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Technological Shocks and Stock Market Volatility Over a Century: A GARCH-MIDAS Approach

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Abstract

This paper provides a novel perspective to the innovation-stock market nexus by examining the predictive relationship between technological shocks and stock market volatility using data over a period of more than 140 years. Utilizing annual patent data for the U.S. and a large set of economies to create proxies for local and global technological shocks and a mixed-sampling data (MIDAS) framework, we present robust evidence that technological shocks capture significant predictive information regarding future realizations of stock market volatility, both in- and out-of-sample and at both the short and long forecast horizons. Further economic analysis shows that investment portfolios created by the volatility forecasts obtained from the forecasting models that incorporate technological shocks as predictors in volatility models experience significantly lower return volatility in the out-of-sample horizons, which in turn helps to improve the risk-return profile of those portfolios. Our findings present a novel take on the nexus between technological innovations and stock market dynamics and paves the way for several interesting avenues for future research regarding the role of technological innovations on asset pricing tests and portfolio models.

Keywords: Patents, Technology shocks, Stock market volatility, Forecasting
JEL Codes: C32, C53, E37, G15, O33

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1. Introduction

There is now a well-established literature that highlights the role of innovation as a driver of economic growth boosted by productivity growth via factor reallocation from the less productive to more productive firms (e.g., Bartelsman and Doms, 2000; Foster et al., 2001), paving the way to further innovations and labor market specialization (Acemoglu et al., 2022). In this setting, economic growth via innovation in products and processes is achieved by what the literature terms as creative destruction, a process in which unproductive firms are replaced by their innovative counterparts (e.g. Aghion and Howitt, 1992; Klette and Kortum, 2004; Lentz and Mortensen, 2008; Hsu and Huang, 2010; Acemoglu et al., 2018; Akcigit and Kerr, 2018; among others). As Akcigit and Kerr (2018) note, however, innovations differ substantially in terms of their type, quality and impact, as many innovations lead to improvements in the existing portfolio of products or technologies, while others create new markets for firms who adopt these new technologies and improve upon them. The nature of such a growth option embedded in the nature and quality of innovations thus leads to variations in expected firm returns as asset betas vary over time with corporate investment decisions driven by the option-like features of those investments (Carlson et al., 2004). Against this backdrop, this paper contributes to the discussions on the asset pricing implications of innovations from a novel perspective by exploring the predictive relationship between innovation and stock market volatility via a mixed-data sampling (MIDAS) framework that allows to disentangle the short- and long-run effects of technological innovations on stock market volatility. By doing so, we present a novel perspective to asset pricing-based explanations of how technological changes drive stock market dynamics.

Our work falls in the strand of the literature that deals with the asset pricing implications of technological innovations along the lines of Pastor and Veronesi (2009), Garleanu et al., (2012a,b), Kogan and Papanikolaou (2014), Kung and Schmid (2015), among others, however from a predictability perspective. In this regard, associated set of empirical studies have depicted evidence in favor of technology shocks predicting stock market returns in the U.S., although without a consensus on the direction of the predictive relationship (e.g. Hsu, 2009; Hirshleifer et al., 2013, 2018; Hou et al., 2022; Sharma and Narayan, 2022). We approach the issue from a forecasting as well as economic perspective and extend this line of empirical research by investigating whether technology shocks capture predictive information regarding stock market volatility, both in- and out-of-sample, along with the economic implications of such predictability. To econometrically provide an answer to our predictive analyses, we first rely on U.S. patent data to obtain a proxy for local technology shocks, which we then use as a predictor of stock market volatility. To contrast the impact of local and global innovations, we also utilize two alternative proxies for global technology shocks based on patent data from 164 countries and the 12 countries in the Organization for Economic Cooperation and Development (OECD). To the best of our knowledge, ours is the first attempt to conduct predictive analyses of the impact of local and global technological shocks on stock market volatility, based on a long span of data involving 143 years.

In our empirical analysis, given that the patent data that we use to create the technological shock series are only available in annual frequency, while the stock market data is monthly, we conduct our predictive tests based on the generalized autoregressive conditional heteroskedasticity (GARCH) variant of mixed data sampling (MIDAS), i.e., the GARCH-MIDAS model. The choice of the mixed data sampling approach is supported by the well-established evidence that volatility effects are less likely to be observed in annual data and also loss of information would result by averaging the monthly data to a lower frequency (Clements and Galvão, 2008; Das et al., 2019). The MIDAS framework has been widely utilized in an extensive list of volatility forecasting applications to model return volatility at the daily frequency using various monthly and/or quarterly predictors (see, for example, Asgharian et al., 2013; Engle et al., 2013; Conrad and Loch, 2015; Fang et al., 2020; Segnon et al., 2022; Salisu et al., forthcoming).[1] This approach is motivated by the argument that volatility is not just volatility, but that there are different components to volatility namely, one pertaining to short-term fluctuations and the other to a long-run component, with the latter likely to be affected by slow-moving economic predictors, which in our context are the local and global technology shocks. It must, however, be noted that while our focus is not on forecasting daily volatility, as is traditionally done with GARCH-MIDAS models, due to the unavailability of such data over a period of more than 140 years, the utilization of historical data with the longest possible span has an important advantage of avoiding sample selection bias. At the same time, the long sample we employ in our analysis that spans over a century allows us to study the entire available information regarding the process of evolution of technology (proxied via patents) and its associated transformative effects on the US macroeconomy and asset price movements.

[1] Earlier works based on spline-GARCH can be found in Engle and Rangel (2008), and Rangel and Engle (2011).

While our main focus is on the US, we also conduct a comparative forecasting exercise for the remaining of the six of the G7 countries, i.e. Canada and Japan (1915−2018), France, Germany and the United Kingdom (1876−2018) and Italy (1906−2018), due to their importance in shaping the risk profile of the global financial system. Since, we are interested in not only carrying out a statistical exercise of the predictive relationships, we also provide an analysis of the economic implications of such predictability in terms of utility gains for a typical investor. Finally, we conduct our analyses over periods of expansions and recessions separately, and with our out-of-sample forecasting based on a rolling-window estimation, we are also able to account for possible time-variation while drawing our predictive inferences. Our findings yield robust evidence that technological shocks capture significant predictive information regarding future realizations of stock market volatility, both in- and out-of-sample. We show that accounting for the innovations in the number of patents granted from resident applications in a country, as a proxy for technological shocks, can significantly improve the accuracy of stock market volatility forecasts, both at the short and long forecast horizons. Further economic analysis shows that investment portfolios created by the volatility forecasts obtained from the forecasting models that incorporate technological shocks as predictors experience significantly lower return volatility in the out-of-sample horizons, which in turn helps to improve the risk-return profile of those portfolios. Accordingly, our findings present a novel take on the nexus between technological innovations and stock market dynamics.

The remainder of the paper is organized as follows. Section 2 presents a brief summary of the literature related to the impact of innovations on stock market dynamics along with some discussion of the literature on stock market volatility forecasting. Section 3 outlines the data and the results from preliminary analysis. Section 4 describes the methodological framework for mixed-data sampling model employed in the forecasting analysis. Empirical findings, associated with both statistical and economic evaluations, are discussed in Section 5, while Section 6 concludes the paper.

2. Literature Review

A growing strand of literature on asset pricing has developed structural models that establish an association between technological innovations and stock market dynamics (see, for example, Hsu and Huang, 2010; Papanikolaou, 2011; Garleanu et al., 2012a,b; Kogan and Papanikolaou, 2014; Kung and Schmid, 2015). The evidence regarding the direction and size of the impact of innovations on the return and volatility dynamics in the stock market, however, is still inconclusive with the literature presenting alternative arguments. One hypothesis in the strand of the literature that links innovation to stock market dynamics is motivated by the theoretical framework of Garleanu et al. (2012b) who argue that growth options of firms exhibit a "life cycle" driven by technological diffusion. In this setting, a disruptive technological shock leads to a rise in growth options, which in turn drives the risk premia (and equity price volatility) higher during the early phase of the technology shock as these growth options are riskier than existing assets in place. However, as the new technology is absorbed and firms start to convert growth options into assets over time, the risk premia on their stock begin to fall due to lower anticipated cash flow growth and interest rate. In contrast, Pastor and Veronesi (2009) present a risk-based explanation, arguing that, during the initial phase of technological shifts in the economy, risk is mostly idiosyncratic to firms associated with the new technology, resulting in stocks of innovative firms to be priced at high valuation ratios. However, as the adoption probability of the new technology increases, the uncertainty related to the new technology transforms into market wide systematic risk, thus pushing up discount rates, in turn, depressing stock prices across the market. Accordingly, the literature offers contrasting arguments regarding the impact of technological shocks on stock market return and volatility dynamics via distinct channels that relate to growth opportunities and discount rates without a consensus, however, on the direction of the impact.

Regarding the focus on volatility in our application, it is well-established that appropriate modelling and forecasting of volatility is of high interest due to several reasons, as outlined in Poon and Granger (2003). Firstly, when volatility is interpreted as uncertainty, it becomes a key input to investment decisions and portfolio choices. Secondly, volatility is the most important variable in the pricing of derivative securities as one needs reliable estimates of the volatility of the underlying assets when it comes to pricing of options and option-like instruments. Thirdly, financial risk management according to the Basel Accord as established in 1996 also requires modelling and forecasting of volatility as a compulsory input to risk-management for financial institutions around the world. Finally, financial market volatility, as witnessed during the Global Financial Crisis and the COVID-19 pandemic, can have wide repercussions on the economy as a whole, via its effect on real economic activity and public confidence. Hence, estimates of market volatility can serve as a measure for the vulnerability of financial markets and the economy, and can help policy makers design appropriate policies. Evidently, appropriate modelling and accurate forecasting of the process of volatility, particularly at higher frequencies, has ample implications for portfolio selection, the pricing of derivative securities and risk management (Rapach et al., 2008).

