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EXPLORING THE LONG-TERM EXCHANGE RATE VOLATILITY IN TURKEY: EVIDENCE FROM A GARCH-MIDAS MODEL*

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Abstract

This study aims to understand the dynamics of long-term exchange rate volatility in Turkey grounded on a mixed data sampling model and see how macroeconomic fundamentals stand for the long-term component of volatility under the floating regime period i.e., for the post-2001 episode. More specifically, we employ the GARCH-MIDAS model to link series sampled at different frequencies and obtain short- and long-term components of volatility. We estimate the model by replacing the realized volatility with exogenous regressors. We control the Beta weights and estimate the model under different samples and for various variables for robustness. Also, we employ the ARDL model to see the long-run relation when series are sampled at the same frequency. We find that the long-term volatility features a high degree of persistence pattern, and the volatility patterns partially occur to absorb shocks to macroeconomic variables.

Keywords: GARCH-MIDAS Model; Exchange Rates; Volatility; Turkey

JEL Classification: E58; F31; G10

TÜRKİYE'DEKİ UZUN DÖNEMLİ DÖVİZ KURU VOLATİLİTESİNİN ARAŞTIRILMASI: BİR GARCH-MİDAS MODELİ ÜZERİNDEN KANIT

Özet

Bu çalışma, karma veri örnekleme modelini kullanarak Türkiye'deki uzun dönemli döviz kuru oynaklığının dinamiklerini anlamayı ve 2001 sonrası serbest kur rejimi döneminde makroekonomik temel değişkenlerin oynaklığın uzun vadeli bileşenini nasıl temsil ettiğini görmeyi amaçlamaktadır. Daha spesifik olarak, farklı frekanslarda örneklenen serileri ilişkilendirmek ve kısa ve uzun vadeli oynaklık bileşenlerini elde etmek için GARCH-MIDAS modelini kullanmaktayız. Gerçekleşen oynaklığı dışsal açıklayıcı değişkenlerle değiştirerek model tahminini gerçekleştirmekteyiz. Beta ağırlıklarını kontrol edip ve modeli farklı örnekler altında ve çeşitli değişkenler için tahmin etmekteyiz. Ayrıca, seriler aynı frekansta örneklendiğinde uzun dönemli ilişkiyi görmek için ARDL modelini kullanmaktayız. Uzun vadeli oynaklığın yüksek derecede kalıcılık özelliğine sahip olduğunu ve oynaklık modellerinin kısmen makroekonomik değişkenlere yönelik şokları absorbe etmek için ortaya çıktığını gözlemlemekteyiz.

Anahtar Kelimeler: GARCH-MİDAS Modeli; Döviz Kurları; Volatilite; Türkiye

JEL Sınıflandırması: E58; F31; G10

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1. Introduction

Most financial time series feature relative tranquil episodes followed by phases of high volatility. The exchange rates are not exceptions to this case. Even though exchange rate volatility essentially behaves as a random-walk process in the short-term periods (Enders, 2014), it may exhibit a clustering pattern in the long-term periods. By using primarily volatility models, this clustering behavior is related to and explained by many factors including economic activity, nominal prices, policy innovations, speculative behaviors, external innovations, and persistence of volatility (see Hausmann et al., 2006; Ganguly and Breuer, 2010; Giannellis and Papadopoulos, 2011; Cevik et al., 2015, among others). Engle et al. (2009; 2013) recently contributed to the analysis of volatility based on the component models to better depict the clustering dynamics of the financial volatility and determine the economic sources of the volatility. They introduce short- and long-term components to the volatility formation and relate the low-frequency macroeconomic data with the high-frequency financial data with the mixed data sampling (MIDAS). In this study, we follow these recent contributions' lead and explore the economic sources of the long-term component of volatility for the Turkish economy. The assumption will be that the exchange rate and its volatility are endogenous to macroeconomic fundamentals. We adopt the GARCH-MIDAS model to directly link the macroeconomic factors and exchange rates sampled at different frequencies. The model combines a GARCH (1,1) model with mean reversion and MIDAS polynomial with low-frequency data. The model prevents the loss of information while using samples at different frequencies.

While the devastating effects of exchange rate volatility on the Turkish economy are quite tangible (see Demir, 2010), there is a significant gap in the literature in examining to what extent the exchange rates fluctuate beyond absorbing the shocks to the domestic macroeconomic factors. The existing literature is relatively sparse and essentially builds upon particular aspects of the economy for affecting the exchange rate and its volatility. Among these studies, Özlü and Ünalmış (2012) find evidence that exchange rates are more responsive to surprises to the current account balance and policy rates, while those to inflation and output do not lead to significant responses on exchange rates. In the transmission of interest rate shocks to the foreign exchange volatility, Tuna (2011) finds that overnight interest rate differentials are effectively used to mitigate the volatility, while in Aysoy and Küçükkocaoğlu (2016), it is argued that rises in policy rates augment the exchange rate volatility. Also, Oduncu et al. (2013) advocate the reserve option mechanism under the multiple-policy framework of the Central Bank of the Republic of Turkey (CBRT) to effectively reduce the exchange rate volatility. Herrera and Özbay (2005) and Tuna (2011) argue that central bank intervention operations in Turkey lead to higher volatility, while Akgül and Sayyan (2008) and Aysoy and Küçükkocaoğlu (2016) find the inability of foreign exchange interventions in affecting the exchange rate volatility. This study aims to contribute to the formation of long-term exchange rate volatility in Turkey for the period between 2001:3 and 2020:2 in various aspects. First, we analyze the sources of the exchange rate volatility using a number of economic series sampled at different frequencies which enables us to prevent potential loss of information grounded on the MIDAS sampling. Second, to the best of our belief, this study is the first one that examines the long memory of the exchange rate in Turkey. That is, we aim to resolve the short-term and long-term components of exchange rate volatility and associate the latter with the economic activity for Turkish economy. Third, contrary to the Turkish literature that centers upon certain aspects of macroeconomic fundamentals in affecting the exchange rate volatility, we consider and compare a wide range of regressors for their impacts on the volatility calculating the magnitude of each particular impact. We consider such a comparison of estimates under different specifications and periods, and for various regressors as quite elucidative in drawing policy implications.

For the rest of the chapter, we provide the theoretical framework and the literature review in Section 2. In Section 3, we introduce the methodology of the GARCH-MIDAS model and the data set. In Section 4, we control for the model fit by estimating GARCH-MIDAS the model, drawing Beta weights and distribution of errors. Then, we estimate the model with selected macroeconomic variables replacing the realized volatility with exogenous regressors. Lastly, we estimate an ARDL model for robustness and employ a bounds test at the monthly frequency. Section 5 concludes.

2. Theoretical framework and literature

The exchange rate volatility can be explained by the sluggish price adjustment mechanism (Mussa, 1986). The volatility is thus assumed to behave differently in the short-term and long-term. It will not be the real exchange rates but the nominal ones to be affected by the monetary (or price) shocks in the long term as provided by the money neutrality assumption (Clarida and Gali, 1994). Also, the volatility formation itself includes two broad components: the short-term component that can be associated with short-lived factors and that behaves as a random-walk process at high frequency (Enders, 2014) and the long-term component that evolves over longer time periods and that absorbs the changes in macroeconomic conditions (Grossmann et al., 2014). Theoretically, the macroeconomic conditions may be volatile “if their actual rates deviate from their long-run (sustainable) values [...and] the exchange rate will be at equilibrium levels if the macroeconomic fundamentals are at their sustainable levels" (Giannellis and Papadopoulos, 2011, 41). Thus, the exchange rate misalignment can be associated with deviations in macroeconomic conditions from their long-run values (or, equivalently, trends). Besides, it is the long-term component of the nominal exchange rate volatility that is explicated by the changes in macroeconomic fundamentals. The remaining part of the volatility associated with the short-term component might arise beyond absorbing the shocks to those fundamentals (Giannellis and Papadopoulos, 2011).

The formation of the exchange rate volatility and its determinants are exhaustively examined in the literature. A vast number of potentially related variables are considered as factors that could exaggerate the volatility. One strand of the literature emphasizes macroeconomic fundamentals and monetary factors including changes in output, inflation, monetary aggregates, and interest rates to explicate the volatility formation in exchange rates (Canales-Kriljenko and Habermeier, 2004; Morana, 2009; Ganguly and Breuer, 2010; Giannellis and Papadopoulos, 2011; Jabeen and Khan, 2014). Others feature news (or announcement) shocks (see Frenkel, 1981; Clarida and Gali, 1994; Andersen and Bollerslev, 1998; Galati and Ho, 2003; Stancik, 2007; Korus and Celebi, 2019) and uncertainty or risk measures (Grydaki and Fountas, 2009; Mavee, Perrelli, and Schimmelpfennig, 2016). Also, a considerable part of the literature explains the exchange rate volatility by external and nonmonetary factors as of terms of trade, commodity and oil prices, productivity, and government spending (Driskill and McCafferty, 1980; Broda, 2004; Calderón, 2004, Balg and Metcalf, 2010). In understanding the relationship between exchange rate volatility and its potential determinants, the empirical literature employs a vast range of estimation techniques including structural models (Clarida and Gali, 1994), rolling regression analysis (Galati and Ho, 2003), GMM estimation (Calderón, 2004), bounds-test and cointegration approaches (Balg and Metcalf, 2010), GARCH models (Giannellis and Papadopoulos, 2011), spectral analysis (Grossmann et al., 2014), and event studies (Korus and Celebi, 2019).

