Asymmetric Exchange Rate Pass-through: Evidence from Nonlinear SVARs*

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February 28, 2016

Abstract

We study the response of headline inflation to exchange rate innovations in a nonlinear context, where we distinguish between positive (depreciation) and negative (appreciation) exchange rate shocks. For that purpose, we specify a nonlinear Structural Vector Autoregressive (SVAR) model and we compute asymmetric impulse response functions for headline inflation after exchange rate innovations. We introduce a bootstrap Monte Carlo routine that allows to compute the error bands for these nonlinear impulse responses. Results for the Peruvian economy exhibit a remarkable statistically significant asymmetry in the response of headline inflation, both on impact and on propagation. In absolute values, the effect of a depreciation shock after one year is about twice the size of that corresponding to an appreciation shock. Roughly speaking, the one-year exchange rate pass-through to prices is 20 percent under a depreciation and only 10 percent under an appreciation.

JEL Classification: C32, E31, F31

Key words: Exchange rate pass-through, asymmetric impulse responses, non-linear SVARs, Bootstrap, Monte Carlo.

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*A previous version of this paper has been circulating under the title "Asymmetric exchange rate pass-through: Evidence from Peru". We acknowledge the comments from participants at the Central Bank of Peru Research Seminar, the XXXI Encuentro de Economistas at BCRP and the 2015 Annual Congress of the Peruvian Economic Association. The views expressed in this paper are those of the authors and do not necessarily represent those of the Central Reserve Bank of Peru (BCRP). All remaining errors are our own.

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1 Introduction

The Exchange rate pass-through to prices (ERPT) never ceases to be a relevant topic. Although there is general evidence of small pass-through to prices in countries with floating exchange rate regimes, the effect is still non negligible. Given the latter argument, in this paper we go one step further and ask whether the response of prices is symmetric across depreciation and appreciation episodes. This question is important since the evidence of a decreasing ERPT during the last decade, at least for the case of Peru, is mainly based on an episode of a persistent domestic currency appreciation relative to the US dollar with occasional, short depreciation periods, as depicted in Figure 1. Moreover, during the period 1999:01-2014:12 we find for the year-on-year depreciation rate that 44% of the observations correspond to a depreciation episode and 56% correspond to an appreciation one. Therefore, we have a considerable amount of information in order to conduct proper inference.

We focus on the case of Peru as a laboratory for our experiment, since it fits several characteristics that are important for our analysis. In particular, the central bank of Peru follows an inflation targeting monetary policy framework. Also, Peru features a partially dollarized financial system and a floating exchange rate. In this context, the imported component of inflation turns out to be relevant. We find that depreciation shocks produce stronger effects than appreciation shocks on headline inflation. This result is relevant for monetary policy because the asymmetry may exacerbate the trade-off between inflation control and output stability concerns when depreciation shocks hit the economy. The trade-off occurs because depreciation shocks may be contractionary as documented in Galindo *et al.* (2003).

There is a large literature that provide ERPT estimates for the Peruvian economy. In particular, we can mention the work of Winkelried (2003), Miller (2003), Maertens Odría *et al.* (2012), Winkelried (2013), among others. The main conclusion of this literature is

