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Recent developments in exchange rate pass-through: What have we learned from uncertain times?

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ABSTRACT

This study analyzes the influence of geopolitical uncertainty on the degree of exchange rate pass-through (ERPT) into domestic prices for a sample of advanced and emerging economies. We implement a dynamic panel threshold regression model to capture the possible presence of regime shifts in the exchange transmission. The estimation results suggest significant regime-dependence of the ERPT to geopolitical factors, which is more apparent for the sample of developed countries. Primarily, recent adverse geopolitical events seem to lead to higher rates of pass-through to both import and consumer prices. As the uncertainty surrounding the Ukrainian crisis is likely to continue, it is challenging for policymakers to prevent exchange rate changes from fueling the growing inflationary pressures.

1. Introduction

The recent global COVID-19 pandemic and Ukrainian conflict have exerted significant inflationary pressures, making monetary policymakers face new and challenging tradeoffs. Understanding how domestic prices are affected by exchange rate shocks in times of uncertainty is of particular importance for central banks, as commodity prices have soared to the highest levels since 2008. In this study, we endeavor to provide new evidence of how exchange rate pass-through (ERPT) has evolved in the recent turbulent times. Contemporary times have witnessed a growing number of geopolitical events that entailed oil supply disruption, such as the 2014 Russian annexation of Crimea, the 2017 Qatar diplomatic crisis, and the 2022 Russia–Ukraine war, among others. As such geopolitical conflicts involve net-oil exporting countries, the uncertainty with respect to the level of the world's oil reserves would substantially increase, causing oil prices to spike. The degree of ERPT is demonstrated to be much higher for homogeneous goods and commodities than for differentiated manufactured products (see, e.g., Campa and Goldberg, 2002; Goldberg and Tille, 2008; Ben Cheikh and Rault, 2017). Adverse events related to energy supply disruptions are expected to entail higher levels of ERPT, which fuels the growing inflationary pressures.

Moreover, it is well known that foreign firms' pricing strategy and the invoicing currency applied will determine the degree to which exchange rate changes impact domestic prices (e.g., Boz et al., 2022; Gagnon and Sarsenbayev, 2021; Gopinath et al., 2020). At the same time, exporters' perceptions regarding the macroeconomic conditions in the destination country are crucial, as they can influence pricing behavior. Foreign producers are susceptible to following a "local currency

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pricing" (LCP) strategy, in which prices in the currencies of countries with stable macroeconomic environments are sticky. If the currency is depreciating in the destination country, a foreign firm could cut its price by reducing its markup. In this case, ERPT tends to be weak. However, in times of macroeconomic instability, the currency denomination is affected as exporters may adopt a "producer-currency pricing" (PCP) strategy, in which prices are preset in their own currency, keeping a constant markup. In doing so, a larger proportion of exchange rate changes are passed through domestic prices, leading to higher levels of pass-through.

The bulk of related empirical literature has agreed that the extent of pass-through is expected to be higher in times of turbulence than during periods of stability (e.g., Ben Cheikh and Rault, 2016; Nogueira and Leon-Ledesma, 2011; Jasova et al., 2019; Wang et al. 2022; Zou et al., 2022). Most studies have focused on the role of macroeconomic uncertainty in affecting responses such as exchange rate volatility (e.g., Campa and Goldberg, 2005), inflation uncertainty (e.g., Baharumshah et al., 2017), output volatility (e.g., McCarthy, 2007), and financial crisis (e.g., Nogueira and Leon-Ledesma, 2011). To the best of our knowledge, no study has considered the influence of recent adverse geopolitical events that have entailed significant disruptions in global commodity markets. Given that the recent global economic crisis gave rise to worsening economic conditions, we examine whether the degree of ERPT is affected during times of uncertainty. As the 2022 Russia–Ukraine war has exacerbated uncertainty in fossil fuel and commodity markets, the pricing behavior of producers around the world could be altered, indicating the presence of a possible nonlinear mechanism in ERPT.

This study proposes a novel approach for investigating the issue of the exchange rate transmission into domestic prices. We implement the dynamic panel threshold regression (PTR) data modeling approach proposed by Seo and Shin (2016), in which the potential nonlinear effects of recent geopolitical crises are properly captured from the data. The panel data model of Seo and Shin (2016) is an extension of Hansen (1999) and Caner and Hansen (2004) methodologies into dynamic panels with an endogenous threshold variable and regressors. The threshold effect in the model reveals the asymmetric effect of the exchanges rate on prices, depending on whether the threshold variable is above or below a certain threshold. To uncover the influence of the recent Russian–Ukraine conflict, we incorporate the geopolitical risk (GPR) index of Caldara and Iacoviello (2022) as a threshold variable in the nonlinear panel data model. The GPR index measures the occurrence of adverse geopolitical events and associated risks, taking higher values in times of uncertainty. This enables us to estimate the ERPT coefficients with respect to geopolitical context (i.e., during episodes of low and high geopolitical risk regimes). Our dynamic PTR models are estimated for a sample of 34 advanced and emerging economies over a recent monthly period from September 2020 to August 2022. The extent of ERPT is estimated for the "first-stage pass-through" (i.e., into import prices) as well as pass-through to consumer prices. For the sake of robustness, we also estimate a fixed-effect PTR model referencing Hansen (1999), and tested whether other types of uncertainty would influence the extent of ERPT.

The remainder of this paper is organized as follows. Section 2 reviews the existing literature on the ERPT and the influence of times of crisis, Section 3 presents the econometric approach used in this paper, and Section 4 outlines the empirical ERPT specification and the data. In Section 5, the main empirical results are reported and discussed. Section 6 provides a robustness analysis. We conclude the study with Section 7.

2. Related literature

There has been a growing body of empirical literature examining nonlinearities in ERPT in recent years; however, minimal studies have investigated the role of changes in macroeconomic conditions due to turbulent events. The family of smooth transition regression models has been commonly used in this strand of literature. For a set of ten new European Union Member States, Ben Cheikh and Ben Zaied (2020) analyzed the transition in the degree of pass-through using a nonlinear panel smooth transition regression model. The authors' empirical results demonstrated a declining exchange rate transmission due to the shift toward a stable inflation regime. In the same vein, Shintani et al. (2013) implemented a smooth transition regression framework to measure the pass-through to US domestic prices under different inflation environments, determining that during periods of stable inflation levels, the degree of ERPT tends to be lower. More recently, Anderl and Caporale (2022) applied a smooth transition regression model to estimate the rate of ERPT in a sample of inflation targeting and non-targeting countries, demonstrating the regime-dependence of ERPT to inflation expectations, which was introduced as a transition variable in the model. Notably, the above studies have not considered the notion of inflation uncertainty and how it could be interacted with the ERPT mechanism.

