Deterministic Effects of Volatility on Mixed Frequency GARCH in Means MIDAS Model: Evidence from Turkey

Fehmi Özsoy and Nükhet Doğan®

Submission Time: 5 January 2022 | **Acceptance Time:** 7 July 2022

ABSTRACT

Volatility is a key concept for understanding the dual relationships between the economic variables since it is inversely related to the stability of economies. Many models such as GARCH models have been constructed through time to understand which determinants and conditions can affect the volatility. These models mostly show the significant relationships between the volatilities generated by the low frequency macroeconomic activities and the high frequency financial variables in a stochastic way. However, it is required to check whether there exist deterministic effects of volatilities on high frequency economic variables. In order to reveal these deterministic effects, we developed a new component-wise model, namely GARCH-M MIDAS model. We formulate this model on stock prices and exchange rates, in which the long run volatility is driven by consumer price and industrial production indexes in a separate way. Hence, our empirical analyses support that both types of volatilities have statistically significant deterministic effects on the asset pricing of high frequency financial variables. We also find that macroeconomic activities have a significant role on the asset pricing in long horizons.

Keywords: *MIDAS, GARCH-MIDAS, Long Run, Short Run, Deterministic Effects*

JEL Codes: C32, C51, C52, G10.

1. INTRODUCTION

Volatility is an important source of fluctuations occurred in the valuation of the assets or currencies over time. It shows the level of risks taken with the price changes of the assets since it is inversely related with the stability of the economies. Therefore, many studies such as Bollerslev (1986), Engle and Rangel (2008), Adrian and Rosenberg (2008), Humpe and Macmillan (2009) and Peiro (2015) have focused on forecasting the volatilities in order to capture the true nature of such changes and their future movements. Since the sources of the volatility differ on the economic activities, volatility has been considered with many components. Thus, we consider the volatility as the sum of short and long run volatilities. The short run volatilities are affected by the unexpected financial events, whereas the long run

® Fehmi Özsoy, PhD of Econometrics, Haci Bayram Veli University, Emniyet Mahallesi Muammer Yaşar Bostanci Caddesi, No:4, Beşevler/Ankara, Turkey, (email: fehmi.286@gmail.com), Tel: +90 536 344 14 74.
Nükhet Doğan, Professor of Econometrics, Haci Bayram Veli University, Emniyet Mahallesi Muammer Yaşar Bostanci Caddesi, No:4, Beşevler/Ankara, Turkey, (email: nukhet.dogan@hbv.edu.tr), Tel: +90 312 216 13 08.
The authors gratefully acknowledge the helpful and substantive comments on concepts related to this paper.

volatilities show the changes on the high frequency variables generated by the low frequency macroeconomic variables. However, some classical volatility models such as GARCH models do not show this difference, we prefer using Mixed Data Sampling (MIDAS) analysis with those variables together in forecasting volatility. Thus, GARCH-MIDAS model of Engle et al. (2013) proposed a way in which both types of volatilities are examined stochastically. However, there may exist deterministic effects of both types of volatilities on the high frequency variables, which is also our main aim in this research. In order to capture those deterministic effects, we define a GARCH-M MIDAS model, in which we allow both long run and short run conditional variances to affect the conditional mean in GARCH-MIDAS model. As far as we know, these effects are not researched with MIDAS regressions before in the volatility literature. In addition, the stock prices and the exchange rates are separately taken as high frequency variables in this research; and the industrial production and the consumer price indexes are chosen as low frequency variables to generate the volatilities, with which changes on each high frequency variables are defined.

Measuring financial market performance is often tied to the volatility of financial variables. Thus, it is important to explain the main factors that can be more effective on pricing of the financial assets. In asset pricing, returns and volatility are fundamental components that describe the properties of financial assets, and better volatility predictions lead to more accurate valuation. Volatility is also used for risk management, as it plays an important role in computing the value at risk (Chun et.al., 2020:1). Therefore, in order to avoid the risks that harm the investments, the volatility will be examined according to their potential sources, which can be defined as short and long runs, mainly. Firstly, the short run volatility is the immediate response of the financial variables to unexpected financial events such as shocks or speculations, and estimated by the past fluctuations on the price of the financial variables. Since this type of volatility is considered as a risk factor, investors must react to hedge their investments when the short run volatility is getting higher as mentioned in the researches of Peng et.al. (2014); and Pati et.al. (2019). On the other hand, even though the short run volatility itself is a necessary risk factor for the financial markets, it is not sufficient to explain the long run effects of the macroeconomic changes over the financial markets since the irrational behaviors of the investors in extreme conditions mislead the expected prices of the financial assets in the long run. Therefore, the low frequency macroeconomic variables and their expectations which drive the business cycles can be considered as the additional risk factors in the analysis of the long run volatility.

In this research, we tried to define how the volatility can affect the stock prices and the exchange rates through both their volatilities and the macroeconomic variables such as the Consumer Price Index (*CPI*) and Industrial Production Index (*IP*) with the help of the data of different frequencies. In financial markets, stock prices are the most common high frequency variable that can be affected by the volatility of both short and long runs. Since the short run volatility is basically a risk-return trade-off, in which investors demand higher risk premiums to compensate their losses generated by the high volatility in the short run, the stock prices are getting higher to increase returns when the short run volatility is high. Moreover, the Consumer Price Index (*CPI*) and Industrial Production Index (*IP*) are mainly considered as the most influential macroeconomic factors that can change the decisions of the investors in the long run. Indeed, they are closely related to the production processes that can affect the expected returns. The first macroeconomic factor in our consideration is the inflation which is the acceleration of the increasing *CPI* and can change the stock prices in two different ways, positive and negative. Gordon (1962) argues that there exist two channels that the inflation affects the stock prices in a positive way: One of which is that the more monetary easing with inflation is, the more growth rate of dividends is, which raises the stock prices. Another channel is that the lower expected rate of returns generated by the monetary expansion raises the demand for equities, which provides increases on the stock prices. However, adversely, inflation uncertainty leads to higher risks associated with the investment and production processes of the corporate sector. This uncertainty implies a non-optimal allocation of investment that leads to a stock price decline (Schwert, 1981; Apergis and Eleftheriou, 2002:232). The second macroeconomic factor considered is *IP*. While Humpe and Macmillan (2009) and Peiro (2015) suggested that the positive change on the *IP* movements has the same sign effects on the stock prices through expected future dividends; Tsagkanos and Siriopoulos (2015) proposed that a rise on *IP* provides increases both current dividends and stock prices, contemporaneously through higher revenues and profits.

