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# Financial Vulnerability and Volatility in Emerging Stock Markets: Evidence from GARCH-MIDAS Models

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# Financial Vulnerability and Volatility in Emerging Stock Markets: Evidence from GARCH-MIDAS Models

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**Abstract**

This paper establishes a predictive relationship between financial vulnerability and volatility in emerging stock markets. Focusing on China and India and utilizing GARCH-MIDAS models, we show that incorporating financial vulnerability can substantially improve the forecasting power of standard macroeconomic fundamentals (output growth, inflation and monetary policy interest rate) for stock market volatility. The findings have significant implications for investors to improve the accuracy of volatility forecasts.

**Keywords:** Stock Market Volatility; Financial Vulnerability; GARCH-MIDAS; Emerging Markets

**JEL Codes:** C32, C53, G15, G17

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## 1. Introduction

Accurate forecasting of stock market volatility has ample implications for portfolio selection, the pricing of derivative securities and risk management (Granger and Poon, 2003; Rapach et al., 2008). Naturally, the existing literature on volatility forecasting for stock markets is massive, to say the least (see Ben Nasr et al., (2016), Salisu et al., (2020) for detailed reviews of this literature). Traditionally, volatility forecasting models for equity markets have utilized daily data within univariate models from the Generalized Autoregressive Conditional Heteroskedasticity (GARCH)-family, incorporating a wide-array of predictors available at the same frequency.[1] A growing number of studies, however, have highlighted the importance of low-frequency macroeconomic variables in forecasting equity market volatility using Mixed Data Sampling (MIDAS)-based GARCH models (see for example, Engle and Rangel, 2008; Rangel and Engle, 2011; Asgharian, et al., 2013; Engle et al., 2013; Conrad and Loch, 2015). The emergence of MIDAS models has, thus, allowed researchers to improve forecasting models by incorporating the information captured by macroeconomic fundamentals over high frequency stock market fluctuations as economic fundamentals can contribute to the long-run component of market volatility.

The role of low-frequency macroeconomic variables as a driver of stock market volatility can in fact be traced back to Schwert (1989) who argues that fluctuations in macroeconomic variables affect both future cash flow projections and the discount factor, thus contributing to stock market volatility. More recently, Opschoor et al., (2014) highlight the role of financial conditions in forecasting, inter alia, the volatility of the US equity market, since financial conditions are an important driver of the economy (monetary policy and macroeconomic variables, i.e., output and inflation) at large (Hatzius et al., 2010; Koop and Korobilis, 2014). Building on this line of work, we utilize the financial vulnerability indexes, recently developed by Acharya et al., (2020), and examine the predictive power of financial vulnerability over daily stock market volatility of the two largest emerging market economies of China and India even after controlling for the standard macroeconomic predictors of output growth, inflation and interest rates.

The novelty of our mixed sampling specification is that we differentiate the short-run component of volatility from the long-run component that can be driven by low-frequency economic fundamentals and examine the predictive contribution of financial vulnerability over and above the standard macro variables. To the best of our knowledge, this is the first paper to incorporate the role of financial vulnerability and the role of uncertainty surrounding monetary policy decisions conditional on such vulnerabilities in forecasting volatility in emerging stock markets within a GARCH-MIDAS framework. Another novelty of our approach is that instead of forecasting monthly realized volatility obtained from the sum of squared returns (Andersen and Bollerslev, 1998), we rely on the GARCH-MIDAS model to produce high-frequency

[1] More recently, with the availability of intraday data, volatility forecasting has also been based on heterogenous autoregressive models of realized volatility (see McAleer and Medeiros (2008), Qiu et al., (2019) for detailed discussions of this literature).

daily forecasts as high-frequency forecasts are crucial for market timing and risk management strategies given that daily volatility forecasts are featured prominently in the context of Value-at-Risk (VaR) estimates (Ghysels and Valkanov, 2012).[2]

The remainder of the paper is organized as follows: Section 2 presents the data and outlies the econometric model, with Section 3 discussing the empirical findings, and Section 4 concluding the paper.

