Econometric modelling of exchange rate volatility using mixed-frequency data

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Abstract

In the paper, we use generalized autoregressive conditional heteroskedasticity-mixed data sampling (GARCH-MIDAS) to study the impact of Australia's commodity price index, Global economic conditions indicator, Global Economic Policy Uncertainty Index, monthly realised volatility of S&P/ASX 200 index and monthly realised volatility of money supply on the volatility of the Australian dollar during the period from 1999 to 2021. The results indicate that exchange rate volatility rises with a rise in fluctuations in S&P/ASX 200 index, money supply volatility, commodity price index and falls with a rise in global economic activity. For the GEPU index, the slope coefficient is positive and significant only in the 3- years lag and not significant in the 1- and 2-years lags. This means that a rise in economic turmoil leads to a rise in exchange rate volatility. We also find strong evidence for asymmetry in the short-term volatility component. The results obtained in the study show that there is co-movement of volatility across various financial markets.

Keywords Exchange rate volatility · GARCH-MIDAS · Macroeconomic and financial variables · Asymmetry

JEL classification C58 · F31

1 Introduction

Since the adoption of floating systems by various industrial economies, unexpected nominal shocks have generated greater exchange rate volatility. Even though the volatility of the Australian dollar was relatively low in the period 1980-1983, due to its less flexible exchange rate regime, its volatility has increased since 1983. In this paper we explore the relationship

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between exchange rate volatility of the Australian dollar and financial markets or economic conditions. It is important to explore this relationship because a higher exchange rate volatility can have a detrimental impact on growth, especially in countries that are less financially developed (Aghion et al. 2009). This negative impact on growth occurs because greater exchange rate volatility can increase volatility in profits of businesses, which lowers the level of investment in the economy (Braun and Larrain 2005; Aghion et al. 2009). Secondly, larger exchange rate volatility can slow down progressions in Foreign Direct Investment (FDI) (Moraghen et al. 2020). Also, high exchange rate volatility can increase inflation uncertainty, that lowers output growth (Grier and Grier 2006). Furthermore, a rise in exchange rate volatility can increase unemployment (Belke 2005). Finally, increases in exchange rate volatility can increase the volatility of the bilateral trade flows as the transaction risks associated with international trade rise (Baum and Caglayan 2010).

In recent years, a large number of scholars have studied the relationship between exchange rate and various economic or financial conditions. For example, Zhang et al. (2016) conduct multi-horizon causality between prices of exporting commodities to exchange rate using high frequency data for the countries Australia, Chile, Norway and Canada. They find strong causality from prices of exporting commodities to exchange rate at low horizons. Inoue and Rossi (2019) adopt a non-parametric approach to study the impact of conventional and unconventional monetary policy shocks on exchange rates. Empirical results show that during both conventional and unconventional periods expansionary monetary policy leads to depreciation of the nominal exchange rate. Other studies investigate the impact of government spending shocks on exchange rate (Ferrara et al. 2021; Kim and Roubini 2008). Several other studies predict exchange rate fluctuations using commodity prices (Chen and Rogoff 2003; Ferraro, Rogoff and Rossi 2015). Using an error correction model Olayeni et al. (2020) show that variables like Nigeria-US exchange rate, Kilian's global economic activity index, oil price, and global oil production have a causal influence on the exchange rate fluctuations in the long run.

A second strand of literature attempts to model and forecast exchange rate volatility. Bailey and Steeley (2018) use GARCH model to forecast volatility of Australian dollar using high frequency data. Baillie and Bollerslev (1990) use high-frequency hourly data to study the relationship between exchange rate return and volatility of four major foreign exchange rates. Christou et al. (2018) in their study for 13 different countries use a quantile regression approach to predict exchange rate volatility and find that economic policy uncertainty can be used to predict exchange rate volatility. Study by Morana (2009) uses fractionally integrated factor vector autoregressive (FI-F-VAR) model to investigate linkages between exchange rate volatility and volatility of macroeconomic variables like the nominal money growth rate, the real industrial production growth rate, the nominal short-term interest, and the CPI inflation rate. Empirical results of the paper show that there is a strong causality from macroeconomic volatility to exchange rate volatility. In his analysis for three industrialized countries, namely the US, the UK and Japan, Kanas (2002) uses EGARCH model to show that the home stock return volatility increases exchange rate volatility in all the three countries. However, most of the previous studies considered exchange rate volatility as well as its potential macroeconomic and financial drivers at the same frequency. Additionally, they do not differentiate between short-term and long-term volatility components.

One exception is the paper by You and Liu (2020), who use GARCH-MIDAS model to study the impact of volatilities of Taylor-rule-based fundamentals on exchange rate volatility. However, in their study, they only use monetary fundamentals as predictors and they do not take into account the asymmetry in the short-term volatility component. The present work accounts for various other macroeconomic and financial fundamentals that have an effect on exchange rate volatility. Additionally, we consider the short-term asymmetry effect by using GJR-GARCH(1,1) specification to model the short-term volatility component. To the best of our knowledge this is the first empirical study that uses the GARCH-mixed data sampling (GARCH-MIDAS) approach of Engle et al. (2013) to study the impact of low frequency macroeconomic and financial variables on the volatility of Australian dollar. We study the volatility of the AUD/USD spot rate since it is the fourth highest traded pair and accounts for about 6.37% of global forex volume. As potential drivers of exchange rate volatility we consider volatility of S&P/ASX 200 index, changes in Australia's commodity price index, global economic conditions indicator, changes in global economic policy uncertainty and volatility of money supply.

The GARCH-MIDAS model is suitable for high frequency dependent variable (exchange rate volatility) and low frequency independent variables (macroeconomic and financial variables). While all the previous studies are based on data of the same frequency, GARCH-MIDAS model allows us to use data occurring naturally in different frequencies. This resolves the problem of information loss and estimation bias that results from aggregating or disaggregating variables to be used in models that rely on same frequency variables. GARCH-MIDAS model also helps us to differentiate between short-term and long-term volatility components. And thus, GARCH-MIDAS model may offer better prediction than GARCH model as it takes into account all the information in the estimation process.

The main contributions of this paper are as follows. To begin with, we find that a rise in fluctuations in S&P/ASX 200 index and money supply volatility increase the exchange rate volatility. This result is consistent with the previous studies that find a positive impact of money supply volatility and stock market volatility on exchange rate volatility (Morana 2009; Kanas 2002). Second, exchange rate volatility rises with a rise in commodity price index and global economic policy uncertainty. For both the commodity price index and the GEPU index, this result holds for the 3 years lag. Finally, global economic conditions indicator has a negative impact on exchange rate volatility. That is, an improvement in GECON reduces the exchange rate volatility. Additionally, we estimate the same model using monthly exchange rate data and monthly explanatory variables. Results show that when we aggregate data, we lose important information and get biased results.

The remainder of this paper is organised as follows: Section 2 presents a review of literature; Section 3 describes the GARCH-MIDAS model; Section 4 discusses the data used in the analysis; Sections 5 and 6 present and discuss the empirical results of the study and the usefulness of GARCH-MIDAS model, respectively; and finally, Section 7 concludes and provides policy implications of the results of the study.