In our application, we build on the recent work of Sharma and Narayan (2022) who document strong evidence of in-sample predictability of the US equity premium, particularly at longer horizons and during economic expansions, principally driven by global technology factors.[2] Although the effect of technological innovations on economic growth and stock market returns is well-studied in the literature (see Hsu and Huang, 2010 and references cited therein), its effect on stock market volatility is relatively understudied. One argument that can be made in this regard is that innovations are likely to reduce the volatility in the factors that reflect future cash flows by lowering economic uncertainty (Bernanke, 1983) and the discount factor (Schwert, 1989). Along the same lines, considering that the present value model of asset prices (Shiller, 1981a, b) can be used to show that stock market volatility depends on the volatility of cash flows and the discount factor, one can argue that positive technology shocks are likely to reduce stock returns variance. The ultimate effect on stock price volatility, however, will be dependent on the strength of these channels, and is obviously an empirical question. Given the importance of volatility forecasts in a wide array of applications from portfolio management, hedging to the pricing of derivatives, our work presents novel contribution to the massive existing literature on the predictability of US stock market volatility based on a wide array of (univariate and multivariate) models and (behavioral, financial, and macroeconomic) predictors, a review of which is beyond the scope and objective of this paper, by considering the role of technological innovations in predicting the future path of stock market volatility.[3]

3. Data and Preliminary Analyses

The first component of our data comprises monthly stock indexes for the US (S&P500 Index), sourced from the Global Financial Database over the period of 1876:01-2018:12 whose

[2] For 11 other OECD countries, Sharma and Narayan (2022) also show evidence of time-varying return predictability for seven countries; however, in-sample and long horizon predictability were, in general, weak.

[3] The reader is referred to the recent works of Ben Nasr et al. (2014, 2016), Boubaker et al. (2022), Gupta et al. (2022), Liu and Gupta (2022), Salisu et al. (2022), and references cited therein to get an understanding of the existing and ever burgeoning number of studies on modeling and forecasting of US stock market volatility.

coverage is governed the available data for Technology shocks. Log-returns are computed by taking the first differences of the natural logarithms of the monthly indexes and following Welch and Goyal (2008), the equity premium is then computed by subtracting the U.S. risk-free rate, obtained from the website of Professor Amit Goyal.[4]

Regarding the construction of the technology shock (TS) series, annual data on patents granted from resident applications in a country is used along the lines of Sharma and Narayan (2022) who adopt the same approach previously proposed in Hsu (2009). In this approach, TS is estimated by detrending the growth in patents in a year based on a 5-year moving window using the formula $TS_{t-1} = \ln(PAT_{t-1})$-$(1/5)\sum_{h=1}^{5} \ln(PAT_{t-h-1})$, where PAT represents the number of patents. The choice of the 5-year window is motivated by the need to control for the effect of delays that may occur during the application process which can take up to five years from the date a patent application is submitted until it is granted (Sharma and Narayan, 2022). In this formulation, TS tracks the technology prospects for an economy, wherein a positive value suggests that technology prospects at time *t* are better than the past. There are two specific advantages of this approach namely, this measure is free from the so-called look-ahead bias, and it takes the weakest assumptions on model parameters. In addition to the TS series based on U.S. patent data, Sharma and Narayan (2022) also create global technology shocks using the sum of patents from 164 countries (GTS_164) for which data are available. As another measure, the authors also aggregate the patents for 12 OECD countries (G7 plus five other major countries namely, Australia, Denmark, Finland, Norway and Spain) to generate an OECD-specific technology shock series (GTS_OECD) based on the above specification.[5] The raw data on patents granted (residents) are available from the World Intellectual Property Organization's (WIPO) website (https://www.wipo.int/portal/en/index.html), which has archived data from 1883 to 1979, while data from 1980 to 2018 are available in non-archived view from: http://www.wipo.int/ipstats/en/statistics/patents/. Note that, the start and the end points of the sample are purely driven by data availability for the excess-returns and the technology shocks at the time of writing this paper.

[4] https://sites.google.com/view/agoyal145

[5] We are indebted to Professor Paresh K. Narayan for kindly providing us with the TS data.

Figure 1 presents a visual representation of the relationship between U.S. excess stock market returns and its country-specific technological shock series along with global technological shocks. The excess stock return series exhibits several notable spikes which appear to coincide with periods of global recession (indicated by the shaded intervals), more prominently during the Great Depression in 1930s, later during the World War II and during the global financial crisis of 2008/2009. Similar high volatility periods characterized by large positive and negative market fluctuations are also observed, although in relatively smaller magnitudes, during the Panic of 1907 and oil embargo of early 1970s. In the case of technology shocks, not surprisingly, a notable positive spike is observed in all three TS series during the dot-com period of the 1990s along with another notable positive spike during the post-World War II boom in 1950s. These patterns are instructive to the separate examination of the effect global recessions and expansions in our subsequent analysis of the technological shock–stock market volatility nexus.

Table 1 presents the summary statistics (mean, standard deviation, kurtosis and skewness) and some preliminary results (ARCH, first and higher order serial correlation) that reflect the inherent salient features of the series employed in the analysis. Panels A and B report the descriptive statistics for the standardized country-specific and global technology shock series (GTS_164 and GTS_OECD) computed at annual frequency, respectively and Panel C reports the same for monthly excess stock market returns for the US. We observe, on average, a positive value for the country-specific TS while that of the global TS is mixed as the global technology shock series (GT_164) has a negative mean while it is positive for the OECD specific technology shock series (GTS_OECD). The dominance of developed/highly industrialized economies in the GTS_OECD may be responsible for the positive value observed for this group of countries relative to the GT_164 that is dominated by the developing countries. Expectedly, we observe a positive mean for the excess stock market returns while as typical for volatile series, we find evidence of conditional heteroscedasticity and serial correlation as well as excess kurtosis in both the stock and TS series. The evidence of volatility in the series further attests to the appropriateness of the GARCH-type model framework in this study as described in the next section.

4. Methodology

Since our focus is to examine the predictive information captured by technological shocks on stock market volatility, given that the technological shock series as the predictor variables are available on an annual frequency while the excess stock market returns series is monthly (to be meaningful from a practical investment perspective), we conclude that a mixed-data sampling (MIDAS) framework would be most appropriate to avoid information loss due to aggregation or observational biases due to the choice of data splicing procedures. The MIDAS model has been employed widely in econometric applications that involve data at mixed frequencies and, in our case, given with the observed significant ARCH effects, we choose the GARCH-MIDAS model for our empirical analysis as the model is well suited to handle a mixed data frequency setting wherein the examined nexus is between a high frequency dependent variable that exhibits conditional heteroscedasticity and a lower frequency predictor variable. Essentially, this framework ensures that every possible information is taken into cognisance when modelling the volatility in the returns. This feat is its merit over the extant uniform frequency methods that are characterized by information loss and observational bias due to distortion of the originality of the data frequency.

We define excess monthly stock returns $\left(r_{i,t}\right)$ as the log returns of the stock price index less the risk-free rate (here, the US treasury bill rate). Given that our series are of mixed frequencies, we note that $i = 1,...,N_t$ and $t = 1,...,T$ respectively denote monthly and annual frequencies with N_t representing the number of months in a given year t. The model specification for the GARCH-MIDAS model is expressed as:

$$r_{i,t} = \tau + \sqrt{\mu_t \times g_{i,t}} \times e_{i,t}, \qquad \forall \ i = 1,...,N_t \tag{1}$$

where τ represents the unconditional mean of excess stock returns; $\sqrt{\mu_t \times g_{i,t}}$ is the conditional variance that comprises two components (i) a long-run component (μ_t) that captures the long-run volatility, (ii) a $\mathrm{GARCH}(1,1)$ based short-run component $(g_{i,t})$ that is characterized by a higher frequency with $e_{i,t} \left| \Sigma_{i-1,t} \sim N\left(0,1\right)\right.$ representing the error distribution, where $\Sigma_{i-1,t}$ denotes the available information at month $i-1$ of year t.[6] The conditional variance part of the short-run component is defined in Equation (2) as:

[6] See Engle et al. (2013) for further technical details on the construction of the GARCH-MIDAS model.

$$g_{i,t} = (1-\alpha-\beta) + \alpha \frac{(r_{i-1,t}-\tau)^2}{\mu_i} + \beta g_{i-1,t} \tag{2}$$

where α and β respectively denote the ARCH and GARCH terms, satisfying the following conditions $\alpha > 0$, $\beta \geq 0$ and $\alpha + \beta < 1$. In this setting, the annual frequency technological shocks (TS) are transformed to monthly frequency, without loss of originality of the model, following Engle et al. (2013). Consequently, our annual varying long-term component (μ_t) is transformed to monthly, rolling back the months across the years without keeping track of it. Equations (3) and (4) respectively define the monthly long-term component (μ_i) for the realized volatility and the exogenous factor:

$$\mu_i = m + \delta \sum_{k=1}^{K} \phi_k(\omega_1, \omega_2) RV_{i-k} \tag{3}$$

$$\mu_i = m + \delta \sum_{k=1}^{K} \phi_k(\omega_1, \omega_2) X_{i-k} \tag{4}$$

where m denotes the long-run component intercept; δ denotes the coefficient of the incorporated predictor, i.e. realized volatility or technological shocks. In our application, we examine four variants of the GARCH-MIDAS long-run component in which the models are distinguished by the comprising predictor(s). These variants are as follows: (i) the benchmark GARCH-MIDAS variant that only incorporates realized volatility (RV); (ii) RV and TS; (iii) RV and GTS_OECD; and (iv) RV and GTS_164. Also note that for the variants interacted with RV, we employed the principal components analysis (PCA) to combine the information of the variables into a single factor.