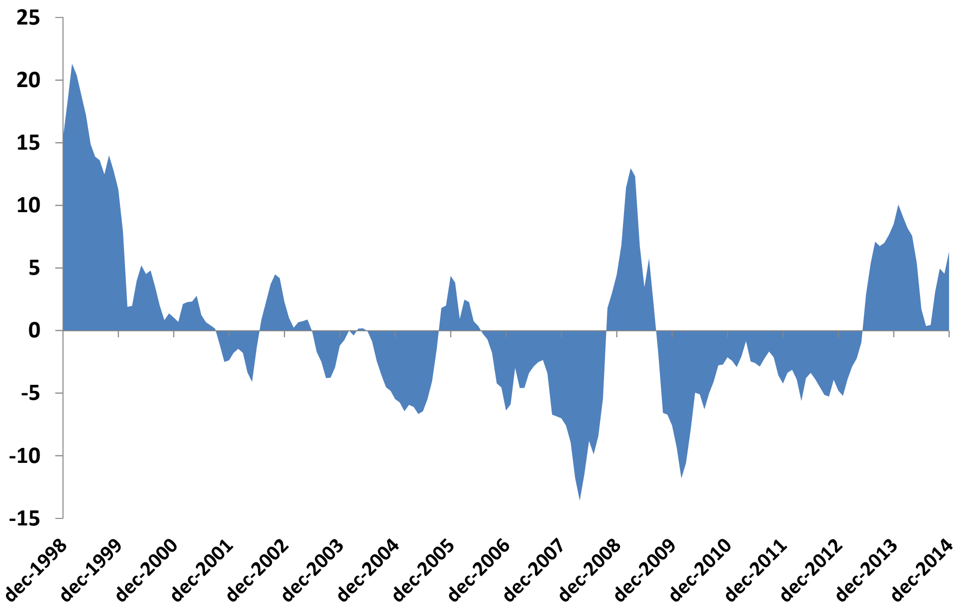

Figure 1. *Year-on-year depreciation rate of the Peruvian Sol (in percentages)*

that the ERPT, if any, is small and has been decreasing during the last decade. Nonlinear ERPT effects were studied in Winkelried (2003) where asymmetry depends on different stages of the business cycle. The state-dependency of the ERPT is captured through smooth transition VAR (STVAR) specifications. On key results is that the ERPT doubles and it can reach up to 30 percent within a year if the economy is the boom phase[1]. We introduce a different notion of asymmetry, we explores the presence of asymmetries in terms of the direction of the exchange rate variation. As far as we know, ours is the first paper that introduces this type of asymmetry in a VAR setup. Somewhat related to our contribution, Delatte and López-Villavicencio (2012) estimates asymmetric cointegrating models for various developed countries and find that depreciations effects are stronger than appreciations effects.

[1]See Shintani *et al.* (2013) for a recent application of the STVAR technique.

Withing the SVAR context, the task of capturing the differences between the responses of prices during depreciation and appreciation episodes is not straightforward. Empirical analysis for asymmetric responses can be found in the oil prices literature. In this context, Hamilton (2010) and Kilian and Vigfusson (2011) propose the use of censored variables in Structural Vector Autoregressive model (SVARs) in order to capture these asymmetries (see the complete debate in Hamilton (2009) and Kilian (2009)). In this paper we extend this setup, so that we present a bootstrap Monte Carlo routine that allows us to compute the error bands for these nonlinear impulse responses in line with Koop *et al.* (1996) and Potter (2000). The proposed routine might be useful for readers interested in the methodology. We apply the latter to the ERPT context, where we take the benchmark specification of Winkelried (2013) for the Peruvian case.

Finally, we link our results to existing theoretical models in the literature. In this regard, the asymmetry in price setting behavior is not new. Since Ball and Mankiw (1994), there exists a vast literature that takes into account some form of asymmetries when studying price setting[2]. In particular, we mention the work of Pollard and Coughlin (2004), who present a price setting model for importing good firms.

The document is organized as follows: section 2 describes the non-linear SVAR model used for the empirical analysis, section 3 presents the main algorithm for computing impulse responses, section 4 discusses the main results, section 5 describes the theoretical background and section 6 concludes.

2 The Model

In this section we study the presence of asymmetries in the responses of prices to exchange rate shocks. We employ the framework described by Hamilton (2010) and Kilian and Vigfusson (2011), a setup previously used to capture the nonlinear responses of output

[2]See Meyer and Von Cramon-Taubadel (2004) for a literature survey.

after oil prices shocks. To the best of our knowledge, this is the first paper that treats the asymmetry of ERPT in this way. We start with a minimal example and then develop the current framework used for the estimation.

2.1 Non-linear models and econometrics

A non-linear relationship can be captured as follows. First, consider the regression model between y and its own past, such that

$$y_t = c + \phi_1 y_{t-1} + e_t$$

The latter model is linear, therefore the relationship between y and its past is symmetric. However, if we wanted to capture a non-linear relationship, then we specify

$$y_t = c + \phi_1 y_{t-1} + \phi_1^F F\left(y_{t-1}\right) + \widetilde{e}_t \tag{1}$$

where $F\left(.\right)$ is a well defined non-linear function. Ideally, we would like to estimate equation (1), and this is what Kilian and Vigfusson suggest. On the other hand, Hamilton (2010) argues that it is preferable to estimate the expression

$$y_t = c + \phi_1^F F\left(y_{t-1}\right) + e_t^* \tag{2}$$

since it is a more parsimonious model. Clearly, in a single equation model this difference is negligible. However, once we turn to a multivariate model with many lags and variables, the context changes dramatically. That is, we consider a $VAR\left(p\right)$ model