Another family of regime-switching models was applied by Baharumshah et al. (2017) to investigate the role of inflation uncertainty using a dataset of six inflation targeting countries. The authors identified two different states (stable and unstable regimes) by implementing a Markov-switching model. According to their main results, the ERPT is incomplete and significantly weaker when inflation uncertainty is low. Other macroeconomic approaches have been proposed that are related to economic crises and financial stress. Correa and Minella (2006) documented that ERPT does not statistically differ from zero during economic contractions in Brazil using a nonlinear threshold model, while the elasticity of pass-through is around 9% when economic activity is booming. In the same vein, Donayre and Panovska (2016) examined the role of business cycles in Canada and Mexico applying Bayesian threshold vector autoregression. The authors' impulse response analysis revealed strong evidence of a nonlinear relationship, suggesting that ERPT is dependent on the state of the economy. Another macroeconomic variable that has been examined in the empirical literature is aggregate demand uncertainty.

In a related literature, Ben Cheikh and Rault (2016) focused on the European sovereign debt crisis, confirming that growing macroeconomic instability has entailed a higher responsiveness in domestic prices. As a proxy for the occurrence of confidence crises, the authors used the 10-year government yield spreads to German bonds. Similarly, Nogueira and Leon-Ledesma (2011) studied the possible nonlinearity of ERPT due to the Mexican crisis, noting that ERPT to consumer prices is higher during episodes of financial or confidence crisis. The Mexican real interest rate differential in comparison to the US was introduced as an indicator of financial stress. Using disaggregated consumer price index (CPI) data, Edwards and Cabezas (2022) analyzed the extent of pass-through in Iceland during a period that includes Iceland's 2008 banking and currency crisis. The results indicate that ERPT declined around the time when Iceland reformed its flexible inflation targeting in 2009–2010. Further investigation on the nexus between ERPT and times of uncertainty emergence is an essential input for policymaking given the recent inflationary pressures. Producers may have different reactions to market uncertainties depending on risk preferences and the perceived persistence of shocks (see e.g., Taylor, 2000). In a recent study, Zou et al. (2022) investigated the sensitivity of export prices to currency changes under conditions of high and low uncertainty. Using Chinese export data for the period 2002–2019, the authors confirmed that ERPT is asymmetric and susceptible to uncertainty.

Our study intends to contribute to this strand of literature by examining whether recent times of uncertainty, such as the Ukrainian crisis, altered the ERPT mechanism. The PTR model has been applied in the empirical ERPT literature. In a large panel data set of 63 countries over the 1992–2012 period, Ben Cheikh and Louhichi (2016) proposed using the PTR framework proposed by Hansen (1999) to test the regime-dependence of ERPT in an inflationary environment. The authors revealed that countries with higher inflation rates experience a higher degree of ERPT. Nevertheless, the estimated PTR model is static, and the implemented fixed-effects estimation requires the strong exogeneity of explanatory variables.

Since the exchange rate in a floating system may fluctuate in reaction to economic policy, treating the exchange rate process as exogenous in the economy while disregarding its potential endogeneity to other variables is not realistic. Also, according to purchasing power parity conditions, there could be a bidirectional causality between the relative price levels and exchange rates. Therefore, it is crucial to adopt a relevant econometric approach to treat them as endogenous. In this study, we propose to use the extension of the static PTR model of Hansen (1999) framework where the presence of threshold effect is allowed within dynamic panels. Seo and Shin (2016) developed a dynamic PTR which allows both threshold variables and regressors to be endogenous.

3. Empirical methodology and data

In our empirical specification, we stipulate the presence of threshold effect in exchange transmission. We suggest that the responsiveness of import prices is nonlinearly dependent on the turbulent times in the sense that ERPT would differ with respect to the state of the economy. The dynamic PTR model allows the determination of whether ERPT changes from one macroeconomic regime to another. The threshold effect in the model determines the asymmetric effect of the exchange rate on import prices, depending on whether the threshold variable is smaller or larger a given threshold. Following Seo and Shin (2016), we implement the first-differenced generalized method of moments (FD-GMM) approach which allows both threshold variables and regressors to be endogenous.

The dynamic PTR model is as follows:

$$y_{it} = (1, x_{it}^{'})\phi_1 \mathbb{I}\{q_{it} \le \gamma\} + (1, x_{it}^{'})\phi_2 \mathbb{I}\{q_{it} > \gamma\} + \varepsilon_{it}, 1 \le i \le N, 1 \le t \le T \tag{1}$$

where y_{it} is the dependent variable of interest, x_{it} the $k_1 \times 1$ vector of time-varying explanatory variables, which may include lagged values of y_{it}, $\mathbb{I}\{.\}$ is an indicator function that indicates the two regimes identified by the transition variable q_{it} and is the threshold parameter γ. ϕ_1 and ϕ_2 are the regression slopes for each regime. The error term ε_{it} has of the following components:

$$\varepsilon_{it} = \alpha_i + v_{it}, \tag{2}$$

where α_i is the fixed individual effects and v_{it} is a zero mean idiosyncratic random disturbance. The first-difference transformation of Eq.(1) is considered to manage the correlation of regressors with individual effects in Eq.(1) and Eq.(2). The first-differenced model has the following form:

$$\Delta y_{it} = \beta^{'} \Delta x_{it} + \delta^{'} X_{it}^{'} \mathbf{1}_{it}(\gamma) + \Delta \varepsilon_{it}, \tag{3}$$

where Δ is the first-difference operator, $\underset{k_1 \times 1}{\beta} = (\phi_{12}, ..., \phi_{1,k_1+1})^{'}$, $\underset{(k_1+1)\times 1 = \phi_2 - \phi_1}{\delta}$, and $\underset{2\times(1+k_1)=}{X_{it}} \begin{pmatrix} (1, x_{it}^{'}) \\ (1, x_{it-1}^{'}) \end{pmatrix}$ and $\underset{2\times 1}{\mathbf{1}_{it}}(\gamma) = \begin{pmatrix} \mathbb{I}\{q_{it} > \gamma\} \\ -\mathbb{I}\{q_{it-1} > \gamma\} \end{pmatrix}$.

