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Are the global economic policy uncertainties blocking the export flows of emerging markets? A heterogeneous panel SVAR analysis

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Abstract

Purpose – This paper examines the effect of global economic policy uncertainty (EPU) on emerging markets (EMs) export flows.

Methods – This paper uses a structural panel vector autoregression modeling approach to capture country interdependencies and the likelihood that EMs' responses are heterogeneous and dynamic. An unbalanced monthly panel data from 2003:01 to 2019:12 is used to estimate impulse responses and variance decompositions not only for the entire panel data but also for each EM.

Findings – The results show that global EPU has a persistent and negative effect on exports, while foreign income and the exchange rate increase export volumes in EMs. Given the different responses of EMs to uncertainty shocks, the second-stage regression estimates suggest that greater sectoral export diversification in an EM can potentially reduce the unfavorable impact of global EPU on their export flows. Meanwhile, the higher technology content of exports leads to a multiplication of global EPU transmissions.

Implication – These findings advance the literature by highlighting the importance of accounting for the transmission effect of global EPU in EMs by considering country heterogeneity.

Originality – This is the sole paper examining the factors that mitigate or amplify GEPU impacts on export flows by estimating second-step ordinary least square equations.

Keywords – Export, emerging markets, global economic policy uncertainty, structural panel VAR.

Introduction

While the United States (US), European Union (EU), and Japan were severely affected by the crisis in 2008 and 2009, emerging economies rarely slowed, and their robust growth (particularly China and India) contributed to the global economy's recovery (Hanson, 2012). Emerging markets (EMs) are characterized as diverse in their revenue, exports of products and services, and engagement with the global economy. According to the data of 28 EMs and China, the percentage of global exports by emerging economies rose dramatically from 28% to 35% from 2006 to 2019. Also, their global gross domestic product (GDP) shares increased from 21.5% to 33.9% by 2019 compared to 2006. When the undeniable contribution of the Chinese economy is ignored, the shares of EMs in the world foreign trade and the world income have followed a stable but slow upward trend in

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the 2000s. Therefore, engaging with the global economy makes EMs open to uncertainties arising from economic policy changes created by developed countries or their global trade partners.

The world trade data of the World Bank suggests a negative association between the growth rate of exports of goods and services and the global economic policy uncertainty index of Baker et al. (2016) in the period of 1997 and 2021[1]. Lower export growth rates since 2011 have also been associated with high levels of economic policy uncertainty, particularly in 2016 and 2018-2020. Economic policy uncertainty (EPU) may reduce the level of international trade volume by shrinking economic activities. Consumers may cut back on spending, investors may opt for a wait-and-see approach, and traders may postpone or terminate trading agreements during higher EPU periods. High global uncertainty may also influence firms' investment decisions in international markets.

A growing body of work investigates the influence of EPU on international trade. The study by Baker et al. (2016), which measures the EPU of the US economy, has boosted the quantity of empirical research. Today, the EPU indices for 28 countries have been produced. The impacts of EPU on export flows can be classified into the studies of a group of countries (e.g., Aslan & Acikgoz, 2021; Borojo, Yushi et al., 2023; Gül & Gupta, 2021; Jia et al., 2020; Khalfaoui et al., 2022; Zhao, 2022) and the studies of individual countries (e.g., Hailemariam & Ivanovski, 2021; He et al., 2021; Hu & Liu, 2021; Liu, Zhang, & Li, 2020). Both time series and panel data estimation methods have been employed, mostly covering the period after 2000. Among these studies, Carballo et al., (2022) and Handley and Limão (2017) explain the effect of EPU on export and trade within the framework of structural modeling that uses calibration methods based on general equilibrium models. One of the general conclusions of these studies is that EPU or global EPU has a detrimental influence on the export flows of countries, regardless of whether they are exporters or importers. Specifically, Khalfaoui et al. (2022) showed that the COVID-19 pandemic has a profound immediate effect on the EPU of the US, Japanese, South Korean, Indian, and Canadian economies. Most of studies also focused on the economies of the United States and China as the key actors in trade conflicts that have the potential to cause EPU on a global scale.

The recent literature on EPU/global EPU and export relationship pays less attention to EMs. As a result, this research aims to investigate the implications of global EPU shocks on EMs export flows, with a particular emphasis on whether these effects differ systematically between EMs. Handling EMs as panel data necessitates dealing with heterogeneity and cross-sectional dependence in estimations. Pedroni (2013) proposed an approach for cross-country panel data sets that simultaneously allow for full panel heterogeneity and dependence. This method is defined as "a new approach to VAR analysis in panels based on a structural decomposition of shocks into common type shocks vs. idiosyncratic type shocks, as well as component shocks within each of these types" (Pedroni, 2013).

With the advantages of the panel SVAR method of Pedroni (2013), this paper contributes to the related literature twofold. First, it integrates data from 28 EMs to assess the effects of global EPU (GEPU) on export for each EM. In other words, the response of exports to GEPU and to the other target variables, which are the exchange rate and foreign income, is estimated separately for each EM using full information of EMs. Second, by investigating the cross-sectional association between various country characteristics such as economic growth, sectoral variety of exports, and technological intensity of exports, this paper looks into the determinants of variation in the impulse responses for each EM. This part of the study relies on ordinary least square regressions where the impulse response functions are taken as a dependent variable, allowing us to discover the transmission of GEPU impacts on export flows in EMs.