Moreover, the exchange rate is one of the key factors that needs to be estimated well for the decision makers due to the globalization. In order to forecast the movements of the exchange rates properly, it is required to examine the exchange rate volatility since exchange rate volatility can affect a country's net international investment position depending on the scale of its international balance sheet and on its currency composition of foreign assets and liabilities (Bush and Noria, 2021:704). In addition, as the same economic events have different effects on the economic variables depending on the status of the economies in different times, the effects of the exchange rate volatility can differ with the variables that are used to estimate the volatility for different time intervals. In the short run, the exchange rate can fluctuate with the past values of its volatility in two opposite ways. The first way is defined as Uncovered Interest Parity (UIP) theory in which while the high interest exchange rates providing high returns tend to depreciate in high volatility. On the other hand, the exchange rates with low interests can provide a hedge in the high volatility environment because high volatility causes a sharp decline on the risky carry trades due to lack of liquidity, rising global risk, and funding constraints (Menkhoff et.al. 2012; Clarida et. al., 2009; and Kaurijoki et al., 2014). The opposite way is called as the Forward Premium Puzzle, in which whenever the exchange rate volatility rises in the domestic market, the Value-at-Risk (VaR) constraints are getting tighter, which limits not only the direct sellers but also the intermediaries, defined as the importers in the foreign exchange markets, to buy foreign risk-free assets. It leads domestic risk-free interest rates to remain lower than the foreign rates, which changes the domestic currency to an attractive one (in which the transaction costs are lower than the realized returns for their carry trades) and makes both the domestic currency and the interest rate differentials to appreciate together (Fang and Liu, 2021; Dupuy et al., 2021; and Adam et al., 2018). Moreover, some researches such as Molodtsova and Papell (2009) and Eichler and Littke (2018) showed that the exchange rate volatility has reflected the changes on macroeconomic variables as well. The theories explaining the short run volatility are also applicable for the long run volatility with some adjustments according to the macroeconomic changes. Whenever the inflation is getting higher, the UIP theory suggests that it leads volatility to get higher, which depreciates the domestic currency since the inflation deteriorates the international carry trades (Clarida et al., 2009). On the other hand, the Forward Premium Puzzle proposes that in high volatility environment, both the governmental and the sectoral precautions to the high inflation can act as the VaR constraints to provide a stability on the domestic markets, which protects the domestic currency from a decreasing trend (Fang and Liu, 2021). In addition, since the exportation is deteriorating in the high volatility, which decreases the returns that the investors expect to get, it leads *IP* to change depending on the dollarization status of the countries. These changes also cause an increasing inflation in highly dollarized countries. Therefore, the *IP* follows the same theories as an inflation for exchange rates in high volatility.

The classical models presented in the researches such as Engle (1982), Bollerslev (1986) and Engle et al. (1987) are generally constructed with the variables of the same frequencies.

However, since the macroeconomic variables are often collected in low frequencies, their effects on the high frequency financial markets cannot be reflected properly in these researches. Therefore, we used the MIDAS regressions proposed by Ghysels et al. (2004) in our research in order to obtain the macroeconomic effects without equating their data. In addition, all the limitations of the data availability are put away so that economic relationships can be identified among the data with different frequencies. Moreover, they eliminate the biases of the estimates generated from aggregations and the problems such as aliasing. In addition, these equations allow to define separate effects in the different time horizons since the same events have macro and micro perspectives that can change the condition of these effects in time. Finally, our main contribution in this research is to show the deterministic changes of the volatilities on the financial variables with more efficient estimates by adding both types of variances to the conditional mean.

In this research, we will present a new class of the component-wise volatility models, namely GARCH-in Means (GARCH-M) MIDAS model. Since this model is constructed to search for the deterministic effects of volatilities on high frequent variables, as far as we know, it is the first research with MIDAS filtering for deterministic effects in the volatility literature. For its applicability, we constructed a single-independent variable model by using two different low frequency variables, namely monthly Industrial Production Index and the Consumer Price Index in a separate way to generate the long run volatilities. Moreover, we selected the daily closing prices of Borsa Istanbul stocks and US Dollar versus Turkish Lira exchange rates as high frequency variables to estimate the short run volatilities. The main findings suggest that adding both types of volatilities to the mean deterministically enhances the asset pricing of both Borsa Istanbul stock prices and US Dollar versus Turkish Lira exchange rates. These effects are statistically significant and positive (negative) in the Borsa Istanbul stock prices (US Dollar vs. Turkish Lira exchange rates) analyses.

The rest of this paper is constructed as follows. Firstly, we will give an introduction of GARCH-MIDAS model in the first part of Section 2 and then construct our new model, namely GARCH-M MIDAS model in the second part of the same section. After that, the empirical implementations of this new model will be presented with details in Section 3. Finally, Section 4 concludes this paper.

2. METHODOLOGY

2.1. GARCH-MIDAS Model

According to the Efficient Market Hypothesis (EMH), all available information is fully reflected in asset prices and it is impossible for investors to gain excess returns or beat the market (Fama, 1965; Xu et al., 2019:170). By contrast, volatility, a statistical measure of the variation of trading price series over time, has already proved to be predictable. Actually, it plays a central role in practical financial decisions, such as option pricing, risk management, asset collection, and so on (Xu et al., 2019:170). Therefore, the proper analysis of volatility is required to make right choices. It is a fact that the unobservable elements such as financial events, speculations or unexpected news can affect the decisions, thus volatility on the short run depending on the economic condition of the states. For example, unexpected poor earnings should have an impact during expansion different from during the recession (Engle et al., 2013:778). Thus, the investors need to take necessary actions against these unforeseen circumstances in a short time. As a result, these changes must be reflected in the short run part of the volatilities. In addition, there exist some researches such as Engle and Rangel (2008), Amendola et al., (2017) and Xu et al. (2019) showing that the macroeconomic changes have dramatic effects on the volatility on the long run. Moreover, since the macroeconomic variables and the unobserved events can interact with each other in time, their effects must be examined in the same analysis. Therefore, instead of working with the conventional GARCH models of the same frequency, it is needed to clarify the effects of long run and short run changes, separately for the volatility models. In order to show both the different and the combined effects of the parts of the volatility, Engle et al. (2013) proposed the GARCH-MIDAS model in their research.

