Journal of Forecasting

WILEY

RESEARCH ARTICLE OPEN ACCESS

Sectoral Corporate Profits and Long-Run Stock Return Volatility in the United States: A GARCH-MIDAS Approach

Afees Salisu[1,2] | Kazeem O. Isah[2,3] | Ahamuefula Ephraim Ogbonna[2]

[1]Department of Economics, University of Pretoria, Pretoria, South Africa | [2]Centre for Econometrics & Applied Research, Ibadan, Nigeria | [3]Department of Economics, School of Accounting, Economics & Finance, College of Law and Management Studies, University of KwaZulu-Natal (UKZN), Durban, South Africa

Correspondence: Afees Salisu (afees.salisu@up.ac.za)

Received: 19 January 2024 | **Revised:** 30 June 2024 | **Accepted:** 23 October 2024

Keywords: corporate profit | GARCH-MIDAS | predictability | stock return volatility | United States

ABSTRACT

This study aims to examine the usefulness of corporate profits in predicting the return volatility of sectoral stocks in the United States. We use a GARCH-MIDAS approach to keep the datasets in their original frequencies. The results show a consistently positive slope coefficient across various sectoral stocks. This implies that higher profits lead to increased trading of stocks and, subsequently, a higher volatility in the long run than usual. Furthermore, the analysis also extends to predictability beyond the in-sample. We find strong evidence that corporate profits can predict the out-of-sample long-run return volatility of sectoral stocks in the United States. These findings are significant for investors and portfolio managers.

JEl Classification: C53, G15, N22, L25

1 | Introduction

The volatility of stock markets is not solely due to demand and supply forces. It is increasingly influenced by external macroeconomic factors such as interest rates, inflation, oil prices, and exchange rates (see Bouri 2015; Bouri, Awartani, and Maghyereh 2016; Bouri, Salisu, and Gupta 2023; Raza et al. 2016; Khan, Nasir, and Rossi 2017; Tachibana 2018; Mahapatra and Bhaduri 2019; Salisu, Gupta, and Demirer 2022). Other factors include uncertainties stemming from historical events, both economic and non-economic in nature. Examples include the 2008 global financial crisis, the COVID-19 outbreak, and geopolitical conflicts such as the Russian/Ukraine war, the September 11 attacks, Iraq-Kuwait war, among others. It is worth noting, however, that macroeconomic factors and geopolitical and economic events indirectly impact stock values by affecting firms' profits, also known as corporate profit. In other words, these external factors influence the stock market by influencing firms' profit through growth and reinvestment opportunities, economic cycles, market expectations, leverage, regulatory changes, and tax policies. Based on this perspective, we suggest that the level and volatility of the stock market rate of return can be directly explained by fundamentals, which we define as the incremental rate of profit in the corporate sector. The underlying idea is that the real incremental rate of profit represents the "required" rate of returns for the stock market (see Shaik 1995).

The above mechanism of the dynamics of connection between stock markets and corporate profits not only gives credence to the idea that corporate insiders have more information about their company than outsiders but also finds support in the efficient market hypothesis (EMH) by Fama (1970). The EMH assumes that markets can fully integrate information, providing equal opportunities for buyers and sellers of securities. One such piece of insider information capable of altering the dynamics of stock markets is corporate profits. It is reasonable to expect that profitability, as a measure of sound financial performance, will impact the pricing and yields of equity securities. This is because maximizing shareholder wealth involves increasing the share prices that investors are targeting. In general, sales revenue reflects the external value created by a firm through favorable sales returns, which in turn affects profitability. It represents internal value and communicates positive information in the market, leading to positive external returns. Once a company declares a dividend, the stock becomes more attractive to investors, and the increased interest in the company creates demand, increasing the value of the stock (see Yin and Nie 2020). This implies that dividend-paying stocks can improve the overall performance of stock markets, even though there has also been an episode of stock markets adversely affected by uncertainty about the reliability of profits disclosed by corporations.

Indeed, the relationship between dividends and the stock market has been increasingly studied in finance literature. Fama and French (2015, 2018) introduced profitability as a factor in new multifactor asset pricing models, and subsequent research by Hou, Xue, and Zhang (2015), Hou et al. (2017), Jiang, Qi, and Tang (2018), Asness, Frazzini, and Pedersen (2019), Kyosey et al. (2020), Yin, Wei, and Han (2020), and Liu, Yang, and Su (2023) has shown that changes in profitability can predict firms' stock returns. However, there has been relatively less exploration into whether corporate profits affect the volatility dynamics of the stock market, despite the potential for stock price fluctuations due to changes in corporate profits. For example, strong earnings (positive earnings surprises) can boost investor confidence and lower volatility. In contrast, disappointing earnings (negative earnings surprises) can create uncertainty and lead to major market fluctuations and increased volatility. In other words, when investors are optimistic about expected earnings, volatility tends to decrease, while the opposite is likely to occur when investors are pessimistic about expected earnings. Given that these investor sentiments contribute to stock market volatility through changes in firms' profits, it is important to examine the role of corporate profit in predicting stock return volatility. To test this predictability, we employ a predictive-based generalized autoregressive conditional heteroscedasticity (GARCH) model with a mixed data sampling (MIDAS) option to contribute to the literature on the following grounds.

First, volatility is the rate of change in the price of a financial asset over a given period; consequently, the greater the volatility, the greater the risk of substantial gain or loss. In conformity with the assertion that many investors would prefer stocks that support more predictable earnings and therefore carry less risk, quite a number of the extant studies reveal compelling evidence in support of the impact of favorable dividends on reducing stock price risk (Anwar, Singh, and Jain 2015; Phan and Tran 2019; Ali and Hegazy 2022; Quaye and Tunaru 2022; Guo, Li, and Wang 2023). However, these studies are predominantly based on impact analyses and, therefore, offer little insight into the forecasting power of corporate profits in the long-run predictability of the volatility dynamics of stock returns. Consequently, conduct both the in-sample and out-of-sample forecast analyses since significant in-sample predictability outcomes do not necessarily translate into improved out-of-sample forecast gains. This exercise enables us to evaluate if the historical data on corporate profits can help us predict future stock market risk. In practice, investors and policymakers rely more on out-of-sample forecasts, as future investment decisions are based on the expected level of risks, which can be estimated from the volatility forecast.

