Financial Turbulence, Systemic Risk and the Predictability of Stock Market Volatility

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Abstract

This paper adds a novel perspective to the literature by exploring the predictive performance of two relatively unexplored indicators of financial conditions, i.e. financial turbulence and systemic risk, over stock market volatility using a sample of seven emerging and advanced economies. The two financial indicators that we utilize in our predictive setting provide a unique perspective on market conditions, as they relate directly to portfolio performance metrics from both volatility and co-movement perspectives and, unlike other macro-financial indicators of uncertainty, or risk, can be integrated into diversification models within forecasting and portfolio design settings. Since the data for the two predictors are available at a weekly frequency, and our focus is to produce forecasts at the daily frequency, we use the generalized autoregressive conditional heteroskedasticity-mixed data sampling (GARCH-MIDAS) approach. The results suggest that incorporating the two financial indicators (singly and jointly) indeed improves the out-of-sample predictive performance of stock market volatility models over both the short and long horizons. We observe that the financial turbulence indicator that captures asset price deviations from historical patterns does a better job when it comes to the out-of-sample prediction of future returns compared with the measure of systemic risk, captured by the absorption ratio. The outperformance of the financial turbulence indicator implies that unusual deviations in not only asset returns, but also in correlation patterns play a role in the persistence of return volatility. Overall, the findings provide an interesting opening for portfolio design purposes, in that financial indicators, which are directly associated with portfolio diversification performance metrics, can also be utilized for forecasting purposes, with significant implications for dynamic portfolio allocation strategies.

Keywords: Systemic risk, Financial turbulence, Stock market, MIDAS models.
JEL Codes: C32, D8, E32, G15

1. Introduction

Unexpected fluctuations in financial markets pose a great challenge for investors in terms of the effectiveness of their diversification strategies. In addition to the appropriate rebalancing of target portfolios, an issue of high concern is the accuracy and stability of the parameters used to build diversified portfolios that can balance out the negative fluctuations experienced in various asset classes. As noted in Ang and Chen (2002), unstable risk parameters might lead portfolio managers to overstate the benefits of diversification, potentially leading to significant losses unanticipated by their diversification schemes. Clearly, one risk parameter of high importance is volatility, which is a key input not only for hedging and portfolio optimization applications but also for the pricing of options. Accordingly, a large strand of the literature has examined the predictability of stock market volatility using a wide range of univariate and multivariate forecasting models (e.g., Poon and Granger, 2003; Engle and Rangel, 2008; Rapach et al. 2008; Rangel and Engle, 2012; Engle et al. 2013; Demirer et al. 2019; Liu et al. 2020; Salisu and Gupta, 2021; Salisu and Ogbonna, 2021; among others) and some others focusing on alternative methodologies to examine volatility during crises (see Inci et al. 2011).

An emerging strand of the literature, however, has shown improved results by combining predictors at different frequencies using Mixed Data Sampling (MIDAS)-based Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models (e.g. Engle et al. 2013). This is indeed an important concern in high-frequency exercises, given the well-established evidence that links macro-financial fundamentals and stock market volatility (e.g. Hamilton and Lin, 1996; Schwert, 2011; Choudhry et al. 2016), despite the availability of most uncertainty and macroeconomic variables at lower frequencies (usually monthly). A second important advantage of the mixed data sampling framework in our context is that it allows us to produce high-frequency daily forecasts via the GARCH-MIDAS model instead of forecasting realized volatility obtained from the sum of squared returns (Andersen and Bollerslev, 1998). Further motivated by the finding that financial conditions are an important driver of the economy at large (e.g. Koop and Korobilis, 2014) and the informational value captured by financial conditions in forecasting the volatility of the US equity market (Opschoor et al. 2014; Demirer et al. 2021), this paper adds to the literature on forecasting stock market volatility the novel perspective of examining the predictive performance of two relatively unexplored indicators of financial conditions, namely, financial turbulence and systemic risk with regard to stock market volatility, using a sample of seven emerging and advanced economies.

The issue of predictability has become especially challenging given the consensus that the variation in aggregate market volatility is higher than what might be expected based on the observed variation in the volatility of the fundamental economic variables (e.g. Bollerslev, et al. 1992), which in turn has led researchers to seek alternative predictors that might improve the performance of volatility forecasting models. To this end, the two financial indicators that we utilize in our predictive setting provide a unique perspective on market conditions as they directly relate to portfolio performance metrics. Originally developed by Chow et al. (1999), based on the Mahalanobis Distance used to analyze resemblances and distances across human populations (Mahalanobis, 1927, 1936), the financial turbulence indicator offers a high frequency (weekly in our case) indicator of uncharacteristic market conditions that are associated with asset price fluctuations and correlation patterns. The systemic risk indicator, on the other hand, captures market fragility, again at high frequency, based on the so-called absorption ratio of Kritzman and Li (2010), which relates to how much of the variation in asset price movements can be explained by a small number of independent factors. These financial indicators thus offer a unique approach to measuring financial risk, as they directly relate to the effectiveness of diversification models from both volatility and co-movement perspectives and – unlike other macro-financial indicators of uncertainty, or risk – can be integrated into diversification models within a forecasting and portfolio design setting.[1] To this end, our forecasting application presents the first evidence of the predictive power of these indicators within a mixed data sampling framework.

In our forecasting application, we examine the out-of-sample predictive performance of the two financial indicators against the benchmark GARCH-MIDAS model with realized volatility at three forecast horizons [5, 10 and 20 days ahead]. The analysis is performed within a rolling-window framework wherein one-day ahead forecasts are generated iteratively over the entire specified out-of-sample horizon. Our analysis of daily data from Brazil, France, Germany, Hong Kong, Japan, the United Kingdom and the United States indicates that incorporating the two financial indicators (singly and jointly) indeed outperforms the benchmark model. While the financial turbulence indicator is found to overwhelmingly outperform the systemic risk indicator in its out-of-sample predictive performance, we also observe that incorporating both financial indicators in the forecasting model significantly improves the predictive accuracy of the alternative models that incorporate only one of the risk proxies, underscoring the marginal predictive information captured by the two financial indicators. Interestingly, the predictive performance of the augmented model is generally higher when the COVID-19 pandemic period is excluded from the analysis, suggesting that the pandemic period may plausibly have peculiarities that have reduced the predictive accuracy of volatility forecasting models. The overall findings provide an interesting opening for portfolio design purposes in that financial indicators, which are directly

[1] See Kritzman and Li (2010) for an application in the context of portfolio management. Our application is the first in a forecasting context.

associated with portfolio diversification performance metrics, can also be utilized for forecasting purposes, with significant implications for dynamic portfolio allocation strategies.

The remainder of the paper is organized as follows. Section 2 presents the description of the data, the two financial indicators employed as predictors of stock market volatility and the GARCH-MIDAS model employed. Section 3 discusses the empirical findings, and section 4 concludes with a discussion on investment implications.

2. Data and Methodology

2.1 Data

Our dataset includes daily stock market index returns for seven advanced and emerging economies, including Brazil, France, Germany, Hong Kong, Japan, the United Kingdom and the United States over the period Oct. 28, 1996-March 31, 2021, obtained from Bloomberg. These seven countries are chosen because the two indicators we describe below are based on the asset pool of these economies. The descriptive statistics for daily returns, presented in Table 1, clearly distinguish the Brazilian stock market as the most volatile one in the sample, with daily returns ranging between a low of -17.225% and a high of 28.824%. Interestingly, although the U.S. stock market offers a mean return that is comparable to that of Brazil, investors were able to enjoy much lower volatility in the U.S. market, achieving a more favorable risk/return tradeoff. All stock market return series experienced high kurtosis values, indicating the presence of extreme fluctuations during the sample period.

Table 1. Descriptive statistics

	U.S.	U.K.	Japan	Germany	France	Hong Kong	Brazil
Mean	0.045%	0.005%	0.000%	0.022%	0.014%	0.012%	0.046%
Std. Dev.	1.24%	1.18%	1.46%	1.48%	1.43%	1.56%	1.99%
Min.	-11.994	-11.512	-12.111	-13.055	-13.098	-14.735	-17.225
Max.	11.354	9.384	13.235	10.797	10.595	17.247	28.824
Skewness	-0.25	-0.274	-0.316	-0.158	-0.15	0.09	0.119
Kurtosis	9.223	7.349	6.145	5.233	5.832	10.693	14.61

Note: This table presents the descriptive statistics for daily stock market index returns for the period Oct. 28, 1996-March 31, 2021. U.S. is represented by the U.S. CRSP aggregate market index, while the remaining stock markets are represented by FTSE 100, Nikkei 225, German DAX, CAC-40, Hang Seng and Bovespa indexes, respectively.