Additionally, this paper differs from similar ones (such as Aslan & Acikgoz, 2021) because it not only shows the negative effect of GEPU on the export of EMs but also highlights the dilutions of export responsiveness to the exchange rate advantages because of heightened uncertainties. The structure of the paper is as follows. The next section details the method used in the estimations. Estimation results are reported in the third section. The paper ends with conclusion.

[1] https://data.worldbank.org/topic/21

Methods

An unbalanced panel data set covering 28 EMs over the period 2003:01-2019:12 is used in the estimations. Details regarding the data set can be found in Appendix Table A1. It should be noted that the data set does not cover the COVID-19 pandemic period because it is still on the agenda of most countries, which is not the focus of this paper (please see Hu & Liu, 2021).

Data sources are the Organization for Economic Co-operation and Development (OECD), the World Trade Organization (WTO), the Trade Map, the Bureau of Industry and Security (BIS), and the databases of the International Monetary Fund (IMF). The real export values are obtained by dividing the nominal export values by the US consumer price index (CPI). The industrial production index (IPI) is a proxy for external income. The real effective exchange rates are calculated using the US economy's CPI and the CPIs of each EM, which are directly taken from the BIS database. According to the calculation method, increases in exchange rates refer to the appreciation of the local currencies.

Baker et al. (2016) measured the US economy's EPU level based on searches of prominent newspapers for combinations of keywords that capture economics, policy, and uncertainty. The index began in 1985 and is updated monthly. This method of measurement has been expanded to 24 developed and developing countries. We derived a GEPU index for each EM in this paper by applying the partial least squares (PLS) factor model to the EPU indexes of those 24 economies. In this way, we distributed the uncertainty generated by the 24 countries among EMs because such an EPU index is unavailable for most of them. The PLS method gives this advantage as it uses the export flows of the EMs in the decomposition process. Detailed information about the PLS method can be found in Bianchi et al. (2019) and Cepni et al. (2020).

The structural panel vector autoregressions (SVAR panel) method of Pedroni (2013) is employed in this paper. He showed that the properties of the sample distributions of these structural dynamics are well, even when the panel's time series dimensions are relatively short.
In this method, the unobserved structural shocks are the composite shocks, which are distributed independently over time but maybe cross-sectionally dependent. The heterogeneous SVAR panel model is expressed by Equation (1).

$$B_i z_{it} = A_i(L) z_{it} + \varepsilon_{it} \text{ where } i = 1, \dots, N \text{ and } t = 1, \dots, T \tag{1}$$

In Equation (1), B_i is the matrix of structural parameters, z_{it} is the matrix of endogenous variables. A well-established export model used in the related literature (e.g. Bahmani-Oskooee, 1986) contains the real export (RE_t), the real external income (EI_t), the real exchange rate (ER_t), and global EPU ($GEPU_t$) which are endogenous variables contained in z_{it}. $A_i(L)$ represents a matrix of lag operators where optimal lag lengths are determined by general to specific (GTOS) criteria in this paper.

In Equation (1), ε_{it} is the structural white noise shocks and they are also called as composite structural shocks and the method allows to divide them into common and idiosyncratic shocks.

To decompose composite structural shocks, ε_{it}, into $M \times 1$ the vector of common, $\bar{\varepsilon}_t$, and idiosyncratic shocks, $\tilde{\varepsilon}_{it}$, the processes followed is as below.

$$\varepsilon_{it} = \Lambda_i \bar{\varepsilon}_t + \tilde{\varepsilon}_{it};\ E(\xi_{it}, \xi_{it}') = \begin{bmatrix} \Omega_{i,\bar{\varepsilon}} & 0 \\ 0 & \Omega_{i,\tilde{\varepsilon}} \end{bmatrix} \forall\, i, t;\ E(\xi_{it}) = 0\ \forall\, i, t;\ E(\xi_{it}, \xi_{is}') = 0\ \forall\, i, s \neq t \text{ and}$$
$$E(\tilde{\varepsilon}_{it}\, \tilde{\varepsilon}_{it}') = 0\ \forall\, t, i \neq j \tag{2}$$

In Equation (2), Λ_i is the $M \times M$ diagonal matrix containing loading coefficients in its' diagonal items. It should be noted that composite error shocks, ε_{it}, of the covariance matrix, $E(\xi_{it}, \xi_{it}')$, also has a diagonal matrix with arbitrarily normalizable variances exposed to extra constraints referred to by Equation (2). This guarantees that the restrictions implemented for the entire panel become consistent with similar restrictions made upon panel members by treating them as if they are individual time series.

The estimation operations are applied firstly to obtain composite shocks, ε_{it}, and associated impulse response and variance decomposition results. For this aim, we estimate $M+1$ (28 + 1 = 29 VAR models in our case) reduced form of VAR models for each country in the panel data and cross-sectional averages.[2]

$$\begin{aligned} z_{1,t} &= C_1(L)z_{1,t} + e_{1,t} \\ z_{i,t} &= C_i(L)z_{i,t} + e_{i,t} \\ z_{m,t} &= C_m(L)z_{m,t} + e_{m,t} \\ \bar{z}_t &= \bar{C}(L)\bar{z}_t + \bar{e}_t \end{aligned} \tag{3}$$

In Equation (3), $C_i(L) = B_i^{-1}A_i(L)$; $e_{i,t} = B_i^{-1}\varepsilon_{it}$, $\bar{C}(L) = \bar{B}^{-1}\bar{A}(L)$ and $\bar{e}_t = \bar{B}^{-1}\bar{\varepsilon}_t$ indicate composite ε_{it} and common shocks $\bar{\varepsilon}_t$ of residuals.

