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EVOLUTION OF THE EXCHANGE RATE PASS-THROUGH INTO PRICES IN PERU: AN EMPIRICAL APPLICATION USING TVP-VAR-SV MODELS

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Evolution of the Exchange Rate Pass-Through into Prices in Peru: An Empirical Application Using TVP-VAR-SV Models*

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Abstract

We use a set of VAR models with time-varying parameters and stochastic volatility (TVP-VAR-SV) to estimate the evolution of the exchange rate pass-through (ERPT) into prices for Peru over 1995Q2-2019Q4. According to two Bayesian selection criteria, the best-fitting models allow most parameters and the variances of shocks to evolve over time. The results are divided into two parts: (i) the ERPTs into import and producer prices decline significantly since the end of the 1990s until 2008. However, since 2014 both ERPTs resurge considerably due to exchange rate depreciation associated with the end of Quantitative Easing (QE), falling commodity prices, and global political events. These findings are in line with recent literature using TVP-VAR-SV and emphasizing ERTP resurgence after the Global Financial Crisis (GFC); (ii) the ERPT into consumer prices declined steadily throughout the sample. This is in line with the existing literature and is explained by a low-inflation context under an Inflation Targeting (IT) regime and by strong Central Bank credibility. Finally, the results are robust to a set of sensitivity exercises, including changes in the variables associated with the external shock and domestic economic activity, as well as in the values of the priors; and an estimation of the ERPT for Colombia.

JEL Classification: C11, C32, E31, F31.

Keywords: Exchange Rate Pass-Through into Prices, Vector Autoregressive Model with Time-Varying Parameters, Stochastic Volatility, Bayesian Estimation and Comparison of Models, Deviance Information Criterion, Marginal Likelihood, Peruvian Economy.

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Evolución del Efecto Traspaso del Tipo de Cambio a Precios en Perú: Una Aplicación Empírica utilizando Modelos TVP-VAR-SV*

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15 de Marzo 2022

Resumen

Utilizamos un conjunto de modelos VAR con parámetros variables en el tiempo y volatilidad estocástica (TVP-VAR-SV) para estimar la evolución del efecto traspaso del tipo de cambio (ERPT) a precios para Perú en el periodo 1995Q2-2019Q4. Según dos criterios de selección de Bayesiana, los modelos que mejor se ajustan a los datos permiten que la mayoría de los parámetros y las varianzas evolucionen en el tiempo. Los resultados se dividen en dos partes: (i) los ERPTs a los precios de importación y producción disminuyen significativamente desde el final de la década de 1990 hasta 2008. Sin embargo, desde 2014, ambos ERPTs resurgen considerablemente debido a la depreciación del tipo de cambio asociada con el final de la flexibilización cuantitativa (QE), caída de los precios de las materias primas y eventos políticos globales. Estos hallazgos están en línea con la literatura reciente utilizando modelos TVP-VAR-SV y que enfatizan el resurgimiento del ERTP después de la crisis financiera mundial (GFC); (ii) el ERPT a los precios del consumidor ha declinado constantemente a lo largo de la muestra. Esto está en línea con la existente literatura y se explica por un contexto de baja inflación bajo un régimen de metas explícitas de inflación (IT) y por la fuerte credibilidad del Banco Central. Finalmente, los resultados son robustos a un conjunto de ejercicios de sensibilidad, incluyendo cambios en las variables asociadas con los choques externos y la actividad económica doméstica, así como en los valores de las priors; y una estimación del ERPT para Colombia.

Clasificación JEL: C11, C32, E31, F31.

Palabras Claves: Efecto Traspaso del Tipo de Cambio a Precios, Modelo de Vectores Autoregresivos con Parámetros Cambiantes en el Tiempo, Volatilidad Estocástica, Estimación Bayesiana y Comparación de Modelos, Criterio de Información de Desviación, Verosimilitud Marginal, Economía Peruana.

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1 Introduction

Over the last three decades, the Peruvian economy experienced significant structural reforms and changes in economic policy (e.g., Inflation Targeting (IT) adoption in 2002), as well as a range of external shocks (e.g., the 2008 Global Financial Crisis (GFC)). As a small, open and partially dollarized economy, Peru is exposed to external shocks that cause exchange rate fluctuations. In the presence of real and financial dollarization, these fluctuations alter firms' cost structures, in turn affecting consumer prices. This phenomenon is known as the Exchange Rate Pass-Through (ERPT) into domestic prices.

In this context, understanding the effect of exchange rate fluctuations on inflation dynamics is key to the monetary authority. Winkelried (2014) and Sansone and Justel (2016) point out that the ERPT is relevant to the design of monetary policy, as it can affect its conduct and the choice of the inflation target. Along these lines, Maertens Odría et al. (2012) and Sansone and Justel (2016) indicate that both ERPT level and velocity affect the transmission mechanism of monetary policy, as well as inflation control and forecasting. Therefore, the assumption of a time-constant ERPT may affect the effectiveness of monetary policy.

In general, the literature shows a global ERPT decline associated with a low-inflation context; see Taylor (2000) and Takhtamanova (2010). Empirical studies for Peru confirm this evidence, supported by IT adoption, a free-floating exchange rate regime, and the enhanced credibility of the Central Reserve Bank of Peru (BCRP); see Maertens Odría et al. (2012), Ghosh (2013), and Borensztein and Queijo (2016), among others. At the same time, Borensztein and Queijo (2016) maintain that, although in decline, the ERPT continues to be a relevant determinant of domestic inflation. Additionally, Winkelried (2014) indicates that such decline should be taken with caution, as the ERPT is a constantly evolving parameter dependent on the state of the economy. Therefore, it is necessary to use approaches that can capture the time variability of the ERPT, as well as the effect of domestic and external shocks on its estimation.

Recent studies like Dahem et al. (2017) and Baxa and Šestořád (2019), among others,[1] estimate the ERPT for several economies using VAR models with time-varying parameters and stochastic volatility (TVP-VAR-SV), showing that its behavior is not constant either over time or in subsamples; and that, while IT adoption has implications for ERPT decline and dynamics,[2] external shocks like the GFC are important for ERPT evolution; see Forbes et al. (2018) and Jašová et al. (2019), among others. This evidence shows an ERPT surge during and after the GFC, and in episodes of depreciation against the U.S. dollar in advanced countries (see Shioji (2014 and 2015) and Alexius and Holmberg (2017), among others) and emerging market economies (EMEs); see Jooste and Jhaveri (2014) and Dahem et al. (2017).

This paper seeks to estimate the ERPT over time for Peru. Following Chan and Eisenstat (2018), we estimate it using a TVP-VAR-SV approach and a set of models with restrictions on the specification of the parameters and/or stochastic volatility (SV). This document does not seek to identify the drivers of ERPT evolution. Therefore, after analyzing such evolution, we associate it with the main economic and political events, both in the country and abroad, over 1995Q2-2019Q4.

The TVP-VAR-SV approach allows the parameters of lagged variables, contemporaneous parameters, intercepts, and the innovation variance to vary over time. Estimating the parameters at each moment in time gives them flexibility to change according to the state of the economy, thereby

[1] Based on Primiceri (2005), Cogley and Sargent (2005), and Nakajima (2011).

[2] As assumed in other studies for Peru.

capturing simultaneous, non-linear, and time-varying relationships between variables, while SV captures the heteroscedasticity of shocks. When estimating the ERPT, these features make it possible to consider the effects of abrupt and gradual changes in structural reforms, economic policy, and external shocks experienced by the Peruvian economy over the period of analysis. Additionally, this approach is flexible enough to consider long-term changes without having to estimate the ERPT in sub-samples. This generalizes the non-linear (asymmetrical) multivariate treatment and the analysis in sub-samples or regimes (pre- and post-IT) of the ERPT carried out for Peru; see Miller (2003), Winkelried (2003), Maertens Odría et al. (2012), Winkelried (2014), Pérez-Forero and Vega (2015), and Cueva (2018), among others.

According to two Bayesian selection criteria (Marginal Log-Likelihood and the Deviation Information Criterion), the best-fitting models allow most parameters to vary over time, emphasizing the role of the SV. In this regard, the estimation results for the time-varying ERPT can be divided into two parts. First, ERPTs into import and producer prices show a considerable reduction since the end of the 1990s until mid-2008. However, post-GFC, particularly since 2014, both ERPTs resurge significantly through the end of the sample. This resurgence is explained by domestic currency depreciation caused by the end of Quantitative Easing (QE) (the 2013 "Taper Tantrum"), the end of the commodity price supercycle, and global political developments (Brexit and the U.S.-China trade war). Additionally, these findings are in line with the new literature adhering to the TVP-VAR-SV approach and stating that there was an ERPT resurgence after the GFC; see Jooste and Jhaveri (2014), Alexius and Holmberg (2017), and Dahem et al. (2017). Second, the ERPT into consumer prices shows evidence of a considerable and sustained decline throughout the sample. This is consistent with the literature (Maertens Odría et al. (2012), Winkelried (2014), BIS (2019), and Castellares and Toma (2020)), and is explained by a low-inflation context in Peru after IT adoption and the BCRP's enhanced credibility in anchoring inflation expectations.

All findings are robust to several sensitivity exercises, which include changes in the variables associated with both external developments and domestic economic activity, changes in the values of priors, and estimation of the ERPT for Colombia.

The remainder of the document is organized as follows. Section 2 reviews the relevant empirical literature. Section 3 describes the methodology. Sections 4 and 5 present the empirical results and the robustness analysis, respectively. Finally, Section 6 shows the conclusions.

2 Literature Review

Empirically, the ERPT is estimated via several approaches, mainly: (i) Dynamic Stochastic General Equilibrium (DSGE) models; (ii) cointegration models; (iii) single-equation models; and (iv) Vector Autoregressive (VAR) models. The latter two are divided into models with time-constant[3] and time-varying models.

Important studies using DSGE models and variants include Buyandelger (2015) for Mongolia, Patra et al. (2018) for India, and Marodin and Portugal (2019) for Brazil. Studies using DSGE and VAR models jointly include Razafindrabe (2016) and Forbes et al. (2018) for the UK, and Palleja (2018) for Chile and Mexico. In general, they find a reduction in the ERPT and highlight the relevance of the state of the economy and external shocks for its evolution.

For their part, the studies by Ponomarev et al. (2016) for Russia, Bada et al. (2016) for Nigeria, and Liu and Chen (2017) and Pan (2018) for China use cointegration models to analyze

[3]For single-equation models with constant parameters, see Takhtamanova (2010).

and estimate the long-rung ERPT; and find that the ERPT declines along the pricing distribution chain.

Additionally, studies using single-equation models with time-varying parameters to analyze the ERPT include Kim (1990) for the U.S.; Darvas (2001) for the Eurozone; Albuquerque and Portugal (2005) for Brazil; Sekine (2006) for six large industrialized economies; De Souza et al. (2013) for Brazil; Ben Ali and Tarek (2014) for Tunisia; Hara et al. (2015) for Japan; and Jiménez-Rodríguez and Morales-Zumaquero (2016) for G-7 countries. In general, they find that the ERPT has declined steadily over time for these economies. Studies using a different estimation approach (rolling windows), like López-Villavicencio and Mignon (2016) and Jašová et al. (2019), obtain similar results.[4]

The literature using VAR models for ERPT estimation is extensive[5] and varied regarding the specification and identification scheme for structural shocks. Studies using linear VAR models with recursive identification include the seminal work by McCarthy (2007) for a set of industrialized economies, Ca'Zorzi et al. (2007) for Mexico and Chile, Miller (2003) and Winkelried (2014) for Peru, and Helmy et al. (2018) for Egypt.

Studies using non-recursive identification of structural shocks include: (i) Shambaugh (2008), who employs long-term identification to examine the relationship between the exchange rate and prices in Chile, Colombia, and other economies; (ii) An and Wang (2012), who use sign restrictions to estimate the ERPT for nine OECD economies; (iii) Comunale and Kunovac (2017), who use a VAR model with zero-value and sign restrictions, estimated with Bayesian techniques, to analyze the ERPT in four Eurozone countries; and (iv) Corbo and Di Casola (2018), who use two VAR models[6] to analyze the ERPT conditional on shocks causing exchange rate fluctuations in Sweden. Karagöz et al. (2016) use VAR and panel VAR models to perform and compare ERPT estimations for EMEs[7]. Borensztein and Queijo (2016) and Tunç and Kılınç (2018) use SVAR-X models[8] to analyze the ERPT for seven South American countries and Turkey, respectively.

All studies using VAR models (irrespective of the method for identifying structural shocks) assess mainly the effect of IT adoption on the ERPT; and conclude that the latter: (i) declined considerably since IT adoption; (ii) is incomplete (less than the unity) and time-varying; (iii) depends on the exchange rate shock. Moreover, exchange rate variations show a steadily declining impact on pricing along a distribution chain (PDC); and this impact is smaller in low-inflation economies.

At the same time, few studies use non-linear VAR models to analyze and estimate the ERPT; and most of them use recursive identification. For Peru, Winkelried (2003) uses a smooth-transition VAR model (ST-VAR); Maertens Odría et al. (2012) use an ST-VAR model with two regimes (pre- and post-IT); and Pérez-Forero and Vega (2015) use a non-linear VAR model estimated with Bayesian techniques. The results indicate that the ERPT: (i) is non-linear and (ii) declined since IT adoption; and that exchange rate depreciation shocks have a higher impact than appreciation shocks.[9]

[4] Except for Gayaker et al. (2021), who find that the ERPT into consumer prices has increased since 2011 in Turkey, due to a loss of central bank credibility post-GFC and high exchange rate volatility.

[5] For a comprehensive review, see Aron et al. (2014) and Tunç (2017).

[6] One with short-run restrictions and another with long-run and sign restrictions.

[7] Latin America (Brazil, Mexico, Chile, and Peru), Asia-Pacific (South Korea, Philippines, and Thailand), and Turkey.

[8] Structural VAR with an exogenous block.

[9] Cueva (2018) also analyzes ERPT non-linearity and asymmetry in Peru and Mexico, although employing the

Studies using non-linear VAR models for other Latin American economies include Rincón-Castro and Rodríguez-Niño (2018), who use a logistic Bayesian ST-VAR model for Colombia. For Mexico, Aleem and Lahiani (2014) use a threshold VAR (T-VAR) model with three regimes; and Donayre and Panovska (2016) use a Bayesian T-VAR model. For Brazil, Balcilar et al. (2019) use an ST-VAR model. These studies focus on the asymmetry and influence of the state of the economy on ERPT estimation. In general, the results indicate that the ERPT: (i) is non-linear; (ii) depends on the state of the economy and the type of shock; (iii) is greater when the size of the shock exceeds the threshold; (iv) is complete for import prices and prices react significantly to exchange rate shocks.[10]

However, linear or non-linear multivariate time-series methodologies[11] do not consider all structural/policy changes and external shocks affecting the economy, nor the evolving nature of the exchange rate. In this context, there are few studies using TVP-VAR-SV models and variants to estimate the ERPT. The studies by Shioji (2012, 2014, and 2015) and Çatık et al. (2016) use the TVP-VAR model proposed by Cogley and Sargent (2001). For their part, Clark and Terry (2010), Arratibel and Michaelis (2014), Jooste and Jhaveri (2014), Alexius and Holmberg (2017), Dahem et al. (2017), and Baxa and Šestořád (2019) use TVP-VAR-SV models;[12] and Moussa (2016) uses a factor-augmented VAR model with time-varying parameters (TVP-FAVAR).