The ordinary least squares estimator obtained from Eq.(3) is biased since the transformed regressors are correlated with $\Delta\varepsilon_{it}$. To address this problem we must find an $l \times 1$ vector of instrumental variables, $(z_{it0}^{'}, ..., z_{iT}^{'})^{'}$ for $2 < t_0 \le T$ with $l \ge k$, such that either

$$\mathrm{E}\left(z_{it0}^{'}\Delta\varepsilon_{it0},\ldots,z_{iT}^{'}\Delta\varepsilon_{iT}\right)^{'}=0 \tag{4}$$

or

$$\mathrm{E}(\Delta\varepsilon_{it}|z_{it})=0,\text{for each}t=t_0,\ldots,T. \tag{5}$$

It is allowed that z_{it} includes lagged values of (x_{it}, q_{it}) and lagged dependent variables and the number of instruments may vary for each time t. Our empirical model follows the standard log-linear ERPT specification used throughout the empirical literature (e.g., Campa and Goldberg, 2005; Choudhri and Hakura, 2006; Gagnon and Ihrig, 2004; Gopinath et al., 2010):

$$p_{it}=\lambda p_{it-1}+\beta e_{it}+\eta w_{it}^{*}+\theta^{'}Z_{it}+\delta com_t+\alpha_i+v_{it}, \tag{6}$$

where p_{it} is the domestic prices; e_{it} is a measure of exchange rate; w_{it}^{*} corresponds to foreign producers costs; Z_{it} is a vector including country-specific variables, including demand conditions and competitor prices in the destination country; and com_t is a measure of global commodity prices which is invariant across countries in the panel. The ERPT is measured for the import price index and CPI. We focus on the ERPT elasticity which can be measured by the coefficient β in Eq.(6). The ERPT coefficient is expected to be bounded between 0 and 1. To capture the changing behavior in ERPT due to global crisis, we use a dynamic PTR model where a grid search permits to endogenously select threshold level(s) to identify different market conditions. Then, the linear ERPT specification in (6) can be rewritten as follows:

$$p_{it}=\left(\lambda_1 p_{it-1}+\beta_1 e_{it}+\eta_1 w_{it}^{*}+\theta_1^{'}Z_t\right)\mathbb{I}(q_{it}\le\gamma)$$

$$+\left(\lambda_2 p_{it-1}+\beta_2 e_{it}+\eta_2 w_{it}^{*}+\theta_2^{'}Z_t\right)\mathbb{I}(q_{it}>\gamma)+\delta com_t+\alpha_i+v_{it}, \tag{7}$$

According to the above model, the extent of pass-through is allowed to be different across the two identified regimes represented by $\beta_1\neq\beta_2$. We estimate the dynamic PTR models using the FD-GMM estimator proposed by Seo and Shin (2016), which allows the threshold variable and explanatory variables to be endogenous. In our applications, the threshold variable, q_{it}, is assumed to be related to global crisis that would also influence the extent of ERPT. We begin by considering the monthly GPR index of Caldara and Iacoviello (2022) as a threshold variable that measures adverse geopolitical events and associated risks. As shown in Fig. 1, there is considerable heterogeneity in geopolitical uncertainty across countries in the panel. Russia, Ukraine, and the United States have the highest levels of risks, followed by the United Kingdom, Germany, and China. From a temporal perspective, Fig. 1 confirms that the GPR index spikes around March 2022 as a result of the outbreak of the Russia–Ukraine war. The dynamic PTR model examines the possible nonlinear ERPT due to observed cross-unit heterogeneity and time variability in the GPR index. To consider the possible delay in perceiving the occurrence of geopolitical risk, we consider a lagged value of the GPR index as a threshold variable, $q_{it}=gpr_{it-1}$. A "high-geopolitical risk regime" is one for which the GPR index in the previous months is higher than the estimated threshold level, i.e., $gpr_{t-j}\ge\widehat{c}_i$. If the lagged GPR index is below the estimated threshold, $gpr_{t-j}<\widehat{c}_i$, this corresponds to a "low-geopolitical risk regime.".

Our empirical model is estimated using monthly data from September 2020 to August 2022 to cover changing ERPT dynamics during the 2022 Russia–Ukraine war. Data are collected for a panel of 34 countries (17 advanced economies and 17 emerging countries) for which the country-specific GPR indices are available. The list of 34 countries with a summary of their country-specific GPR indexes are displayed in Table A1 in the Appendix.[1] We use import price index and CPI to proxy for domestic import prices, mp_{it}, and consumer prices, cpi_{it}. The nominal effective exchange rate is collected as a measure of the exchange rate e_{it}, where the increase corresponds to a depreciation of the local currency.

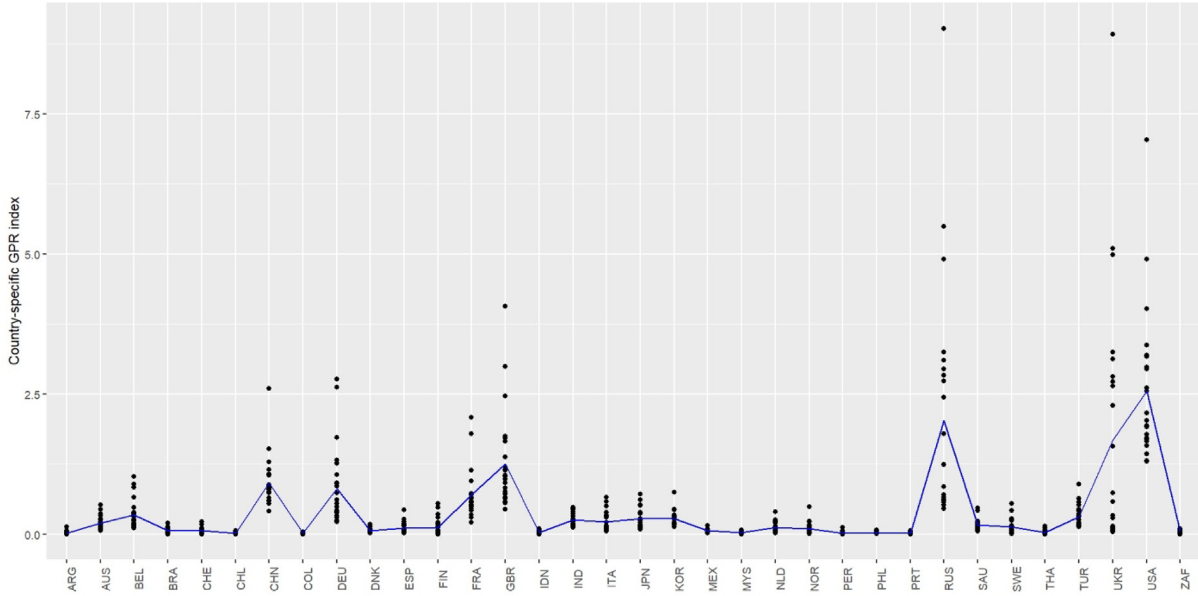
We construct an exporter partners' cost indicator to proxy for changes in foreign costs computed as: $w_{it}^{*}\equiv r_{it}-e_{it}+ulc_{it}$, where ulc_{it} is the domestic unit labor cost (ULC) and r_{it} is the ULC-based real effective exchange rate (see e.g., Campa and Goldberg, 2005). To proxy for changes in domestic demand conditions, we use the output gap (gap_{it}) computed as the difference between actual and the Hodrick–Prescott filter of the industrial production index. To test the robustness of our ERPT specification, we include domestic producer price index, ppi_{it}, as a proxy for competitor prices. The data above are collected from the International Financial Statistics database of the IMF and the Thomson Reuters DataStream. Furthermore, as is well known, exchange rate changes can affect domestic prices indirectly through their effects on commodity prices (see e.g., Ihrig et al., 2006). To consider this channel as a robustness test, we proxy for commodity prices, com_t, using the Global Price Index of All Commodities from the Federal Reserve Economic Data of Federal Reserve Board of St. Louis.

