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RESEARCH ARTICLE

Key Macroeconomic Variables under Exchange Rate Volatility: Time-Varying Causality in the Presence of Structural Breaks and Nonlinearity

Oğuz Tümtürk[1]

[1] (Doç Dr.), Ordu University Faculty of Economics and Administrative Sciences, Department of Economics, Ordu, Türkiye

ABSTRACT
This paper explores the causal relationship running from exchange rate volatility to three macroeconomic variables in the case of Turkey. To that end, we first apply the classical Granger causality test introduced by Toda and Yamamoto (1995). We also use the time-varying Granger causality test developed by Shi, Hurn, and Phillips (2020) within the lag-augmented VAR model in the presence of empirically documented structural breaks and nonlinearities. A clear pattern that can be drawn from the causality results is that the causal channel from volatility to inflation is more sustained than causality from volatility to real GDP irrespective of size of the windows and selected recursive estimation algorithms. Besides, the causal channel from volatility to inflation coincides with time periods in which Turkey exhibits political and economic policy changes and suffers from increasing economic uncertainties during financial crises. The CBRT must strictly adhere to the CBRT Law and maintain its independence in order to ensure price stability as the unconventional monetary policy dictated to the bank by the government is itself the source of inflation. Finally, exchange rate volatility does not have predictive power for interest rates over the entire sample since the CBRT uses its foreign exchange reserves to offset the adverse effects of unexpected exchange rate shocks.

Keywords: *Volatility, causality, structural break, nonlinearity*

Introduction

Since the failure of Bretton Woods in 1973, IMF members are free to choose any form of exchange rate system. From this time, a large group of countries adopted different forms of flexible exchange rate arrangements. However, the liberalization of capital flows and excessively increased cross-border financial transactions have generated high degree of volatility and uncertainty on exchange rate movements. As a result, the vast empirical exchange rate literature has been focused on exploring the relationships between exchange rates volatility and various macroeconomic variables.

The empirical exchange rate literature present numereous macroeconomic variables to explain the determinants of the exchange rate volatilities (e.g. terms of trade (Hausmann, Panizza and Rigobon, 2006; De Gregorio and Wolf, 1994), output changes (Ghosh et al.,1997; Alexius, 2005), interest rates (Mueller et al. 2017), external debt (Devereux and Lane; 2003), trade and financial openness (Obstfeld and Rogoff, 1995; Hau, 2002; Sutherland, 1996; Calderon and Kubata, 2018) and foreign reserves (Hviding et al., 2004), etc.) However, exchange rate volatility itself can be predictive of macroeconomic variables such as output and prices. Many authors have found evidence that large swings in exchange rates produce negative impacts on international trade (Peree and Steinherr, 1989; Arize et al., 2008; Lin et al., 2018; Baak et al., 2007), investments (Aghion et al., 2009; Furceri and Borelli, 2008), balance sheets of banks and enterprises (Eichengreen and Hausmann 1999), and economic growth (Aghion et al., 2009; Schnabl, 2008; Demir, 2008; De Grauwe and Schnabl, 2005). Even though the empirical literature mostly reports that exchange rate volatility can be counterproductive for output growth due to the increasing uncertainties, some authors have concluded that exchange rates simply do not matter for growth (Baxter and Stockman, 1989; Levy-Yeyati and Sturzenegger, 2003; Gadanecz and Mehrotra, 2013).

The impacts of exchange rate movements on domestic prices are measured by the pass-through effect. Empirical evidence

Corresponding Author: Oğuz Tümtürk **E-mail:** oguz.tumturk@gmail.com
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shows that a depreciation of local currency passes through to consumer prices and raises inflation (Feenstra, 1989; Hahn, 2003; McCarthy, 2007; Campa and Goldberg, 2005; Edwards, 2006). There is extensive literature on exchange rate pass-through; however, the literature exploring the effects of volatility on domestic prices remains very limited (Osabuohien et al., 2018; Adeniji, 2018; Albuquerque and Portugal, 2005). The results largely suggested that exchange rate volatilities raise prices. When future prices are hard to estimate because of the uncertainties generated by a high degree of exchange rate volatility, firms may change their prices by precautionary motive.

In the context of time series econometrics, the relationship between exchange rates and different macroeconomic variables is mostly identified by vector autoregressive (VAR) models (Kim and Roubini, 2000; Bjornland, 2009; Peersman and Smet, 2001; Kim and Lim, 2018; Grilli and Roubini, 1996, Barnett et al., 2016). VAR models estimate the impulse responses of the relevant macroeconomic variables to a one standard deviation shock in exchange rates. However, the impulse responses are generated based on widely accepted and justified recursive or nonrecursive theoretical restrictions. If such restrictions do not exist, the concept of causality developed by Granger (1969, 1988) emerges as an important statistical method in applied macroeconomics. Classical Granger causality tests assume VAR coefficients are constant with respect to time whereas encountered structural breaks may easily change the parameters and require time-varying causality analysis.

This paper investigates the causal relationship running from exchange rate volatility to three macroeconomic factors: real GDP, inflation and interest rates in the case of a developing open market economy, Turkey. To that end, we first measure the volatility of the exchange rate by the conditional variance obtained from Nelson's (1991) exponential generalized autoregressive conditional heteroscedasticity (EGARCH) model. Then, a constant parameter Granger causality test within the framework of a Lag-Augmented VAR (LAVAR) model is conducted. Since the constant parameter LAVAR model exhibits structural breaks and nonlinearities, we also follow Shi, Hurn, and Phillips (2020) and use the time-varying Granger causality analysis. To follow the time variation of Granger causality, two different recursive estimation methods are employed: the forward expanding window and the rolling window.

One major difficulty may arise when interpreting the results in time-varying causality analysis. If the statistically identified causal periods appear and disappear again over short periods of time and do not pursue any clear pattern, then it is not an easy task to assign theoretically justified causal channels to these causal periods. This paper detects several causal episodes in the Turkish economy and explains in detail how the relevant causal channels emerged based on the theoretical and empirical explanations in the exchange rate literature. To the best of our knowledge, this is the first study to analyze time-varying causality running from exchange rate volatility to the three main macroeconomic variables. Our findings showed that the classical Granger causality framework produces incorrect statistical and economic inferences due to the statistically documented nonlinearities and parameter instabilities in Turkish data. Second, exchange rate volatility has more predictive power for inflation than real GDP whereas it has never never preceded interest rates. When the minimum window size is shortened, our results provided relatively strong support for the argument that exchange rate volatility is predictive of real GDP. Finally, detected causal episodes between volatility and inflation coincide with time periods in which political and economic policy changes occur and economic uncertainty increases.

