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Global Uncertainty and Exchange Rate Volatility

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Abstract

This paper investigates the impact of global uncertainty on Turkey's exchange rate volatility via quantile regression approach. Using quantile regression approach, estimated uncertainty coefficients are allowed to differ over quantiles of the exchange rate volatility. The EGARCH model is the best fit for measuring exchange rate volatility due to the fact that exchange rate series exhibit “asymmetric volatility”. In this study we employed global economic policy uncertainty index-GEPU constructed by Baker et al. (2013) as a proxy of global uncertainty. Empirical results suggest that higher volatility of exchange rate is associated with a greater positive shock of GEPU. However, estimated parameters are statistically significant at lower exchange rate volatility since the CBRT intervenes the foreign exchange markets and restricts the excessive fluctuations in exchange rates to achieve financial stability.

Keywords

Economic Policy Uncertainty, Exchange Rate Volatility, Quantile Regression

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1.Introduction

The macroeconomic effects of uncertainty have received a great deal of attention after the highly influential paper published by Bloom (2009). Bloom documented that uncertainty shocks generate short but effective recession periods. Following by Bloom, a vast number of studies have been published to measure the impact of uncertainty shocks at macroeconomic level. For example, Colombo (2013), Nodari (2014), Alam (2015), Leduc and Liu (2016), Caldara et al. (2016), Alam and Istiak (2020) investigated the impact of uncertainty on prices, output and employment. In a similar vein, Balcilar, Gupta and Pierdzioch (2015), Balcılar et al (2015), Phan et al. (2018), Gupta et al. (2018), Li et al. (2018), Fang et al. (2018), Dong et al. (2019) indicated that uncertainty also has impacts on asset and commodity prices such as oil, stock, gold prices etc., insurance premium and bitcoins. In empirical literature, several indicators (e.g Chicago Board Options Exchange Volatility Index-VIX (Bloom, 2009), Thomson Reuters/University of Michigan consumer surveys (Leduc ve Liu, 2016), political events such as uncertainty in election periods or legislative bills (Leblang and Bernhard, 2006)) have been considered as proxy of uncertainty. However, it is worth noting that, since the seminal paper published by Baker et al. (2013), uncertainty shocks have mostly been identified by the policy-related "economic policy uncertainty (EPU) index" . They constructed the EPU index for the US based on three basic components: newspaper-based component, the number of federal tax code provisions set to expire and a measure of disagreement among forecasters.[1]

In addition to the above, there is an extensive literature on the determinants of exchange rate volatility. The related empirical literature has proposed numereous factors to explain exchange rates changes and their volatilities (e.g. terms of trade (De Gregorio and Wolf, 1994; Cashin, Cesbedes, Sahay, 2004; Broda, 2004; Hausmann, Panizza and Rigobon, 2006), inflation (Ferson and Harvey, 1991; Al Abri, 2013; Liming, Ziqing and Zhihao, 2020), output changes (Ghosh et al.,1997; Alexius, 2005), interest rates (Mueller, Tahbaz-Salehi, Vedolin, 2017; Liming, Ziqing, Zhihao, 2020), external debt (Devereux and Lane; 2003), trade openness (Obstfeld and Rogoff, 1995 and 1996; Hau, 2002; Calderon and Kubata, 2018), financial openness (Sutherland, 1996; Calderon and Kubata, 2018) etc.

Even though there have been a large amount of empirical attempts to explain the potential impacts of uncertainty and the main determinants of exchange rate volatility, the literature exploring the effects of uncertainty on exchange rate volatility remains limited. The transmission mechanism behind the link between uncertainty and exchange rate volatility can be explained by macroeconomic fundamentals. In the long run, exchange rates are determined by fundamentals such as prices, output, money supply, interest rates etc. . An increase in uncertainty will therefore change

1 More detailed information of EPU indices for countries around the world and its methodology can be found at https://www.policyuncertainty.com/methodology.html

the expectations of economic agents on the fundamentals and generate exchange rate fluctuations. Additionally, empirical studies frequently support and document the positive impacts of uncertainty on exchange rate volatility. Balcılar et al. (2016) employed a causality-in-quantile approach and found evidences that EPU has a causal impact on the variance of exchange rate return but not on the returns themselves. Krol (2014), investigated the impacts of EPU uncertainty on exchange rate volatility for both industrial and emerging economies. He presented evidence that domestic or US economic policy uncertainty tend to rise volatility. Additionally, only domestic uncertainty produced significant effect during recessions. Similarly, Bartsch (2019), Li and Zhong (2020), Wang, Li and Wu (2022), Zhou et al (2020), Liming, Ziqing and Zhihao (2020), Abit and Rault (2021), Bush and Noria (2021) documented that EPU shocks exert positive effects on exchange rate fluctuations. However, literature about the impact of uncertainty on exchange rate volatility in Turkey is still very scarce. Guney (2020) investigated the impacts of the US and Euro area EPU indices on Turkish Lira/dollar and Turkish Lira/Euro nominal exchange rates by ARDL approach. She presented evidence that uncertainty in the US increases the volatility in the Dollar/TL exchange rate. Demirgil (2011) measured uncertainty using six political stability indicators (coups, strikes, general and local elections, referandums and coalition periods) and indicated that the impact of political instability on exchange rates is not significant.