Equations (3) and (4) comprise beta polynomial weights $\phi_k(w_1, w_2) \geq 0,\ \ k = 1,...,K$, with a summation constrained to unity in order to achieve the identification of the model's parameters. The secular component of the MIDAS weights is filtered using $(K = 10)$ MIDAS years, which is the optimal lag for our specification. Hinging on the flexibility of the beta weighting scheme as highlighted by Colacito et al. (2011), we adopt the one-parameter beta polynomial. The weighting scheme allows for the transformation of a two-parameter beta weighting function defined by $\phi_k(w_1, w_2) = \left[k/(K+1)\right]^{w_1-1} \times \left[1-k/(K+1)\right]^{w_2-1} \Big/ \sum_{j=1}^{K}\left[j/(K+1)\right]^{w_1-1} \times \left[1-j/(K+1)\right]^{w_2-1}$ to a one-parameter beta weighting function $\left[\phi_k(w) = \left[1 - k/(K+1)\right]^{w-1} \Big/ \sum_{j=1}^{K} \left[1 - j/(K+1)\right]^{w-1}\right]$, by constraining w_1 to unity and setting $w = w_2$. This imposes a monotonically decreasing function (Engle et al. 2013) where the weights (ϕ_k) are positive and sum to one $\left(\sum_{k=1}^{K} \phi_k = 1\right)$. Also, the imposition of a constraint on the parameter (w), such that it is greater than unity $(w>1)$ ensures that more recent observation lags are assigned larger weights compared to those that are more distant.

The in-sample predictability of the comprising predictor(s) is ascertained by testing the hypothesis of the statistical significance of the slope parameter (δ) such that a statistically significant estimate implies predictability for excess stock return volatility based on the corresponding predictor. Given our earlier discussion regarding the possible link between technological shocks and stock market returns along with the mixed findings reported in Sharma and Narayan (2022), a priori, technological shocks can be expected to impact stock market returns either negatively or positively although one can argue that higher TS would be associated with greater market uncertainties regarding the impact of the new technologies on firm returns thus, drawing mixed reactions from investors with varying degrees of risk preferences and access to information, which in turn would contribute positively to volatility. Aside from the sign and size of the effect of these shocks on volatility, however, of particular interest in our context is the out-of-sample forecast performance of the contending model variants that incorporate these shocks as predictors in comparison with the conventional GARCH-MIDAS model used as the benchmark model.

In our empirical application, we use the full sample for the in-sample predictability analysis and where the data sample is partitioned into expansion and recession periods, their corresponding full data samples are used as well. However, for the purpose of forecast evaluation in an out-of-sample setting, we employ a 75:25 data split between the in- and out-sample periods and conduct the modified Diebold-Mariano (DM) test (see Harvey, Leybourne, and Newbold, 1997) to assess the relative performance of the competing models. The modified DM test, extends the Diebold and Mariano (1995) test, by accounting for potential autocorrelation and heavy-tailed distributions. The modified DM statistic represented as DM^* is expressed as:

$$DM^{*} = \left(\sqrt{\frac{T+1-2h+T^{-1}h\left(h-1\right)}{T}} \right) DM \tag{5}$$

where $DM = \bar{d} \Big/ \sqrt{V\left(d\right) \big/ T} \sim N\left(0,1\right)$ is the conventional DM test equation; $\bar{d} = \frac{1}{T}\sum_{t=1}^{T} d_t$ is the mean of the loss differential between the two competing models, $V\left(d_t\right)$ is the unconditional variance of the loss differential where $d_t \equiv l\left(\varepsilon_{TS}\right) - l\left(\varepsilon_{RV}\right)$, $l\left(\varepsilon_{TS}\right)$ is the loss function of the forecast error of the GARCH-MIDAS-TS model, $l\left(\varepsilon_{RV}\right)$ is the loss function of the forecast error of the GARCH-MIDAS-RV model; and h is the forecast horizon. The null hypothesis of equality of the accuracy of the two model variants, that is, $H_0 : E(d_t) = 0$, is tested against the alternative hypothesis $\left(H_1 : E(d_t) \neq 0\right)$ that the forecast accuracy differs between the two contending models. A negatively significant test statistic implies the superiority of the augmented GARCH-MIDAS model that incorporates technological shocks as a predictor over the benchmark model that includes only the RV factor (i.e. GARCH-MIDAS-RV) and converse is true if the test statistic is significantly positive. On the forecast-evaluation, we focus on the out-of-sample forecast evaluations in a rolling window setting and consider 3-, 6- and 12- months-ahead forecasts as the out-of-sample forecast horizons.

5. Empirical Findings

5.1 In-Sample Predictability Analyses

Table 2 presents the in-sample predictability results from the estimation of a GARCH-MIDAS model that incorporates annual technological shock series as the predictor for the US stock market volatility. The reported parameters include the unconditional mean excess stock returns (μ), the ARCH term (α), the GARCH term (β), the slope coefficient (δ), the adjusted beta polynomial weight (w), and the long run constant term (m) for four contending GARCH-MIDAS model variants. Note that the GARCH-MIDAS-RV model is the benchmark model that is based on the past realizations of realized volatility only, without any of the predictors. Similarly, the GARCH-MIDAS- (TS, GTS_OECD, GTS_164) models denote the alternative variants supplemented with the technological shock series for the US, 12 OECD countries and the larger sample of 164 economies, respectively. Panels A, B and C present the findings for the whole sample, and the recession and expansion periods, respectively, (see Table A1 in the appendix). Specifically, the recession (expansion) periods are incorporated in the model using dummy variables that take on the value one to indicate the period of recession (expansion) and zero otherwise, as the case may be. The dummy variables are thereafter combined with TS, GTS_OECD and GTS_164 to reflect the period being considered.

The model results reported in Table 2 yield significant estimates for all estimated parameters in the GARCH-MIDAS model except for the case of the long run constant term in the GARCH-MIDAS variant with global technological shocks. We find the ARCH and GARCH terms under all four GARCH-MIDAS variants to be statistically significant, with the summation less than unity, indicating the presence of high but temporal persistence in stock market volatility, which may only require a longer time to fizzle out. Imperatively, shocks emanating from the stock market itself are not likely to cause a structural shift in the historic pattern of the market volatility. Also, the beta weight estimates are found to be greater than unity, which implies that the weights assigned to more recent observation lags are higher than weights assigned to far distant observation lags, indicating that more importance is attached to immediate past than distant past observations. On the predictability stance, we find that the US excess stock return volatility responds positively to its realized volatility, which implies that the market volatility is aggravated by the uncertainties within the market. However, the models yield negative slope coefficient (δ) estimates, significant at the highest statistical level, across all alternative TS proxies, i.e., the country specific as well as the global variants. This suggests that positive technological shocks, irrespective of the source (country-specific or global), are generally associated with lower subsequent stock market volatility.

The feat of predictability observed in the full sample period is not markedly altered when we consider the recession (Panel B) and expansion (Panel C) periods. We observe that the nexus is still negative and statistically significant, suggesting that innovations generally predict lower stock market returns in subsequent periods irrespective of the business cycle. The negative predictive relationship between technological shocks and stock market volatility could be a manifestation of the life cycle in growth options suggested by Garleanu et al. (2012b) wherein the risk premia (and equity price volatility) begin to fall as the new technology is absorbed and firms start to convert growth options into assets over time. It is also possible that the flexibility of firms to adapt to fundamental economic restructuring, as noted by Berk et al. (1999), plays a significant role in how stock market volatility evolves as a result of the realization of the real growth options created by those innovations. Nevertheless, the consistent negative effect of innovations on stock market volatility across the local and global technological shock series and the business cycle is in contrast with the findings by Sharma and Narayan (2022) for the equity premium who find relatively stronger effect for local technological shocks and for global shocks during expansions. Accordingly, we conclude that effect of technological innovations on stock market dynamics is primarily concentrated on volatility rathe than the risk premium. Considering that in-sample predictability does not necessarily suggest a predictive relation out-of-sample, we next perform out-of-sample evaluation to ascertain whether the observed predictability transcends the in-sample period.

5.2 Out-of-Sample Predictability Analyses

Having examined the predictive power of technological shocks for the US excess stock returns volatility within an in-sample setting, we next subject the contending GARCH-MIDAS models to out-of-sample forecast evaluations for 3-, 6- and 12- months ahead forecast horizons. To this end, we perform two forms of comparisons: First, we compare the benchmark GARCH-MIADS-RV model with the variants augmented with the technological shocks as predictors, i.e. the GARCH-MIDAS-G(TS) model variants. Next, we perform a horse race within the set of augmented models by comparing the forecasting performance of local against global technological shocks by setting the GARCH-MIDAS-TS as a benchmark against the GARCH-MIDAS-GTS model variants. Table 3 presents the out-of-sample forecast performance analysis for the benchmark forecasting model (labelled in each column in Panels A and B) against its augmented variations that incorporate technological shocks as predictors of stock market volatility. We employ the modified Diebold and Mariano test statistics under a null of equality in the forecast performances of the contending GARCH-MIDAS models. Reported in each cell is the estimated Diebold and Mariano statistic where a negative and significant DM statistic value indicates better out-of-sample forecast performance of the augmented model compared to the benchmark model. In Panel A, the benchmark model is the conventional GARCH-MIDAS-RV model which includes only the past realizations of realized volatility (RV) as the predictor. The benchmark is compared to three alternative augmented models that incorporate TS, GTS_OECD and GTS_164 as predictors. In Panel B, the benchmark model is the GARCH-MIDAS-TS model which incorporates

TS as the predictor and is compared against the model variations that include GTS_OECD and GTS_164 as predictors.