Second, the factors that influence corporate profits often differ from stock prices and market developments. Stock market trading occurs daily, while companies typically distribute earnings to shareholders in cash or stock reinvestment each quarter. As a result, corporate actions, such as dividend pay-outs, tend to change slowly relative to stock prices that change frequently. Therefore, assuming the same frequency for the two variables (by aggregating higher frequency to lower frequency) may reduce the predictive value of the key feature of daily frequency. Thus, accommodating these variables at their natural frequencies provides more useful insights into understanding the connection and shows how such information can be utilized from both in-sample and out-of-sample perspectives. In other words, analyses focused on changes in profitability and stock returns/volatility have consistently used a data-slicing and averaging approach (Yin, Wei, and Han 2020; Liu, Yang, and Su 2023). However, relying on the same approach, especially when interested in out-of-sample volatility forecasts, may produce less realistic results. For example, the main reason that high-frequency data can greatly improve forecast accuracy is that volatility is highly persistent, so a more accurate measure of current volatility, which high-frequency data provides, is valuable for forecasting future volatility. Thus, rather than altering the natural flow of daily trading activity of the stock market by converting the daily stock prices to quarterly frequency using the data-aggregation method, we instead employ a mixed data sampling technique within a volatility modeling framework to circumvent the loss of information from aggregation and consequently strengthen the accuracy and reliability of the estimates.

Finally, the dividend policy involves deciding whether a company should keep its earnings or distribute them as dividends. This decision may be affected by the firm's net profits and justifies differences in firms' performance. For example, a company that retains a significant portion of profit may experience significant expansion in its scale of operation compared to others that distribute more than they retain. However, this strategy relies on the expectation that shareholders understand the philosophy of the former firm, valuing the firm's growth in the short and medium term over immediate benefits for shareholders, in order to have greater and more sustainable earnings to share in the long run. Recently, there has been an emerging trend regarding the role of innovation in explaining differences in firms' performance and corporate profit. Given the importance of innovation in driving long-term growth, we expect differences in adopting new technology and innovation across industries to lead to variations in firm performance and earnings. As of January 31, 2023, for example, the top 3 most profitable American firms are Apple in the Technology sector, with an annual profit of $99.8 billion for the 2022 fiscal year, followed by Exxon Mobile in the Energy sector with annual profits of $55.7 billion and JPMorgan Chase in the financial sector with annual profits of $37.7 billion. Pfizer and Verizon Communications ranked fourth and fifth with annual profits of $31.3 billion and $21.3 billion in the health and communication sectors, respectively. Given this heterogeneous behavior of corporate profits, as demonstrated herein for different firms of the different sectors listed in the S&P 500, it may be inadequate to generalize the role of corporate profits in the long-run volatility dynamics of the stock markets. To this end, we favor a sectoral approach to capture the potential of heterogeneity in the nexus between corporate profits and the long-run volatility of stock returns of the different sectors listed in the S&P500.

Foreshadowing the study's results, we find that, true to our hypothesis of a positive nexus between stock market volatility and corporate profits, both the aggregate and sectoral stock returns favorably respond to US corporate profits, suggesting increased stock volatility in the face of higher corporate profits. Our findings are supported by several existing studies (see Piotroski 2000; Novy-Marx 2013; Jiang, Qi, and Tang 2018; Asness, Frazzini, and Pedersen 2019; Kyosey et al. 2020; Yin, Wei, and Han 2020; Liu, Yang, and Su 2023). Unlike these studies, we not only focus on investment returns but also demonstrate the forecasting ability of corporate profits in the volatility dynamics of stock returns. Our results have a compelling implication for investors and portfolio managers who are always looking for the best-performing stocks in terms of profitability to invest. Our study reveals that corporate profit is a reliable indicator of stock return volatility across different sectors and forecast horizons, providing evidence-based insights for financial market stakeholders making investment decisions.

Following this introduction, the rest of the paper is structured as follows: Section 2 presents the data and some preliminary analyses. Section 3 documents the technique upon which the study is premised, while Section 4 offers the empirical results and associated discussions. Section 5 finally concludes the paper with some suggestions for further studies.

2 | Data and Preliminary Analyses

The dataset used in this study consists of a number of 11 US sectoral stock prices, including communication, energy, financial, health care, industrials, information technology, real estate, utilities, and materials, among others, as well as their profits. Essentially, these variables, comprising quarterly sectoral corporate profits and daily stock prices, are sourced from the data stream of the Bloomberg online database. Covering 2000 to 2022, the total number of observations for the high-frequency sectoral stock return series—computed as the log of the first difference of the stock prices—is 5766, barring real estate stock, which has its start date as 10/9/2001, thus having 5380 observations. Similarly, the number of observations for the quarterly sectoral corporate net profit is 92, except for health care, which has the first quarter of 2019 as its end date, with 77 observations.

Table 1 illustrates the preliminary results for the two variables. The table summarizes the two variables' mean, standard deviation, skewness, and kurtosis. The reported mean values represent the average values for each variable represented. On the other hand, the standard deviation shows how clustered/dispersed the series are around their means. While skewness shows the direction of the movement/fluctuations (to either right–positive or left–negative), kurtosis shows the heaviness or thinness of the tail from what is known to be typical of a normal distribution. The table (Table 1a) shows that the sectoral net corporate profit is positive for the real estate and financial sectors, ranging between 128.25 and 1166.71, respectively. This indicates that, on average, the corporate profit after tax is highest in the US financial sector compared to other sectors. While the communication sector has the least return on its stock, the daily stock return is the highest in the healthcare sector, with −0.01 and 0.03, respectively.

With respect to stock market volatility, given the value of standard deviation, as shown in Table 1a, real estate appears to be

TABLE 1A | Summary statistics.

	Corporate profit					Sectoral stock return				
Sector	**Mean**	**Std. dev.**	**Skew.**	**Kurt.**	**Obs.**	**Mean**	**Std. dev.**	**Skew.**	**Kurt.**	**Obs.**
Communication services	1041.63	746.79	1.05	3.78	92	−0.01	1.45	−0.06	9.85	5766
Consumer discretionary	284.58	166.02	0.19	3.12	92	0.02	1.44	−0.28	10.15	5766
Consumer staple	591.60	157.98	0.14	2.79	92	0.02	0.97	−0.27	14.98	5766
Energy	607.30	1078.87	−3.31	22.25	92	0.02	1.82	−0.59	16.28	5766
Financial	1166.71	1090.70	−0.50	4.08	92	0.01	1.90	−0.18	18.81	5766
Health care	369.49	118.75	0.56	3.03	77	0.03	1.16	−0.12	10.88	5766
Industrials	341.37	95.23	−0.07	2.44	92	0.02	1.39	−0.40	10.57	5766
IT	529.36	310.95	1.00	3.58	92	0.02	1.75	0.10	9.72	5766
Materials	203.26	133.51	1.15	4.52	92	0.02	1.56	−0.30	9.90	5766
Real estate	128.25	63.34	0.47	2.38	92	0.02	1.92	−0.20	22.01	5380
Utilities	311.92	86.58	0.00	5.07	92	0.02	1.28	−0.10	14.92	5766
Aggregate	512.86	211.18	0.00	3.90	92	0.02	1.25	−0.38	13.21	5766

Note: While the corporate profit is expressed in billion dollars, the sectoral stock return, on the other hand, is computed as $[\ln (S_i/S_i(-1))*100]$, where S_i is the associated sector's stock price.
Abbreviations: Kurt., kurtosis; Obs., observations; Skew., skewness; Std. dev., standard deviation.

the most volatile with a standard deviation value of 1.92, while the consumer staple market, on the other hand, is the most stable (with 0.97 standard deviation value). Regarding the statistics relating to the distribution of the variables, we find the skewness negative for all the US sectoral stock returns, while that of corporate profit is mixed. Particularly, all the sectoral corporate profit save energy, financial, and industrials are positively skewed. Furthermore, we find the kurtosis statistic to be leptokurtic for all the sectoral stock returns, while the statistic is mixed for corporate profits. Specifically, the kurtosis statistic for all the sectors but consumer staple, industrials and real estate are in excess of 3 and are thereby leptokurtic. The foregoing outcomes suggest that the variables are not normally distributed.