2 Literature review

In this section, we divide the literature review into two parts. In the first part we discuss the relation between macroeconomic and financial variables and exchange rate volatility. In the second part, the applications of GARCH-MIDAS model are discussed.

First, we review literature that investigates the relationship between economic or financial conditions and exchange rate volatility. In his study Feldmann (2011) carries out a comprehensive analysis to study the impact of exchange rate volatility on unemployment rate for 17 major industrial economies. After controlling for several major factors, he concludes that higher exchange rate volatility is associated with higher unemployment. Bagella et al. (2006) in their study conclude that the volatility of real effective exchange rate has a negative and significant impact on the growth of per capita income. Koosakul and Shim (2021) in their study for Thailand use vector auto-regression (VAR) to study the impact of US dollar–Thai baht exchange rate volatility. They conclude that as exchange rate volatility rises trading volume also rises, which means higher volatility encourages market participation. Other authors analyse the impact of exchange rate volatility on exports and Foreign Direct Investment (FDI) (Baum et al. 2004; Moraghen et al. 2020). This is the strand of literature that studies the impact of exchange rate volatility on the macroeconomic and financial conditions of the economy. Another strand of literature focuses on the impact of macroeconomic and financial variables on exchange rate volatility. You and Liu (2020) in their study forecast daily exchange rate volatility by including monthly monetary fundamentals like industrial productions, consumer prices, money supplies (M1), and short-term interest rates as predictors. Zhou et al. (2020) use GARCH-MIDAS model to study the impact of relative economic policy uncertainty between China and the United States on the Chinese exchange rate volatility. They observed that increasing relative economic policy uncertainty between China and the United States leads to increasing long-term Chinese exchange rate volatility. They also conclude that GARCH-MIDAS model can better forecast exchange rate volatility. Bush and Noria (2021) use GMM methodology to estimate the impact of domestic and international uncertainty on the MXN/USD exchange rate return volatility. They find that domestic economic and political uncertainty, VIX and EPU indices have a positive impact of exchange rate return volatility. Grossman and Orlov (2014) use panel regressions to study the influence of numerous macroeconomic and policy variables on high-frequency components of exchange rate volatility.

Second, we review literature that discusses various applications of GARCH-MIDAS model. Engle et al. (2013) first introduced GARCH-MIDAS model to study the influence of low frequency macroeconomic variables like monthly PPI (producer price index) inflation rate and IP (industrial production) growth rate on high frequency stock market volatility. Since the introduction of GARCH-MIDAS model many applied researchers have used it to study the impact of several other macroeconomic variables on stock market volatility. For instance, Asgharian et al. (2013) in their study use GARCH-MIDAS model to predict stock market volatility. They conclude that macroeconomic variables contain information that can help predict the long-term and short-term components of the stock return volatility and GARCH-MIDAS has better predictive ability. Su et al. (2017) employ GARCH-MIDAS model to study the influence of news-based implied volatility on the long-term volatility of the US financial markets that includes the stock, commodity, bond and exchange markets. They observed that the monthly NVIX has a positive impact on the volatility of the financial markets. Wang et al. (2020) extend the model to take into account the asymmetry effect in the long-term and the short-term volatility components of the stock return volatility and observed that the models considering the asymmetry effect perform better than the traditional models. Several other authors use GARCH-MIDAS model to study the impact of economic conditions on stock market volatility[3]. Another study by Su et al. (2019) uses a bivariate GARCH-MIDAS model to investigate the spill over of economic uncertainty from the United States to the stock market volatility of other economies.

Several other researchers have used this model to predict commodity price volatility. Nguyen and Walther (2020), applied GARCH-MIDAS model to model and forecast volatility of commodities like crude oil, gold, silver and platinum futures by identifying the potential low frequency factors that drive the long-term volatility component of commodity futures. Fang et al. (2018) studied whether various macroeconomic variables can help predict the short-term and long-term volatility of U.S. gold futures. Empirical results show that macroeconomic variables have a significant impact on the long-term volatility component of gold futures. In the past decade, some scholars have also tried to model and forecast volatility of cryptocurrencies. For example, Conrad et al. (2018) used GARCH-MIDAS model to understand the impact of various financial and economic variables on the long-term fluctuations in Bitcoin. Empirical results show that long-term fluctuations in Bitcoin are closely related to global economic activity and stock market volatility.

A large number of researchers have extended the GARCH-MIDAS model to forecast oil price volatility, gold price volatility, bitcoin volatility and so forth. Therefore, we try to cover gap in the literature by employing GARCH-MIDAS model to study the impact of low frequency macroeconomic and financial variables on the volatility of the Australian dollar.

3 Methodology

We define the daily exchange rate return as $r_{it} = (lnEX_{i,t} - lnEX_{i-1,t})$, where t = 1, 2, …, T denotes monthly frequency; $i = 1,2, \dots, N_t$; N_t is the number of trading days in month t. We assume the exchange rate return on day i in month t follows the following process:

$$r_{i,t} = \mu + \sqrt{\tau_i g_{i,t} \varepsilon_{i.t}} \tag{1}$$

$$\varepsilon_{i,t} |\ \Phi_{i-1,t} \sim N(0,1) \tag{2}$$

[3] See, for instance, Conrad et al. (2014), Conrad et al. (2015), Girardin and Joyeux (2013), Li et al. (2020)

where $\Phi_{i-1,t}$ is the information set-up to the $(i-1)^{th}$ day of period t. μ represents the expected return for each day. In Equation (1) the short- and long-term component of the conditional variance are represented by $g_{i,t}$ and τ_t, respectively. The conditional variance dynamics of the component $g_{i,t}$ is assumed to follow a mean-reverting unit-variance GJR-GARCH (1,1) process as follows:

$$g_{i,t} = (1 - \alpha - \gamma/2 - \beta) + (\alpha + 1_{\{r_{i-1,t}<0\}}\gamma)\frac{(r_{i-1,t} - \mu)^2}{\tau_t} + \beta g_{i-1,t} \tag{3}$$

where $\alpha > 0$, $\beta > 0$ and $\alpha + \beta + \gamma/2 < 1$. $1_{\{r_{i-1,t}<0\}}$ is an indicator function, which takes value 1 when the return is negative, and zero otherwise.

Long-run component τ_t varies at the monthly frequency.

$$\tau_t = m + \theta \sum\nolimits_1^K \varphi_k(\omega_1, \omega_2) X_{t-k} \tag{4}$$

where $\varphi_k(\omega_1, \omega_2)$ denotes a certain weighing scheme and X_t is the monthly macroeconomic or financial variable. We choose the Beta weighing scheme given by

$$\varphi_k(\omega_1, \omega_2) = \frac{\left(\frac{k}{K+1}\right)^{\omega_1 - 1}\left(1 - \frac{k}{K+1}\right)^{\omega_2 - 1}}{\sum_{j=1}^{K}\left(\frac{j}{K+1}\right)^{\omega_1 - 1}\left(1 - \frac{j}{K+1}\right)^{\omega_2 - 1}} \tag{5}$$

where K denotes the maximum lag order of Beta polynomial. By this way of weighting, the weight, $\varphi_k(\omega_1, \omega_2) \geq 0, k = 1, \ldots, K$, sum to one. Two different methods can be used to estimate the parameters ω_1 and ω_2. In the first method, a restricted beta weighing scheme is selected. In the restricted beta weighing scheme, we fix $\omega_1 = 1$ and estimate the value of ω_2. In the restricted beta weighing scheme optimal weights are monotonically declining. In the unrestricted beta weighing scheme, ω_1 and ω_2 are estimated directly in the model. In the paper, we impose the restricted Beta weighting scheme, that is we set $\omega_1 = 1$.