## 2. Data and Methodology

### *2.1. Data*

Daily stock market returns are computed from the MSCI indexes (in US dollars) for China and India, obtained from Datastream. Macroeconomic predictors include the month-on-month growth rate in industrial production (*IPG*) and CPI-based inflation (*INF*) as well as the levels of short-term interest rates (*r*), obtained from the IHS Global Insight database. Financial vulnerability (*fv*) is proxied by three alternative measures recently constructed by Acharya et al., (2020): (i) *fv1* captures the domestic price of risk constructed from equity market volatility and risk spreads;[3] (ii) *fv2* captures the domestic price of risk and external stress (*fv1* plus dollar-based exchange rate option implied volatility); and (iii) *fv3* captures the domestic price of risk, external sector and credit market tightness (*fv2* plus NYU Volatility Risk Institute systemic risk index for domestic banks and prime lending rate).[4] The sample period covers January 1, 2004- May 29, 2020 for China, and January 1, 2003- May 29, 2020 for India, with the start and end dates being purely driven by the availability of the vulnerability indexes.

### *2.2. GARCH-MIDAS Methodology*

Let $e_{i,t}$ denote the log-return for the stock market index for day $i$ of an arbitrary period $t$ which may be a month or a quarter that includes $N_t$ days. Following Engle et al., (2013) and You and Liu (2020), we specify the daily stock market return as a GARCH-MIDAS process

$$e_{i,t} = \mu + \sqrt{\tau_t g_{i,t}}\varepsilon_{i,t}, \quad \forall i = 1, \ldots, N_t, \quad t = 1, \ldots, T \tag{1}$$

where $\varepsilon_{i,t}|\mathcal{F}_{i-1,t} \sim \mathrm{N}(0,\ 1)$ is the normal error term conditional on the past information set, $\mathcal{F}_{i-1,t}$, available up to day $i-1$ of period $t$. The dynamics of the short-run volatility component $g_{i,t}$ follow a (daily) GARCH(1,1) process

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

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[2] Ghysels et al. (2019) compare the GARCH and RV methodologies by producing multiperiod-ahead forecasts and conclude that the MIDAS-based model yields the most precise forecasts of in-and out-of-sample volatility. Furthermore, our approach avoids the loss of valuable information as we do not average the daily GARCH-based volatility into monthly frequency (Clements and Galvão, 2008, Das et al., 2019).

[3] The authors also augment the *fv1* index for China with lending rate and inflation. Our analysis with the augmented *fv1* index yields qualitatively similar results and are available upon request.

[4] The data is publicly available on Viral V. Acharya's website at: http://pages.stern.nyu.edu/~sternfin/vacharya/public_html/~vacharya.htm.

In particular, (2) implies that $E_{t-1}(g_{i,t}) = 1$, which ensures that $\tau_t$ in (1) is the well-defined long-run conditional variance of daily returns as $E_{t-1}\left(e_{i,t-1} - \mu\right)^2 = \tau_t$. Volatility in (1) has two components. The first component $(g_{i,t})$ accounts for daily fluctuations and is related to the day-to-day short-lived factors. The second $(\tau_t)$ is the long-run component that relates to economic fundamentals and models that are assumed to reveal this source of stock market index volatility. As different news events may have different impacts on the stock market, depending on whether they have consequences over short- or long-term horizons, this component volatility specification allows the same news to have different impacts depending on economic conditions (e.g. low-frequency economic fundamentals are expected to influence the long-run component of volatility, but not the short-run component).

Following Engle et al., (2013), we incorporate low-frequency economic fundamentals to specify the slow-moving volatility component $\tau_t$ in (1). A variety of specifications for $\tau_t$ can be considered ranging from specific to general. However, for the purpose of yielding predictions, we present GARCH-MIDAS models with a one-sided filter, involving past economic fundamentals. Specifically, we specify the long-run volatility process as

$$log(\tau_t) = \delta + \varphi' \sum_{k=1}^{K} \omega_k(a_1, a_2) f_{t-k} \quad (3)$$

where $f_t$ is the vector of economic fundamentals available at the low frequency $t$ and $\omega_k(a_1, a_2)$ is the weighting function, specified as a beta-lag structure

$$\omega_k(a_1, a_2) = \frac{\left(\frac{k}{K}\right)^{a_1-1}\left(1-\frac{k}{K}\right)^{a_2-1}}{\sum_{p=1}^{K}\left(\frac{p}{K}\right)^{a_1-1}\left(1-\frac{p}{K}\right)^{a_2-1}} \quad (4)$$

where $\sum_{k=1}^{K} \omega_k(a_1, a_2) = 1$ is imposed to ensure that $\varphi$ can be identified. In the setting, (4) is flexible to accommodate various weighting structures that can represent a monotonically increasing, decreasing or a hump-shaped weighting scheme, although it is limited to unimodal shapes (Ghysels et al., 2007).