Shioji (2012) analyzes the ERPT into import prices and a set of export and domestic prices (at the aggregate and disaggregate level) over time for Japan, finding that the ERPT into import prices is higher than into aggregate consumer prices; and that it declines considerably since the end of the 1990s. Additionally, the ERPT into aggregate consumer prices shows a fall since the 1980s; and the ERPT into domestic intermediate good prices drops significantly since 1980. Additionally, Shioji (2014) estimates the ERPT and the pass-through of import prices into a set of domestic prices in Japan. The author identifies a fall in the ERPT in 1980-1995 and a resurgence since 2012, except for the ERPT into service consumer prices. ERPT evolution is largely explained by Japan's cost structure changes over time.

In the same line, Shioji (2015) revisits the ERPT into consumer prices in Japan in a context of high yen depreciation and close-to-zero interest rates; and identifies a significant ERPT resurgence in recent years for regular household consumption goods (e.g., gasoline). For their part, Çatık et al. (2016) analyze the evolution of the ERPT into import, producer, and consumer prices in Turkey; and find evidence of an evolving behavior over time. They also find that the ERPT into import prices is low and non-significant; and that the ERPTs into producer and consumer prices show a declining trend throughout the period of analysis, explained by IT adoption. However, they highlight that the ERPTs into producer and consumer prices peaked during the 1994 financial crisis and increased slightly during the GFC.

For their part, Clark and Terry (2010) analyze the pass-through from energy prices into core inflation in the U.S.; and identify a significant pass-through fall over 1974Q1-1985Q1, explained by declining energy consumption. Additionally, Arratibel and Michaelis (2014) study the reaction of output and prices to interest rate and exchange rate shocks in Poland, finding that the ERPT has

semiparametric local projection technique.

[10] We also underscore the studies by Hernández and Leblebicioğlu (2012) and Khemiri and Ben Ali (2013), who employ Markov-switching models to analyze the ERPT in the U.S. and Tunisia, respectively. The former find that monetary stability explains over 50% of ERPT decline; and the latter find a low-level association between the ERPT and a low-inflation regime.

[11] Where the changes in the parameters are captured via estimation of the model by sub-samples or regimes.

[12] Based on Primiceri (2005), Cogley and Sargent (2005), and Nakajima (2011).

fallen significantly over time; and that the ERPT into import prices is higher than into producer or consumer prices, thereby supporting the evidence of ERPT reduction along the distribution chain.

Jooste and Jhaveri (2014) estimate the ERPT and identify their main determinants for South Africa, finding that the ERPT changes over time and depends on the state of the economy. The ERPT peaked in 2002-2003, in a context of considerable exchange rate volatility and inflation; but began to decline since 2004. Additionally, they indicate that the average ERPT does not change significantly between the pre- and post-IT periods. For their part, Alexius and Holmberg (2017) analyze the effect over time of the ERPT and foreign prices on domestic inflation for a set of economies[13] with a floating exchange rate regime and low inflation, finding that a unit exchange rate shock has a greater effect on inflation in small economies; and that the pass-through of external prices into domestic prices is much larger and instantaneous than the ERPT. Moreover, they find that the ERPT into domestic prices: (i) peaks during the GFC and (ii) resurges post-GFC (the 2014-2015 low-inflation period) in Australia and the U.S., as inflation deviated from target.

Dahem et al. (2017) study the evolution over time of the effect of monetary and exchange rate shocks on prices in Tunisia, finding a time-varying ERPT; and that the ERPT into government-controled prices (food and fuel) surges after the 2010-2011 political developments in that country. For their part, Baxa and Šestořád (2019) estimate the ERPT and the pass-through into output growth for the Czech Republic, in a context of depreciation and low inflation, finding that the ERPT into consumer prices is incomplete but instantaneous; and that it has declined significantly since the 2000s. However, they also find that depreciation of the Czech koruna against the euro pushed prices up at end-2013.

Finally, Moussa (2016) uses a TVP-FAVAR model to analyze ERPT evolution in Japan, finding that it differs across prices in magnitude and time variation; and that it declines along the distribution chain. Additionally, the study finds that the ERPT into import and domestic prices (at the aggregate and disaggregate level) fell since 1985 until the end of the 2000s (except for the Asian crisis) and resurged thereafter through the end of the sample.

The review of the literature shows that use of the TVP-VAR-SV approach for ERPT estimation is work in progress. However, given its specification features, this approach is usually more appropriate for ERPT estimation than studies using rolling-window VAR models or single-equation models with time-varying parameters. At the same time, most studies employing TVP-VAR-SV models and their variants focus on developed countries, and their use for EMEs is still incipient.[14] In this light, this paper adheres to the TVP-VAR-SV approach to estimate the ERPT for Peru following the methodology proposed by Chan and Eisenstat (2018), which we describe below.

3 Methodology

Following the methodology proposed by Chan and Eisenstat (2018), we use a set of TVP-VAR-SV models to estimate the time-varying ERPT.

3.1 General Model: TVP-VAR-SV

Following Chan and Eisenstat (2018), a TVP-VAR-SV model has the following specification:

[13] Large (Australia, Japan, UK, and U.S.) and small (Canada, New Zealand, Sweden, and Switzerland).

[14] Except for Jooste and Jhaveri (2014) and Dahem et al. (2017).

$$\mathbf{B}_{0,t}\mathbf{y}_t = \boldsymbol{\mu}_t + \mathbf{B}_{1,t}y_{t-1} + ... + \mathbf{B}_{p,t}y_{t-p} + \boldsymbol{\epsilon}_t, \qquad \boldsymbol{\epsilon}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_t), \tag{1}$$

where μ_t is an $n \times 1$ vector of time-varying intercepts, $\mathbf{B}_{1,t}...\mathbf{B}_{p,t}$ are the $n \times n$ matrices of coefficients associated with the vector of lagged endogenous variables, $\mathbf{B}_{0,t}$ is the $n \times n$ lower triangular matrix of contemporary effects with diagonal unit values, and $\boldsymbol{\Sigma}_t = diag(\exp(h_{1,t}), ..., \exp(h_{n,t}))$. The movement law for the logs of all variables $\mathbf{h}_t = (h_{1,t}, ..., h_{n,t})'$ is specified as an independent random walk:

$$\mathbf{h}_t = \mathbf{h}_{t-1} + \boldsymbol{\zeta}_t, \qquad \boldsymbol{\zeta}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_h), \tag{2}$$

where the initial conditions $\mathbf{h}_0$ are also parameters to be estimated.

As the system in (1) is in structural form and the variance matrix $\boldsymbol{\Sigma}_t$ is diagonal, the estimation can be carried out recursively. For this purpose, we rewrite the model. We consider the $k_\beta \times 1$ vector of intercepts and coefficients associated with the lagged observations $\boldsymbol{\beta}_t = vec((\boldsymbol{\mu}_t, \mathbf{B}_{1,t}, ..., \mathbf{B}_{p,t})')$. The second $k_\gamma \times 1$ vector, containing the time-varying coefficients that characterize contemporaneous relationships between variables, is denoted by $\boldsymbol{\gamma}_t$. It should be noted that $k_\beta = n(np + 1)$ and $k_\gamma = n(n-1)/2$. Therefore, equation (1) can be rewritten as:

$$\mathbf{y}_t = \widetilde{\mathbf{X}}_t\boldsymbol{\beta}_t + \mathbf{W}_t\boldsymbol{\gamma}_t + \boldsymbol{\epsilon}_t, \qquad \boldsymbol{\epsilon}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_t),$$

where $\widetilde{\mathbf{X}}_t = \mathbf{I}_n \otimes (1, \mathbf{y}'_{t-1}, ..., \mathbf{y}'_{t-p})$ and $\mathbf{W}_t$ is an $n \times k_\gamma$ matrix containing the appropriate elements of $-y_t$[15]. If $\mathbf{X}_t = (\widetilde{\mathbf{X}}_t, \mathbf{W}_t)$, we can simplify the above model to obtain a generic space-state representation:

$$\mathbf{y}_t = \mathbf{X}_t\boldsymbol{\theta}_t + \boldsymbol{\epsilon}_t, \quad \boldsymbol{\epsilon}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_t), \tag{3}$$

where $\boldsymbol{\theta}_t = (\boldsymbol{\beta}'_t, \boldsymbol{\gamma}'_t)'$ has a $k_\theta = k_\beta + k_\gamma$ dimension and the coefficients have a random walk behavior:

$$\boldsymbol{\theta}_t = \boldsymbol{\theta}_{t-1} + \boldsymbol{\eta}_t, \quad \boldsymbol{\eta}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_\theta), \tag{4}$$

where the initial conditions $\boldsymbol{\theta}_0$ are also parameters to be estimated. The values of priors and hyperparameters are defined in Section 3.2.

3.2 Restricted Models

Equation (1) defines (i) the general TVP-VAR-SV model. Based on the latter, as in Chan and Eisenstat (2018), we use restricted models, considering the parameters that we choose to keep constant: (ii) TVP-VAR: VAR with time-varying parameters and homoscedastic variance ($\mathbf{h}_t = \mathbf{h}_0$); (iii) TVP-VAR-R1-SV: VAR with constant parameters for the lagged variables and the intercepts ($\boldsymbol{\beta}_t = \boldsymbol{\beta}_0$) and SV; (iv) TVP-VAR-R2-SV: VAR with constant parameters for the contemporaneous

[15] For example, when $n = 3$, $\mathbf{W}_t$ has the form:

$$\mathbf{W}_t = \begin{bmatrix} 0 & 0 & 0 \\ -y_{1,t} & 0 & 0 \\ 0 & -y_{1,t} & -y_{2,t} \end{bmatrix}$$

where y_{it} is the ith element of $\mathbf{y}_t$ for $i = 1, 2$.

relationships ($\boldsymbol{\gamma}_t = \boldsymbol{\gamma}_0$) and SV; (v) TVP-VAR-R3-SV: VAR with time-varying intercepts and SV; (vi) CVAR-SV: VAR with constant intercepts, parameters for the lagged variables ($\beta_t = \beta_0$), and parameters for the contemporaneous relationships ($\boldsymbol{\gamma}_t = \boldsymbol{\gamma}_0$) but with SV; and (vii) CVAR: VAR with constant parameters and homoscedastic variance.

3.3 Estimation Algorithm: Gibbs Sampling[16]

We estimate the posterior parameters using the Gibbs sampling method, which consists in dividing the parameters in blocks and estimating each one separately, conditional on updates in the other blocks. The draws are based on the precision sampling proposed by Chan and Jeliazkov (2009) and developed by Chan and Eisenstat (2018). The algorithm for estimating the TVP-VAR-SV models is described as follows: (i) the draws are obtained from $(\boldsymbol{\theta}|\mathbf{y}, \mathbf{h}, \boldsymbol{\Sigma}_\theta, \boldsymbol{\Sigma}_h, \boldsymbol{\theta}_0, \mathbf{h}_0) \sim \mathcal{N}(\widehat{\boldsymbol{\theta}}, \mathbf{K}_\theta^{-1})$, where $\mathbf{K}_\theta = \mathbf{H}_\theta' \mathbf{S}_\theta^{-1} \mathbf{H}_\theta + \mathbf{X}' \boldsymbol{\Sigma}^{-1} \mathbf{X}$ and the mean $\widehat{\boldsymbol{\theta}} = \mathbf{K}_\theta^{-1}(\mathbf{H}_\theta' \mathbf{S}_\theta^{-1} \mathbf{H}_\theta \boldsymbol{\alpha}_\theta + \mathbf{X}' \boldsymbol{\Sigma}^{-1} \mathbf{y})$, with $\boldsymbol{\alpha}_\theta = \mathbf{H}_\theta^{-1} \widetilde{\boldsymbol{\alpha}}_\theta$. The matrices $\mathbf{H}_\theta$, $\mathbf{S}_\theta$, $\boldsymbol{\Sigma}$ and $\widetilde{\boldsymbol{\alpha}}_\theta$ are described in Appendix A of Chan and Eisenstat (2018); (ii) using the conditional distributions of the diagonal elements in $\boldsymbol{\Sigma}_\theta$, the draws are obtained from $(\sigma^2_{\theta_i}|\mathbf{y}, \boldsymbol{\theta}, \mathbf{h}, \boldsymbol{\theta}_0, \mathbf{h}_0) \sim \mathcal{IG}(\nu_{\theta_i} + \frac{T}{2}, S_{\theta_i} + \frac{1}{2}\sum_{t=1}^{T}(\theta_{it} - \theta_{i,t-1})^2)$ for $i = 1, \ldots, k_\theta$ and the hyperparameters ν_{θ_i} and S_{θ_i} are defined in Section 4.2; (iii) the draws are obtained from the diagonal elements in $\boldsymbol{\Sigma}_h$ with the form $(\sigma^2_{h_j}|\mathbf{y}, \boldsymbol{\theta}, \mathbf{h}, \boldsymbol{\theta}_0, \mathbf{h}_0) \sim \mathcal{IG}(\nu_{h_j} + \frac{T}{2}, S_{h_j} + \frac{1}{2}\sum_{t=1}^{T}(h_{jt} - h_{j,t-1})^2)$ for $j = 1, \ldots, k_h$ and the hyperparameters ν_{h_j} and S_{h_j} are defined in Section 4.2; (iv) the draws are obtained for the initial condition θ_0 from $(\boldsymbol{\theta}_0|\mathbf{y}, \boldsymbol{\theta}, \mathbf{h}, \boldsymbol{\Sigma}_\theta, \boldsymbol{\Sigma}_h) \sim \mathcal{N}(\widehat{\boldsymbol{\theta}}_0, \mathbf{K}_{\theta_0}^{-1})$, where $\mathbf{K}_{\theta_0} = \mathbf{V}_\theta^{-1} + \boldsymbol{\Sigma}_\theta^{-1}$ and $\widehat{\boldsymbol{\theta}}_0 = \mathbf{K}_{\theta_0}^{-1}(\mathbf{V}_\theta^{-1}\mathbf{a}_\theta + \boldsymbol{\Sigma}_\theta^{-1}\boldsymbol{\theta}_1)$ and values for $\mathbf{a}_\theta$ and $\mathbf{V}_\theta$ are given in Section 4.2; (v) the draws are obtained for the initial condition $\mathbf{h}_0$ from $(\mathbf{h}_0|\mathbf{y}, \boldsymbol{\theta}, \mathbf{h}, \boldsymbol{\Sigma}_\theta, \boldsymbol{\Sigma}_h) \sim \mathcal{N}(\widehat{\mathbf{h}}_0, \mathbf{K}_{h_0}^{-1})$, where $\mathbf{K}_{h_0} = \mathbf{V}_h^{-1} + \boldsymbol{\Sigma}_h^{-1}$ and $\widehat{\mathbf{h}}_0 = \mathbf{K}_{h_0}^{-1}(\mathbf{V}_h^{-1}\mathbf{a}_h + \boldsymbol{\Sigma}_h^{-1}\mathbf{h}_1)$ and values for $\mathbf{a}_h$ and $\mathbf{V}_h$ are given in Section 4.2; (vi) steps (i)-(v) are repeated N times.