4. Empirical results

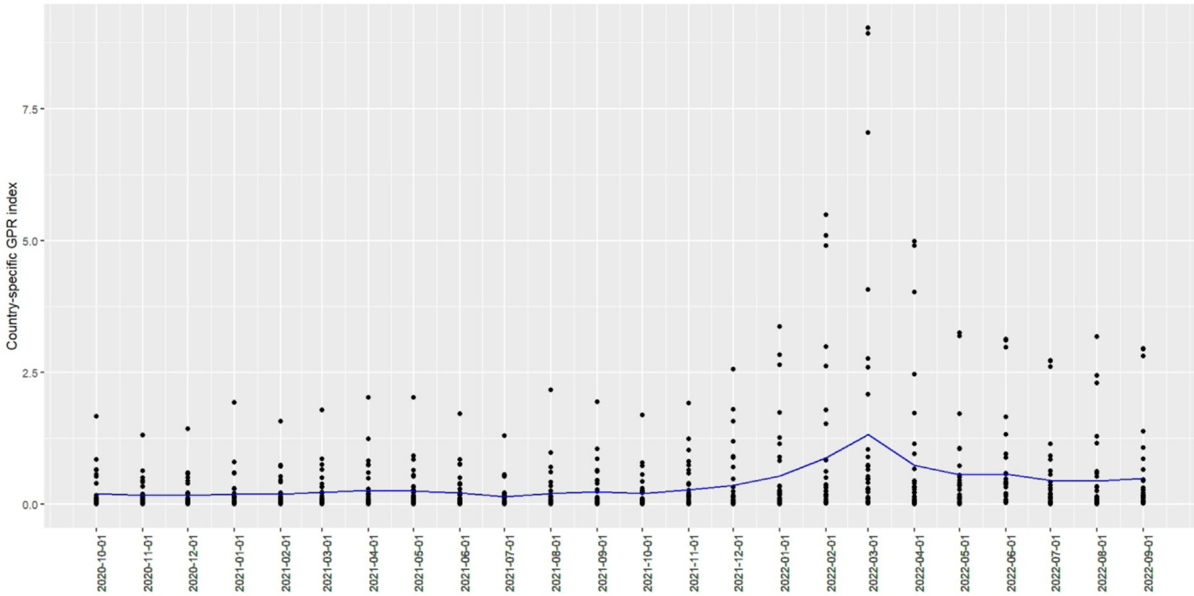
As a starting point and for comparison, we begin our empirical exercise by estimating the linear panel data version of ERPT Eq.(6) using first logarithmic differences as follows:[2]

[1] The monthly country-specific GPR index of Caldara and Iacoviello (2022) is obtained from https://www.matteoiacoviello.com/gpr.htm.

[2] We have checked for the stationarity of our variables of interest using panel unit root test of Pesaran (2007) which accounts for cross-sectional dependence. The results indicated the presence of unit root in all data series, except for GPR index. Panel cointegration test of Westerlund (2007) have been implemented indicating that the null assumption of no cointegration cannot be rejected. Therefore, we use the first differences of nonstationary series within our dynamic PTR model.



(a) Heterogeneity across countries



(b) Heterogeneity across time periods

Fig. 1. GPR index heterogeneity in the panel data. Notes: Plots represent the average geopolitical risk (GPR) index across the panel of 34 countries and over the monthly period from September 2020 to August 2022.

$$\Delta p_{it} = \lambda \Delta p_{it-1} + \beta \Delta e_{it} + \eta \Delta w^*_{it} + \theta' Z_{it} + \delta \Delta com_t + \alpha_i + v_{it}, \quad (8)$$

We estimate the above specification using a fixed-effect estimator. As we expect a regime-switching behavior, it is assumed that ERPT estimates will differ depending on the selected period of time. We then estimate the panel data model over three different time ranges to examine the changing dynamic in ERPT elasticities, which include September 2020–August 2022, September 2020–August 2021, and September 2021–August 2022. Results from the linear panel data model

Table 1
Estimation from linear panel models: ERPT to import prices.

	Dependent variable: Δmp_{it}					
	Sep. 2020–Aug. 2022		Sep. 2020–Aug. 2021		Sep. 2021–Aug. 2022	
	(1)	(2)	(3)	(4)	(5)	(6)
Δmp_{it-1}	0.076*	0.005	−0.214***	−0.247***	0.088*	0.018
	(0.040)	(0.040)	(0.079)	(0.083)	(0.047)	(0.047)
Δe_{it}	0.641***	0.648***	0.416***	0.402***	0.742***	0.747***
	(0.054	(0.055)	(0.092)	(0.100)	(0.064)	(0.065)
Δw^*_{it}	0.530***	0.367***	0.118	0.420**	0.597***	0.330**
	(0.132)	(0.082)	(0.196)	(0.201)	(0.186)	(0.099)
gap_{it}	0.013	0.019	−0.020	−0.018	0.015	0.023
	(0.017)	(0.018)	(0.049)	(0.051)	(0.020)	(0.021)
Δwcp_t	0.011		0.166***		−0.016	
	(0.028)		(0.034)		(0.037)	
Δppi_{it}		0.543***		0.910***		0.542***
		(0.077)		(0.201)		(0.091)
Observations	782	782	374	374	374	374
Adjusted R-squared	0.741	0.715	0.546	0.579	0.692	0.727
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	No	Yes	No	Yes	No	Yes
F-statistic	9.686	9.556	8.177	8.022	8.786	8.782
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Notes: The results above are derived from the linear panel data model in Eq.(8) using import price index as a dependent variable. Robust standard errors are in parentheses. *F* significance is in square brackets. The estimation results are reported for three periods: September 2020–August 2022 in Columns (1) and (2); September 2020–August 2021 in Columns (3) and (4); and September 2021–August 2022 in Columns (5) and (6). *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

are reported in Tables 1 and 2. The exchange rate transmission to import prices is found to be significant but varies across the selected periods. The measures of output gap and commodity prices are insignificant, while producer price index as a proxy for competitor prices are strongly significant in most cases. Notably, pass-through elasticities differ greatly across sub-periods. As reported in column (3) of Table 2, a 1% increase in exchange rate raises import prices by 0.41% during the September 2020–August 2021 period; however, the rates of pass-through are much higher during the following period, September 2021–August 2022, as the responsiveness of import prices increases by 0.74% using the same specification as displayed in column (5) in Table 1.