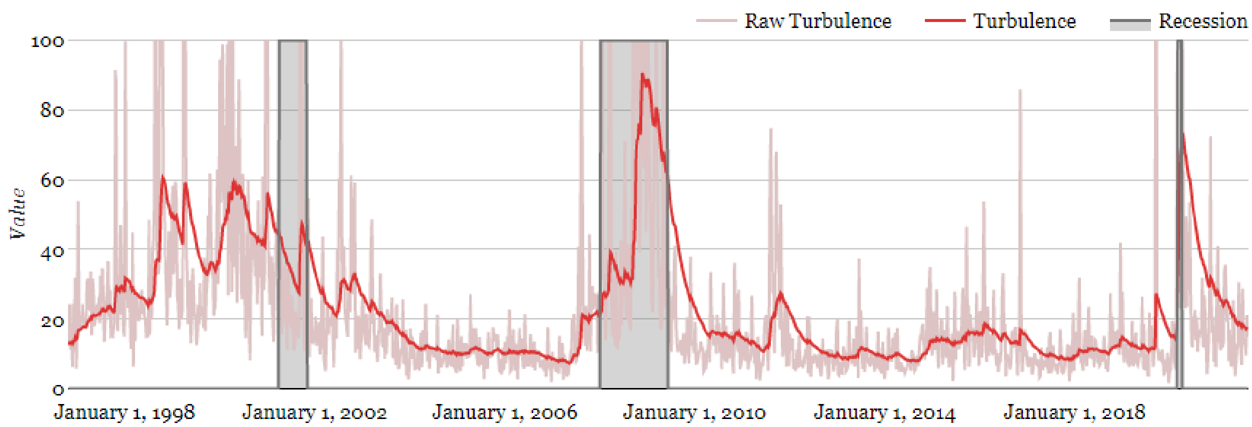
The predictive variables employed in the MIDAS model include weekly measures of financial conditions, i.e. financial turbulence and systemic risk (Zhang, 2021). By construction, the financial turbulence indicator measures unusual asset price patterns, including extreme fluctuations and the decoupling of correlated assets, which are uncharacteristic compared with past observed patterns. Originally developed by Chow et al. (1999), given a $(1 \times n)$ vector y_t of n asset returns for period t and the sample average vector, μ, of historical returns, the financial turbulence index (ft_t) captures the unusual patterns in the cross-section of asset returns relative to their historical multivariate distributions, formulated as

$$ft_t = (y_t - \mu)\Sigma^{-1}(y_t - \mu)' \tag{1}$$

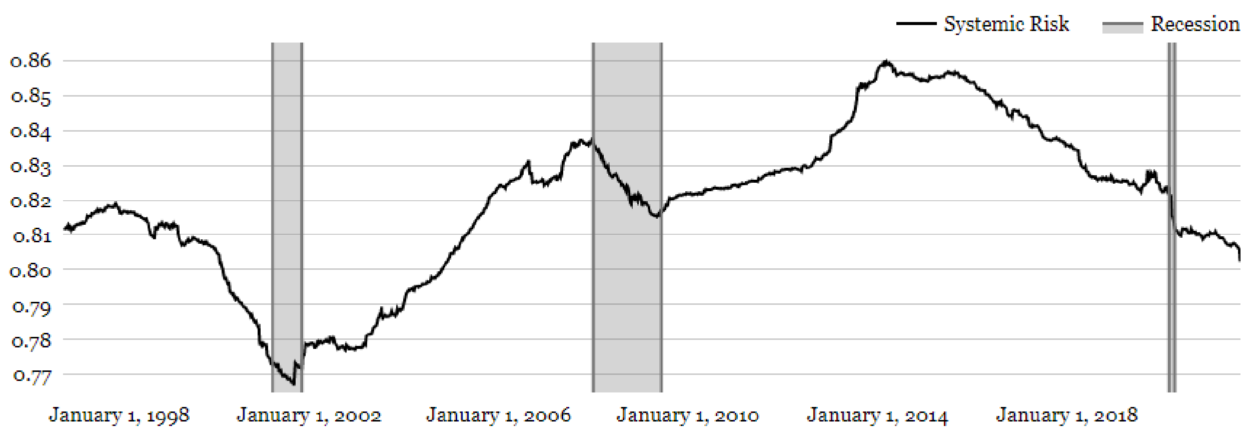
where Σ is the $(n \times n)$ sample covariance matrix of historical returns. As Kritzman and Li (2010) note, high levels of this indicator coincide with wild price fluctuations and regime changes in asset correlations, i.e. assets either decouple or become more correlated, which is indeed visible in Figure 1a, where we observe notable spikes in the financial turbulence index during the dot-com bubble period in the late 1990s, later during the 2008 Global Financial Crisis period and most recently, during the COVID-19 pandemic. From an economic point of view, considering the evidence of volatility persistence and long memory in financial markets (e.g. Andersen et al. 2001; 2003), because financial turbulence would be persistent, one could argue that a predictive relationship exists between financial turbulence and future volatility.

Figure 1. Time-series plots

a) Financial turbulence indicator



b) Systemic risk indicator



The second predictor employed in the GARCH-MIDAS model is the systemic risk indicator, which captures market conditions from a different aspect. Based on the absorption ratio, developed by Kritzman et al. (2011), the systemic risk indicator captures the extent to which financial markets are tightly coupled or unified. More specifically, utilizing principal component analysis, the authors measure what fraction of the total variance of a group of asset returns can be explained by a fixed number of eigenvectors. This procedure yields an indirect proxy for systemic risk in the marketplace such that a high value indicates that asset price movements can be explained by a small number of common factors, whereas a low value indicates that idiosyncratic factors are more dominant in the cross-sectional patterns of asset returns.

As seen in Figure 1b, the market has experienced a steady rise in systemic risk since the early 2000s, followed by a decline during the Global Financial Crisis period, suggesting that individual market-specific factors have gained relative importance during this period. The decline in the systemic risk indicator during this period is indeed consistent with the finding by Didier et al. (2012) that emerging markets, in general, displayed a more heterogeneous pattern in the reaction and recovery rates following the Global Financial Crisis. Interestingly, a similar downward pattern is also observed during the COVID-19 pandemic period. From an economic perspective – considering that high systemic risk corresponds with periods when global markets are tightly connected, thus facilitating the propagation of financial shocks more quickly and broadly – one could argue that a predictive relation should exist between systemic risk and future volatility because a broader propagation of market shocks would induce volatility spillovers across global financial markets. Finally, we observe that the two predictors are negatively correlated at -0.26, suggesting that they capture market conditions from distinctly different aspects.

2.2 Methodology

We employ the GARCH-MIDAS modelling framework, which simultaneously accommodates data with mixed frequencies, to investigate the role of the financial turbulence and systemic risk indicators in volatility forecasts for equity markets.[2] This is premised on the naturally

[2] It must be noted that a low (response) – high (predictor) frequency mix also exists and has computational advantages over uniform-frequency-based models (see Salisu and Ogbonna, 2019).

occurring frequencies of the data – daily stock returns (Brazil, France, Germany, Hong Kong, Japan, the United Kingdom and the United States) and weekly measures of financial indicators (turbulence and systemic risk). The GARCH-MIDAS model is well suited to high-frequency dependent and low-frequency independent variables mix, and circumvents the possible loss of information and estimation bias that is occasioned by aggregation or disaggregation, as is the case with most uniform-frequency-based models. This framework allows one to incorporate every bit of information in the estimation model, thus contributing to improving the predictability of the model over the uniform-frequency-based models.