The GARCH-MIDAS Model, inspired from the research of Engle and Rangel (2008) which allows the unconditional volatility is changeable in time, is constructed as follows:

Let $y_{i,t}$ be the high frequency variable. Also, suppose that $\varepsilon_{i,t} \mid \Phi_{(i-1),t} \sim N(0,1)$ such that $\Phi_{(i-1),t}$ is the information set up to *(i-1)th* day of the period *t*. Assume that the period *t* consists of N_t days. Therefore, the general heteroscedastic GARCH-MIDAS equation is constructed as:

$$y_{i,t} = \mu + \sqrt{g_{i,t} \times \tau_t}\ \varepsilon_{i,t} \quad \forall i = 1{:}N_t \tag{1}$$

where μ is the unconditional mean of $y_{i,t}$ and $(g_{i,t} \times \tau_t)$ is the conditional variance consisting of two parts, namely, the short run component $g_{i,t}$ and the long run component τ_t.

The short run variance, namely $g_{i,t}$, is assumed to be generated from both the daily liquidity changes and short-term factors. Therefore, the short run equation is defined with mean-reverting unit GARCH (1,1) under the assumptions of $\alpha > 0$, $\beta \geq 0$ and $\alpha + \beta < 1$ as follows:

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

Moreover, in order to ensure that the τ_t is pre-determined, $E_{t-1}\ (g_{i,t}) = 1$ must be assumed (Engle et al., 2013).

Since the long run variance, namely τ_t is assumed to be received from the effects of the low frequency macroeconomic changes or realized volatilities over time, it is constructed with the MIDAS polynomials using the low frequency data of the macroeconomic variables. If the data of the macroeconomic variables consists of only past values, then τ_t is called as one-sided filter whereas if there exist both past and expected values, then τ_t is called as two-sided filter.

The one-sided filter is defined as follows:

$$\log(\tau_t) = m + \theta \sum_{k=1}^{K} \varphi_k(w_1, w_2) x_{t-k}\ , \tag{3}$$

where $\varphi_k(w_1, w_2)$ are the weight functions which are calculated in either way of (4):

$$\varphi_k(w_1, w_2) = \begin{cases} \dfrac{(\frac{k}{K})^{w_1-1}(1-\frac{k}{K})^{w_2-1}}{\sum_{j=1}^{K}(\frac{j}{K})^{w_1-1}(1-\frac{j}{K})^{w_2-1}}, & for\ Beta\ weights, \\ \dfrac{w^k}{\sum_{j=1}^{K} w^j}, & for\ Expo.\ weights, \end{cases} \tag{4}$$

where $\sum_{k=1}^{K} \varphi_k(w_1, w_2) = 1$.

The beta function is very flexible, allowing for equally, increasingly or decreasingly weighting schemes, provided that $w_n \geq 1$ with n = 1, 2. For instance, $w_1 = w_2 = 1$ yields the equally weighting scheme, $w_1 > w_2$ the monotonically increasing weighting scheme (farther observations are weighted more) and $w_1 < w_2$ the monotonically decreasing weighting scheme (closer observations are weighted more) (Amendola et al., 2017:160).

It is noted that the short run volatility can be predicted directly while it is recommended to take the natural logarithm of the long run volatility in case of negative values taken by the low frequency macroeconomic variables. Also, if $\theta = 0$, then there exists no effect of macroeconomic variable on the long run volatility under the assumption of $E_{t-1}\left(g_{i,t}\right) = 1$ as:

$$E\left((y_{i,t} - \mu)^2\right) = exp(m)E\left(g_{i,t}\right) = exp(m). \tag{5}$$

The two-sided filter is constructed as in equation (6):

$$\log(\tau_t) = m + \theta^{lag} \sum_{k=1}^{K^{lag}} \varphi_k^{lag}\left(w_1^{lag}, w_2^{lag}\right) x_{t-k} + \theta^{lead} \sum_{k=-K^{lead}}^{0} \varphi_k^{lead}\left(w_1^{lead}, w_2^{lead}\right) x_{t-k\,|t-1}^{E}, \tag{6}$$

where, $x_{t-k\,|t-1}^{E}$ is the expected value of *x* at the time *(t-1)* up to K^{lead} periods ahead.

An additional macroeconomic variable expands the parameter space to be estimated as three more parameters, namely (θ, w_1, w_2) in one-sided filter, while six more parameters, namely (θ^{lag}, θ^{lead}, w_1^{lag}, w_2^{lag}, w_1^{lead}, w_2^{lead}) are estimated for two-sided filter.

Finally, the GARCH-MIDAS model uses Quasi Maximum Likelihood (QML) estimation method with the following likelihood function (LLF) defined as in (7):

$$LLF = -\frac{1}{2} \sum_{t=1}^{T} \{ \sum_{i=1}^{N_t} (\log(2\pi) + \log(g_{i,t} \times \tau_t) + \frac{\left(y_{i,t} - \mu\right)^2}{\left(g_{i,t} \times \tau_t\right)}) \}. \tag{7}$$

2.2. GARCH-M MIDAS Model

Although, the GARCH-MIDAS Model has many advantages such as explaining the stochastic effects of both the long run and the short run volatilities, it is needed to improve this model to a more efficient form of GARCH-M. There is a set of reasons for this:

- Some series are keen to have serial correlations which were generated from the volatility process. GARCH-M model gives smoother estimations with lower variances to eliminate high correlations.

- Another reason in financial theory is that GARCH-M model can explain the asymmetries in the volatility since volatility feedback amplifies large negative stock returns and dampens large positive returns, making stock returns negatively skewed and increasing potential for large crashes (Campbell and Ludger, 1992).