The rest of the paper is organized as follows. Section 2 gives details about the classical and time-varying Granger causal framework with recursive estimation algorithms while Section 3 includes the data and introduces the EGARCH modelling of exchange rate volatility. Structural break, nonlinearity tests and estimation results are presented in Section 4. Finally, conclusions are drawn in Section 5.

Methodology

Classical (Constant Parameter) Granger Causality and Toda-Yamamoto Approach

Granger causality simply states that a variable Xt is Granger-cause a variable Yt if past values of Xt are useful for predicting current value of Yt, conditional on past values of Yt. Consider the bivariate p-order linear vector autoregressive (VAR(p)) model with stationary Xt and Yt variables given by

$$X_t = b_1 + \Sigma_{i=1}^{p} \alpha_{1,i} Y_{t-i} + \Sigma_{i=1}^{p} \beta_{1,i} X_{t-i} + u_{x,t} \tag{1}$$

$$Y_t = b_2 + \Sigma_{i=1}^{p} \alpha_{2,i} Y_{t-i} + \Sigma_{i=1}^{p} \beta_{2,i} X_{t-i} + u_{y,t} \tag{2}$$

Where b_1 and b_2 are constants. To put it simply, suppose we investigate whether X_t is Granger-cause Y_t. Null hypothesis H_0: $\beta_{2,1} = \beta_{2,2} = \ldots\ldots = \beta 2_p = 0$ in Granger causality test states that X_t is not Granger- cause of Yt while alternative hypothesis H_a: not

H_0 refers at least one of the $\beta_{2,i}$'s are not equal to zero. If any lagged coefficients on X_t are statistically significant then Xt is said to Granger-cause of Y_t. The linear restrictions on the null hypothesis are tested by the usual Wald test. However, if some of the data in the VAR model are non-stationary, then Wald test statistics depart from its usual asymptotic chi-square distribution under the null hypothesis. To account for the possibility of integrated variables, Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996) suggest a Lag-Augmented VAR (LAVAR) model. The LAVAR approach in levels for any two variables X_t and Y_t are described as follows:

$$X_t = b_1 + \Sigma_{i=1}^{p} \alpha_{1,i} Y_{t\text{-}i} + \Sigma_{i=1}^{p} \beta_{1,i} X_{t-i} + \Sigma_{j=p+1}^{p+m} \lambda_{1,j} X_{t-j} + \Sigma_{j=p+1}^{p+m} \theta_{1,j} Y_{t-j} + u_{x,t} \tag{3}$$

$$Y_t = b_2 + \Sigma_{i=1}^{p} \alpha_{2,i} Y_{t\text{-}i} + \Sigma_{i=1}^{p} \beta_{1,i} X_{t-i} + \Sigma_{j=p+1}^{p+m} \lambda_{2,j} X_{t-j} + \Sigma_{j=p+1}^{p+m} \theta_{2,j} Y_{t-j} + u_{y,t} \tag{4}$$

where m is the maximum order of integration of the variables. Additional m lags of each variable are included in each equation in the VAR(p) model and the resulting VAR(p+m) model is estimated in levels no matter what the integration level of the variables. When the Wald test is performed, the linear restrictions are imposed on the coefficients of p lags and additional m lags are not considered to be part of linear zero restrictions. With the small correction in the test statistics, the Wald test statistic again follows an asymptotic chi-square distribution with p degrees of freedom under the null.

Time-Varying Granger Causality and Recursive Estimation Process

The classical Granger causality test follows the assumption that the VAR coefficients remain constant with respect to time. However, structural breaks due to economic and governmental policy changes or financial and political turmoils may easily change the parameters and require time-varying coefficients. Besides, the relationships between the variables may be well characterized by nonlinearities. For this purpose, we also follow time-varying Granger causality analysis and allow the VAR parameters to change in time in the presence of structural breaks and nonlinearities. Fortunately, structural breaks and nonlinear dependencies in relationships between variables can be detected based on statistical tests.

The time-varying Granger causality stands out for the cases where Granger causality between variables may be detected at one period of time, but may be sensitive with respect to different selections of subperiods. Shi, Hurn, and Phillips (2020) extended to the concept of Granger causality within the LAVAR framework and detected changes in causal relationships over time based on recursive estimation methods. We also follow Shi, Hurn, and Phillips and identify the time variation of Granger causality with following two recursive estimation methods:

i) The Forward Expanding Window (FEW): The first Wald test statistic is calculated based on the selected minimum window size, w. Then, each window is expanded sequentially by one observation. That is, the second window contains m+1 observations whereas the third one contains m+2 observations, and so on. The Wald test statistics are calculated from each expanding window until the last sample point is included by the entire sample. In the FEW algorithm, the lower bound of each expanded window is the first data point.

ii) The Rolling Window (ROW): The first Wald test statistic is again computed based on the selected minimum window size. Then, the second rolling window contains observations for the first data point through m+1, the third rolling window contains observations for the second data point through m + 2, and so on. The rolling process continues until the last data point is included by the last rolling window. Note that the Wald test statistics are sequentially calculated from a sample of the same size. The ROW algorithm refreshes the information in each window by adding the newest observation and removing the oldest one. With this set-up, the ROW procedure gives more weight to current information than the FEW procedure.

Data

This paper investigates the causality relationship running from exchange rate volatility to the three macroeconomic variables, real GDP, inflation and interest rates. For the purpose of our empirical analysis, a four-variable VAR specification is selected for monthly Turkish data over the flexible exchange rate period of 2002:M1-2022:M2. Real GDP is proxied by the industrial production index and expressed in logarithms (PROD). The inflation variable is obtained by the log-differenced consumer price index and denoted by INF. The interest rate (IR) reflects the monetary policy stance of the Central Bank of the Republic of Turkey (CBRT) and is expressed in percentage terms. The nominal effective exchange rate (NEER) is calculated as geometric weighted averages of bilateral exchange rates and expressed in logarithms. An increase in the exchange rate indicates an appreciation of the Turkish Lira against a broad basket of currencies. Finally, exchange rate volatility is denoted by VOL.[1]

Measuring Exchange Rate Volatility

Table 1. Descriptive Summary Statistics on Exchange Rate Return Series

Skewness		-1.792
Kurtosis		10.736
Shapiro-Wilk W Test Statistics[a] (p-value >z)		0.000
ARCH-LM (k) Test Statistics[b] (p-value > chi-square)	**k=1**	0.000
	k=3	0.003
	k=6	0.048

Notes: [a] The null of Shapiro-Wilk's (1965) W Test states that the return series is normally distributed.
[b] The null of Engle's (1982) ARCH-LM test states that the disturbances of return series do not have an ARCH effect up to order k.