For Eq. 4, we take the logarithm value of the long-term component. We use fixed window method under this rule. For a more comprehensive analysis, we consider three kinds of lagging order, including k = 12, k = 24 and k = 36.

$$\log(\tau_t) = m + \theta \sum_1^K \varphi_k(\omega_1, \omega_2) X_{t-k} \tag{6}$$

To calculate the monthly volatility of money supply we follow the method of Schwert (1989). We fit the following auto-regression model with 12 monthly dummy variables M_{jt}. In particular, $\hat{\varepsilon}_t^{\,2}$ from the following regression is used to estimate monthly macroeconomic volatility:

$$X_t = \sum_1^{12} \alpha_j M_{jt} + \gamma t + \sum_1^{12} \beta_i X_{t-i} + \varepsilon_t \tag{7}$$

We calculate the variance ratio (see Engle et al. 2013) to evaluate the explanatory value of the long-term volatility. It is the ratio of variance in the (log) long-term component and variance in the (log) conditional volatility. The ratio is given by:

$$\mathrm{VR} = \mathrm{var}(\log(\tau_t))/\mathrm{var}(\log(\tau_t g_t)) \tag{8}$$

4 Data

4.1 Data description

We consider daily AUD/USD exchange rate, that is, the US dollar value of the Australian dollar. Daily exchange rates are collected from the Federal Reserve Economic Data for the period 1 February 1999 to 30 November 2021. Exchange rate returns are defined as the first-differences of the natural logarithmic values of the exchange rates. The monthly realized volatility of the exchange rate return and volatility of S&P/ASX 200 index is calculated by the cumulative sum of squares of daily return. As potential drivers of exchange rate volatility we consider:

1. volatility of S&P/ASX 200 index
2. global economic conditions indicator (GECON)[4] (Baumeister et al. 2020)
3. volatility of money supply (M1)
4. changes in Australia's commodity price index[5] and
5. Changes in Global Economic Policy Uncertainty Index[6] (Davis 2016)

[4] GECON is a measure of global economic activity.

[5] Index of commodity prices of all commodities in the US.

[6] Since Australia is closely integrated with the global markets, volatility of the Australian exchange rate may be influenced not only by the relative economic policy uncertainty between Australia and the United States (Chen et al. 2020, Christou et al. 2018) but also global economic policy uncertainties. Exchange rate volatility is impacted by daily news related to new government policies and natural

Since the commodity price index and GEPU are not stationary, these variables are transformed for further analysis. The changes in Australia's commodity price index and Global Economic Policy Uncertainty Index[7] are calculated as $\Delta X_t = \ln(X_t) - \ln\,(X_{t-1})$ The statistical description, frequency and data source of the variables are presented in Table 1 and Table 2.

4.2 Descriptive statistics

Table 1 shows the means, standard deviation, skewness, kurtosis, augmented Dicky-Fuller test statistic, start date and end date of the variables used in the study. It can be inferred from Table 1 that the exchange rate return series is negatively skewed and leptokurtic, which means that it is more peaked and has fatter tails than the Gaussian distribution. As far as the explanatory variables are concerned, in terms of kurtosis, volatility of S&P/ASX 200 index, GECON and volatility of money supply are leptokurtic, while other variables are platykurtic. In terms of skewness, change in commodity price index is fairly symmetrical, change in GECON is negatively skewed, while other dependent variables are positively skewed. The ADF statistic for all the variables indicates that the null hypothesis of unit root can be rejected at 1% level of significance. And hence there is no need to transform any variable for further analysis. Table 2 shows the frequency and source of variables used in the study.

Table 1 Descriptive statistics for all variables

Variable	Mean	SD	Skewness	Kurtosis	Adf	Start	End
Exchange rate return	0.002	0.753	-0.747	11.526	-31.9	01-02-1999	30-11-2021
Volatility of S&P/ASX 200 index	13.681	32.805	8.817	102.651	-8.58	01-02-2000	01-11-2021
GECON	0.429	21.131	-0.496	3.401	-7.63	01-02-1999	01-11-2021
ΔGEPU	0.003	0.176	0.557	1.223	-11.2	01-02-1999	01-11-2021
Volitility of money supply	0.648	4.756	13.249	187.618	-12.1	01-01-2000	01-11-2021
ΔCommodity price index	0.005	0.031	0.263	1.662	-7.83	01-02-1999	01-11-2021

disasters as investors take into account these factors while investing. Investors lose confidence in currency of a country facing political turmoil and may choose to move capital to more stable economies. Therefore, how Australian exchange rate volatility is directly affected by global economic activity and global economic uncertainty is yet to be studied.

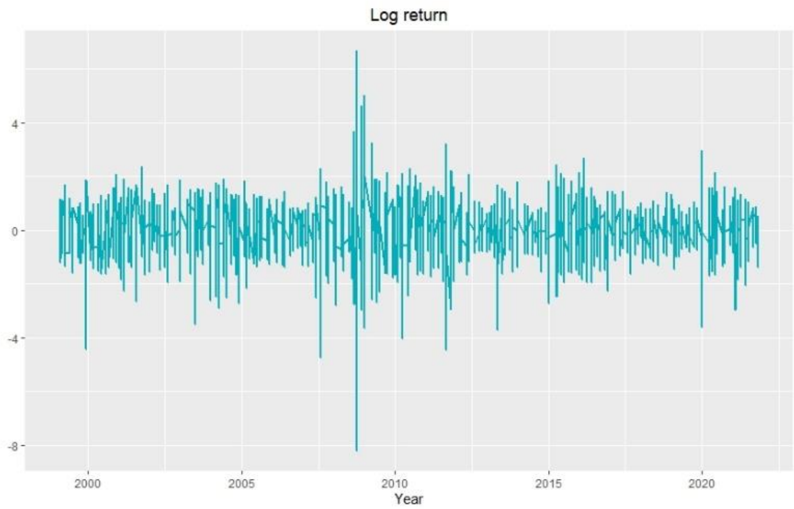
[7] GEPU index is computed as a GDP-weighted average of the national EPU indices of 21 countries.