This paper investigates the spillover impact of global uncertainty on Turkey's exchange rate volatility. Simply put, we address the following question: Does elavated global uncertainty produce exchange rate volatility in Turkey? We employ heavily used "global economic policy uncertainty index-GEPU" to represent global uncertainty since GEPU covers uncertainty more broadly than other uncertainty indices as noted by Istiak and Serletis (2018). This paper has three distinctive features. First, most of the traditional methods estimating the impacts of uncertainty on exchange rate volatility rely on the conditional mean of the volatility. This study, however, will employ the quantile regression approach since the conditional mean of the our exchange rate volatility series is not thought to capture the whole picture of the patterns in the data due to fat tails, skewed data, more outliers, nonnormality, and such like. Using quantile regressions, exchange rate volatility with respect to a change in uncertainty varies over quantiles of the conditional distribution of the exchange rate volatility. Second, GARCH (generalized autoregressive conditional heteroscedasticity)-based models appear to be the best fit for measuring exchange rate volatility based on the descriptive statistics and conducted statistical tests of exchange rate return series. However, observed "leverage effect" in our data indicates "asymmetric" volatility in exchange rate series and hence necessitates the usage of the EGARCH model over the GARCH model. Third, even though empirical evidence frequently documents the positive impact of domestic uncertainty on volatility, the spillover impact of global uncertainty is a somewhat more contentious issue. When considering the very limited literature on Turkey, this paper intends to clarify the spillover impact of uncertainty in the case of Turkey. The empirical results, on the other hand, revealed that GEPU generates significant positive impacts on exchange rate volatility in Turkey. The remainder of the paper is organized as follows. Section 2 includes methodology and gives details on GEPU and other variables. While empirical results are documented in Section 3, conclusions are drawn in Section 4.

2. Methodology and Data

Our sample covers the monthly period of 2002:M1-2021:M12 in which a floating exchange rate regime prevailed. The impacts of global economic policy uncertainty on exchange rate volatility over different quantiles will be analyzed by quantile regression approach. Quantile Regressions have gained popularity, particularly in finance, after a paper was published by Koenker and Basset on the topic (1978). These regressions can be considered as an extension of linear regressions when the conditions of linear regression are not satisfied.

Classical linear regression estimates the mean responses of dependent variables. Simply put, the slope in a classical linear model reveals how much the mean response changes with respect to a one point change in independent variables. By assuming key assumptions of linear regressions such as normality and equal variance, all quantiles of the conditional distribution of the response variable have same slope. However, there are many cases where these assumptions are not met. If the conditional distribution is asymmetric or the tails are fat or the variance of the conditional distribution depends on a dependent variable, then its quantiles change at their own speed with an increasing dependent variable. This immediately gives rise to distinct estimates over the quantiles. That the impacts of the estimated coefficients may differ with a dependency over quantiles of the conditional distribution is a major advantage of quantile regressions over traditional mean regressions.

This study employs quantile regressions since the conditional mean of the exchange rate volatility series is not considered to capture the whole picture of the patterns in the data due to fat tails, skewed data, more outliers, nonnormality etc. Instead, by using quantiles of the conditional distribution of the exchange rate volatility, the relationship between uncertainty and exchange rate volatility is allowed to vary over quantiles. That is, global uncertainty might have a larger effect on the higher quantiles than on the lower quantiles of the volatility series or vice versa.

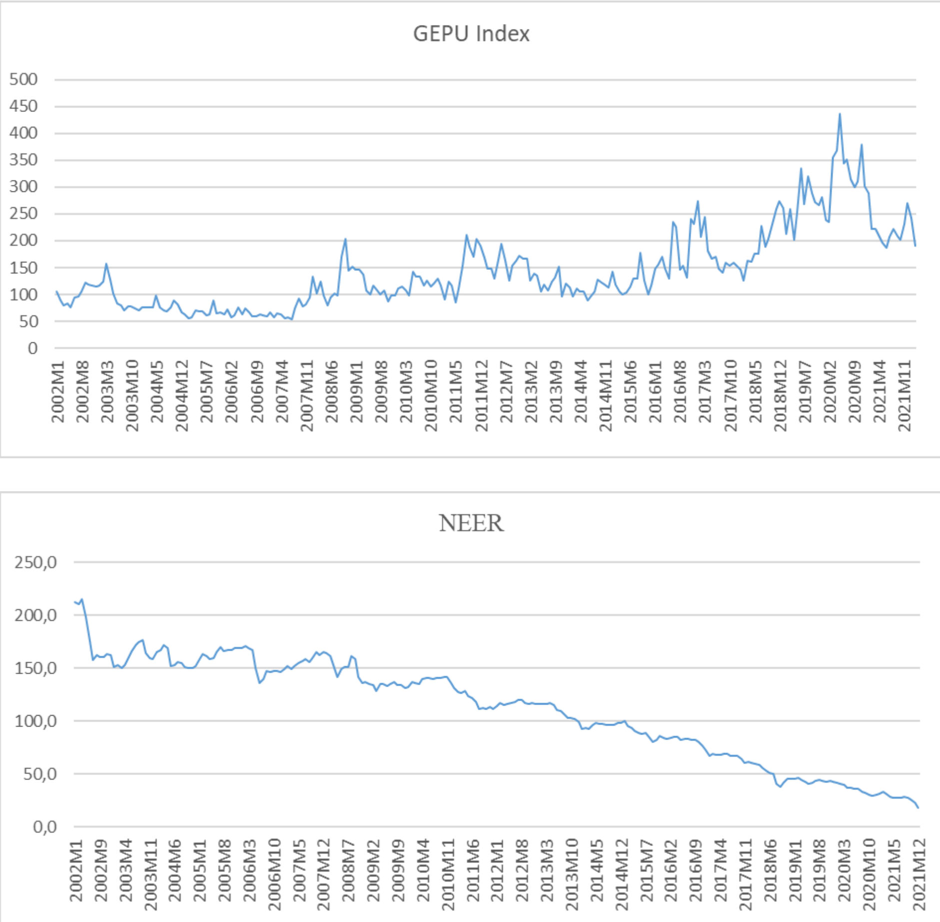

Figure 1. Plots of Time Series of GEPU Index and NEER (2002:M1-2021:M12)