In order to improve our estimations due to these reasons and show the deterministic effects of both long run variance and the short run variance in the volatility analysis, we propose a new model namely the GARCH in Means MIDAS (GARCH-M MIDAS) model in which we added both variance parts into the mean and changed the equation (1) with the following equation:

$$y_{i,t} = \mu' + \kappa g'_{i,t} + \lambda \tau'_t + \sqrt{g'_{i,t} \times \tau'_t}\ \varepsilon_{i,t} \quad \forall i = 1{:}N_t \ . \tag{8}$$

This model consists of two steps in order to both improve the efficiency of the GARCH-MIDAS model and search for whether there exist deterministic effects or not:

Step 1. Use the original GARCH-MIDAS model; and find all the initial estimates and the stochastic volatility components without examining the residuals of the model for whether they are highly correlated or not. Choose weights as exponential weights for simplicity.

Step 2. Use GARCH-M MIDAS model with incomplete variables and take the estimates of Step 1 as the initial values of Step 2. The process compiled in Step 2 is described as follows:

Since both parts of the variance are going to be analyzed deterministically, only one low frequency macroeconomic variable is used in this new model for simplicity. In order to examine the deterministic effects on the volatility, the equation (2) is adjusted as follows:

$$g'_{i,t} = (1 - \alpha' - \beta') + \alpha' \frac{\left(y_{i-1,t} - \mu' - \kappa g_{i-1,t} - \lambda \tau_t\right)^2}{\tau'_t} + \beta' g'_{i-1,t}, \qquad (9)$$

where $g_{i-1,t}$ is the short run component of the GARCH-MIDAS model at *(i-1)*th day of the period *t* generated from equation (2) and τ_t is the long run component of the GARCH-MIDAS model at the period *t* predicted from equation (3). In this case, $g'_{i,t}$ is our new short run component at *i*th day of the period *t* using the GARCH-M MIDAS estimates. The coefficients with primes are the same as the ones in the step 1 in theory but the estimates of the counterparts in step 1 are taken as initial values for the estimations of iterations in step 2. Also, τ'_t is the new long run component predicted similarly with equation (3) but for only one variable as follows:

$$\log(\tau'_t) = m' + \theta' \sum_{k=1}^{K} \varphi_k(w') x_{t-k}, \qquad (10)$$

where $\varphi_k(w')$ is the exponential weight as in equation (4) using w' in which the results of *w* predicted in step 1 is used as initial values in the iterations of step 2. The procedure of *m* is also the same. This process is used for only one-sided filter since the aim is to find a meaningful relationship between the monthly macroeconomic variables and the daily ones.

It is noted that since GARCH-MIDAS model is constructed with the normal distribution, the LLF of GARCH-M MIDAS is also calculated as in GARCH-MIDAS model using the newly found components of the volatility and the result of the mean calculated in step 1 as:

$$LLF = -\frac{1}{2} \sum_{t=1}^{T} \{ \sum_{i=1}^{N_t} (\log(2\pi) + \log(g'_{i,t} \times \tau'_t) + \frac{\left(y_{i,t} - \mu'\right)^2}{\left(g'_{i,t} \times \tau'_t\right)})\} . \qquad (11)$$

3. EMPIRICAL ANALYSES

In this part, we report the estimates of GARCH-MIDAS and GARCH-M MIDAS specifications with the daily Closing Prices of Borsa Istanbul Stocks (*BIST100*) and US Dollar versus Turkish Lira Exchange Rates (*ER*) taken from The Electronic Data Distribution System of the Central Bank of the Republic of Turkey. Here, we would like to assess the effects of the short and long run volatilities on the high frequency variables. Firstly, we take the *BIST100* as dependent high frequency variable and monthly Industrial Production Index (*IP*) and Consumer Price Index (*CPI*) as independent low frequency determinants of the long run volatility from November, 1997 to October, 2020. The choice of these dates for the *BIST100* analyses is because the *IP* of Turkey started to fluctuate and the rise of *CPI* in Turkey has lost its momentum on November 1997 due to the lack of liquidity generated from the sharp decrease of Turkish exports as a result of the 1997 Asian Financial Crisis. Moreover, in the second part of our analyses, *ER* is chosen as high frequency variable and *IP* and *CPI* are used separately for the estimations of the parameters on each *ER* analysis from July 2002 to October 2020. It is because *ER* has experienced a high depreciation in the local currency on May 2002 and US Dollar lost about 7% value against the currencies of the key emerging countries.

In order to capture the deterministic effects of the monthly macroeconomic variables on the daily variables, our analyses have been performed within two steps, first of which gives the estimates of the analyses with the GARCH-MIDAS model which will be used as the initial values for the analyses with the GARCH-M MIDAS model and the second step shows the application of the GARCH-M MIDAS model by using the same data. We take the lag (K) of the secular component by the MIDAS weights as 32 for BIST100 analyses and 100 for *ER* analyses in Panel C.

On the first two columns of Table 3.1, the estimated coefficients and their standard deviations of implementing the GARCH-MIDAS model between *BIST100* and either *IP* or *CPI* are presented for the November, 1997 - October, 2020 period. In Panel A, the mean of *BIST100* change over the sample is around 0.001% for both analyses. In addition, in the short run part of the GARCH-MIDAS model shown in Panel B, the sum of coefficients α and β is less than 1 but high in both analyses, which suggests that there exists a volatility persistence. Besides, a high β-estimate suggests that low frequency macroeconomic variables have a persistent effect on the long run volatility as well. It is also consistent with the research of the Beltratti and Morana

(2006) in which they proposed macroeconomic factors have memory long enough to change the volatility in the future. According to Panel C, high *IP* lowers the long run volatility of the *BIST100* since θ-estimate is -10.2950 while increase on *CPI* provides a rise for the long run volatility of the *BIST100* since θ-estimate is 43.5700. In addition, MIDAS weight *(w)* of *BIST100* estimation with the *IP* are statistically insignificant at 5% level.