$$\mathbf{Y}_t = \mathbf{c} + \mathbf{\Phi}_1 \mathbf{Y}_{t-1} + \mathbf{\Phi}_2 \mathbf{Y}_{t-2} + \cdots + \mathbf{\Phi}_p \mathbf{Y}_{t-p} + \mathbf{E}_t \tag{3}$$

where $\mathbf{E}_t \sim iidN(\mathbf{0}, \Omega)$ and where $\dim \mathbf{Y}_t = M \gg 2$. The model in this form has $K = M^2p + M$ coefficients. Furthermore, if we want to consider a nonlinear relationship then

$$\begin{aligned} \mathbf{Y}_t &= \mathbf{c} + \mathbf{\Phi}_1 \mathbf{Y}_{t-1} + \mathbf{\Phi}_2 \mathbf{Y}_{t-2} + \cdots + \mathbf{\Phi}_p \mathbf{Y}_{t-p} \\ &\quad + \mathbf{\Phi}_1^F \mathbf{F}(\mathbf{Y}_{t-1}) + \mathbf{\Phi}_2^F \mathbf{F}(\mathbf{Y}_{t-2}) + \cdots + \mathbf{\Phi}_p^F \mathbf{F}(\mathbf{Y}_{t-p}) + \widetilde{\mathbf{E}}_t \end{aligned} \tag{4}$$

where $\mathbf{F}(.)$ is a vector-valued non-linear function. Now the model has parameters

$$K^F = 2M^2p + M \gg M^2p + M = K \tag{5}$$

Clearly, controlling for non-linearity implies a large cost in terms of degrees of freedom, which means that the model is far from being parsimonious. Once this problem is presented, then it is clear that Hamilton's suggestion is the more reasonable one. Of course, in an ideal world we would have an infinite sample and this discussion would not be relevant anymore. Given that this is not the case, it is reasonable to estimate the expression

$$\mathbf{Y}_t = \mathbf{c} + \mathbf{\Phi}_1^F \mathbf{F}(\mathbf{Y}_{t-1}) + \mathbf{\Phi}_2^F \mathbf{F}(\mathbf{Y}_{t-2}) + \cdots + \mathbf{\Phi}_p^F \mathbf{F}(\mathbf{Y}_{t-p}) + \mathbf{E}_t^* \tag{6}$$

Naturally, the exclusion of the linear terms generates a potential source for the omitted variable bias. On the other hand, as it is clear in (5), the cost in terms of degrees of freedom implies that the estimation of (4) might be either unfeasible or highly unstable. As we can see, we face trade-off between consistency and parsimony. We take the lead of Hamilton and estimate the most parsimonious specification through OLS.

2.2 The nonlinear SVAR model

In order to estimate the response of prices to exchange rates we specify a Structural Vector Autoregressive model (SVAR). We explore the recent literature, since it will give us light about which is the most suitable information set for the estimation. In particular, a recent paper by Winkelried (2013) explores the time variation in the ERPT for Peru, and concludes that if any, it has been decreasing during the last decade. Since this is the most recent work for ERPT, we take its information set as a benchmark. Ideally, we could use a larger information set and estimate a Factor-Augmented model (FAVAR) or even assume a more sophisticated identification scheme than the standard Cholesky decomposition. However, these technical details are out of the scope of this paper, and the current specification is enough for answering our main research question.

Consider the vector $\mathbf{Y}_t = \left[\Delta RER_t, \Delta GDP_t, \Delta ER_t, \pi_t^{WM}, \pi_t^{WD}, \pi_t^{CPI}\right]'$. All variables are expressed in year-on-year changes and they are:

- ΔRER_t: Year-on-year real exchange rate percentage change.
- ΔGDP_t: Year-on-year GDP growth.
- ΔER_t: Year-on-year nominal exchange rate depreciation.
- π_t^{WM}: Year-on-year imported goods inflation (wholesale price index).
- π_t^{WD}: Year-on-year domestic goods inflation (wholesale price index).
- π_t^{CPI}: Year-on-year headline inflation (consumer price index).

Winkelried (2013) shows that plausible ERPT estimates can be obtained using this information set. As a benchmark, we use the same information set[3]. Furthermore,

[3] See Appendix A for details about the data description.

consider the nonlinear function

$$\mathbf{F}(\mathbf{Y}_t) = \begin{cases} \mathbf{Y}_t, & \text{if } \Delta ER_t > 0 \\ \mathbf{Y}_t^* & \text{otherwise} \end{cases} \tag{7}$$

where $\mathbf{Y}_t^*$ has $\Delta ER_t = 0$ and keeps the other elements of $\mathbf{Y}_t$ 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 ($\Delta ER_t < 0$) changes in the exchange rate (depreciation and appreciation, respectively), but we include the same information for the remaining variables.