In broad strokes, the above-mentioned literature is deprived of an explicit analysis that examines distinctively the short-term and long-term determinants or components of volatility and rather delves into either short-run fluctuations or structural dynamics of exchange rates. Grounded on the theoretical argument that the exchange rate volatility formation itself might include different components determined by different exogenous factors, an alternative strand of the literature articulated largely over the GARCH model has arisen. An early contribution was made by Engle and Bollerslev (1986) who model the persistency of conditional volatility using ARCH and integrated GARCH models. Engle and Lee (1999) model the long memory behavior of the volatility as the combination of the permanent component corresponding to the presence of a unit root and the transitory component model associated with more rapid time decay. They replace the unconditional variance (see Engle and Bollerslev, 1986) with the long-term volatility and obtain a stochastic trend component and a transitory component. Recently, Engle et al. (2009; 2013) contribute to the volatility analysis based on the volatility component model by relating directly the low-frequency macroeconomic data with the high-frequency financial data using the MIDAS scheme (see Ghysels et al., 2005). Even though the component models are used in the related literature (see, Adrian and Rosenberg, 2008 among others), Engle et al. (2009) suggest clear-cut specifications for components i.e., GARCH-MIDAS, in directly relating financial volatility with economic fundamentals. In this way, they aim to better determine the economic sources of financial volatility. They find that macroeconomic factors are significant in explaining financial volatility even at short intervals. More recently, Zhou et al. (2019) and You and Liu (2020) utilize GARCH-MIDAS model to understand the exchange rate volatility formation and both studies find that the model performs better than other GARCH-type models.

3. The methodology and data set

3.1. Methodology

In explaining the underlying methodology, we follow Engle and Rangel (2008) and Engle et al. (2009, 2013). Let's define a $\mathrm{GARCH}(1,1)$ model for convenience. Assume that r_t is the logarithmic change of exchange rate returns at period t. Then, the $\mathrm{GARCH}(1,1)$ model can be defined as follows:

$$r_t = E_{t-1}(r_t) + \varepsilon_t \tag{1}$$

$$\varepsilon_t = \sqrt{\sigma_t^2 \chi_t} \tag{2}$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{3}$$

where $E_{t-1}(r_t)$ is the conditional expectation, χ_t is the innovation process, ε_t is the residual, σ_t^2 is the conditional variance, and ω, α and β are the model parameters.

GARCH-MIDAS model proposed by Engle et al. (2009; 2013) builds upon the $\mathrm{GARCH}(1,1)$ model and relates directly the long-term volatility driven by the exogenous regressors with daily financial data. It is achieved by combining the GARCH component with the MIDAS component. Below we explain the GARCH-MIDAS setting.

Assume that r_{it} is the logarithmic change of exchange rate returns on a day i during the month t having the following process:

$$r_{it} = E_{i-1,t}(r_{it}) + \sqrt{\tau_t g_{it} \chi_t}, \quad \forall i = 1, \dots, N_t, \tag{4}$$

where $E_{i-1,t}(r_{it})$ is the conditional expectation given information $\varepsilon_{it}|\Phi_{i-1,t} \sim N(0,1)$ set up to the day $(i-1)$, and N_t is the number of trading days in each month. Notice that subtracting conditional expectations from the daily returns, i.e. $r_{it} - E_{i-1,t}(r_{it})$, gives the unexpected part of the returns $\left(\varepsilon_t = \sqrt{\tau_t g_{it} \chi_t}\right)$. That is $\sqrt{\sigma_t^2} = \sqrt{\tau_t g_{it}}$. The term $\sqrt{\tau_t g_{it} \chi_t}$ stands for volatility with g_{it} as a short-run component corresponding to daily fluctuations and τ_t as a long-term component. The underlying idea of equation (1) is that different events may impact financial markets differently, depending on whether they have consequences over short or long horizons (Engle et al., 2013). The g component is related to short-lived factors of daily liquidity conditions, speculative or external shocks. In contrast, the τ component has to do with macroeconomic conditions where the past values of those conditions are assumed to be informative in depicting the volatility in the exchange rate market and contribute to the long memory of the volatility a la Baillie et al. (1996).

Equation (4) is rewritten as follows:

$$r_{it} = \mu + \sqrt{\tau_t g_{it} \chi_t}, \quad \forall i = 1, \dots, N_t, \tag{5}$$

given that for high-frequency, there is such a low degree of feedback or predictability in returns, $E_{i-1,t}(r_{it})$ is taken as equal to μ. The g_{it} component is assumed to follow a daily GARCH(1,1) process:

$$g_{it} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \mu)^2}{\tau_t} \beta g_{i-1,t}. \tag{6}$$

To measure the long-run volatility the realized volatility, RV_t, is defined (over a month in our case) to feature the long-term component (τ_t) of the volatility. The model with the realized volatility can be taken as a benchmark case "against which we will measure the success of empirical specifications involving macroeconomic variables" (Engle et al., 2013, p. 777). The τ_t component can be specified by smoothing RV_t and utilizing a rolling-window MIDAS filter as follows:

$$\tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, RV_{t-k}, \tag{7}$$

where m and θ stand for intercept and slope coefficient of the filter, respectively; K is the number of periods over which the smoothed volatilities are obtained, and RV_{t-k} is the realized volatilities at a lag k, so that

$$RV_t = \sum_{i=1}^{N_t} r_{i,t}^2 \tag{8}$$

Accordingly, when $N = 22$, the rolling window RV_t is obtained monthly. Under a fixed period, τ_t is assumed to be the same throughout the month.

To close the model, we need to define the weighting polynomial $\varphi_k(\omega)$ to specify the long-run component of volatility. The choice of weights arises as to the leading ingredient of the GARCH MIDAS model specification (Colacito et al., 2011). It determines how we include the lagging behavior of the long-term component. One candidate is the Beta weighting scheme suggested Ghysels et al. (2004, 2005):[2]

$$\varphi_k(\omega) = \frac{(k/K)^{\omega_1-1}(1-k/K)^{\omega_2-1}}{\sum_{j=1}^{K}(j/K)^{\omega_1-1}(1-j/K)^{\omega_2-1}} \tag{9}$$

where weighting parameters are ω_1 and ω_2. Those weights represent the impact of past information on volatility. The higher degree of weight corresponds to higher explanatory power. The simple averaging of the high-frequency data is reached with $\omega_1 = \omega_2 = 1$ (Armesto et al., 2010). A declining pattern is guaranteed when $\omega_2 > 1$.

One other candidate is the Exponential Almon Polynomial weighting scheme due to Ghysels (2007). It builds upon the conventional Almon modeling in estimating the distributed lags. We can define the Almon polynomial scheme as

$$\varphi_k(\omega) = \frac{\omega_2}{\sum_{j=1}^{K}(\omega^j)} \tag{10}$$

where the simple averaging of high-frequency data is reached with $\omega_1 = \omega_2 = 0$ (Armesto et al., 2010). A declining pattern is guaranteed when $\omega_2 \leq 0$.

We select the Beta polynomial as the weighting scheme for its high flexibility for generating various shapes with a parsimonious number of parameters.[3] For instance, setting $\omega_1 = 1$ and letting $\omega_2 = \omega$ leads to a slowly declining functional form (Ghysels et al., 2006). In this case, $\varphi_k(\omega)$ becomes:

$$\varphi_k(\omega) = \frac{(1-k/K)^{\omega-1}}{\sum_{j=1}^{K}(1-j/K)^{\omega-1}}. \tag{11}$$

Equations (5) through (9) generate a GARCH-MIDAS model for time-varying conditional volatility with a fixed span and parameter space $\Theta = \{\mu, \alpha, \beta, m, \theta, \omega_1, \omega_2\}$.

Considering a rolling window specification for the MIDAS filter, the restriction that τ_t is fixed for month t is removed, making both g and τ vary at the daily frequency. We can define the rolling window RV as

$$RV_i^{(rw)} = \sum_{j=1}^{N'} r_{i-j}^2 \tag{12}$$

[2] We introduce the weighting schemas following the formation used by Engle et al. (2013).