The benchmark model includes *IPG*, *INF*, and *r* as the well-established macro fundamentals with explanatory power for stock market volatility. We then sequentially add the various vulnerability indexes (*fv*'s), as summarized in Table 1, and evaluate the predictive performance against the benchmark.

## 3. Empirical Results

Panels A and B in Figure 1 plot the optimal MIDAS weights estimated from all GARCH-MIDAS models described in Table 1. The weighting function is estimated with a lag of 24 months. As shown in the two figures, the shapes of the estimated optimal weights are quite flexible and all decay to zero after a lag of 24 months. Panels A and B in Figure 2 plot the time series of the fitted conditional volatilities $\tau_t g_{i,t}$ and the corresponding long-run volatility components $\tau_t$ for China and India, respectively.

Table 2 compares the forecasting performances over selected horizons within a month. Given the large structural change imposed by the 2007-2009 global financial crisis, we consider three subperiods: the full sample (2004:01 to 2020:05 for China and 2003:01

to 2019:05 for India), pre-crisis (until 2007:09) and post-crisis (after 2009:9). The in-sample period is the sample size minus one month, and the out-of-sample forecasting period is the last month of the sample size. Forecasting performance is measured by the ratio of the mean squared error (MSE) of conditional variance forecasts for models 1-3 compared to the benchmark model. A value less than 1 in Table 2 suggests that the augmented model outperforms the benchmark model. As shown in the table, incorporating financial vulnerability as a predictor significantly improves forecasting power, implied by a ratio less than 1 in all cases in almost all forecasting horizons. These results are also statistically significant as the Diebold and Mariano (1995) test, which can only be calculated for the one-month-ahead horizon (given the forecast set-up), yields a *p*-value of 0 for almost all cases, implying the strong rejection of the null of equal forecast performance between the benchmark and the augmented models. Overall, our findings yield significant evidence of the predictive role played by financial vulnerability for domestic stock market volatility over and above the information contained in macroeconomic fundamentals.

## 4. Conclusion

This paper contributes to the literature on the macroeconomic drivers of stock market volatility by examining the role of financial vulnerability as a predictor of stock market volatility in a GARCH-MIDAS framework. Focusing on the major emerging economies of China and India, we find that incorporating financial vulnerability can substantially improve the forecasting power of macroeconomic fundamentals (such as output growth, inflation and monetary policy interest rate) for equity market volatility. The results suggest that the informational content captured by financial vulnerability of an economy can be used to improve the accuracy of volatility forecasts over and above macroeconomic models for the purpose of portfolio selection, the pricing of derivative securities and risk management.

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**Table 1.** GARCH-MIDAS model specifications

| Fundamentals | *IPG* | *INF* | *r* | *fv1* | *fv2* | *fv3* |
|---|---|---|---|---|---|---|
| Benchmark | x | x | x | | | |
| Model 1 | x | x | x | x | | |
| Model 2 | x | x | x | | x | |
| Model 3 | x | x | x | | | x |

**Note:** The symbol, "x", represents which specific fundamentals in the column-heading are included in GARCH-MIDAS model specification. IPG: industrial production growth rate, INF: CPI-based inflation; *r*: short-term interest rate associated with monetary policy decisions. *fv1*, *fv2* and *fv3* are the financial vulnerability proxies per Acharya et al., (2020).