2.3 Impulse responses computations

The computation of impulse responses in a nonlinear dynamic model is not straightforward. In fact, the literature of nonlinear impulse-response computations starts with Koop *et al.* (1996) and Potter (2000). Moreover, as it is pointed out by Hamilton (2010), since we use censored variables the responses must be consistent with this assumption. In this regard, the literature suggests the use of conditional forecasts for a given horizon. Let the expression

$$IR_Y^j(t,h) = E\left(\mathbf{Y}_{t+h} \mid \Sigma_t^1\right) - E\left(\mathbf{Y}_{t+h} \mid \Sigma_t^2\right), \quad h = 1, 2, \ldots \tag{8}$$

be the response of vector Y_t to a shock in variable j of size δ at date t. Where

$$\Sigma_t^1 = \left\{\mathbf{Y}^t, \Pi, J, U_{j,t}^{\delta}, U_{-j,t}\right\}$$

$$\Sigma_t^2 = \left\{ \mathbf{Y}^t, \Pi, J, U_t \right\}$$

where J is the Cholesky factor of the covariance matrix of error terms Ω such that

$$\Omega = JJ'$$

The latter expression fits with the definition of Generalized Impulse Responses for nonlinear models given by Potter (2000). Forecasts in (8) are optimal in the sense of Ordinary Least Squares (OLS). However, as Hamilton (2010) and Kilian and Vigfusson (2011) pointed out, if some variable is censored to be positive (the converse hold for negative censoring), and the optimal forecast is negative, then something else must be done. In our case, if the optimal forecast for a given horizon is negative, then the forecast is also censored[4]. It is important to remark the fact that all the conditional forecasts depend on i) the parameter values (Π, Ω), ii) the starting date t and the information set available at that date, i.e. F_t and iii) the shock realizations U_t, since innovations come from a normal distribution. That is, we have three sources of uncertainty in order to compute the impulse responses. As a result, we have to integrate out these three dimensions in order or assess the uncertainty properly. Last but not least, the size of the shock given δ is going to be treated as fixed. Therefore, we can notice that our setup is sufficiently flexible to explore another source of nonlinearity, which is to test whether responses are different depending on the size of the shock δ. In the next section we describe the proposed algorithm to compute impulse responses in a nonlinear context.

[4]Strictly speaking, we apply the nonlinear function $F(.)$ to the forecast $\mathbf{Y}_{t+h}$ at each horizon h.

3 A Bootstrap Monte Carlo routine for computing impulse responses in a nonlinear SVAR model

Since Sims (1980), the use of SVARs for macroeconomic empirical analysis became tremendously popular. In particular, the use of impulse responses as the main output of these models is now standard in the literature and turns out to be the starting point for constructing the so-called Dynamic Stochastic General Equilibrium (DSGE) models. Nevertheless, error bands computation for impulse responses is still a relevant topic in time series analysis. For instance, Sims and Zha (1999), Lutkepohl (2000), Inoue and Kilian (2013), Lutkepohl *et al.* (2015) among others, suggest different alternative routines in order to achieve this goal. In this section we propose a bootstrap Monte Carlo routine in which we have three dimensions of uncertainty: parameter values, initial forecasting point and shocks realization. Because of the latter, we have a nested loop which is illustrated as follows[5]:

0. Recover the residuals of the model and subtract the mean $\widehat{\mathbf{E}}^* = \left\{\widehat{\mathbf{E}}^*_t - (1/T)\sum_{t=1}^{T}\left(\widehat{\mathbf{E}}^*_t\right)\right\}_{t=1}^{T}$.

1. Set the numbers N, L and M, the horizon h and the size of the shock δ and the shock number j.

2. For each $n = 1, \ldots, N$ do:

   a. Draw $\widetilde{\mathbf{E}}^* = \left\{\widetilde{\mathbf{E}}^*_t\right\}_{t=1}^{T}$ as random draws with replacement from $\widehat{\mathbf{E}}^*$.

   b. Simulate $\widetilde{\mathbf{Y}}$ using $\widetilde{\mathbf{E}}^*$ and equation (6).

   c. Estimate the model parameters by OLS using the simulated data $\widetilde{\mathbf{Y}}$ and get the Cholesky decomposition matrix $\widetilde{\mathbf{P}}$ from the Covariance matrix of residuals.