The quantile regression model equation for the τth quantile can be represented as:

$$Q_\tau(\mathrm{EXVOL/GEPU}) = \alpha + \beta^\tau \mathrm{GEPU} + \delta^\tau Z + e^\tau \;, \quad \tau \in (0,1) \qquad (1)$$

Quantile regression equation (1) expresses the quantiles of the conditional distribution of the dependent variable as a linear function of the independent variables. EXVOL denotes nominal effective exchange rate volatility. Nominal effective exchange rate (NEER) is calculated as geometric weighted averages of bilateral exchange rates. An increase in exchange rate indicates an appreciation of the home currency-Turkish lira against a broad basket of currencies. $Q_\tau(\mathrm{EXVOL/GEPU})$ refers to the conditional quantile function of exchange rate volatility at τ^{th} quantile. The global uncertainty is represented by "global economic policy uncertainty index (GEPU)" developed by Baker et al. (2013). The GEPU Index is identified as a GDP-weighted average of national economic policy uncertainty indices for 21 countries: Australia, Brazil, Canada, Chile, China, Colombia, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, the Netherlands, Russia, South Korea, Spain, Sweden, the UK, and the US. Each national uncertainty index is constructed by reflecting the relative frequency of own-country newspaper articles that contain the words "economy", "policy" and "uncertainty".[2] The coefficient vector $\beta\tau$ measures the impact of GEPU on exchange rate volatility at different quantiles. Z represents a set of control variables including terms of trade (TOT), consumer prices (CPI), real productivity (PROD) and domestic interest rates (IR) for presenting monetary policy.[3] Non-normal exchange rate returns stimulate us to make statistical inferences based on a bootstrapped estimate of the variance–covariance matrix of the estimators. The bootstrapping approach enables us to detect the statistical significance of the estimates more precisely since it does not assume any underlying distribution of the response variable. Finally, all variables except domestic interest rate are expressed in logarithm and the quantile regression model (1) is estimated using first-differenced stationary data.[4]

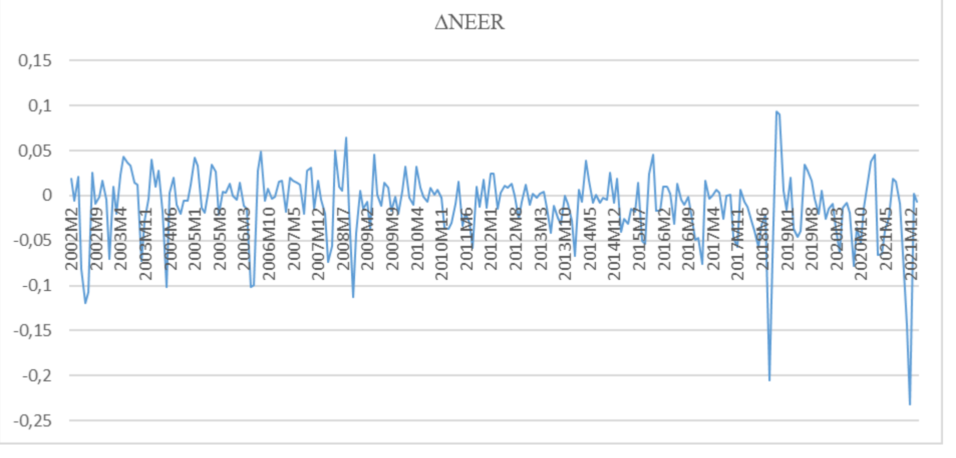

Figure 2. Monthly Exchange Rate Return Series

Descriptive statistics on the return series are presented in Table 1. The Shapiro-Wilk W test (1965) for normality reports that the return series exhibit departures from normality. Besides, similar to many financial time series, the log differenced exchange rate data reveal the presence of excess kurtosis and negative skewness. Leptokurtic distributions, which have kurtosis larger than three, generate more outliers since their tails have more probability mass with respect to a Gaussian normal. Additonally, negatively skewed returns suggest that more values are concentrated on the right tail of the distribution. Since the return series do not follow Gaussian normal with documented excess kurtosis and negatively skewed data, the volatility should be estimated with fat tail distributions such as Student's t, Generalized Error Distribution

2 For more detailed information on GEPU, see https://www.policyuncertainty.com/global_monthly.html

3 For more detailed data definitions and data sources, see Appendix, Table A.1.

4 Time series properties of the data set can be found in Appendix, Table A.2. The first difference of logged variables is considered as growth rates of the original variables.

(GED), and Laplace among others. Westerfield (1977) and Hsieh (1989) indicated that leptokurtic returns tend to exhibit volatility clustering.[5] More importantly, volatility clustering suggests conditionally heteroscedastic disturbances which are mostly, and succesfully, run by GARCH-based models. Finally, a constant-only model is fitted by OLS and ARCH (autoregressive conditional heteroskedasticity) and the effect of exchange rate return series is investigated by the ARCH-LM Test. The test rejects the null of no ARCH effects. This justifies the existence of autoregressive conditional heteroskedasticity in the disturbances of log differenced exchange rate data. Overall, since all the preliminary findings suggest some empirical irregularities such as volatility clustering, ARCH effect and nonnormality, GARCH-based models with fat tail distributions appear to be the best fit when measuring volatility of exchange rate data.