In addition to the summary statistics above, we test—in Table 1b—for the presence of heteroscedasticity and autocorrelation typical of high-frequency data, using autoregressive conditional heteroscedasticity (ARCH) test and a Q-statistic with its squared form based on the Ljung-Box autocorrelation test. This was done across different lag lengths, including 2, 4, and 6. We find strong evidence of both conditional heteroscedasticity and autocorrelations in both variables across the sample sectors. This supports our preference for the GARCH-MIDAS model as the most suitable to account for the possibility of corporate profit serving as the fundamental cause of stock return volatility in the United States.

Finally, we complement the preliminary analyses with graphical illustrations of the possible co-movements between US sectoral corporate profits and stock returns (see Figure 1). A priori, we expect a positive co-movement between corporate profit and stock returns. This underscores the fact that part of the profits earned by corporate firms are distributed to investors as dividends; thus, higher profit would translate to higher returns to shareholders (investors) and vice versa. This relationship is observed across the graphs showing the co-movement between corporate profits and stock returns of various sectors examined, including the aggregate profit and stock returns (see Appendix A). However, the graphical illustrations of our data are never sufficient to draw any conclusion at this point; thus, our data are further subjected to empirical analysis using the GARCH-MIDAS approach.

3 | Methodology

Our primary objective is to investigate the predictive insights derived from the US corporate profit on sectoral stock market volatility. The available data are, however, in disparate frequencies. The US corporate profit, our predictor variable in this study, is measured quarterly, while the stock returns are measured daily. Traditionally, we would have to either aggregate the higher frequency series to the lower frequency or splice the lower frequency series to the higher frequency. Both options have been shown to respectively lead to loss of information or introduce systematic bias into the transformed series, which may consequentially affect the outcome of the parameter estimates. Therefore, to address plausible potential information loss from aggregation or observational biases stemming from data splicing procedures, we adopt the Mixed-Data Sampling (MIDAS) framework. The MIDAS model framework has gained widespread application in econometrics for scenarios involving data at mixed frequencies. Also, given that our daily US stock returns exhibit evidence of ARCH effects, suggesting the appropriateness of a GARCH model framework, we employ the GARCH-MIDAS model in our empirical analysis. This model is well-suited for handling a mixed data frequency setting, especially when dealing with a high-frequency dependent variable exhibiting conditional heteroscedasticity and a lower-frequency predictor variable. The GARCH-MIDAS framework ensures comprehensive consideration of all available information when modeling volatility in returns, distinguishing the method from extant uniform frequency methods that are prone to information loss and observational bias and, consequently, distortion of the original data frequency.

The daily sectoral stock returns are defined as $r_t = 100^* \left[\ln\left(P_t\right) - \ln\left(P_{t-1}\right)\right]$, with P_t denoting the sectoral stock prices at time t. Taking cognizance of the disparate frequencies of our series, we denote daily and quarterly frequencies as $i = 1, \dots, N_t$ and $t = 1, \dots, T$, respectively, such that the number of days in a given quarter is represented by N_t. The GARCH-MIDAS model specification is defined as follows:

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

where τ is the unconditional mean of US sectoral stock returns; $\sqrt{\mu_t \times g_{i,t}}$ is the conditional variance consisting of a long-run component $\left(\mu_t\right)$ that captures the long-run volatility and a short-run component $\left(g_{i,t}\right)$ that follows a GARCH(1, 1) process and is marked by higher frequency, with $e_{i,t}|\Sigma_{i-1,t} \sim N(0,1)$ representing the error distribution and $\Sigma_{i-1,t}$ denoting the available information at day $i-1$ of quarter t. The short-run component of the conditional variance part is defined in Equation (2) as

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

where α and β are, respectively, the ARCH and GARCH terms, satisfying the following conditions $\alpha > 0$, $\beta \geq 0$, and $\alpha + \beta < 1$. In this setup, the quarterly frequency corporate profit is transformed to daily frequency without losing the original model's essence, following Engle, Ghysels, and Sohn (2013). Consequently, our quarterly varying long-term component is converted to a daily frequency, rolling back across the quarters without keeping track of it. Equations (3) and (4), respectively, define the daily long-term component for realized volatility and an exogenous factor:

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

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

where m is the long-run intercept; δ is the coefficient of the incorporated predictor (realized volatility or corporate profit).

TABLE 1B | Conditional heteroscedasticity and autocorrelation tests.