Descriptive summary statistics on the log-differenced exchange rate data are presented in Table 1. First, the return series exhibits the usual features of GARCH-type models such as negative skewness and excess kurtosis. The negatively skewed returns suggest that more probability mass is concentrated on the right tail of the distribution. Since the estimated kurtosis is greater than three, the return series is said to be "leptokurtic. Leptokurtic distributions produce more outliers in their tails relative to a Gaussian normal. As stated by Westerfield (1977) and Hsieh (1989), leptokurtic returns tend to have "volatility clustering". More importantly, volatility clustering property in financial time series mostly produces conditionally heteroscedastic disturbances. In order to investigate whether the return series exhibits autoregressive conditional heteroskedasticity (ARCH effect) or not, a constant-only model is fitted by OLS and an ARCH-LM test is performed. The test results statistically confirm the existence of the ARCH(k) effect in the disturbances of return series at 5% significance level. Finally, volatility will be more accurately estimated by a heavy tail distribution such as Student's t, Generalized Error Distribution (GED), Laplace etc. because Shapiro-Wilk W test (1965) reports departure from Gaussian normal. Consequently, all these preliminary findings strongly suggest that exchange rate returns are well predictable by GARCH-type models with heavy tail distributions.

EGARCH Modelling of Exchange Rate Volatility

In the empirical literature, GARCH models proposed by Bollerslev (1986) are heavily used when measuring exchange rate volatility. GARCH models estimate current volatility as a function of past volatility and more importantly propose "volatility symmetry" assumption. This assumption simply states that positive and negative unanticipated shocks in foreign exchange markets produce equal impacts on current volatility. However, as stated by Black (1976) and Nelson (1991), large unanticipated negative shocks are more likely to generate higher volatility than large positive shocks of the same size (negative leverage). Hence, this paper employs Nelson's (1991) exponential GARCH model to capture the asymmetry feature of exchange rate volatility. EGARCH(1,1) model with conditional mean (5) and variance equation (6) is shown below:[2]

$$\Delta NEER_t = \alpha + \varepsilon_t \tag{5}$$

$$log(\sigma_t^2) = \delta_0 + \delta_1 z_{t-1} + \delta_2 ln(\delta_{t-1}^2) + \delta_3\left(|z_{t-1}| - \sqrt{\frac{2}{\pi}}\right) \tag{6}$$

$$\varepsilon_t = z_t\sigma_t \sim GED(0, {\sigma_t}^2, \tau) where z_t \sim iidN(0,1) \tag{7}$$

Where ε_t is the disturbance term or shocks and follows a GED distribution with a shape parameter τ. The disturbances are not

[1] For more detailed data definitions and data sources, see Appendix/Table A1.
[2] There are mainly two reasons that this study employs the EGARCH(1,1) specification. First, Akaike and Schwarz information criteria both selected one lag. Second, GARCH models with (1,1) specification is mostly used when measuring exchange rate volatility in related literature (see Bollerslev, 1986; Dominguez, 1998; Hsieh, 1989; Narayan, Narayan and Prasad, 2008; Wang and Barrett, 2007; Hall et al., 2010; Ghosh, 2011; Demir, 2013 etc.)

assumed to follow the Gaussian normal since the returns are leptokurtic as shown in Table 1. If the estimated shape parameter is less than two, then using the heavy tail GED distribution over a Gaussian normal is statistically validated. $Sigma_t^2$ is called the time-dependent conditional variance of the disturbances and expresses the volatility of the monthly exchange rate data. zt is standardized disturbances or shocks and follows the standard normal. Since standardized shocks are either positive or negative, $\delta 1$ measures volatility asymmetry. If the asymmetry term is negative then negative unanticipated shocks in the foreign exchange market generate higher volatility than positive shocks of the same size. $\delta 2$ represents the "GARCH effect" and predicts the impact of the conditional past volatility on current volatility. Finally, $\delta 3$ denotes the size impact of a shock on the current volatility.

Table 2. Estimation Results of Exchange Rate Volatility

EGARCH (1,1)		
Mean Equation		
α		-.0028***
Variance Equation		
$\boldsymbol{\delta_0}$		-4.2240**
$\boldsymbol{\delta_1}$		-.3657*
$\boldsymbol{\delta_2}$		.3851**
$\boldsymbol{\delta_3}$		.4960 **
Diagnostics		
ARCH-LM (k)Test (p-value > chi-square)	**k=1**	0.2291
	k=3	0.6716
	k=6	0.8994
Box Pierce Q_Z Test[a] (p-value > chi-square)		0.2210
Box Pierce Q_{Z^2} Test[a] (p-value > chi-square)		0.9395
Shapiro-Wilk W Test (p-value > z)		0.1522
τ		1.1249

Notes: ***, Significance at 10%; **, significance at 5%; *, significance at 1%.
(a) The null of Box-Pierce test states "no autocorrelation".

Table 2 presents estimation results of the EGARCH model. Negative and highly significant $\delta 1$ confirms the presence of negative leverage effect and hence volatility asymmetry in the data. An estimated shape parameter of less than two statistically confirms the use of heavy tail GED distribution. Positive and significant GARCH parameter $\delta 2$ suggests the persistence of past conditional volatility on current volatility. Finally, the size effect $\delta 3$ is statistically significant.

The bottom of Table 2 also documents some post-estimation diagnostics. Since zt is independent and identically (iid) normally distributed based on the distributional assumptions in the EGARCH model, the Shapiro-Wilk W test (1965) for normality is performed for the standardized disturbances. The test results confirm that zt is normally distributed. Q_z and Q_z^2 represent the Box-Pierce Q-statistic to test white noise for standardized disturbances and the squared standardized disturbances, respectively. The test results cannot reject the null of "no autocorrelation". Additionally, the ARCH-LM test reports that standardized disturbances are free from the ARCH(k) effect. Overall, the EGARCH (1.1) process provides a good fit for Turkish exchange rate data.

Unit Root Tests

Before implementing the classical Granger causality tests, the order of integration of the variables will be empirically determined. For this purpose, two unit root tests are implemented: the Augmented Dickey-Fuller (ADF) (1979) unit root tests without structural breaks as formal assessments of stationarity and Zivot-Andrews (1992) unit root tests based on the principle of endogenous determination of a single structural break. Test results are presented at Tables 3 and 4.[3] All test results reveal that the maximum order of integration of the series is one (m=1). Since not all the series in the VAR model are stationary, the LAVAR model framework will be conducted to account for the existence of integrated variables based on Toda and Yamamoto (1995) and Dolado and Lütkepohl (1996).