The findings in Table 3 yield robust evidence supporting the predictive information captured by technological shocks over stock market volatility, indicated by the outperformance of the GARCH-MIDAS-G(TS) model variants over the GARCH-MIDAS-RV model, consistently across all forecast horizons and sample periods (full, recession and expansion). The negative and highly significant DM statistics reported in Panel A suggest that incorporating any of the (country-specific or global) technological shock series in the forecasting model improves the stock market volatility forecasts over the conventional GARCH-MIDAS-RV model. These feats transcend the three stated forecast horizons up to one year, which is an indication of the robustness of the model results to forecast horizons. Examining the forecasting performance of local against global technological shocks by setting the GARCH-MIDAS-TS model as the benchmark, we observe in Panel B that none of the models that incorporate global shocks can improve the volatility forecasts for the US stock market over and above the model that incorporates technological shocks associated with the US, implied by the largely insignificant and, in some cases positive, DM statistics in the panel. This suggests that the predictive power of innovations on stock market volatility in the US is primarily driven by local technological innovations rather than global developments. This finding is not unexpected considering that US has been at the forefront of technological innovations throughout the sample period and it is only natural that US stock market volatility is primary dominated by the technological shocks associated with the US.

On the second strand of comparison however, we show that the GARCH-MIDAS-TS offers as much useful predictive value as the GARCH-MIDAS-GTS_164 and even offers a higher predictive value at a lower forecast horizon. In other words, the US-specific TS that captures technological innovations specifically for the US environment appears to be more connected with the country's stock market particularly in terms of improving its out-of-sample forecasts.

5.3 Economic Significance

Having presented evidence in favour of the in- and out-of-sample forecasting gains from incorporating technological shocks as predictors of stock market volatility, we now extend our analysis to the economic implications of the findings. Specifically, we examine whether incorporating different variants technological shocks as predictor variables in our GARCH-

MIDAS framework provides any economic gains as another way to ascertain that the technological shocks series are relevant in the modelling of the US stock market volatility. Essentially, this provides an economic-based confirmation to lend support to the earlier reached statistical conclusions drawn from the modified DM statistics. Assuming that a characteristic mean-variance utility investor would optimize the available portfolios in contrast to a risk-free asset by apportioning shares among investment options, we define the optimal weight, w_t as

$$w_t = \frac{1}{\gamma} \frac{\theta \hat{r}_{t+1} + (\theta - 1)\hat{r}^f_{t+1}}{\theta^2 \hat{\sigma}^2_{t+1}} \tag{6}$$

where γ denotes the risk aversion coefficient; θ is a leverage ratio which we set to 6 and 8 on the premise of a 10% margin often maintained by investors; $\hat{r}_{t+1}$ represents the US stock market realized volatility forecast at time $t+1$; $\hat{r}^f_{t+1}$ is a risk-free asset (Treasury bill rate); and $\hat{\sigma}^2_{t+1}$ denotes return volatility estimate, obtained as a 6-month moving window of monthly returns. The goal here is to quantify the economic gains of different GARCH-MIDAS-G(TS) model variants that incorporate different variants of technological shocks, compared with the benchmark GARCH-MIDAS-RV model that is based on the past realizations of realized volatility. To this end, the economic significance is then determined by maximizing the objective utility function formulated as

$$U(R_p) = E(R_p) - 0.5(1/\gamma)Var(R_p) = w\theta(r - r^f) + (1-w)r^f - 0.5(1/\gamma)w^2\theta^2\sigma^2 \tag{7}$$

where $Var(R_p) = w^2\theta^2\sigma^2$ is the variance of the portfolio return; σ^2 denotes excess return volatility; R_p is the portfolio return defined as $R_p = w\theta(r - r^f) + (1-w)r^f$. The contending models are then compared on the basis of the economic gains achieved by the investor in terms of the highest returns and Sharpe ratio, $SR = \frac{(R_p - r^f)}{\sqrt{Var(R_p)}}$; along with minimum volatility (Liu et al., 2019). Given that transaction costs are an important consideration in a practical investment setting, we also account for the cost of implementing the portfolio investment strategy by incorporating the transaction costs in the computation of the economic significance for each contending models. To that end, drawing from Callot et al. (2017), we compute the average portfolio turnover (*TO*) for the out-of-sample period by

$$TO_t = \left| \hat{w}_t - \hat{w}_{t-1}^{hold} \right| \tag{8}$$

where $\hat{w}_{t-1}^{hold} = \hat{w}_{t-1}\left[(1+r_{t-1})/(1+R_{p,t-1})\right]$ denotes the weight of the holding portfolio. In this formulation, turnover is measured by the average change in the portfolio weights, which is well suited for the case where a combination of the risk-free and a risky asset is considered, hence, only the transaction cost (c) for the risky asset is required. The adjusted portfolio returns for the risky asset is then defined as $R_p^{adjust} = R_p - cTO$; and the corresponding volatility, and Sharpe ratios are computed for the adjusted portfolio returns.

Table 4 reports the results from the economic analysis based on the mean portfolio return, volatility, and Sharpe Ratio (SR) values for the investment portfolios obtained from the contending volatility models. The benchmark model, reported in shaded rows, is the conventional GARCH-MIDAS-RV model which includes only the past realizations of realized volatility (RV) as the predictor. The leverage ratio is denoted by θ with a value of one indicating no leverage. We set the leverage ratio to 6 and 8; and set the risk aversion level to 3. Panels A and B report the results without transaction costs and with transaction costs of c=0.5%, respectively. In Panel A, we observe that the benchmark forecasting model (GARCH-MIDAS-RV) that is based on the past realizations of volatility yields the highest volatility in portfolio returns compared to the models that are supplemented by the technological shock series as a predictor. Although the mean portfolio return associated with the benchmark model is higher, we observe that the forecasting models that utilize the predictive information of technological shocks offer improved risk adjusted returns indicated by higher Sharpe ratios associated with the GARCH-MIDAS-G(TS) model variants. This shows that the incorporation of technological shocks in a GARCH-MIDAS model framework can help achieve economic gains compared to the forecasting models that ignore the predictive information captured by these shocks. We find that this feat of higher economic gains achieved from the incorporation of TS variants is replicated under the recession and expansion periods.

The inferences obtained in Panel A are further strengthened when we account for transaction costs in Panel B. We find that the economic gains of incorporating TS, GTS_OECD and GTS_164 are consistently higher than the economic gains associated with the benchmark forecasting model that utilizes only historical realized volatility as a predictor of subsequent volatility patterns. Clearly, this highlights the importance of accounting for the transaction costs in portfolio performance analysis, as neglect could lead to understatement of the economic gains of an incorporated predictor variable(s). Further comparing the models based on the nature of the technological shocks used in the predictor set (i.e., local or global), we find that the portfolios created using the volatility forecasts obtained from the model that incorporates global technological shocks generally yield more favourable economic outcomes than those that incorporate US technological shocks. Specifically, we find that the portfolios based on the GARCH-MIDAS-GTS_164 model enjoy lower return volatility, which in turn, helps to improve the risk-adjusted returns for these portfolios. This result is further confirmation to the stance in the modified DM statistics that indicates the statistical importance of technological shocks as a predictor for US excess returns volatility. These inferences are also supported by several robustness checks across the alternative leverage parameters as reported in the table. Overall, the analysis of the economic outcomes from the predictive relationships show that technological shocks are indeed relevant predictors, both statistically and economically, for the prediction of stock market volatility.

5.4 International Evidence

The analysis so far has focused solely on U.S. stock market volatility and the predictive information captured by the local and global innovations regarding subsequent volatility dynamics in this leading economy globally. In this section, we extend our analysis to the remaining G7 nations in order to ascertain whether there exists some international evidence of the innovation-volatility nexus as is the case for the US. To that end, we conduct similar out-of-sample estimations and report the statistical measure of forecast performances as well as the corresponding economic analysis of the portfolios obtained from the volatility forecasts. Our goal here is twofold. First, we aim to ascertain whether the stance of improvement of the forecast precision of the predictive model for stock market volatility over the GARCH-MIDAS-RV variant is robust to the choice of the country being considered. Second, we explore whether or not any differences exists in the innovation-volatility nexus across markets. Table A2 in the Appendix presents the out-of-sample forecast performance analysis for the benchmark forecasting model (labelled in each column in Panels A and B) against its augmented variations that incorporate technological shocks as volatility predictors. In Panel A, the benchmark model is the conventional GARCH-MIDAS-RV model which includes only the past realizations of realized volatility (RV) as the predictor. The benchmark is compared to three alternative augmented models that incorporate TS, GTS_OECD and GTS_164 as predictors. In Panel B, the benchmark model is the GARCH-MIDAS-TS model which incorporates TS as the predictor and is compared against the model variations that include GTS_OECD and GTS_164 as predictors.