In the second stage, idiosyncratic shocks, $\tilde{\varepsilon}_{it}$ and the loading matrix Λ_i are estimated using the orthogonality properties of the shocks. Estimated loading matrix $\widehat{\Lambda}_i$ contains $M \times M$ sample estimates of $E[\epsilon_{it,m}\epsilon_{t,m}]/E[\epsilon_{t,m}^2]$ for $m = 1, 2, \dots, M$. Diagonal elements of $\widehat{\Lambda}_i$ matrix is the loading coefficient of common structural shocks. These loading coefficients are used to decompose the composite structural shocks into common and idiosyncratic shocks that are equal to simple correlation coefficients between ε_{it} and $\bar{\varepsilon}_t$ shocks (Góes, 2016).

The panel SVAR system for the model given in Equation (1) can be formulated as in Equation (4). Structural shocks of these variables can be ordered from exogenous to endogenous as shown in Equation (5).

$$Z_{it} = (GEPU_{it}, EI_{it}, ER_{it}, RE_{it}) \tag{4}$$
$$\varepsilon_{it}^{z} = (\varepsilon_{it}^{GEPU}, \varepsilon_{it}^{EI}, \varepsilon_{it}^{ER}, \varepsilon_{it}^{RE}) \tag{5}$$

Results and Discussion

Implementing a structurally identified VAR to estimate the VAR coefficients for a wide set of countries, as stated by Mishra et al. (2014;) and Pedroni (2013), faces two empirical issues. For example, some or many of the countries in the sample may have relatively limited data spans available, and data from some or many of the countries may be noisy. A typical time series-based study for any single country may be unreliable under these conditions. To strengthen the reliability of the inferences, we used a panel data set of EMs. This section of the paper reports both the estimated impulse responses with variance decompositions estimated by panel SVAR and the second-stage OLS regressions estimates.

Impulse Responses

The composite, common, and idiosyncratic impulse response functions obtained with the panel SVAR model are reported in Figure 1, Figure 2, and Figure 3, which depict the composite, common, and idiosyncratic median responses, respectively. While solid lines show the median responses, dashed lines represent the associated 25% and 75% quantiles in these figures. The distance between the median responses and the 25% and 75% quantiles shows the degree of heterogeneity. The closer median values to the upper or lower limits imply the more heterogeneous responses of the variables. As seen in Figures 1-3, the reactions of the real export to GEPU shocks are heterogeneous. Mainly, heterogeneity is obviously observed in common impulse response functions of exchange rate shocks. According to the outcomes, GEPU significantly and negatively affects the real export of emerging markets that seems stable and permanent. This finding is compatible with the results of the related literature (Constantinescu, Mattoo, & Ruta, 2020; Krol, 2018; Liu et al., 2020). Shocks of increasing external income cause a remarkable increase in exports. This is an expected result and is consistent with the findings of Aslan and Acikgoz (2021) and Gül (2018).

[2] Equation (3) is the vector moving average (VMA) representation of the main model given in Equation (1).