	Corporate profit									Sectoral stock return								
Sector	**ARCH (2)**	**ARCH (4)**	**ARCH (6)**	**Q(2)**	**Q(4)**	**Q(6)**	**$Q^2(2)$**	**$Q^2(4)$**	**$Q^2(6)$**	**ARCH (2)**	**ARCH (4)**	**ARCH (6)**	**Q(2)**	**Q(4)**	**Q(6)**	**$Q^2(2)$**	**$Q^2(4)$**	**$Q^2(6)$**
Communication services	4.8[b]	2.6[b]	1.7	4.8[c]	5.9	7.8	9.7[a]	10.6[b]	11.6[c]	396.3[a]	236.3[a]	194.5[a]	6.1[b]	9.4[b]	18.1[a]	839.6[a]	1333.3[a]	1979.6[a]
Consumer discretionary	10.6[a]	6.2[a]	4.0[a]	15.4[a]	17.3[a]	17.5[a]	19.4[a]	19.7[a]	20.3[a]	486.1[a]	299.1[a]	239.4[a]	2.2	2.5	8.8	9556.0[a]	1635.0[a]	2436.2[a]
Consumer staple	0.20	1.8	1.5	8.3[b]	14.6[a]	15.6[b]	0.4	7.9[c]	12.1[c]	622.5[a]	368.3[a]	293.4[a]	4.5	16.5[a]	20.3[a]	1366.7[a]	2269.9[a]	3166.1[a]
Energy	0.4	0.22	0.15	1.7	2.7	3.0	0.9	1.0	1.2	381.6[a]	310.2[a]	242.9[a]	3.9	6.6	8.0	784.4[a]	1694.6[a]	2477.4[a]
Financial	1.8	2.6[b]	2.2[c]	0.2	1.3	1.8	3.9	7.3	9.2	455.5[a]	320.0[a]	295.3[a]	0.04	10.5[b]	33.9[a]	1014.8[a]	1945.0[a]	3199.9[a]
Health care	13.6[a]	9.6[a]	8.7[a]	16.0[a]	31.1[a]	31.2[a]	26.2[a]	44.7[a]	46.4[a]	741.1[a]	395.4[a]	334.7[a]	11.9[a]	16.3[a]	22.6[a]	1523.1[a]	2155.0[a]	3102.4[a]
Industrials	5.5[a]	3.1[b]	3.6[a]	1.1	8.2[c]	14.7[b]	11.1[a]	11.6[b]	23.5[a]	663.7[a]	391.9[a]	330.6[a]	0.03	0.9	8.5	1319.2[a]	2246.0[a]	3494.3[a]
IT	1.5	0.7	0.5	8.7[b]	15.1[a]	17.0[a]	3.1	3.6	3.6	428.0[a]	252.7[a]	206.0[a]	8.9[b]	9.3[c]	15.6[b]	941.9[a]	1516.2[a]	2246.9[a]
Materials	1.9	1.1	1.5	2.7	10.3[b]	16.2[b]	4.4	6.0	12.5[c]	532.0[a]	334.1[a]	330.8[a]	0.3	3.9	7.9	1085.4[a]	1931.2[a]	3344.9[a]
Real estate	3.6[b]	1.9	1.4	15.7[a]	17.0[a]	19.3[a]	9.0[b]	10.1[c]	11.4[c]	454.4[a]	485.2[a]	382.3[a]	1.8	14.5[a]	19.0[a]	993.3[a]	2622.7[a]	3977.2[a]
Utilities	0.5	3.6[a]	6.0[a]	2.4	13.7[a]	16.8[b]	0.9	4.9	7.7	904.9[a]	529.2[a]	419.0[a]	0.2	5.5	16.6[b]	1889.6[a]	3235.4[a]	4798.9[a]
Aggregate	1.0	0.5	0.4	1.3	7.3	9.3	2.0	2.1	2.2	817.0[a]	442.1[a]	361.4[a]	1.7	5.3	14.9[b]	1555.0[a]	2441.4[a]	3630.9[a]

Note: The reported figures are *F*-statistics for the ARCH test and Ljung–Box Q-statistics for the autocorrelation test, considered at three different lag lengths (k = 2, 4, and 6). The null of no conditional heteroscedasticity and serial correlation are tested for ARCH and autocorrelation tests, respectively. Statistical significance of tests at 1%, 5%, and 10% levels, denoted by a, b, and c, respectively, indicates the rejection of the null hypotheses.

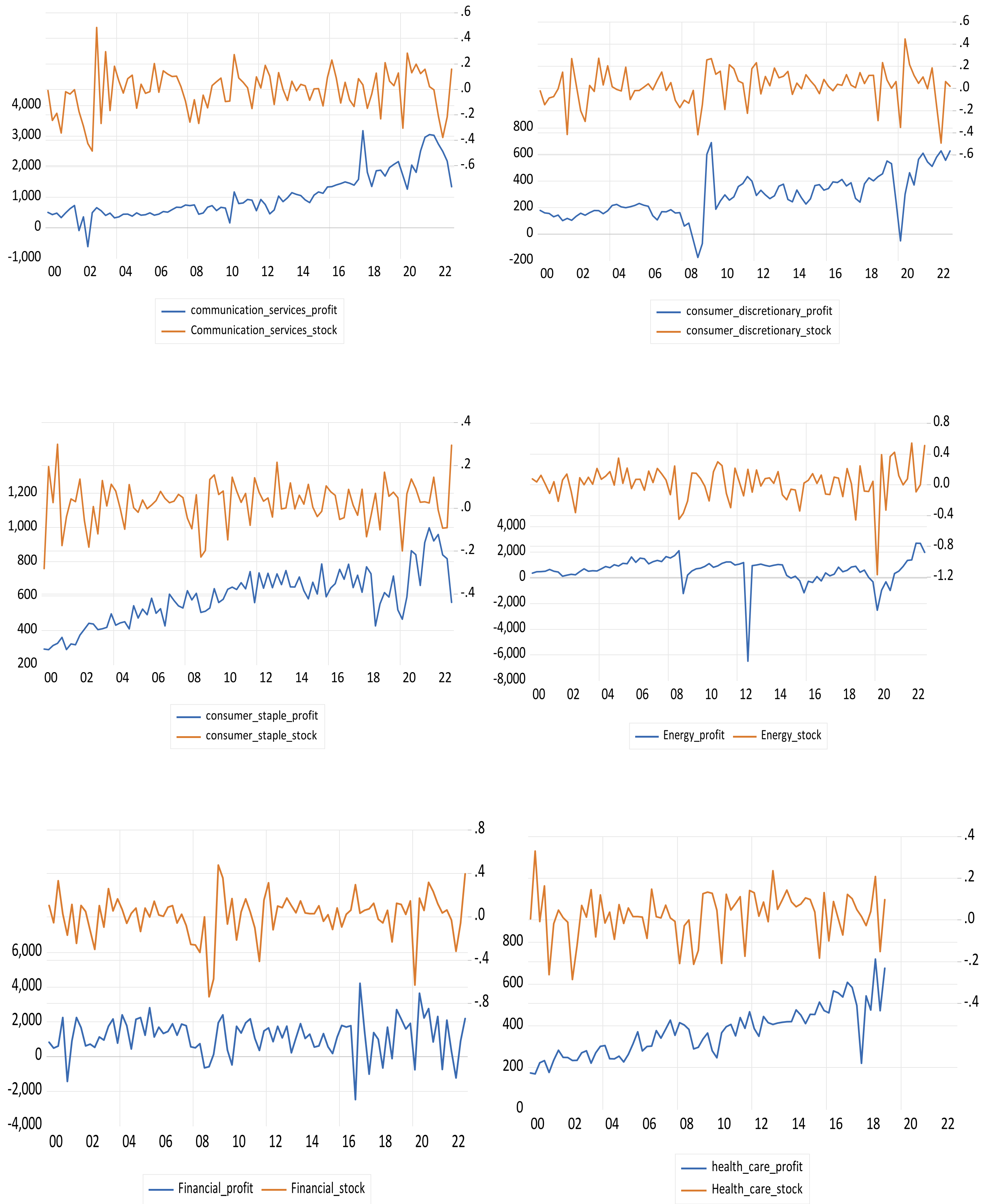

FIGURE 1 | Graphical illustrations of possible co-movements between sectoral corporate profits and stock returns.