   d. For each $m = 1, \ldots, M$ do:

[5]This algorithm can be associated with the seminal papers of Koop *et al.* (1996) and Potter (2000).

i. Draw $\mathbf{U}_{1,T^*}$ from $N(0,I)$ and create $\mathbf{U}_{2,T^*}$ such that the j-th component is δ and the other components are equal to $\mathbf{U}_{1,T^*}$.

ii. For each $l = 1, \ldots, L$ do:

***.** Draw $r \sim U(1,T)$ and take $T^* = round(r)$.

****.** Compute recursive forecasts for h periods starting from $\widetilde{\mathbf{Y}}_{T^*}$. Use $\widetilde{\mathbf{E}}^*_{1,T^*} = \widetilde{\mathbf{P}}\mathbf{U}_{1,T^*}$, $\widetilde{\mathbf{E}}^*_{2,T^*} = \widetilde{\mathbf{P}}\mathbf{U}_{2,T^*}$ and equation (6). Call them $\widetilde{\mathbf{Y}}^l_1 = \left\{\widetilde{\mathbf{Y}}^l_{1,t}\right\}_{t=T^*+1}^{T^*+h}$ and $\widetilde{\mathbf{Y}}^l_2 = \left\{\widetilde{\mathbf{Y}}^l_{2,t}\right\}_{t=T^*+1}^{T^*+h}$.

iii. Take the averages $\widetilde{\mathbf{Y}}^m_1 = \sum_{l=1}^{L}\widetilde{\mathbf{Y}}^l_1$ and $\widetilde{\mathbf{Y}}^m_2 = \sum_{l=1}^{L}\widetilde{\mathbf{Y}}^l_2$.

e. Take the averages $\widetilde{\mathbf{Y}}^n_1 = \sum_{m=1}^{M}\widetilde{\mathbf{Y}}^m_1$ and $\widetilde{\mathbf{Y}}^n_2 = \sum_{m=1}^{M}\widetilde{\mathbf{Y}}^m_2$.

f. Compute the difference $IRF_n = \widetilde{\mathbf{Y}}^n_1 - \widetilde{\mathbf{Y}}^n_2$.

3. Collect all $IRF = \{IRF_n\}_{n=1}^{N}$ and compute percentiles.

We set the number of draws $N = 1000$, as well as $L = 100$, since the number of observations T is around 200 and we also set $M = 100$ and $\delta = 1$, $j = 3$. In our application, results do not improve if we increase either N, L or M, meaning that convergence has been achieved. However, we recommend to not reduce these values, since in typical bootstrap Monte Carlo exercises the value of $N = 1000$ is standard, the value of L should cover at least the 50% percent of the sample size and also the value of $M = 100$ ensures a good coverage of the support of a standard normal distribution.

4 Results

In this section we explore the response of prices for the case of a depreciation ($\Delta ER_t > 0$) and an appreciation ($\Delta ER_t < 0$) separately. We compute the impulse responses for the nonlinear SVAR through the use of conditional forecasts as in Kilian and Vigfusson (2011). In addition, we compute the error bands using the bootstrap routine described in section

3. Since there is no consensus about how to sort impulse responses and compute these bands (see e.g. Inoue and Kilian (2013)), we follow the literature and plot the median values and percentiles for each horizon.

Results exhibit a noticeable asymmetry in the response of headline inflation, as it is depicted in Figure 2. For comparison purposes we present the effects of an appreciation with the opposite sign, so that in both regimes we have the same shock size. Symmetry would imply that the impulse responses of both regimes coincide.