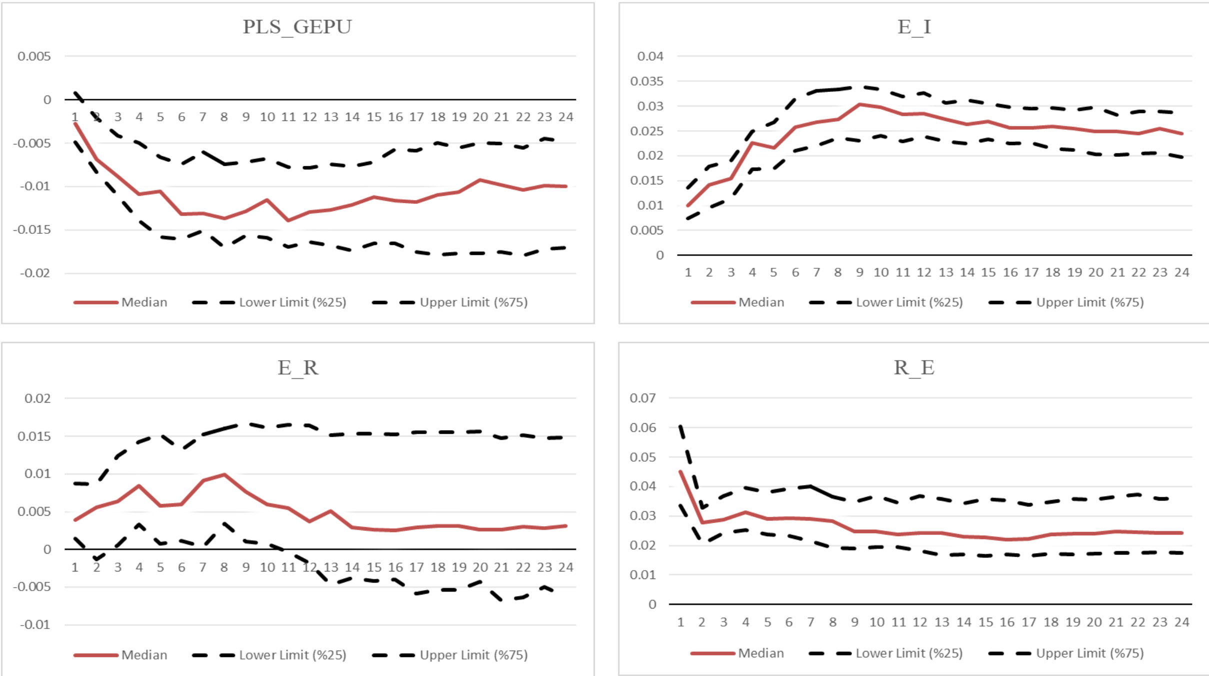

Figure 1. Composite Impulse Responses

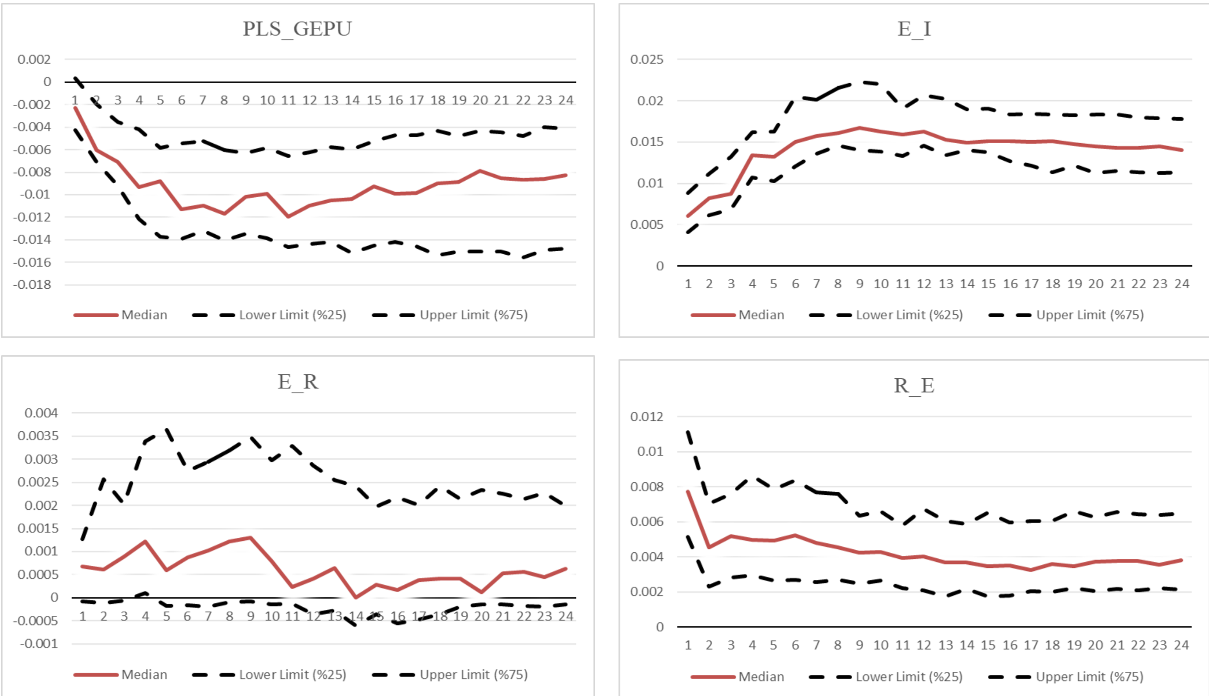

Figure 2. Common Impulse Responses

Composite and idiosyncratic responses of export flows of EMs to the real effective exchange change are significantly positive in the first ten and twelve periods. For the rest of the time interval of composite and idiosyncratic and entire periods of common responses, export responses to exchange rate shocks are found to be positive but insignificant. This result contradicts our expectations implying that local currency appreciations precipitate the reduction in export volumes by making export products more expensive. Although this result contradicts expectations, an extensive literature study argues that the link between exchange rate and export has weakened. Ahmed et al. (2015) and Amiti et al. (2014) raised the fact that exporter countries are also in importers' position. In this scenario, exchange rate advantages for export flows become disadvantages for import flows. Therefore, for EMs recognized as needing a high level of intermediate imported inputs to go on production and export actions exchange rate advantages would even turn into disadvantages on the contrary. Hlatshwayo and Saxegaard (2016) argued that increasing EPU hinders the expected positive effects of exchange rate advantages on exports. To sum up, this finding is logical as particularly considering that we studied with EMs.[3]