This outcome reveals that the extent of ERPT increased during the last episode of geopolitical instability. These results corroborate those of Jasova et al. (2019), who investigated whether ERPT changed since the 2008 financial crisis, demonstrating a decline in pass-through coefficients for emerging countries, while the exchange rate transmission have also remained weak for advanced economies. The authors argued that the lowering ERPT in emerging economies implies that the exchange rate channel of monetary policy could have been less influential in affecting inflation following the global financial crisis. Similarly, the degree of exchange rate transmission to CPI is found to vary depending on the considered time period, as shown in Table 2. It is important to note that ERPT is weak or insignificant in the pre-geopolitical crisis period of September 2020–August 2021; however, the responsiveness of consumer prices has become statistically significant more recently, with a pass-through coefficient of 0.14%. Of course, the ERPT to import prices is higher than that to CPI which includes more non-tradable goods (e.g., Ben Cheikh and Louhichi, 2015; Anderl and Caporale, 2022).

As the ERPT coefficients seem to be changing with a more pronounced effect in the recent period, we assume that a non-linear panel data could better capture the changes in behavior due to recent geopolitical events. The nonlinear PTR version of the ERPT Eq.(7) using first differences has the following form:

$$\Delta p_{it} = \left(\lambda_1 \Delta p_{it-1} + \beta_1 \Delta e_{it} + \eta_1 \Delta w^*_{it} + \theta_1' Z_t\right) \mathbb{I}(q_{it} \leq \gamma)$$

$$+ \left(\lambda_2 \Delta p_{it-1} + \beta_2 \Delta e_{it} + \eta_2 \Delta w^*_{it} + \theta_2' Z_t\right) \mathbb{I}(q_{it} > \gamma) + \delta \Delta com_t + \alpha_i + v_{it}, \tag{9}$$

The FD-GMM estimation results using the GPR index as a threshold variable, $q_{it} = gpr_{it-1}$, are reported in Tables 3 and 4.[3] As our sample of 34 countries includes both advanced and emerging economies, ERPT coefficients are computed for each group of countries as well as for the whole sample. It is well known that ERPT is typically higher in emerging and developing countries than in advanced economies (e.g., Forbes et al., 2020; Jasova et al., 2019). We apply the bootstrapping linearity test proposed by Seo and Shin (2016). As shown in Table 4, the bootstrap p-values related to the supW test are almost equal to zero throughout

Table 2
Estimation from linear panel models: ERPT to consumer prices.

	Dependent variable: Δcpi_{it}					
	Sep. 2020–Aug. 2022		Sep. 2020–Aug. 2021		Sep. 2021–Aug. 2022	
	(1)	(2)	(3)	(4)	(5)	(6)
Δcpi_{it-1}	0.095***	0.093**	0.098	0.093	0.028**	0.031**
	(0.038)	(0.038)	(0.082)	(0.084)	(0.014)	(0.015)
Δe_{it}	0.054***	0.043***	0.027*	0.033	0.139***	0.138***
	(0.010)	(0.010)	(0.016)	(0.023)	(0.017)	(0.017)
Δw^*_{it}	−0.042	0.046***	−0.020	0.008	0.088*	0.097***
	(0.029)	(0.016)	(0.061)	(0.060)	(0.054)	(0.035)
gap_{it}	−0.002	−0.003	−0.006	−0.006	−0.001	−0.001
	(0.002)	(0.002)	(0.004)	(0.004)	(0.003)	(0.003)
Δwcp_t	0.034***		0.024**		0.046***	
	(0.006)		(0.010)		(0.009)	
Δppi_{it}		0.092***		0.047*		0.086***
		(0.014)		(0.027)		(0.020)
Observations	782	782	374	374	374	374
Adjusted *R*-squared	0.507	0.520	0.452	0.434	0.583	0.575
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	No	Yes	No	Yes	No	Yes
F-statistic	7.182	7.820	6.591	6.388	8.943	8.625
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Notes: The results above are derived from the linear panel data model in Eq.(8) using consumer price index as a dependent variable. Robust standard errors are in parentheses. *F* significance is in square brackets. The estimation results are reported for three periods: September 2020–August 2022 in Columns (1) and (2); September 2020–August 2021 in Columns (3) and (4); and September 2021–August 2022 in Columns (5) and (6). *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 3
Results for import prices using dynamic panel threshold models.

	Dependent variable: Δmp_{it}					
	Whole sample		Emerging countries		Advanced countries	
	(1)	(2)	(3)	(4)	(5)	(6)
q_{it}	gpr_{it-1}	gpr_{it-1}	gpr_{it-1}	gpr_{it-1}	gpr_{it-1}	gpr_{it-1}
$\hat{\gamma}$	0.192**	0.196**	0.177***	0.158***	0.116**	0.137**
	(0.091)	(0.087)	(0.057)	(0.034)	(0.045)	(0.066)
Δmp_{it-1}	0.115**	0.022	−0.056***	−0.116*	−0.048	−0.130
	(0.046)	(0.040)	(0.072)	(0.066)	(0.070)	(0.094)
Δw^*_{it}	0.678***	0.539***	0.569***	0.241**	0.378***	0.421**
	(0.151)	(0.110)	(0.218)	(0.130)	(0.081)	(0.187)
gap_{it}	0.009**	0.025***	0.084**	0.022	0.005	0.014
	(0.004)	(0.006)	(0.033)	(0.039)	(0.007)	(0.028
Δwcp_t	0.029		0.002		0.038	
	(0.032)		(0.041)		(0.044)	
Δppi_{it}		0.445***		0.753***		0.358***
		(0.058)		(0.129		(0.128)
Lower regime:						
Δe_{it}	0.217**	0.242**	0.386***	0.339***	0.125**	0.127***
	(0.086)	(0.109)	(0.156)	(0.154)	(0.059)	(0.051)
	[0.075; 0; 396]	[0.062; 0.421]	[0.162; 0.609]	[0.086; 0.591]	[0.028; 0.223]	[0.042; 0.211]
Upper regime:						
Δe_{it}	0.641***	0.638***	0.761***	0.754***	0.575***	0.529***
	(0.115)	(0.135)	(0.101)	(0.116)	(0.132)	(0.177)
	{0.419; 0.862}	{0.416; 0.860}	{0.596; 0.927}	{0.564; 0.944}	{0.391; 0.758}	{0.240; 0.819}
Observations	782	782	391	391	391	391
Linearity (*p*-value)	(0.000)	(0.000)	(0.001)	(0.002)	(0.000)	(0.000)
J-test	16.34	13.42	13.66	12.73	14.33	15.54
	[0.165]	[0.186]	[0.179]	[0.192]	[0.176]	[0.171]

Notes: The estimation results are obtained from the dynamic panel threshold model in Eq.(9) over the period September 2020–August 2022 using import price index as a dependent variable. Robust standard errors are in parentheses. 95% confidence intervals are reported between braces. For the linearity test, the bootstrap *p*-values of the supW test are reported in addition to *J*-test of the validity of the overidentifying moment conditions with *p*-values between square brackets. The estimation results are reported for three groups: the whole sample in Columns (1) and (2), emerging economies in Columns (3) and (4), and advanced countries in Columns (5) and (6). *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 4
Results for consumer prices using dynamic panel threshold models.