Examining the estimated modified DM statistics in Panel A, the comparison of the GARCH-MIDAS-G(TS) models against the benchmark GARCH-MIDAS-RV model yields generally consistent results with those observed for the US. While we observe some heterogeneity across the countries, we observe that the nexus between technological innovations and stock market volatility is generally robust for the majority of the G7 economies, leading to improved stock market volatility forecasts in most stock markets. Specifically, we find that incorporating the volatility models with the technological shock predictors yields more accurate out-of-sample volatility forecasts, particularly for Canada, France, Japan and UK, indicated by the negative and significant DM statistic values. The findings, however, highlight the predictive role of global shocks relative to local shocks, with the GARCH-MIDAS-GTS_OECD model resulting in stronger performance against the benchmark model for four out of the six G7 nations in the sample, consistently across both the expansionary and recessionary states. This finding could be a manifestation of the predictive impact of the innovations driven by the US over global economies, which in turn, drives the outperformance of the model that incorporates the technological shocks for the OECD as a whole. Interestingly, however, the results yield no evidence of such predictability in the case of Germany and Italy, for which we find outright outperformance of the benchmark GARCH-MIDAS-RV model over the GARCH-MIDAS variants that incorporate technological shocks. This suggests that idiosyncratic factors at the market level could be playing a role in how the innovation-volatility nexus plays out in a given market.

In the comparison of the GARCH-MIDAS-GTS model variants with GARCH-MIDAS-TS benchmark in Panel B, we find that the volatility models that incorporate global technological shock series outperform their counterparts based on local shocks in four out of the six markets, particularly Canada, Germany, Italy and Japan. The predictive power of innovations over the stock market is largely concentrated on recessionary market states for Japan and Italy, while we do not observe a clear pattern regarding the role of business cycles for the other economies. Interestingly, in the case of France and UK, we find that incorporating the local technological shocks as a predictor of stock market volatility yields more accurate out-of-sample volatility forecasts compared to models that incorporate global shocks, possibly highlighting the investments made by these economies in research and development throughout much of the sample period. These results transcend the forecast horizons and data sample (full, recession and expansion), and is indicative of the robustness of results to forecast horizons and data sample, and sensitivity of results to the choice of country stocks.

Further extending the international evidence to the economic implications of the findings, Table A3 in the Appendix reports the mean portfolio return, volatility, and Sharpe Ratio (SR) values, computed over the out-of-sample forecasting horizon. The benchmark model, reported in shaded rows, is the benchmark GARCH-MIDAS-RV model which includes only the past realizations of realized volatility (RV) as the predictor. Panels A and B report the results with and without transaction costs, respectively. We observe similar feats for the large majority of countries including France, Italy, Japan and UK as observed for the US, indicating that the portfolios created from volatility models that incorporate technological shocks generally yield more favorable economic outcomes for a mean-variance investor compared to those based on the benchmark forecasting model. We find that incorporating technological shocks, particularly the OECD-based series, in the forecasting model helps to reduce portfolio volatility in the out-of-sample horizon, thus yielding more favorable risk-adjusted return, implied by higher Sharpe ratios for those portfolios. The largest improvement in the risk-adjusted returns are observed in the case of France, Italy, Japan and UK, while Germany experienced negative mean returns and Sharpe ratios, likely due to the inclusion of the two world wars in the long sample that led to devastation in this country's economy. Nevertheless, comparing the economic outcomes for Germany for the benchmark against the augmented models, we find that incorporating technological shocks help improve the risk-adjusted returns positively, further supporting the economic value of these shocks as a predictor. Overall, our analysis of the remaining G7 stock markets suggests that technological shocks are indeed a relevant predictor for stock market volatility, not only by helping to improve the accuracy of out-of-sample forecasts, but also by yielding higher economic gains than the benchmark forecasting model that excludes technological shocks.

6. Concluding Remarks

The nexus between technological innovations and economic growth is well studied in the literature. The asset pricing implications of technological innovations, particularly on stock market volatility however, is relatively understudied without a consensus on the significance and direction of the predictive relationship. This paper presents a novel perspective to this nexus by investigating the predictive power of technological shocks over stock market volatility dynamics, both in- and out-of-sample, using data over a period of more than 140 years and whether or not such a predictive relationship can be used to create economic gains for investors. To this end, given the mixed frequency nature of the data available to capture technological innovations and stock market dynamics, we adopt a mixed data sampling approach via a GARCH-MIDAS model framework that allows for simultaneously incorporating mixed data frequencies within a volatility model framework. Specifically, we use a proxy for technological shocks based on annual patent data from a large number of economies and compare stock market volatility forecasts obtained from forecasting models that incorporate technological shocks as predictors against a benchmark model that is based only on past realizations of volatility. We then examine the economic implications of our findings by creating portfolios using the volatility forecasts obtained from each contending model and comparing their economic outcomes.

Both in- and out-of-sample tests for the U.S. yield robust evidence that technological shocks capture significant predictive information regarding future realizations of stock market volatility. Our findings suggest that accounting for the innovations in the number of patents granted from resident applications in a country, as a proxy for technological shocks, can significantly improve the accuracy of stock market volatility forecasts, both at the short and long forecast horizons. While our findings are in line with the presence of a life cycle in growth options wherein the risk premia (and equity price volatility) evolves over time based on how firms adapt to the new technology, one can also argue that the predictive power of innovations on stock market volatility is a manifestation of how technological shifts in the economy transforms from primarily an idiosyncratic, firm (or industry) specific risk into a market wide systematic risk as the adoption probability of the new technology increases over time. Whatever the underlying reason might be, however, our findings show that the predictive relationship between technological innovations and stock market volatility can indeed be utilized by mean-variance investors to create economic gains. Our economic analysis shows that investment portfolios created by the volatility forecasts obtained from the forecasting models that incorporate technological shocks as predictors experience significantly lower return volatility in the out-of-sample horizons, which in turn helps to improve the risk-return profile of those portfolios.

Extending our analysis to the remaining G7 economies further supports our inferences regarding the nexus between technological innovations and stock market volatility in most of the G7 countries. We observe, however, some heterogeneity in the predictive importance of local versus global technological shocks over stock market volatility across the G7 economies although no clear pattern is observed regarding the role of the business cycle. While the predictive relationship between innovations and stock market volatility could be driven by what Jiang (2010) terms as the heterogeneous effects associated with the changes in the relative competitive advantage of firms and resource allocation as a result of technological shifts, our findings provide a novel opening, both from the portfolio management and asset pricing perspectives. From a portfolio management perspective, our analysis of the economic implications of the predictive nexus between innovations and volatility suggests that the improved volatility forecasts obtained from forecasting models that incorporate measures of technological innovations can help portfolio risk and improve portfolio performance on a risk-adjusted basis. From an asset pricing perspective, considering the well-documented evidence that establishes a link between idiosyncratic volatility and the real option opportunities associated with a firm (e.g. Cao et al., 2008; Chen and Petkova, 2012, among others), our analysis suggests that asset pricing models could be improved by incorporating sensitivity to technological innovations as a driver of idiosyncratic volatility at the firm or industry levels. This, in turn, can help improve the outcomes from cross-sectional analysis of firm returns as the difference in returns among firms sorted on various firm-level characteristics including idiosyncratic volatility is largely driven by their differences in exposures to a common systematic risk factor associated with these firms' sensitivities to technology shocks (Kogan and Papanikolaou, 2014). Nevertheless, our work paves the way for several interesting avenues for future research regarding the impact of innovations on stock market dynamics.

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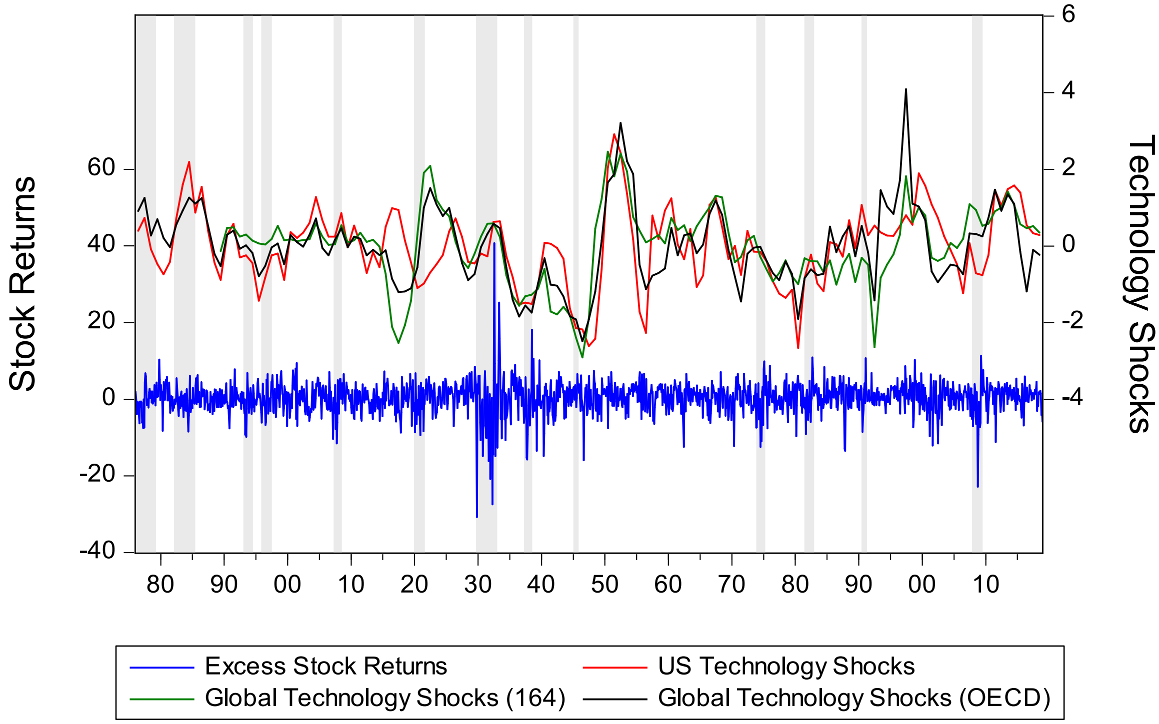
Figure 1. Technological shocks and U.S. excess returns



Note: The figure plots the time series of annual excess stock market returns for the U.S. along with the technological shock series for the U.S., OECD economies and larger sample of 164 global economies.