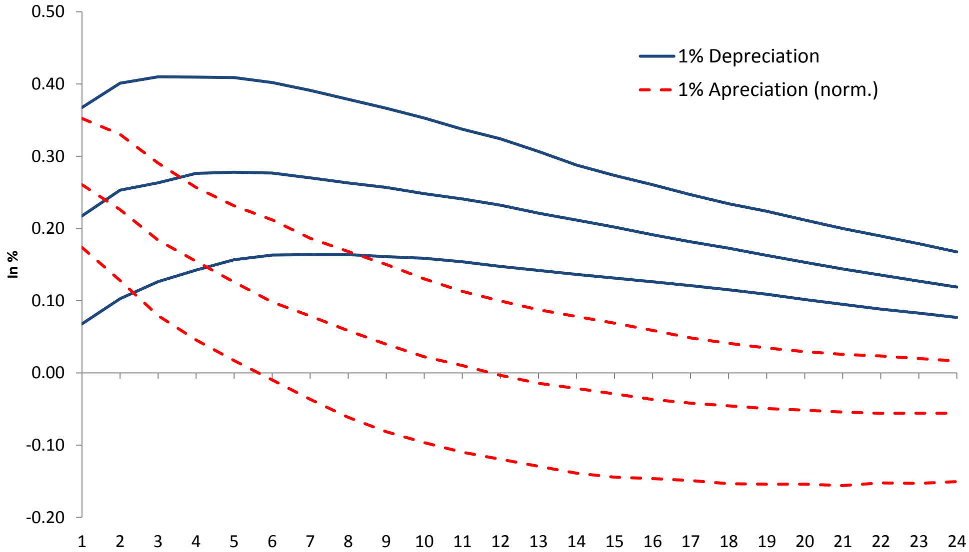

Figure 2. *Responses of headline inflation, median value and 68% bands. The IRF for appreciation shock has an inverted sign.*

When there is a 1% depreciation, headline inflation raises up to 0.3%, reaching this point in six months. Moreover, this effect is persistent and statistically significant for almost two years. On the other hand, when there is an 1% appreciation, headline inflation roses up to 0.3% as well, reaching this point in one month. Moreover, this effect is less persistent than the case of depreciation and it turns to be statistically insignificant at the 68% confidence level after one year.

Overall, we observe substantial differences in the transmission of exchange rate shocks to prices, both on impact and propagation. Price responses exhibit a hump-shaped pattern, meaning that the ERPT, if any, is not complete neither on impact, nor after many periods. Moreover, these responses are larger and more persistent under a depreciation with respect to an appreciation episode.

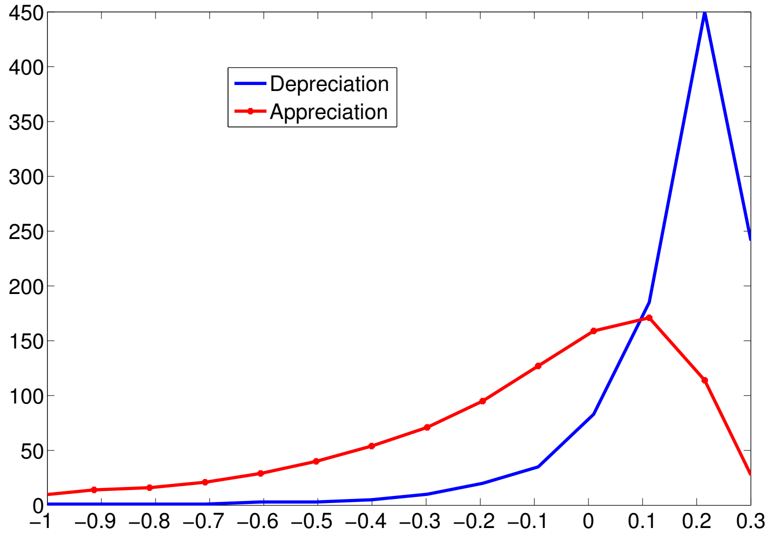

Figure 3. *Exchange Rate Pass-Through to Prices after one year*

Figure 3 depicts the distribution of ERPT estimates after one year obtained from the bootstrap procedure. The mode ERPT for appreciation shocks is close to 0.1% while the mode ERPT for a depreciation shock is about 0.2%. These asymmetric results are of the same nature to those results reported in Delatte and López-Villavicencio (2012) for the long run.

The results can be explained by the simple framework outlined in Figure 4. There we see that the difference between depreciation and appreciation shocks do not only rely on the downward rigidity of prices which would directly make appreciation shocks weaker than depreciation shocks. We also need to take macroeconomic effects into account. Two possible aggregate demand effects arise due to exchange rate shocks. The traditional expenditure switching effect and wealth effects due to financial dollarization of assets and liabilities of households and firms. The wealth effect of a depreciation shock is negative and the wealth effect of an appreciation shock is positive. We postulate that the extent of the wealth effect due to appreciations has been much stronger than the extent of wealth effect due to a depreciation. This has been so because the effect of depreciation shocks over aggregate demand conditions are softened by macroeconomic policy.