Coeff.	**BIST100-IP Nov.97-Oct.20**	**BIST100-CPI Nov.97-Oct.20**	**ER-IP Jul.02-Oct.20**	**ER-CPI Jul.02-Oct.20**
Panel A: $y_{i,t} = \mu + \sqrt{g_{i,t}.\tau_t} \, .\varepsilon_{i,t}$				
μ	0.0011*	0.0012*	9.89e-05	0.0001
	(0.0002)	(0.0002)	(8.69e-05)	(8.88e-05)
Panel B: $g_{i,t} = (1-\alpha-\beta) + \alpha\frac{(y_{i-1,t}-\mu)^2}{\tau_t} + \beta g_{i-1,t}$				
α	0.0996*	0.1160*	0.1390*	0.1379*
	(0.0046)	(0.0059)	(0.0051)	(0.0052)
β	0.8906*	0.8308*	0.8528*	0.8506*
	(0.0044)	(0.0082)	(0.0041)	(0.0041)
Panel C: $\log(\tau_t) = m + \theta\sum_{k=1}^{K}\varphi_k(w)x_{t-k}$				
m	-7.3675*	-8.6267*	-8.4833*	-9.2838*
	(0.1968)	(0.0568)	(0.3404)	(0.2437)
θ	-10.2950*	43.5700*	-26.7800*	33.1550*
	(2.2567)	(2.1881)	(6.9288)	(9.7551)
w	1.5960	1.0600*	1.0155*	3.3520
	(0.6942)	(0.0888)	(0.0374)	(2.5294)
Lags	*Ljung-Box-Q Statistics*			
5	[0.0000]	[0.0000]	[0.0000]	[0.0000]
10	[0.0000]	[0.0000]	[0.0000]	[0.0000]
20	[0.0000]	[0.0000]	[0.0000]	[0.0000]
60	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Lags	*Arch-LM Test Statistics*			
5	[0.0000]	[0.0000]	[0.0000]	[0.0002]
10	[0.0000]	[0.0000]	[0.0000]	[0.0011]
20	[0.0000]	[0.0000]	[0.0016]	[0.0311]
60	[0.0000]	[0.0000]	[0.5997]	[0.9267]

* indicates the level of significance at 5%.
** indicates the level of significance at 10%.
(.) includes Standard Errors, [.] includes Probability values.
Table 3.1: The Estimates of GARCH-MIDAS model

On the last two columns of Table 3.1, the same GARCH-MIDAS analyses are implemented between *ER* and either *IP* or *CPI* for the July, 2002 – October, 2020 period. The mean of *ER* change over the sample is almost 0.0001% for the analysis of *IP* effects on *ER*, whereas the mean is predicted as 0.0001% for the analysis of *CPI* effects on the volatility of *ER*. However, both estimates are statistically insignificant at 5% level. The both reactions of *ER* against both macroeconomic variables have also the same volatility persistence according to Panel B since the sum of coefficients α and β are less than 1 but high, again. In Panel C, a rising *IP* decreases the long run volatility of *ER* since θ-estimate is -26.7800, whereas an increase on *CPI* rises the volatility of *ER* due to the fact that θ-estimate is 33.1550. However, the MIDAS weight *(w)* in the volatility estimation of *ER* with the *CPI* is statistically insignificant at 5% level. To sum up, *IP* has strong negative stochastic effects on the long run volatility due to macroeconomic performance while inflation has firmly expanded the variation of both *BIST100* and *ER*.

The last part of Table 3.1 reports the probability values for the Ljung-Box-Q (LBQ) tests of autocorrelation and for the ARCH-LM tests of heteroscedasticity problems on residuals. Their null hypotheses are no residual autocorrelation and no residual heteroscedasticity for LBQ and ARCH-LM tests, respectively. For convenience, we choose the lag values as 5, 10, 20 and 60. As they are shown, the residuals of all analyses in Table 3.1 have autocorrelation problem since the null hypotheses are rejected at the 5% level with all lags. Moreover, the heteroscedasticity problem exists for the residuals of *BIST100* analyses since the null hypotheses are rejected at the 5% level with all lags, again. On the other hand, although residual heteroscedasticity problem remains in the first three lags of both *ER* analyses, ARCH effect is not observed with residuals since no heteroscedasticity hypothesis cannot be rejected at the 5% level at the lag 60.

In Table 3.2, we examine the same data sets within the same time intervals as on Table 3.1 using the GARCH-M MIDAS model since we want to show the hidden deterministic effects of two types of volatilities on asset pricing. The first two columns of Table 3.2 are for the analyses of *BIST100* in the November, 1997- October, 2020 period, again. As shown in Panel A in Table 3.2, the mean of *BIST100* change over the sample is 0.0007% for the first analysis, while it is predicted as 0.0008% in the second analysis. Moreover, in the same panel, there exist positive coefficients κ and λ for both short and long run volatilities, respectively in both analyses, which suggests that both the past volatilities of the *BIST00* and the volatilities generated by both *IP* and *CPI* deterministically affect the *BIST100* with the same sign. In other words, an increase on either long run or short run volatilities causes a rise on the *BIST100* prices. This result is consistent with the research of Pati et al. (2019) arguing that risk averse investors demand higher returns for their investments. More specifically, κ-estimates of both *BIST100* analyses are positive and statistically significant suggesting that the increase on past variations on the *BIST100* prices also rises the current *BIST100* prices. In addition, as shown in the first column of Table 3.2, a rise of the long run volatility based on *IP* increases *BIST100* because λ-estimate is 7.2971 in Panel A, which can support the work of Tsagkanos and Siriopoulos (2015) suggesting that a positive productivity shock in the industrial output provides higher stock prices through higher revenues and profits. Besides, the long run volatility based on *CPI* has also positive explanatory power on *BIST100* because λ-estimate is 6.4805 in Panel A. This is also consistent with the work of the Gordon (1962) suggesting that high inflation can increase the stock prices by either increasing the dividend returns or decreasing the expected returns of investments. The volatility persistence appears again in all analyses according to Panel B since the sum of coefficients α' and β' is less than 1 but high. As they are shown in Panel C, while *IP* negatively affects the long run volatility in the analysis of *BIST100* with *IP* since its θ'-estimate is -37.4080, *CPI* has a statistically significant effect on the long run volatility with the same sign because θ'-estimate is 46.9270. Moreover, the MIDAS weights (w') of *BIST100* estimation with *IP* and *CPI* are statistically significant at 5% level.