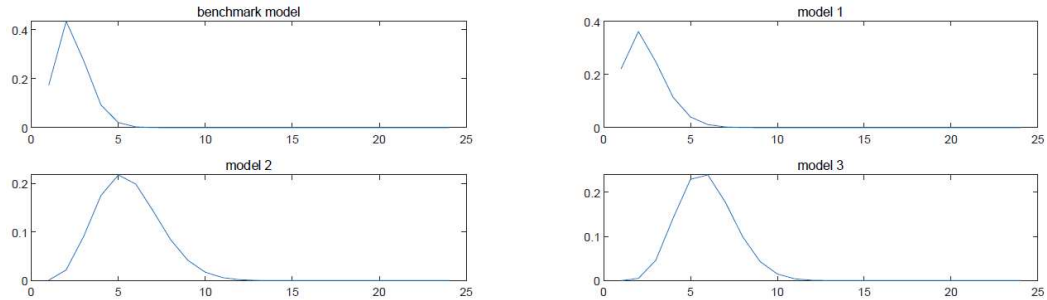
**Table 2.** Comparison of forecasting performance of the GARCH-MIDAS models across three subsamples

| ***China*** | ***Full-sample*** | | | ***Pre-crisis period*** | | | ***Post-crisis period*** | | |
|---|---|---|---|---|---|---|---|---|---|
| ***Forecast Horizon*** | ***Model1*** | ***Model2*** | ***Model3*** | ***Model1*** | ***Model2*** | ***Model3*** | ***Model1*** | ***Model2*** | ***Model3*** |
| 1 day | 0.974 | 0.942 | 0.972 | 0.790 | 0.790 | 0.815 | 0.976 | 0.976 | 0.879 |
| 2 days | 0.972 | 0.937 | 0.969 | 0.925 | 0.925 | 0.917 | 0.977 | 0.977 | 0.867 |
| 3 days | 0.971 | 0.935 | 0.968 | 0.934 | 0.934 | 0.921 | 0.979 | 0.979 | 0.865 |
| 4 days | 0.969 | 0.932 | 0.966 | 0.948 | 0.948 | 0.930 | 0.980 | 0.980 | 0.860 |
| 5 days | 0.968 | 0.929 | 0.965 | 0.949 | 0.949 | 0.930 | 0.980 | 0.980 | 0.856 |
| 1 week | 0.967 | 0.927 | 0.964 | 0.978 | 0.978 | 0.953 | 0.979 | 0.979 | 0.852 |
| 2 weeks | 0.981 | 0.972 | 0.989 | 1.007 | 1.007 | 0.986 | 0.990 | 0.990 | 0.944 |
| 3 weeks | 0.985 | 0.973 | 0.988 | 1.009 | 1.009 | 0.982 | 0.988 | 0.988 | 0.938 |
| 1 month | 0.990 | 0.984 | 0.994 | 0.972 | 0.972 | 0.959 | 0.992 | 0.992 | 0.962 |
| DM test *p*-value | 0.000 | 0.000 | 0.000 | 0.060 | 0.060 | 0.000 | 0.000 | 0.000 | 0.000 |
| ***India*** | ***Full-sample*** | | | ***Pre-crisis period*** | | | ***Post-crisis period*** | | |
| ***Forecast Horizon*** | ***Model1*** | ***Model2*** | ***Model3*** | ***Model1*** | ***Model2*** | ***Model3*** | ***Model1*** | ***Model2*** | ***Model3*** |
| 1 day | 0.928 | 0.915 | 0.892 | 0.817 | 0.818 | 0.890 | 0.898 | 0.861 | 0.854 |
| 2 days | 0.919 | 0.907 | 0.881 | 0.811 | 0.813 | 0.915 | 0.887 | 0.846 | 0.842 |
| 3 days | 0.915 | 0.903 | 0.876 | 0.820 | 0.821 | 0.922 | 0.881 | 0.838 | 0.836 |
| 4 days | 0.913 | 0.901 | 0.873 | 0.819 | 0.820 | 0.928 | 0.877 | 0.832 | 0.831 |
| 5 days | 0.951 | 0.944 | 0.931 | 0.815 | 0.815 | 0.928 | 0.949 | 0.933 | 0.931 |
| 1 week | 0.947 | 0.940 | 0.925 | 0.810 | 0.811 | 0.926 | 0.942 | 0.923 | 0.922 |
| 2 weeks | 0.946 | 0.937 | 0.919 | 0.827 | 0.828 | 0.935 | 0.931 | 0.909 | 0.908 |
| 3 weeks | 0.952 | 0.945 | 0.928 | 0.835 | 0.834 | 0.934 | 0.938 | 0.920 | 0.919 |
| 1 month | 0.956 | 0.947 | 0.930 | 0.838 | 0.836 | 0.930 | 0.938 | 0.921 | 0.920 |
| DM test *p*-value | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