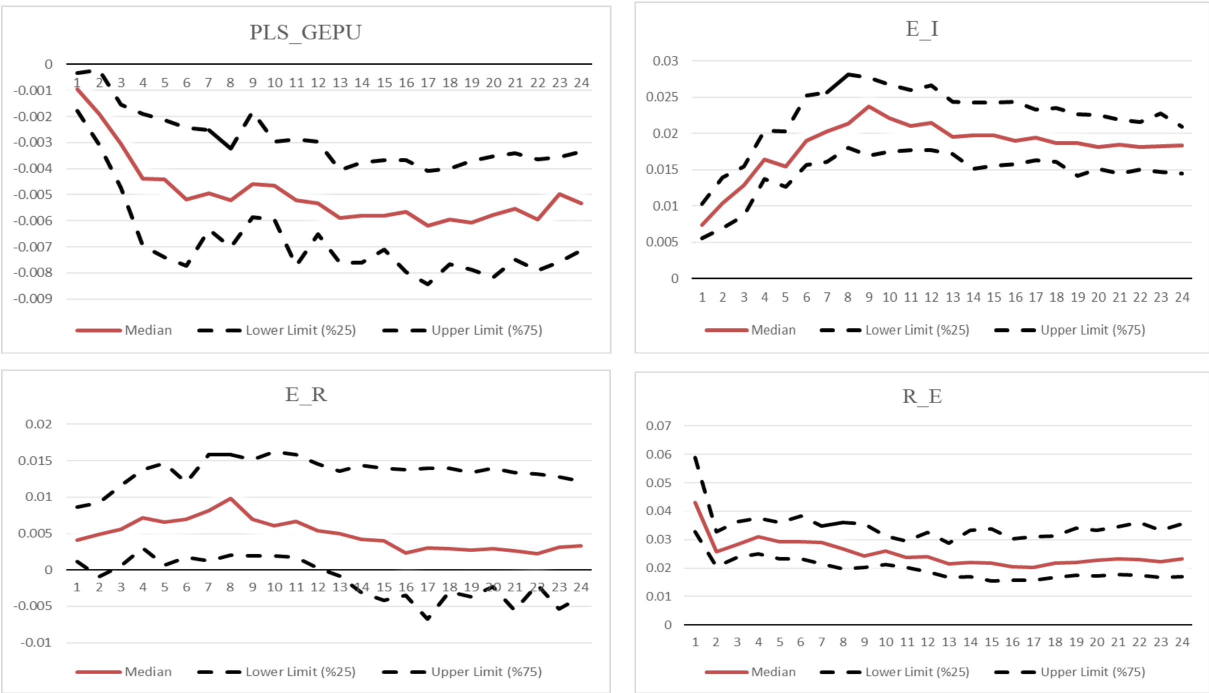

Figure 3. Idiosyncratic Impulse Responses

Variance Decompositions

Variance decomposition results of composite, common, and idiosyncratic shocks are summarized in Table 1. Unlike impulse responses, the results differ depending on the types of shocks. The real export contributes to the composite total variance by 82% on average in the first six periods. Although this contribution decreases in the coming periods, it is about 50%. According to common variance decompositions, this share is 55% and immediately drops in the coming periods. Idiosyncratic variance decompositions show country-specific variance decompositions. Again, the real export explains 80% and 96% of the total idiosyncratic variance in the first periods. The real external income explains 25%-34% of the common total variance of the real export, especially after the first nine months. A similar contribution is also observed for the idiosyncratic variance decompositions. However, the real external income outshines when it comes to common shocks, and its contribution increases in the next periods. Although the explanation percentages of the GEPU shocks are quite limited for composite and idiosyncratic variance decomposition, 4 % on average, its contribution to the common variance decompositions is considerable, with 24% on average. These results imply that export flows of emerging markets have their own patterns, and global EPU has a meaningful total effect on export flows of emerging markets when these countries meet the uncertainty shocks together. The explanation power of exchange rate shocks in export flows of EMs is very small for all types of variance decompositions. The findings of export reactions to the GEPU shocks for composite and idiosyncratic variance decomposition are consistent with the variance decomposition outputs of Aslan and Acikgoz (2021). Moreover, this paper's common variance decomposition results confirm Wei's (2019) variance decomposition results.

[3] We also estimated the model by changing GEPU indices to check the robustness of the main findings. We estimated the second GEPU series with factor-based Principal Component Analysis (PCA) and took the third GEPU series reported by Baker et al. (2016) according to the Gross Domestic Product (GDP) calculation. The estimated impulse responses of the second and third models confirm our baseline findings. To save space we did not report these results; however, they are available upon request.