We explore two GARCH-MIDAS long-run component variants distinguished by the included predictor(s): (i) the benchmark GARCH-MIDAS variant incorporating only realized volatility (RV) and (ii) the proposed GARCH-MIDAS variant that incorporates corporate profit. Equations (3) and (4) comprise beta polynomial weights, denoted by $\phi_k(w_1, w_2) \geq 0,\ k = 1, \ldots, K$, with a unity constraint imposed on the summation of the weights to identify the model's

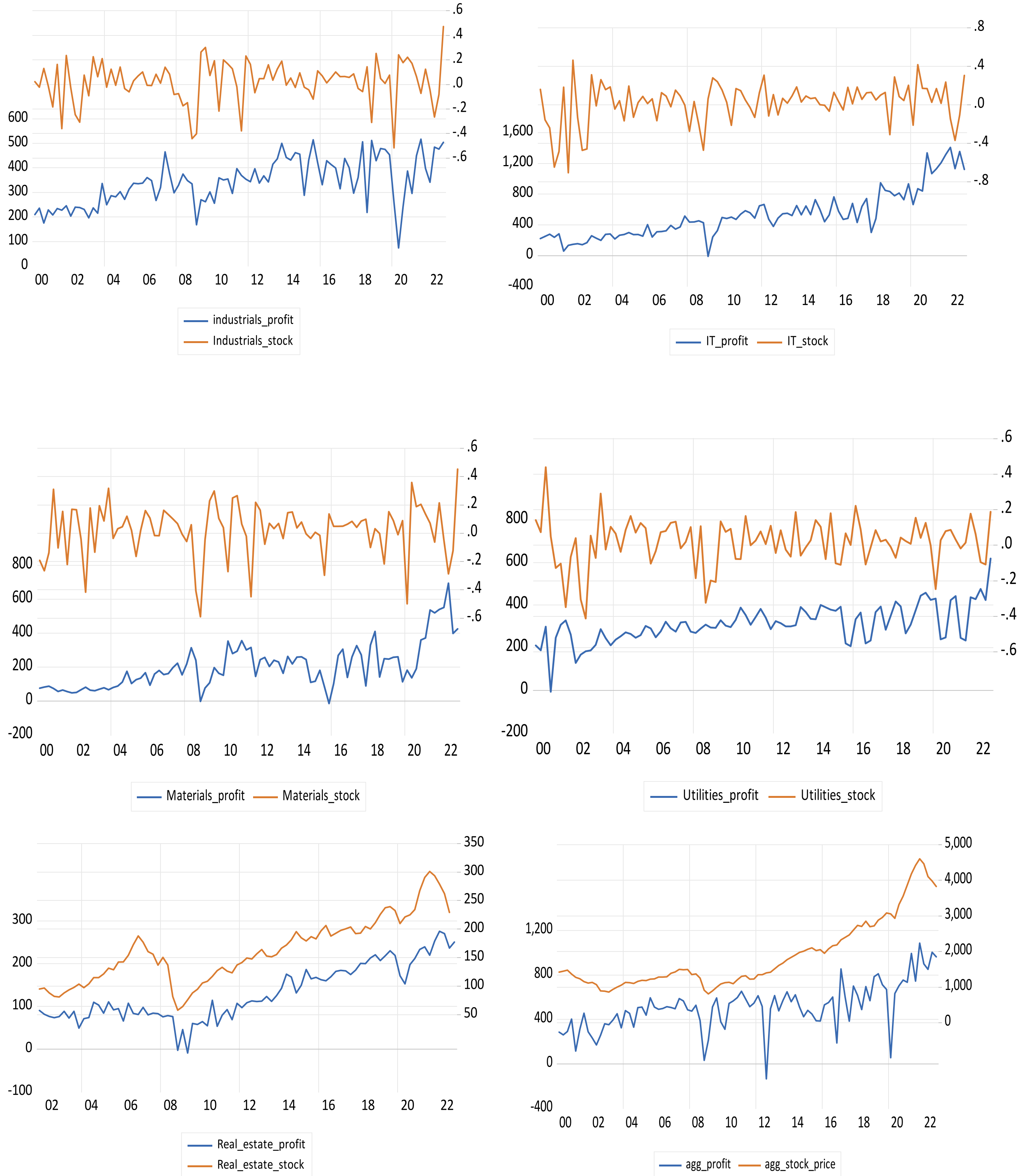

FIGURE 1 | (Continued)

parameters. The secular component of the MIDAS weights is filtered using $(K = 10)$ MIDAS years, the optimal lag for our specification. Leveraging the flexibility of the beta weighting scheme, we adopt the one-parameter beta polynomial. This scheme allows transforming a two-parameter beta weighting function defined by $\phi_k(w_1, w_2) = [k/(K+1)]^{w_1-1} \times [1-k/(K+1)]^{w_2-1} / \sum_{j=1}^{K} [j/(K+1)]^{w_1-1} \times [1-j/(K+1)]^{w_2-1}$ to a one-parameter beta weighting function $\left[\phi_k(w) = [1-k/(K+1)]^{w-1} / \sum_{j=1}^{K} [1-j/(K+1)]^{w-1}\right]$, constraining w_1 to unity and setting $w = w_2$. This imposes a monotonically decreasing function (Engle, Ghysels, and Sohn 2013), where the weights (ϕ_k) are positive and sum to one $\left(\sum_{k=1}^{K} \phi_k = 1\right)$. Additionally, imposing a constraint on the parameter (w), ensuring it is greater than unity $(w > 1)$, ensures that immediate past observation lags receive larger weights than more distant ones.

The in-sample predictability of the predictors is tested by examining the statistical significance of the slope coefficient (δ), where a statistically significant estimate suggests predictability for the US sectoral stock return volatility based on the corresponding predictor. The a priori expectation is a positive nexus between corporate profit and stock returns. We are also interested in the out-of-sample forecast performance of the GARCH-MIDAS model variant incorporating corporate profit as a predictor in comparison with the conventional GARCH-MIDAS model, which is the benchmark model. To achieve these, we employ a 75:25 data split, using the first 75% of the full data sample for parameter estimation (in-sample predictability) and the remaining 25% of the full data sample for the out-of-sample forecast evaluation of competing GARCH-MIDAS model variants using the modified Diebold and Mariano (DM*) test (Harvey, Leybourne, and Newbold 1997). The DM* test accounts for potential autocorrelation and heavy-tailed distributions and the statistic is defined as

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

where $DM = \overline{d} / \sqrt{V(d)/_T} \sim N(0,1)$ is the conventional DM test equation; $\overline{d} = \frac{1}{T}\sum_{t=1}^{T} d_t$ is the mean of the loss differential between the two competing models; $V\left(d_t\right)$ denotes the unconditional variance of the loss differential where $d_t \equiv l\left(\varepsilon_{Cprofit}\right) - l\left(\varepsilon_{RV}\right); l\left(\varepsilon_{TS}\right)$ and $l\left(\varepsilon_{RV}\right)$ respectively represents the loss functions of the forecast errors of the GARCH-MIDAS-[Cprofit] model and GARCH-MIDAS-[RV] model; and h is the forecast horizon. The tested null is the assertion of equality of the forecast precision of both GARCH-MIDAS model variants $\left(H_0 : E\left(d_t\right) = 0\right)$ against a mutually exclusive alternative hypothesis $\left(H_1 : E\left(d_t\right) \neq 0\right)$ that the competing GARCH-MIDAS variants' forecast precision differs between the paired competing models. A negatively significant test statistic implies the superiority of the augmented GARCH-MIDAS model that incorporates corporate profit as a predictor over the benchmark model (GARCH-MIDAS-RV). The converse is true if the DM* statistic is significantly positive. We consider different forecast horizons (20-, 60- and 120- days ahead) in a rolling window setup.