Table 1

Descriptive Statistics on Exchange Rate Return Series

Mean	-.0101
Max	.0935
Min	-.2325
Skewness	-1.7378
Kurtosis	9.9677
Shapiro-Wilk W Test Statistics[a]	0.8804*
ARCH-LM Test Statistics[b]	12.975*

Notes: ***, Significance at 10%; **, significance at 5%; *, significance at 1%.

[a] Null hypothesis Shapiro-Wilk (1965) W Test is "data are normally distributed".

[b] Null hypothesis for the Engle's (1982) ARCH-LM test is "No ARCH effect "

2.1. GARCH-Based Modelling of Exchange Rate Volatility

This paper first employs a generalized autoregressive conditional heteroscedasticity- GARCH model proposed by Bollerslev (1986) to capture the symmetry effect in exchange rate data.[6] Standard GARCH(1,1) process for exchange rate returns with conditional mean and variance equations is written as:[7]

$$\Delta \mathrm{NEER}_t = \alpha + \varepsilon_t \tag{2}$$

$$\sigma_t^2 = \omega_0 + \omega_1 \varepsilon_{t-1}^2 + \omega_2 \sigma_{t-1}^2 \tag{3}$$

$$\varepsilon_t = z_t \sigma_t \sim \mathrm{GED}(0, \sigma_t^2, \eta) \text{ where } z_t \sim \mathrm{iidN}(0,1)$$

5 Volatility clustering simply states that large changes in exchange rates are followed by large changes and small changes are followed by small changes.

6 In empirical literature, there can be seen different volatility measures such as standard deviation of differenced exchange rate, moving standard deviation measure of volatility and GARCH-based measures.

7 This paper employs the GARCH(1,1) specification since GARCH(1,1) appeared to be the most used specification by many authors in the related literature (see Bollerslev, 1986; Dominguez, 1998; Hsieh, 1989; Narayan, Narayan and Prasad, 2008; Wang and Barrett, 2007; Ghosh, 2011, Hall, Hondroyiannis, Swamy, Tavlas ve Ulan, 2010; Huchet-Bourdon and Korinek, 2011 etc.)

Where ε_t is disturbance term or shocks and follows GED distribution with a shape parameter η. The disturbances do not follow the Gaussian normal since our exchange rate returns are leptokurtic and hence have fatter tails than the normally distrubuted disturbances as previously reported in Table 1. The GED's tails are fatter than the Gaussian normal's when η is less than two. ω_1 is the ARCH parameter and ω_2 is the GARCH parameter.σ^2_t is called time dependent conditional variance of the disturbances and simply expresses the volatility of the monthly return series. GARCH models extend ARCH models by adding lagged values of volatility of the return series. That is, future volatility is estimated as a function of past volatility. By volatility symmetry assumption, GARCH models suggest that positive (good news) and negative unanticipated shocks (bad news) have identical impacts on conditional volatility.

Since positive and negative unanticipated shocks might have differents weights on exchange rate volatility, this paper also employs Nelson's (1991) exponential GARCH model (EGARCH) to capture the potential asymmetry in exchange rate. According to Black (1976) and Nelson (1991), large unanticipated negative shocks tend to produce higher volatility than large positive shocks of the same size. This is called "negative leverage effect". To capture the possible asymmetric effect, the EGARCH model attaches standardized disturbances z_t into the conditional variance equation. The EGARCH(1,1) model with conditional mean (4) and variance equation (5) is illustrated below:

$$\Delta S_t = \alpha + \varepsilon_t \tag{4}$$

$$\log(\sigma_t^2) = \beta_0 + \beta_1 z_{t-1} + \beta_2 \ln(\sigma_{t-1}^2) + \beta_3\left(|z_{t-1}| - \sqrt{\frac{2}{\pi}}\right) \tag{5}$$

$$\varepsilon_t = z_t\sigma_t \sim GED(0, \sigma_t^2, \eta) \text{ where } z_t \sim iidN(0,1)$$

Again, ε_t follows GED. z_t is distributed standard normal. β_0, β_1, β_2 and β_3 are the parameters to be estimated from the EGARCH(1,1) model. The parameter β_1 is "volatility asymmetry" parameter. When $\beta_1 > 0$, then positive shocks generate higher volatility than negative shocks of the same size. Similarly, when $\beta_1 < 0$, then negative shocks produce higher volatility than positive shocks. Volatility persistent term β_2 represents the "GARCH effect" and estimates the persistence of past conditional volatility on current volatility. Finally, magnitude effect β_3 measures the size impact of a shock on the current volatility regardless of whether an unanticipated shock is positive or negative.

3. Estimation Results

3.1. GARCH/EGARCH Estimation of Exchange Rate Volatility

Table 2

Estimation Results of Exchange Rate Volatility

	GARCH (1,1)	EGARCH (1,1)
	Mean Equation	
α	-.0038*	-.0031***
	Variance Equation	
ω_0	.0007*	--
ω_1	.6466**	--
ω_2	-.0218	--
β_0	--	-3.9079*
β_1	--	-.3059**
β_2	--	.4240**
β_3	--	.5369**
	Diagnostics	
ARCH-LM Test Stat.	0.917	1.6720
Box Pierce Q_Z(m) Stata.	34.2402	47.6175
Box Pierce Q_Z^2 (m) Stata.	6.6491	29.9520
Shapiro-Wilk W Test Statistics	.9732	.9891
η	1.0459	1.0865

Notes: ***, Significance at 10%; **, significance at 5%; *, significance at 1%.