[3] Two additional unit root tests are also conducted: Phillips-Perron (PP) (1988) unit root tests and Clemente, Montanes, Reyes (1998) unit root tests with two endogenous breaks. Both test results showed that the maximum order of integration level of the series remained same. The results are available upon request.

Table 3. Augmented Dickey Fuller Unit Root Test Results

		ADF TEST (5% Critical Values)		Test Result
		Level	Δ	
PROD	Constant and Trend	-2.900(-3.432)	-8.821 (-3.432)	I(1)
	Constant	-0.774(-2.881)	-8.838 (-2.881)	I(1)
	none	-3.135(-1.950)	---	I(0)
INF	Constant and Trend	-3.115(-3.431)	-12.131(-3.432)	I(1)
	Constant	-2.765 (-2.881)	-11.944(-2.881)	I(1)
	none	-1.403(-1.950)	-11.924(-1.950)	I(1)
VOL	Constant and Trend	-14.685(-3.431)	--	I(0)
	Constant	-14.608(-2.880)	--	I(0)
	none	-13.471(-1.950)	--	I(0)
IR	Constant and Trend	-2.433(-3.431)	-11.646 (-3.431)	I(1)
	Constant	-3.919 (-2.881)	--	I(0)
	none	-4.110(-1.950)		I(0)

Notes: The null hypothesis of ADF test states the existence of unit root. The optimum lag level is selected based on the following three criteria: Akaike information criterion (AIC), Schwarz information criterion (SIC), and Hannan-Quinn information criterion (HQIC). The lags most often suggested by the above criteria were selected as optimal lag levels. The optimum lag level is four for PROD, three for INF, zero for VOL and one for IR.

Table 4. Zivot-Andrews Unit Root Test Results

	Break	Level Minimum T- Statistic (5% Critical Value)	Δ Minimum T- Statistic (5% Critical Value)	Test Result
PROD	Trend	-3.269(-4.42)	-11.630(-4.42)	I(1)
	Intercept	-3.433(-4.80)	-11.646(-4.80)	I(1)
	Intercept and Trend	-3.847(-5.08)	-11.826 (-5.08)	I(1)
INF	Trend	-5.809(-4.42)	--	I(0)
	Intercept	-4.252(-4.80)	-12.318(-4.80)	I(1)
	Intercept and Trend	-6.211(-5.08)	---	I(0)
VOL	Trend	-14.776(-4.42)	--	I(0)
	Intercept	-15.020(-4.80)	--	I(0)
	Intercept and Trend	-15.564(-5.08)	--	I(0)
IR	Trend	-3.409(-4.42)	-7.463(-4.42)	I(1)
	Intercept	-2.906(-4.80)	-7.786(-4.80)	I(1)
	Intercept and Trend	-2.944(-5.08)	-7.909(-5.08)	I(1)

Notes: The null of the Zivot-Andrews test indicates the existence of a unit root. The test results are reported based on three models: break in trend, break in intercept and break in both. The break date is selected where the t-statistic from the ADF test of unit root is at minimum. The optimum number of lag is selected via t-test and is three for PROD, two for INF and zero for both VOL and IR.

Estimation Results

Constant Parameter Granger Causality Test Results

To carry out the classical Granger causality test, the optimal VAR specification must be determined. The max lag length is set to twelve and optimum lag length of p was chosen based on AIC, SIC and HQIC. The lag length p=1, most often selected by the three criteria, was included in the VAR model. Exogenous deterministic components of the VAR(1) model - both a constant and a time trend - are also determined by the above criteria. The Lagrange Multiplier (LM) test at the lag level p=1 revealed that the disturbances of the VAR(1) model are free from autocorrelation. The selected VAR model satisfies the stability condition because all the eigenvalues lie inside the unit circle.[4] As the maximum order of integration level of the series is one, the VAR(1) will be augmented by extra one lag. As a result, the resulting model is denoted by VAR(1+1).

Table 5 summarizes the constant parameter Granger causality test results. The Granger causality Wald tests detect a causal relationship from exchange rate volatility to inflation. However, the null of no causality from volatility to real GDP and interest rates cannot be rejected. Now, we can ask the following question: Can the presence of structural breaks and nonlinearities in

[4] The stability test results can be seen in Appendix/Table A2

Table 5. Constant Parameter Granger Causality Test Results

Null Hypotheses	Degree of Freedom, v	Chi-Square Test Statistics	P-Value > Chi-Square
VOL is not Granger-cause of PROD	1	.7749	0.379
VOL is not Granger-cause of INF	1	7.5075	0.006
VOL is not Granger-cause of IR	1	.0087	0.925

Notes: Classical Granger causality test results based on the LAVAR model with p=1, m=1 and a trend. The degree of freedom is one because the second lag enters the LAVAR system as an exogenous variable.

the relationship between the variables of interest invalidate the statistical and economic inferences obtained from the constant parameter Granger causality tests? We will conduct the following structural break and nonlinearity tests to be able to answer this question statistically.

Structural Break Tests

Considering the relatively long study period of the paper, the relationships between the variables are more likely to encounter structural breaks. For this purpose, we first test structural breaks and examine the parameter stability of each one of the four equations in the LAVAR model. Andrews (1993), and Andrews and Ploberger (1994) proposed a parameter stability test of whether the coefficients in a time-series regression vary over the periods. The test can be either a Wald or a Likelihood Ratio (LR) test. The supremum, an average, or the exponential of the average of the tests are calculated at each possible break date. However, it is not possible to consider each sample point as a break date since the break dates too near the starting or the ending points of the samples will have insufficient observations for estimation. To deal with the identification problem, we follow Andrews' (1993) advice and use symmetric trimming of 15%. Therefore, the parameter stability test covers [0.15 0.85] of the our entire sample. The LR and Wald test results are reported in Tables 6 and 7, respectively. The Supremum, Average, and Exponential LR and Wald test results almost always reject the null hypothesis of no structural break. This result provides strong statistical evidence that the parameters estimated from the LAVAR model do not remain constant over time (parameter instability). It is important to note that these results are obtained from the trimmed sample, and it is also very likely to encounter break dates in the first and last 15

Table 6. Structural Break Tests, LR Test Results

Dependent Variable	Supremum LR test P-Value	Average LR test Prob. P-Value	Exponential LR Test P-Value
PROD	0.000	0.004	0.000
INF	0.003	0.001	0.002
VOL	0.000	0.367	0.000
IR	0.000	0.001	0.000

Note: The null hypothesis states no structural break

Table 7. Structural Break Tests, Wald Test Results

Dependent Variable	Supremum Wald test P-Value	Average Wald test P-Value	Exponential Wald Test P-Value
PROD	0.000	0.006	0.000
INF	0.003	0.002	0.003
VOL	0.000	0.437	0.000
IR	0.000	0.002	0.000

Note: The null null hypothesis states no structural break

Nonlinearity Tests

In the preceding section, equations in the constant parameter LAVAR model are shown to be exposed to structural breaks. Besides, the relationships between the variables of interest may be nonlinear, which invalidates the linear structure of the model. To deal with the issue of nonlinearity, we conduct Brock, Dechert, and Scheinkman (BDS) test proposed by Brock et al. (1987) and Brock et al. (1996). The null hypothesis of the test states that the disturbances are independent and identically distributed. However, when implemented to the disturbances from a fitted linear time series model, the BDS test can be employed to reveal remaining dependence and the presence of omitted nonlinear structure (Zivot and Wang, 2006). If the null hypothesis is rejected, then the fitted linear model is mis-specified and it can be concluded that a nonlinear relationship exists.