The stock returns for the equity markets considered are generated using $r_{i,t} = ln(P_{i,t}) - \ln(P_{i-1,t})$, where $P_{i,t}$ is the stock price of the i^{th} day of the t^{th} week; $i = 1, \dots, N$ and $t = 1, \dots, T$ indicate daily and weekly frequencies, respectively, while N_t indicates the number of days in any given week$t$. The GARCH-MIDAS model for the daily stock returns is defined as

$$r_{i,t} = \mu + \sqrt{\tau_t \times h_{i,t} \times \varepsilon_{i,t}}, \qquad \forall\, i = 1, \dots, N_t \tag{2}$$

$$\varepsilon_{i,t} | \Phi_{i-1,t} \sim N(0,1) \tag{3}$$

where the first component of equation (2), that is, μ, is the unconditional mean of the stock returns, while the second part of the same equation, that is, $\sqrt{\tau_t \times h_{i,t} \times \varepsilon_{i,t}}$, captures the conditional variance with the error distribution defined in equation (3). The conditional variance is further decomposed into a short-run component ($h_{i,t}$) that is a higher frequency series characterized by a $GARCH(1,1)$ process and a long-run component that captures the long-run volatility characterized by the parameter τ_t.[3] Note that the information that is available at day $i-1$ of month t is denoted by $\Phi_{i-1,t}$. The short-run component of the conditional variance is given in equation (4) as:

[3] Engle et al. (2013) provide some technical details of the multiplicative decomposition of conditional variance into high- and low-frequency components of the MIDAS model.

$$h_{i,t} = (1 - \alpha - \beta) + \alpha\left(r_{i,t} - \mu\right)^2/\tau_t + \beta h_{i-1,t} \tag{4}$$

where the ARCH and GARCH terms are respectively denoted by α and β, such that $\alpha > 0$, $\beta \geq 0$, and $\alpha + \beta < 1$. Following Engle et al. (2013), all series are transformed into a daily frequency without distorting the original GARCH-MIDAS framework. The weekly varying long-term component (τ_t) is transformed into a daily frequency, rolling back the days across the weeks without keeping track of them. The daily-structured long-term component (τ_i) is given in equations (5) and (6) respectively for the realized volatility and the exogenous factor:

$$\tau_i^{(rw)} = m^{(rw)} + \theta^{(rw)} \sum_{k=1}^{k} \phi_k(\omega_1, \omega_2) RV_{i-k}^{(rw)} \tag{5}$$

$$\ln\left(\tau_i^{(rw)}\right) = m^{(rw)} + \theta^{(rw)} \sum_{k=1}^{K} \phi_k(\omega_1, \omega_2) X_{i-k}^{(rw)} \tag{6}$$

where "rw" indicates the implementation of a rolling-window framework[4]; m is the constant in the long-run component; θ is the MIDAS slope coefficient – a measure of the predictability of the realized volatility and/or the incorporated predictor X_{i-k}. Note that the beta polynomial weights $\phi_k(\omega_1, \omega_2) \geq 0, k = 1, \ldots, K$ must sum to one for the model's parameters to be identified. Finally, we choose the lag-length $K = 10$, which corresponds to ten MIDAS weeks, to filter out the secular component of the MIDAS weights.

The predictors are obtained by combining the risk measures with the model-derived realized volatilities; hence, the emergence of three different model structures in addition to the GARCH-MIDAS model with realized volatility (Model 1), which is our benchmark model. The alternative augmented models include (i) Model 2, which incorporates the PCA factor, obtained by combining the financial turbulence indicator and realized volatility; (ii) Model 3, which incorporates the PCA factor obtained by combining the systemic risk indicator and realized volatility; and (iii), Model

[4] The rolling-window framework is an estimation procedure that allows for the long-run component to vary for every period (daily in our case).

4, which incorporates the PCA factor obtained by combining both the financial turbulence and systemic risk indicators and realized volatility. Following Colacito et al. (2011), who show the flexibility of the beta weighting scheme, the two-parameter beta-polynomial weight is transformed into a one-parameter beta-polynomial weight by setting ω_1 to one and $\omega_2 = \omega$, to optimally obtain a monotonically decreasing weighting function (Engle et al. 2013). The weighting function is defined in equation (7) as:

$$\phi_k(\omega_1, \omega_2) = \frac{[k/(K+1)]^{\omega_1 - 1} \times [1 - k/(K+1)]^{\omega_2 - 1}}{\sum_{j=1}^{K} [j/(K+1)]^{\omega_1 - 1} \times [1 - j/(K+1)]^{\omega_2 - 1}} \Leftrightarrow \phi_k(\omega) \frac{[1 - k/(K+1)]^{\omega - 1}}{\sum_{j=1}^{K} [1 - j/(K+1)]^{\omega - 1}} \qquad (7)$$

where the weights are positive and sum to one. To ensure that distant lags of the observations are weighted lower than more recent observations, the restriction, $\omega > 1$, is imposed.

The in-sample predictability is ascertained by testing whether θ statistically differs from zero, where a non-rejection of the null would imply no predictability. A rejection of the null would, however, imply that the corresponding risk measures affect stock return volatility. An a priori expected relationship could be either positive or negative, which suggests higher (lower) risks associated with lower (higher) returns. However, in this study, for practical portfolio management purposes, we focus primarily on the out-of-sample forecast performance of the different GARCH-MIDAS specifications, which incorporate the turbulence and systemic risk indicators as predictor variables, in comparison with the benchmark GARCH-MIDAS model, which incorporates realized volatility only.

We employ the Diebold and Mariano (1995; DM) test for pairwise comparisons to formally ascertain whether the observed difference between a given pair of contending GARCH-MIDAS models is statistically significant. The test statistic is specified in equation (8) as:

$$DMStat = \bar{d}/\sqrt{V(d)/T} \sim N(0,1) \qquad (8)$$

where $\bar{d} = \frac{1}{T}\sum_{t=1}^{T} d_t$ is the sample mean of the loss differential $d_t \equiv g(\varepsilon_{it}) - g(\varepsilon_{jt})$, with $g(\varepsilon_{it})$, and $g(\varepsilon_{jt})$ representing the loss functions of the forecast errors, ε_{it} and ε_{jt}, corresponding to the two return forecasts, $\hat{r}_{it}$ and $\hat{r}_{jt}$, and $V(d_t)$ is the unconditional variance of d_t. The null hypothesis asserts the relative equality of the forecast accuracy of the paired competing models, such that $E[d_t] = 0$. The rejection of the null would thus imply statistically different forecast errors.

Drawing on Hansen et al's. (2011) model confidence set and Patton's (2011) argument on the consistency of the loss function for model ranking, we also subject the contending models to further evaluations using two loss functions MSE and QLIKE, which are defined as follows:

$$MSE_i = \frac{1}{T}\sum_{t-1}^{T}\left(\widehat{RV_{\iota,t}} - RV_t\right)^2 \qquad (9)$$

$$QLIKE_i = (1/T)\sum_{t-1}^{T}\left(RV_t/\widehat{RV_{\iota,t}} - ln\, RV_t/\widehat{RV_{\iota,t}} - 1\right) \qquad (10)$$

where $\widehat{RV_{\iota,t}}$ is the realized variance forecast from the i^{th} model at time t; RV_t is a proxy of the realized volatility, computed as a five-day rolling-window realized variance, while T is the number of out-of-sample forecast horizons considered. The aforementioned loss functions measure the magnitude of the difference between the actual and predicted realized volatility. Hence, a model will be adjudged preferred if the associated MSE or QLIKE value is smaller than that of the contending model.

3. Empirical Results

This section presents the empirical results for the in-sample and out-of-sample predictability of selected equity market returns using the aforementioned financial turbulence and systemic risk indicators. In essence, we are interested in the role that these financial indicators play in the forecasting of stock market returns. Consequently, we evaluate the forecasts emanating from the four GARCH-MIDAS model variants via the DM statistic, which is well suited to pairwise comparisons of contending models, and two alternative loss functions – MSE and QLIKE. As noted earlier, the models differ in terms of the comprising predictor variable. Model 1 (benchmark model) is a GARCH-MIDAS model with realized volatility; Model 2 is GARCH-MIDAS model with a PCA factor combining financial turbulence and realized volatility; Model 3 is a GARCH-MIDAS model with a PCA factor combining systemic risk and realized volatility; and Model 4 is GARCH-MIDAS model with a PCA factor combining financial turbulence, systemic risk and realized volatility. In addition to the in-sample predictability stance of each of the contending models, the model pairs are evaluated at three forecast horizons [$h = 5$, $h = 10$ and $h = 20$ days ahead] and in a rolling-window framework, wherein one-day ahead forecasts are generated iteratively over the entire specified out-of-sample horizons. For robustness purposes, we also consider different sub-sample periods in addition to the full-data sample period.

As noted earlier, the sample of countries in our analysis is selected based on the asset pool that is used to generate the financial turbulence and systemic risk indicators. However, given the strong integration of the emerging economies with their advanced counterparts, one would not expect a significant difference in the predictive relationship between these indicators and volatility patterns in emerging markets when compared with advanced markets. However, considering the rise in the relative importance of market-specific factors during the Global Financial Crisis period, implied by a decline in systemic risk – observed in Figure 1b – during this period, and the evidence by Didier et al. (2012) that emerging markets, in general, displayed a more heterogeneous pattern in their reaction to the Global Financial Crisis, one could argue that the predictive relation between systemic risk and market volatility would be more heterogeneous and market specific in the case of emerging markets. In this regard, one could argue that the predictive power of the systemic risk and turbulence indicators might be dominated by the degree to which a particular emerging market is connected to advanced economies, either through economic trade relations or the fragility of their economies to external shocks or currency market fluctuations, or both.