[a] The null of Box-Pierce test implies absence of autocorrelation up to lags(m). m specifies the number of autocorrelations to calculate for Box-Pierce Q-statistics. Since there is no consensus on how to determine the correct number of m to run the test in empirical literature, the following rule of thumb is used: m = min(‖n/2‖-2,40) where n is sample size and (‖n/2‖) is the greatest integer less than or equal to n/2. Based on the rule of thumb, m is selected as 40. However, the Box-Pierce test results are robust with respect to different selections of m such that m = 5, 10, 20, 30. The results are available upon request.

Table 2 compares the two competitive models: the GARCH(1,1) with volatility symmetry and the EGARCH(1,1) with volatility asymmetry. First, the shape parameters which are less than two in both specifications confirm the validity of using fat tail GED disturbances over Gaussian normal. Second, negative and significant volatility asymmetry parameter β_1 is an indication of (negative) leverage effect or asymmetric volatility. This simply implies that negative unanticipated shocks in the market are more destabilizing than positive shocks. More importantly, highly significant volatility asymmetry term indicates that the EGARCH model outperforms the GARCH model. Third, positive and significant GARCH parameter β_2 suggests the persistence of past conditional volatility on current volatility. Finally, magnitude effect β_3 is statistically significant.

A number of diagnostics for the EGARCH model are also documented in Table 2. According to the distributional assumptions in the model, z_t is assumed to be independently and identically (i.i.d) normally distributed. Shapiro-Wilk W test (1965) cannot reject the null of normality of z_t for any conventional significance level. Q_Z (m) and Q_Z^2 (m) represents the Box-Pierce Q-statistic to test for white noise for z_t

and the squared z_t, respectively. The results indicate that the EGARCH (1,1) model of exchange rate volatility is free from autocorrelation. Additionally, the ARCH-LM test reports no ARCH effects in z_t. Overall, all statistical results strongly suggest that the EGARCH (1,1) model emerges as the best candidate for measuring volatility of exchange rate in Turkey.

3.2. Estimation Results of the Quantile Regression

This section reveals quantile regression estimation of the impact of GEPU on exchange rate volatility measured by EGARCH(1,1). The results are reported at different quantiles and presented in Table 3 and Figure 3.

Table 3

Impact of GEPU on Exchange Rate Volatility over Quantiles

Quantiles,τ	**5%**	**15%**	**40%**	**50%**	**70%**	**95%**
β^{τ}	.0010	.016**	.031***	.028***	.037	.031

Notes: ***, Significance at 10%; **, significance at 5%; *, significance at 1%.

Significance of the GEPU estimates are reported based on boostrapped estimates of the variance-covariance matrix with 250 replications.

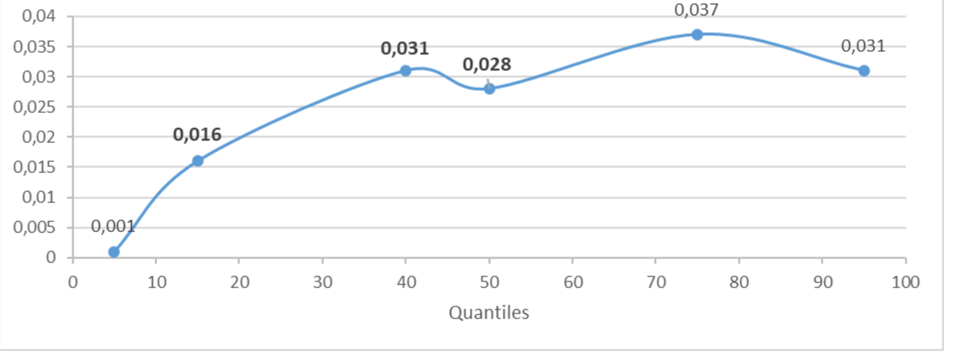

Figure 3. Impact of GEPU on Exhange Rate Volatility at Different Quantiles

Note: Bold numbers represent statistically significant estimates.

As shown in Table 3 and Figure 3, estimated values of GEPU are positive at all volatilities of exchange rates. The highest impact is observed at 75% quantile. Additionally, higher volatility of exchange rate is associated with a greater positive shock of GEPU. That is, global uncertainty has a positive larger effect on the higher quantiles than on the lower quantiles of the conditional distribution of exchange rate volatility in Turkey. However, estimated parameters are not significant at higher quantiles (>%50) while they are mostly significant at lower quantiles (<%50).[8] The

8 On the other hand, classical linear regression estimates the mean response of volatility with respect to a change in GEPU as 0.004 and more importantly, it is insignificant at any conventional significance levels. However, unlike the mean regression, the quantile regression (1) presents significant estimates in lower quantiles. This result provides support for employing the quantile regression (1).

following question, then, naturally arises: What might the reason for global uncertainty being significantly associated with lower volatilities be?

This might be explained by monetary and exchange rate policies conducted by the Central Bank of the Republic of Turkey (CBRT). After the severe economic crisis in 2001, Turkey adopted floating exchange rate regime in which exchange rates are not used as a policy instrument. On the other hand, the global financial turbulence in 2008 and 2009 also hit Turkey hard. The greatest experience gained from the 2008-2009 crisis was the fact that ignoring financial stability might also endanger price stability. Hence, the CBRT designed a monetary policy framework with the aim of achieving financial stability without compromising price stability. More importantly, the bank may intervene in the foreign exchange market and use foreign exchange transactions including spot or forward purchases and sales and foreign exchange swaps to offset the adverse effects of unexpected exchange rate shocks. As reported in Table 3, a rise in uncertainty changes the expectations on economics fundamentals and triggers the exchange rates fluctuations positively at each one of the quantiles. However, increasing uncertainty leads the CBRT to take measures against extreme volatility of the value of the Turkish lira. Consequently, the CBRT interventions which desire to maintain financial stability lessen the volatility of exchange rates and GEPU's impact is only significant at lower quantiles.