3.4 Selection Criteria

For comparing models and selecting the best fit, we use the log of the Marginal Likelihood calculated via the cross-entropy method (logML$_{CE}$) and the Deviance Information Criterion (DIC).

3.4.1 Marginal Likelihood (ML$_{CE}$)[17]

Chan and Eisenstat (2015) propose a better alternative for estimating the marginal likelihood using the cross-entropy method (ML$_{CE}$). This estimation is based on the importance sampling density $g(\boldsymbol{\theta}_n)$:

$$\widehat{p}_{IS}(\mathbf{y}) = \frac{1}{N}\sum_{n=1}^{N}\frac{p(\mathbf{y}|\boldsymbol{\theta}_n)\, p(\boldsymbol{\theta}_n)}{g(\boldsymbol{\theta}_n)}, \tag{5}$$

where $\boldsymbol{\theta}_1, \ldots, \boldsymbol{\theta}_N$ are the independent draws obtained from the importance sampling density. The $\widehat{p}_{IS}$ estimator is consistent and unbiased irrespective of the value of $g(\boldsymbol{\theta}_n)$, but is sensitive to the $g(\boldsymbol{\theta}_n)$ variance. If the importance sampling is denoted by g^*, and using the posterior density

[16] Complete details about the algorithm for estimating the TVP-VAR-SV model and other restricted models can be found in Section 4 and Appendix A of Chan and Eisenstat (2018).

[17] Complete details may be found in Section 4 and Appendix B of Chan and Eisenstat (2018).

to represent it, we infer that $\widehat{p}_{IS}(\mathbf{y})$ is equivalent to $p(\mathbf{y})$. Therefore, the solution is choosing a g similar to g^* such that the variance of the estimator is minimized. We obtain g via the cross-entropy method, which is used to measure the distance between two densities.

Given the parametric family $\mathcal{F} = \{f(\boldsymbol{\theta}, \mathbf{v})\}$ indexed by vector $\mathbf{v}$, we need to select the importance sampling $f(\boldsymbol{\theta}, \mathbf{v}) \in \mathcal{F}$ that is closer to g^*. Therefore, it is necessary to choose the density $f(\boldsymbol{\theta}, \mathbf{v}^*_{ce}) \in \mathcal{F}$ that minimizes the cross-entropy distance between the optimal density g^* and the chosen density $f(\boldsymbol{\theta}, \mathbf{v})$ as follows:

$$\begin{aligned}
\mathbf{v}^*_{ce} &= \arg\min_{\{\mathbf{v}\}}\left(\int g^*(\boldsymbol{\theta}) \log g^*(\boldsymbol{\theta})\, d\boldsymbol{\theta} - p(\mathbf{y})^{-1} \int p(\mathbf{y}|\boldsymbol{\theta})\, p(\boldsymbol{\theta}) \log f(\boldsymbol{\theta}, \mathbf{v})\, d\boldsymbol{\theta}\right), \\
\mathbf{v}^*_{ce} &= \arg\max_{\{\mathbf{v}\}} \int p(\mathbf{y}|\boldsymbol{\theta})\, p(\boldsymbol{\theta}) \log f(\boldsymbol{\theta}, \mathbf{v})\, d\boldsymbol{\theta},
\end{aligned}$$

whose estimator is:

$$\widehat{\mathbf{v}}^*_{ce} = \arg\max_{\{\mathbf{v}\}} \frac{1}{R} \sum_{r=1}^{R} \log f(\boldsymbol{\theta}_r, \mathbf{v}), \tag{6}$$

and we obtain the draws $\boldsymbol{\theta}_1, ..., \boldsymbol{\theta}_R$ using the posterior density[18].

3.4.2 Deviance Information Criterion (DIC)

The deviation information criterion (DIC) was proposed initially by Spiegelhalter et al. (2002). Based on Chan and Grant (2016), the deviance of the model's goodness of fit is defined as:

$$D(\boldsymbol{\theta}) = -2 \log f(\mathbf{y}|\boldsymbol{\theta}) + 2 \log h(\mathbf{y}), \tag{7}$$

where $f(\mathbf{y}|\boldsymbol{\theta})$ is the model's likelihood function and $h(\mathbf{y})$ is a function of the data. Additionally, we use a measure of model complexity via the effective number of parameters, defined as:

$$p_D = \overline{D(\boldsymbol{\theta})} - D(\widetilde{\theta}), \tag{8}$$

where $\overline{D(\boldsymbol{\theta})} = -2E_{\boldsymbol{\theta}}[\log f(\mathbf{y}|\boldsymbol{\theta})|\mathbf{y}] + 2 \log h(\mathbf{y})$ is the posterior mean deviance and $\widetilde{\boldsymbol{\theta}}$ is an estimate of $\boldsymbol{\theta}$ (posterior mean or mode). Using these definitions, the DIC can be represented as the sum of the mean posterior deviation and the effective number of parameters; i.e., $DIC = \overline{D(\boldsymbol{\theta})} + p_D$. Assuming $h(\mathbf{y}) = 1$ and substituting the previous definitions, we obtain:

$$DIC = -4E_\theta[\log f(\mathbf{y}|\boldsymbol{\theta})|\mathbf{y}] + 2 \log f(y|\widetilde{\boldsymbol{\theta}}), \tag{9}$$

where the estimate $\widetilde{\boldsymbol{\theta}}$ of $\boldsymbol{\theta}$ is set as the posterior mode $\widehat{\boldsymbol{\theta}}$ and the first term of (9) can be estimated by averaging the log-integrated likelihoods $\log f(\mathbf{y}|\boldsymbol{\theta})$ over the posterior draws of $\boldsymbol{\theta}$. In order to

[18] Gelfand and Dey (1994), Chib (1995) and Chib and Jeliazkov (2001), among others, propose alternative methods for calculating the marginal likelihood. However, Frühwirth-Schnatter and Wagner (2008) show that using the conditional likelihood or the complete data likelihood obtained through the method suggested by Chib (1995) results in an incorrect choice of models. Moreover, Chan and Eisenstat (2015) use empirical results to show that the cross-entropy method is faster and more accurate that the three mentioned before.

approximate the posterior mode $\widehat{\boldsymbol{\theta}}$, we obtain the parameter set that yields the maximum value for $f(\mathbf{y}|\boldsymbol{\theta})f(\boldsymbol{\theta})$, where $f(\boldsymbol{\theta})$ is the prior density. Finally, the version used is the following:

$$DIC = -4E_\theta[\log f(\mathbf{y}|\boldsymbol{\theta})|\mathbf{y}] + 2\log f(\mathbf{y}|\widehat{\boldsymbol{\theta}}).$$

There are other versions of this selection criterion based on complete-data likelihood or conditional likelihood[19]. However, in this study we used the DIC based on integrated likelihood, taking into consideration the results obtained by Chan and Grant (2016), since other DIC forms favor over-parameterized models and yield high standard errors.

4 Empirical Results

4.1 Data

The variables in the vector of endogenous variables y_t are based on the PDC model proposed by McCarthy (2007), where the identification of three stages in domestic pricing (import, producer, and consumer prices; i.e., the first, second, and third stages, respectively) is instrumental in analyzing their reaction to external, domestic, and exchange rate shocks.

The variables associated with inflation at each PDC stage are import, producer, and consumer price inflation (IPI, PPI, and CPI, respectively). The variables that complete the model are the growth rate of the export price index (XPI), the growth rate of the nominal exchange rate (NER), and GDP growth.[20] All variables were seasonally adjusted using Census X-13 and are expressed as quarterly growth rates.

The selected period is limited by data availability. Information from the BCRP and National Statistics Institute (INEI) databases is available for 1995Q2-2019Q4, with a total of 99 observations.[21] Figure 1 shows the evolution of the variables in the baseline model (Panel A) and the external variables (Panel B) used in the robustness analysis. Panel A highlights the declining trend of the CPI since the beginning of the sample until around 2000, as a result of the macroeconomic stabilization process launched in the mid-1990s. It also shows that the behavior of nominal exchange rate variation is more volatile around economic/political domestic and external events (i.e., the Russian-Brazilian and Asian crises of the end of the 1990s and the 2008 GFC).

Panel B shows a set of external variables representing external shocks associated with commodities and external inflation; i.e., the Global Price Index of All Commodities (GPIAC), the S&P GSCI, the price of copper, and the terms of trade, as well as two measures of U.S. inflation: consumer price inflation and the rate of growth of the GDP price deflator.[22].

[19] Spiegelhalter et al. (2002) provide the DIC expressions presented here; and Celeux et al. (2006) propose up to eight DIC versions, each with a different calculation method for likelihood according to the treatment of latent variables.

[20] The series employed are: Export Price Index (2007=100), Gross Domestic Product (millions of 2007 soles), nominal exchange rate (quarterly average), Wholesale Import Price Index (2013=100), Wholesale Price Index (2013=100), and Consumer Price Index (2009=100).

[21] We used quarterly data, as estimations based on monthly data yield volatile ERTPs, given the characteristics of the approach used (SV), and because there are no appropriate monthly economic activity indicators. ERPT estimations using monthly data are available on request.

[22] In particular, we use the Global Price Index of All Commodities (2016=100), the S&P GSCI, the global price of copper (U.S. dollars per metric ton), the U.S. implicit price deflator for GDP (2012=100), and the U.S. Consumer Price Index for All Urban Consumers (1982-1984=100). All these variables are expressed as quarterly growth rates and were obtained from the Federal Reserve Bank of St. Louis and Yahoo! Finance websites.

4.2 Priors

The priors of the initial conditions $\boldsymbol{\theta}_0$ and $\mathbf{h}_0$ are both Gaussian: $\boldsymbol{\theta}_0 \sim \mathcal{N}(\mathbf{a}_\theta, \mathbf{V}_\theta)$ and $\mathbf{h}_0 \sim \mathcal{N}(\mathbf{a}_h, \mathbf{V}_h)$. We also assume that the error covariance matrices for the state equations are diagonal; i.e., $\boldsymbol{\Sigma}_\theta = diag(\sigma^2_{\theta_1}, \ldots, \sigma^2_{\theta_n})$ and $\boldsymbol{\Sigma}_h = diag(\sigma^2_{h_1}, \ldots, \sigma^2_{h_n})$. The elements of $\boldsymbol{\Sigma}_\theta$ and $\boldsymbol{\Sigma}_h$ are independently distributed as $\sigma^2_{\theta_i} \sim \mathcal{IG}(\nu_{\theta_i}, S_{\theta_i})$, $i = 1, \ldots, k_\theta$, $\sigma^2_{h_j} \sim \mathcal{IG}(\nu_{h_j}, S_{h_j})$, $j = 1, \ldots, k_h$ where $\mathcal{IG}$ represents the Inverse Gamma distribution. The priors established for the hyperparameters are non-informative in all models. For the general TVP-VAR-SV, we establish that $\mathbf{a}_\theta = \mathbf{0}$, $\mathbf{V}_\theta = 10 \times \mathbf{I}_{k_\theta}$, $\mathbf{a}_h = \mathbf{0}$, $\mathbf{V}_h = 10 \times \mathbf{I}_n$, and $\nu_{\theta_i} = \nu_{h_j} = 5$. We also assume that $S_{\theta_i} = 0.01^2$ for the coefficients of the lagged variables and $S_{\theta_i} = 0.1^2$ for the intercepts. Additionally, we fix $S_{h_j} = 0.1^2$. The priors for restricted models follow the same criteria according to the restrictions imposed on them.

4.3 Identification Strategy

The identification of the VAR structural shocks is recursive and is based on the PDC model proposed by McCarthy (2007), which is standard in ERPT literature; see Maertens Odría et al. (2012) and Winkelried (2014), among others. The PDC model is instrumental in analyzing the effect of external, domestic demand, and exchange rate shocks on each PDC stage. It also predicts that, given the nominal rigidities in the economy, the ERPT should decline along the distribution chain.

Along these lines, we considering the following ordering: $y_t = [XPI_t, GDP_t, NER_t, IPI_t, PPI_t, CPI_t]'$. Therefore, structural shocks associated with XPI, GDP, NER, IPI, PPI, and CPI are interpreted as external, domestic demand, NER depreciation, and domestic supply shocks along the distribution chain (import, producer, and consumer inflation), respectively.

In this regard, the ordering implies that external, domestic demand, and exchange rate shocks have contemporaneous impacts on the three types of prices; and that the exchange rate reacts immediately to external and domestic demand shocks. Additionally, exchange rate shocks have a contemporaneous effect on PDC; and import and producer prices have an immediate impact on consumer prices but not vice versa; see McCarthy (2007).

4.4 Evidence of Time-Varying Parameters

We use two statistics to verity the hypothesis of time-varying parameters based on the estimation of a TVP-VAR-SV model. We employ the Kolmogorov-Smirnov test and the t-test to establish whether the distribution and mean of the parameters at different points in time are the same, respectively. For this purpose, we divide the sample into two sub-samples.

The first sub-sample covers 1995Q2-2006Q4 (the pre-GFC period). The second sub-sample covers the post-GFC period (2007Q1-2019Q4). The results in Table 1 show that most coefficients associated with the intercepts and lagged variables are time-varying (31 and 32 out of 42 coefficients in the first and second sub-samples, respectively). Additionally, we find that all coefficients associated with contemporaneous relationships and the shock variances are time-varying.

In order to confirm these results, we apply two tests on other sub-samples; i.e., the pre- and post-IT periods (1995Q2-2001Q4 and 2002Q1-2019Q4, respectively) and find similar results to those mentioned above. Along these lines, an examination of the medians of the posteriors of the coefficients associated with intercepts and lagged variables in the TVP-VAR-SV model shows significant time-variation in the intercepts of all equations. However, time-variation in the coefficients of lagged variables is not so evident. These findings indicate that the impact of intercepts and lagged variables tends to evolve over time, in contrast with the assumptions for a CVAR model.

4.5 Model Selection

All models have been estimated using $N = 11,000$ simulations, discarding the first $1,000$ in 10 parallel chains. Out of the remaining $100,000$ simulations we take 1 in 10, resulting in $10,000$ simulations, which we use to calculate the values of the log-ML$_{CE}$ and the DIC. The number of lags is 1, according to the BIC obtained from estimating the CVAR model.