3.1. In-Sample Predictability

We proceed with the in-sample predictability of our four GARCH-MIDAS models. The difference in the model structure is based on whether the predictor variable incorporated is the realized volatility or an exogenous variable (financial turbulence or systemic risk, or both simultaneously). The GARCH-MIDAS parameters for the contending models are presented in Table 2 (for the full sample) and Table 3 (for the full sample without COVID period). These parameters include an unconditional mean for the stock return (μ); the ARCH term (α); the GARCH term (β); the slope coefficient (θ) which indicates the stance of predictability of weekly risk measures for daily return volatility; the adjusted beta polynomial weight (w); and the long-run constant term (m). The short-run component ARCH and GARCH terms are statistically significant, with evidence of high but mean-reverting volatility persistence, since the sum of the ARCH and GARCH terms is less than unity. This implies that the impact of shocks to return volatility will only be temporary, though, taking a long time to fizzle out. This feat is consistently confirmed across model constructs, countries and sample data periods. The adjusted beta weight coefficients are mostly statistically insignificant, especially for the GARCH-MIDAS model, which incorporates any of the risk measures as predictors. This implies that there may not be a marked difference in the weights assigned to immediate past and far-apart lag observations.

Table 2. In-sample predictability results (full sample)

Model	μ	α	β	θ	ω	m
Brazil						
RV	6.50E-04*** [1.99E-04]	5.27E-02*** [6.18E-03]	9.38E-01*** [7.02E-03]	4.64E-02*** [1.18E-02]	4.30E+01*** [1.41E+01]	3.35E-04*** [4.60E-05]
$RV + Turb$	8.18E-04*** [1.99E-04]	8.96E-02*** [4.43E-03]	8.87E-01*** [6.15E-03]	-3.33E-01** [1.57E-01]	1.22E+01 [2.12E+01]	-7.98E+00*** [7.45E-02]
$RV + Sys$	8.25E-04*** [1.98E-04]	9.07E-02*** [4.55E-03]	8.78E-01*** [7.02E-03]	1.21E+01*** [1.88E+00]	1.31E+01 [1.74E+02]	-8.02E+00*** [5.97E-02]
$RV + Turb + Sys$	8.21E-04*** [1.99E-04]	8.90E-02*** [4.43E-03]	8.87E-01*** [6.13E-03]	-6.93E-01*** [2.01E-01]	1.39E+00* [7.45E-01]	-7.99E+00*** [7.45E-02]
France						
RV	4.64E-04*** [1.38E-04]	7.52E-02*** [7.60E-03]	9.17E-01*** [8.33E-03]	3.12E-02** [1.43E-02]	3.08E+01* [1.66E+01]	2.06E-04*** [4.39E-05]
$RV + Turb$	5.25E-04*** [1.37E-04]	9.81E-02*** [5.28E-03]	8.90E-01*** [5.80E-03]	-1.90E+00 [1.70E+00]	4.87E+01 [3.05E+02]	-8.45E+00*** [1.61E-01]
$RV + Sys$	5.78E-04*** [1.35E-04]	1.75E-01*** [8.23E-03]	8.25E-01*** [8.23E-03]	3.82E+00 [3.29E+00]	5.64E+00 [2.11E+02]	-3.25E-01 [3.84E-01]
$RV + Turb + Sys$	5.95E-04*** [1.30E-04]	1.99E-01*** [9.32E-03]	8.01E-01*** [9.32E-03]	-1.90E+01*** [2.83E+00]	4.11E+00*** [1.30E+00]	-5.26E-01 [4.13E-01]
Germany						
RV	5.97E-04*** [1.41E-04]	9.22E-02*** [8.69E-03]	8.25E-01*** [3.50E-02]	1.41E-01*** [1.65E-02]	1.71E+00*** [5.64E-01]	5.29E-05*** [1.28E-05]
$RV + Turb$	6.55E-04*** [1.38E-04]	9.21E-02*** [5.44E-03]	8.95E-01*** [6.18E-03]	-1.79E+00 [1.68E+00]	4.53E+01 [2.72E+02]	-8.47E+00*** [1.45E-01]
$RV + Sys$	6.62E-04*** [1.38E-04]	9.18E-02*** [5.43E-03]	8.94E-01*** [6.21E-03]	5.71E+00* [3.01E+00]	1.56E+01 [4.49E+02]	-8.49E+00*** [1.35E-01]
$RV + Turb + Sys$	6.58E-04*** [1.37E-04]	9.21E-02*** [5.44E-03]	8.95E-01*** [6.17E-03]	-1.80E+00 [2.10E+00]	4.14E+00 [1.05E+01]	-8.47E+00*** [1.45E-01]
Hong Kong						
RV	3.80E-04** [1.49E-04]	6.34E-02*** [5.88E-03]	8.52E-01*** [2.21E-02]	1.55E-01*** [8.88E-03]	1.01E+00*** [3.82E-02]	4.29E-05*** [5.82E-06]
$RV + Turb$	4.03E-04*** [1.27E-04]	4.68E-02*** [2.30E-03]	9.52E-01*** [2.51E-03]	-3.72E-02** [1.85E-02]	1.50E+00* [7.90E-01]	-8.65E+00*** [2.85E-01]
$RV + Sys$	3.94E-04*** [1.32E-04]	5.77E-02*** [2.98E-03]	9.42E-01*** [3.05E-03]	-5.45E+02*** [1.80E+02]	2.91E+01 [8.22E+01]	-7.42E+00*** [4.70E-01]
$RV + Turb + Sys$	4.50E-04*** [1.42E-04]	1.11E-01*** [5.38E-03]	8.89E-01*** [5.38E-03]	4.46E-02* [2.47E-02]	3.07E+00 [2.75E+00]	-7.01E-01** [3.27E-01]
Japan						
RV	3.00E-04* [1.57E-04]	7.94E-02*** [7.71E-03]	7.79E-01*** [7.50E-02]	1.38E-01*** [1.87E-02]	3.70E+00*** [1.14E+00]	6.28E-05*** [1.51E-05]
$RV + Turb$	4.54E-04*** [1.51E-04]	9.67E-02*** [4.99E-03]	8.86E-01*** [6.15E-03]	-1.78E+00 [1.48E+00]	4.73E+01 [2.26E+02]	-8.31E+00*** [1.16E-01]
$RV + Sys$	4.52E-04*** [1.53E-04]	9.51E-02*** [4.96E-03]	8.84E-01*** [6.34E-03]	9.27E+00*** [2.35E+00]	3.33E+01 [6.56E+02]	-8.40E+00*** [9.06E-02]
$RV + Turb + Sys$	5.12E-04*** [1.49E-04]	1.48E-01*** [6.71E-03]	8.52E-01*** [6.71E-03]	2.36E+00 [1.61E+00]	7.09E+00 [1.47E+01]	7.97E-01** [3.53E-01]
United Kingdom						
RV	1.64E-04 [1.10E-04]	3.96E-02*** [6.11E-03]	9.55E-01*** [6.67E-03]	9.59E-02*** [2.36E-02]	2.44E+01*** [4.46E+00]	9.37E-05*** [1.95E-05]
$RV + Turb$	3.17E-04*** [1.07E-04]	1.02E-01*** [6.20E-03]	8.83E-01*** [6.90E-03]	-3.47E+00** [1.69E+00]	4.01E+01 [1.30E+02]	-8.95E+00*** [1.46E-01]
$RV + Sys$	3.18E-04*** [1.07E-04]	1.01E-01*** [6.06E-03]	8.85E-01*** [6.78E-03]	2.09E+00 [2.99E+00]	2.05E+01 [1.89E+03]	-8.94E+00*** [1.49E-01]
$RV + Turb + Sys$	3.67E-04*** [1.04E-04]	2.04E-01*** [9.59E-03]	7.96E-01*** [9.59E-03]	-2.53E+00 [2.56E+00]	4.89E+00 [1.20E+01]	-3.28E-01 [4.10E-01]
United States						
RV	7.61E-02*** [1.12E-02]	1.29E-01*** [7.98E-03]	8.09E-01*** [1.44E-02]	1.09E-01*** [1.13E-02]	1.00E+00*** [4.11E-02]	5.57E-01*** [6.53E-02]
$RV + Turb$	7.71E-02*** [1.09E-02]	1.22E-01*** [6.55E-03]	8.59E-01*** [7.32E-03]	-4.63E+00*** [1.70E+00]	4.99E+01 [1.46E+02]	3.48E-01*** [1.29E-01]
$RV + Sys$	7.84E-02*** [1.08E-02]	1.24E-01*** [6.75E-03]	8.51E-01*** [7.97E-03]	1.25E+01*** [1.91E+00]	1.06E+00 [7.47E+00]	2.89E-01*** [1.04E-01]
$RV + Turb + Sys$	7.71E-02*** [1.09E-02]	1.22E-01*** [6.55E-03]	8.59E-01*** [7.32E-03]	-4.63E+00*** [1.70E+00]	4.99E+01 [1.46E+02]	3.48E-01*** [1.29E-01]

Note: RV is the model with realized volatility only; $RV + Turb$ is the model with PCA factor that combines turbulence and realized volatility; $RV + Sys$ is the model with PCA factor that combines systemic risk and realized volatility; $RV + Turb + Sys$ is the model with PCA factor that combines turbulence, systemic risk and realized volatility. The figures in each cell are the estimated coefficients with the associated standard errors in square brackets; and ***, ** and * respectively denote statistical significance at 1%, 5% and 10%.