4 | Empirical Findings

4.1 | In-Sample Predictability Analyses

The in-sample predictability results for the US sectoral stock returns volatility are presented in Table 2, showing the estimated GARCH-MIDAS model parameters, which is the basis for assessing the volatility persistence status of the sectoral stocks as well as the information inherent in own market (realized volatility) and the incorporated exogenous predictor (quarterly corporate profit). The reported results include the unconditional mean sectoral stock returns (τ), the ARCH term (α), the GARCH term (β), the MIDAS slope coefficient δ, the adjusted beta polynomial weight (w), and the long run constant term (m) for the GARCH-MIDAS-[Cprofit] model. The predictability result for the benchmark (GARCH-MIDAS-RV) model (presented in Table A1 in Appendix A) is based on the past realizations of realized volatility only. The GARCH-MIDAS-[Cprofit] model denotes the exogenous-based alternative variant incorporating the corporate profit series (see Table 2).

Table 2 consistently yields significant parameter estimates for all the parameters (except the beta weight and long-run intercept) in our corporate profit-based GARCH-MIDAS model across the US sectoral stocks. We find the unconditional mean returns across the sectors to be significantly positive, indicating that the sectoral market stocks have had average gains for the studied period. Essentially, periods and/or magnitudes of gains outweigh those of losses for all the sector stocks. There is evidence of volatility persistence across the sectors as the sum of the ARCH and GARCH terms is less than unity. The observed persistence is temporal or mean-reverting, only requiring a longer time to fizzle out. Imperatively, own market shocks are less likely to distort the historic pattern of market volatility permanently. Most of the beta weight estimates are greater than unity, which implies the assignment of larger weights to more recent observation lags than far distant observation lags.

On the predictability stance, own market shocks tend to aggravate the volatility in the stocks of the different US sector stocks (see results in Table A1 in Appendix A). This is not unexpected. We, however, are more interested in the response of the sectoral stock returns volatility to corporate profit. The US sectoral stock return volatility responds positively to corporate profit, given the significantly positive slope coefficient δ that is consistently observed across the sectoral and aggregate stocks. This outcome that higher corporate profits could increase the volatility of sectoral stocks lends support to Fama and French (2015, 2018) proposition to include profitability as a factor in new multifactor asset pricing models. This implication is based on the idea that rising profits may lead to increased investment, posing a challenge in allocating funds across various stocks, focusing on those offering higher returns. Redirecting funds to profitable stocks may lead to increased stock volatility. While it is recognized that similar studies have shown profitability can be used for stock pricing (Yu and Huang 2021), it is important to note that the ability to predict corporate profit within a specific sample may not guarantee similar results in an out-of-sample scenario. Therefore, it is important to consider this when making future predictions. A forecast beyond the sample period can provide insight into future volatility, aiding risk management, asset allocation, and option pricing for investors and market participants.

4.2 | Out-of-Sample Predictability Analyses

We further consider the performance of the competing GARCH-MIDAS models in the forecast for out-of-sample

TABLE 2 | In-sample predictability results.

Sectors	τ	α	β	δ	w	m
Aggregate	0.066*** [0.014]	0.119*** [0.010]	0.844*** [0.013]	0.241*** [0.038]	22.029** [8.575]	0.030 [0.103]
Communication services	0.036** [0.017]	0.085*** [0.009]	0.870*** [0.016]	0.174*** [0.041]	24.766* [13.419]	0.140** [0.065]
Consumer discretionary	0.068*** [0.017]	0.098*** [0.010]	0.874*** [0.013]	0.191*** [0.046]	21.568 [13.282]	0.258** [0.114]
Consumer staples	0.064*** [0.020]	0.127*** [0.009]	0.862*** [0.009]	0.079*** [0.017]	5.596** [2.401]	0.959*** [0.327]
Energy	0.045** [0.021]	0.071*** [0.006]	0.925*** [0.006]	−0.360 [0.296]	2.530* [1.485]	0.512 [0.343]
Financial	0.073*** [0.018]	0.122*** [0.008]	0.862*** [0.009]	0.079*** [0.013]	9.810*** [2.974]	0.810*** [0.212]
Health care	0.061*** [0.015]	0.107*** [0.010]	0.850*** [0.015]	0.215*** [0.061]	33.669 [25.212]	−0.113 [0.081]
Industrial	0.062*** [0.017]	0.098*** [0.010]	0.868*** [0.013]	0.233*** [0.039]	31.848* [17.606]	0.254*** [0.095]
Information technology	0.089*** [0.018]	0.100*** [0.010]	0.868*** [0.014]	0.183*** [0.044]	28.661* [16.839]	0.410*** [0.100]
Materials	0.063*** [0.020]	0.098*** [0.009]	0.878*** [0.011]	0.183*** [0.038]	8.320** [3.418]	0.615*** [0.132]
Real estate	0.064*** [0.020]	0.127*** [0.009]	0.862*** [0.009]	0.079*** [0.017]	5.596** [2.401]	0.959*** [0.327]
Utilities	0.048*** [0.016]	0.097*** [0.009]	0.875*** [0.013]	0.151*** [0.057]	16.728 [12.370]	0.079 [0.107]

Note: The table reports the estimated coefficients and their associated standard errors in square brackets for our predictive GARCH-MIDAS model for US sectoral Stock returns volatility incorporating corporate profit as a predictor. The conventional GARCH-MIDAS model that includes realized volatility (RV) is considered the benchmark, and each row corresponds to the US sector whose stocks are considered. The model parameters reported in the table include the unconditional mean sectoral stock returns (τ), the ARCH term (α), the GARCH term (β), the MIDAS slope coefficient that indicates the predictability stance (δ), the adjusted beta polynomial weight (w), and the long run constant term (m).
***, **, and *, respectively, denote statistical significance at 1%, 5%, and 10% levels of significance.

TABLE 3 | Out-of-sample forecast evaluation using modified Diebold and Mariano test.