4. Conclusion

It is crucial for policymakers to determine which factors lead to exchange rate volatility since previous studies have frequently documented a negative relationship between exchange rate volatility and economic activity (Dollar, 1992; Bleaney and Greenaway, 2001; Schnabl, 2008; Aghion et al., 2009; Feldmann, 2011; Belke and Kaas, 2004; Feldman, 2011; Bahmani-Oskooee and Hajilee, 2013). Hence, any factor elevating exchange rate volatility is also expected to cause a decline in economic activities. This paper, however, analyzes the impact of global uncertainty on the volatility of exchange rate in Turkey. Theoretically, an increase in uncertainty is expected to change the expectations of economic agents on the exchange rate fundamentals and hence generates exchange rate fluctuations.

The empirical results first suggested that GARCH-based models appeared to be the best fit for measuring exchange rate volatility in Turkey. This is mainly due to the fact that nominal exchange rate data generate some empirical irregularities such as volatility clustering, non-normality and ARCH effect. Additionally, the EGARCH model outperforms the GARCH model since our data exhibit "asymmetry" in exchange rate series. We employed quantile regression approach that expresses the quantiles of the conditional distribution of the exchange rate volatility as a linear function of the uncertainty. Using quantile regression approach, the estimated uncertainty coefficients are allowed to differ over quantiles. Our result empirically revealed that higher volatility of exchange rate is associated with a greater positive shock of GEPU. However, estimated parameters are significant at lower quantiles (<%50) since the CBRT intervenes in the foreign exchange markets to achieve and maintain financial stability and restricts the extensive movements in exchange rates.

This result confirms the spillover impact of global uncertainty on a domestic country, Turkey. Maintaining exchange rate stability with the documented spillover effect is not an easy task for policymakers in Turkey since exchange rate stability also necessitates successfully conducted international economic policies that enable a reduction in global uncertainty. Policymakers should take into account that not only domestic uncertainty, but also global uncertainty triggers extensive movements in the exchange rate and generates negative impacts on the Turkish economy.

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References

Abid, A., & Rault, C. (2021). On The Exchange Rates Volatility and Economic Policy Uncertainty Nexus: A Panel Var Approach For Emerging Markets. *Journal of Quantitative Economics, 19*, 403–425.

Aghion, P., P., Bacchett, R. R., & Rogoff, K. (2009). Exchange Rate Volatility and Productivity Growth: The Role of Financial Development. *Journal of Monetary Economics*, *56(4),* 494–513.

Al-Abri, A. (2013). Real Exchange Rate Volatility, Terms-Of-Trade Shocks, and Financial Integration in Primary-Commodity Exporting Economies. *Economics Letters, 120(1*), 126-129.

Alam, M.R. (2015). Economic Policy Uncertainty in the US: Does It Matter for Canada? *Economics Bulletin, 35(4*), 2725-2732.

Alam, M.R., & Istiak, K. (2020). Impact of US Policy Uncertainty on Mexico: Evidence from Linear and Nonlinear Tests. *Quarterly Review of Economics & Finance, 77*, 355-366.

Alexius, A. (2005). Productivity Shocks and Real Exchange Rates. *Journal of Monetary Economics, 52(3)*, 555-566.

Bahmani-Oskooee, M., & Hajilee, M. (2013). Exchange Rate Volatility and Its Impact on Domestic Investment. *Research in Economics, 67(1),* 1–12.

Baker, S., Bloom, N., & Davis, S. (2013). Measuring Economic Policy Uncertainty. *Chicago Booth Paper No: 13-02*

Balcilar, M., Gupta, R., Kim, W-J., & Kyei, C. (2015). The Role of Domestic and Global Economic Policy Uncertainties in Predicting Stock Returns and their Volatility for Hong Kong, Malaysia and South Korea: Evidence from a Nonparametric Causality-in-Quantiles Approach. Department of Economics, University of Pretoria, Working Paper No. 201586

Balcilar, M., Gupta, R., Kyei, C., & Wohar, M.E. (2016). Does Economic Policy Uncertainty Predict Exchange Rate Returns and Volatility? Evidence from a Nonparametric Causality-in-Quantiles Test. *Open Economies Review*, 27, 229–250

Balcilar, M., Gupta, R., & Pierdzioch, C. (2015). Does Uncertainty Move the Gold Price? New Evidence from a Nonparametric Causality-in-Quantiles Test. Department of Economics, University of Pretoria, Working Paper No. 201592

Bartsch, Z. (2019). Economic Policy Uncertainty And Dollar-Pound Exchange Rate Return Volatility. *Journal of International Money and Finance,* 98:102067.

Belke, A., & Kaas, L. (2004). Exchange Rate Movements And Employment Growth: An OCA Assessment Of The CEE Economies. *Empirica*, 31: 247–80.

Black, F. (1976). Studies of Stock Price Volatility Changes. Proceedings of the American Statistical Association. Business and Economics Statistics, 177-181.

Bleaney, M., & Greenaway, D. (2001). The impact of terms of trade and real exchange rate volatility on investment and growth in Sub-Saharan Africa. *Journal of Development Economics*, 65, 491–500.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroscedasticity. *Journal of Econometrics, 31,* 307-327.

Broda, C., (2004). Terms of Trade and Exchange Rate Regimes in Developing Countries. *Journal of International Economics 63*, 31–58.