Table 3. In-sample predictability results (full less COVID period)

Model	μ	α	β	θ	ω	m
Brazil						
RV	5.76E-04*** [2.02E-04]	4.19E-02*** [5.82E-03]	9.52E-01*** [6.52E-03]	5.74E-02*** [1.36E-02]	4.07E+01*** [1.13E+01]	3.24E-04*** [5.12E-05]
$RV + Turb$	7.76E-04*** [2.03E-04]	8.14E-02*** [4.27E-03]	8.98E-01*** [5.74E-03]	-5.42E+00*** [2.10E+00]	1.34E+00 [9.44E-01]	-8.01E+00*** [8.04E-02]
$RV + Sys$	7.22E-04*** [1.95E-04]	7.71E-02*** [3.90E-03]	9.16E-01*** [4.54E-03]	-1.73E+01*** [4.76E+00]	1.29E+01 [1.16E+02]	-7.74E+00*** [2.19E-01]
$RV + Turb + Sys$	7.72E-04*** [2.02E-04]	8.19E-02*** [4.27E-03]	8.98E-01*** [5.72E-03]	-1.29E+00 [1.59E+00]	3.04E+01 [1.82E+02]	-8.00E+00*** [8.12E-02]
France						
RV	4.85E-04*** [1.40E-04]	1.03E-01*** [9.28E-03]	8.13E-01*** [2.71E-02]	1.46E-01*** [1.30E-02]	1.25E+00*** [2.90E-01]	4.74E-05*** [8.76E-06]
$RV + Turb$	5.20E-04*** [1.39E-04]	9.08E-02*** [5.32E-03]	8.98E-01*** [5.79E-03]	-1.05E-01 [2.42E-01]	2.52E+00 [1.01E+01]	-8.51E+00*** [1.68E-01]
$RV + Sys$	5.27E-04*** [1.39E-04]	9.16E-02*** [5.41E-03]	8.95E-01*** [6.07E-03]	8.70E+02*** [3.26E+02]	1.33E+01 [2.29E+02]	-8.55E+00*** [1.43E-01]
$RV + Turb + Sys$	5.19E-04*** [1.39E-04]	9.07E-02*** [5.35E-03]	8.98E-01*** [5.81E-03]	-6.92E-02 [1.77E-01]	4.67E+01 [7.81E+02]	-8.51E+00*** [1.68E-01]
Germany						
RV	6.26E-04*** [1.42E-04]	9.29E-02*** [8.66E-03]	8.38E-01*** [2.78E-02]	1.33E-01*** [1.82E-02]	1.30E+00*** [4.32E-01]	5.78E-05*** [1.43E-05]
$RV + Turb$	5.67E-04*** [1.11E-04]	6.32E-02*** [2.92E-03]	9.37E-01*** [3.26E-03]	7.15E-01 [1.80E+00]	6.63E+00 [3.72E+01]	-8.96E+00*** [6.39E-01]
$RV + Sys$	6.89E-04*** [1.38E-04]	1.41E-01*** [7.45E-03]	8.59E-01*** [7.45E-03]	-7.57E+00** [3.60E+00]	5.41E+00 [9.71E+01]	-3.13E-01 [3.69E-01]
$RV + Turb + Sys$	7.21E-04*** [1.33E-04]	1.63E-01*** [8.62E-03]	8.37E-01*** [8.62E-03]	2.51E+00 [2.51E+00]	3.75E+00 [8.68E+00]	-3.43E-01 [3.94E-01]
Hong Kong						
RV	3.66E-04** [1.52E-04]	6.07E-02*** [5.76E-03]	8.60E-01*** [2.17E-02]	1.55E-01*** [9.30E-03]	1.01E+00*** [3.87E-02]	4.20E-05*** [6.04E-06]
$RV + Turb$	4.64E-04*** [1.45E-04]	1.19E-01*** [6.07E-03]	8.81E-01*** [6.07E-03]	9.56E-03 [2.66E-02]	2.01E+00 [8.13E+00]	-2.92E-01 [3.40E-01]
$RV + Sys$	4.03E-04*** [1.46E-04]	5.93E-02*** [3.62E-03]	9.34E-01*** [4.13E-03]	4.29E+00 [4.02E+00]	2.53E+01 [8.85E+02]	-8.46E+00*** [1.44E-01]
$RV + Turb + Sys$	4.04E-04*** [1.47E-04]	5.94E-02*** [3.65E-03]	9.34E-01*** [4.16E-03]	-3.03E-02 [2.11E-02]	1.43E+00 [1.20E+00]	-8.46E+00*** [1.48E-01]
Japan						
RV	1.75E-04 [1.62E-04]	6.81E-02*** [7.29E-03]	6.70E-01*** [1.19E-01]	1.55E-01*** [8.87E-03]	5.24E+00*** [9.65E-01]	4.89E-05*** [6.11E-06]
$RV + Turb$	4.85E-04*** [1.51E-04]	1.51E-01*** [6.96E-03]	8.49E-01*** [6.96E-03]	4.74E+00*** [1.69E+00]	7.20E+00 [7.63E+00]	4.44E-01 [3.59E-01]
$RV + Sys$	4.16E-04*** [1.50E-04]	9.68E-02*** [4.70E-03]	9.00E-01*** [4.92E-03]	-1.53E+01*** [4.65E+00]	1.03E+01 [7.71E+01]	-7.30E+00*** [5.67E-01]
$RV + Turb + Sys$	4.12E-04*** [1.55E-04]	9.48E-02*** [4.98E-03]	8.90E-01*** [6.04E-03]	-1.15E+00 [1.53E+00]	4.90E+01 [3.75E+02]	-8.29E+00*** [1.29E-01]
United Kingdom						
RV	3.26E-04*** [1.07E-04]	9.90E-02*** [6.98E-03]	8.87E-01*** [7.66E-03]	-6.26E-03 [5.20E-03]	2.49E+00 [2.72E+00]	1.26E-04*** [2.00E-05]
$RV + Turb$	3.22E-04*** [1.08E-04]	9.67E-02*** [6.42E-03]	8.89E-01*** [7.06E-03]	-4.34E+00* [2.56E+00]	1.35E+00 [1.36E+00]	-9.03E+00*** [1.46E-01]
$RV + Sys$	3.22E-04*** [1.08E-04]	9.65E-02*** [6.38E-03]	8.88E-01*** [7.14E-03]	4.01E+00 [3.01E+00]	2.51E+01 [1.33E+03]	-9.03E+00*** [1.42E-01]
$RV + Turb + Sys$	3.91E-04*** [1.04E-04]	2.22E-01*** [1.03E-02]	7.78E-01*** [1.03E-02]	-1.89E+00 [2.77E+00]	2.70E+00 [8.62E+00]	-3.20E-01 [4.26E-01]
United States						
RV	7.30E-02*** [1.15E-02]	1.18E-01*** [7.63E-03]	8.22E-01*** [1.61E-02]	1.09E-01*** [1.40E-02]	1.00E+00*** [4.19E-02]	5.24E-01*** [7.59E-02]
$RV + Turb$	7.46E-02*** [1.13E-02]	1.13E-01*** [6.27E-03]	8.69E-01*** [7.24E-03]	-3.63E+00** [1.74E+00]	4.99E+01 [1.86E+02]	2.67E-01** [1.26E-01]
$RV + Sys$	7.64E-02*** [1.12E-02]	1.15E-01*** [6.50E-03]	8.59E-01*** [8.09E-03]	1.40E+01*** [1.93E+00]	1.07E+00 [7.44E+00]	1.99E-01** [9.69E-02]
$RV + Turb + Sys$	7.46E-02*** [1.13E-02]	1.13E-01*** [6.27E-03]	8.69E-01*** [7.24E-03]	-3.63E+00** [1.74E+00]	4.99E+01 [1.86E+02]	2.67E-01** [1.26E-01]

Note: RV is the model with realized volatility only; $RV + Turb$ is the model with PCA factor that combines turbulence and realized volatility; $RV + Sys$ is the model with PCA factor that combines systemic risk and realized volatility; $RV + Turb + Sys$ is the model with PCA factor that combines turbulence, systemic risk and realized volatility. The figures in each cell are the estimated coefficients with the associated standard errors in square brackets; and ***, ** and * respectively denote statistical significance at 1%, 5% and 10%.