Table2 Frequency and source of all variables

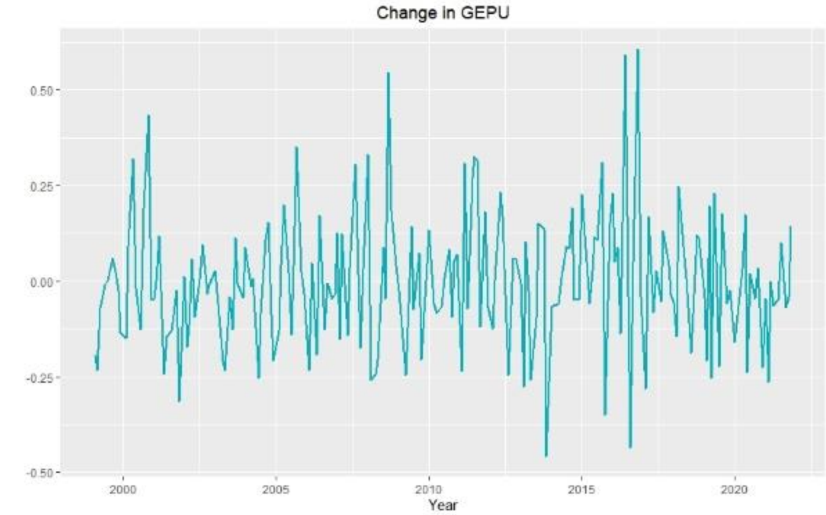
Variable	Frequency	Source
AUD/USD exchange rate	Daily	FRED
S&P/ASX 200 index	Daily	Yahoo! Finance
GECON	monthly	https://sites.google.com/site/cjsbaumeister/research
GEPU	monthly	https://www.policyuncertainty.com/global_monthly.html
Money supply (M1)	monthly	FRED
Commodity price index	monthly	https://www.rba.gov.au/statistics/frequency/commodity-prices/2021/

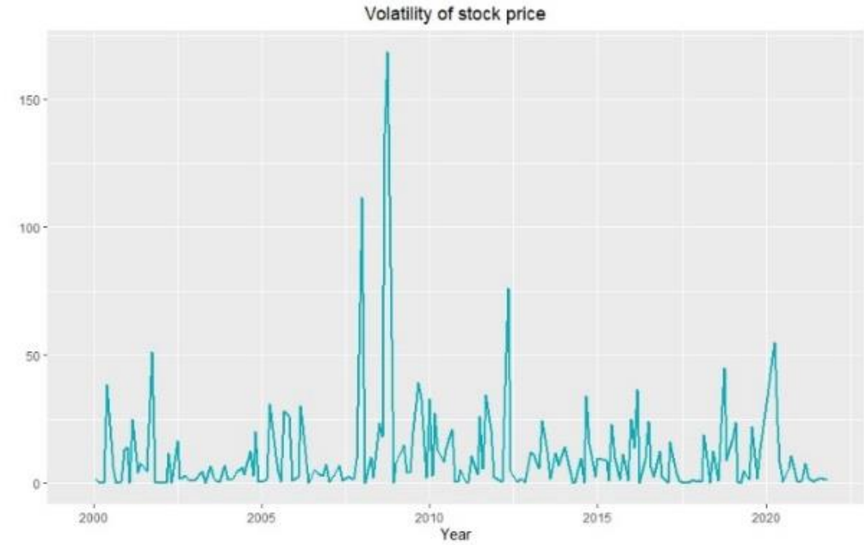
Time series plots of the variables used in the study are shown in Fig. 1. Panel A in Fig.1 shows the daily log returns of the Australian dollar. From the Figure it is clearly evident that there is volatility clustering and the amplitude of volatility varies with time. Also, the abnormal fluctuations can be seen during the Global Financial Crisis of 2007-2008. Panel B of Fig. 1 shows the time series plot of the macroeconomic and financial variables. It is evident from the Figure that all variables are trend stationary. Change in GEPU and change in commodity price index fluctuate around zero. The plot of the stock price volatility exhibits high volatility, especially during the Global Financial Crisis of 2007-2008.

Panel A Time series plot of the daily log return of Australian dollar



Panel B Time series plot of the monthly macroeconomic and financial variables.





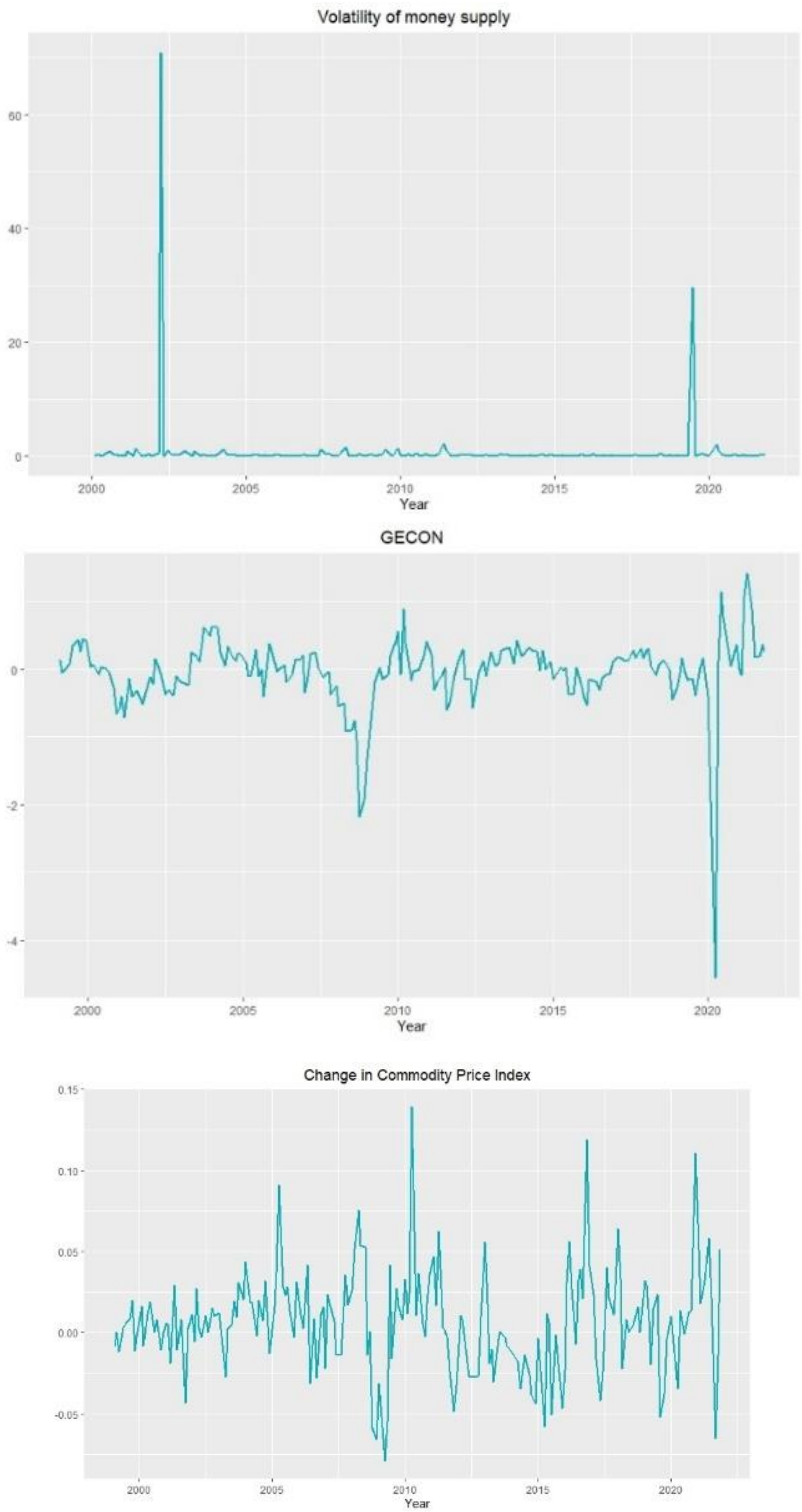


Fig.1 Time series plot of the log return of exchange rate and macroeconomic and financial variables