Table 1. Summary Statistics and Preliminary Analyses

	Mean	Standard Deviation	Skewness	Kurtosis	N	$ARCH(1)$	$ARCH(6)$	$ARCH(12)$	$Q(1)$	$Q(6)$	$Q(12)$	$Q^2(1)$	$Q^2(6)$	$Q^2(12)$
						Panel A: Country-specific technological shocks								
US	2.27E-16	1.00E+00	-1.03E-01	3.41E+00	143	0.431	3.645***	1.885**	2.693	27.618***	40.967***	3.201*	14.598**	29.312***
						Panel B: Global technological shocks								
GTS_164	-1.49E-16	1.00E+00	-4.06E-01	3.68E+00	130	0.017	0.105	0.270	5.957**	22.378***	30.125***	5.828**	16.634**	21.251**
GTS_OECD	3.63E-17	1.00E+00	5.70E-01	4.59E+00	143	3.148*	1.850*	1.753*	0.828	24.009***	27.863***	8.517***	35.363***	37.681***
						Panel C: Excess stock market returns								
US	8.10E-02	4.10E+00	-4.02E-01	1.42E+01	1716	15.659***	39.180***	25.636***	0.795	22.093***	26.246***	15.570***	272.790***	457.950***

Note: Panels A and B report the descriptive statistics for the standardized country-specific and global technology shock series computed at annual frequency, respectively and Panel C reports the same for monthly excess stock market returns. $ARCH(\#)$, $Q(\#)$ and $Q^2(\#)$ are formal tests for the presence of ARCH effects, first and higher order serial correlation respectively, at the specified lags. ***, ** and * respectively denote statistical significance of the formal tests at 1%, 5% and 10% levels of significance. Statistical significance of these tests indicates evidence of the presence of conditional heteroscedasticity and serial correlation.

Table 2. GARCH-MIDAS In-Sample Predictability Result (*United States*)

Model	μ	α	β	δ	w	m
			Panel A: *Full Sample Period*			
RV	0.3317*** [0.0869]	0.1702*** [0.0155]	0.7569*** [0.0257]	0.0378*** [0.0101]	1.0011*** [0.3284]	9.6813*** [2.0649]
TS	0.1994*** [0.0620]	0.0846*** [0.0049]	0.9154*** [0.0051]	-0.0229*** [0.0068]	4.8249*** [1.8514]	-0.7220* [0.3700]
GTS_OECD	0.2005*** [0.0620]	0.0846*** [0.0049]	0.9154*** [0.0051]	-0.0223*** [0.0068]	4.8280** [1.9025]	-0.7228* [0.3703]
GTS_164	0.1999*** [0.0647]	0.0815*** [0.0048]	0.9185*** [0.0050]	-0.0217*** [0.0067]	4.9109** [1.9506]	-0.2445 [0.4031]
			Panel B: *Recession Period*			
RV	0.3317*** [0.0869]	0.1702*** [0.0155]	0.7569*** [0.0257]	0.0378*** [0.0101]	1.0011*** [0.3284]	9.6813*** [2.0649]
TS	0.1975*** [0.0619]	0.0846*** [0.0049]	0.9154*** [0.0051]	-0.0227*** [0.0068]	4.8542*** [1.8681]	-0.7317** [0.3690]
GTS_OECD	0.1989*** [0.0619]	0.0847*** [0.0049]	0.9153*** [0.0051]	-0.0219*** [0.0068]	4.8536** [1.9303]	-0.7345** [0.3693]
GTS_164	0.1954*** [0.0646]	0.0816*** [0.0048]	0.9184*** [0.0050]	-0.0216*** [0.0067]	4.9090** [1.9502]	-0.2546 [0.4024]
			Panel C: *Expansion Period*			
RV	0.3317*** [0.0869]	0.1702*** [0.0155]	0.7569*** [0.0257]	0.0378*** [0.0101]	1.0011*** [0.3284]	9.6813*** [2.0649]
TS	0.1913*** [0.0650]	0.0849*** [0.0050]	0.9151*** [0.0052]	-0.0365*** [0.0093]	2.9097*** [0.7988]	-0.2030 [0.4215]
GTS_OECD	0.2029*** [0.0622]	0.0846*** [0.0049]	0.9154*** [0.0051]	-0.0226*** [0.0069]	4.8055** [1.8777]	-0.7146* [0.3714]
GTS_164	0.2043*** [0.0647]	0.0815*** [0.0048]	0.9185*** [0.0050]	-0.0217*** [0.0067]	4.9083** [1.9665]	-0.2373 [0.4036]

Note: The table reports the estimated coefficients and their associated standard errors in square brackets for the GARCH-MIDAS model described in Equations 1-4. RV is realized volatility and TS, GTS_OECD, GTS_164 refer to the technological shock series for the U.S., OECD economies and 164 global economies, respectively. The conventional GARCH-MIDAS model that includes realized volatility (RV) is considered as the benchmark and each row corresponds to the model variation augmented with the predictor variable listed in the first cell. Panels A, B and C report the in-sample predictability results for the whole sample, recessions and expansions based on NBER dates summarized in Table A1 in the Appendix, respectively. ***, ** and * respectively denote statistical significance at 1%, 5% and 10% levels of significance.

Table 3. Out-of-Sample Forecast Evaluation via Diebold and Mariano Tests (*United States*).

Model	**TS**	**GTS_OECD**	**GTS_164**	**GTS_OECD**	**GTS_164**
	Panel A: Benchmark model, GARCH-MIDAS-RV			**Panel B:** Benchmark model, GARCH-MIDAS-TS	
Full Sample Period					
$h = 3$	-7.2415^{***}	-7.2618^{***}	-7.0988^{***}	1.7359^{*}	2.2635^{**}
$h = 6$	-5.5903^{***}	-5.6019^{***}	-5.4630^{***}	1.3932	1.7448^{*}
$h = 12$	-4.3470^{***}	-4.3659^{***}	-4.2608^{***}	0.9837	1.3772
Recession Period					
$h = 3$	-7.2533^{***}	-7.2830^{***}	-7.1455^{***}	1.6814^{*}	1.4104
$h = 6$	-5.5962^{***}	-5.6149^{***}	-5.4968^{***}	1.3479	1.0877
$h = 12$	-4.3512^{***}	-4.3782^{***}	-4.2863^{***}	0.9501	0.8628
Expansion Period					
$h = 3$	-7.3447^{***}	-7.2342^{***}	-7.0719^{***}	1.7945^{*}	2.1523^{**}
$h = 6$	-5.7073^{***}	-5.5839^{***}	-5.4444^{***}	1.3192	1.5832
$h = 12$	-4.3560^{***}	-4.3499^{***}	-4.2508^{***}	0.9294	1.1203

Note: The table presents the out-of-sample forecast performance analysis for the benchmark forecasting model (labelled in each column in Panels A and B) against its augmented variations that incorporate technological shocks as volatility predictors. Reported in each cell is the estimated Diebold and Mariano statistic where a negative and significant DM statistic value indicates better out-of-sample forecast performance of the augmented model compared to the benchmark model. In Panel A, the benchmark model is the conventional GARCH-MIDAS-RV model which includes only the past realizations of realized volatility (RV) as the predictor. The benchmark is compared to three alternative augmented models that incorporate TS, GTS_OECD and GTS_164 as predictors. In Panel B, the benchmark model is the GARCH-MIDAS-TS model which incorporates TS as the predictor and is compared against the model variations that include GTS_OECD and GTS_164 as predictors. ***, ** and * respectively denote statistical significance at 1%, 5% and 10% levels of significance.

Table 4: Economic Analysis.