The BDS test is implemented on the disturbances of each equation in the LAVAR model to detect nonlinear dependence in time-series data with different correlation dimensions (d) of the process. The test results are presented in Table 8. When the dependent variables are INF, VOL and IR, the null hypotheses that residuals are independent and identically distributed are always rejected irrespective of the correlation dimensions. These test results strongly confirm the nonlinearities in the relationship between the variables.

Table 8. Structural Break Tests, Wald Test Results

Dependent Variable: PROD			Dependent Variable: INF		Dependent Variable: VOL		Dependent Variable: IR	
Correlation Dimension (d)	BDS Test Statistics	P-Value	BDS Test Statistics	P-Value	BDS Test Statistics	P-Value	BDS Test Statistics	P-Value
2	0.000	0.936	0.020	0.004	0.026	0.000	0.053	0.000
3	0.000	0.936	0.034	0.004	0.040	0.000	0.085	0.000
4	0.000	0.924	0.039	0.004	0.042	0.000	0.095	0.000
5	0.000	0.928	0.048	0.000	0.044	0.000	0.093	0.000
6	0.000	0.896	0.049	0.000	0.047	0.000	0.081	0.000

Not: The p-values for the BDS test statistics are the bootstrapped p-values based on 500 repetitions.

Time-Varying Granger Causality Test

Whole Sample Analysis

Since the preceding section presented empirical evidence that the constant LAVAR model exhibits parameter instabilities and nonlinearities, we also follow time-varying Granger causality analysis. The null hypothesis for the whole sample analysis is that exchange rate volatility is not the Granger-cause of the relevant macroeconomic variable at any time during the entire sample.

The time-varying causality results with the minimum window size of 72 months are reported in Table 9. Both FEW and ROW maximal Wald test statistics reject the null of no Granger causality from volatility to inflation at any time during the sample. Similarly, the ROW algorithm finds evidence of Granger causality from volatility to GDP at some point in the sample. Finally, the two recursive estimation algorithms confirmed that volatility of the exchange rate is not the Granger-cause of interest rate over the entire sample. The last result is not unexpected as the CBRT does not use an interest rate policy to drive or protect the value of the Turkish lira. Under the executed current monetary policy, the bank conducts foreign exchange transactions including spot or forward purchases and sales and foreign exchange swaps to render the economy resilient against unexpected exchange rate shocks. Consequently, the causal channel from volatility to interest rate has never appeared. Finally, recall that constant parameter causality analysis does not suggest a causality from exchange rate volatility to real GDP. However, when considering the hidden structure of structural breaks and nonlinearities, the causal relationship that could not be statistically detected earlier is apparent now.

Table 9. Time-varying Granger Causality Test Results, Whole Sample

Null Hypotheses	Minimum window size (w)	Maximal Wald Test Stat. FEW	Maximal Wald Test Stat. ROW
VOL is not Granger-cause of PROD at any time during the whole sample	72	4.694 (10.095)	11.141 (10.880)
VOL is not the Granger-cause of INF at any time during the whole sample	72	18.969 (14.365)	36.170 (14.699)
VOL is not Granger-cause of IR at any time during the whole sample	72	3.112 (11.666)	3.069 (12.301)

Notes: Time-varying Granger causality analysis based on the LAVAR model with p=1, m=1 and a trend. The 5% bootstrapped critical values based on 500 repetitions are shown in parentheses. Maximal Wald test statistics are robust to heteroskedasticity.

Graphical Examination

Now, the sequence of maximal Wald test statistics and critical values from the each recursive estimation algorithm can be graphically analysed to examine how the causal relationships vary over time. Figure 1 plots the sequence of Wald test statistics and associated 5% bootsrapped critical values based on the minimum window size set at 72 months. Additionally, Table 10 reports the time intervals of causal periods identified in Figure 1.