On the last two columns of Table 3.2, we implement GARCH-M MIDAS model to the *ER* with *IP* and *CPI* for the July, 2002 - October, 2020 sample. As it is shown in Panel A on Table 3.2, the mean of *ER* change over the sample is 0.0002% for the third analysis, while it is predicted as 0.0003% in the fourth analysis. In addition, the negative κ-estimates in both analyses shown in Panel A suggest that an increase on the short run volatility generated by the past variations of *ER* can appreciate the Turkish Lira. It is due to the governmental contingency plans such as reforms on the economic structures for the price stability after 2002. In other words, since Turkey adopted an inflation targeting system including the privatization of some government-owned companies to compensate the negative effects of the volatility in 2002, which provides the sufficient confidence and liquidity to the economy, the demand for Turkish Lira increases for the investors, which makes Turkish Lira appreciate when *ER* has a high short run volatility. However, the stronger effects on *ER* are observed with the volatilities generated by the macroeconomic variables due to high absolute values for their estimated λ-coefficients. Moreover, the rise on the *IP*-generated long run volatility of *ER* is associated with an appreciation of Turkish Lira since λ-estimate is negative in Panel A. This condition can be considered as Value-at-Risk (VaR) constraint for our *ER* analyses. Therefore, since especially the financial intermediaries cannot invest on the foreign assets with their full discretion, the interest rate differentials are getting higher, which also appreciates the Turkish Lira. In addition, as the *CPI*-generated long run volatility of *ER* is getting higher, it also appreciates Turkish lira as suggested by the negative λ-estimate in Panel A. These estimates are consistent with the Forward Premium Puzzle suggesting that any increase on the exchange rate volatility can appreciate the currencies with high interest rates due to the fact that VaR constraints limit especially the intermediaries to invest on the foreign assets of high risk-free rates (Fang and

Liu, 2021). According to Panel B, the estimated volatilities have lasted in the future, again due to the condition of the sum of the coefficients α' and β'. As they are shown in Panel C, an increase on *IP* also significantly lowers the long run volatility, while a rise on inflation provides an increase on the long run volatility significantly since θ'-estimates are -10.4540 for the third analysis and 63.4530 for the fourth analysis. Moreover, the MIDAS weights *(*w'*)* of *ER* estimation with *IP* and *CPI* are statistically significant at 5% level, again.

Coeff.	**BIST100-IP Nov.97-Oct.20**	**BIST100-CPI Nov.97-Oct.20**	**ER-IP Jul.02-Oct.20**	**ER-CPI Jul.02-Oct.20**
Panel A: $y_{i,t} = \mu' + \kappa g'_{i,t} + \lambda\tau'_t + \sqrt{g'_{i,t}.\tau'_t}\ .\varepsilon_{i,t}$				
μ'	0.0007*	0.0008*	0.0002*	0.0003*
	(0.0002)	(0.0002)	(9.40e-05)	(9.39e-05)
κ	0.0040*	0.0069*	-0.0012*	-0.0011*
	(0.0011)	(0.0009)	(0.0005)	(0.0004)
λ	7.2971*	6.4805*	-9.6771*	-14.2670*
	(1.1134)	(1.9630)	(1.5392)	(2.1880)
Panel B: $g'_{i,t} = (1-\alpha'-\beta') + \alpha'\frac{(y_{i-1,t}-\mu'-\kappa g_{i-1,t}-\lambda\tau_t)^2}{\tau'_t} + \beta' g'_{i-1,t}$				
α'	0.1120*	0.1186*	0.1309*	0.1269*
	(0.0054)	(0.0071)	(0.0060)	(0.0060)
β'	0.8531*	0.7603*	0.8483*	0.8484*
	(0.0073)	(0.0160)	(0.0045)	(0.0045)
Panel C: $\log(\tau'_t) = m' + \theta'\sum_{k=1}^{K}\varphi_k(w')x_{t-k}$				
m'	-7.9861*	-9.0576*	-9.5246*	-10.3880*
	(0.0829)	(0.0558)	(0.1834)	(0.2338)
θ'	-37.4080*	46.9270*	-10.4540*	63.4530*
	(4.4325)	(2.0808)	(4.4026)	(14.3520)
w'	1.0010*	1.0653*	4.9455**	1.0010*
	(0.0064)	(0.1154)	(2.9532)	(0.0755)
Lags	*Ljung-Box-Q Statistics*			
5	[0.3376]	[0.4022]	[0.0000]	[0.0001]
10	[0.1909]	[0.0821]	[0.0001]	[0.0003]
20	[0.3506]	[0.0150]	[0.0001]	[0.0004]
60	[0.6617]	[0.0951]	[0.0174]	[0.0464]
Lags	*Arch-LM Test Statistics*			
5	[0.1495]	[0.0021]	[0.0199]	[0.0240]
10	[0.1640]	[0.0005]	[0.0825]	[0.1149]
20	[0.1932]	[0.0671]	[0.2724]	[0.3691]
60	[0.4988]	[0.0712]	[0.9269]	[0.9610]

* indicates the level of significance at 5%.
** indicates the level of significance at 10%.
(.) includes Standard Errors [.] includes Probability values.
Table 3.2: The Estimates of GARCH-M MIDAS model

For the last part of Table 3.2, we tested our residuals of the analyses in Table 3.2 for autocorrelation and heteroscedasticity with LBQ and ARCH-LM tests. The test statistics suggest that the residuals of *BIST100* analyses on Table 3.2 are not autocorrelated since the null hypotheses cannot be rejected at the 5% level with all but the residual lag is 20. However, the null hypothesis cannot be rejected at 1% level with 20 lags, which makes that all residuals of *BIST100* analyses are not autocorrelated for all lags at this level. Moreover, the test statistics suggest that the heteroscedasticity problem only exists for the residuals of *BIST100* analyses using *CPI* with 5 or 10 lags. The other residuals of the *BIST100* analyses do not suggest to have heteroscedasticity since the null hypotheses cannot be rejected at the 5% level for these residuals. On the other hand, only the residuals of both *ER* analyses with 60 lags do not have autocorrelation problem at 1% level. Although residual autocorrelation problem remains in most *ER* analyses, the heteroscedasticity problem is diminished for them since all residuals of *ER* analyses hold the homoscedasticity property with all lags at 1% level.