Table 2 shows the ranking for the seven models estimated according to the average log-ML$_{CE}$ and the DIC, the effective number of parameters (pD), and their respective standard deviations. The log-ML$_{CE}$ shows that the best-fitting model is TVP-VAR-SV. However, the log-ML$_{CE}$ for the TVP-VAR-R1-SV, TVP-VAR-R3-SV, CVAR-SV, and TVP-VAR-R2-SV models, in that order, is quite close to that for the preferred model. In this regard, the Bayes Factor (BF) indicates that the TVP-VAR-SV model is just 1.02 times preferred over the TVP-VAR-R1-SV model. Additionally, the TVP-VAR-SV model is 2.64 and 4.26 times preferred over the TVP-VAR-R3-SV and CVAR-SV models, respectively. At the same time, the DIC indicates that the best-fitting model is CVAR-SV, followed by TVP-VAR-R3-SV and TVP-VAR-R1-SV, in that order.

Moreover, we highlight the importance of SV in the specification of the models, as the least-fitting ones (CVAR and TVP-VAR) do not include SV. Therefore, using the CVAR and TVP-VAR models would not be appropriate for modeling the dynamic interrelationships between variables and estimating the ERPT. Figure 2 shows the evolution of SV over time for each equation in the baseline model. The SV associated with external variables (XPI, NER, and IPI growth) shows a growing trend since the beginning of the sample, reaches a peak during the GFC, and declines until the end of the sample.

For their part, the SV for domestic variables (GDP, PPI, and CPI growth) declines throughout the sample. In particular, the SV for GDP and CPI growth decreases significantly since the beginning of the sample until 2002; and remain constant and low through the end of the sample. This behavior is associated with macroeconomic stabilization policies in the mid-1990s, IT adoption, and sound monetary and fiscal policy implementation in recent decades. These results are consistent with Castillo et al. (2007), who show that the standard deviation of inflation dropped from 6% to 0.5% after IT adoption. Additionally, Castillo et al. (2016) identify a significant attenuation in output and inflation volatility since the beginning of the 2000s (which they call the Great Moderation of Peru's economy). Primiceri (2005) and Cogley and Sargent (2005) find similar evidence for the U.S. Finally, the standard deviations for the TVP-VAR and CVAR models are constant throughout the sample and show similar values to the average SV in SV models.

4.6 Estimation of Time-Varying ERPT

With the purpose of estimating ERPT evolution, we first calculate the Impulse-Response Functions (IRFs) of NER and the three domestic inflations (IPI, PPI, and CPI growth) to a 1% exchange rate depreciation shock for the seven models. We then estimate the ERPT following Maertens Odría et al. (2012); i.e., based on the IRFs of each inflation for an exchange rate shock, we calculate the cumulative IRFs through a horizon $\tau = s$. Therefore, we define the ERPT in period t over a horizon s as:

$$ERPT_t^s = \frac{\sum_{\tau=0}^{s} \frac{\partial PI_{i,t+\tau}}{\partial \epsilon_t}}{\sum_{\tau=0}^{s} \frac{\partial NER_{t+\tau}}{\partial \epsilon_t}},$$

where the numerator and the denominator on the right-hand side of the formula represent the percent variation in inflation for price i ($PI_{i,t+\tau}$, where i = importer, producer, consumer) and the exchange rate ($NER_{t+\tau}$), respectively, in response to a 1% exchange rate shock in period t (ϵ_t) for a horizon $t+s$. We underscore that the estimation of the ERPT into each price is carried out separately, following the transmission mechanism described in the PDC model proposed by McCarthy (2007). The IRF of each price for a depreciation shock extends over a maximum (s) horizon of 20 periods (quarters).

Figure 3 shows the evolution of ERPTs into import, producer, and consumer prices, respectively, in a three-dimension form for the entire sample and for the seven models. Both ERPT levels and evolution differ according to the specification of each model. Qualitatively, ERPT evolution is similar between the best-fitting models (TVP-VAR-SV and TVP-VAR-R1-SV); i.e., ERPT into import prices falls steadily since the beginning of the sample until mid-2008. However, since 2013 the ERPT resurged considerably through the end of the sample. In 2008-2013, the ERPT into import prices remains stable, although with a slightly increasing trend. Additionally the ERPT into producer prices shows a distinctly growing trend since mid-2009, while the ERPT into consumer prices declines throughout the sample. For their part, the TVP-VAR-R2-SV, TVP-VAR-R3-SV, and CVAR-SV models indicate that the ERPT into import and producer prices show a declining trend; and that the ERPT into consumer prices is relatively constant throughout the sample. Finally, the behavior of the least-fitting models (TVP-VAR and CVAR) differs from that of the rest of the models.

Figure 4 shows the median ERPTs calculated for the entire sample over a horizon of 20 quarters. We verify that the medians for the three types of prices at the moment of impact ($s = 0$) and over the long term ($s = 20$) are in line with the predictions of the model PDC of McCarthy (2007); i.e., the ERPT declines along the distribution chain due to price rigidities, market structure, and the composition of the basket of goods. For instance, in the best-fitting models (for $s = 20$), the ERPT into import prices is the highest, followed by the ERPT into producer and consumer prices, at 0.52-0.57, 0.37-0.39, and 0.09-0.15, respectively. Additionally, the median ERPT into import and producer prices for the best-fitting models are higher during the first year (i.e., four quarters, $s = 4$) and then tend to decline over the long run. For its part, the median ERPT into consumer prices is low for $s = 4$ and then stabilizes over the long run. These results are in line with international literature and previous findings for Peru; see Miller (2003), Maertens Odría et al. (2012), and Winkelried (2014), among others.

The median ERPTs are somewhat heterogenous, given the differing specifications across models. Table 3 shows the long-run median ERPTs for all models, where ERPTs into import, producer, and consumer prices are 0.33-0.57, 0.22-0.39, and 0.06-0.17, respectively. Additionally, the best-fitting models (TVP-VAR-SV and TVP-VAR-R1-SV) yield the highest median values. In particular, the ERPTs into import and producer prices obtained from these models are 0.52-0.57 and 0.37-0.39, respectively; and the lowest ERPTs into import and producer prices are obtained from the least-fitting models, with values of 0.33-0.39 and 0.22-0.26, respectively. For their part, median ERPTs into consumer prices obtained from the best- (least-) fitting models are 0.09-0.15 (0.06-0.12).

In this context, we point out that the CVAR model (one of the most used in the literature) tends to underestimate the ERPT into import and producer prices, as neither the median ERPT nor its confidence interval are within the confidence interval of the best-fitting models. However, in the case of the ERPT into consumer prices, the median ERPT for the CVAR model falls within the range of the median ERPT values for the best-fitting models.

4.7 ERPT Evolution

For Peru, the only existing estimation of the ERPT evolution was carried out by Winkelried (2014) in recursive form using rolling-window linear VAR models. In this section we estimate and assess ERPT evolution over the period of analysis using the TVP-VAR-SV approach for each moment t of the sample.

Figure 5 shows the ERPTs for $s = 0, 4, 8$, and 20 (quarters) for each model. ERPT evolution both at the period of impact ($s = 0$) and the long run ($s = 20$) is somewhat heterogenous across models due to their particular specifications. In line with the PDC model, we find that the ERPT into import prices for $s = 0$ is much higher than after one year ($s = 4$) and in the long run. This implies that the effects of exchange rate fluctuations on pricing are significant and instantaneous at the first PDC stage, but later decline over time. Additionally, the ERPT into producer prices for $s = 0$ is only greater than the ERPT for $s = 4$ and the long-run ERPT since the beginning of the 2000s; and the ERPT into consumer prices for $s = 0$ is much less than the ERPT for $s = 4$ and the long-run ERPT ($s = 20$).

Figure 6 shows ERPT evolution for $s = 20$ in the seven models (Panel A) and the evolution of the three ERPTs for each model taking the ERPTs from the CVAR model as benchmarks (Panel B). In sum, we find that the ERPT: (i) varies over time; (ii) depends on the state of the economy; and (iii) declines along the distribution chain. These findings are in line with domestic and international literature.[23] Additionally, Panel A (Figure 6) shows that time-varying ERPTs obtained from the best-fitting models show a similar behavior.

4.7.1 ERPT into Import Prices

Figure 6 (Panel A) shows that the evolution and magnitude of ERPT into import prices differ across the estimated models. The best-fitting models indicate that the ERPT into import prices at the beginning of the sample was around 0.55; and increased to a first peak by the end of the 1990s. We underscore that the TVP-VAR-SV model yields a higher value than the TVP-VAR-R1-SV model for this peak (0.71 and 0.64, respectively); i.e., the ERPT for the best-fitting models is higher that for the CVAR model (Panel B).

Since 1995 until the end of the 1990s, ERPT evolution is explained by high dollarization and significant exchange rate depreciation. In the wake of the 1980s hyperinflation episode, the domestic currency was partially displaced by the dollar during the 1990s. Castillo et al. (2007), Rossini et al. (2016), and Contreras et al. (2017), among others, show evidence of high financial and transactions dollarization as a consequence of hysteresis among market participants and financial deregulation in the 1990s. In particular, Castillo et al. (2007) maintain that liquidity and credit dollarization in local financial markets surged from 38.4% and 39% to 66.3% and 77.2% between 1979-1993 and 1994-2005, respectively. Contreras et al. (2017) indicate that transactions dollarization persists

[23] See Winkelried (2003, 2014), Maertens Odría et al. (2012), Arratibel and Michaelis (2014), Moussa (2016), Donayre and Panovska (2016), and Rincón-Castro and Rodríguez-Niño (2018), among others.

at close to 60%. Moreover, in a context of domestic political instability[24] and financial crises, both international (Asian crisis, Russian crisis, FX crises in Argentina and Brazil, and the dot-com crash) and domestic (sudden stop in capital flows triggered by the Russian crisis), the local currency depreciated significantly against the dollar.[25]

However, the ERPT into import prices for other Latin American economies like Colombia (where transactions dollarization is almost nil) are similar to our findings. In this line, Rincón-Castro and Rodríguez-Niño (2018) indicate that ERPT endogeneity to the state of the economy and non-linear nature contribute to explaining its evolution. In particular, they suggest that high and/or more volatile inflation tends to boost ERPT levels; and emphasize the role of the size of depreciation shocks on ERPT evolution.[26]

At the same time, since the end of the 1990s until mid-2005, the ERPT into import prices tends to decline. In 2005-2008 the reduction becomes even more significant, to 0.32-0.36. ERPT behavior during this period coincides with an appreciation from 3.60 to 2.74 soles per dollar between 1999 and 2008 due to higher capital inflows in a context of high commodity prices, domestic macroeconomic stabilization, and de-dollarization since the beginning of the 1990s, and IT adoption in 2002.

In this line, Gondo and Pérez-Forero (2019) show evidence of a surge in capital inflows from advanced economies into Latin American EMEs in 2004-2007, resulting from a perceived improvement in macroeconomic fundamentals and high commodity prices. They emphasize that large capital inflows caused an appreciation of the domestic currency, in turn resulting in a lower ERPT into import prices.

In 2008-2013, the ERPT into import prices remained relatively stable, although with a slightly increasing trend. ERPT values in this period fluctuate between 0.33-0.44. This behavior is due to depreciation pressures during the GFC, although later the exchange rate maintained a declining trend until the beginning of 2013, which contributed to keeping the ERPT into import prices partially stable.

However, in contrast with the existing literature for Peru, we identify a resurgence of the ERPT into import prices post-GFC. Since 2013 the ERPT experiences a significant and sustained increase, to 0.70-0.80 by the end of the sample. This resurgence is associated with a sustained exchange rate increase due mainly to four factors: (i) the end of the high commodity price cycle and the beginning of a period of domestic political uncertainty; (ii) strong capital outflows triggered by announcement of the end of the Federal Reserve's (Fed) QE program (Taper Tantrum) at the beginning of 2013; (iii) the Fed's first interest rate hike after the GFC in 2016; and (iv) two relevant international political events: Brexit (2016) and the U.S.-China trade war.

In this context, Gondo and Pérez-Forero (2019) provide evidence of a resurgence of the ERPT into import prices after the GFC, when EMEs experienced considerable capital inflows from advanced economies due to low international interest rates and EMEs' solid macroeconomic fundamentals. They also indicate that the trend of capital flows reverted since 2013 due to monetary policy normalization in the U.S.; i.e., increased external interest rates triggered strong capital outflows from Latin American economies, in turn leading to strong exchange rate depreciation. This

[24] Mainly the disclosure of corruption cases under the administration of Alberto Fujimori and his resignation as President of Peru.

[25] In this line, Humala and Rodríguez (2010) show evidence of greater exchange rate volatility during some of the episodes mentioned above.

[26] A higher currency depreciation increases the opportunity cost of keeping prices unchanged, resulting in an increased ERPT.

external interest shock had negative impacts on the financial sector (lower funding to local banks and higher domestic interest rates) and the domestic economic (higher inflation resulting from an ERPT surge).

This finding is in line with recent ERPT literature, which identifies an ERPT resurgence resulting from the conduct of monetary policy in advanced economies during and after the GFC (i.e., QE and the taper tantrum) and is empirically supported by studies using models with time-varying parameters and SV to estimate ERPT evolution. Ozkan and Erden (2015)[27] and Alexius and Holmberg (2017), among others, show that after the ERPT decline in advanced economies during the 1990s, it increased since the GFC and during episodes of considerable depreciation of domestic currencies against the dollar. Forbes et al. (2018) find similar evidence for the UK using a different approach. Alexius and Holmberg (2017) indicate that, since the GFC, FX markets in advanced economies have remained volatile and inflation has increased. However, the evidence for EMEs is still incipient. In this regard, Jooste and Jhaveri (2014) for South Africa and Dahem et al. (2017) for Tunisia show evidence of a considerable ERPT surge during and after the GFC.[28]

4.7.2 ERPT into Producer Prices

Similarly to the findings for the ERPT into import prices, Figure 6 (Panel A) shows that the evolution and level of the ERPT into producer prices differ between best- and least-fitting models. Additionally, the ERPT for best-fitting models is higher than for the CVAR model throughout the sample (Panel B).

The best-fitting models indicate that the ERPT into producer prices at the beginning of the sample was around 0.34, in contrast with 0.23-0.32 for the least-fitting models. From the beginning of the sample until mid-2005, the best-fitting models show a relatively stable ERPT, with values around 0.39. However, since end-2005 until mid-2008, all estimated models show a slight ERPT reduction; and in 2008-2013 the ERPT remained relatively stable, although with a slight increase to 0.29-0.40. Like in the case of the ERPT into import prices, in 2014-2019 the ERPT experiences a significant resurgence. In particular, the best-fitting models indicate that the ERPT by the end of the sample fluctuates between 0.45-0.55.