	Dependent variable: Δcpi_{it}					
	Whole sample		Emerging countries		Advanced countries	
	(1)	(2)	(3)	(4)	(5)	(6)
q_{it}	gpr_{it-1}	gpr_{it-1}	gpr_{it-1}	gpr_{it-1}	gpr_{it-1}	gpr_{it-1}
$\hat{\gamma}$	0.139**	0.130**	0.107**	0.116**	0.169***	0.182***
	(0.063)	(0.058)	(0.042)	(0.050)	(0.033)	(0.026)
Δcpi_{it-1}	−0.042	0.024	0.165**	0.065	0.215***	0.159***
	(0.041)	(0.041)	0.075)	(0.070)	(0.059)	(0.061)
Δw_t^*	0.025	0.035*	0.086	0.055	0.029	0.080***
	(0.029	(0.018)	(0.053)	(0.036)	(0.033)	(0.020)
gap_{it}	−0.012***	−0.007*	−0.011	0.001	−0.013**	−0.014**
	(0.004)	(0.004)	(0.007)	(0.006)	(0.006)	(0.006)
Δwcp_t	0.037***		0.053***		0.023***	
	(0.006)		(0.011)		(0.007)	
Δppi_{it}		0.460***		0.207***		0.091***
		(0.068)		(0.025)		(0.021)
Lower regime:						
Δe_{it}	0.103***	0.115***	0.139***	0.145***	0.043***	0.052***
	(0.026)	(0.022)	(0.031)	(0.016)	(0.023)	(0.018)
	[0.059; 0.147]	[0.077; 0.153]	[0.087; 0.191]	[0.118; 0.172]	[0.005; 0.081]	[0.022; 0.082]
Upper regime:						
Δe_{it}	0.202***	0.218***	0.254***	0.265***	0.165***	0.150***
	(0.024)	(0.025)	(0.034)	(0.018)	(0.039)	(0.034)
	{0.163; 0.241}	{0.175; 0.261}	{0.198; 0.310}	{0.235; 0.295}	{0.101; 0.229}	{0.093; 0.207}
Observations	782	782	391	391	391	391
Linearity (*p*-value)	0.000	0.000	0.000	0.000	0.000	0.000
J-test	13.33	15.24	10.53	15.33	19.32	18.18
	[0.164]	[0.149]	[0.195]	[0.142]	[0.136]	[0.143]

Notes: Estimates are obtained from the dynamic panel threshold model in Eq.(9) over the period September 2020–August 2022 using consumer price index as a dependent variable. Robust standard errors are in parentheses. 95% confidence intervals are reported between braces. For the linearity test, the bootstrap *p*-values of the supW test are reported in addition to *J*-test of the validity of the overidentifying moment conditions with *p*-values between square brackets. The estimation results are reported for three groups: the whole sample in Columns (1) and (2), emerging economies in Columns (3) and (4), and advanced countries in Columns (5) and (6). *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

the different specifications. There is strong evidence of threshold effects due to the recent times of uncertainty (i.e., the recent Russia–Ukraine war). Also, the validity of the dynamic PTR specifications has been tested using *J*-test of overidentifying restrictions (see Hansen, 1982). The *J*-statistic confirms that the null of the validity of the overidentifying moment conditions is not rejected for the different cases in which the GPR index is used as the transition variable.

We start by looking at the results from the import price index in Table 3. The estimated threshold levels $\hat{\gamma}$ appear to be strongly significant across the different specifications. The threshold values are useful for identifying the geopolitical risk regimes with the panel data. As shown in column (1) of Table 3, the estimated threshold value, $\hat{\gamma} = 19.2$, permits to identify two regimes in the degree of pass-through with respect to the global COVID-19 pandemic. The ERPT estimates clearly differ across the two identified states as reported through the different specifications in Table 3. For instance, as shown in column (1), the estimated threshold value, $\hat{\gamma} = 0.19$, allows to distinguish two regimes in the degree of pass-through with respect to the (log) level of the GPR index, i.e., the lower regime when $gpr_{t-1} \leq 0.19$, which corresponds to a *low-geopolitical risk regime*, and the upper regime when $gpr_{t-1} > 0.19$, which can be designated as a *high-geopolitical risk* regime.

With respect to ERPT elasticities, the point estimates clearly differ across the two identified states, as reported through the different specifications of Table 3. For the whole sample, column (1) indicates that the rate of pass-through is 0.22% under a low-geopolitical risk regime. However, the sensitivity of import prices is much higher when uncertainties related to geopolitical tensions are rising. More specifically, a 1% currency depreciation would raise the import prices by 0.64% when $gpr_{t-1} > 0.19$. This is not surprising, as foreign producers that may expect less stable economic conditions in the destination country could shift towards PCP strategy. For a sample of euro area countries, Ben Cheikh and Rault (2016) pointed out that the 2012 European sovereign debt crisis has entailed a higher degree of ERPT. For the case of Greece, the authors reported a complete pass-through with the increased macroeconomic instability.

Indeed, considering a threshold effect within our panel data model confirms the fact that firms do not frequently change their pricing strategies. Studies have shown that foreign firms would respond to shifts in macroeconomic conditions in the importing country depending on the size and the persistence of these shifts (e.g., Coughlin and Pollard, 2003; Bussière, 2012). For example, due to the presence of rising menu costs, exporters may leave their prices unchanged if macroeconomic vari-