Testing the null hypothesis of the insignificance of the MIDAS slope coefficient (θ) to ascertain the predictability of the risk measures for return volatility, we find predictability in a few cases, with a mostly negative nexus between return volatility and the risk measures (financial turbulence and financial turbulence and systematic risk combined); and a positive nexus between return volatility and systematic risk, for the full-data sample period. The cases of insignificant predictability of the risk measures are indicative of the dependence of the result on some country-specific features that may not have been captured within the model framework. However, we do not discard the predictive stance outright, as incorporating the risk measures provides some information to improve out-of-sample forecasts.

We expect a negative relationship between the risk factors and return volatility, such that the higher the risks, the lower the trading for risk-averse investors. Under the full-data sample period, our a priori expectation is met in the cases of the nexus between return volatility and financial turbulence (Brazil, Hong Kong, UK and USA) and systemic risk (Hong Kong). Also, when the sample period excludes the COVID period, the result seems to remain unchanged, especially for Brazil and the USA. The a priori is however met for systemic risk in the cases of Brazil, Germany and Japan. This shows that the COVID period does have some impact on the volatility-risk nexus. Overall, the relationship between volatility and risk measures (especially financial turbulence) is negative. The predictability plot of realized vs predicted volatilities for the full-sample data is presented in Figure 2.

Figure 2. Predictability plot of realized vs predicted volatility (full sample)

Country	Model 1	Model 2	Model 3	Models 1, 2 & 3
Brazil				
France				
Germany				
Hong Kong				
Japan				
U.K.				
USA				

3.2. Forecast Evaluation

The out-of-sample forecast performance results for the seven equity markets considered are presented in Table 4. In Panel 1, Models 2 – 4 are each compared with Model 1 as the benchmark model. This is a bid to ascertain whether incorporating any of the two risk proxies (financial turbulence and systemic risk), both singly and jointly, could improve the out-of-sample forecast performance. In conforming with the DM statistics, a significantly negative value indicates a preference for the contending model over the benchmark model, while a significantly positive value supports the benchmark model in the compared model pair. In Panel 2, we show a comparison of Models 2 and Model 3, with the latter used as the benchmark model. Consequently, a significantly negative DM value implies a preference for Model 2 over Model 3. Finally, in Panel 3, Models 2 and 3 are separately compared with Model 4 as the benchmark model. The intuition here is to ascertain whether including both risk proxies would outperform the single incorporation of these risk proxies.

In Panel 1, we observe a generally higher proportion of outperformance of Model 2 over Model 1, consistently across the three considered forecast horizons and equity markets (except for Hong Kong and Japan ($h = 5$), where Model 1 was preferred). This is an indication of improvement in the forecast precision, which is occasioned by incorporating financial turbulence as a predictor variable in the model. Clearly, the financial turbulence indicator that captures unusual deviations in asset return and correlation patterns compared with past trends contains valuable predictive information regarding the future path of stock market returns, possibly as a result of the volatility persistence effects, well documented in the literature. In the case of Model 3, which incorporates systemic risk as a predictor, the degree of outperformance is somewhat mixed. We observe that Model 3 outperforms Model 1 only in several exceptional cases, i.e. Brazil ($h = 5$), France ($h = 5$

and 10) and Hong Kong ($h = 20$). In contrast with the benchmark Model 1 (the GARCH-MIDAS model with realized volatility), incorporating systemic risk in the GARCH-MIDAS model does not seem to improve the forecasts of equity market returns in Germany, Japan the United Kingdom and the United States. The forecast performance of Model 4 supersedes that of Model 1, given that the significantly negative DM values cut across the equity markets considered. Overall, the findings presented in Panel 1 suggest that the unusualness of returns relative to their historic patterns, captured by the financial turbulence indicator, carries significant predictive information regarding the future path of asset returns, while the absorption ratio of Kritzman and Li (2010), captured by the systemic risk indicator, does not by itself add to the predictive accuracy of the forecasting model.

We present in Panel 2 of Table 4 the comparison of the forecast performance of Model 2 and Model 3, with the latter considered as the benchmark. In essence, this analysis allows us to compare the predictive performance of financial turbulence against the systemic risk indicator. We find that Model 2 overwhelmingly outperforms Model 3, consistently across all forecast horizons and equity markets for all the considered countries except Hong Kong and France. This implies that incorporating financial turbulence as a predictor in the forecasting models yield forecasts of out-of-sample stock returns with much less forecast error than the GARCH-MIDAS model, which incorporates only systemic risk. Kritzman et al. (2011) show that the absorption ratio, captured by the systemic risk indicator, systematically rose in advance of market turbulence, and stock prices depreciated significantly following spikes in the absorption ratio. However, our results show that, in terms of predictive ability, the financial turbulence indicator, which captures asset price deviations from historical patterns, does a better job when it comes to predicting out-of-sample future returns, compared with the measure of market connectedness, captured by the absorption ratio. This finding highlights the long memory feature in financial market volatility patterns, driven by how information is processed and absorbed by market participants. It is, however, interesting that the financial turbulence predictor captures marginal predictive information over and above what is captured in historical realized volatility. Thus, one could argue that unusual deviations not only in asset returns, but also in correlation patterns play a role in the persistence of return volatility, thus leading to improved out-of-sample forecasting performance, observed in our analysis.

Table 4. Diebold and Mariano results (full sample)

Out-of-Sample Forecast Horizon	Panel 1 (Benchmark is Model 1)			Panel 2 (Benchmark is Model 3)	Panel 3 (Benchmark is Model 4)	
	Model 2	Model 3	Model 4	Model 2	Model 2	Model 3
			Brazil			
$h = 5$	-7.87***	-3.97***	-7.81***	-27.92***	-4.11***	18.79***
$h = 10$	-5.30***	-1.20	-4.73***	-24.29***	-8.44***	22.37***
$h = 20$	-6.26***	0.39	-6.26***	-40.17***	-2.81***	25.96***
			France			
$h = 5$	-1.97**	-2.02**	-3.12***	2.04**	3.44***	9.11***
$h = 10$	-3.52***	-2.97***	-5.15***	2.75***	5.47***	18.18***
$h = 20$	-5.39***	-1.39	-5.61***	0.51	5.50***	28.80***
			Germany			
$h = 5$	-1.37	6.72***	0.10	-20.28***	-10.02***	26.75***
$h = 10$	-1.08	6.50***	0.04	-41.25***	-5.84***	26.43***
$h = 20$	-4.68***	2.08***	-3.80***	-68.25***	-2.72***	28.54***
			Hong Kong			
$h = 5$	11.68***	4.15***	-14.75***	35.24***	13.42***	10.64***
$h = 10$	5.95***	0.53	-10.88***	20.85***	8.40***	6.40***
$h = 20$	3.52***	-2.25**	-5.04***	11.86***	4.50***	2.88***
			Japan			
$h = 5$	2.90***	6.33***	-10.18***	-27.51***	5.64***	7.96***
$h = 10$	0.44	3.63***	-6.33***	-52.28***	2.95***	4.93***
$h = 20$	-1.67*	3.13***	-6.54***	-57.64***	3.58***	6.57***
			United Kingdom			
$h = 5$	1.03	1.74*	-2.38**	-15.99***	3.95***	4.95***
$h = 10$	-0.30	0.80	-1.30	-32.84***	0.75	1.44
$h = 20$	-0.78	1.17	-0.54	-43.60***	-0.03	1.14
			United States			
$h = 5$	-1.86*	11.40***	-1.86*	-12.53***	52.34***	12.53***
$h = 10$	-4.22***	5.83***	-4.22***	-16.81***	23.10***	16.81***
$h = 20$	-8.70***	6.75***	-8.70***	-30.66***	18.37***	30.66***

Note: Model 1 is GARCH-MIDAS model with realized volatility; Model 2 is GARCH-MIDAS model with PCA factor obtained by combining financial turbulence and realized volatility; Model 3 is GARCH-MIDAS model with PCA factor obtained by combining systemic risk and realized volatility; and Model 4 is GARCH-MIDAS model with PCA factor obtained by combining financial turbulence, systemic risk and realized volatility. The figures in each cell are the estimated D.M. statistics, with ***, ** and * respectively denoting statistical significance at 1%, 5% and 10%.