An initial explanation for these finding is provided by Contreras et al. (2017), who use data from the 2015-2016 BCRP Macroeconomic Expectations Survey to show that dollarization of transactions and production costs persists.[29] Along these lines, they maintain that dollarization of input costs for non-financial firms is high (around 54%); and that the financial costs of 44% of these firms are denominated in dollars. They also indicate that high dollarization of input sales/purchases hamper the replacement of foreign for domestic currency, given the rigidity in price and transaction dollarization in Peru's economy. They also find that dollarization of administrative expenses is higher in the mining and fishing industries. Rossini et al. (2016) show similar evidence.

Regarding the dollarization of sales by Peruvian non-financial firms, Contreras et al. (2017) indicate that most durable goods (e.g., real estate and cars, among others) are negotiated in dollars;

[27] The authors use a combination of a Dynamic Conditional Correlation (DCC) model and a Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model.

[28] It should be noted that Shioji (2012, 2014, and 2015) shows evidence of ERPT resurgence post-GFC in Japan, although using TVP-VAR models.

[29] Despite the fact that credit dollarization has declined considerably (from around 80% in 1990 to less than 30% in 2017) and that over 90% of domestic firms pay salaries and administrative costs in soles.

and find that 55% of these firms fix their sales contracts in dollars. Around 92% of sales by export-oriented industries (mining and industrial fishing) are denominated in dollars. Additionally, 72.3%, 65%, 56.7%, 52%, and 27.9% of sales by the transportation/communications, export agriculture, commerce, services, and construction industries, respectively, are denominated in dollars; and dollar sales are the least in energy industries. Moreover, the authors indicate that around 43% of non-financial firms show a negative mismatch (i.e., dollar liabilities exceed dollar assets), which make them vulnerable to exchange rate fluctuations. These elements boost the ERPT into import and producer prices and contribute to explaining the ERPT resurgence since 2013.

A second explanation for the evolution of the ERPT into producer and import prices is associated with the fact that both are directly connected to the exchange rate. In particular, these ERPTs follow closely the behavior of the exchange rate during the period of analysis. In this context, it should be taken into account that the BCRP performs interventions in the FX market to offset the negative effects of extreme exchange rate volatility. At the same time, the objective of these interventions is attenuating volatility (not reversing the exchange rate trend), which enhances the persistence of a depreciation shock and induces its internalization by importers and producers. In response, both tend to change their prices, thereby increasing the ERPT during exchange rate depreciation episodes. In this line, Miller (2003) indicates that an alternative ERPT increase mechanism is associated with expectations and credibility about exchange rate behavior; i.e., if market participants know that FX market interventions do not seek to revert the exchange rate trend, they will adjust their prices in response to an exchange rate increase.

4.7.3 ERPT into Consumer Prices

In line with the predictions of the PDC model, the ERPT into consumer prices has the least value in all models and at each moment in time. Figure 6 (Panel A) shows that, in the best-fitting models, the ERPT decreases steadily and significantly in two parts of the sample: from the beginning of the sample through 2000; and since mid-2005 until 2008, after which it remains relatively stable through the end of the sample. The ERPT for these models is higher than for the CVAR models until the end of the 1990s (Panel B). Since 2000, the ERPT always lies below the ERPT for the CVAR model.[30]

Additionally, we emphasize that the TVP-VAR-R1-SV model shows that the ERPT into consumer prices in mid-1995 was higher than for the TVP-VAR-SV models, with values of 0.26 and 0.17, respectively. ERPT levels at the beginning of the sample are likely associated with Peru's high dollarization level. Later, as a consequence of macroeconomic stabilization (initial efforts to reduce dollarization, IT adoption, and the passing of Law 28300), the ERPT contracted considerably to a historic low (0.07) in mid-2010. It is worth noting that, after IT adoption, the ERPT decreased significantly to around 0.10. These findings are in line with the existing literature for Peru; see Maertens Odría et al. (2012) and Winkelried (2014). For EMEs see BIS (2019) and Jašová et al. (2019), among others.

Particularly, Winkelried (2014) shows that the ERPT into producer and consumer prices begins to fall at the end of the 1990s, to a minimum around IT adoption in 2002. Later, the ERPT into consumer prices fluctuates between 0.08-0.20 and does not increase again significantly due to Peru's low-inflation context after IT adoption. In this regard, the main reasons for the differing results between this paper and Winkelried (2014) include the methodology used, the data frequency, and

[30] According to this model, the ERPT into consumer prices has a value of 0.12 for the whole sample.

the period chosen for estimating ERPT evolution. We adopt the TVP-VAR-SV approach, where the best-fitting models highlight the importance of SV, while Winkelried (2014) calculates the ERPT over time using fixed-size, rolling-windows linear VAR models on a sample ending in 2011.

Therefore, the decrease in ERPT into consumer prices and subsequent stability are associated with the hypothesis of a low-inflation context, proposed by Taylor (2000), which highlights the role of BCRP credibility in anchoring inflation expectations. The hypothesis of an inflationary context indicates that market participants adjust their prices if, and only if, the depreciation shock is perceived as persistent; if not, they absorb higher costs by narrowing profits to preserve competitiveness. In this regard, Rossini et al. (2016) show that a 1% depreciation induces an increase in inflation expectations of around 5 basis points over a 6-month horizon, as this scenario creates stronger signals of a potential price increase. They also show that inflation expectations increased in 2013-2015, a period characterized by higher financial volatility.

From a theoretical perspective, Maertens Odría et al. (2012) argue that, after IT adoption, the BCRP prioritized inflation volatility over exchange rate fluctuations. This resulted in higher exchange rate volatility, in turn lowering the share of domestic firms fixing their prices in dollars and reducing the ERPT into consumer prices.

From another point of view, Montoro (2006) argues that, after implementation of Law 28300 (which obliged firms to establish their prices in soles), domestic firms have a disincentive to establish their prices in foreign currency, as they incur in menu costs when adjusting their prices in response to exchange rate variations. In this line, at a more disaggregated level, Castellares (2017) and Castellares and Toma (2020) show evidence of a decreasing ERPT into consumer prices after implementation of Law 28300. In particular, Castellares and Toma (2020) show that the ERPT into non-durable goods drops to 0.19 and practically disappears after implementation of the Law.

For their part, the TVP-VAR-R2-SV, TVP-VAR-R3-SV, and CVAR-SV models indicate that the ERPT into consumer prices at the beginning of the sample was low (0.10-0.15) and that its behavior over time remains relatively constant, although with a slight upward trend, throughout the period of analysis. These models indicate that the ERPT into consumer prices fluctuates around the ERPT for the CVAR model (0.12). Therefore, we can infer that these models are not appropriate for ERPT estimation, as they contradict the existing evidence of ERPT decline since the mid-1990s in a context of macroeconomic stabilization.

Finally, another explanation for ERPT evolution (for the three types of prices) results from the theory of invoicing (explained in Montoro (2006)), which argues that, if most of a firm's costs are denominated in dollars, the firm hedges against exchange rate fluctuations by establishing its prices in dollars; i.e., prices indexed to a foreign currency (the dollar) are affected by exchange rate fluctuations. This poses a challenge to monetary policy in the face of high exchange rate volatility, as it affects domestic inflation via the ERPT.

5 Robustness Analysis

In order to validate the results obtained from the baseline model, we perform four robustness exercises consisting in: (i) changing the first variable of the baseline VAR model associated with an external shock; (ii) replacing the variable related to the supply-side domestic shock with two other economic activity variables; (iii) changing the values of the priors; and (iv) estimating the ERPT for another Latin American country (Colombia). The robustness exercises focus on estimating long-run ERPT evolution for the three types of prices. An appendix containing all figures for the robustness analysis is available on request.

5.1 Change in the External Variable

In the first robustness exercise, we replace the XPI, the first variable within the ordering of the baseline VAR model, with six other variables representing external shocks. The latter are associated with commodities and external inflation. In this regard, Rodríguez et al. (2018), Chávez and Rodríguez (2022), Ojeda Cunya and Rodríguez (2022), and Rodríguez and Vassallo (2022) show evidence of the relevance of external shocks for the economic performance of Peru and Pacific Alliance countries. In line with Miller (2003), we replace the XPI with the GPIAC, S&P GSCI, copper price, and terms of trade growth rates. Additionally, like in Winkelried (2014), we replace the XPI with proxies for external inflation (U.S. GDP deflator growth and consumer price inflation).

Table 4 shows the two Bayesian selection criteria. When the XPI is replaced with the GPIAC or S&P GSCI, the DIC indicates that CVAR-SV is the best performer in both cases. However, according to the log-ML, the best performer is the TVP-VAR-SV model, followed by the TVP-VAR-R1-SV and TVP-VAR-R2-SV models. In this regard, the BF indicates that the TVP-VAR-SV model is 6.36 and 6.82 times preferred over the TVP-VAR-R1-SV and TVP-VAR-R2-SV models, respectively; and the TVP-VAR-SV model is 214.86 and 5.49E+18 times preferred over the CVAR-SV and CVAR models, respectively. This results are in line with the baseline model, as the GPIAC and S&P GSCI, like the XPI, are price indices for a representative group of Peru's commodity exports.

Additionally, when using the U.S. GDP deflator, both selection criteria indicate that TVP-VAR-R1-SV is the best-fitting model. The BF indicates that this model is 26.84, 107.77, and 4.01E+31 times preferred to the TVP-VAR-R3-SV, CVAR-SV, and CVAR models, respectively. Moreover, when using U.S. consumer price inflation, the DIC indicates that CVAR-SV is the best-fitting model. However, according to the log-ML, the TVP-VAR-R1-SV model is the best performer; and according to the BF, it is 13.20, 60.34, and 6.51E+18 times preferred over the TVP-VAR-SV, CVAR-SV, and CVAR models, respectively.

Finally, the ranking of the models changes drastically only when the XPI is replaced with the price of copper and the terms of trade, as the selection criteria indicate that the best performers are the CVAR-SV and TVP-VAR-R3-SV models, respectively. However, the BF indicates that CVAR-SV is slightly preferred (1.05 times) over TVP-VAR-R3-SV when using the price of copper; and that TVP-VAR-R3-SV is 1.20 times preferred to TVP-VAR-R1-SV when using the terms of trade. Additionally, the CVAR-SV model is 3.30E+45 times preferred over the CVAR model.

Regarding the evolution of the ERPT into the three types of prices for all models when the XPI is replaced with the other six variables representing external shocks, the ERPT ranking remains the same; i.e., the ERPT declines along the distribution chain. Therefore, the change in the first variable reinforces the results from the baseline model. Additionally, most ERPT trends remain the same over time. However, ERPT levels tend to differ from those calculated using the baseline model; i.e., the price of copper and U.S. consumer price inflation tend to increase the ERPT for most models and over a considerable part of the sample. For example, when using the price of copper (U.S. consumer price inflation), the ERPT into import prices at the first peak (end of the 1990s) reaches 0.97 (0.82), higher than using the baseline model (0.71).

Additionally, ERPT evolution into producer and consumer prices changes slightly; and the ERPTs at the beginning and end of the sample are higher that in the baseline model. In particular, the high ERPTs obtained using the price of copper are due to the high negative correlation between the price of copper and the U.S. dollar; and to the fact that copper has a considerable share within Peru's mining exports.

At the same time, using the terms of trade results in lower ERPTs relative to the baseline model, but their behavior is similar, as the terms of trade include the XPI.

For its part, the change in the first variable does not alter ERPT evolution over time. In particular, the best fitting models (TVP-VAR-SV and TVP-VAR-R1-SV) indicate that the ERPTs into import and producer prices tend to decline significantly until mid-2008; but in the following period (post-GFC) both ERPT tend to increase through the end of the sample. Moreover, the ERPT into consumer prices remains low since the end of the 1990s. In this light, we conclude that the time-varying ERPTs obtained are robust to a change in the first variable within the ordering of the baseline model.

5.2 Change in the Variable Associated with Domestic Economic Activity

The second group of robustness exercises consists in replacing total GDP growth with non-primary GDP growth and domestic demand. These changes do not modify the long-term evolution of ERPTs, but affect their levels.

Table 5 shows that, when using non-primary GDP, the log-ML indicates that TVP-VAR-SV is the best-fitting model, followed by TVP-VAR-R1-SV, CVAR-SV, and TVP-VAR-R2-SV, in that order; and the BF indicates that the TVP-VAR-SV model is 3.46, 3.63, and 10.07 times preferred to the TVP-VAR-R1-SV, CVAR-SV, and CVAR models, respectively. At the same time, the DIC indicates that TVP-VAR-R1-SV is the best performer, followed by CVAR-SV, CVAR, and TVP-VAR-R2-SV. When using domestic demand, the log-ML indicates that TVP-VAR-SV is the best-fitting model, followed by TVP-VAR-R1-SV, TVP-VAR-R2-SV, and CVAR; and the BF indicates that the TVP-VAR-SV model is 5.87, 11.82, and 1.6E+01 times preferred over those models. However, according to the DIC, the best-performing models are TVP-VAR-R1-SV, CVAR-SV, CVAR, and TVP-VAR-R2-SV, in that order.

Inclusion of these alternative indicators of domestic economic activity (notably domestic demand growth) tends to raise the ERPTs throughout much of the sample. In particular, the ERPTs into import, producer, and consumer prices for the TVP-VAR-SV model at the beginning of the sample fluctuate between 0.60-0.76, 0.30-0.45, and 0.15-0.22, respectively (higher than for the baseline model). There is also a considerable increase in the ERPTs from the TVP-VAR, TVP-VAR-R1-SV, CVAR-SV, and CVAR models. Additionally, except for TVP-VAR-R3-SV and CVAR-SV, the rest of the models show higher ERPTs post-GFC relative to the baseline model.

In consequence, we conclude that inclusion of the primary sectors tends to reduce the ERPT, as activities like mining and industrial fishing carry out most of their transactions in dollars.

5.3 Change in the Values of Priors

The third group of robustness exercises consists in changing the values of priors. The estimations for the baseline model are based on the priors proposed by Chan and Eisenstat (2018), which are non-informative. Therefore, we test the sensitivity of ERPT levels and evolution using a set of priors obtained from a training sample with different SV values. Like Primiceri (2005), we use a sub-sample covering 1995Q3-2003Q2 to establish the priors of the hyperparameters. We calculate these priors by estimating the CVAR model using ordinary least squares (OLS); and we obtain the SV priors by multiplying the variance of this model times 4, 8, and 20.

Table 6 shows the two Bayesian selection criteria for the baseline model when using priors obtained from a training sample with an SV equal to 20 times the variance of a CVAR model. According to the log-ML, TVP-VAR-R1-SV is the best-fitting model, followed by TVP-VAR-SV, CVAR, and CVAR-SV; and the BF indicates that the TVP-VAR-R1-SV model is 5.37 times preferred over the TVP-VAR-SV and CVAR models; and 26.31 times over the CVAR-SV model. Additionally, the DIC indicates that TVP-VAR-R1-SV is the best-fitting model, followed by CVAR-SV, CVAR, and TVP-VAR-R2-SV.