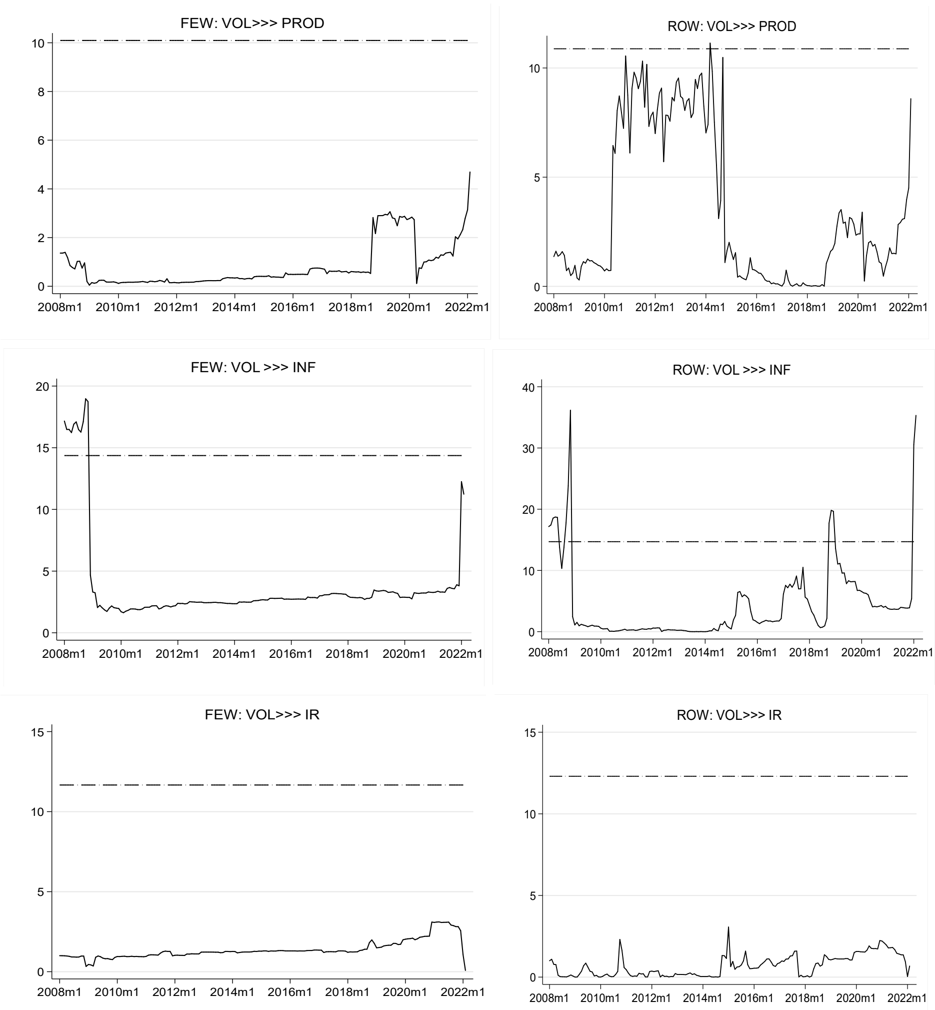


Figure 1. Time-varying Granger Causality Test Statistics and Critical Values Over Time, w=72

Note: Time-varying Granger causality tests from VOL to PROD, INF and IR, respectively with a minimum window size of 72 months The left column plots the Wald test statistics and 5% bootsrapped critical values obtained from the FEW algorithm, whereas right column reports the Wald test statistics and 5% bootstrapped critical values obtained from the ROW algorithm

As shown in Figure 1 and Table 10, the maximal ROW test statistic detects causality from exchange rate volatility to real GDP at only one sample point, 2014:M3. When this result is considered with the FEW result that reports no causality over time, we can conclude that there is very little support for the argument that volatility precedes real GDP. A possible explanation relates to the fact that real macroeconomic aggregates are determined by real variables in the longer run. This result is consistent with some of the existing studies. Gadanecz and Mehrotra (2013) concluded that exchange rate volatility does not exert a statistically significant impact on long-run growth. Additionally, Baxter and Stockman (1989) found no evidence that output depends on the exchange rates and suggested the real models of determination of output. Similarly, Levy-Yeyati and Sturzenegger (2003) documented that exchange rates do not appear to have any significant impact on growth.

In contrast to real GDP results, the FEW and ROW maximal Wald test statistics reveal a longer causal relationship from volatility to inflation. As shown in Table 10, both test procedures identify a causal episode in 2008. Besides, the ROW test statistic extends this casual relationship with two additional causal episodes: 2018:M10-2018:M12 and 2022:M1-2022:M2. Now, let us explore them in more detail.

The first causal episode is detected for most of 2008. What happened in the first causal episode was that the global financial crisis after the bursting of the US housing bubble also hit Turkey.[5] The Turkish economy suffered significantly from the financial crisis, as measured by a decline in the real GDP between the beginning of 2008 and mid–2009. Unfortunately, the initial impact of the 2008-2009 crisis on Turkey was the biggest among the OECD countries (Rawdanowicz, 2010).

The second causal episode (2018:M10-2018:M12) coincides with three important incidents: one of the most important political milestones in Turkey's political history, the 2018 financial crisis and US economic sanctions on the Turkish economy. Turkish President Recep Tayyip Erdogan transformed the country's long-standing parliamentary system into a heavily centralized and strengthened "Presidential System of Government" introduced in July 2018. Besides, the economic growth collapsed again in the third and fourth quarter of 2018. The value of the Turkish lira significantly eroded as a result of an excessive amount of current account deficits and private foreign-currency-denominated debts. Finally, following the detention of the US citizen pastor Andrew Brunson in Turkey, the Trump administration imposed economic sanctions and doubled the tariffs on Turkish steel and aluminium imports, which also accelerated the rapid fall in the Turkish lira.

Table 10. Time-varying Granger Causality Test and Identified Causal Episodes, w=72

	FEW Algorithm	ROW Algorithm
VOL >>> PROD	---	1) 2014:M3
VOL >>> INF	1) 2008:M1-2008:M11	1) 2008:M1-2008:M5 and 2008:M9-2008:M11
		2) 2018:M10-2018:M12
		3) 2022:M1-2022:M2

Note: The dates include the causal episodes that Wald test statistics that exceed 5% critical values.

The last causal episode (2022:M1-2022:M2) emerged after the conducted unconventional monetary policy performed by interest rate cuts despite the increasing inflation rates. The CBRT Law introduced in April 2001 (Article 4) states that "*The primary objective of the CBRT is to achieve and maintain price stability. The Bank determine on its own discretion the monetary policy that it will implement and the monetary policy instruments that it is going to use in order to maintain price stability.*" President Erdogan, however, has been a strong supporter of the unconventional hypothesis that reducing interest rates lowers the inflation rate. The Erdogan administration has officially announced that Turkey adopted the 'Chinese Growth Model' as a new economic plan in December 2021. The mainstay of the new plan was to reduce interest rates as quickly as possible since low interest rates were considered to decrease the value of the Turkish lira and hence stimulate export, production and employment levels of the country. Even though the primary objective of the CBRT is to ensure price stability, the bank which has been independent since 2001 eventually could not resist the political pressure to loosen the monetary policy. The policy rate, which was 19% in September, 2021 was reduced to 14% at the end of December 2021 despite the accelerating inflation rates. The CBRT's policy rate became much lower than the rapidly rising inflation rates and inflation expectations. The negative real interest rates triggered the pressure on Turkish Lira due to the long-standing current deficits, tightening global monetary policies and high political tension in the country. Rapidly rising inflation and negative interest rates also led Turkish citizens and companies to continue saving in US dollars and other major currencies. Consequently, the Turkish Lira had precipitous falls against a very large group of currencies. With the aim of supporting the value of the lira and reversing dollarization, the government announced a new financial investment account in December, 2021 to encourage customers (citizens, corporations and non-resident Turkish nationals) to switch their foreign-exchange deposits to exchange-rate-protected Turkish lira time deposits. If the depreciation rate of the exchange rate on the customer's new holdings exceeds the gains of the interest rate on the lira, the authorities will cover the cost. In the few hours following the announcement, the Turkish lira appreciated by 30% against the US dollar and other major currencies.

Figure 2 plots the exchange rate volatility measured by the EGARCH process in Section 3.1. First, note that all three causal episodes in Figure 1 perfectly match with the periods of excessive volatilities. This result empirically shows that the causal channels running from volatility to inflation appear when the exchange rate is excessively volatile. One can conclude that there seems to be a threshold point beyond which exchange rate volatility starts to hurt the price stability objective.