Finally, we present in Panel 3 of Table 4, the comparison of the GARCH-MIDAS models, which incorporates each risk proxy singly against the GARCH-MIDAS model, which jointly incorporates the two risk proxies. We observe that, in most cases, the joint incorporation of the two risk proxies performs better than singly incorporating the same risk proxies except for Model 2 for Brazil and Germany. In the case of the United Kingdom, there seems not to be significant outperformance in favor of the single or joint incorporation of risk proxies in the longer out-of-sample periods. Nevertheless, the findings in Panel 3 show that incorporating risk proxies (especially financial turbulence), singly and jointly, indeed improves the forecasting performance of the GARCH-MIDAS model significantly.

In the last part of our analysis, considering the growing literature that establishes a link between the COVID-19 pandemic and increased volatility and uncertainty in financial markets (e.g., Bouri et al. 2020, 2021; Haldar and Sethi 2020; Alexakis et al. 2021; Salisu et al. 2021; Scherf et al. 2021; among others), next, we repeat our analysis by excluding the pandemic period from the sample to ascertain the predictive role of the two financial indicators examined. Considering that the pandemic has turned an unprecedented health crisis into an economic one, our goal is to verify our findings without including this exceptional period. Table 5 presents the results for the full sample without the COVID-19 period (Oct. 28, 1996-December 31, 2020). We find, to a great extent, a similar pattern of performance as for the full sample presented in Table 4. The models with the two financial indicators incorporated (singly and jointly) mostly outperformed the benchmark GARCH-MIDAS model with realized volatility. Likewise, the GARCH-MIDAS model with financial turbulence as a predictor also overwhelmingly outperforms its counterpart that incorporates only systemic risk, while the model with jointly incorporated risk proxies is found to outperform the alternative with singly incorporated financial indicators for

Model 2 (Brazil, France, Hong Kong, Japan and the US) and Model 3 (for all equity market returns). Interestingly, however, the magnitude of performance of Models 2 – 4 compared with Model 1 appears to be higher when the COVID period is excluded from the analysis than for the full-sample data periods. This suggests that the results may be sensitive to the sample period considered, wherein the COVID period may plausibly have peculiarities that differ from those of the full sample without the COVID period.

Table 5. Diebold and Mariano results (full sample excluding COVID-19 pandemic)

Out-of-Sample Forecast Horizon	Panel 1 (Benchmark is Model 1)			Panel 2 (Benchmark is Model 3)	Panel 3 (Benchmark is Model 4)	
	Model 2	Model 3	Model 4	Model 2	Model 2	Model 3
Brazil						
$h = 5$	-17.97***	-3.47***	-11.64***	-102.94***	-108.87***	74.38***
$h = 10$	-23.57***	-2.22**	-16.57***	-77.99***	-29.10***	26.08***
$h = 20$	-34.09***	-3.54***	-19.68***	-123.90***	-9.85***	26.90***
France						
$h = 5$	7.18***	8.48***	7.77***	-28.90***	-11.23***	15.17***
$h = 10$	1.19	2.14**	1.34	-48.37***	-10.22***	23.57***
$h = 20$	-1.80*	-0.46	-1.66*	-36.40***	-3.55***	19.21***
Germany						
$h = 5$	36.29***	-17.17***	-13.71***	30.90***	24.69***	9.17***
$h = 10$	15.87***	-12.52***	-7.71***	15.51***	12.53***	3.79***
$h = 20$	15.45***	-13.13***	-8.01***	16.18***	12.94***	2.41**
Hong Kong						
$h = 5$	-11.96***	-50.20***	-32.21***	-7.44***	-7.67***	4.01***
$h = 10$	-8.18***	-8.20***	-7.62***	-4.55***	-4.47***	1.97*
$h = 20$	-5.10***	-5.06***	-4.31***	-3.74***	-3.91***	-1.22
Japan						
$h = 5$	-2.60***	1.47	-2.55**	-5.52***	-2.20**	31.27***
$h = 10$	-1.61	1.12	-1.91*	-2.74***	-1.48	13.94***
$h = 20$	-1.81*	3.26***	-0.49	-3.82***	-2.09**	16.04***
United Kingdom						
$h = 5$	4.94***	15.89***	-8.20***	-8.48***	8.32***	8.41***
$h = 10$	4.88***	14.39***	-4.84***	-6.75***	4.92***	5.03***
$h = 20$	9.94***	15.75***	-2.88***	-3.97***	3.06***	3.11***
United States						
$h = 5$	63.61***	36.38***	63.60***	-11.45***	-3.56***	11.44***
$h = 10$	10.30***	17.15***	10.30***	-23.07***	-7.94***	23.05***
$h = 20$	2.08**	7.61***	2.09**	-26.25***	-13.39***	26.24***

Note: Model 1 is GARCH-MIDAS model with realized volatility; Model 2 is GARCH-MIDAS model with PCA factor obtained by combining financial turbulence and realized volatility; Model 3 is GARCH-MIDAS model with PCA factor obtained by combining systemic risk and realized volatility; and Model 4 is GARCH-MIDAS model with PCA factor obtained by combining financial turbulence, systemic risk and realized volatility. The figures in each cell are the estimated D.M. statistics, with ***, ** and * respectively denoting statistical significance at 1%, 5% and 10%.

In another form of comparison, we compare the out-of-sample forecast performance using two alternative loss functions – MSE and QLIKE. Considering the MSE and QLIKE statistics over the full sample period, we find both loss functions to yield consistent inferences with respect to the comparative performance of the models. Models 2 and 4 consistently outperform the benchmark model in the cases of Germany, Japan and the USA (across all the out-of-sample forecast horizons) and Brazil (when the forecast horizon is 5); while Model 3 outperform Model 1 in the case of Germany (across all the forecast horizons) and Hong Kong (for shorter out-of-sample horizons). In the case of the UK, none of the other models that incorporated the risk measure, either singly or jointly, outperform the benchmark model (see the results in Table 6). The stance of performance is markedly different when the sample period excludes the COVID period. We find consistent outperformance of the exogenous-based models over the benchmark, across all forecast horizons, for France only. Model 2 outperformed Model 1 for the UK (across all forecast horizons), Germany and the USA (forecast horizons 10 and 20), while Models 3 and 4 perform best for France, Hong Kong and the USA (horizons 5 and 10) (see the results in Table 7). The above performance comparisons align and contrast the comparisons for the Diebold and Marino statistics, which is not unexpected as the measures are considered from different perspectives. One major point of agreement between the DM, MSE and QLIKE results is the consistent outperformance of Model 2 over Model 3, which shows the incorporation of financial turbulence to improve the out-of-sample forecast more than the incorporation of the systematic risk proxy. Generally, the effects of the incorporated risk measures are market-dependent. However, the maintained stance of outperformance of Model 2, regardless of the sample period, implies that the incorporation of risk measures (especially, financial turbulence) in the predictive model for return volatility is necessary for improved out-of-sample forecasts.

Table 6. MSE and QLIKE results (full sample)