Inclusion of more diffuse SV priors (i.e., multiplying the CVAR variance times 20) yields a better performance than less diffuse priors (i.e., multiplying the variance times 4 and 8), as the ERPTs are closer to those obtained from the baseline model. These results confirm that the priors based on Chan and Eisenstat (2018) (which are non-informative/diffuse) used in the baseline model are more appropriate for estimating ERPT evolution. Additionally, although ERPT evolution does not change over time, ERPT values tend to be higher in the first part of the sample. Moreover, the ERPTs for the TVP-VAR-R3-SV and CVAR-SV models depart the most from the baseline model.

5.4 ERPT estimation for another country: Colombia

Finally, the fourth robustness exercise consists in estimating ERPT evolution for Colombia, an economy with similar features to Peru (sound macroeconomic policy implementation, IT adoption, and exposure to external shocks). The period covered by the estimation is dictated by data availability: 1999Q2-2019Q4.

Table 7 shows two Bayesian criteria to select the baseline model for Colombia. According to the log-ML, the best fitting model is CVAR-SV, followed by TVP-VAR-R2-SV, TVP-VAR-R1-SV, CVAR, and TVP-VAR-SV, in that order; and the BF indicates that the CVAR-SV model is 4.57, 4.95, and 6.89 times preferred over the TVP-VAR-R2-SV, TVP-VAR-R1-SV, and CVAR models. Additionally, the DIC indicates that the best-performing model is CVAR, followed by CVAR-SV and TVP-VAR-R1-SV. In this context, it is worth mentioning that the existing literature for Colombia uses only linear and non-linear VAR models with different shock identification schemes (see Shambaugh (2008) and Rincón-Castro and Rodríguez-Niño (2018), among others), but has not yet considered SV in ERPT estimation.

Regarding long-run ERPT evolution, except for TVP-VAR and CVAR, ERPT evolution is similar across models. In general, the best-fitting models indicate that the ERPT into import prices begins to decline since the beginning of the 2000s to a minimum around 2007. Later (post-GFC), the ERPT resurges considerably until the end of the sample. For their part, the ERPTs into producer and consumer prices show a slightly declining trend and tend to remain relatively constant throughout the sample.

We also calculate that, according to the CVAR model, the ERPTs into import, producer, and consumer prices are 0.57, 0.29, and 0.12, respectively. Regarding the CVAR-SV model, the ERPT into import prices at the end of the 1990s was 0.66; and declines steadily since then to a minimum of 0.3 in mid-2007. Post-GFC, the ERPT resurges significantly through the end of the sample, to 0.72. It is worth noting that the ERPT into import prices in the CVAR-SV model is only lower than in the CVAR model over 2004-2015.

For its part, the ERPT into producer prices in the CVAR-SV model is always lower than in the

CVAR model. The ERPT in the CVAR-SV model at the beginning of the sample was 0.22 and declined slightly to 0.18 by 2008. Post-GFC it remained relatively constant around 0.18. Finally, the ERPT into consumer prices in the CVAR-SV model always remains below the ERPT in the CVAR model through most of the sample. From the beginning of the sample until 2004 it remains al levels close to the CVAR model, and later falls slightly to a minimum in 2007 (0.08). Post-GFC it rises slightly; and reaches the ERPT in the CVAR model by mid-2016.

In sum, the robustness exercises show that most results obtained from the baseline model hold up. In general, ERPT evolution does not vary significantly when we change the first variable and the economic activity indicator, and when we establish priors based on the training sample with high SV values. However, in some cases the ERPT levels are higher relative to the baseline model. Additionally, the estimations for Colombia confirm that the ERPTs into import and producer prices resurge post-GFC, while the ERPT into consumer prices remains relatively constant throughout the sample.

6 Conclusions

This paper uses the TVP-VAR-SV approach based on Chan and Eisenstat (2018) to estimate and assess the evolution of ERPT into three types of prices for Peru over 1995Q2-2019Q4. The variables used, their ordering, and the shock identification scheme within the baseline VAR model are in line with the PDC model proposed by McCarthy (2007).

According to the two Bayesian selection criteria, the best-fitting models (TVP-VAR-SV and TVP-VAR-R1-SV) allow most parameters to vary over time, emphasizing the role of SV. The estimations reveal that the ERPT varies over time, depends on the state of the economy, and its level and evolution are in line with the predictions of the PDC model. The ERPT into import prices is higher, followed by the ERPT into producer and consumer prices; and ERPT evolution is similar across the best-fitting models.

We find that the ERPTs into import and producer prices are high at the beginning of the sample; and begin to fall since 2000 (most notably from 2006, to a minimum in mid-2008) as a consequence of macroeconomic stabilization, an initial wave of de-dollarization policies, and surging commodity prices. However, unlike the existing literature for Peru (notably Winkelried (2014)), the ERPTs tend to increase post-GFC for all models (except CVAR) due to an exchange rate increase, in turn caused by the end of QE (the 2013 tamper tantrum) and two recent international political developments (Brexit and the U.S.-China trade war). These results, which adhere to recent ERPT literature (regarding the post-GFC ERPT resurgence), are explained by BCRP interventions in the FX market. The latter only attenuate exchange rate volatility, but do not seek to influence its trend. In this context, importers and producers adjust their prices; i.e., the ERPT increases under exchange rate depreciation.

At the same time, the ERPT into consumer prices falls steadily throughout the sample in a context of macroeconomic stabilization, IT adoption, and implementation of Law 28300. This finding reinforces the abundant evidence on the low-inflation hypothesis enunciated by Taylor (2000); i.e., ERPT is low in economies experiencing low and stable inflation, and whose monetary authorities enjoy credibility in anchoring inflation expectations around the inflation target.

Two possible policy recommendations for reducing ERPT emerge in light of these results: (i) implementing a de-dollarization program focused on the input/raw material purchase stage; and (ii) encouraging importers and domestic industries to use financial instruments to hedge against the exchange rate risk.

Finally, this paper does not address the drivers of ERPT evolution. Therefore, a future research agenda could consider studying them. Additionally, it is necessary to examine the endogenous sources (i.e., the types of shocks) that govern ERPT evolution using the methodologies proposed by Leiva-León and Uzeda (2021) and Koop et al. (2009). Other issues to address include: (i) assessing the impact of the recent COVID-19 health crisis and the presidential election on the exchange rate and on ERPT evolution; and (ii) analyzing domestic prices at a disaggregated level and defining a non-recursive shock identification scheme.

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Table 1. Tests for Time Variation in Coefficients and Volatility

Kolmogorov-Smirnov test			
Pre and Post GFC		Pre and Post IT adoption	
γ_t			
1995Q3-2006Q4	2007Q1-2019Q4	1995Q3-2001Q4	2002Q1-2019Q4
15/15	15/15	14/15	15/15
β_t			
1995Q3-2006Q4	2007Q1-2019Q4	1995Q3-2001Q4	2002Q1-2019Q4
31/42	32/42	28/42	31/42
h_t			
1995Q3-2006Q4	2007Q1-2019Q4	1995Q3-2001Q4	2002Q1-2019Q4
6/6	6/6	6/6	6/6
t-test			
Pre and Post GFC		Pre and Post IT adoption	
γ_t			
1995Q3-2006Q4	2007Q1-2019Q4	1995Q3-2001Q4	2002Q1-2019Q4
15/15	15/15	15/15	15/15
β_t			
1995Q3-2006Q4	2007Q1-2019Q4	1995Q3-2001Q4	2002Q1-2019Q4
32/42	28/42	25/42	31/42
h_t			
1995Q3-2006Q4	2007Q1-2019Q4	1995Q3-2001Q4	2002Q1-2019Q4
6/6	6/6	6/6	6/6

γ_t represents the coefficients of contemporaneous relationships, β_t represents the coefficients associated to intercepts and lagged variables, and h_t represents the coefficients associated to volatility. In the fraction expression, the numerator indicates the number of parameters that vary and the denominator indicates the total number of parameters.

Table 2. Models Selection

Baseline Specification					
Model	log-ML$_{CE}$	Rank	DIC	Rank	pD
TVP-VAR-SV	-1105.49 (0.09)	1	1929.74 (1.12)	6	60.29 (0.44)
TVP-VAR	-1142.79 (0.07)	7	1963.73 (1.27)	7	55.67 (0.58)
TVP-VAR-R1-SV	-1105.51 (0.07)	2	1900.54 (0.39)	3	65.83 (0.18)
TVP-VAR-R2-SV	-1107.79 (0.08)	5	1918.72 (0.91)	4	61.35 (0.37)
TVP-VAR-R3-SV	-1106.46 (0.12)	3	1897.09 (0.19)	2	66.78 (0.12)
CVAR-SV	-1106.94 (0.03)	4	1886.05 (0.18)	1	67.90 (0.10)
CVAR	-1140.09 (0.01)	6	1920.32 (0.20)	5	60.79 (0.11)

Standard deviations are presented in parentheses. For each model we obtain a total of 100,000 posterior draws from 10 parallel chains after a burn-in of 1,000 in every chain, and keep every 10th draw for 10,000 final posterior draws. Log-ML$_{CE}$ estimates are based on 10,000 evaluations of the integrated likelihood, where the importance sampling density is constructed using the 10,000 posterior draws. DIC estimates are computed using 10 parallel chains. In each chain the integrated likelihood is evaluated for the 1,000 posterior draws kept from each estimation chain, getting a total of 10,000 evaluations.

Table 3. Median Long Run ERPT into Prices ($s = 20$)

Model	Import Prices	Producer Prices	Consumer Prices
TVP-VAR-SV	0.57	0.39	0.10
	[0.53 - 0.61]	[0.37 - 0.42]	[0.07 - 0.12]
TVP-VAR	0.39	0.26	0.06
	[0.36 - 0.42]	[0.24 - 0.27]	[0.04 - 0.08]
TVP-VAR-R1-SV	0.52	0.37	0.14
	[0.47 - 0.58]	[0.33 - 0.40]	[0.12 - 0.16]
TVP-VAR-R2-SV	0.47	0.39	0.11
	[0.44 - 0.51]	[0.35 - 0.42]	[0.08 - 0.14]
TVP-VAR-R3-SV	0.43	0.33	0.11
	[0.40 - 0.46]	[0.30 - 0.38]	[0.09 - 0.14]
CVAR-SV	0.43	0.34	0.17
	[0.39 - 0.47]	[0.30 - 0.38]	[0.15 - 0.19]
CVAR	0.33	0.22	0.12
	[0.29 - 0.38]	[0.19 - 0.25]	[0.10 - 0.15]

Median ERPTs are calculated as the median of the evolution of ERPT rates over horizon $s = 20$ quarters and over time from 1995Q3 to 2019Q4. Confidence intervals are presented in brackets.

Table 4. Robustness Analysis 1: Models Selection Exchanging the First Variable in VAR

	GPIAC Growth Rate				S&P GSCI Growth Rate				Copper Prices Inflation			
Model	log-ML_{CE}	Rank	DIC	Rank	log-ML_{CE}	Rank	DIC	Rank	log-ML_{CE}	Rank	DIC	Rank
TVP-VAR-SV	−1125.41 (0.16)	1	1970.16 (1.16)	6	−1125.65 (0.17)	1	1970.92 (1.32)	6	−1195.97 (0.18)	4	2101.85 (0.84)	6
TVP-VAR	−1172.76 (0.16)	7	2014.26 (1.22)	7	−1173.06 (0.12)	7	2015.69 (1.11)	7	−1242.24 (0.11)	7	2138.42 (1.28)	7
TVP-VAR-R1-SV	−1127.26 (0.07)	2	1940.93 (0.37)	3	−1127.17 (0.07)	3	1940.40 (0.49)	3	−1192.23 (0.09)	3	2068.28 (0.30)	3
TVP-VAR-R2-SV	−1127.33 (0.13)	3	1955.14 (1.30)	4	−1127.07 (0.13)	2	1952.18 (0.88)	4	−1196.23 (0.21)	5	2085.88 (1.29)	5
TVP-VAR-R3-SV	−1129.15 (0.12)	4	1936.43 (0.30)	2	−1129.14 (0.09)	4	1936.36 (0.30)	2	−1129.38 (0.13)	2	2085.20 (0.31)	2
CVAR-SV	−1130.78 (0.03)	5	1927.89 (0.24)	1	−1130.65 (0.04)	5	1928.03 (0.23)	1	−1129.33 (0.03)	1	2045.49 (0.34)	1
CVAR	−1168.56 (0.01)	6	1963.96 (0.25)	5	−1168.59 (0.01)	6	1964.33 (0.17)	5	−1234.14 (0.01)	6	2083.68 (0.20)	4

Standard deviations are presented in parentheses. For each model we obtain a total of 100,000 posterior draws from 10 parallel chains after a burn-in of 1,000 in every chain, and keep every 10th draw for 10,000 final posterior draws. Log-ML_{CE} estimates are based on 10,000 evaluations of the integrated likelihood, where the importance sampling density is constructed using the 10,000 posterior draws. DIC estimates are computed using 10 parallel chains. In each chain the integrated likelihood is evaluated for the 1,000 posterior draws kept from each estimation chain, getting a total of 10,000 evaluations.

Table 4 (Continues). Robustness Analysis 1: Models Selection Exchanging the First Variable in VAR

	Terms of Trade Growth Rate				US Consumer Inflation Rate				US GDP Deflator Rate			
Model	log-ML$_{CE}$	Rank	DIC	Rank	log-ML$_{CE}$	Rank	DIC	Rank	log-ML$_{CE}$	Rank	DIC	Rank
TVP-VAR-SV	−1096.76 (0.09)	4	1019.46 (0.61)	6	−882.55 (0.19)	2	1486.51 (0.81)	5	−793.63 (0.11)	4	1319.86 (1.32)	4
TVP-VAR	−1126.95 (0.10)	7	1939.04 (0.88)	7	−926.61 (0.04)	7	1558.10 (0.85)	7	−870.78 (0.13)	7	1421.01 (1.19)	7
TVP-VAR-R1-SV	−1095.20 (0.10)	2	1880.47 (0.25)	3	−879.97 (0.16)	1	1454.20 (0.58)	2	−788.95 (0.26)	1	1277.02 (0.52)	1
TVP-VAR-R2-SV	−1097.21 (0.14)	5	1898.26 (1.03)	4	−886.07 (0.09)	5	1484.44 (0.79)	4	−729.91 (0.12)	5	1322.55 (1.07)	5
TVP-VAR-R3-SV	−1095.02 (0.18)	1	1877.33 (0.33)	2	−885.36 (0.19)	4	1469.03 (0.37)	3	−792.24 (0.21)	2	1295.19 (0.25)	3
CVAR-SV	−1095.70 (0.06)	3	1866.45 (0.18)	1	−884.07 (0.03)	3	1452.29 (0.35)	1	−793.63 (0.04)	3	1281.27 (0.26)	2
CVAR	−1124.34 (0.02)	6	1898.55 (0.26)	5	−923.29 (0.01)	6	1522.29 (0.18)	6	−861.72 (0.01)	6	1374.74 (0.25)	6

Standard deviations are presented in parentheses. For each model we obtain a total of 100,000 posterior draws from 10 parallel chains after a burn-in of 1,000 in every chain, and keep every 10th draw for 10,000 final posterior draws. Log-ML$_{CE}$ estimates are based on 10,000 evaluations of the integrated likelihood, where the importance sampling density is constructed using the 10,000 posterior draws. DIC estimates are computed using 10 parallel chains. In each chain the integrated likelihood is evaluated for the 1,000 posterior draws kept from each estimation chain, getting a total of 10,000 evaluations.