Now, a natural question then arises: Why are all three episodes associated with excessive exchange volatilities? This is important since the answer may help us to find a clear pattern to explain under what conditions a causal link from volatility to inflation appears. The first causal episode between volatility and inflation coincides with a period of increasing economic uncertainties due to the 2008-2009 financial crisis. In exchange rate literature, there exists a large amount of studies to investigate the effects

[5] According to the NBER business cycle dates, the financial crisis in the US lasted from December 2007 to June 2009.

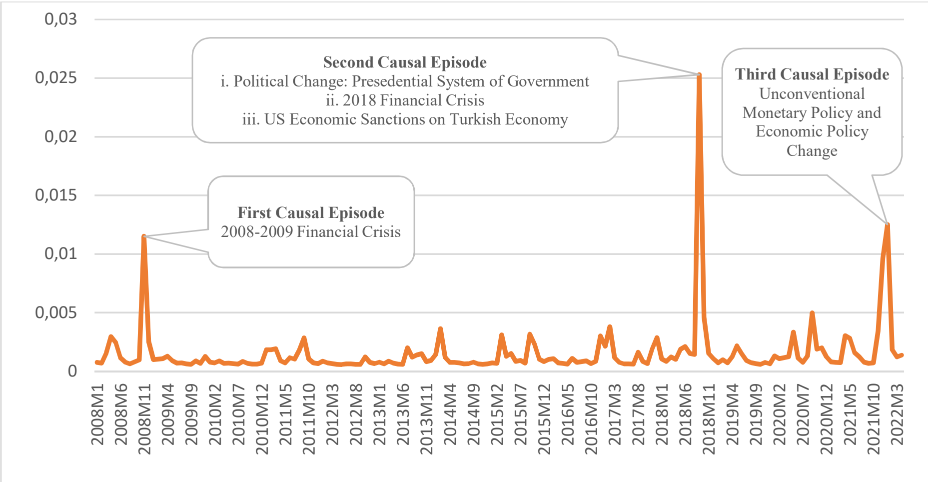


Figure 2. EGARCH (1,1) Modelling of Monthly Exchange rate Volatility

of uncertainty on exchange rate volatility. Balcılar et al. (2016), Krol (2014) 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), Leduc and Liu (2016) and many others documented a causal relationship from economic uncertainty to exchange rate volatilities. Besides, the transmission mechanism behind the link between uncertainty and exchange rate volatility can be theoretically explained by macroeconomic fundamentals. Exchange rates are determined by economic fundamentals such as prices, output, money supply, interest rates etc. An increase in uncertainty will therefore change the expectations of economic agents on the fundamentals and generate higher exchange rate volatilities.

The second causal episode contains the most exceptional political change in Turkey's political history and another financial crisis with increasing uncertainties. As stated by Leblang and Bernhard (2006), currency traders are uncertain about the future of government policies during periods of political change, and hence these periods will exhibit higher volatilities. Finally, the last causal episode generated an excessive amount of exchange rate volatilities due to the i) unconventional monetary policy dictated by the Erdogan administration to the CBRT and ii) economic policy change which has targeted output and employment level instead of price stability objective set in the CBRT Law.

A clear pattern that can be drawn from the results is that the causal channel from volatility to inflation opens up when Turkey exhibits political and economic policy changes and suffers from increasing economic uncertainties during the financial crises. Excessive exchange rate volatilities generate uncertainties on the exchange rate movements and hence the production cost of domestic goods since the import content of domestic goods is very high in Turkey. Higher uncertainty in production costs makes the future prices of firms difficult to predict. As an insurance, firms can change their prices by a precautionary motive (Redl, 2015).

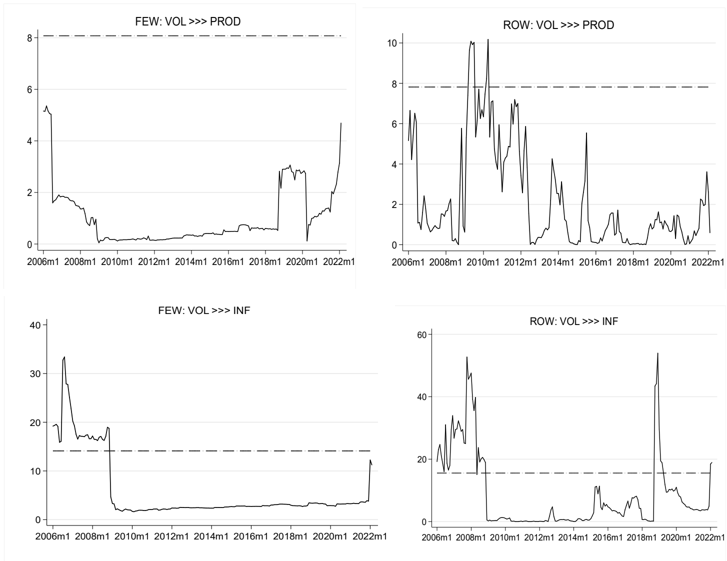
Table 11. Time-varying Granger Causality Test Results, Whole Sample

Null Hypotheses	Minimum window size, (w)	Maximal Wald Test Stat. FEW	Maximal Wald Test Stat. ROW
VOL is not the Granger-cause of PROD at any time during the whole sample	w: 48	5.356 (8.077)	10.179 (7.816)
VOL is not the Granger-cause of INF at any time during the whole sample	w: 48	33.404 (14.118)	53.970 (15.546)
VOL is not the Granger-cause of IR at any time during the whole sample	w: 48	3.112 (11.524)	4.109 (12.980)

Notes: Time-varying Granger causality analysis based on the LAVAR model with p=1, m=1 and a trend. The 5% bootstrapped critical values based on 500 repetitions are shown in parentheses. Maximal Wald test statistics are robust to heteroskedasticity.

Now, the maximal Wald test statistics were recomputed with a minimum window size of 48 months to control the validity of the argument that volatility may have more predictive power for real GDP in the shorter run. The time-varying causality test results are reported in Table 11. Figure 3 plots the sequence of maximal Wald test statistics and associated 5% critical values with respect to time while Table 12 documents the time intervals of causal periods identified in Figure 3.

First, consider the causality test results running from volatility to real GDP. While there is very little support for the argument that volatility is predictive of real GDP in Figure 1, the ROW test procedure in Figure 3 now identifies a relatively stronger causal



Note: Time-varying Granger causality tests from VOL to PROD and INF, respectively with a minimum window size of 48 months. Since no causality from VOL to IR were reported as shown in Table 11, the relevant causality graphs over time were not presented. The left column plots the Wald test statistics and 5% bootstrapped critical values obtained from the FEW recursive estimation algorithms while the right column reports the Wald test statistics and 5% bootstrapped critical values obtained from the ROW recursive estimation algorithm.