Table 1. Variance Decompositions

	Composite Variance Decompositions				Common Variance Decompositions				Idiosyncratic Variance Decompositions			
Period	PLS_GEPU	E_I	E_R	R_E	PLS_GEPU	E_I	E_R	R_E	PLS_GEPU	E_I	E_R	R_E
1	0.00	0.05	0.01	0.94	0.07	0.37	0.01	0.55	0.00	0.03	0.01	0.96
2	0.02	0.09	0.02	0.88	0.16	0.48	0.01	0.35	0.01	0.06	0.02	0.92
3	0.02	0.11	0.03	0.84	0.26	0.48	0.01	0.24	0.01	0.07	0.03	0.89
4	0.04	0.14	0.03	0.79	0.25	0.53	0.01	0.21	0.01	0.09	0.03	0.86
5	0.04	0.16	0.04	0.76	0.24	0.55	0.01	0.20	0.01	0.11	0.04	0.84
6	0.05	0.20	0.04	0.71	0.24	0.56	0.01	0.18	0.01	0.14	0.04	0.80
7	0.05	0.23	0.04	0.67	0.24	0.60	0.01	0.16	0.02	0.17	0.05	0.77
8	0.06	0.25	0.04	0.65	0.24	0.62	0.01	0.13	0.02	0.20	0.05	0.74
9	0.06	0.29	0.04	0.61	0.23	0.64	0.01	0.11	0.02	0.22	0.05	0.71
10	0.06	0.30	0.05	0.59	0.23	0.65	0.01	0.10	0.02	0.22	0.05	0.70
11	0.06	0.32	0.05	0.57	0.24	0.65	0.01	0.10	0.02	0.23	0.06	0.69
12	0.06	0.33	0.05	0.55	0.24	0.65	0.01	0.09	0.02	0.24	0.06	0.68
13	0.07	0.34	0.05	0.54	0.25	0.65	0.01	0.09	0.02	0.25	0.06	0.67
14	0.07	0.34	0.05	0.54	0.25	0.65	0.01	0.09	0.02	0.26	0.06	0.66
15	0.07	0.34	0.05	0.54	0.25	0.65	0.01	0.09	0.02	0.27	0.06	0.65
16	0.07	0.34	0.05	0.54	0.25	0.65	0.01	0.08	0.02	0.28	0.06	0.64
17	0.07	0.35	0.05	0.54	0.26	0.65	0.01	0.08	0.03	0.28	0.06	0.64
18	0.07	0.35	0.05	0.54	0.26	0.66	0.01	0.07	0.03	0.28	0.05	0.64
19	0.07	0.35	0.05	0.53	0.26	0.66	0.01	0.07	0.03	0.28	0.05	0.64
20	0.07	0.35	0.05	0.53	0.26	0.66	0.01	0.07	0.03	0.28	0.05	0.64

Second Stage Regression Estimation Results

To further explore the determinants of the variation in impulse responses, we next examined the cross-section association between specific country characteristics, explained below, and the strength of the impulse responses. For this reason, several OLS regressions were estimated. Our aim is here to determine the factors that mitigate the negative effect of global EPU on EMs' export flows. To the best of our knowledge, this is the first study that combines impulse responses with other factors that influence country export flows.

One of the goals of growing and developing economies is to diversify their exports. A more diverse export basket, for example, is associated with lower production volatility or stronger long-term output growth (Haddad et al., 2013; Hnatkovska & Loayza, 2003; Ramey & Ramey, 1995). Most developing countries' export baskets are concentrated on a few raw commodities with fluctuating international pricing (Salinas, 2021). This also exposes them to the shocks of global EPU growth. As a result, we evaluated whether high sectoral diversity in EM exports makes export flows more resilient to external shocks in this research. Because of the high sectoral diversity in production and export, domestic exporters may have more options by establishing a resistance mechanism against uncertainty shocks. This will also assist EMs boost future economic growth.

Only innovative and advanced technology opportunities allow for producing and exporting high-tech goods and services. Given that high-tech goods include aviation and space, computers, pharmaceuticals, scientific instruments, and electrical machinery, firms would face significant fixed costs in addition to R&D expenses. They, too, would occasionally have to hire qualified and technical personnel at high wages. As a result, increasing export technology density is predicted to amplify unfavorable GEPU effects on export flows. To estimate the effects of export diversification (diversification) and the density of the high-tech export level (technology), we also controlled comparative growth (cgrowth). Export concentration index (cindex), and trade-in value added (tiva) are used as alternative proxies for diversity and density of the high-tech export level, respectively, for robustness check. Comparative growth shows each country's relative per capita GDP and is calculated as the per capita GDP of each country divided by the US per capita GDP. The high-tech export data has calculated the basis of the ISIC Rev. 3 classification.[4] The added

[4] Detailed calculations are available upon request.

value in trade[5] is exchanged with the technology variable in the OLS estimations. The sectoral concentration index of export (cindex) is used to indicate sectoral export diversification. Descriptive statistics for EMs in terms of these variables are reported in Table 2. Logarithmic values are used except for economic growth.[6]

The average comparative economic growth of EMs is about −3.7%, and growth rates vary between −1% and −7% in the sample period. The average diversification measure of EMs is −0.34), meaning the sample countries do not have a much-diversified export basket. The standard deviation of this variable is also the smallest one among the others, implying that it does not vary between EMs. Descriptive statistics show a similar pattern for the export concentration index with a slightly higher standard deviation. However, their high-tech export density is higher on average, showing their potential. Their trade in value-added changes between 2.2 and 4.1 with a 3.2 average and 0.50 variation. These descriptive statistics show that the density of the high-tech export level and economic growth are varied across EMs.

Table 2. Descriptive Statistics Variables Used for Second-Stage Regressions

Statistic	diversification	technology	cgrowth	cindex	tiva
Mean	-0.350	2.387	-3.689	-1.784	3.158
Median	-0.276	2.316	-3.735	-1.879	3.134
Maximum	-0.142	3.976	-1.024	-0.932	4.125
Minimum	-1.229	-0.693	-7.067	-2.614	2.227
Std. Dev.	0.234	1.142	1.466	0.484	0.500
Observations	28	28	28	28	28

Authors' calculation from the related data sources.