[3] In examining the model fit, we observe that exponentially weighted Almon polynomial performs equivalently well.

where r_{i-j} indicates that we restore the days across various periods t. When $N' = 22$, we can call it a monthly rolling window RV. The MIDAS filter can be re-defined as

$$\tau_i^{(rw)} = m^{(rw)} + \theta^{(rw)} \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_2)\, RV_{i-k}^{(rw)}. \quad (13)$$

Now, Equations (5), (6), and (9), along with Equations (12) and (13) generate a GARCH-MIDAS model with rolling window RV.

The GARCH-MIDAS model structure introduced is grounded on a MIDAS filter involving only the RVs. The GARCH-MIDAS model can be grounded on the MIDAS filter that involves past macroeconomic variables replacing the realized volatilities. It requires the long-term component to change in formation. That is,

$$\log\tau_t = m_l + \theta \sum_{k=1}^{K_l} \varphi_k\left(\omega_{1,l}, \omega_{2,l}\right) X_{t-k} \quad (14)$$

where the long-term component is expressed in the log-form to opt for the macroeconomic series, and each of the macroeconomic variables is represented by the term X_{t-k}. The parameters θ and φ_k are of primary importance in drawing the very abstract link between the macroeconomic variables and exchange rate volatility. Equations (5), (6), (8), and (9), along with equation (14), generate a GARCH-MIDAS model with an exogenous regressor and under the fixed span.

3.2. Data

The sample period covers the period between 2001:3 and 2020:2, belonging floating exchange rate regime in Turkey. We use two different data groups that change in terms of sampling frequency: one is the exchange rate series with daily data (five-days data), and the other belongs to the macroeconomic series with monthly data. To stand for the exchange rate, we use the daily nominal exchange rate of the Turkish lira against the U.S. Dollar. The exchange rate series are collected between 03/01/2001 and 02/28/2020 and are used in the percentage change form to serve as a proxy for daily returns.[4]

Since the GARCH-MIDAS model by formation allows only one regressor to be used in estimation, we utilize a variety of variables to capture the characteristic dynamics of the economy and draw implications in policymaking. We use potential macroeconomic drivers

[4] The logarithmic change of the nominal exchange rates $r_t = log\left(\frac{e_t}{e_{t-1}}\right)$ gives similar parameter estimates.

of the exchange rate market, i.e., total foreign currency reserves, foreign currency interventions,[5] external debts, net exports, and net capital flows, besides industrial production, inflation, money stock, and interest rate. Still, we acknowledge that some determinants that could potentially lead to the exchange rate volatility are excluded from the analysis primarily because of the data limitations or problems in measures of fit.[6] Table 1 gives the list of macroeconomic series used in estimation. We express all series except the one for the interest rate as month-over-month percentage changes to induce stationarity. For the interest rate series, we take The TL Libor rate as the reference interest rate and take the difference of the series. Besides, it is only the series of foreign currency auctions expressed in levels but featuring stationarity.

Table 1: List of the Exogenous Regressors

Exogenous Regressors	Source
Industrial Production Index[1]	TUIK
CPI Index[2]	TUIK
Money Supply[3]	CBRT
Interest Rate[4]	TBB
Foreign Currency Reserves[5]	CBRT
Foreign Currency Debt Stock[6]	CBRT
Net Export[7]	TUIK
Capital Inflows[8]	CBRT
Foreign Currency Buying/Selling Auctions[9]	CBRT

Note: [1]Seasonally and calendar adjusted (2005:100); [2](2003:100); [3]Broadly defined money stock, M2, for the observations before 2005:12 M2Y is taken; [4]TRLibor Rate, due to data availability, it covers the period 2002:8 through 2020:2; [5]Official foreign currency reserve assets that include cash, deposit accounts, securities, and financial derivatives, million$; [6]Short-term foreign currency debt stock, million$; [7]Total net export volume, seasonally adjusted, million$, [8]Sum of FDI and portfolio investment liabilities, million$. [9]Monthly sum of selling or buying auctions made by the CBRT. The series is used in their logarithms, million$

5 The CBRT occasionally uses foreign exchange controls to mitigate the exchange rate volatility. In our study, we relate the volatility formation at t with foreign currency interventions at t-1 to prevent any potential endogeneity.

6 Due to data limitations, we cannot analyze the effects of financial expectations and political risk indicators on the formation of volatility.

4. Results

4.1 Model fit and estimation with RV

To estimate the parameter space $\Theta = \{\mu, \alpha, \beta, m, \theta, \omega_1, \omega_2\}$ of the GARCH-MIDAS model, we use the maximization of the following log-likelihood function (LLF):[7]

$$LLF = -\frac{1}{2}\sum_{t=1}^{T} \text{x} \left[\log(2\pi) + \log g_t(\Phi)\tau_t(\Phi) + \frac{(r_t-\mu)^2}{g_t(\Phi)\tau_t(\Phi)}\right] \qquad (15)$$

To control if the Turkish exchange rate market fits well to the GARCH-MIDAS model and any identification problem arises, we estimate the Beta weighting functions for both full-sample and two subsamples. Also, we examine the distribution of estimation errors and control parameter consistency across different periods.

To capture if there exists any identification problem resulting from the model fit, we choose two different sub-periods: i. 2001:3 – 2008:9 and 2008:10 – 2020:2 and ii. 2001:3 – 2010:9 and 2010:10 – 2020:2. For the former choice (i.e., 2001:3 – 2008:9 and 2008:10 – 2020:2), we determine the sub-samples to distinguish potential differences between the pre-crisis and post-crisis episodes in the Turkish economy. In this way, we aim to capture the transition dynamics to the floating exchange regime over the first years in which the adjustment process generated relatively higher volatilities of exchange rates (see Figure 4). Besides, we plan to evaluate the post-crisis episode that possesses its dynamics on the policy-making side. We determine the date of 2008:9 as the contagion of the global financial crisis to Turkey had become more prominent with the beginning of the last quarter of 2008 (Rodrik, 2012). Following the last quarter of 2008, a sudden tumble in its industrial production and employment rate, fall in export volume, sizable net capital outflows, and depreciation of its domestic currency confronted the Turkish economy (Uygur, 2010). For the latter (2001:3 – 2010:9 and 2010:10 – 2020:2), we determine the sub-samples to account for a policy shift in the monetary policy stance that officially targeted the financial variables in the aftermath of the crisis. The CBRT adopted new instruments under a multiple-policy framework to smooth the fluctuations in the financial markets, e.g., to control better capital flows or mitigate the volatility of the exchange rates (Kara, 2016). Also, at the end of 2010, CBRT conducted important policy changes in regulations on foreign currency reserves, required reserve ratios, and liquidity management (CBRT, 2011).

[7] The GARCH-MIDAS codes for estimation are taken from Hang Qian (2020), who provides MIDAS Matlab Toolbox in MATLAB Central File Exchange (https://www.mathworks.com/matlabcentral/fileexchange/45150-midas-matlab-toolbox). Retrieved August 30, 2021.

To control any structural break in exchange rate series and examine the difference in goodness-of-fit of two nested models (of full-sample and sum of sub-samples), we follow Engle et al. (2013) and apply a likelihood ratio test (LR) to LLF values. That is,

$$LR = -2\left[LLF_{fullsample} - \left(LLF_{subsample1} + LLF_{subsample2}\right)\right] \sim \chi^2 \text{ with } df \qquad (16)$$

We set the number of restrictions (df) as $\text{the number of parameters} * (\text{the number of subsamples} - 1)$. We compare the LLF of the full sample with the sum of sub-samples of RV and different economic variables and provide the results in Table 2. LR indicates the existence of structural break across full-sample and considered sub-samples. Thus, we estimate all the models for both full sample and sub-samples.