Figure 3. Time-varying Granger Causality Test Statistics and Critical Values Over Time, w=48

channel toward the end of the 2008-2009 financial crisis. There are several interesting features in these results. First, when we shorten the minimum window size, volatility gains more predictive power for real GDP. A possible explanation for this result is that real macroeconomic variables can be driven by monetary variables in the shorter run. This result is consistent with the results of Razin and Rubinstein (2006) who also concluded that exchange rate and capital-market liberalization regimes have both a direct effect on short-term growth rates. However, our finding cannot be generalized beyond the 2008-2009 financial crisis as excessive exchange rate volatilities observed in Figure 2 do not open another causal channel running from volatility to real GDP. Second, it is theoretically reasonable that the causal channel emerges at the end of the financial crisis since industrial production is expected to react with a delay to changes in the financial environment as a result of high adjustment costs to production (Bjornland, 2009; Barnett et al., 2016; Kim and Lim, 2018; Peersman and Smets, 2001; Kim and Roubini, 2000).

Table 12. Time-varying Granger Causality Test and Reported Causal Episodes, w=48

	FEW Algorithm	**ROW Algorithm**
VOL >>> PROD	---	1) 2009:M4-2009:M7 and 2010:M3-2010:M4
VOL >>> INF	1) 2006:M1-2008:M11	1) 2006:M1-2008:M11 2) 2018:M10-2019:M3 3) 2022:M1-2022:M2

Note: The dates include the causal episodes that Wald test statistics exceed 5% critical values.

The causal effects of volatility on inflation and interest rates are almost identical to those obtained in Figure 1. The causal channel from volatility to inflation is again more sustained than causality from volatility to real GDP. Similarly, both test procedures still identify a causality for most of 2008 while the ROW results detect additional two causal episodes: 2018:M10-2019:M3 and 2022:M1-2022:M2. This result is particularly of interest because it suggests that monetary factors have more predictive power on nominal aggregates than real aggregates irrespective of the window sizes. Finally, there is still no support for the argument that volatility is predictive of interest rates. Consequently, the causality results running from volatility to inflation and interest rates are robust to the selection of different minimum window sizes. [6]

Concluding Remarks

This paper investigates the causal relationship running from exchange rate volatility to the three macroeconomic variables: real GDP, inflation and interest rate using monthly Turkish data. Exchange rate volatility is measured by Nelson's (1991) exponential

[6] The Wald test statistics and 5% critical values were also recomputed with even a shorter window size of 36 months as a robustness check. The conclusions drawn from the graphical examination are identical to those obtained from a minimum window size of 48 months. More specifically, the ROW test again identifies a causality

GARCH model to capture the asymmetric characteristic of volatility. Significant and negative asymmetry parameter suggested that the negative unexpected news in Turkish foreign exchange market generates more volatility than positive unexpected news. This result is quite consistent with what has been observed in the Turkish foreign exchange market. We then conducted the classical constant parameter Granger causality analysis. In the presence of empirically documented structural breaks and nonlinearities, the time-varying Granger causality analysis with the recursive estimation methods is also employed. The results obtained from the Granger causality framework can be summarized as follows:

i. Comparing the constant parameter and time-varying Granger causality test results showed that ignoring the presence of parameter instability and nonlinearity leads to incorrect statistical and economic inferences.

ii. Exchange rate volatility is not the Granger-cause of interest rates. This result is robust to conducted classical or time-varying causality tests and different selections of minimum window sizes. Our finding is completely reasonable since the CBRT uses its foreign exchange reserves and foreign exchange swaps to offset the adverse effects of excessive exchange rate shocks. As a result, we can expect volatility to be more likely to have predictive power for foreign reserves.

iii. We empirically showed that the causality periods running from volatility to inflation appear when the exchange rate is excessively volatile. Hence, we can conclude excessively volatile exchange rate is predictive of inflation. The causal channel opens when Turkey exhibits political and economic policy changes and suffers from increasing economic uncertainties during the financial crises. The causality running from volatility to inflation is more sustained than causality from volatility to real GDP irrespective of the size of the windows and selected recursive estimation algorithm. This result also implies that monetary factors have more predictive power on nominal changes in the economy than real changes.

iv. The CBRT must decisively adhere to the CBRT Law and maintain its independence in order to ensure price stability because the unconventional monetary policy dictated to the bank by the government is itself the source of inflation.

v. When we expand the minimum window size, the predictive power of exchange rate volatility for real GDP weakens and volatility almost never precedes real GDP. However, this result is not robust to the selection of shorter minimum window sizes. When the selected minimum window size is reduced, exchange rate volatility appears to have more predictive power for GDP. This result can be explained by distinction between short-run and long-run determination of output. That is, determination of output level can be well-explained by real variables over the longer run; however, monetary factors can produce shorter run real impacts.

vi. Volatility is predictive of real GDP at the end of the 2008-2009 financial crisis. The causality appears toward the end of the crisis due to the high adjustment costs to production. This result cannot be generalized beyond the 2008-2009 financial crisis because excessive exchange rate volatilities observed in the following periods do not open another causal channel running from volatility to real GDP. Since the shorter minimum window size detects the causal episode around the 2008-2009 financial crisis, we can suggest that the volatility of the exchange rate in Turkey has been preceded by 2008-2009 financial crisis.

Table 13. A1: Data Definitions and Sources

Variables	Abbreviation	Source
Nominal Effective Exchange Rate (2015:100)	NEER	Federal Reserve Bank St. Louis (FRED)
Volatility of Exchange Rate	VOL	EGARCH(1,1)
Inflation	INF	The inflation variable is calculated as the logged difference of CPI data (2015:100). CPI data is obtained from the FRED database.
Interest Rates	IR	It is the discount rate of the CBRT and obtained from the bank's electronic data delivery system (EDDS)
Industrial Production Index, (2015:100) (seasonally adjusted)	PROD	FRED

Note: All variables except the industrial production index are seasonally adjusted by the TRAMO-SEATS seasonal adjustment method. The industrial production index is available in a seasonally adjusted format in FRED database.

Table 14. A2: Eigenvalue Stability Condition

Eigenvalue	Modulus
0.974	0.974
0.853	0.853
0.561	0.561
0.012	0.012

Note: VAR(1) satisfies the stability condition as all the eigenvalues lie inside the unit circle

Peer Review: Externally peer-reviewed.

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ORCID:

Oğuz Tümtürk 0000-0002-1935-0858

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