	$h = 20$	$h = 60$	$h = 120$
Aggregate	−2.8149***	−2.8493***	−2.9041***
Communication services	−4.5164***	−4.6017***	−4.8414***
Consumer discretionary	−4.4128***	−4.4771***	−4.5990***
Consumer staples	−5.4259***	−5.4408***	−5.4649***
Energy	−5.8195***	−5.7394***	−5.6090***
Financial	−5.3936***	−5.4084***	−5.4153***
Health care	−5.7971***	−5.8373***	−5.9052***
Industrial	1.6153	1.5947	1.5632
Information technology	−0.7598	−0.7906	−0.8556
Materials	−4.999***	−5.0779***	−5.2040***
Real estate	−5.4259***	−5.4408***	−5.4649***
Utilities	−3.572***	−3.5696***	−3.5829***

Note: The table presents the out-of-sample forecast performance analysis for the benchmark forecasting model (GARCH-MIDAS-RV) against its augmented variants incorporating corporate profit as a predictor for US sectoral stock returns volatility. The reported value in each cell is the estimated modified Diebold and Mariano statistic, where a negative and significant DM statistic value indicates better out-of-sample forecast performance of our predictive corporate profit-based GARCH-MIDAS model compared to the benchmark model. Each row corresponds to the US sector whose stocks are considered.
***, **, and *, respectively, denote statistical significance at 1%, 5%, and 10% levels of significance.

observations. This is to confirm that the in-sample predictability transcends the estimation period to the out-of-sample periods. We consider 20-, 60-, and 120- ahead forecast horizons for robustness. Consequently, we compare our GARCH-MIDAS-[Cprofit] with the benchmark GARCH-MIDAS-RV model using the modified Diebold and Mariano test. Table 3 presents the out-of-sample forecast precision comparison of the model pairs (our predictive and benchmark models). The modified Diebold and Mariano test null of equality in the forecast precision of the competing GARCH-MIDAS models is tested against an alternative of significant difference in forecast precision. We find consistently significantly negative modified Diebold and Mariano statistics across the forecast horizons and the sectors being considered. The significant negative implies that our predictive GARCH-MIDAS model is data-supported, which further confirms the stance of predictability of the corporate profit. In other words, corporate profit is statistically confirmed to be a relevant predictor of US sectoral stock volatility. Also, the results are robust to the sample interval definition.

5 | Conclusion

This study examines the possibility of fluctuation in sectoral stock prices amid variations in corporate profits. While the sample country is the United States, a GARCH-MIDAS approach is employed to investigate the relationship, owing to the need to maintain the datasets in their natural frequencies. Since the MIDAS model framework circumvents the likely information bias associated with data aggregation into a uniform frequency, it has found extensive use in econometrics for situations involving data at mixed frequencies. The impetus to adopt a methodology that takes into account this data phenomenon essentially stems from the fact that the stock returns are available on a daily frequency, whereas the predictor variable, US corporate profit, is available on a quarterly frequency. The study offers three contributions to the body of knowledge on the relationship between corporate profits and stock volatility: (i) the predictability—in- and out-of-sample—analyses of the nexus in contrast to the impact analysis that is popular in the literature, (ii) adoption of MIDAS framework to avoid loss of information that is peculiar to data aggregation or data splicing, and (iii) favoring the sectoral approach to capture the potential of heterogeneity in the nexus between corporate profits and the long-run volatility of stock returns of the different sectors listed in the S&P500.

The prominent conclusions from this study are drawn from both the in- and out-of-sample predictability results. Focusing on the MIDAS slope coefficient for the former, we show that given the consistently substantial positive slope coefficient across sectoral stocks, the US sectoral stock return volatility responds favorably to corporate profit. Although temporal, we equally find evidence of volatility persistence across these sectors. Moreover, in order not to be entrapped in the debates whether or not significant in-sample predictability evidence guarantees significant out-of-sample, we further extend our analysis to cover out-of-sample predictability of corporate profits for sectoral stock returns. We find robust evidence that confirms the position of the predictability of corporate profit for sectoral stock returns. Our results have implications for investors and portfolio managers who are constantly on the lookout for best-performing stocks in terms of profitability to invest. The study provides investors and other stock market participants with an understanding of future volatility, which can assist in their risk management, asset allocation, and option pricing. Further empirical studies could delve into whether or not higher corporate profits and increased stock performance translate into wider economic prosperity, especially for the government in terms of revenue and households in terms of higher income via more job opportunities.

Data Availability Statement

The data supporting this study's findings are available on request from the corresponding author. However, the data are not publicly available due to privacy or ethical restrictions.

References

Ali, H., and A. Y. Hegazy. 2022. "Dividend Policy, Risk and the Cross-Section of Stock Returns: Evidence From India." *International Review of Economics and Finance* 79, no. C: 169–192.

Anwar, S., S. Singh, and P. K. Jain. 2015. "Cash Dividend Announcements and Stock Return Volatility: Evidence From India." *Procedia Economics and Finance* 30: 38–49.

Asness, C. S., A. Frazzini, and L. H. Pedersen. 2019. "Quality Minus Junk." *Review of Accounting Studies* 24, no. 1: 34–112.

Bouri, E. 2015. "Oil Volatility Shocks and the Stock Markets of Oil-Importing MENA Economies: A Tale From the Financial Crisis." *Energy Economics* 51: 590–598. https://doi.org/10.1016/j.eneco.2015.09.002.

Bouri, E., B. Awartani, and A. Maghyereh. 2016. "Crude Oil Prices and Sectoral Stock Returns in Jordan Around the Arab Uprisings of 2010." *Energy Economics* 56: 205–214.

Bouri, E., A. A. Salisu, and R. Gupta. 2023. "The Predictive Power of Bitcoin Prices for the Realized Volatility of US Stock Sector Returns." *Financial Innovation* 9: 62. https://doi.org/10.1186/s40854-023-00464-8.

Engle, R. F., E. Ghysels, and B. Sohn. 2013. "Stock Market Volatility and Macroeconomic Fundamentals." *The Review of Economics and Statistics* 95, no. 3: 776–797.

Fama, E. 1970. "Efficient Capital Markets: A Review of Theory and Empirical Work." *Journal of Finance* 25: 383–423.

Fama, E. F., and K. R. French. 2015. "Choosing Factors." Working Paper. The University of Chicago.

Fama, E. F., and K. R. French. 2018. "Choosing Factors." *Journal of Financial Economics* 128: 234–252.

Guo, P., S. Li, and Y. Wang. 2023. "Asset Pricing With Dividend Surprises." https://ssrn.com/abstract=4494809.

Harvey, D., S. Leybourne, and P. Newbold. 1997. "Testing the Equality of Prediction Mean Squared Errors." *International Journal of Forecasting* 13, no. 2, 281–291.

Hou, K., H. Mo, C. Xue, and L. Zhang. 2017. "Which Factors? Working Paper, Fisher College of Business".

Hou, K., C. Xue, and L. Zhang. 2015. "Digesting Anomalies: An Investment Approach." *Review of Financial Studies* 28: 650–705.