Table 2: Results of Likelihood Ratio Test Statistic

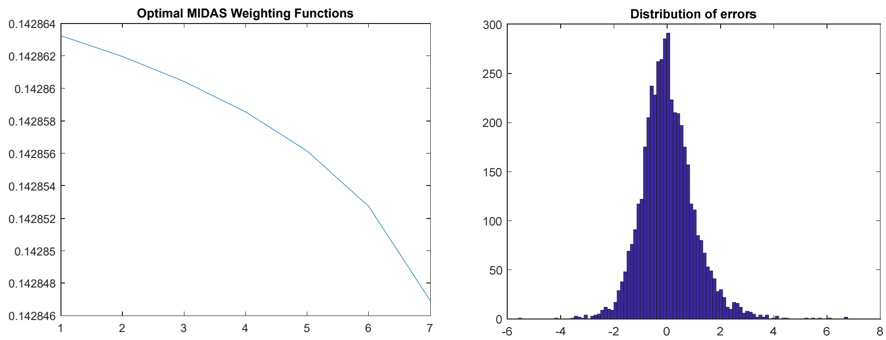
		Full-sample and sub-samples: 2001:1-2010:9 2010:10-2020:2		**Full-sample and sub-samples: 2001:1-2008:9 2008:10-2020:2**	
Long-term Component	**df**	**LR value**	**P-value-χ^2**	**LR value**	**P-value-χ^2**
Fixed Window RV	6	808	0%	726	0%
Rolling Window RV	6	856	0%	724	0%
Industrial Production Growth	7	5388	0%	4742	0%
CPI Inflation	7	5387	0%	4815	0%
Money Growth	7	5403	0%	4794	0%
Interest Rate changes	7	5437	0%	4796	0%
Change in the FX Reserves	7	5393	0%	4785	0%
Change in the FX Debt Stock	7	5436	0%	4757	0%
Net Export Changes	7	5388	0%	4817	0%
Change in the Capital Inflow	7	5395	0%	4812	0%

Before drawing the Beta weighting functions and estimating the model, we determine the number of MIDAS lags (K). In the lag selection of the MIDAS filter, the guidebook is to choose "the smallest number of MIDAS lags after which the log-likelihoods of the volatilities seem to reach their plateau" (Colacito et al., 2011, p.50). In this regard, we use the LLF firstly to shoot for an optimal number of lags and exploit Beta weights polynomials to control if the determined MIDAS lags (K) suffice to obtain all relevant information provided by the previous values. We found that the likelihood values do not result in any plateau while the MIDAS weighting function approaches zero around the 8th month. Thus, we determined the lag number as eight to avoid sacrificing observations further for initialization. The history of eight months' realized volatility is averaged by the MIDAS weights to assess the long-run conditional variance (Ghysels, 2017). It costs 176 observations for the sake of initialization.

Next, to control for homogeneity of MIDAS weighting parameters across different periods, we draw MIDAS weighting functions for the full-sample and sub-samples. To obtain a decaying pattern of the Beta weighting functions to give higher weights to the recent past, we set ω_1 equal to one and allow only ω_2 to change.[8]

Figures 1 to 3 reveal the Beta weights. We reach that for the full sample, ω_2 is close to 1, implying almost equal weights across the lagged values. Also, we observe that the beta polynomials feature monotonically decreasing patterns for nearly all sub-samples (see Figures 2 and 3). Thus, the more recent observations, the more contribution they provide to the long-term component volatility. Therefore, as different lagged effects of the long-term component arise across different periods, we estimate the model parameters under different samples. Such an endeavor enables us to control if different Beta weights generate various impacts on the volatility. We also draw the distribution of error terms and see that the distribution of errors essentially fits the normal distribution as assumed while computing the log-likelihood functions under different periods.[9]

Figure 1: MIDAS Weighting Functions and Distribution of Errors for the Full Sample



[8] Setting $\omega_1 > 1$ generates hump-shaped patterns which are not in line with the volatility literature.

[9] To control if the initial adjustment process to the floating regime alters the estimation results, we take the full-sample period as 2002:1 – 2020:2. We reveal similar Beta weights with improvements in the distribution of error terms.

Figure 2: MIDAS Weighting Functions and Distribution of Errors for the Sample between 2001:3 – 2008:9

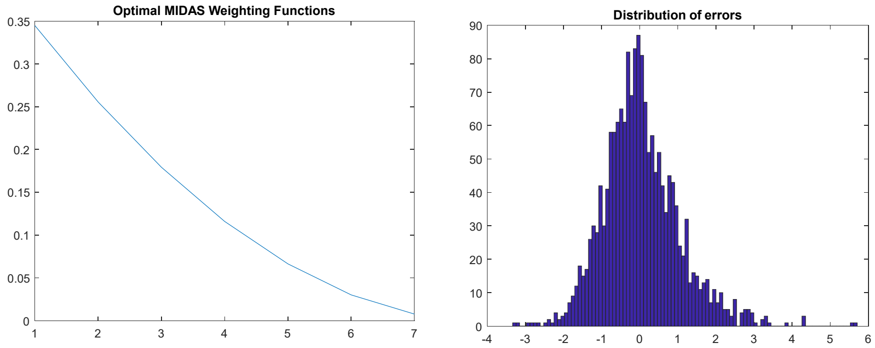


Figure 3: MIDAS Weighting Functions and Distribution of Errors for the Sample between 2008:10 – 2020:2

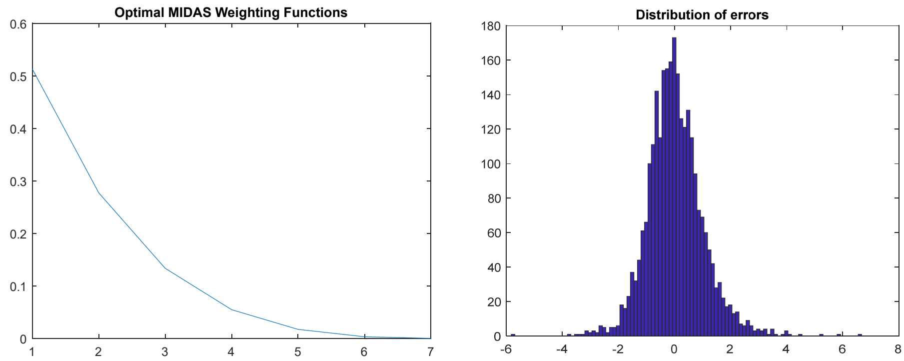


Figure 4 displays the total volatility of the exchange rates along with its long-term component calculated at a monthly base with rolling window RV.[10] The figure reveals firstly that the exchange rate series feature volatility at a higher degree in the pre-crisis episode. Also, we observe a dramatic rise in volatility during two periods of time: during the 2008 – 2009 financial crisis episode and the political crisis of August 2018, justifying the counter-cyclical pattern of exchange volatility during the economic turmoil. Besides, even though the long-term component follows the total volatility, it is during more turbulent periods that the volatility expands dramatically in the long run.

[10] The estimation under fixed window RV gives the same long-term volatility pattern, but as τ varies daily under rolling window RV, that under rolling window RV is smoother.

Figure 4: Total Volatility of Exchange Rate and its Long-term Component

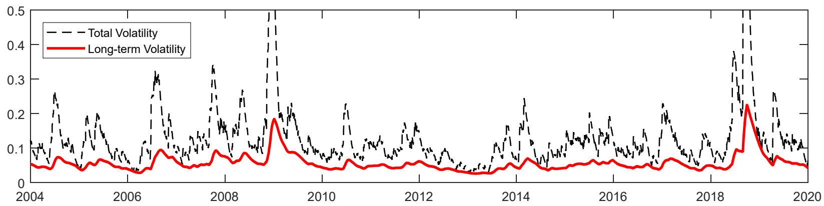


Table 3 gives RV parameter estimates under the fixed and rolling windows for the full-sample, sub-samples, and GARCH(1,1) model. The table indicates no appreciable difference between holding the long-term τ constant throughout the month or allowing it to vary every day during the month for the likelihood of the data. The parameter μ is the sample average of observations, α and β stand for coefficients for the short-term component, θ for the long-term component, ω for the Beta weighting parameter, and m for the location parameter for the long-term component.

We observe that parameter estimates under different samples are significant and, thus, promote the goodness of the model fit. Under all specifications, the term θ is significant and positive, implying a worth-mentioning information content of the realized volatility of the last eight months in explaining the long-term volatility. The term θ rises when estimation is upheld under sub-samples pointing to the clustering pattern of the realized volatility for sub-periods. The sums of α and β are close to 1, implying a stationary solution and mean-reversion for the GARCH(1,1) part. The estimated GARCH(1,1) process implicitly assumes $\theta = 0$. It gives similar coefficients to those of the short-term component of the GARCH-MIDAS model but with a smaller likelihood value.

Table 3: Parameter Estimates for GARCH-MIDAS with Realized Volatility

Period	μ	α	β	θ	ω	m
Full Sample-	0.0002***	0.0696***	0.9204***	0.0887***	1.0001***	0.0013*
Fixed RV	(0.0094)	(0.0002)	(0.0002)	(0.0173)	(0.1392)	(0.0000
Full Sample-	0.0002***	0.0697***	0.9202***	0.0893***	1.0002***	0.0012*
Rolling RV	(0.0087)	(0.0002)	(0.0002)	(0.0001)	(0.5427)	(0.0008
2001:1 – 2010:9^{+}	-0.003**	0.1351***	0.8120***	0.12793***	1.0450*	0.0073*
	(0.0001)	(0.0112)	(0.0292)	(0.0295)	(0.6746)	(0.0011
2010:10- 2020:2^{+}	0.0003***	0.1490***	0.8276***	0.1787***	6.0002**	0.0006*
	(0.0092)	(0.0000)	(0.0000)	(0.0000)	(0.0420)	(0.0000
2001:3 – 2008:9^{+}	-0.0003**	0.1999***	0.7367***	0.1434***	2.9458*	0.0006*
	(0.0165)	(0.0185)	(0.0204)	(0.0194)	(1.0177)	(0.0000
2008:10 – 2020:2^{+}	0.0003***	0.0690***	0.9309***	0.09000***	4.9963***	0.0013*
	(0.0001)	(0.0032)	(0.0029)	(0.0180)	(0.7256)	(0.0000
GARCH(1, 1)	0.0001***	0.0979***	0.8979***	-	-	-
Model	(0.0002)	(0.0059)	(0.0049)			

Note: $^{+}$ The estimation is made under the Rolling Window. ***, **, * represent the significance levels at 1%, 5%, and 10%, respectively. Standard errors are denoted in parenthesis.

