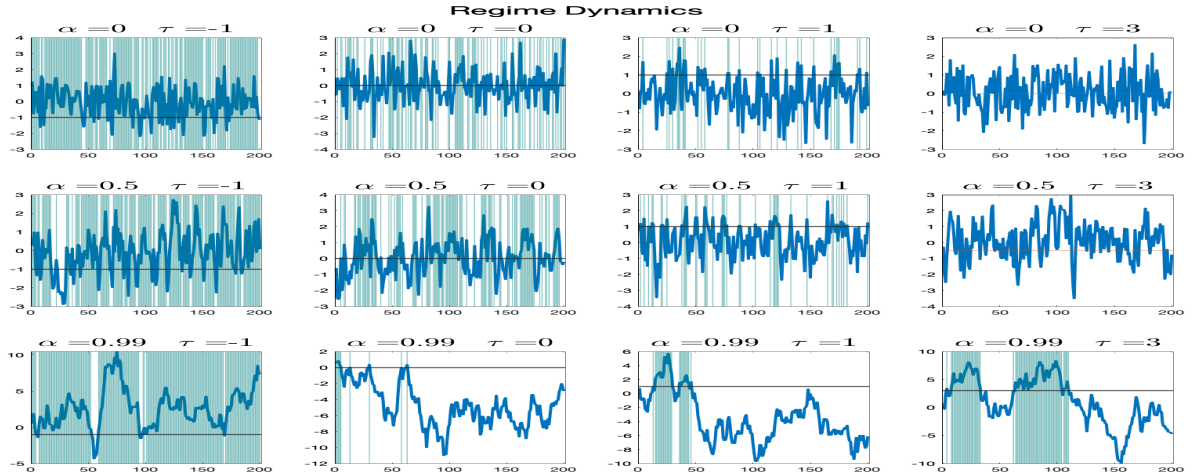
**Figure 10:** Pass-through effect in Costa Rica. The red line represents the PTE during the high-regime and the blue line the PTE during the low-regime. The shaded area represent the 68% confidence bands estimated using bootstrapping methods. **Source:** Own elaboration.

## B Regime Dynamics

The regime dynamics are dictated by the combination of the parameters  $\alpha$  and  $\tau$ . We show here how different combinations of values of these parameters can generate virtually all dynamics between regimes.



**Figure 11:** Negative values of  $\alpha$  generate rapid switching between periods causing regimes to be short. With positive (negative) values of  $\tau$  the high (low) regime becomes sporadic. When values of  $\alpha$  are positive and close to one, then the regimes become persistent (longer duration). Simulated processes with illustration purposes. **Source:** Own elaboration.



**Figure 12:** Large values of  $\tau$  generate one regime more recurrent. In the right panels the second regime barely appears. Simulated processes with illustration purposes. **Source:** Own elaboration.