Table 3. Coefficient Estimates

Impulse responses of log real export to GEPU Shocks	1st Month	4th Month	8th Month	12th Month
constant	-0.0046*** (0.0016)	-0.0096*** (0.0019)	-0.0113*** (0.0027)	-0.0089*** (0.0020)
cgrowth	0.0009* (0.0004)	0.0009* (0.0005)	0.0013* (0.0007)	0.0008 (0.0005)
technology	0.0012*** (0.0004)	0.0015*** (0.0005)	0.0017** (0.0007)	0.0011** (0.0005)
diversification	-0.0110*** (0.0025)	-0.0115*** (0.0003)	-0.0188*** (0.0042)	-0.0089*** (0.0031)
Observations	28	28	28	28
R^2	0.5605	0.5004	0.5495	0.3499
Adjusted R^2	0.5056	0.4379	0.4931	0.2686
F-Stat.	10.2026*** [0.0002]	8.0120*** [0.0007]	9.7565*** [0.0016]	4.3050** [0.0016]
LM(1) p-value	0.0788 [0.7571]	0.3759 [0.5022]	0.0124 [0.9023]	0.6312 [0.3871]
LM(4) p- value	0.0823 [0.9779]	0.2588 [0.8480]	0.0549 [0.9896]	0.4234 [0.7016]
White p- value	8.0692 [0.1145]	0.9766 [0.5631]	0.7897 [0.0967]	0.5158 [0.3999]

Notes: (.) denotes standard errors. [.] denotes p-values. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

The ordinary least squares (OLS) estimates are presented in Table 3. According to the results, even though estimates of the coefficient of technology are too small, a 1% increase in high

[5] More details about trade-in-value added (TIVA) data can be found at https://www.oecd.org/sti/ind/tiva/TiVA2018_Indicators_Guide.pdf (Accsess Date 14.07.2021)

[6] Data sources for the variables used in the OLS regressions are from UNCTAD and OECD databases.

technology intensity of an EM leads to a significant 0.0012-point increase in responses of the real export to global EPU on average in the first month, and that will be followed by in the next months. This result supports the hypothesis that the high technology density of export assists in the transmission of impacts of global EPU on export flows. Estimates of the coefficient of diversification are negatively significant in all periods and show that sectoral diversification has higher impact, in absolute values, on responses than technology. A more diversified emerging economy means global economic uncertainties have less effect on the export of emerging markets. High technology density, sectoral diversity, and comparative economic growth explain variations in impulse response across emerging markets by about 50% in the first eight months. However, the coefficient of adjusted determination decreases to 27% at the end of the first year.

To check whether the estimates are robust, we use two alternative proxies for both high technology intensity and sectoral diversification: the added value in trade (tiva) and the sectoral concentration index of export (cindex). Increases in tiva mean higher value added in foreign trade and are expected to respond similarly to the technology density variable. On the other hand, cindex implies the opposite side with diversification and implies sectoral contraction in export. Hence, cindex is expected to expand negative GEPU effects on export flows.

These OLS estimates are given in Table 4 and Table 5, respectively. The coefficient of tiva is estimated positively and significantly in the first eight months, confirming that the transmission of negative global EPU effects on export volume is likely to amplify with increasing tiva levels. Table 7 shows that the concentration index positively affects responses to global EPU shocks of export. Since diversification and cindex represent opposite sides, a positive coefficient implies that more concentrated emerging markets will be more affected by global EPU shocks. Our findings are robust to alternative variables regarding the density of technology export and sectoral export diversification. After that, we performed diagnostic checking. Both autocorrelation and heteroscedasticity (which might arise from the noise in the impulse-responses) issues are tested using the Breush-Pagan LM test and the White test, respectively. For all models, the autocorrelation problem does not exist. Constant variance assumption is also satisfied for all models except for the 8th-month prediction model of the third model.

Table 4. Coefficient Estimates with tiva

Impulse responses of log real export to GEPU Shocks	1st Month	4th Month	8th Month	12th Month
constant	-0.0083** (0.0032)	-0.0143*** (0.0042)	-0.0192*** (0.0045)	-0.0101** (0.0042)
cgrowth	0.0011** (0.0005)	0.0015** (0.0007)	0.0019** (0.0007)	0.0009 (0.0007)
tiva	0.0021* (0.0011)	0.0030* (0.0015)	0.0039** (0.0015)	0.0011 (0.0011)
diversification	-0.0141*** (0.0029)	-0.0136*** (0.0038)	-0.0258*** (0.0041)	-0.0116*** (0.0038)
F-Stat.	9.8363*** [0.0003]	5.3652*** [0.0063]	16.9638*** [0.0000]	3.5967** [0.0297]
R^2	0.5729	0.4225	0.6982	0.3291
Adjusted R^2	0.5146	0.3438	0.6570	0.2376
Observations	28	28	28	28
LM(1) p-value	0.0831 [0.7488]	1.6378 [0.1702]	0.0353 [0.8346]	2.5220 [0.1272]
LM(4) p- value	0.0968 [0.9687]	0.4480 [0.6709]	0.0115 [0.9995]	0.8525 [0.3873]
White p- value	0.4291 [0.6502]	0.6796 [0.7664]	0.3928 [0.6458]	0.7172 [0.5878]

Notes: (.) denotes standard errors. [.] denotes p-values. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Coefficient Estimates with cindex