4.2. Model Estimation with macroeconomic series

In this section, we replace the realized volatility with the macroeconomic variables to understand the macroeconomic determinants of the long-term volatility. Such an attempt requires equation (14) in estimation. The Beta weights are drawn using the past eight months of the selected macroeconomic variables. Besides indicators of economic activity and prices, we include the foreign currency reserves, debt stock, and net capital flows in our analysis to serve as proxies for the degree of liquidity management, overall risk level, and indebtedness. Figure 5 to 8 display the total volatility, $g \times \tau$, and the long-term component represented by exogenous regressors, τ. Due to lack of space, we display the figures and report the individual tables for industrial production growth, interest rate, foreign currency reserve, and net export changes. We see that inflation rate and net export changes fail to track the exchange rate volatility even in turbulent periods. Still, industrial production growth, money growth, changes in interest rate, reserves, debts, and capital inflows consistently follow the exchange rate ups and downs. All the variables' power is relatively low compared to RV in explaining the long-term component, true to form.

Figure 5: Total Volatility of Exchange Rate and the Industrial Production Growth

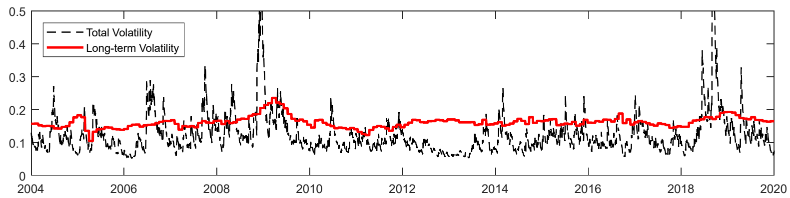


Figure 6: Total Volatility of Exchange Rate and the Interest Rate Changes

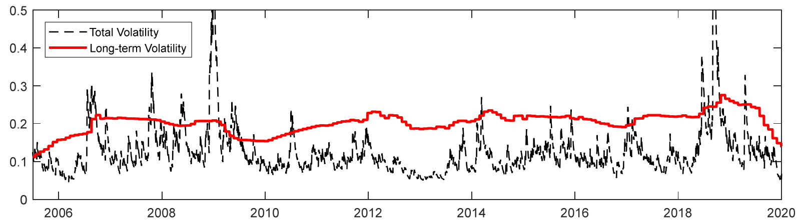


Figure 7: Total Volatility of Exchange Rate and the Change in Foreign Currency Reserves

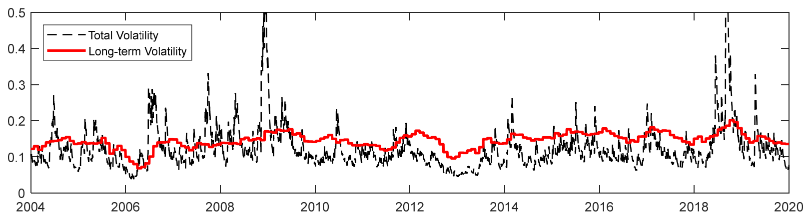
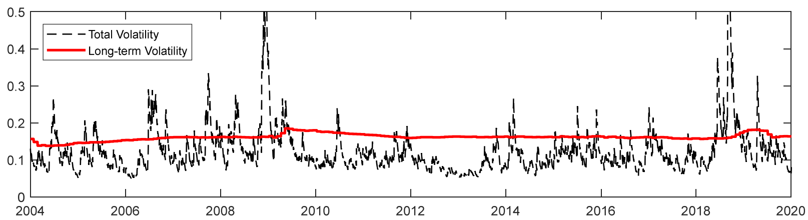


Figure 8: Total Volatility of Exchange Rate and the Net Export Changes



Next, we make the GARCH-MIDAS model estimation with individual macroeconomic series under different samples (see Tables 4 through 7). The parameters μ and m are significantly located around zero in almost all cases. The parameters of α and β are also significant and close to one in all the instances, denoting a low degree of clustering patterns of short-term volatility. The parameters θ and ω are broadly significant and promote the counter-cyclical pattern of exchange rate volatility. Thus, we can consider the GARCH-MIDAS model with macroeconomic series to feature a sufficiently good model fit.

Following Engle et al. (2013), we use the formula $\left(\hat{\tau} = e^{\theta * \varphi_k(\omega)} - 1\right)$ to capture the magnitude of the particular impact of each variable on the exchange rate volatility. It is assumed a positive shock to the selected macroeconomic variable, and the model does not postulate any asymmetry between negative and positive surprises, which can be taken as a downside of the model. Notice that the term $\varphi_k(\omega)$ corresponds to the Beta weights defined in equation 11 for the kth lag. We report the calculated impacts, $\hat{\tau}$, for all the series and under all the periods in Table A.1 in Appendix.

When the industrial production growth at $t-1$ stands for the exogenous regressor in explaining the long-term volatility at t, the estimated parameters for the full sample are obtained as $\theta = -0.0035$ and $\omega = 1.1284$. The latter puts the 0.1563 on the first lag. Thus, a 1% increase in industrial production growth during the current month leads to a $e^{-0.0035*1.1563} - 1 \approx -0.05\%$ fall in the exchange rate volatility in the next month. This negligible impact improves only for the subsample of 2001:3 – 2010:9 and materializes as a -0.27% fall in the volatility.

In the case of CPI inflation, even though the inflation does not lead to the exchange rate volatility when the estimation is upheld under the full sample, the analysis under sub-samples features different patterns. For the sub-sample of 2001:3 – 2008:9 witnessing a transition from a two-digit inflation period to one-digit for the Turkish economy, a rise in CPI inflation negatively impacts volatility and generates a -0.44% fall in volatility. Contrarily, for the period of 2010:10 – 2020:2, the increase in CPI inflation leads to higher volatility (0.32%) in exchange rates. The inclusion of the observations belonging 2008-2009 crisis years blurs the corresponding link. The money growth creates a similar impact on volatility with the CPI inflation under the sub-samples. As in the case of CPI inflation, the money growth contributes negatively to the exchange rate volatility in the pre-crisis episode (by -0.26%) while the corresponding impact turns out to be positive after that (by 0.36%).

Using the TRlibor rate as a leading reference rate in policymaking (see Gürkaynak et al., 2015), we reach a consistently positive impact of the short-term rates on exchange rate volatility for both full-sample and sub-samples. In this regard, a 1% increase in the interest rates during the current month leads to a 0.46% rise in the exchange rate volatility in the subsequent month. Besides, the term $\hat{\tau}$ displays that the link becomes more pronounced in the post-crisis episode in which the CBRT practiced more tools to achieve the financial stability objectives.

To control if the degree of the liquidity management of the CBRT matters for the exchange rate volatility, we consider the total official foreign currency reserves as another exogenous regressor. The official foreign currency reserves of the bank can also be taken as a buffer against windy days. We observe that the parameters θ and $\hat{\tau}$ consistently reveal a negative link between reserves held in foreign currency and volatility under all estimation periods and promote the functioning of augmenting reserves to control exchange rate movements. The corresponding impact is still far from a proportional change in exchange rate volatility.[11] Considering the lead impact of the external debt stock changes on the volatility, we reach a negative link under all samples. A 1% rise in the foreign currency debt stock leads to a mild but significant fall in exchange rate volatility (with a coefficient of around 0.10%). Besides, we reach that a rise in the net export leads to a pronounced fall in the volatility for only the more recent period, i.e., 2010:10 – 2020:2. Hence, a 1% rise in net exports of Turkey in the current month results in a -0.37% decline in volatility in the next month. This result also promotes the well-functioning relationship between the trade structure of the Turkish economy and the dynamics of the exchange rates.