Table 3 Parameter estimation of GARCH-MIDAS: Realized volatility

Lags	μ	α	β	γ	m	θ	ω_2	LLF	BIC	VR
1 year	-0.0003 (0.011)	0.027*** (0.005)	0.958*** (0.005)	0.011* (0.006)	-0.893*** (0.122)	0.007*** (0.001)	4.567* (1.288)	-5900.549	11861.93	24.915
2 years	0.0003 (0.011)	0.028*** (0.005)	0.958*** (0.008)	0.011* (0.006)	-0.905*** (0.121)	0.007*** (0.001)	8.448*** (0.001)	-5888.751	11838.32	26.321
3 years	-0.0006 (0.001)	0.028*** (0.005)	0.958*** (0.005)	0.010* (0.006)	-0.898*** (0.122)	0.007*** (0.001)	12.553* (2.755)	-5879.758	11820.32	26.597

This table reports estimation results for parameters. Bollerslev–Wooldridge standard errors are reported in parentheses. We take the lags for 1,2 and 3 years respectively.
*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.
LLF is the value of the maximized log-likelihood function and BIC denotes Bayesian information criterion. The variance ratio VR is the proportion of long-term variance to the total variance.

Table 3 presents the estimation results of the realized volatility of the exchange rate on the long-term volatility of the exchange rate for three kinds of lagging years. From the Table it can be seen that the parameter μ is not significant for all the three lags. However, the parameter θ is highly significant, which means that higher realized volatility tends to increase the long-term exchange rate volatility. Additionally, the parameter γ is significant, which means that there is evidence of asymmetry.

5 Empirical results

In this section we analyse the impact of macroeconomic and financial conditions on exchange rate volatility. We do the analysis for three kinds of lagging years and for each financial and macroeconomic variable we see how they impact exchange rate volatility in the long run by looking at the value of parameter θ and its significance. Finally, we also plot the conditional variance the conditional variance ($\sqrt{\tau \times g}$) and long-term volatility component ($\sqrt{\tau}$) of the MIDAS model with 3 years of lag. As a benchmark model, we estimate a simple GARCH(1,1) model for the exchange rate returns using the student's t-distribution . The parameter estimates are shown in Table 4[8]. It can be seen from Table 4 that the parameters μ, α, and β are significant.

Table 4 Parameter estimation of GARCH(1,1), iGARCH(1,1), and GJR-GARCH(1,1)

Model	μ	α	β	γ	m	LLF	BIC
GARCH(1,1)	0.013*	0.049***	0.952***	-	-0.003***	-5822.281	11679.34
	(0.007)	(0.003)	(0.002)		(0.0007)		
iGARCH(1,1)	0.013*	0.045***	0.955***	-	0.001***	-5826.554	11687.890
	(0.007)	(0.004)	(0.003)		(0.0004)		
GJR-GARCH(1,1)	0.011	0.025***	0.956***	0.021***	0.003***	-5818.178	11679.833
	(0.007)	(0.004)	(0.0051)	(0.007)	(0.0006)		

This table reports estimation results for parameters. HAC-type standard errors are shown in the parentheses. We take the lags for 1,2 and 3 years respectively.
*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.
LLF is the value of the maximized log-likelihood function and BIC denotes Bayesian information criterion.

We also estimate an iGARCH(1,1) and a GJR-GARCH(1,1) model. For the fitted iGARCH(1,1) model, the sum of parameters α and β is above one, which means that the estimated iGARCH model does not satisfy covariance stationarity. Moreover, for the estimated GJR-GARCH(1,1) model, the parameter γ is highly significant. And thus, we found the evidence of asymmetry in the conditional volatility.

[8] We carry out the estimation process using mfGARCH package in R (Conrad and Kleen 2020).

5.1 The impact of stock market volatility on exchange rate volatility

Table 5 Parameter estimation of GARCH-MIDAS: Stock return volatility

Lags	μ	α	β	γ	m	θ	ω_2	LLF	BIC	VR
1	0.001	0.035***	0.945***	0.021***	-0.779***	0.008**	14.658	-5314.533	10689.16	5.609
year	(0.011)	(0.007)	(0.006)	(0.007)	(0.152)	(0.003)	(9.160)			
2	-0.001	0.034***	0.947***	0.018***	-0.824***	0.009***	29.920*	-4970.567	10000.72	6.797
years	(0.008)	(0.008)	(0.005)	(0.007)	(0.192)	(0.003)	(17.695)			
3	-0.010	0.035***	0.948***	0.026***	-0.067	0.008***	51.320*	-4524.285	9107.555	5.425
years	(0.008)	(0.007)	(0.005)	(0.007)	(0.450)	(0.003)	(27.973)			

This table reports estimation results for parameters. Bollerslev–Wooldridge standard errors are reported in parentheses. We take the lags for 1,2 and 3 years respectively.
*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.
LLF is the value of the maximized log-likelihood function and BIC denotes Bayesian information criterion. The variance ratio VR is the proportion of long-term variance to the total variance.

Table 5 shows the parameter estimations of the impact of the volatility of stock returns on the fluctuations of the exchange rate. In the analysis, we set 1, 2 and 3 years of lags. As shown in Table 5 that the estimation of parameter μ is not significant for all the three lags. However, the parameter estimates of α, β and m are highly significant. In Table 5, the slope parameter θ (estimated from Eq. 6) represents the influence of stock market volatility on the exchange rate fluctuation. It can be seen from Table 4 that value of θ is positive and statistically significant at 1% level of significance. This means that higher levels of stock return volatility tend to increase the long-term exchange rate volatility. From Table 2, it can also be seen that the weighting function with $\omega_1 = 1 \; and \; \omega_2 = 51.320$ puts weight 0.760 on the first lag (the maximum of the weights) of the stock index volatility (according to Eq. 5 where we set k=36), we find that a 1% increase in stock volatility in the current month would increase exchange rate volatility the next month by $e^{0.008*0.760} - 1 = 0.00609 \; or \; 0.609\%$. These results are consistent with the research by Kanas (2002) on the relation between stock market volatility and exchange rate volatility. A potential explanation might be that since financial markets are highly integrated, a rise in stock market volatility would increase exchange rate volatility. For all the three lags, the variance ratio is more than 5, which means that long-run stock volatility driven component contributes more than 5% to the total volatility.

5.2 The impact of change in commodity price index on exchange rate volatility

Table 6 Parameter estimation of GARCH-MIDAS: Change in commodity price index

Lags	μ	α	β	γ	m	θ	ω_2	LLF	BIC	VR
1 year	-0.0005 (0.011)	0.036*** (0.006)	0.944*** (0.005)	0.024*** (0.007)	-0.629*** (0.164)	2.901 (4.832)	3.609* (8.070)	-5618.808	11298.04	0.847
2 years	0.006 (0.008)	0.052*** (0.007)	0.940*** (0.006)	0.024*** (0.007)	-0.619* (0.243)	2.573 (4.810)	6.030 (3.806)	-5191.988	10443.92	0.664
3 years	-0.004 (0.012)	0.038*** (0.008)	0.942*** (0.005)	0.025*** (0.008)	-0.535* (0.220)	2.835*** (0.605)	11.820 (33.985)	-4874.785	9808.975	0.769

This table reports estimation results for parameters. Bollerslev–Wooldridge standard errors are reported in parentheses. We take the lags for 1,2 and 3 years respectively.
*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.
LLF is the value of the maximized log-likelihood function and BIC denotes Bayesian information criterion. The variance ratio VR is the proportion of long-term variance to the total variance.