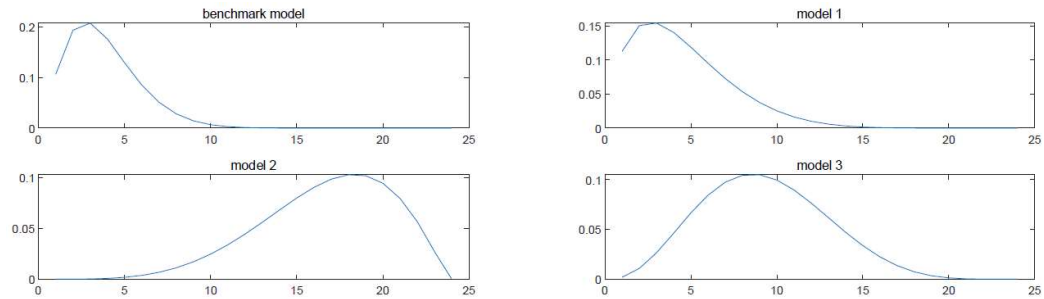
**Note:** The entries correspond to mean squared errors (MSEs) of a specific model relative to the benchmark model specified in Table 1 for the corresponding forecasting horizon and the subsample. A value less than 1 suggests that the competing model outperforms the benchmark. DM test *p*-value corresponds to the null of equal forecasting performance of models.

**Figure 1.** Optimal MIDAS weights for the benchmark and augmented models

**Panel A:** China



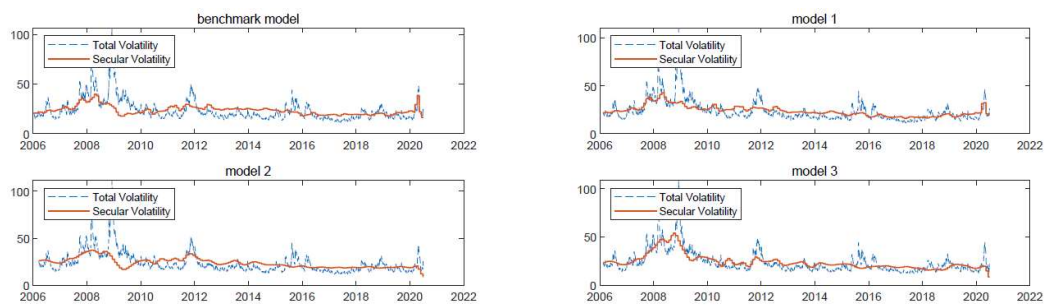

**Panel B:** India



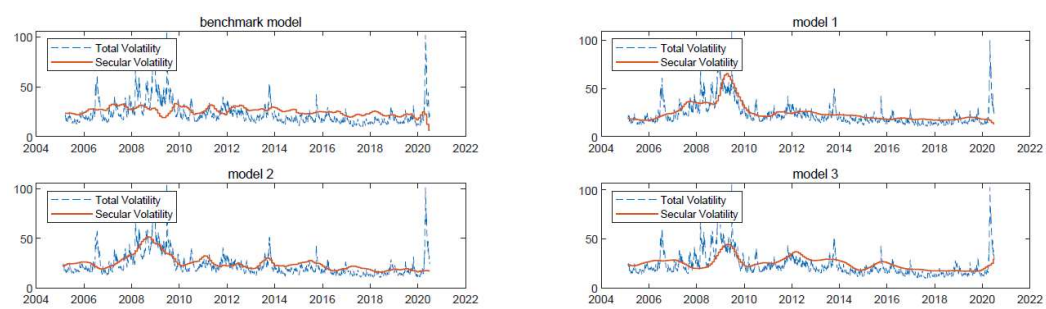

**Note:** The figures plot the optimal MIDAS weights estimated from all GARCH-MIDAS models described in Table 1.

**Figure 2.** Conditional volatility estimates of stock returns of China

**Panel A:** China




**Panel B:** India




**Note:** The figures plot the time series of the fitted conditional volatilities $\tau g$ (blue dashed line) and the corresponding long-run volatility components $\tau_t$ (red solid line), respectively.