Jiang, F., X. Qi, and G. Tang. 2018. "Q-Theory, Mispricing, and Profitability Premium: Evidence From China." *Journal of Banking and Finance* 87: 135. https://doi.org/10.1016/j.jeca.2023.e00342.

Khan, K., M. A. Nasir, and M. Rossi. 2017. "The Calendar Anomalies on Performance and Volatility of Stock Market: The Effects of Ramadan on Karachi Stock Exchange." *Global Business and Economics Review* 19, no. 1: 54–69. https://doi.org/10.1504/GBER.2017.080775.

Kyosey, G., M. X. Hanauer, J. Huij, and S. Lansdorp. 2020. "Does Earnings Growth Drive the Quality Premium?" *Journal of Banking and Finance* 114: 105785. https://doi.org/10.1016/j.jbankfin.2020.105785.

Liu, Y., B. Yang, and Y. Su. 2023. "Changes in Firm Profitability, Heterogeneous Investor Beliefs, and Stock Returns." *Journal of Management Science and Engineering* 8, no. 2: 258–272. https://doi.org/10.1016/j.jmse.2022.10.004.

Mahapatra, M., and S. N. Bhaduri. 2019. "Dynamics of the Impact of Currency Fluctuations on Stock Markets in India: Assessing the Pricing of Exchange Rate Risks." *Borsa Istanbul Review* 19, no. 1: 15–23. https://doi.org/10.1016/j.bir.2018.04.004.

Novy-Marx, R. 2013. "The Other Side of Value: The Gross Profitability Premium." *Journal of Financial Economics* 108, no. 1: 1–28. https://doi.org/10.1016/j.jfineco.2013.01.003.

Phan, T. K. H., and N. H. Tran. 2019. "Dividend Policy and Stock Price Volatility in an Emerging Market: Does Ownership Structure Matter?" *Cogent Economics & Finance* 7, no. 1: 1637051. https://doi.org/10.1080/23322039.2019.1637051.

Piotroski, J. D. 2000. "Value Investing: The Use of Historical Financial Statement Information to Separate Winners From Losers." *Journal of Accounting Research* 38: 1–41.

Quaye, E., and R. Tunaru. 2022. "The Stock Implied Volatility and the Implied Dividend Volatility." *Journal of Economic Dynamics and Control* 134, no. C: 104276. https://doi.org/10.1016/j.jedc.2021.104276.

Raza, R., S. J. H. Shahzad, A. K. Tiwari, and M. Shahbaz. 2016. "Asymmetric Impact of Gold, oil Prices and Their Volatilities on Stock Prices of Emerging Markets." *Resources Policy* 49: 290–301. https://doi.org/10.1016/j.resourpol.2016.06.011.

Salisu, A. A., R. Gupta, and R. Demirer. 2022. "Oil Price Uncertainty Shocks and Global Equity Markets: Evidence From a GVAR Model." *Journal of Risk and Financial Management* 15, no. 8: 1–26.

Shaik, A. M. 1995. *The Stock Market and the Corporate Sector: Profit Based Approach. Working Paper, No. 146*. Annandale-on Hudson, NY: Levy Economics Institute of Bard College.

Tachibana, M. 2018. "Relationship Between Stock and Currency Markets Conditional on the US Stock Returns: A Vine Copula Approach." *Journal of Multinational Financial Management* 46, no. C: 75–106.

Yin, L., and J. Nie. 2020. "Adjusted Dividend-Price Ratios and Stock Return Predictability: Evidence From China." *International Review of Financial Analysis* 73: 101618. https://doi.org/10.1016/j.irfa.2020.101618.

Yin, L., Y. Wei, and Y. Han. 2020. "Firms' Profit Instability and the Cross-Section of Stock Returns: Evidence From China." *Research in International Business and Finance* 53: 101203. https://doi.org/10.1016/j.ribaf.2020.101203.

Yu, X., and Y. Huang. 2021. "The Impact of Economic Policy Uncertainty on Stock Volatility: Evidence From GARCH–MIDAS Approach." *Physica A: Statistical Mechanics and its Applications* 570: 125794. https://doi.org/10.1016/j.physa.2021.125794.

Appendix A

TABLE A1 | GARCH-MIDAS-RV results.

Sectors	τ	α	β	δ	w	m
Aggregate	0.065*** [0.015]	0.118*** [0.011]	0.835*** [0.017]	0.007*** [0.001]	37.073** [17.053]	0.501*** [0.078]
Communication services	0.035** [0.017]	0.084*** [0.010]	0.857*** [0.021]	0.006*** [0.002]	37.374* [20.358]	0.654*** [0.105]
Consumer discretionary	0.068*** [0.017]	0.099*** [0.010]	0.867*** [0.016]	0.006*** [0.002]	26.521* [15.22]	0.687*** [0.150]
Consumer staples	0.068*** [0.019]	0.144*** [0.011]	0.824*** [0.017]	0.013*** [0.003]	49.977** [25.388]	0.586*** [0.222]
Energy	0.058** [0.023]	0.079*** [0.007]	0.914*** [0.008]	−0.001* [0.001]	49.504 [48.758]	3.428*** [1.142]
Financial	0.071*** [0.018]	0.137*** [0.010]	0.825*** [0.015]	0.011*** [0.002]	37.714*** [13.439]	0.684*** [0.156]
Health care	0.061*** [0.015]	0.106*** [0.010]	0.845*** [0.018]	0.004** [0.002]	49.704 [47.348]	0.624*** [0.104]
Industrial	0.062*** [0.017]	0.099*** [0.011]	0.856*** [0.018]	0.008*** [0.002]	49.889** [24.566]	0.559*** [0.112]
Information technology	0.088*** [0.018]	0.101*** [0.011]	0.858*** [0.018]	0.007*** [0.002]	39.33* [23.42]	0.719*** [0.162]
Materials	0.064*** [0.020]	0.101*** [0.010]	0.864*** [0.015]	0.009*** [0.002]	17.022** [7.494]	0.698*** [0.193]
Real estate	0.068*** [0.019]	0.144*** [0.011]	0.824*** [0.017]	0.013*** [0.003]	49.977** [25.388]	0.586*** [0.222]
Utilities	0.049*** [0.016]	0.102*** [0.010]	0.853*** [0.018]	0.006*** [0.002]	49.859 [35.47]	0.593*** [0.108]

Note: The table reports the estimated coefficients and their associated standard errors in square brackets for our predictive GARCH-MIDAS model for US sectoral Stock returns volatility incorporating corporate profit as a predictor. The conventional GARCH-MIDAS model that includes realized volatility (RV) is considered the benchmark, and each row corresponds to the US sector whose stocks are considered. The model parameters reported in the table include the unconditional mean sectoral stock returns (τ), the ARCH term (α), the GARCH term (β), the MIDAS slope coefficient that indicates the predictability stance (δ), the adjusted beta polynomial weight (w), and the long run constant term (m).
***, **, and *, respectively, denote statistical significance at 1%, 5%, and 10% levels of significance.