Lastly, we control the impact of capital inflows on the volatility given the former's highly-voiced reputation in influencing distinctive dynamics of the Turkish economy and financial stability. The variable of capital inflows is taken as the sum of the net portfolio investments and the foreign direct investments to Turkeys and a rough proxy of the degree of openness and net export changes. A rise in net investment and liabilities leads to a decline in exchange rate volatility in all cases except for the period 2001:3 – 2008:9.[12]

We also include volatilities of macroeconomic variables as their second moments to see the degree to which the volatility in the economic activity matters for long-term exchange rate volatility. Theoretically, the macroeconomic variables may be volatile "if their actual rates deviate from their long-run (sustainable) values [...and] the exchange rate will be at equilibrium levels if the macroeconomic fundamentals are at their sustainable levels" (Giannellis and Papadopoulos, 2011, 41). We acknowledge this theoretical argument as too strong since it excludes many other factors that could lead to the exchange rate volatility even if the

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[11] We also examine how the CBRT's foreign exchange interventions as a spot-on instrument within its reserve policy via foreign exchange buying and selling auctions pertain to the long-term component of volatility. The central bank's foreign exchange interventions raise the long-term volatility, as found in the previous findings (Herrera and Ozbay, 2005; Tuna, 2011). The corresponding impact in magnitude, however, is mainly subordinate.

[12] As the foreign direct investments differ from portfolio investments by formation, we control both variables separately and reach that even though they feature significant and mitigating impacts on the volatility, the former dominates in magnitude.

macroeconomic fundamentals do not deviate from their long-run levels. We estimate a GARCH(1,1) model for each series and take the monthly GARCH variance series to account for monthly macroeconomic volatility.[13] [14] Table A.1 gives the impact of volatilities of exogenous regressors on the exchange rate volatility under the full-sample period. It arises that replacing the level of the series with their corresponding volatilities results in a loss of significance for most of the macroeconomic variables. Only the variables of foreign currency debt stock and capital flows generate notable impacts on exchange rate volatility. A 1% rise in the volatilities of external debt stock changes and change in net investment at $t-1$ generates a 0.13% and 0.14% rise in the volatility of exchange rates at t, respectively.

Table 4: Parameter Estimates for GARCH-MIDAS with Industrial Production Growth

Time Period	μ	α	β	θ	ω	m	LLF
Full Sample-	0.0001***	0.1242***	0.8639***	-0.0035**	1.1284***	0.0001***	15019.6
Rolling Window	(0.0000)	(0.0000)	(0.0000)	(0.0014)	(0.0006)	(0.0000)	
2001:3-2010:9	-0.0003*	0.1290***	0.8460***	-0.0053**	4.2397***	0.0001***	6201.94
	(0.0000)	(0.0099)	(0.0094)	(0.0017)	(1.2443)	(0.0000)	
2010:10 – 2020:2	0.0004***	0.1659***	0.7947***	0.0062**	1.0599***	0.0001***	6123.52
	(0.0000)	(0.0000)	(0.0000)	(0.0014)	(0.6746)	(0.0000)	
2001:3-2008:9	-0.0003**	0.1675***	0.7953***	-0.0106*	2.1298*	0.0001***	4452
	(0.0000)	(0.0187)	(0.0199)	(0.0057)	(1.1363)	(0.0000)	
2008:10 – 2020:2	0.0004***	0.1187***	0.8731***	-0.0002	33.323	0.0001***	8196.86
	(0.0000)	(0.0059)	(0.0064)	(0.0000)	(140.25)	(0.0003)	

Note: ***,**,* represent the significance levels at 1%, 5%, and 10%, respectively. Standard errors are denoted in parenthesis.

[13] We do not include the corresponding volatility patterns of the series and parameter estimates in the paper due to lack of space, and they are available upon request.

[14] Alternatively, it can be estimated using an AR model following Schwert (1989). Engle et al. (2013) point out that estimation under GARCH or AR models reveals similar results.

Table 5: Parameter Estimates for GARCH-MIDAS with Interest Rate Change

Time Period	μ	α	β	θ	ω	m	*LLF*
Full Sample-	0.0001*	0.1222***	0.8704***	0.01339**	2.9473***	0.0001***	13708.1
Rolling Window	(0.0000)	(0.0051)	(0.0046)	(0.0059)	(0.4888)	(0.0000)	
2001:3-2010:9	-0.0001	0.1252***	0.8499***	0.01159***	1.0319***	0.0001***	4886.33
	(0.0001)	(0.0107)	(0.0105)	(0.0029)	(0.0586)	(0.0000)	
2010:10 – 2020:2	0.0004***	0.2112***	0.6639***	0.0129***	1.4393***	0.0000*	6137.38
	(0.0001)	(0.0152)	(0.0271)	(0.0021)	(0.1460)	(0.0000)	
2001:3-2008:9	-0.0002	0.1688***	0.7800***	0.0100***	1.012***	0.0001***	3135.65
	(0.0002)	(0.0220)	(0.0260)	(0.0024)	(0.0349)	(0.0000)	
2008:10 – 2020:2	0.0003***	0.1373***	0.8285***	0.0218***	1.251***	0.0001***	8168.71
	(0.0001)	(0.0076)	(0.0098)	(0.0023)	(0.0212)	(0.000)	

Note: ***,**,* represent the significance levels at 1%, 5%, and 10%, respectively. Standard errors are denoted in parenthesis.

Table 6: Parameter Estimates for GARCH-MIDAS with Change in Foreign Currency Reserves

Time Period	μ	α	β	θ	ω	m	*LLF*
Full Sample-	0.0001	0.1259***	0.8527***	-0.0016***	8.0416***	0.0001***	15031.4
Rolling Window	(0.0000)	(0.0052)	(0.0047)	(0.0002)	(2.1552)	(0.0000)	
2001:3-2010:9	-0.0002*	0.1243***	0.8517***	-0.0012***	10.619*	0.0001***	6196.68
	(0.0001)	(0.0094)	(0.0081)	(0.0004)	(5.8863)	(0.0000)	
2010:10 – 2020:2	0.0004***	0.2125***	0.6623***	-0.0025***	6.8644***	0.0001*	6138.21
	(0.0001)	(0.0157)	(0.0277)	(0.0003)	(0.8223)	(0.0000)	
2001:3-2008:9	-0.0003**	0.1703***	0.7771***	-0.0011***	20.719***	0.0002***	4453.61
	(0.0001)	(0.0191)	(0.0219)	(0.0001)	(6.6553)	(0.0001)	
2008:10 – 2020:2	0.0002***	0.1434***	0.8021***	-0.0021***	5.0609***	0.0001***	8184.91
	(0.0001)	(0.0080)	(0.0113)	(0.0004)	(0.7149)	(0.000)	

Note: ***,**,* represent the significance levels at 1%, 5%, and 10%, respectively. Standard errors are denoted in parenthesis.

Table 7: Parameter Estimates for GARCH-MIDAS with Net Export Change

Time Period	μ	α	β	θ	ω	m	LLF
Full Sample-	0.0001	0.1224***	0.8663***	-0.0089	1.6898	0.0001***	15016.8
Rolling Window	(0.0000)	(0.0049)	(0.0045)	(0.0059)	(1.1617)	(0.0000)	
2001:3-2010:9	-0.0002*	0.1251***	0.8582***	-0.0035	4.3495	0.0001***	6194.53
	(0.0001)	(0.0091)	(0.0072)	(0.051)	(7.6491)	(0.0000)	
2010:10- 2020:2	0.0004***	0.1695***	0.7767***	-0.0092**	3.6971**	0.0002***	6127.82
	(0.0001)	(0.0096)	(0.0122)	(0.0045)	(1.7277)	(0.0000)	
2001:3-2008:9	-0.0004**	0.1735***	0.7954***	0.0030	21.361	0.0000***	4447.52
	(0.0001)	(0.0187)	(0.0189)	(0.0043)	(43.2)	(0.0001)	
2008:10 – 2020:2	0.0003***	0.1151***	0.8781***	0.0044	25.689	0.0001***	8160.74
	(0.0001)	(0.0059)	(0.0061)	(0.0031)	(22.781)	(0.0000)	

Note: ***,**,* represent the significance levels at 1%, 5%, and 10%, respectively. Standard errors are denoted in parenthesis

4.3. Robustness control: ARDL model and bounds test

For robustness, we control if there exists any long-term relationship between the long-term exchange rate volatility and selected exogenous regressors when sampled at the same frequency. We transform the daily long-term volatility component into the realized volatility at a monthly frequency. The period covers 2001:10 through 2020:2.[15] Figure 8 displays the monthly realized volatility. We estimate the autoregressive distributed lag model (ARDL) to uphold the estimation of the intertemporal dynamics. We employ the Pesaran et al. (2001) bounds test to see if any long-run relation arises at levels of the series.