Table 6 reports the impact of the change in commodity price index on the exchange rate volatility. It can be seen from the table that the parameter μ is not significant in all the cases. However, parameters α and β are highly significant. For the 3 years lag, the value of the parameter θ is positive and highly significant, suggesting that an increase in commodity price index would exacerbate exchange rate volatility. Since Australian economy depends on commodity exports, fluctuations in Australian dollar can be seen with commodity prices.

5.3 The impact of change in GEPU on exchange rate volatility

Table 7 Parameter estimation of GARCH-MIDAS: Change in GEPU

Lags	μ	α	β	γ	m	θ	ω_2	LLF	BIC	VR
1 year	-0.0008 (0.011)	0.035*** (0.006)	0.945*** (0.005)	0.021*** (0.007)	-0.640*** (0.150)	2.095 (1.634)	3.349 (2.797)	-5614.429	11289.28	4.647
2 years	0.001 (0.011)	0.036*** (0.007)	0.944*** (0.006)	0.020*** (0.007)	-0.691*** (0.146)	1.630 (1.664)	8.278 (9.564)	-5188.537	10437.02	3.033
3 years	-0.005 (0.012)	0.038*** (0.007)	0.942*** (0.006)	0.020*** (0.008)	-0.377* (0.234)	1.682*** (0.182)	11.625*** (16.11)	-4871.001	9801.408	2.923

This table reports estimation results for parameters. Bollerslev–Wooldridge standard errors are reported in parentheses. We take the lags for 1,2 and 3 years respectively.
*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.
LLF is the value of the maximized log-likelihood function and BIC denotes Bayesian information criterion. The variance ratio VR is the proportion of long-term variance to the total variance.

We also discuss the impact of change in GEPU on the volatility of exchange rate. From the estimation results in Table 7, it can be inferred that that the parameter μ is not significant, parameter m is significant at 1% significance level in the 1 year and 2 years lags and parameter θ is significant at 1% level of significance in the 3 years lag. A rise in GEPU shows economic turmoil, that increases fluctuations in exchange rate. However, the slope coefficient is not significant in 1- and 2-years lags. he parameter γ is significant, which means that there is evidence of asymmetry.

5.4The impact of GECON on exchange rate volatility

Table 8 Parameter estimation of GARCH-MIDAS: GECON

Lags	μ	α	β	γ	m	θ	ω_2	LLF	BIC	VR
1	-0.0008	0.035***	0.942***	0.025***	-0.645***	-0.512	1.000	-5618.007	11296.44	4.969
year	(0.011)	(0.006)	(0.005)	(0.007)	(0.148)	(0.349)	(0.830)			
2	0.001	0.032***	0.940***	0.030***	-0.833***	-1.399***	1.411***	-5189.568	10439.08	14.263
years	(0.011)	(0.007)	(0.006)	(0.008)	(0.116)	(0.508)	(0.425)			
3	-0.004	0.034***	0.939***	0.029***	-0.788***	-2.138***	1.718***	-4871.491	9802.388	21.853
years	(0.012)	(0.008)	(0.006)	(0.008)	(0.130)	(0.719)	(0.566)			

This table reports estimation results for parameters. Bollerslev–Wooldridge standard errors are reported in parentheses. We take the lags for 1,2 and 3 years respectively.
*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.
LLF is the value of the maximized log-likelihood function and BIC denotes Bayesian information criterion. The variance ratio VR is the proportion of long-term variance to the total variance.

In this section, we study the impact of global economic activity on exchange rate volatility. In Table 8, parameter μ is not significant; nevertheless, parameters α and β are highly significant. For the 2- and 3-years lags, the parameter θ is negative and significant at 1% level of significance, indicating that a rise in global economic activity would reduce the exchange rate fluctuations. This means if the global economic activity rises by 1% during the current month would reduce the next month exchange rate volatility by $e^{0.046*2.138} - 1 = 10.33\%$. Thus a rise in global economic activity would stabilize exchange rate volatility. This supports the view expressed in Hamilton (2019) that global economic activity is a key determinant of exchange rate fluctuations.

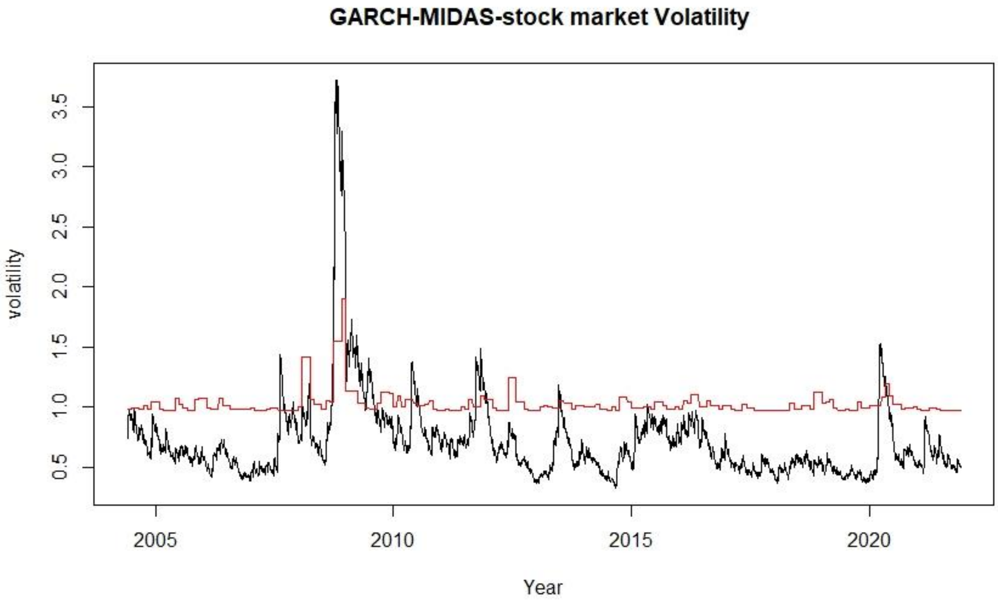
5.5 The impact of money supply volatility on exchange rate volatility