Finally, in the appendix A, we extended our research with various examples using the same variables in three different time intervals. We have found that all estimates in Table A.2 are statistically significant at the 5% level. It suggests that our proposed method is applicable for different time samples with the same variables. Therefore, GARCH-M MIDAS model can be considered as robust for volatility estimation processes.

4. CONCLUSION

This paper has developed the novel GARCH-in Means MIDAS Model to measure how the low frequency macroeconomic variables affect the high frequency ones through the volatilities. The aim of this paper is to give a proper explanation for possible deterministic effects of both long and short run volatilities. To do so, we allow both components of the conditional variance to change the conditional means in the GARCH-MIDAS model, proposed by Engle et al. (2013).

We have proposed such an approach that can be considered as the MIDAS filtering in the long run volatility analysis; and GARCH-M (1,1) in the short run volatility estimation. The life span of data is chosen long enough to distinguish the deterministic effects we have looked for. Although this model can be generated in a multivariable framework, for convenience, we constructed a single-independent variable model by using monthly *IP* or *CPI* and the previous values of daily *BIST100* prices or *ER* to estimate the long and short run volatilities, respectively.

In the empirical analyses, we have found that there exist hidden deterministic effects of both volatility components on *BIST100* and *ER*. More specifically, the long run volatilities are stronger deterministic determinants compared to short run volatilities on the valuation of

BIST100 and *ER*. Our analyses support the idea that inflation and productivity on the industry can change the stock prices directly through volatilities in both short and long runs. Besides, the analyses show that a high volatility on inflation or productivity make Turkish lira appreciate since Turkish lira always has higher interest rates than foreign currencies for investors. It is also shown that the effects of volatilities on prices always have persistence along with the long horizons. In addition, since we obtained accurate estimates as our results by using different time intervals, our model can be considered as robust.

In conclusion, our research suggests that this novel GARCH-M MIDAS model can explain the changes of the high frequency variables through both volatility components generated by the low frequency ones in a deterministic way. Finally, this model may be extended to the multi-factorial settings or used for analyzing different specifications in further studies.

Appendix A:

Coeff.	**BIST100-CPI Feb.97-Oct.20**	**ER-IP Sep.99-Oct.20**	**ER-CPI Feb.02-Oct.20**
	Panel A: $y_{i,t} = \mu + \sqrt{g_{i,t}.\tau_t}\ .\varepsilon_{i,t}$		
μ	0.0012*	0.0003*	0.0001
	(0.0002)	(7.74e-05)	(8.76e-05)
	Panel B: $g_{i,t} = (1-\alpha-\beta) + \alpha\frac{(y_{i-1,t}-\mu)^2}{\tau_t} + \beta g_{i-1,t}$		
α	0.1246*	0.2390*	0.1368*
	(0.0062)	(0.0055)	(0.0052)
β	0.8439*	0.7609*	0.8489*
	(0.0072)	(0.0055)	(0.0042)
	Panel C: $\log(\tau_t) = m + \theta\sum_{k=1}^{K}\varphi_k(w)x_{t-k}$		
m	-8.3016*	-2.4853	-9.5051*
	(0.0962)	(1.9973)	(0.1944)
θ	37.5890*	-74.2980*	39.9510*
	(1.8742)	(2.1408)	(9.1851)
w	1.0256*	7.0912*	4.0005
	(0.1449)	(0.4136)	(2.8405)
Lags	*Ljung-Box-Q Statistics*		
5	[0.0000]	[0.0000]	[0.0000]
10	[0.0000]	[0.0000]	[0.0000]
20	[0.0000]	[0.0000]	[0.0000]
60	[0.0000]	[0.0000]	[0.0000]
Lags	*Arch-LM Test Statistics*		
5	[0.0000]	[0.9999]	[0.0004]
10	[0.0000]	[0.9999]	[0.0022]
20	[0.0000]	[0.9999]	[0.0488]
60	[0.0000]	[0.9999]	[0.9372]

* indicates the level of significance at 5%.
(.) includes Standard Errors, [.] includes Probability values.
Table A.1: The Estimates of GARCH-MIDAS model

Coeff.	BIST100-CPI Feb.97-Oct.20	ER-IP Sep.99-Oct.20	ER-CPI Feb.02-Oct.20
Panel A: $y_{i,t} = \mu' + \kappa g'_{i,t} + \lambda\tau'_t + \sqrt{g'_{i,t}.\tau'_t}\ .\varepsilon_{i,t}$			
μ'	0.0008*	0.0003*	0.0003*
	(0.0002)	(8.41e-05)	(9.28e-05)
κ	0.0069*	0.0049*	-0.0010*
	(0.0010)	(0.0006)	(0.0003)
λ	5.9404*	-0.0253*	-19.5680*
	(1.4350)	(0.0004)	(2.5704)
Panel B: $g'_{i,t} = (1-\alpha'-\beta') + \alpha' \frac{(y_{i-1,t}-\mu'-\kappa g_{i-1,t}-\lambda\tau_t)^2}{\tau'_t} + \beta' g'_{i-1,t}$			
α'	0.1171*	0.2409*	0.1233*
	(0.0066)	(0.0079)	(0.0060)
β'	0.7819*	0.6816*	0.8465*
	(0.0135)	(0.0063)	(0.0047)
Panel C: $\log(\tau'_t) = m' + \theta' \sum_{k=1}^{K} \varphi_k(w') x_{t-k}$			
m'	-8.9478*	-8.9279*	-10.7390*
	(0.0552)	(0.1099)	(0.2046)
θ'	39.0970*	-63.1910*	83.8630*
	(1.6700)	(9.1544)	(12.3110)
w'	1.0010*	1.0029*	1.0015*
	(0.0586)	(0.0075)	(0.0877)
Lags	*Ljung-Box-Q Statistics*		
5	[0.2588]	[0.9994]	[0.0001]
10	[0.1721]	[0.9999]	[0.0001]
20	[0.0618]	[0.9999]	[0.0003]
60	[0.2011]	[0.9999]	[0.0544]
Lags	*Arch-LM Test Statistics*		
5	[0.2610]	[0.9999]	[0.0444]
10	[0.0062]	[0.9999]	[0.1165]
20	[0.0503]	[0.9999]	[0.3939]
60	[0.0951]	[0.9999]	[0.9661]

* indicates the level of significance at 5%.
(.) includes Standard Errors, [.] includes Probability values.
Table A.2: The Estimates of GARCH-M MIDAS model

REFERENCES

Adam, T., S. Benecka and J. Mateju (2018). Financial Stress and its Non-Linear Impact on CEE Exchange Rates. *Journal of Financial Stability*, 36, 346-360.