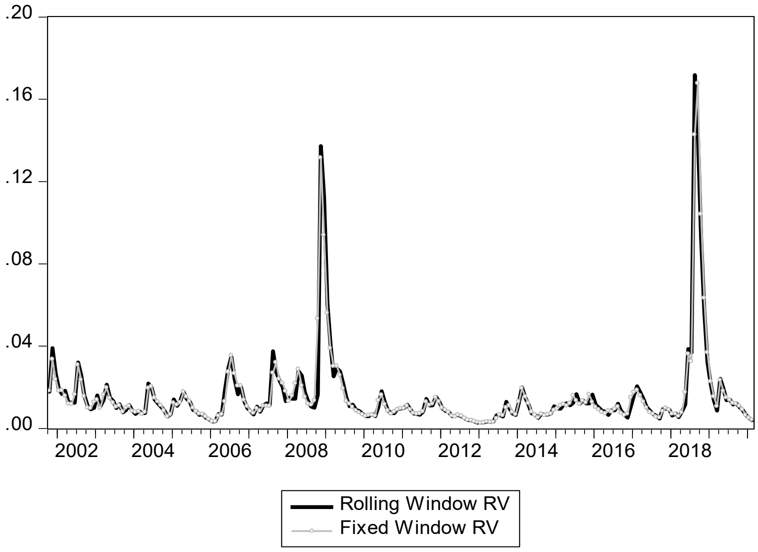
$$RV_t = a_0 + \sum_{i=1}^{p} \psi_i RV_{t-i} + \sum_{j=1}^{k} \sum_{l_j=1}^{q_j} \gamma_{j,l_j} X_{j,t-l_j} + \epsilon_t \tag{17}$$

where RV_t stands for the long-term volatility component at time t with a maximum lag number of p, X_j for the exogenous regressors with a maximum lag number of q_j, ϵ_t for the residual term, the term a_0 for the constant term. The terms ψ_i and γ_{j,l_j} are the estimated coefficients of lagged values. To be compatible with the GARCH-MIDAS model setting, we estimate the ARDL model and bounds test considering only one regressor. We relate the lagged

[15] We use the observations belonging first eight months for initialization.

values of X_j to the current exchange rate volatility as in the GARCH-MIDAS model. We restrict the constant parameter from entering the equation as the realized volatility does not center around zero, while we do not assume any linear trend. Table 8 gives the estimation results.[16]

Figure 9: Monthly Realized Volatility in Fixed and Rolling Windows



Two lags are detected to enter the equation for the realized volatility, while the exogenous regressors feature different numbers of lags ranging from zero to three.[17] In all model specifications, the past two values of long-term volatility arise as significant in which RV_{t-1} positively (and with a coefficient of about 0.8) while RV_{t-2} negatively (and with a coefficient of about -0.17) affects the current realized volatility. It implies the existence of a high persistence in the long-term volatility of exchange rates. The table reveals that the individual impacts of the exogenous regressors on the long-term exchange volatility are limited in both magnitude and significance. Among them, only the past values of the series of money supply, the foreign currency reserves, and debt stock arise as significant in affecting the current realized volatility. Their corresponding impacts in magnitude and direction are in line with the findings in the GARCH-MIDAS model. Also, the forceful impact of the effective interest

[16] We do not confront serial correlation in the estimated errors but use robust standard errors as we observe heteroscedasticity for CPI index and net export. Also, the estimated models are found to be dynamically stable.

[17] The selection of the optimal lag length is made among 20 candidates, i.e., $p * (q + 1)^k$.

rate on the exchange rate volatility that we encounter in the volatility model does not come into sight under the ARDL setting, which may be attributed to the additional information provided by the MIDAS function.

Next, we use the bounds test to control for the joint significance of lagged values of RV_t and X_{t-1} and the linear long-run relation as it allows for different integration orders at the same level. Among exogenous regressors, the series of interest rate, net export, reserves, and capital inflows are found to be $\mathrm{I}(0)$, while the rest of the series is $\mathrm{I}(1)$. Re-arranging the equation (17), we obtain

$$\Delta RV_t = a_0 + \sum_{i=1}^{p} \psi_i \Delta RV_{t-i} + \sum_{j=1}^{k} \sum_{l_j=1}^{q_j} \gamma_{j,l_j} \Delta X_{j,t-l_j} + \theta_0 RV_{t-1} + \theta_1 X_{t-2} + e_t \qquad (18)$$

The null hypothesis will be $H_0: \theta_0 = \theta_1 = 0$ against the alternative, $H_1: \theta_0 = \theta_1 \neq 0$. Table 9 displays the estimation results with $k = 1$ and corresponding asymptotic critical values of lower $\mathrm{I}(0)$ and upper bounds $\mathrm{I}(1)$ due to Pesaran et al. (2001).[18] Under all the cases, the resulting F-statistic is higher than the asymptotic values at the different significance levels.[19] The bounds test signals a long-run relationship between the long-term volatility and macroeconomic variables. We also define the error correction term (Z_{t-1}) as being equal to ($RV_t - \theta_1 X_{t-1} - a_0$) to draw the long-term coefficients of X_{t-1} along with the constant term (see Table 10). Even though the bounds test promotes the existence of a long-run relationship, the long-run level equations report quite negligible coefficients of the macroeconomic sources. The direction of the coefficients largely conforms with the GARCH-MIDAS estimates.[20]

[18] See Table CI(ii) in Pesaran et al. (2001), which determines the critical values of the bounds test with a restricted constant term and no linear trend.

[19] As our sample size is sufficiently large, i.e., n=219, we do not use adjusted critical values for small samples, i.e., $n < 80$ (see Narayan, 2005).

[20] We also intrinsically assume that the exchange rate volatility might feature conditional heteroscedasticity as there are points in which the variance gets relatively higher (in periods of 2008:10 – 2008:11 and 2018:08 – 2018:10). In contrast, the long-run variance is close to a constant (see Enders, 2014). We use, accordingly, time dummies for these data points. The estimation results provide that the long-run link still exists but with a loss in the persistence pattern of the volatility, true to form.

Table 8: ARDL Model: Estimation Results

	Industrial Production Index	CPI Index+	Money Supply	Interest Rate	Foreign Currency Reserves	Foreign Currency Debt Stock	Net Export+	Capital Inflows
Model Selection (p, q)	(2,0)	(2,0)	(2,1)	(2,1)	(2,3)	(2,3)	(2,2)	(2,3)
RV_{t-1}	0.8540****	0.8538****	0.8056****	0.8466****	0.7868****	0.8186*****	0.8607***	0.8052***
	0.0667	(0.0205)	(0.0686)	(0.0690)	(0.0708)	(0.0688)	(0.0296)	(0.0711)
RV_{t-2}	-0.1706**	-0.174****	-0.111	-0.177***	-0.1713**	-0.1414**	-0.1901***	-0.1715**
	0.0067	(0.0299)	(0.0701)	(0.0687)	(0.0681)	(0.0685)	(0.0414)	(0.0714)
X_{t-1}	0.0001	0.0001	0.1191**	0.0012	-0.0631**	-0.085****	0.0001	0.0000
	0.0002	(0.0001)	(0.0467)	(0.0007)	(0.0280)	(0.0316)	(0.0000)	(0.0000)
X_{t-2}			-0.1186**	-0.0011	0.0116	0.0835*	0.0000	0.0000
			(0.0462)	(0.0008)	(0.0383)	(0.459)	(0.0000)	(0.0000)
X_{t-3}					0.0114	0.0226	0.0000	0.0000
					(0.0372)	(0.0458)	(0.0000)	(0.0000)
X_{t-4}					0.0381	0.1050**		0.0000
					(0.0272)	(0.0423)		(0.0000)
c	0.0027	0.0034	-0.0087	0.0036*	0.0286		0.0393**	0.0069***
	0.0042	(0.0024)	(0.0206)	(0.0019)	(0.0222)		(0.0018)	(0.0020)
Adj. R^2	0.5444	0.5445	0.5555	0.5502	0.5562	0.5613	0.5510	0.5585
SSR	0.0396	0.0396	0.0385	0.0386	0.0380	0.0374	0.0386	0.0378
LLF	632.8679	632.9059	636.0771	601.7047	630.6715	629.0543	632.2680	631.2358
F – statistic	87.8228	87.8781	69.1017	64.6189	46.1150	40.2986	54.2622	46.5380
Prob(F – statistic)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
AIC	-5.7431	-5.7434	-5.7633	-5.7101	-5.7481	-5.7505	-5.7456	-5.7533

Note:+ denotes the models for which Newey – West (HAC) standard errors are used to correct for the heteroscedasticity. ***,**,* represent the significance levels at 1%, 5%, and 10%, respectively. Standard errors are denoted in parenthesis. SSR denotes the values of the sum of squared residuals, LLF denotes the log-likelihood value, and AIC denotes the value of the Akaike information criterion.