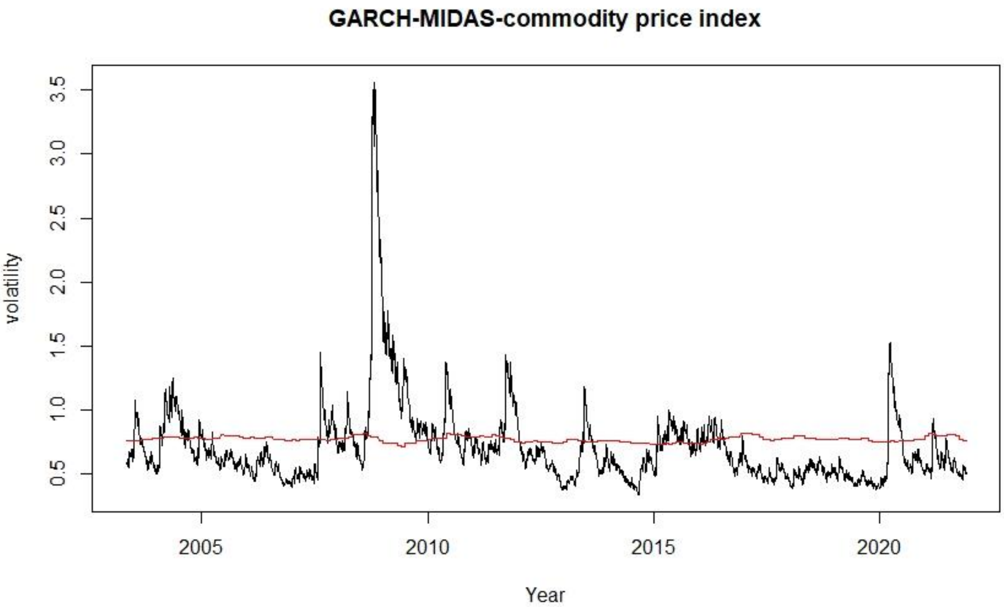
Table 9 Parameter estimation of GARCH-MIDAS: Volatility of money supply

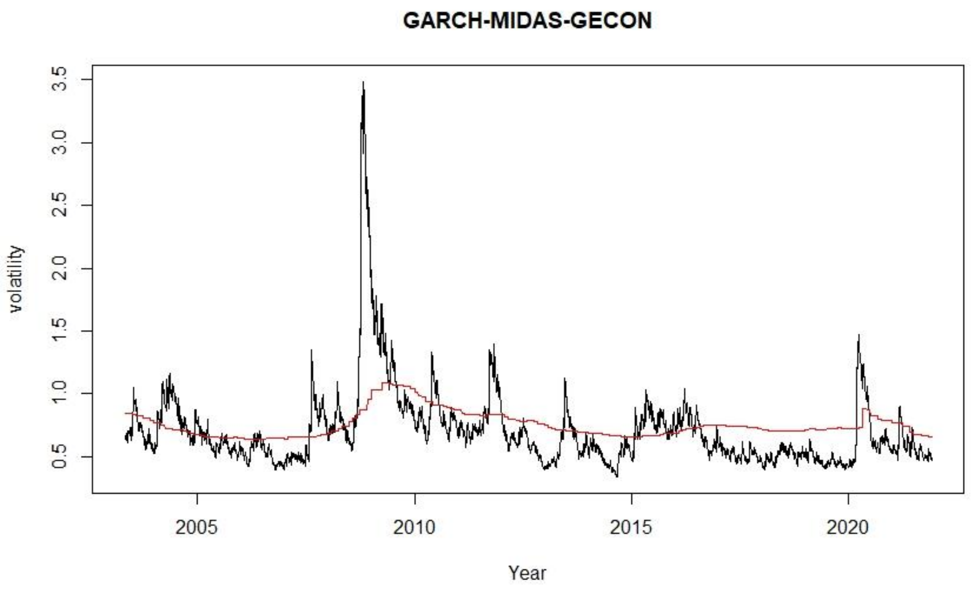
Lags	μ	α	β	γ	m	θ	ω_2	LLF	BIC	VR
1 year	0.001	0.037***	0.942***	0.024***	-0.641***	-0.004	6.210	-5323.718	10707.53	0.056
	(0.011)	(0.006)	(0.005)	(0.007)	(0.158)	(0.032)	(41.286)			
2 years	-0.007	0.037***	0.943***	0.022***	-0.677***	-0.018	12.964	-4981.415	10022.42	0.129
	(0.012)	(0.007)	(0.007)	(0.007)	(0.159)	(0.054)	(34.118)			
3 years	-0.008	0.035***	0.943***	0.030***	-0.697***	0.298*	1.395*	-4532.326	9123.638	8.253
	(0.012)	(0.007)	(0.005)	(0.008)	(0.268)	(0.157)	(0.708)			

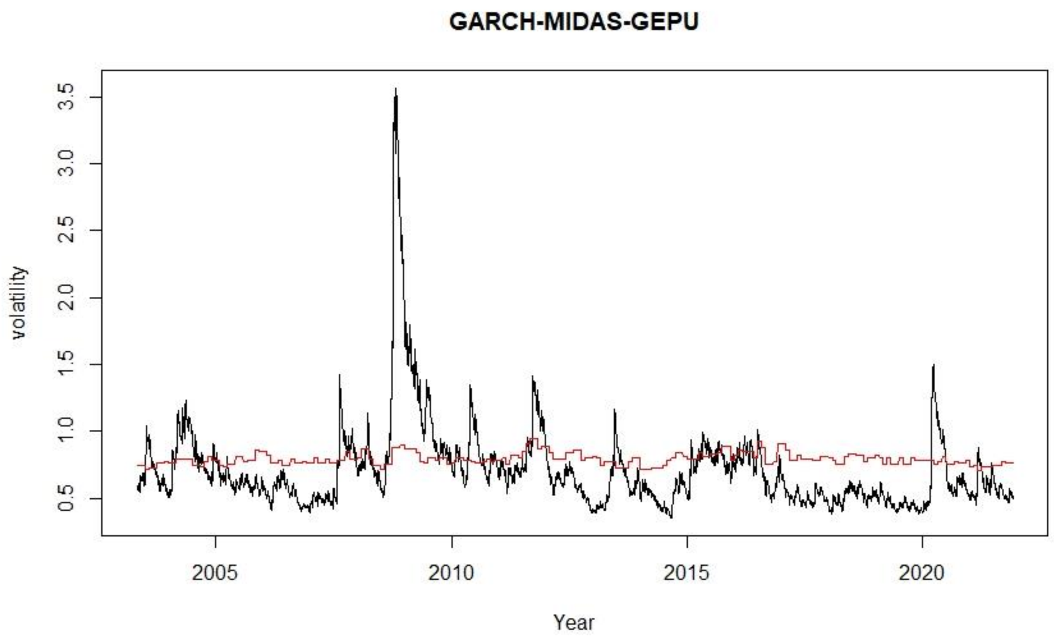
This table reports estimation results for parameters. Bollerslev–Wooldridge standard errors are shown in parentheses. We take the lags for 1,2 and 3 years respectively.
*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.
LLF is the value of the maximized log-likelihood function and BIC denotes Bayesian information criterion. The variance ratio VR is the proportion of long-term variance to the total variance.

In this section, we discuss the impact of volatility of money supply on fluctuations in exchange rate. The estimated results are shown in Table 9. In the table, the slope parameter is positive and statistically significant at 10% level of significance for the 36 months lag. However, it is not significant for the 12- and 24-months lags. This means that a rise in fluctuations in money supply would increase exchange rate volatility.