Table 5. Robustness Analysis 2: Models Selection Exchanging the Domestic Economic Activity Variable

	Non-Primary GDP				Domestic Demand Growth			
Model	log-ML$_{CE}$	Rank	DIC	Rank	log-ML$_{CE}$	Rank	DIC	Rank
TVP-VAR-SV	-1101.33 (0.16)	1	1921.56 (0.82)	6	-1143.66 (0.14)	1	2002.84 (0.62)	6
TVP-VAR	-1141.63 (0.06)	7	1961.45 (1.19)	7	-1186.39 (0.08)	7	2043.85 (0.87)	7
TVP-VAR-R1-SV	-1102.57 (0.05)	2	1877.85 (0.18)	1	-1145.43 (0.06)	2	1961.67 (0.20)	1
TVP-VAR-R2-SV	-1103.48 (0.12)	4	1910.10 (0.85)	4	-1146.13 (0.11)	3	1991.66 (0.91)	4
TVP-VAR-R3-SV	-1138.96 (0.01)	6	1916.38 (0.23)	5	-1184.30 (0.01)	6	2000.37 (0.28)	5
CVAR-SV	-1102.62 (0.08)	3	1889.32 (0.24)	2	-1146.55 (0.14)	5	1974.51 (0.35)	2
CVAR	-1103.64 (0.03)	5	1894.89 (0.46)	3	-1146.45 (0.03)	4	1978.96 (0.38)	3

Standard deviations are presented in parentheses. For each model we obtain a total of 100,000 posterior draws from 10 parallel chains after a burn-in of 1,000 in every chain, and keep every 10th draw for 10,000 final posterior draws. Log-ML$_{CE}$ estimates are based on 10,000 evaluations of the integrated likelihood, where the importance sampling density is constructed using the 10,000 posterior draws. DIC estimates are computed using 10 parallel chains. In each chain the integrated likelihood is evaluated for the 1,000 posterior draws kept from each estimation chain, getting a total of 10,000 evaluations.

Table 6. Robustness Analysis 3: Models Selection Exchanging the Priors Values Based on Training Sample with 20 times the Variance of CVAR Model

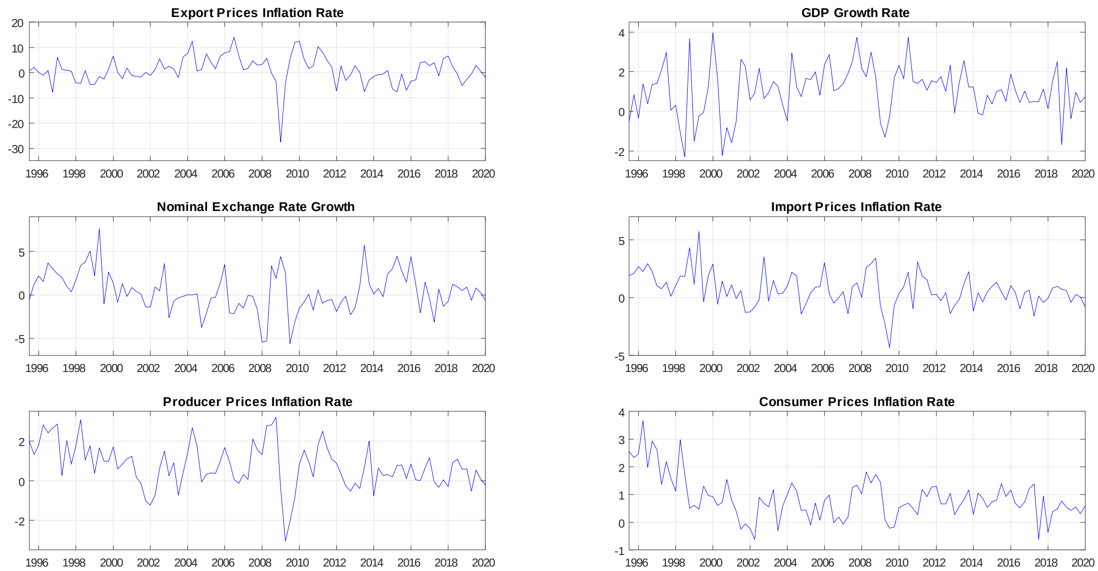
Model	log-ML$_{CE}$	Rank	DIC	Rank
TVP-VAR-SV	-1038.66 (0.16)	2	1926.22 (10.96)	6
TVP-VAR	-1075.09 (0.17)	7	1962.65 (1.03)	7
TVP-VAR-R1-SV	-1036.98 (0.13)	1	1884.45 (0.28)	1
TVP-VAR-R2-SV	-1040.68 (0.30)	5	1917.24 (0.99)	4
TVP-VAR-R3-SV	-1071.77 (0.01)	6	1919.19 (0.16)	5
CVAR-SV	-1040.25 (0.11)	4	1896.19 (0.35)	2
CVAR	-1038.66 (0.04)	3	1900.46 (0.29)	3

Standard deviations are presented in parentheses. For each model we obtain a total of 100,000 posterior draws from 10 parallel chains after a burn-in of 1,000 in every chain, and keep every 10th draw for 10,000 final posterior draws. Log-ML$_{CE}$ estimates are based on 10,000 evaluations of the integrated likelihood, where the importance sampling density is constructed using the 10,000 posterior draws. DIC estimates are computed using 10 parallel chains. In each chain the integrated likelihood is evaluated for the 1,000 posterior draws kept from each estimation chain, getting a total of 10,000 evaluations.

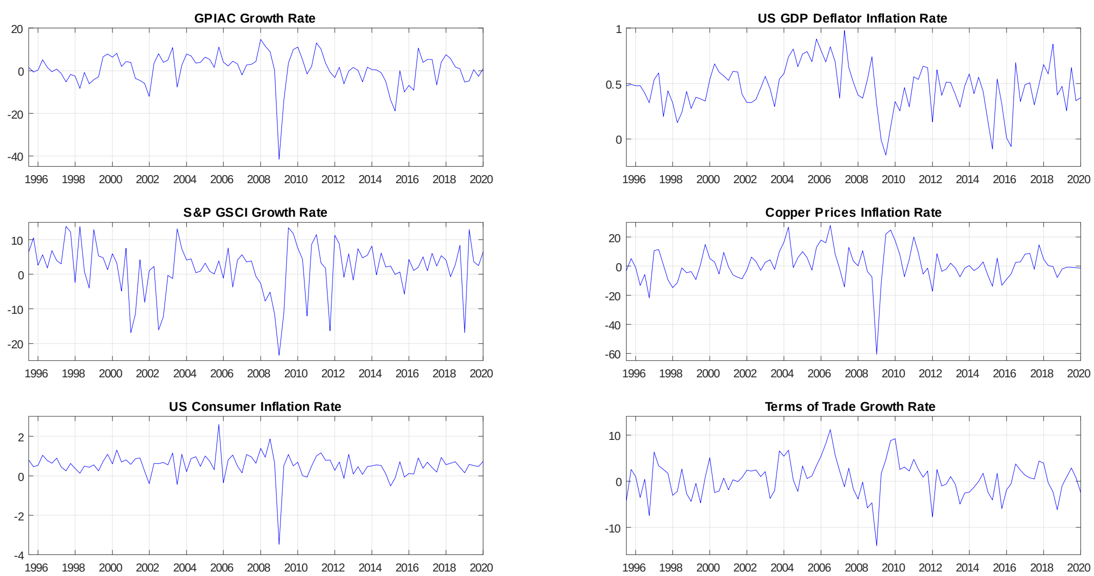
Table 7. Robustness Analysis 4: Models Selection for Colombia

Model	log-ML_{CE}	Rank	DIC	Rank
TVP-VAR-SV	-1083.60 (0.22)	5	1887.83 (1.69)	6
TVP-VAR	-1131.11 (0.15)	7	1936.99 (1.35)	7
TVP-VAR-R1-SV	-1083.15 (0.10)	3	1863.90 (0.50)	3
TVP-VAR-R2-SV	-1083.07 (0.17)	2	1874.78 (1.58)	4
TVP-VAR-R3-SV	-1125.08 (0.01)	6	1887.58 (0.24)	5
CVAR-SV	-1081.55 (0.15)	1	1854.04 (0.33)	2
CVAR	-1083.48 (0.03)	4	1849.80 (0.03)	1

Standard deviations are presented in parentheses. For each model we obtain a total of 100,000 posterior draws from 10 parallel chains after a burn-in of 1,000 in every chain, and keep every 10th draw for 10,000 final posterior draws. Log-ML_{CE} estimates are based on 10,000 evaluations of the integrated likelihood, where the importance sampling density is constructed using the 10,000 posterior draws. DIC estimates are computed using 10 parallel chains. In each chain the integrated likelihood is evaluated for the 1,000 posterior draws kept from each estimation chain, getting a total of 10,000 evaluations.



Panel A. Baseline Variables



Panel B. External Variables

Figure 1. Variables in Growth Rates

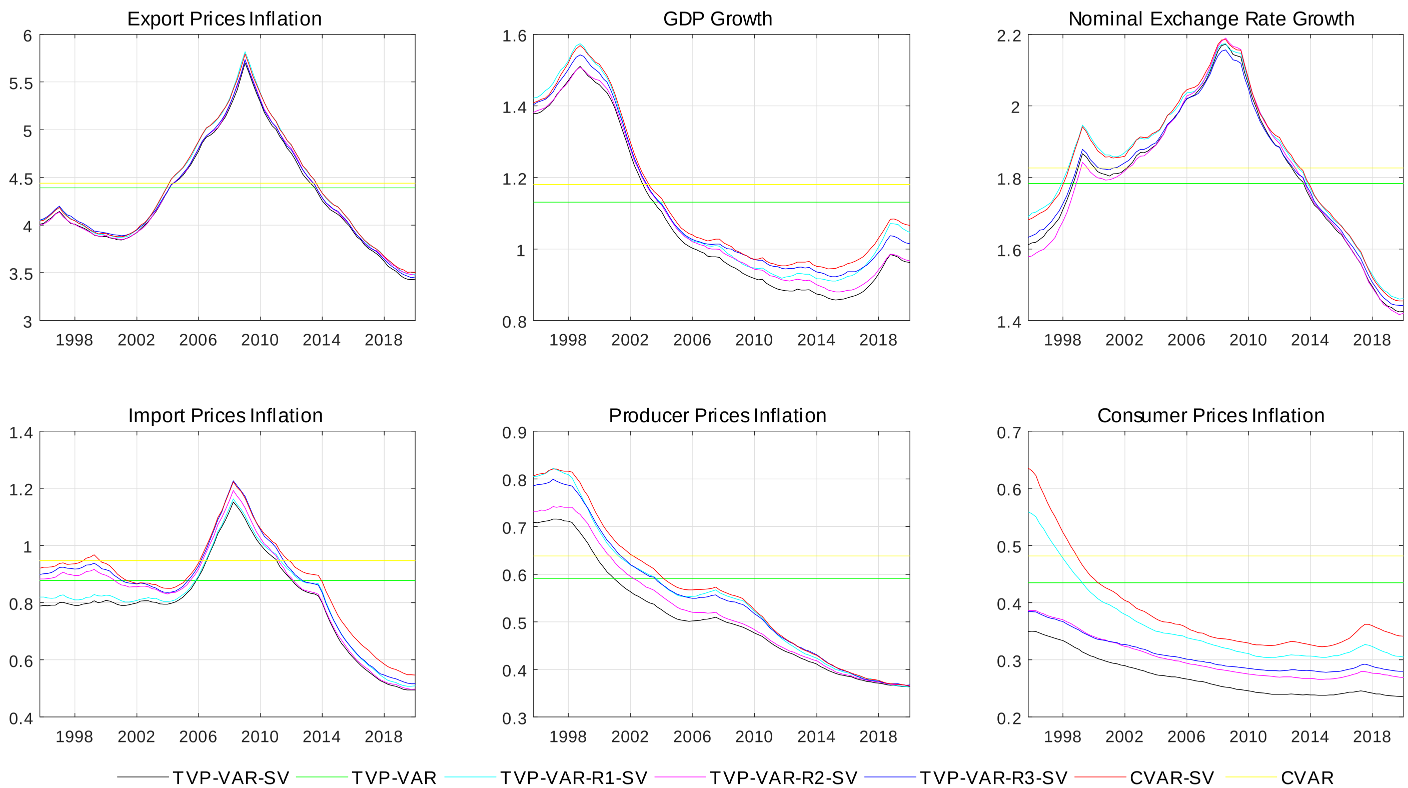


Figure 2. Standard Deviation of the Innovations in each Equation, Median Values.