Bush, G., & Noria, G.L. (2021).Uncertainty and exchange rate volatility: Evidence from Mexico. *International Review of Economics & Finance, 75*, 704-722

Caldara, D., Fuentes-Albero, C., Gilchrist, S., & Zakrajšek E. (2016). The Macroeconomic Impact of Financial and Uncertainty Shocks. *European Economic Review, 88*, 185-207.

Calderón, C., & Kubota, M. (2018). Does Higher Openness Cause More Real Exchange Rate Volatility?, *Journal of International Economics, 110*, 176-204.

Cashin, P., Cespedes, L., & Sahay, R. (2004). Commodity currencies and the real exchange rate. *Journal of Development Economics*, 75, 239–268.

Colombo, V. (2013). Economic Policy Uncertainty in the US: Does it Matter for the Euro Area?. *Economics Letters, 121(1),* 39–42.

De Gregorio, J., & Wolf, H. (1994). Terms of Trade, Productivity, And The Real Exchange Rate. NBER Working Paper No. 4807.

Demirgil, H. (2011). Politik İstikrarsızlık, Belirsizlik ve Makroekonomi: Türkiye Örneği (1970-2006). *Marmara Üniversitesi İktisadi ve İdari Bilimler Dergisi, 31(2)* , 123-144 .

Devereux, M.B., & Lane, P.R. (2003).Understanding Bilateral Exchange Rate Volatility. *Journal of International Economics, 60,* 109–132

Dollar, D. (1992). Outward Oriented Developing Countries Really Do Grow More Rapidly. *Economic Development and Cultural Change*, 4, 523–54.

Dominguez, K. M. (1998). Central Bank İntervention And Exchange Rate Volatility. *Journal of International Money and Finance, 17(1),* 161-190.

Dong, H., Liu, Y., & Chang, J. (2019). The Heterogeneous Linkage Of Economic Policy Uncertainty And Oil Return Risks. *Green Finance*, *1(1),* 46–66.

Fang, L., Chen, B., Yu, H., & Qian, Y. (2018). The Importance Of Global Economic Policy Uncertainty in Predicting Gold Futures Market Volatility: A Garch-Midas Approach. *Journal of Future Markets, 38 (3),* 413–422.

Feldmann, H. (2011). The Unemployment Effect Of Exchange Rate Volatility in Industrial Countries. *Economics Letters*, *111*, 268–71.

Gupta, R., Lahiani, A., Lee, CC., & Wohar, M. (2018). Asymmetric Dynamics Of Insurance Premium: The Impacts Of Output And Economic Policy Uncertainty. *Empirical Economics, 57,* 1959–1978.

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity With Estimates Of The Variance Of United Kingdom Inflation. *Econometrica, 50(4),* 987–1007.

Ferson, W.E., & Harvey, C.R., (1991). The Variation Of Economic Risk Premiums. *Journal of Political Economy, 99,* 385–415.

Ghosh, S. (2011). Examining Crude Oil Price – Exchange Rate Nexus For India During the Period of Extreme Oil Price Volatility. *Applied Energy, 88(5),* 1886–1889.

Ghosh, Atish R. & Gulde, A-M., Ostry, J. D., & Wolf, H. C. (1997). Does the Nominal Exchange Rate Regime Matter? NBER Working Paper No. w5874.

Guney, P.O. (2020), Ekonomik Politika Belirsizliği ve Döviz Kuru Oynaklığı, *Bankacılar Dergisi, 31(114)*, 3-16.

Hall, S., Hondroyiannis, G., Swamy, P.A.V.B., Tavlas, G. & Ulan, M. (2010). Exchange-Rate Volatility and Export Performance: Do Emerging Market Economies Resemble Industrial Countries or Other Developing Countries? *Economic Modelling, 27,* 1514–1521.

Hau, H. (2002). Real Exchange Rate Volatility and Economic Openness: Theory and Evidence. *Journal of Money, Credit and Banking, 34(3),* 611–630.

Hausmann, R., Panizza, U., & Rigobon, R. (2006). The Long-Run Volatility Puzzle of the Real Exchange Rate, *Journal of International Money and Finance, 25*, 93-124

Hsieh, D. A. (1989). Modeling Heteroscedasticity In Daily Exchange Rates. *Journal of Business and Economic Statistics*, *7(3),* 307-317.

Huchet-Bourdon, M. & Korinek, J. (2011). To What Extent Do Exchange Rates And Their Volatility Affect Trade? OECD Trade Policy Papers, No. 119, OECD Publishing, Paris.

Istiak, K. and A. Serletis (2018). Economic Policy Uncertainty and Real Output: Evidence from the G7 Countries. *Applied Economics, 50(39),* 4222-4233.

Koenker, R. & Bassett, G. (1978). Regression Quantiles. *Econometrica, 46(1),* 33-50.

Krol, R. (2014). Economic Policy Uncertainty and Exchange Rate Volatility. *International Finance, 17*(2), 241–56.

Leblang, D., & Bernhard, W. (2006). Parliamentary Politics and Foreign Exchange Markets: The World According to GARCH, *International Studies Quarterly, 50(1)*, 69–92.

Leduc, S. & Liu, Z. (2016). Uncertainty Shocks Are Aggregate Demand Shocks. *Journal of Monetary Economics, 82*, 20-35.

Li, Z., Dong, H., Huang, Z., & Failler, P. (2018). Asymmetric Effects On Risks Of Virtual Financial Assets (VFAs) In Different Regimes: A Case Of Bitcoin. *Quantitative Finance and Economics, 2(4),* 860–883.