Out-of-Sample Forecast Horizon	MSE				QLIKE			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
				Brazil				
$h = 5$	1.74E-06	**1.74E-06**	2.01E-06	**1.71E-06**	0.668	**0.662**	0.962	**0.636**
$h = 10$	**1.46E-06**	1.51E-06	1.75E-06	1.49E-06	**0.533**	0.572	0.840	0.552
$h = 20$	**7.61E-07**	7.86E-07	9.38E-07	7.74E-07	**0.293**	0.312	0.493	0.300
				France				
$h = 5$	4.20E-08	**4.07E-08**	4.52E-01	5.56E-01	0.146	**0.140**	6.245	6.349
$h = 10$	5.00E-08	**4.96E-08**	4.52E-01	5.82E-01	0.222	**0.221**	6.562	6.687
$h = 20$	**3.69E-08**	3.83E-08	4.52E-01	6.22E-01	**0.297**	0.306	7.123	7.282
				Germany				
$h = 5$	5.41E-07	**4.22E-07**	**4.59E-07**	**4.25E-07**	1.501	**0.724**	**0.902**	**0.736**
$h = 10$	4.47E-07	**3.65E-07**	**3.91E-07**	**3.66E-07**	1.240	**0.735**	**0.854**	**0.743**
$h = 20$	2.26E-07	**1.88E-07**	**1.99E-07**	**1.89E-07**	0.658	**0.427**	**0.473**	**0.430**
				Hong Kong				
$h = 5$	2.09E-06	2.23E-06	**4.58E-07**	2.19E-01	1.393	1.721	**0.069**	4.642
$h = 10$	1.15E-06	1.24E-06	**7.82E-07**	2.18E-01	0.839	1.053	**0.158**	4.955
$h = 20$	**6.26E-07**	6.80E-07	1.16E-06	2.15E-01	0.505	0.638	**0.302**	5.272
				Japan				
$h = 5$	1.12E-06	**1.11E-06**	1.21E-06	4.63E+00	0.664	**0.629**	0.848	6.759
$h = 10$	5.70E-07	**5.64E-07**	6.09E-07	4.60E+00	0.369	**0.358**	0.457	7.267
$h = 20$	4.44E-07	**4.06E-07**	4.60E-07	4.56E+00	0.464	**0.345**	0.495	7.107
				UK				
$h = 5$	**1.08E-07**	1.28E-07	1.33E-07	5.51E-01	**0.246**	0.379	0.426	6.606
$h = 10$	**5.78E-08**	6.97E-08	7.12E-08	5.55E-01	**0.275**	0.369	0.377	7.282
$h = 20$	**2.96E-08**	3.57E-08	3.63E-08	5.61E-01	**0.148**	0.198	0.199	7.333
				USA				
$h = 5$	9.45E+01	**8.65E+01**	9.73E+01	**8.65E+01**	1.551	**1.218**	1.691	**1.218**
$h = 10$	5.36E+01	**4.86E+01**	5.56E+01	**4.86E+01**	0.948	**0.729**	1.053	**0.729**
$h = 20$	2.97E+01	**2.64E+01**	3.12E+01	**2.64E+01**	0.615	**0.450**	0.716	**0.450**

Note: Model 1 is GARCH-MIDAS model with realized volatility; Model 2 is GARCH-MIDAS model with PCA factor obtained by combining financial turbulence and realized volatility; Model 3 is GARCH-MIDAS model with PCA factor obtained by combining systemic risk and realized volatility; and Model 4 is GARCH-MIDAS model with PCA factor obtained by combining financial turbulence, systemic risk and realized volatility. Models with smaller MSE and QLIKE are considered better.

Table 7. MSE and QLIKE results (full sample)

Out-of-Sample Forecast Horizon	MSE				QLIKE			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Brazil								
$h = 5$	**5.80E-08**	7.31E-08	2.88E-07	5.96E-08	**0.241**	0.277	0.569	0.245
$h = 10$	**6.98E-08**	8.45E-08	3.09E-07	7.15E-08	**0.380**	0.416	0.731	0.384
$h = 20$	**5.43E-08**	6.23E-08	2.36E-07	5.48E-08	**0.245**	0.265	0.508	0.247
France								
$h = 5$	1.99E-07	**1.25E-07**	**1.55E-07**	**1.26E-07**	1.137	**0.396**	**0.615**	**0.406**
$h = 10$	1.01E-07	**6.75E-08**	**7.94E-08**	**6.81E-08**	0.597	**0.254**	**0.341**	**0.258**
$h = 20$	5.25E-08	**4.35E-08**	**4.51E-08**	**4.36E-08**	0.351	**0.273**	**0.278**	**0.274**
Germany								
$h = 5$	1.21E-07	**1.20E-07**	7.46E-01	4.88E-01	0.744	**0.727**	6.559	6.347
$h = 10$	6.20E-08	**6.12E-08**	7.44E-01	4.94E-01	0.392	**0.379**	7.033	6.829
$h = 20$	**3.34E-08**	3.39E-08	7.41E-01	5.04E-01	**0.268**	0.284	7.469	7.276
Hong Kong								
$h = 5$	6.55E-08	5.47E-01	**3.57E-08**	**2.96E-08**	0.324	6.495	**0.111**	**0.083**
$h = 10$	1.88E-07	5.49E-01	**1.40E-07**	**1.29E-07**	0.647	6.326	**0.325**	**0.274**
$h = 20$	1.45E-07	5.53E-01	**1.18E-07**	**1.12E-07**	0.621	6.842	**0.444**	**0.419**
Japan								
$h = 5$	1.52E-08	2.36E+00	5.67E-07	**6.36E-09**	0.201	7.698	0.634	**0.043**
$h = 10$	7.90E-08	2.43E+00	5.07E-07	**4.74E-08**	0.685	7.822	0.815	**0.362**
$h = 20$	6.93E-08	2.51E+00	6.12E-07	**6.18E-08**	0.605	8.197	1.105	**0.515**
UK								
$h = 5$	1.07E-07	**1.06E-07**	1.17E-07	5.43E-01	0.604	**0.592**	0.736	6.322
$h = 10$	9.78E-08	**9.75E-08**	1.06E-07	5.38E-01	0.518	**0.514**	0.628	6.466
$h = 20$	7.81E-08	**7.80E-08**	8.33E-08	5.31E-01	0.524	**0.521**	0.584	7.035
USA								
$h = 5$	4.70E-01	**1.32E-01**	**4.04E-01**	**1.32E-01**	0.106	**0.020**	**0.085**	**0.020**
$h = 10$	3.08E-01	**1.62E-01**	**2.59E-01**	**1.62E-01**	0.074	**0.033**	**0.058**	**0.033**
$h = 20$	2.29E-01	4.69E-01	2.74E-01	4.69E-01	0.090	0.160	0.111	0.160

Note: Model 1 is GARCH-MIDAS model with realized volatility; Model 2 is GARCH-MIDAS model with PCA factor obtained by combining financial turbulence and realized volatility; Model 3 is GARCH-MIDAS model with PCA factor obtained by combining systemic risk and realized volatility; and Model 4 is GARCH-MIDAS model with PCA factor obtained by combining financial turbulence, systemic risk and realized volatility. Models with smaller MSE and QLIKE are considered better.

4. Conclusion

An issue of great concern when it comes to building turbulence-resistant portfolios is the accuracy and stability of the parameters used to build diversified portfolios that can balance out the negative fluctuations experienced in various asset classes. A key parameter of interest in stress testing investment portfolios and managing exposure to risk factors is volatility. Recent research suggests that the performance of volatility forecasting models can be improved significantly by combining predictors at different frequencies using Mixed Data Sampling (MIDAS)-based

Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. This is particularly important considering that most uncertainty and risk proxies are available at low frequencies. This paper adds a novel perspective to the literature by exploring the predictive performance of two relatively unexplored indicators of financial conditions, i.e. financial turbulence and systemic risk, for stock market volatility, using a sample of seven emerging and advanced economies. The two financial indicators that we utilize in our predictive setting provide a unique perspective on market conditions as they directly relate to portfolio performance metrics from both volatility and co-movement perspectives and – unlike other macro-financial indicators of uncertainty, or risk – can be integrated into diversification models within forecasting and portfolio design settings.

The results suggest that incorporating the two financial indicators (singly and jointly) indeed improves the out-of-sample predictive performance of stock market volatility models over both the short and long horizons. We observe that the financial turbulence indicator, which captures asset price deviations from historical patterns, does a better job when it comes to the out-of-sample prediction of future returns compared with the indicator of market connectedness, captured by the absorption ratio. This finding highlights the long memory feature in financial market volatility patterns, driven by how information is processed and absorbed by market participants. At the same time, the outperformance of the financial turbulence indicator implies that unusual deviations in not only asset returns, but also correlation patterns play a role in the persistence of return volatility. Interestingly, however, the predictive performance of the augmented model is found to be generally higher when the COVID-19 pandemic period is excluded from the analysis, suggesting that the pandemic period may plausibly have peculiarities that reduce the predictive accuracy of volatility forecasting models.

An important investment implication of our results is that the findings provide an interesting opening for portfolio design purposes in that financial indicators that are directly associated with portfolio diversification performance metrics can also be utilized for forecasting purposes with significant implications for dynamic portfolio allocation strategies. Given the predictive information captured by both the financial turbulence and systemic risk indicators, portfolio managers can utilize these indicators within a predictive setting using a GARCH-MIDAS specification in order to stress-test their portfolios. This can then be used to identify optimal asset allocations to create a turbulence-resistant portfolio, by computing optimal portfolio weights based on the forecasts obtained from the predictive models. For future work, it would be interesting to utilize these financial indicators in a predictive setting in order to compute out-of-sample hedge ratios and examine the effectiveness of dynamic hedging strategies, as opposed to utilizing the static alternatives or those based on DCC-based models.

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