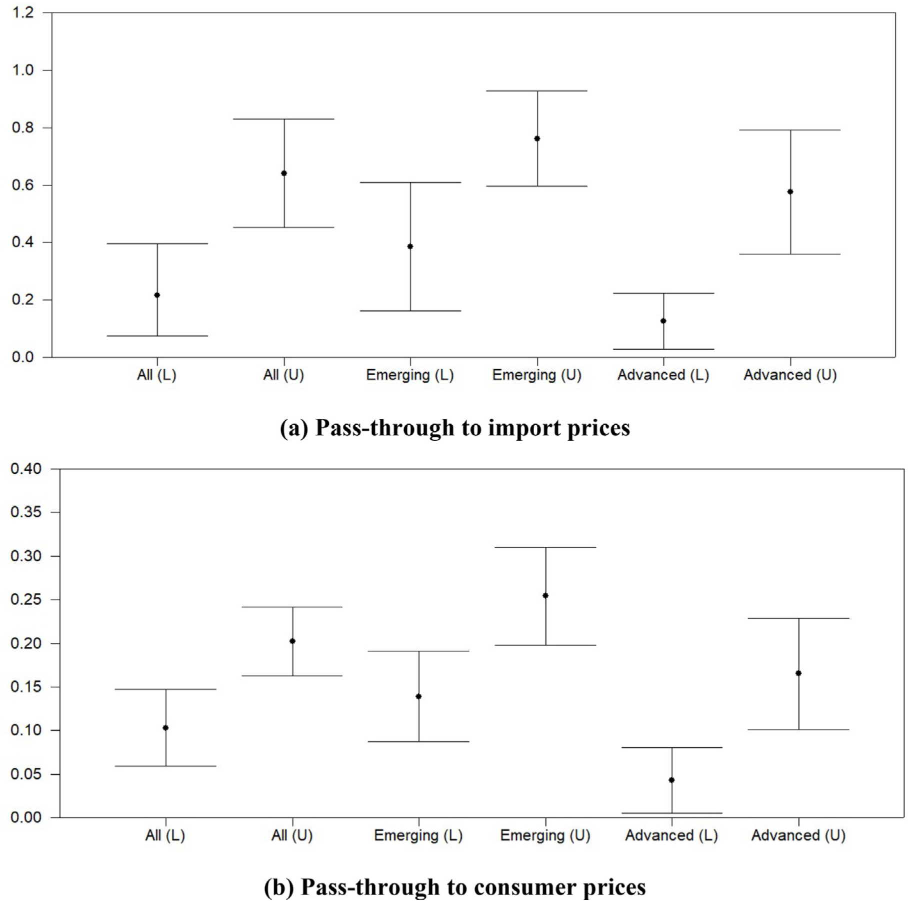


Fig. 2. ERPT across geopolitical regimes with 95% confidence intervals. Notes: The figures above indicate pass-through elasticities with 95% confidence intervals. (L) corresponds to ERPT in the lower regime, and (U) corresponds to the ERPT in the upper regime.

ability is transitory or small (below a given threshold). However, firms would change their pricing behavior if changes were perceived as persistent or higher than a certain threshold. Our results show that not all geopolitical events will entail a change in the extent of ERPT. When the risks associated with geopolitical conflicts surpass a certain level of uncertainty, there will be a significant increase in ERPT.

For more accuracy, the 95% confidence band is presented in braces below the ERPT coefficients and also displayed in Fig. 2. The significant difference across the identified geopolitical regimes is confirmed, and is more apparent for advanced countries. However, as shown, confidence intervals are slightly overlapping for emerging economies. It is worth highlighting that ERPT estimates do not statistically differ among advanced and emerging countries for the same geopolitical regime, as recent geopolitical events have affected economies through an excessive spike in energy and commodity prices regardless of their level of development. It is not surprising that ERPT is found to be similar between advanced and emerging countries.

The regime-switching behavior has also been confirmed for the case of consumer prices. Table 4 indicates that the impact of currency depreciation is significantly different due to the geopolitical context, which is now true for both emerging and developed countries. For the case of developed economies in Column (5), the ERPT elasticity is around 0.04% within a low-geopolitical risk regime, when the GPR index is under the threshold of $\hat{\gamma} = 0.17$. Consumer price sensitivity becomes four times higher when $gpr_{t-1} > 0.17$ (i.e., for higher uncertainty levels, to reach an ERPT coefficient around 0.16%). There is evidence of a positive relationship between geopolitical risk and pass-through rate. The higher the geopolitical stress, the more currency changes are transmitted to prices. This outcome confirms the intuition that uncertainty and times of crisis influence exchange rate transmission. Given the deteriorating macroeconomic environment in the destination country, exporters may choose to transmit a larger amount of exchange rate changes. Thereby, the rates of pass-through tend to be higher, as exporters would follow a PCP strategy. As the uncertainty surrounding the Russia–Ukraine conflict are likely to continue, monetary authorities should be able to estimate how significant ERPT is likely to be to assess the underlying inflation pressures are still present and whether any changes to monetary policy are necessary to manage them.

Table 5
Results from fixed-effect panel threshold models.

	Dependent variable: Δmp_{it}			Dependent variable: Δcpi_{it}		
	Whole sample (1)	Emerging (2)	Advanced (3)	Whole sample (4)	Emerging (5)	Advanced (6)
q_{it}	gpr_{it-1}	gpr_{it-1}	gpr_{it-1}	gpr_{it-1}	gpr_{it-1}	gpr_{it-1}
$\widehat{\gamma}$	0.107***	0.173***	0.133**	0.138***	0.166***	0.141**
	(0.043)	(0.026)	(0.065)	(0.042)	(0.019)	(0.074)
Δw_t^*	0.471***	0.554***	0.581***	0.076***	0.081***	0.095***
	(0.175)	(0.121)	(0.098)	(0.017)	(0.027)	(0.045)
gap_{it}	−0.004	−0.001	0.028	0.001	0.001	−0.012
	(0.021)	(0.023)	(0.024)	(0.002)	(0.002)	(0.004)
Δwcp_t	0.018	0.528	0.058	0.017**	0.047***	0.053***
	(0.040)	(0.107)	(0.054)	(0.008)	(0.016)	(0.021)
Lower regime:						
Δe_{it}	0.220***	0.359***	0.194	0.094**	0.107***	0.056***
	(0.075)	(0.109)	(0.127)	(0.048)	(0.015)	(0.009)
Upper regime:						
Δe_{it}	0.574***	0.641***	0.354***	0.176***	0.222***	0.135***
	(0.188)	(0.124)	(0.108)	(0.051)	(0.020)	(0.015)
Observations	782	391	391	782	391	391
Adjusted R-squared	0.726	0.786	0.745	0.546	0.563	0.478
Linearity (p-value)	0.000	0.000	0.000	0.000	0.000	0.000
F-statistic	416.56	458.27	519.94	504.24	486.50	482.21
	[0.002]	[0.007]	[0.000]	[0.001]	[0.003]	[0.002]

Notes: Estimates are obtained from a static panel threshold model over the period September 2020–August 2022. Robust standard errors are in parentheses. For the linearity test, the bootstrap p-values of the Hansen (1999) test for a single threshold are reported. The bootstrapped p-values are obtained from 1,000 bootstrap replications. *** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 6
Estimation results using EPU index as a threshold variable.

	Dependent variable: Δmp_{it} Whole sample (1)	Dependent variable: Δcpi_{it} Whole sample (4)
q_{it}	epu_{it-1}	epu_{it-1}
$\widehat{\gamma}$	5.881***	5.544***
	(0.472)	(0.673)
Δpi_{it-1}	0.133*	0.027**
	(0.071)	(0.012)
Δw_t^*	0.148**	0.149***
	(0.074)	(0.035)
gap_{it}	−0.032	0.014
	(0.041)	(0.010)
Δwcp_t	0.015	0.049*
	(0.016)	(0.027)
Lower regime:	0.587***	0.203***
Δe_{it}	(0.120)	(0.031)
Upper regime:		
Δe_{it}	0.233	0.218*
	(0.211)	(0.132)
Observations	528	528
Linearity (p-value)	0.020	0.004
J-test	15.45	18.43
	[0.154]	[0.186]

Note: Estimates are obtained from the dynamic panel threshold model as specified in Eq.(9). using monthly data over September 2020-August 2022 for a sample of 16 countries; Robust standard errors are displayed in parentheses. For the linearity test the bootstrap p-values of the supW test are reported in addition to J-test of the validity of the overidentifying moment conditions with p-values in square brackets. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$.