Li, Z., & Zhong. J. (2020). Impact Of Economic Policy Uncertainty Shocks On China's Financial Conditions. *Finance Research Letters,* 35:101303.

Liming C., Ziqing, D., & Zhihao H. (2020). Impact Of Economic Policy Uncertainty On Exchange Rate Volatility Of China. *Finance Research Letters*, 32: 101266

Mandelbrot, B. B. (1963). The Variation Of Certain Speculative Prices. *Journal of Business, 36(4),* 394-419.

Mueller, P., Tahbaz-Salehi, A., & Vedolin, A. (2017). Exchange Rates And Monetary Policy Uncertainty. *Journal of Finance 72*, 1213–1252.

Narayan, P. K., Narayan, S., & Prasad, A. (2008). Understanding the Oil Price-Exchange Rate Nexus for The Fiji Islands. *Energy Economics, 30(5),* 2686-2696.

Nelson, D. B. (1991). Conditional Heteroscedasticity in Asset Returns: A New Approach. *Econometrica, 59(2),* 347-370.

Nodari, G. (2014). Financial Regulation Policy Uncertainty and Credit Spreads in the US. *Journal of Macroeceonomics, 41*, 122-132

Obstfeld, M., & Rogoff, K.S. (1995). Exchange Rate Dynamics Redux. *Journal of Political Econnomics, 103(3)*, 624-660

Obstfeld, M., & Rogoff, K.S. (1996). Foundations of International Macroeconomics. The MIT Press, Cambridge, MA

Phan, D.H.B., Sharma, S.S., & Tran, V.T. (2018). Can Economic Policy Uncertainty Predict Stock Returns? Global Evidence. *Journal of International Financial Markets, Institutions and Money* 55, 134-150.

Schnabl, G. (2008). Exchange Rate Volatility And Growth İn Small Open Economies At The EMU Periphery, *Economic Systems, 32(1)*, 70-91.

Shapiro, S. S., & Wilk, M. B. (1965). An Analysis Of Variance Test For Normality (Complete Samples). *Biometrika, 52*, 591–61

Sutherland, A. (1996) Financial Market Integration And Macroeconomic Volatility, *Scandinavian Journal of Economics, 98 (4),* 521-539.

Wang, K.L., & Barrett, C.B. (2007). Estimating The Effects of Exchange Rate Volatility on Export Volumes. *Journal of Agricultural and Resource Economics, 32(2),* 225-255.

Wang, P., Li, Y., & Wu, S. (2022). Time-varying Effects of U.S. Economic Policy Uncertainty on Exchange Rate Return and Volatility in China. *Emerging Markets Finance and Trade, 58(7),* 1807-1820.

Westerfield, J. (1977). An Examination Of Foreign Exchange Risk Under Fixed And Floating Rate Regimes. *Journal of International Economics, 7(2),* 181-200.

Zhou, Z., Fu, Z., Jiang, Y., Zeng, X., & Lin, L. (2020). Can Economic Policy Uncertainty Predict Exchange Rate Volatility? New Evidence From The GARCH-MIDAS Model, *Finance Research Letters,* 34:101258

Appendix

Table A1

Data Definitions and Sources

Variables	Abbreviations	Data Sources
Nominal Effective Exchange Rate (2015:100)	NEER	Federal Reserve Bank St. Louis (FRED)
Volatility of Exchange Rate	EXVOL	EGARCH(1,1)
Global Economic Policy Uncertainty Index	GEPU	Baker et al. (2013) https://www.policyuncertainty.com/global_monthly.html
Terms of Trade (2015:100)	TOT	Turkish Statistical Institute (TSI)
Consumer Prices (2015:00)	CPI	FRED
Interest Rates (Discount interest rate)	IR	The Central Bank of the Republic of Turkey Statistics (EVDS)
Real Productivity (Industrial Porduction Index, 2015:100)	PROD	FRED

Table A2

Phillips Perron Unit Root Test Results

Variables	Phillips-Perron Test Statistics (5% Critical Values)		Result
GEPU	Level	Δ	
Trend and Constant	-4.779(-3.431)	--	I(0)
Constant	-2.016(-2.881)	-19.897(-2.881)	I(1)
None	0.329(-1.950)	-19.906(-1.950)	I(1)
NEER			
Trend and Constant	0.656(-3.431)	-10.580(-3.431)	I(1)
Constant	2.577(-2.881)	-10.420(-2.881)	I(1)
None	-3.139(-1.950)	--	I(0)
TOT			
Trend and Constant	-2.260(-3.431)	-15.967(-3.431)	I(1)
Constant	-2.141(-2.881)	-15.966(-2.881)	I(1)
None	-0.827(-1.950)	-15.956(-1.950)	I(1)
CPI			
Trend and Constant	1.533(-3.431)	-6.137(-3.431)	I(1)
Constant	1.745(-2.881)	-6.027(-2.881)	I(1)
None	9.926(-1.950)	--	I(0)
IR			
Trend and Constant	-2.072(-3.431)	-16.094(-3.431)	I(1)
Constant	-3.476(-2.881)	--	I(0)
None	-3.715(-1.950)	--	I(0)
PROD			
Trend and Constant	-4.008(-3.431)	--	I(0)
Constant	-1.045 (-2.881)	-17.395(-2.881)	I(1)
None	2.771(-1.950)	--	I(0)

Note: Null of Phillips-Perron (1988) test indicates the existence of unit root. The test uses Newey-West heteroscedasticity and autocorrelation consistent (HAC) covariance estimator. The estimated Newey-West lag truncation parameter is four.