Period	Model	Return	Volatility	SR		Return	Volatility	SR
		$\theta=3$ and $\gamma=6$				$\theta=3$ and $\gamma=8$		
Panel A: *Without Transaction Costs*								
Full Sample Period	RV	3.096	0.145	7.704		4.083	0.257	7.724
	TS	2.340	0.068	**8.323**		3.075	0.121	**8.353**
	GTS_OECD	2.339	0.068	**8.335**		3.074	0.121	**8.365**
	GTS_164	2.345	0.063	**8.687**		3.082	0.112	**8.718**
Recession Period	RV	3.096	0.145	7.704		4.083	0.257	7.724
	TS	2.339	0.068	**8.328**		3.073	0.121	**8.358**
	GTS_OECD	2.338	0.068	**8.334**		3.072	0.121	**8.364**
	GTS_164	2.342	0.062	**8.699**		3.077	0.111	**8.731**
Expansion Period	RV	3.096	0.145	7.704		4.083	0.257	7.724
	TS	2.368	0.066	**8.596**		3.112	0.117	**8.626**
	GTS_OECD	2.341	0.068	**8.330**		3.077	0.121	**8.360**
	GTS_164	2.348	0.063	**8.669**		3.085	0.113	**8.700**
Panel B: *With Transaction Costs*								
Full Sample Period	RV	3.296	0.145	8.229		4.349	0.257	8.249
	TS	2.565	0.068	**9.185**		3.375	0.121	**9.215**
	GTS_OECD	2.561	0.068	**9.184**		3.369	0.121	**9.214**
	GTS_164	2.566	0.063	**9.567**		3.376	0.112	**9.598**
Recession Period	RV	3.296	0.145	8.229		4.349	0.257	8.249
	TS	2.563	0.068	**9.189**		3.372	0.121	**9.219**
	GTS_OECD	2.559	0.068	**9.183**		3.366	0.121	**9.213**
	GTS_164	2.562	0.062	**9.580**		3.371	0.111	**9.610**
Expansion Period	RV	3.296	0.145	8.229		4.349	0.257	8.249
	TS	2.590	0.066	**9.461**		3.408	0.117	**9.491**
	GTS_OECD	2.563	0.068	**9.179**		3.372	0.121	**9.209**
	GTS_164	2.569	0.063	**9.548**		3.380	0.113	**9.579**

Note: For each model variation, we report the Return, Volatility, and Sharpe Ratio (SR) values, computed over the out-of-sample forecasting horizon. The benchmark model, reported in shaded rows, is the conventional GARCH-MIDAS-RV model which includes only the past realizations of realized volatility (RV) as the predictor. The leverage ratio is denoted by θ with a value of one indicating no leverage. We set the leverage ratio to 6 and 8; and set the risk aversion level to 3. Panels A and B report the results without transaction costs and with transaction costs based on portfolio turnover formulated in Equation (8), respectively. Bold figures indicate cases where the augmented GARCH-MIDAS model variants yield higher economic gains than the benchmark GARCH-MIDAS-RV.

Appendix

Table A1. Periods of Global Recession

Period
1873 – March 1879
March 1882 – May 1885
February 1893 – June 1894
December 1895 – June 1897
May 1907 – June 1908
January 1920 – July 1921
October 1929 – 1932
May 1937 – June 1938
February 1945 – October 1945
December 1973 – March 1975
July 1981 – November 1982
July 1990 – March 1991
December 2007 – June 2009
February 2020 – April 2020

Source: https://blogs.worldbank.org/opendata/understanding-depth-2020-global-recession-5-charts

Table A2. Out-of-Sample Forecast Evaluation via Diebold and Mariano Tests (*Other G7 Countries*).

Forecast Horizon	TS	GTS_OECD	GTS_164	TS	GTS_OECD	GTS_164	TS	GTS_OECD	GTS_164	GTS_OECD	GTS_164	GTS_OECD	GTS_164	GTS_OECD	GTS_164
	Panel A: BENCHMARK Model: GARCH-MIDAS-RV									**Panel B:** BENCHMARK Model: GARCH-MIDAS-TS					
	Full Sample Period			**Recession Period**			**Expansion Period**			**Full Sample Period**		**Recession Period**		**Expansion Period**	
								Canada							
h=3	5.0158***	-2.1642**	5.0213***	5.0242***	-2.1921**	5.0300***	3.7775***	-2.1298**	5.0130***	-5.0287***	4.9285***	-5.0369***	4.9439***	-3.8369***	6.6258***
h=6	3.5534***	-1.6721*	3.5537***	3.5604***	-1.6931*	3.5608***	2.7004***	-1.6460	3.5468***	-3.5657***	3.4312***	-3.5724***	3.4428***	-2.7434***	4.6849***
h=12	2.5048**	-1.3181	2.5042**	2.5096**	-1.3330	2.5091**	1.9055*	-1.2991	2.4994**	-2.5144**	2.4193**	-2.5190**	2.4276**	-1.9350*	3.3646***
								France							
h=3	-12.9034***	-12.9173***	-10.6687***	-12.9399***	-12.9527***	-10.5957***	-12.8635***	-12.8783***	-10.6379***	0.7922	6.7010***	0.8120	6.0923***	0.7765	6.3902***
h=6	-9.2615***	-9.2726***	-7.6190***	-9.2863***	-9.2964***	-7.5496***	-9.2342***	-9.2459***	-7.5868***	0.5811	4.9728***	0.5959	4.5500***	0.5694	4.7654***
h=12	-6.7418***	-6.7480***	-5.6059***	-6.7562***	-6.7618***	-5.5594***	-6.7257***	-6.7324***	-5.5903***	0.4424	3.8870***	0.4529	3.6259***	0.4341	3.7731***
								Germany							
h=3	3.7172***	5.1501***	1.2851	2.7234***	5.2601***	1.3007	3.2071***	3.0189***	1.2322	2.0752**	-3.7311***	4.5761***	-2.6660***	-1.1375	-3.3834***
h=6	2.6417***	3.5485***	0.9298	2.0592**	3.5732***	0.9411	2.3401**	2.1795**	0.8932	1.4227	-2.6053***	3.1128***	-2.0050**	-0.7990	-2.4049**
h=12	2.0270**	2.5341**	0.7276	1.7071*	2.5006**	0.7422	1.8463*	1.6905*	0.6945	1.0187	-1.9494*	2.1808**	-1.6428	-0.5953	-1.8166*
								Italy							
h=3	1.9017*	1.7702*	1.7432*	1.9280*	1.7944*	1.7668*	1.8749*	1.7452*	1.7191*	-7.0488***	-4.8183***	-7.0607***	-4.8585***	-7.0438***	-4.7799***
h=6	1.5789	1.4697	1.4437	1.5995	1.4888	1.4622	1.5578	1.4500	1.4247	-4.9889***	-3.5007***	-4.9940***	-3.5291***	-4.9884***	-3.4733***
h=12	1.5267	1.4231	1.3873	1.5436	1.4390	1.4026	1.5093	1.4066	1.3716	-3.5799***	-2.5639**	-3.5818***	-2.5844***	-3.5812***	-2.5440**
								Japan							
h=3	-4.2396***	-6.7568***	-4.2630***	-4.3575***	-6.0453***	-7.2112***	-4.2319***	-3.7757***	-4.2219***	-5.2727***	-0.3037	-2.2188**	-5.9313***	0.2199	1.8567*
h=6	-3.3112***	-5.5581***	-3.3312***	-3.4155***	-4.9732***	-6.0015***	-3.3134***	-2.9229***	-3.4008***	-3.9337***	-0.2256	-1.645	-4.4140***	0.1671	1.3922
h=12	-2.5253**	-4.3567***	-2.5409**	-2.6093***	-3.8906***	-4.7366***	-2.5295**	-2.2170**	-2.6240***	-2.9907***	-0.1693	-1.2551	-3.3655***	0.1255	1.0719
								UK							
h=3	-6.6320***	-6.7007***	-6.9286***	-6.8401***	-6.6468***	-6.9253***	-6.8245***	-6.8199***	-6.9283***	-1.6650*	-0.4689	-0.6044	0.6638	0.5876	0.7611
h=6	-4.8055***	-4.8695***	-5.0457***	-4.9756***	-4.8295***	-5.0433***	-4.9476***	-4.9595***	-5.0450***	-1.215	-0.3357	-0.4324	0.4735	0.4277	0.5486
h=12	-3.5459***	-3.6025***	-3.7461***	-3.6870***	-3.5707***	-3.7440***	-3.6527***	-3.6743***	-3.7457***	-1.0015	-0.2637	-0.3141	0.3554	0.3484	0.4357

Note: The table presents the out-of-sample forecast performance analysis for the benchmark forecasting model (labelled in each column in Panels A and B) against its augmented variations that incorporate technological shocks as volatility predictors. Reported in each cell is the estimated Diebold and Mariano statistic where a negative and significant DM statistic value indicates better out-of-sample forecast performance of the augmented model compared to the benchmark model. In Panel A, the benchmark model is the conventional GARCH-MIDAS-RV model which includes only the past realizations of realized volatility (RV) as the predictor. The benchmark is compared to three alternative augmented models that incorporate TS, GTS_OECD and GTS_164 as predictors. In Panel B, the benchmark model is the GARCH-MIDAS-TS model which incorporates TS as the predictor and is compared against the model variations that include GTS_OECD and GTS_164 as predictors. ***, ** and * respectively denote statistical significance at 1%, 5% and 10% levels of significance.

Table A3. Economic Analysis (*Other G7 countries*).