Impulse responses of log real export to GEPU Shocks	1st Period	4th Period	8th Period	12th Period
constant	-0.0012	-0.0039	0.0017	-0.0015
	(0.0032)	(0.0035)	(0.0046)	(0.0031)
cgrowth	-0.0004	-0.0003	-0.0006	-0.0001
	(0.0004)	(0.0004)	(0.0006)	(0.0003)
technology	0.0012**	0.0015**	0.0018**	0.0012**
	(0.0005)	(0.0006)	(0.0007)	(0.0005)
cindex	0.0022*	0.0034**	0.0074***	0.0041***
	(0.0013)	(0.0015)	(0.0018)	(0.0012)
F-Stat.	3.0813**	4.3962**	8.2159***	5.2467***,
	[0.0465]	[0.0134]	[0.0006]	[0.0063]
R^2	0.2781	0.3546	0.5067	0.3961
Adjusted R^2	0.1878	0.2740	0.4450	0.3206
Observations	28	28	28	28
LM(1) p-value	0.0770	0.2786	0.1481	0.6587
	[0.7599]	[0.5627]	[0.6722]	[0.1699]
LM(4) p- value	0.1868	0.9110	0.4198	0.4793
	[0.9085]	[0.3650]	[0.7047]	[0.1717]
White p- value	5.4283	0.4021	10.4165	1.4122
	[0.0153]	[0.8607]	[0.0052]	[0.2542]

Notes:(.) denotes standard errors. [.] denotes p-values. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

The result of this paper highlighted that increasing global EPU hinders the EMs' export level. This finding is confirmed by estimating the model with two alternative different GEPU variables and it accords well with existing literature such as Jia et al. (2020) and Krol (2018). The main reason behind this negative impact is that sunk and irreversible cost concerns delay investments in high uncertainty periods (Bernanke, 1983; Dixit, 1989; Krol, 2018). EPU harms trade flows via global supply chains since it is globally based. This can be another explanation for negative GEPU influences on trade flows. As a control variable, external income assists in expanding the export volume of EMs as consistent with expectations. Besides, this is the most dominant variable explaining the export level. Contrary to expectations, it is interesting that the exchange rate positively affects exports. This unexpected result can be explained as (i) a high level of global EPU prevents taking the exchange rate advantages for enhancing the export level depending on postponing investments, and (ii) although the exchange rate depreciation provides opportunities to increase the export level, it creates unfavorable conditions for the import level at the same time. EMs described as having high import needs to export would have faced a lack of intermediate goods supply. In this case, due to the depending on import demand, exchange rate advantages are reversed for export flows.

Conclusion

This paper examines the effects of global EPU on the export flows of 28 emerging markets. Data is an unbalanced monthly panel data from 2003 to 2019. The structural panel VAR model proposed by Pedroni (2013) is used in the estimations. This method allows full heterogeneity among panels and estimates the individual response behavior of all EMs in the sample. To the best of our knowledge, this is the sole paper examining the factors that mitigate or amplify GEPU impacts on export flows by estimating second-step ordinary least square equations. For this aim, sectoral diversification and technology intensity of export are analyzed. Sectoral diversification prevents unfavorable GEPU impacts while the technology intensity of export multiplies them.

Our paper has remarkable policy implications. As the most used economic policy application, the exchange rate would become useless in amplifying export flows. In highly import-dependent economies, exchange rate appreciations would hamper export volume instead of assisting. Additionally, it should be noted that local macroeconomic policies would be insufficient in many cases hence, policymakers should assess the global economic conditions when they take acquired precautions. The subject of economic policy uncertainty and its unwanted impacts on economic activities such as export should be taken seriously. Such large-scale economic trade agreements could be applied to control the negative effects of global economic policy uncertainties.

Moreover, sectoral diversification is another way to hamper GEPU influences. Governments should encourage new sectors to increase the sectoral spread of production and export. Since export sectors manufacturing high-tech products are more sensitive to GEPU movements, policymakers should follow these sectors more closely, especially in high uncertainty times. Even some regulated support incentives can be provided to prevent decreased production levels if necessary.

This paper stresses the nexus between GEPU and the export flows of 28 emerging markets. Empirical analyses are performed with total export values. However, a deeper analysis could be implemented with less aggregated export data. For example, empirical analyses with firm basis sectoral export data would offer more detailed and interesting information. Furthermore, a different, maybe wider country group could be preferred. In summary, there are still avenues waiting to be explored in this subject.

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APPENDIX

Table A1. List of Emerging Economies

No	Country Name	Data Period
1	Brazil	2003:01-2019:12
2	Bulgaria	2004:01-2019:12
3	Chile	2003:01-2019:12
4	Colombia	2003:01-2019:12
5	Costa Rica	2003:01-2019:12
6	Croatia	2004:01-2019:12
7	Czechia	2003:01-2019:12
8	Greece	2003:01-2019:12
9	Hungary	2003:01-2019:12
10	India	2003:01-2019:12
11	Indonesia	2003:01-2019:12
12	Latvia	2004:01-2019:12
13	Lithuania	2004:01-2019:12
14	Macedonia	2006:01-2019:12
15	Malaysia	2004:01-2019:12
16	Malta	2004:01-2019:12
17	Mexico	2003:01-2019:12
18	Peru	2006:01-2019:12
19	Philippines	2006:01-2019:12
20	Poland	2003:01-2019:12
21	Romania	2004:01-2019:12
22	Russian Federation	2003:01-2019:12
23	Singapore	2006:01-2019:12
24	South Africa	2003:01-2019:12
25	Republic of Korea	2003:01-2019:12
26	Tunisia	2003:01-2019:12
27	Turkey	2003:01-2019:12
28	Uruguay	2003:01-2019:12