5. Robustness analysis

To ensure the robustness of the results achieved, we also estimate the fixed-effect PTR model developed by Hansen (1999). Using this approach, in addition to the dynamic PTR model of Seo and Shin (2016), we aim to assess the reliability of our estimates given the large time dimension of our panel. As is well known, the use of the FD-GMM procedure is specifically designed for a circumstance in which time dimension T is small and the number of panels N is large (i.e., $N > T$) to overcome dynamic panel bias (e.g., Roodman, 2009). Within our panel data, the time dimension length is not too small relative to the number of cross-section units. To check the reliability of our results, a static PTR model is estimated using a fixed-effect procedure. As shown in Table 5, our results remain robust to the use of Hansen's fixed-effects estimator. The events and rising of geopolitical conflicts continue to lead to higher rates of ERPT for the different groups of countries. In particular, the responsiveness of both import and consumer prices more than doubled for advanced economies with the occurrence of geopolitical crisis.

Finally, for comparison, we test a measure of uncertainty in addition to the GPR index of Caldara and Iacoviello (2022), using the Economic Policy Uncertainty (EPU) index of Baker et al. (2016), which is a newspaper-based measure of the economic risk associated with undefined future government policies and regulatory frameworks.[4] Data are collected for a sample of 16 countries for which the monthly EPU data are available from the website https://www.policyuncertainty.com/. Recently, Wang et al. (2022) investigated the role of uncertainty in China within a time-varying parameter vector autoregressive framework. The authors suggested that a higher uncertainty, which is proxied by the EPU index, would result in a more pronounced degree of ERPT.

We then reestimate the dynamic PTR model in Eq.(9) using the lagged value of EPU as a threshold variable, $q_{it} = epu_{it-1}$. Estimation results for both import and consumer prices and across the country groups are reported in Table 6. The point estimates for ERPT are found to be generally significant under the lower regime. However, for higher levels of EPU index, the effect of exchange rate depreciation is not significant for the import prices, and weakly significant for the consumer prices. Taking a closer look to the results in Table 6, we realize that the estimated thresholds do not allow for usable enough observation in the upper regime. For the case of pass-through into import prices, the threshold value is around $\hat{\gamma} = 5.9$ which leaves very few observations in the upper regime, less than 10%. As explained by Hansen (1999), it is not convenient to select a threshold which splits too few observations into one or the other regime. Finally, we can assert that risks associated to geopolitical conflicts are more relevant as they are found to be tightly linked to disruptions in global energy and commodity markets. The adverse events that are related to oil supply disruptions would entail higher levels of ERPT which may fuel the growing inflationary pressures.

6. Conclusion

In this study, we investigated whether rising geopolitical tensions have altered the ERPT mechanism. We implemented a dynamic PTR model to capture the possible regime shift in the ERPT due to geopolitical factors. To uncover the influence of the recent Russian–Ukraine conflict, we consider the GPR index of Caldara and Iacoviello (2022) as a threshold variable in the nonlinear panel data model. This enabled us to estimate the ERPT coefficients with respect to geopolitical context (i.e., during episodes of low and high geopolitical risk regimes). Our dynamic PTR models are estimated for a sample of 34 advanced and emerging economies over the recent monthly period from September 2020 to August 2022. The empirical results reveal a strong regime-dependence of the ERPT to times of uncertainty, as domestic prices sensitivity is found to be higher during adverse geopolitical events. The increase in the rates of ERPT is more apparent for advanced economies, whereas consumer price sensitivity becomes four times higher under the identified high-geopolitical risk regime. It is well known that the recent global events have exerted important inflationary effects, and monetary policymakers are facing new and challenging tradeoffs. Understanding how exchange rate shocks are transmitted into prices in times of crisis is of particular interest for central banks as commodity prices soar to their highest level since 2008. As the uncertainty surrounding the Ukrainian crisis is likely to continue, it is challenging for policymakers to prevent exchange rate changes from fueling the growing inflationary pressures.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

[4] In recent years, several indices of uncertainty have been proposed that allow the tracking of risks related to economic policy (e.g., Baker et al., 2016; Husted et al., 2020), infectious diseases (e.g., Ahir et al., 2022; Baker et al., 2020), and climate policy (e.g., Gavriilidis, 2021), among other relevant concerns.

Appendix

Table A1
Country list and GPR index summary statistics.

Country	Code	GPR index			
		Mean	SD	Min.	Max.
Argentina	ARG	0.03	0.01	0.02	0.07
Australia	AUS	0.07	0.04	0.03	0.21
Belgium	BEL	0.11	0.03	0.06	0.17
Brazil	BRA	0.05	0.02	0.01	0.09
Chile	CHL	0.02	0.01	0.01	0.06
China	CHN	0.32	0.09	0.18	0.58
Colombia	COL	0.05	0.02	0.02	0.11
Denmark	DNK	0.03	0.02	0.01	0.08
Finland	FIN	0.03	0.02	0.01	0.09
France	FRA	0.52	0.16	0.27	1.06
Germany	DEU	0.36	0.12	0.15	0.66
India	IND	0.19	0.08	0.08	0.52
Indonesia	IDN	0.05	0.03	0.02	0.17
Italy	ITA	0.15	0.05	0.07	0.27
Japan	JPN	0.24	0.09	0.12	0.52
Mexico	MEX	0.03	0.02	0.02	0.09
Malaysia	MYS	0.09	0.03	0.06	0.19
Netherlands	NLD	0.08	0.03	0.04	0.13
Norway	NOR	0.04	0.02	0.02	0.11
Peru	PER	0.03	0.02	0.01	0.10
Philippines	PHL	0.05	0.03	0.02	0.11
Portugal	PRT	0.04	0.02	0.01	0.07
Russia	RUS	0.78	0.30	0.30	1.38
Saudi Arabia	SAU	0.21	0.21	0.05	0.87
South Africa	ZAF	0.08	0.03	0.04	0.13
South Korea	KOR	0.22	0.12	0.10	0.67
Spain	ESP	0.11	0.05	0.06	0.29
Sweden	SWE	0.04	0.01	0.02	0.06
Switzerland	CHE	0.06	0.03	0.03	0.14
Thailand	THA	0.04	0.01	0.02	0.07
Turkey	TUR	0.17	0.07	0.06	0.37
Ukraine	UKR	0.11	0.09	0.02	0.26
United Kingdom	GBR	0.92	0.44	0.57	2.45
United States	USA	2.37	0.89	1.07	5.07

Notes: Country-specific geopolitical risk indices are constructed by Caldara and Iacoviello (2022). Monthly data are obtained from https://www.matteoiacoviello.com/gpr_country.htm.

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