Adrian, T. and J. Rosenberg (2008). Stock Returns and Volatility: Pricing the Short-Run and Long-Run Components of Market Risk. *The Journal of Finance*, 63(6), 2997-3030.

Amendola, A., V. Candila and A. Scognomillo (2017). On the Influence of US Monetary on Crude Oil Price Volatility. *Empirical Economics*, 52, 155-178.

Apergis, N. and S. Eleftheriou (2002). Interest Rates, Inflation and Stock Prices: The Case of the Athens Stock Exchange. *Journal of Policy Modeling*, 24, 231-236.

Beltratti, A. and C. Morana (2006). Breaks and Persistency: Macroeconomic Causes of Stock Market Volatility. *Journal of Econometrics*, 131(1), 151-177.

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

Bush, G. and G.L. Noria (2021). Uncertainty and Exchange Rate Volatility: Evidence from Mexico. *International Review of Economics and Finance,* 75, 704-722.

Campbell, J.Y. and H. Ludger (1992). No news is good news: An asymmetric model of changing Volatility in Stock Returns. *Journal of Financial Economics*, 31(3), 281-318.

Chun, D., H. Cho and D. Ryu (2020). Economic Indicators and Stock Market Volatility in an Emerging Economy. *Economic Systems*, 44(2).

Clarida, R., J. Davis and L. Pedersen (2009). Currency Carry Trade Regimes: Beyond the Fama Regression. *Journal of International Money and Finance*, 28, 1375–1389.

Dupuy, P., J. James and I.W. Marsh (2021). Attractive and Non-Attractive Currencies. *Journal of International Monetary and Finance*, 110(C).

Eichler, S. and H.C.N. Littke (2018). Central Bank Transparency and the Volatility of Exchange Rates. *Journal of International Money Finance*, 89, 23-49.

Engle, R., D. Lilien and R. Robins (1987). Estimating Time Varying Risk Premia in the Term Structure: The Arch-M Model. *Econometrica*, 55(2), 391-407.

Engle, R.F. (1982). Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, 50, 987-1007.

Engle, R.F. and J.G. Rangel (2008). The Spline GARCH Model for Low Frequency Volatility and Its Global Macroeconomic Causes. *Review of Financial Studies,* 21, 1187-1220.

Engle, R.F., E. Ghysels and B. Sohn (2013). Stock Market Volatility and Macroeconomic Fundamentals. *The Review of Economics and Statistics*, 95(3), 776-797.

Fama, E.F. (1965). The Behavior of Stock-Market Prices, *The Journal of Business*, 38 (1), 34–105

Fang, X. and Y. Liu (2021). Volatilities, Intermediaries and Exchange Rates. *Journal of Financial Economics*, 114, 217-233.

Ghysels, E., P. Santa-Clara and R. Valkanov (2004). The MIDAS Touch: Mixed Data Sampling Regression Models. https://escholarship.org/uc/item/9mf223rs (accessed August 06, 2019).

Gordon, M.J. (1962). *The Investment, Financing and Valuation of the Corporation*. R.D. Irwin, Homewood, IL.

Humpe, A., and P. Macmillan (2009). Can Macroeconomic Variables explain Long-term Stock Market Movements? A Comparison of the US and Japan. *Applied Financial Economics*, 19, 111-119.

Kaurijoki, M., J. Nikkinen and J. Aijo (2014). Return-Implied Volatility Dynamics of High and Low Yielding Currencies. *The Journal of the Future Markets*, 35, 1026-1041.

Lütkepohl, H., (1981). A Model for Non-Negative and Non-Positive Distributed Lag Functions. *Journal of Econometrics,* 16(2), 211-219.

Menkhoff, L., L. Sarno, M. Schmeling and A. Schrimpf (2012). Carry Trades and Global Foreign Exchange Volatility. *The Journal of Finance*, 67(2), 681-718.

Molodtsova, T. and D. Papell (2009). Out of Sample Exchange Rate Predictability with Taylor Rule Fundamentals. *Journal of International Economics*, 77(2), 167-180.

Pati, P.C., P. Rajib and P. Barai (2019). The Role of the Volatility Index in Asset Pricing: The Case of the Indian Stock Market. *The Quarterly Review of Economics and Finance*, 74, 336-346.

Peiro, A. (2015). Stock Prices and Macroeconomic Factors: Some European Evidence. *International Review of Economics and Finance,* 41, 287-294.

Peng, D., J. Wang and Y. Rao (2014). Applications of Nonferrous Metal Price Volatility to Prediction of China's Stock Market. *Transactions of Nonferrous Metal Society of China*, 24(2), 597-604.

Schwert, P. (1981). The Adjustment of Stock Prices to Information About Inflation. *The Journal of Finance*, 36(1), 15–29.

Tsagkanos, A. and C. Siriopoulos (2015). Stock Markets and Industrial Production in North and South of Euro-Zone: Asymmetric Effects via Threshold Cointegration Approach. *Journal of Economic Asymmetries,* 12, 162-172.

Xu, Q., Z. Bo, J. Jiang and Y. Liu (2019). Does Google Search Index Really Help Predicting Stock Market Volatility? Evidence from the Modified Mixed Sampling Model on Volatility. *Knowledge-Based Systems*, 166, 170-185.