Table 9: Bounds Test: Estimation Results

Regressors	F-statistic Value	Significance Levels	Bounds	
Industrial Production Index	13.9604		**I(0)**	**I(1)**
CPI Index	13.9901		Asymptotic: n=1000	
Money Supply	14.4662	10%	3.02	3.51
Interest Rate	13.8092	5%	3.62	4.16
Foreign Currency Reserves	16.302	1%	4.94	5.58
Foreign Currency Debt Stock	12.863			
Net Export	14.5451			
Capital Inflows	15.6139			

Table 10: Long-run Level Equation: Estimation Results

$\mathbf{X_{t-1}}$	**Level Equation**
Industrial Production Index	$\mathrm{EC_t} = \mathrm{RV_t} - (0.0001 * X^{*}_{t-1} + 0.0088)$
CPI Index	$\mathrm{EC_t} = \mathrm{RV_t} - (0.0000 * \mathrm{X_{t-1}} + 0.0107)$
Money Supply	$\mathrm{EC_t} = \mathrm{RV_t} - (0.0019 * X^{*}_{t-1} + 0.0107)$
Interest Rate	$\mathrm{EC_t} = \mathrm{RV_t} - (0.0003 * X^{*}_{t-1} + 0.0107)$
Foreign Currency Reserves	$\mathrm{EC_t} = \mathrm{RV_t} - (-0.005 * X^{*}_{t-1} + 0.0744)$
Foreign Currency Debt Stock	$\mathrm{EC_t} = \mathrm{RV_t} - (-0.0008 * X^{*}_{t-1} + 0.0251)$
Net Export	$\mathrm{EC_t} = \mathrm{RV_t} - (-0.0000 * \mathrm{X_{t-1}} + 0.0119)$
Capital Inflows	$\mathrm{EC_t} = \mathrm{RV_t} - (0.0001 * X^{*}_{t-1} + 0.0190)$

Note: *denotes the significant long-run coefficient of exogenous regressor at 10%. $\mathrm{EC_t}$ denotes the error correction term.

5. Conclusion

We tacked the exchange rate and macroeconomic series together sampled at different frequencies for Turkey using the GARCH-MIDAS model, which prevents a potential veiling of the volatility patterns resulting from a temporal aggregation of the former. Grounded on the mixed data sampling, we aimed to disclose the extent to which the economic sources are responsible for the long-term exchange rate volatility in the Turkish economy. In visualizing the economic determinants of the exchange rate volatility thoroughly, we controlled each potentially relevant series representing different aspects of the Turkish economy, i.e., economic activity, monetary policy stance, and foreign exchange and liquidity conditions. Also, as the GARCH-MIDAS model setting enables us to differentiate between short- and long-term volatility components, we explored the degree to which the economic determinants capture the realized volatility. At first, to control if the Turkish exchange rate data fits the GARCH-MIDAS model and if any identification problem arises, we drew the Beta weighting functions, examined the distribution of errors, and controlled parameter consistency across different periods. We decided on two sub-periods: one was determined to distinguish potential differences across the pre-crisis and post-crisis episodes for the Turkish economy. The other was set to account for the policy shift in the monetary policy stance in late 2010 towards more on the financial stability objective and compared the full sample with sub-samples accordingly.

Tests for consistency of parameter estimates and distribution of estimation errors across different samples gave promoting evidence for the goodness of model fit. Further, we controlled the homogeneity of MIDAS weighting schemas across different periods and obtained various lagged effects of the long-term components under different samples. The model with realized volatility provided that there exists information content of the past months in explaining the long-term volatility. We also estimated a high degree of persistence for the short-term volatility component. We observed a smoother long-term component of exchange rate volatility when exogenous regressors, true to type, replaced the realized volatility. We still reached that economic fundamentals are relevant in explaining the long-term component of the volatility. However, the resulting change in macroeconomic variables generated less than a proportional change in the volatility in magnitude. The ARDL model estimates with monthly realized volatility also confirmed the estimation results of the GARCH-MIDAS model and pointed to limited effects of macroeconomic determinants. A rise in industrial production growth, official foreign exchange reserves, short-term debt stock, and capital inflows lead to a fall in long-term exchange rate volatility under different samples. The improvement in the export structure mitigates the long-term volatility but only during the new monetary policy period. A rise in the TRlibor rate and foreign exchange interventions via auctions causes the long-term volatility to rise. Besides, with increases in money growth and CPI inflation, exchange rate volatility increases but only during the post-crisis episode.

In the policymaking, the empirical evidence proves that the CBRT aimed to cope seriously with the excess volatility in the exchange rate market under the floating regime period of the last two decades (Değerli and Fendoğlu, 2013). This study promotes this fact by pointing out the pertinent transmission of money supply, interest rate, and official foreign exchange reserve changes directly designated by the monetary authority towards the long-term exchange rate volatility. However, the foreign exchange interventions slightly increase the volatility, contrary to the intention of the CBRT. Overall, this study reached that the long-term volatility features a high degree of persistence pattern and this pattern partially occurs to absorb shocks to macroeconomic variables.

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Appendix: Table A.1: The impact of Macroeconomic Series on the Long-term Volatility of Exchange Rate

	Industrial Production Growth				CPI Inflation		
	θ	$\varphi_k(\omega)$	$\hat{t}$		θ	$\varphi_k(\omega)$	$\hat{t}$
Full Sample	-0.0035	0.1563	-0.0547*	**Full Sample**	0.0038	0.4789	0.1821
2001:3-2010:9	-0.0053	0.4567	-0.2417*	**2001:3-2010:9**	-0.005	0.8596	-0.4288
2010:10-2020:2	0.0062	0.1491	0.0924*	**2010:10-2020:2**	0.0033	0.9851	0.3255*
2001:3-2008:9	-0.0106	0.2636	-0.279*	**2001:3-2008:9**	-0.0047	0.9553	-0.4479*
2008:10-2020:2	-0.0002	0.9963	-0.0199*	**2008:10-2020:2**	0.0089	0.3448	0.3073
Full Sample-volatility	-0.0014	0.2766	-0.0387*	**Full Sample-volatility**	0.00001	0.6567	0.0006
	Money Growth				**Interest Rate Changes**		
	θ	$\varphi_k(\omega)$	$\hat{t}$		θ	$\varphi_k(\omega)$	$\hat{t}$
Full Sample	0.0096	0.2476	0.2379*	**Full Sample**	0.01339	0.3450	0.4629*
2001:3-2010:9	0.0057	0.3066	0.1748	**2001:3-2010:9**	0.01159	0.1461	0.1694*
2010:10-2020:2	0.0035	0.6869	0.2406*	**2010:10-2020:2**	0.0129	0.1897	0.2449*
2001:3-2008:9	-0.0037	0.7142	-0.2638*	**2001:3-2008:9**	0.01	0.1441	0.1441*
2008:10-2020:2	0.0179	0.2060	0.3693*	**2008:10-2020:2**	0.0218	0.1694	0.3699*
Full Sample-volatility	0.0055	0.8427	0.4645	**Full Sample-volatility**	0.0012	0.8611	0.1033
	Change in Foreign Currency Reserves				**Change in Foreign Currency Debt Stock**		
	θ	$\varphi_k(\omega)$	$\hat{t}$		θ	$\varphi_k(\omega)$	$\hat{t}$
Full Sample	-0.0016	0.6891	-0.1101*	**Full Sample**	-0.0019	0.6605	-0.1254*
2001:3-2010:9	-0.0012	0.7868	-0.0943*	**2001:3-2010:9**	-0.0014	0.6495	-0.0908*
2010:10-2020:2	-0.0025	0.6292	-0.1571*	**2010:10-2020:2**	-0.0004	0.5302	-0.0212
2001:3-2008:9	-0.0011	0.9542	-0.1049*	**2001:3-2008:9**	-0.004	0.2059	-0.0823*
2008:10-2020:2	-0.0021	0.5177	-0.1086*	**2008:10-2020:2**	-0.0033	0.5213	-0.1718*
Full Sample-volatility	-0.0010	1.0428	-0.1042	**Full Sample-volatility**	0.0015	0.9244	0.13874*
	Net Export Changes				**Change in Capital Inflows**		
	θ	$\varphi_k(\omega)$	$\hat{t}$		θ	$\varphi_k(\omega)$	$\hat{t}$
Full Sample	-0.0089	0.366	-0.3251	**Full Sample**	-0.0031	0.1437	-0.0445*
2001:3-2010:9	-0.0035	0.4653	-0.1627	**2001:3-2010:9**	-0.0024	0.1443	-0.0346*
2010:10-2020:2	-0.0092	0.4123	-0.3785*	**2010:10-2020:2**	-0.0014	0.5495	-0.0768*
2001:3-2008:9	0.0030	0.9586	0.2879	**2001:3-2008:9**	0.0019	0.8452	0.1607
2008:10-2020:2	0.0044	0.9789	0.4316	**2008:10-2020:2**	-0.0021	0.3122	-0.0655*
Full Sample-volatility	-0.0019	0.1491	-0.0283	**Full Sample-volatility**	0.0098	0.1482	0.14532*

Note: *denotes the cases where both parameters of θ and ω are significant at least 10% level. $\hat{\tau}$ denotes the impact of a 1% change in X_{t-1} on the long-term volatility.