Country	Period	Model	Returns	Volatility	SR	Returns	Volatility	SR	Returns	Volatility	SR	Returns	Volatility	SR
			$\theta=3$ and $\gamma=6$			$\theta=3$ and $\gamma=8$			$\theta=3$ and $\gamma=6$			$\theta=3$ and $\gamma=8$		
			Panel A: *Without transaction costs*						***Panel B:*** *With transaction costs*					
Canada		RV	3.478	0.182	7.763	4.593	0.323	7.781	3.845	0.182	8.622	5.082	0.323	8.641
	Full Sample	TS	3.241	0.251	6.138	4.276	0.446	6.155	3.723	0.251	7.102	4.919	0.446	7.119
		GTS_OECD	3.600	0.138	**9.230**	4.754	0.246	**9.252**	4.038	0.138	**10.409**	5.339	0.246	**10.430**
		GTS_164	3.217	0.252	6.077	4.245	0.448	6.093	3.675	0.252	6.988	4.854	0.448	7.004
	Recession	TS	3.241	0.251	6.134	4.276	0.446	6.150	3.724	0.251	7.098	4.920	0.446	7.114
		GTS_OECD	3.600	0.139	**9.209**	4.755	0.247	**9.230**	4.036	0.139	**10.379**	5.337	0.247	**10.401**
		GTS_164	3.219	0.253	6.072	4.246	0.449	6.088	3.677	0.253	6.985	4.858	0.449	7.001
	Expansion	TS	3.292	0.141	**8.324**	4.344	0.250	**8.347**	3.872	0.141	**9.870**	5.118	0.250	**9.894**
		GTS_OECD	3.599	0.138	**9.252**	4.754	0.245	**9.273**	4.039	0.138	**10.439**	5.341	0.245	**10.460**
		GTS_164	3.216	0.251	6.082	4.242	0.447	6.098	3.671	0.251	6.991	4.850	0.447	7.008
France		RV	3.111	0.032	16.462	4.102	0.057	16.502	2.561	0.032	13.386	3.367	0.057	13.417
	Full Sample	TS	2.664	0.011	**23.859**	3.506	0.019	**23.927**	2.004	0.011	**17.549**	2.623	0.019	**17.598**
		GTS_OECD	2.716	0.012	**23.639**	3.575	0.021	**23.705**	2.043	0.012	**17.397**	2.675	0.021	**17.445**
		GTS_164	2.757	0.016	**20.543**	3.630	0.028	**20.600**	2.056	0.016	**14.982**	2.692	0.028	**15.022**
	Recession	TS	2.665	0.011	**23.793**	3.507	0.020	**23.861**	2.007	0.011	**17.525**	2.627	0.020	**17.574**
		GTS_OECD	2.718	0.012	**23.576**	3.578	0.021	**23.643**	2.048	0.012	**17.380**	2.681	0.021	**17.428**
		GTS_164	2.732	0.016	**20.366**	3.597	0.028	**20.423**	2.008	0.016	**14.619**	2.629	0.028	**14.658**
	Expansion	TS	2.664	0.011	**23.913**	3.506	0.019	**23.981**	2.001	0.011	**17.563**	2.619	0.019	**17.612**
		GTS_OECD	2.714	0.012	**23.688**	3.573	0.021	**23.755**	2.038	0.012	**17.403**	2.669	0.021	**17.451**
		GTS_164	2.721	0.017	**19.779**	3.582	0.030	**19.834**	2.015	0.017	**14.311**	2.638	0.030	**14.350**
Germany		RV	0.022	0.000	-47.301	-0.016	0.000	-44.667	0.006	0.000	-52.312	-0.037	0.000	-49.703
	Full Sample	TS	-0.004	0.000	**-17.048**	-0.051	0.000	**-16.264**	-0.007	0.000	**-17.310**	-0.056	0.000	**-16.613**
		GTS_OECD	-0.005	0.000	**-22.920**	-0.052	0.000	**-21.864**	-0.021	0.000	**-24.995**	-0.073	0.000	**-23.978**
		GTS_164	-0.005	0.000	**-23.918**	-0.052	0.000	**-22.816**	-0.021	0.000	**-26.148**	-0.074	0.000	**-25.084**
	Recession	TS	-0.015	0.000	**-12.336**	-0.065	0.000	**-11.785**	-0.038	0.000	**-13.890**	-0.095	0.000	**-13.331**
		GTS_OECD	-0.005	0.000	**-23.338**	-0.052	0.000	**-22.258**	-0.023	0.000	**-25.795**	-0.076	0.000	**-24.738**
		GTS_164	-0.005	0.000	**-24.374**	-0.052	0.000	**-23.248**	-0.023	0.000	**-26.931**	-0.076	0.000	**-25.829**
	Expansion	TS	-0.003	0.000	**-16.984**	-0.049	0.000	**-16.201**	-0.001	0.000	**-16.745**	-0.048	0.000	**-16.074**
		GTS_OECD	-0.005	0.000	**-21.960**	-0.052	0.000	**-20.953**	-0.018	0.000	**-23.612**	-0.070	0.000	**-22.659**
		GTS_164	-0.005	0.000	**-23.171**	-0.052	0.000	**-22.107**	-0.019	0.000	**-25.012**	-0.071	0.000	**-24.001**
Italy		RV	4.333	0.224	8.805	5.732	0.398	8.821	4.305	0.224	8.747	5.694	0.398	8.761
	Full Sample	TS	4.515	0.032	**24.171**	5.975	0.058	**24.212**	4.026	0.032	**21.452**	5.320	0.058	**21.485**
		GTS_OECD	4.515	0.032	**24.253**	5.974	0.057	**24.294**	4.017	0.032	**21.474**	5.308	0.057	**21.508**
		GTS_164	4.507	0.032	**24.130**	5.963	0.057	**24.172**	4.017	0.032	**21.407**	5.308	0.057	**21.440**
	Recession	TS	4.514	0.032	**24.152**	5.973	0.058	**24.193**	4.024	0.032	**21.434**	5.318	0.058	**21.467**
		GTS_OECD	4.513	0.032	**24.235**	5.972	0.057	**24.277**	4.015	0.032	**21.457**	5.306	0.057	**21.491**
		GTS_164	4.505	0.032	**24.114**	5.961	0.058	**24.155**	4.015	0.032	**21.390**	5.306	0.058	**21.423**
	Expansion	TS	4.517	0.032	**24.191**	5.977	0.057	**24.232**	4.027	0.032	**21.470**	5.322	0.057	**21.503**
		GTS_OECD	4.516	0.032	**24.271**	5.976	0.057	**24.312**	4.018	0.032	**21.492**	5.310	0.057	**21.525**
		GTS_164	4.508	0.032	**24.148**	5.965	0.057	**24.189**	4.018	0.032	**21.424**	5.310	0.057	**21.457**

Table A3 (continued).

Japan	Full Sample	RV	3.773	0.101	**11.354**		4.985	0.179	**11.377**		3.038	0.101	**9.042**		4.003	0.179	**9.060**
		TS	3.428	0.081	**11.455**		4.525	0.144	**11.478**		2.407	0.081	**7.869**		3.161	0.144	**7.886**
		GTS_OECD	3.765	0.101	**11.306**		4.974	0.180	**11.329**		3.036	0.101	**9.017**		4.000	0.180	**9.035**
		GTS_164	3.635	0.442	5.217		4.802	0.786	5.229		3.837	0.442	5.520		5.071	0.786	5.532
	Recession	TS	3.523	0.089	**11.233**		4.652	0.159	**11.256**		2.580	0.089	**8.077**		3.392	0.159	**8.094**
		GTS_OECD	3.355	0.079	**11.372**		4.427	0.140	**11.396**		2.305	0.079	**7.628**		3.025	0.140	**7.645**
		GTS_164	3.763	0.101	**11.312**		4.972	0.180	**11.334**		3.022	0.101	**8.978**		3.981	0.180	**8.996**
	Expansion	TS	3.821	0.102	**11.466**		5.048	0.181	**11.488**		3.119	0.102	**9.265**		4.111	0.181	**9.283**
		GTS_OECD	3.785	0.105	**11.167**		5.001	0.187	**11.189**		3.050	0.105	**8.900**		4.019	0.187	**8.917**
		GTS_164	3.783	0.103	**11.280**		4.998	0.183	**11.302**		3.062	0.103	**9.031**		4.034	0.183	**9.048**
UK	Full Sample	RV	2.501	0.251	**4.661**		3.290	0.446	**4.678**		2.851	0.251	**5.361**		3.757	0.446	**5.377**
		TS	2.497	0.219	**4.981**		3.284	0.389	**4.998**		2.842	0.219	**5.718**		3.744	0.389	**5.736**
		GTS_OECD	2.491	0.219	**4.964**		3.277	0.390	**4.981**		2.837	0.219	**5.702**		3.738	0.390	**5.720**
		GTS_164	3.067	0.769	3.307		4.044	1.367	3.316		3.429	0.769	3.720		4.527	1.367	3.729
	Recession	TS	2.498	0.218	**4.993**		3.285	0.387	**5.011**		2.843	0.218	**5.732**		3.745	0.387	**5.750**
		GTS_OECD	2.492	0.220	**4.958**		3.277	0.391	**4.976**		2.837	0.220	**5.695**		3.738	0.391	**5.713**
		GTS_164	2.478	0.225	**4.875**		3.259	0.400	**4.892**		2.822	0.225	**5.600**		3.718	0.400	**5.618**
	Expansion	TS	2.495	0.221	**4.956**		3.282	0.392	**4.974**		2.840	0.221	**5.691**		3.742	0.392	**5.709**
		GTS_OECD	2.491	0.219	**4.969**		3.277	0.389	**4.987**		2.837	0.219	**5.708**		3.738	0.389	**5.726**
		GTS_164	2.490	0.252	**4.627**		3.275	0.448	**4.643**		2.837	0.252	**5.317**		3.737	0.448	**5.334**

Note: For each model variation, we report the Return, Volatility, and Sharpe Ratio (SR) values, computed over the out-of-sample forecasting horizon. The benchmark model, reported in shaded rows, is the conventional GARCH-MIDAS-RV model which includes only the past realizations of realized volatility (RV) as the predictor. The computed statistics for GARCH-MIDAS-RV is the same for the full sample, recession and expansion periods. The leverage ratio is denoted by θ with a value of one indicating no leverage. We set the leverage ratio to 6 and 8; and set the risk aversion level to 3. Panels A and B report the results with and without transaction costs, respectively. Bold figures indicate cases where the augmented GARCH-MIDAS model variants yield higher economic gains than the benchmark GARCH-MIDAS-RV.