GARCH-MIDAS-stock market Volatility
volatility
0.5
1.0
1.5
2.0
2.5
3.0
3.5
2005
2010
2015
2020
Year


GARCH-MIDAS-commodity price index
volatility
0.5
1.0
1.5
2.0
2.5
3.0
3.5
2005
2010
2015
2020
Year


GARCH-MIDAS-GECON
volatility
Year
0.5
1.0
1.5
2.0
2.5
3.0
3.5
2005
2010
2015
2020


GARCH-MIDAS-GEPU
volatility
Year
0.5
1.0
1.5
2.0
2.5
3.0
3.5
2005
2010
2015
2020

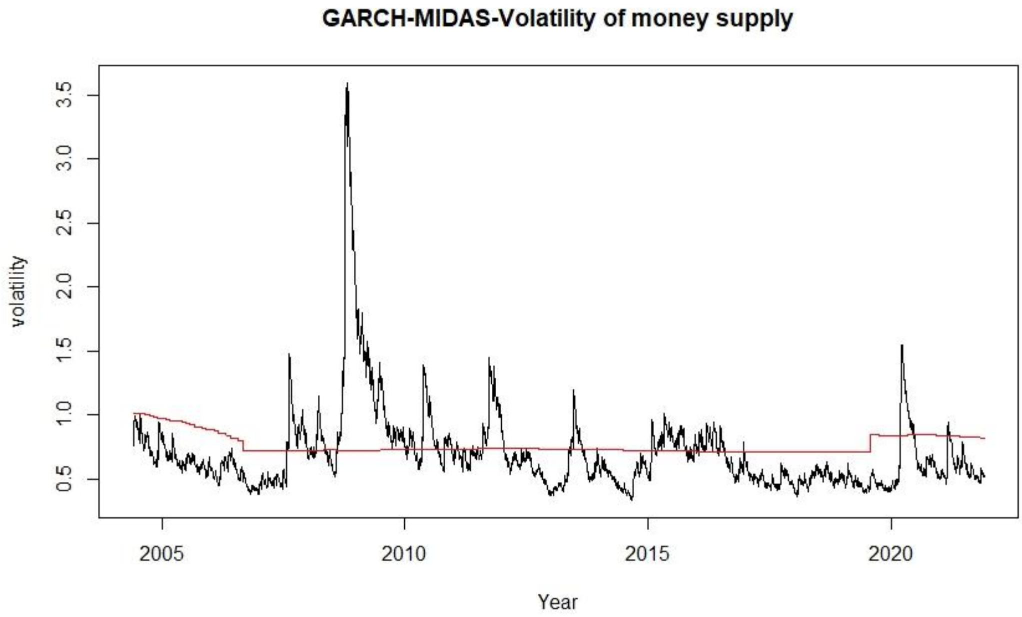


Fig.2 The figure shows the short-term (black line) and the long-term (red line) volatility components. (a) GARCH-MIDAS-stock return volatility,
(b) GARCH-MIDAS-commodity price index, (c) GARCH-MIDAS-GEPU, (d) GARCH-MIDAS-GECON, (e) GARCH-MIDAS- money supply volatility

Figure 2 reports the long-term component ($\sqrt{\tau}$) and the conditional variance ($\sqrt{\tau \times g}$) of the daily logarithmic exchange rate return based on the GARCH-MIDAS model with 36 months lag for the macroeconomic and financial variables used in the study. It can be seen from the figure that the volatility of the long-term component is smaller in comparison to the volatility of the conditional variance. Also, the long-term volatility component is most consistent with the conditional variance for the variable stock return volatility and least consistent for the variable money supply volatility.

6 Usefulness of GARCH-MIDAS technique

In this section, we fit GARCH-MIDAS model with synchronous data. That is, we use monthly exchange rate data and monthly macroeconomic and financial variables to discuss the usefulness of MIDAS technique. We do the analysis for the 1-year lag and look at the significance of various parameters. Results are given in Table 10.

Table 10 GARCH-MIDAS for exchange rate volatility

Variable	μ	α	β	γ	m	θ	ω_2	LLF	BIC	VR
Stock market volatility	0.104	0.000	10.174***	-0.041*	-0.298*	0.026***	11.599***	-583.678	1206.008	83.047
	(0.011)	(0.020)	(0.018)	(0.024)	(0.143)	(0.005)	(4.339)			
GECON	0.041	0.013	0.785***	0.159	1.794***	0.005	1.000	-621.775	1282.528	44.064
	(0.173)	(0.055)	(0.103)	(0.141)	(0.152)	(0.078)	(1.697)			
ΔGEPU	-0.154	0.087*	0.884***	0.056	0.300	1.875	14.213	-629.153	1297.286	12.495
	(0.199)	(0.051)	(0.036)	(0.051)	(1.459)	(1.541)	(28.410)			
Volatility of money supply	-0.046	0.090*	0.883***	0.052	0.293	-0.023	3.255	-604.438	1247.555	0.459
	(0.233)	(0.049)	(0.031)	(0.054)	(3.224)	(0.100)	(14.781)			
ΔCommodity price index	-0.069	0.097*	0.876**	0.052	0.311	2.615	3.618	-633.390	1305.76	0.715
	(0.228)	(0.056)	(0.034)	(0.056)	(1.952)	(8.108)	(18.450)			

This table reports estimation results for parameters. Bollerslev–Wooldridge standard errors are shown in parentheses.
*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.
LLF is the value of the maximized log-likelihood function and BIC denotes Bayesian information criterion. The variance ratio VR is the proportion of long-term variance to the total variance.

When GARCH-MIDAS model is estimated with same frequency data, the parameter γ is significant only for the variable stock return volatility. However, when the model was estimated with high-frequency exchange rate data and low-frequency macroeconomic variable, the parameter γ was significant for all the variables. This shows that when data is aggregated, we lose important information and the model fails to give evidence for asymmetry in the short-run volatility component. Furthermore, the value of parameter θ is significant only for the stock return volatility. Thus, after aggregating data, GARCH-MIDAS model can't be used to evaluate the impact global economic activity, change in commodity price, volatility of money supply, and change in global economic uncertainty on exchange rate volatility.

7 Conclusion and policy implications

This paper combines high-frequency Australian exchange rate return data with the low frequency macroeconomic and financial data using the GARCH-MIDAS model. Our results show the significant impact of financial and macroeconomic variables on exchange rate volatility. Additionally, we find evidence of asymmetry in the short-term volatility component. We find that a rise in volatility in S&P/ASX 200 index and money supply volatility increase the exchange rate volatility. Second, exchange rate volatility rises with a rise in commodity price index and global economic policy uncertainty. Finally, a rise in global economic conditions stabilises exchange rate volatility. Additionally, we find that when we estimate the same model using the low-frequency exchange rate data, we lose important information and we get biased estimates. To get unbiased results, it is imperative that we use data occurring naturally in different frequencies.

The results have implications for policy makers and investors. The investors should take into account not only the monetary fundamentals, but also various other macroeconomic and financial variables, and their volatilities, while making asset allocation decisions. Furthermore, there are implications for policy makers. Policy makers need to pay attention to variable like economic activity, due to its significant influence in improving the exchange rate volatility. Due to the spill over of volatility between exchange rate market, commodity and financial markets, the policy makers can also reduce the exchange rate volatility by stabilising fluctuations in money supply, fluctuations in stock prices, commodity prices and uncertainty in global economic policy. Thus, the results show that the policy makers need to take into account global factors in order to manage exchange rate volatility.

Declarations

The authors have no competing interests to declare that are relevant to the content of this article.

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