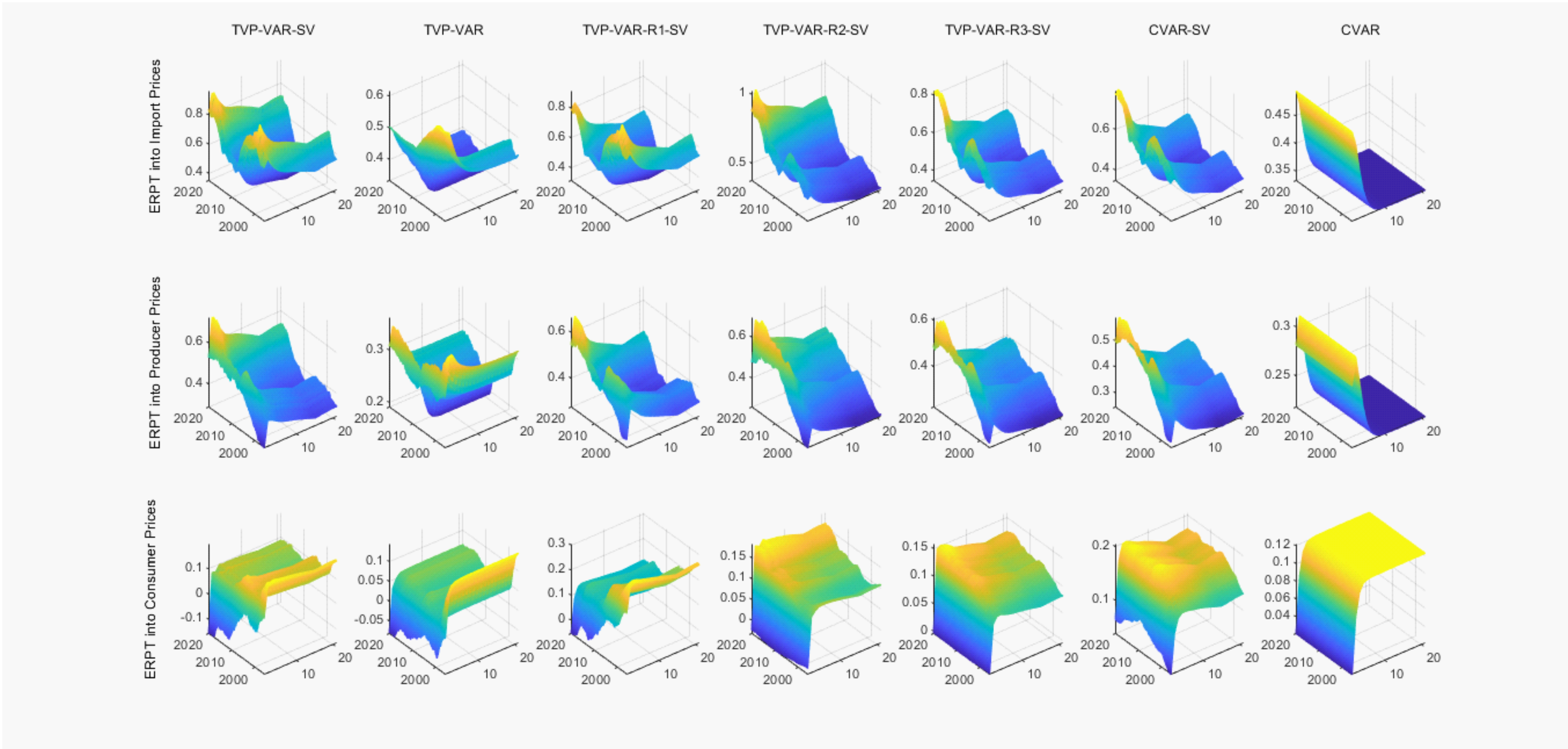


Figure 3. Three-dimensional plots of the evolution of rates of ERPT into Import Prices (first row), Producer Prices (second row) and Consumer Prices (third row), over horizon $s = 20$ quarters and over time from 1995Q3 to 2019Q4, for all models.

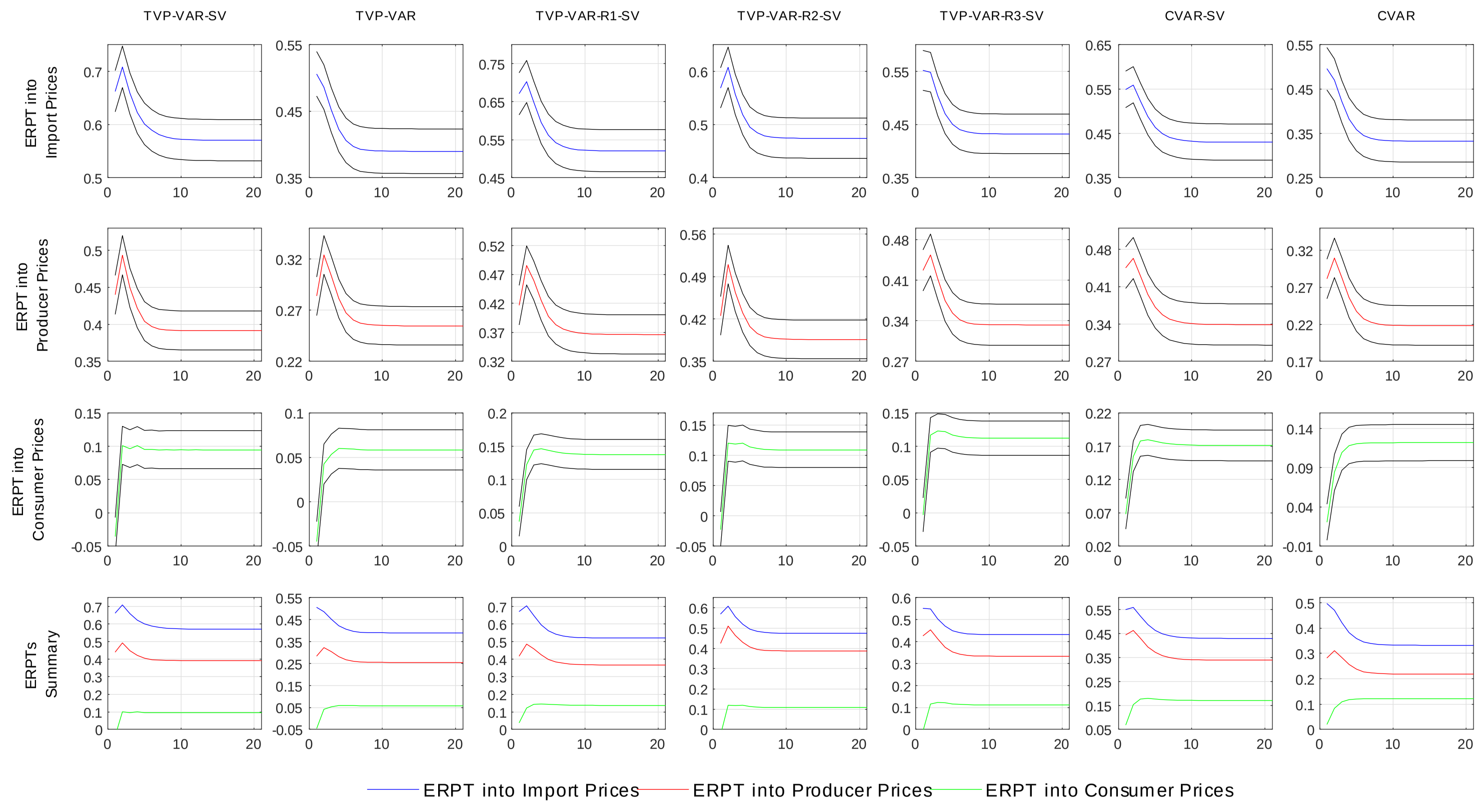


Figure 4. Median ERPT into Import (first row), Producer (second row) and Consumer (third row) Prices. The black lines represent the 68% error bands. The fourth row presents the ERPTs summary for each model.

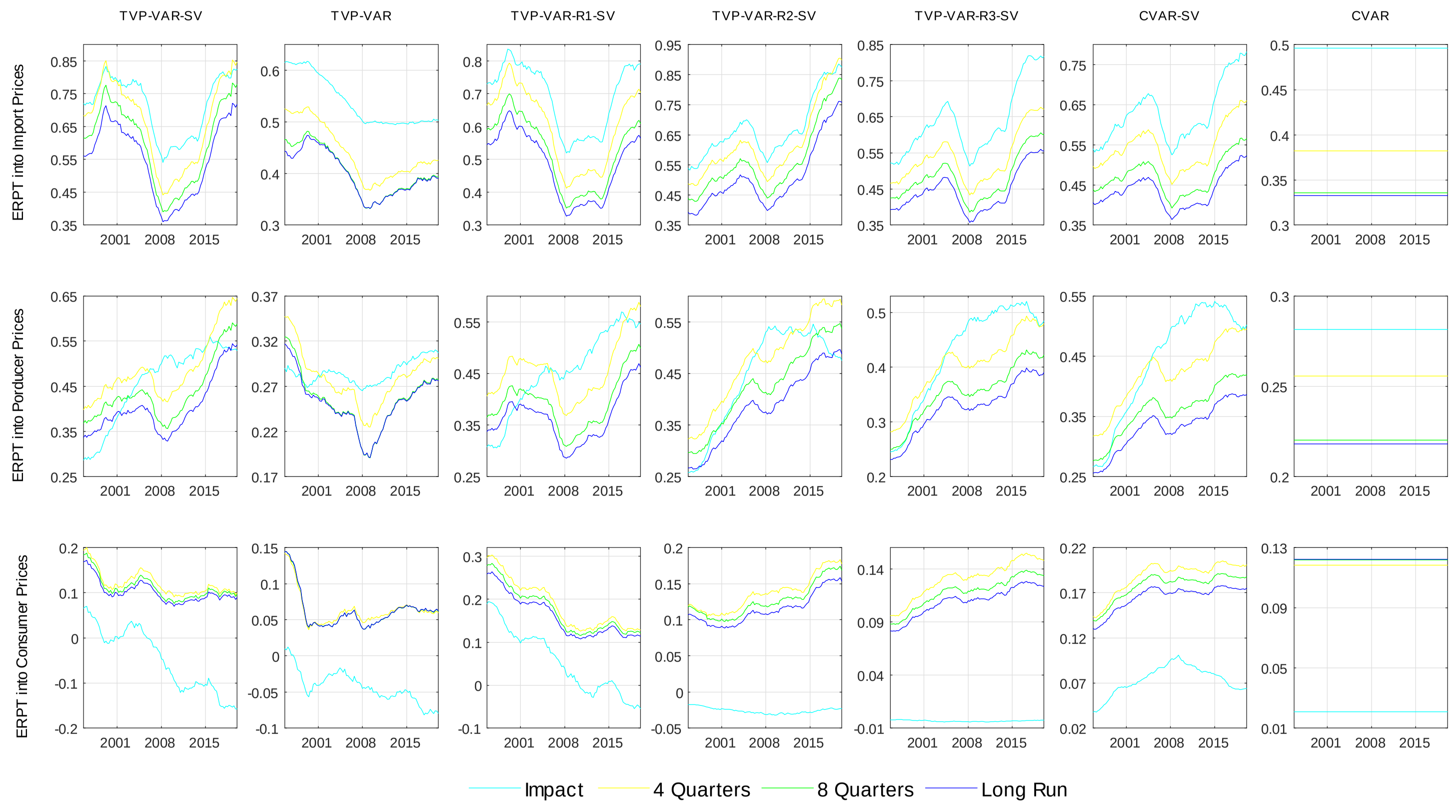
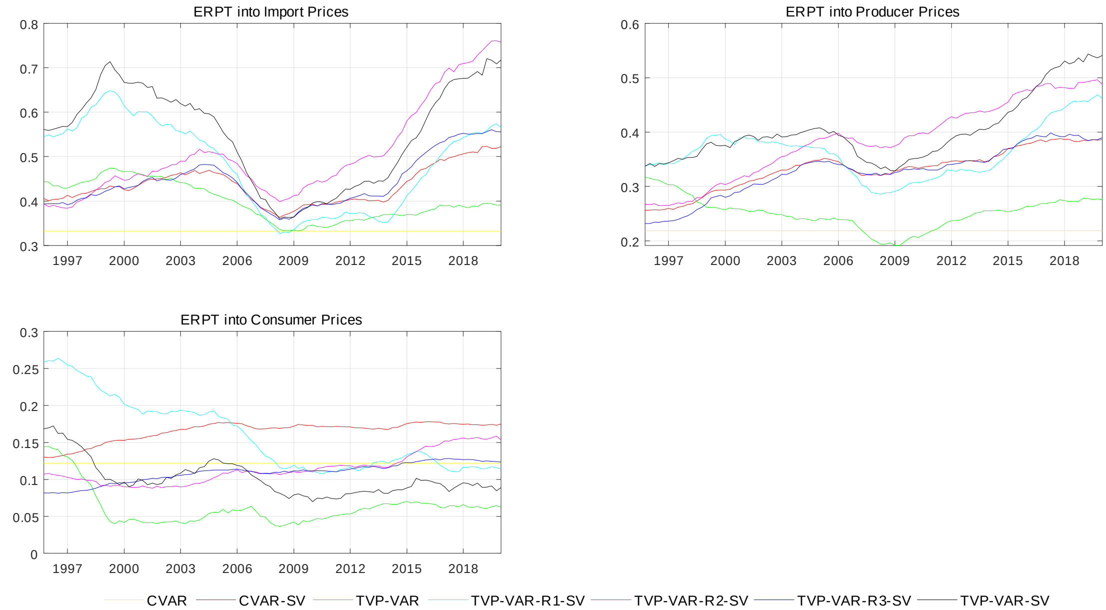
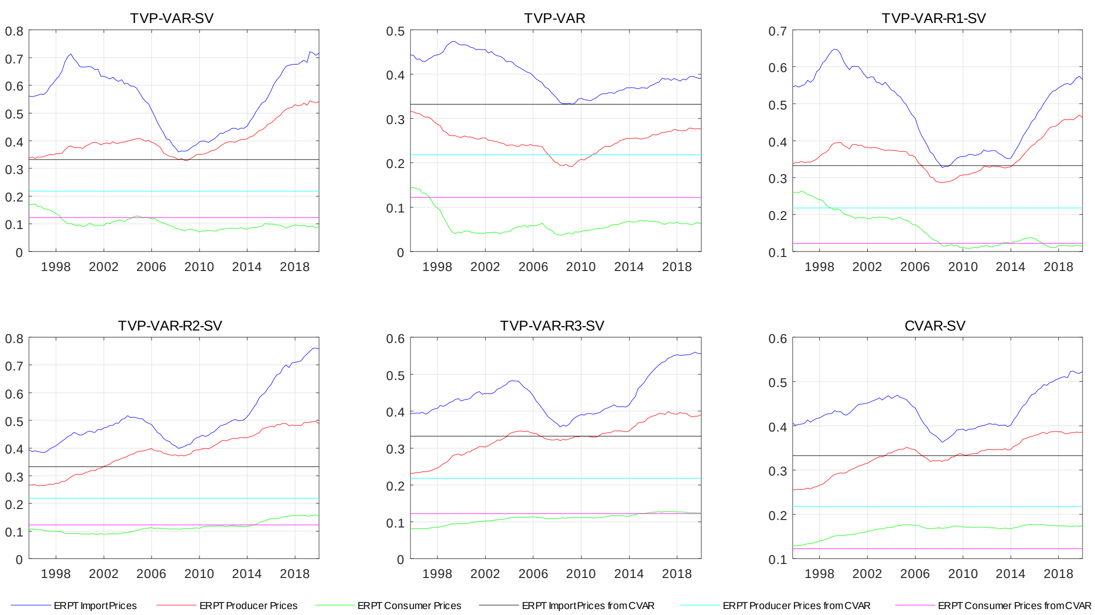


Figure 5. Time-Varying Impact ERPT, 4, 8 quarters and Long Run ERPT into Import (first row), Producer (second row) and Consumer (third row) Prices for each Model.



Panel A. Time-Varying Long Run ERPT into Import, Producer and Consumer Prices, All Models.



Panel B. Time-Varying Long Run ERPT into Import, Producer and Consumer Prices for each Model.

Figure 6. Evolution of Long Run ERPT into Prices

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