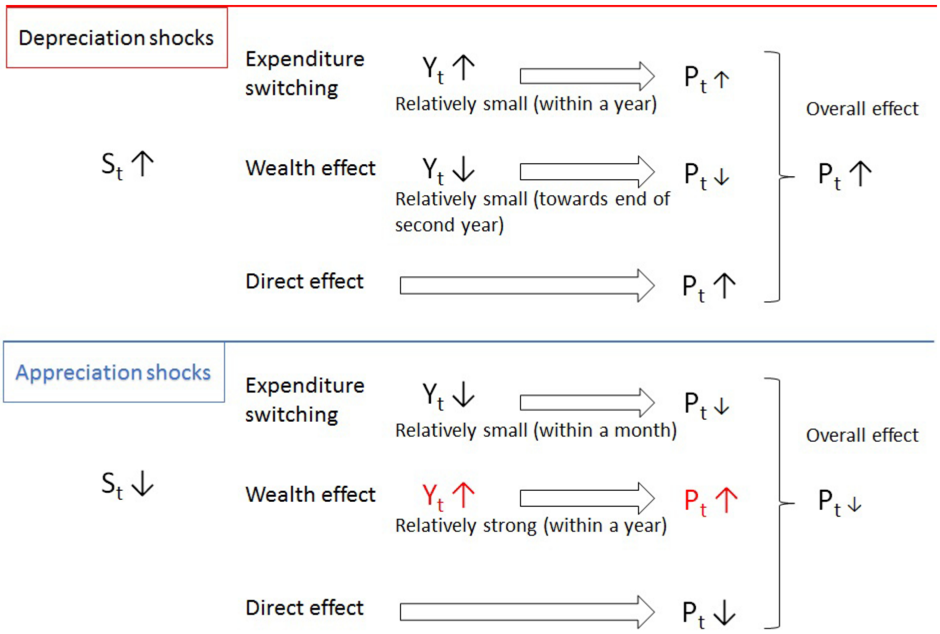

Figure 4. *Macroeconomic effects of exchange rate shocks*

Therefore, it is the extend of the positive wealth effect of an appreciation shock that may explain an upward bias in prices when the exchange rate appreciates. Overall, the effect on prices is dampened by the two countervailing forces: prices falling due to the exchange rate appreciation versus prices rising due to positive wealth effects in aggregate demand. Figure 5 shows that a depreciation shock has the strongest positive effect on GDP during month 4 and 5. At the end of the second year the effect is inverted in sign. This means that the expenditure switching effect seems to be more important in the short run while a weak negative wealth effect kicks in in the long run. Conversely, the effects of an exchange rate appreciation shock (inverted in sign) show a strong positive wealth effect within a year. This result helps explains the overall asymmetric exchange rate pass-through to prices.

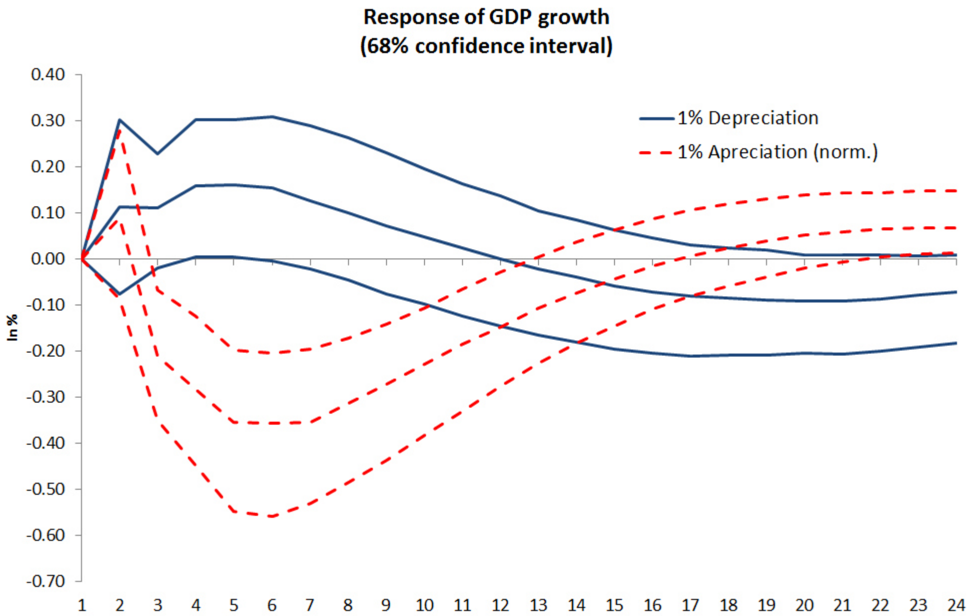

Figure 5. *Responses of GDP, 68% bands.The IRF for appreciation shock has an inverted sign.*

5 Theoretical Explanations for asymmetries in price setting behavior

Having observed the marked asymmetry in price responses, conditional on being in either a depreciation or an appreciation episode, one may wonder whether there is a rational and fully grounded explanation for this results. In this section we briefly review the existing models that treat this topic. One limitation of the models presented below is the fact that they are static. Therefore, the theoretical background that we will provide only explains the impact effect, but not the propagation of the responses observed in the data.

5.1 Ball and Mankiw's model

This is the first approach to the theme. The authors analyze the price setting problem in the context where there exists shocks to the firm's desired relative price and where prices are set for two periods (even periods). However, the firm can choose to reset its price in an odd period by paying a menu cost, which is internalized by the firm.

The crucial point in this model is the fact that desired prices also vary with a positive inflation rate. Therefore, if there is a negative shock to the price, then this is compensated by the positive inflation. As a result, the firm will be less inclined to reset its price. On the other hand, if there is a positive shock to the price, the opposite will occur. As it can be noticed, this asymmetry will disappear in a zero inflation context. Furthermore, the size of the shock also matters for the final decision. For example, a big negative shock is less likely to be compensated than a small one.

5.2 Pollard and Coughlin's model

The authors present a simple framework for exploring the effects of changes in the value of foreign currency to prices. In particular, they focus their attention on importing good firms. The idea is that exchange rates affect prices through the costs channel. That is, changes in costs will affect markups and therefore the price setting decision. They find that, in cases where firms can use both domestic and imported inputs, a shock in exchange rates will alter the profit margins. How much? It depends on the elasticity of factor prices to exchange rates and depends on the elasticity of markups to prices. The final decision of price resetting depends on the firm. Crucially, firms face strategic complementarities, and they will modify their prices according to their best response correspondence given the price of the competitor. As a result, if the exchange rate shock increases profit margins, then the firm could maintain its price and get additional profits or strategically cut it to gain some market share. On the other hand, if the exchange rate shock decreases profit margins, then the firm could raise its price to restrain it or strategically maintain its price to keep its market share constant.

We interpret the decisions related with market share as the ones that depend on the demand elasticity of each market and the market power of the firm. In addition, as it is somewhat obvious, monopolistic competitors will be more resilient to cut their prices, but will accept increases in their prices.

Pollard and Coughlin (2004) also mention that one possibility of incomplete ERPT is the fact that firms may switch between domestic and imported inputs, depending on their price. Therefore, if there is an exchange rate shock that affects price factors, firms could re-compose their input bundle such that the effect on the margin is, at least, partially mitigated. Thus, this reduces the possibility of price adjustments. Overall, we can notice that there are many reasons of why the ERPT may be asymmetric, so that our empirical evidence is somewhat plausible.

5.3 Remarks

Clearly, in line with Ball and Mankiw (1994) and Pollard and Coughlin (2004), our empirical results say that firms react differently when there are positive shocks to prices than negative ones. The observed asymmetry might be caused by one of the motives mentioned above. However, these are static models without inter temporal decisions. Therefore, the next step in our research would be to write down a dynamic model capable of replicate these facts.

6 Concluding Remarks

The central question of this paper is whether prices respond in a symmetric fashion to exchange rate shocks. We have found aggregated evidence for the 'no' using statistical methods, i.e. we specify a nonlinear SVAR and propose a bootstrap Monte Carlo routine for computing impulse responses with error bands. The proposed routine might be useful for readers interested in the methodology. We find an asymmetric ERPT that depends on whether the current episode is a depreciation or an appreciation. This result is relevant in terms of monetary policy design, since we provide aggregate evidence of different behavior of prices under the two considered regimes, and price stability is the ultimate goal for a Central Bank that actively implements the Inflation Targeting scheme. Furthermore, our analysis can be easily extrapolated to similar Small Open Economies and Emerging Market ones, but we leave this for future research agenda.

A Data Description

Monthly 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 1998 to December 2014. All variables were expressed in year-on-year percent changes. These variables are:

- RER_t: Bilateral Real Exchange Rate Index (2009=100).
- GDP_t: Gross Domestic Product Index (2007=100) [6].
- ER_t : Nominal Exchange Rate (S/. per US$).
- WMP_t: Wholesale Prices of Imported Goods Index (1994=100).
- WDP_t: Wholesale Prices of Domestic Goods Index (1994=100).
- CPI_t: Consumer Price Index of Lima (2009=100).

[6] Growth rates for dates before 2003 were recovered using the index of base 1994=100

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