Firm-level Business Uncertainty and the Predictability of the Aggregate U.S. Stock Market Volatility during the COVID-19 Pandemic

Riza Demirer*, Rangan Gupta**, Afees A. Salisu*** and Reneé van Eyden****

Abstract

In this paper, we analyze the predictive role of firm-level business expectations and uncertainties derived from a panel survey of U.S. 1,750 business executives from 50 states for the realized variance (sum of daily squared log-returns over a month) of the S&P500 over the monthly period of September, 2016 to July, 2021. Unlike standard models, our predictive framework adopts a time-varying approach due to the existence of multiple structural breaks in the relationship between volatility and the predictors in the model, which in turn leads to statistically insignificant causal effects in a constant parameter set-up. Our time-varying results reveal the predictive power of firm-level business uncertainty is concentrated during the early part of the sample associated with the U.S.-China trade war, and towards the end of our data coverage in the wake of the outbreak of the COVID-19 pandemic. Since, in-sample predictability does not guarantee the same over an out-sample, we also conducted a full-fledged forecasting exercise to show that subjective expectations and uncertainties associated with sales growth rates and employment produces statistically significant predictability gains over January, 2020 to July, 2021, given an in-sample of September, 2016 to December, 2019. Our results suggest that subjective measures of business uncertainty at the firm-level indeed captures predictive information regarding aggregate stock market uncertainty which has important implications for investors and economic projections at the policy level.

Keywords: S&P500 Realized Variance; Firm-Level Expectations and Uncertainties; Time-Varying Predictability

JEL Codes: C32; C53; D80; G10

1. Introduction

Uncertainty is a key consideration in corporate investment planning and household spending projections. Despite the theoretical expectation that uncertainty at the firm-level should not matter for a fully diversified investor when it comes to portfolio decisions, in practice, from the perspective of corporate decision makers and business analysts, uncertainty at the firm-level poses a significant challenge, often leading to inaccurate cashflow projections and asset valuations. In the academic literature, a number of studies document a noticeable increase in firm-level volatility over the past several decades (e.g. Campbell et al., 2001; Comin and Philippon, 2005, Comin and Mulani 2006). The rise in uncertainty at the firm-level is argued to be driven in part by higher competition in the goods market, deregulation, high research and development activity, greater access to financing through debt and equity markets, and uncertainty due to monetary policy actions (Clance et al., 2020). Whatever the driving factors might be, one can argue that uncertainty at the firm-level can contribute to uncertainty at the aggregate market level as micro- or industry-level uncertainty can deter firms from undertaking new investment opportunities with serious implications for labor and product markets, thus affecting the whole economy. Against this

* Department of Economics and Finance, Southern Illinois University Edwardsville, Edwardsville, IL 62026- 1102, USA. Email: rdemire@siue.edu.

** Department of Economics, University of Pretoria, Private Bag X20, Hatfield, 0028, South Africa. Email: rangan.gupta@up.ac.za.

*** Corresponding author. Centre for Econometric & Allied Research, University of Ibadan, Ibadan, Nigeria; Department of Economics, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa. Email: adebare1@yahoo.com.

**** Department of Economics, University of Pretoria, Private Bag X20, Hatfield 0028, South Africa; Email: renee.vaneyden@up.ac.za.

backdrop, this paper takes on a novel approach to the predictability of stock market volatility by examining the predictive information captured by firm-level business expectations and uncertainties derived from a panel survey of U.S. 1,750 business executives from 50 states over the aggregate stock market volatility in the U.S. By doing so, this paper presents new insight to the propagation of uncertainty from the micro, firm-level to the aggregate stock market.

Clearly, subjective uncertainty perceived by business executives could be driven either by firm/industry level factors or by macro-level uncertainty drivers like policy actions, sentiment changes that affect funding conditions and investor behavior or disasters risks that affect production costs and labor market conditions, among others. One can thus argue that uncertainty in business conditions is a dynamic, time-varying phenomeon, and could change gradually or abruptly, as witnessed during the outbreak of the recent COVID-19 pandemic, thus immediately altering the outlook for corporate decision makers and affecting their investment and employment decisions. Naturally, the need for flexible measures of uncertainty is of paramount importance when it comes to modelling and predicting financial market dynamics. In this regard, there are primarily three approaches (Gupta et al., (2018)): First, past conditional volatility of asset returns, under the assumptions of rational expectations and stationarity, is used as a metric of uncertainty. Second, dispersion in point forecasts and? surprises in economic data releases is used to proxy for uncertainty (this sentence was not clear to me). Third, textual analysis of media coverage from newspapers and other text sources are used to construct uncertainty measures.

However, as pointed out by Altig et al., (2020), these approaches do not adequately capture the subjective uncertainty that business executives perceive at the micro-level, which is basically what drives their investment and employment decisions. Given this, Altig et al., (2020) develop a new survey instrument to measure the perceived uncertainty of senior decision makers in a large panel of U.S. firms. This innovative panel survey measures the one-year-ahead expectations and uncertainties that firms (across all regions of the U.S. economy, every industry sector except agriculture and government, and a broad range of firm sizes) have about their own employment and sales. Understandably, these indexes should be helpful in assessing the outlook for the U.S. economy, and the extent of uncertainty about the outlook around events like the coronavirus outbreak in the beginning of 2020. In our approach, we explore the propagation of firm-level uncertainty to the aggregate market by analysing the predictive power of these recently introduced subjective measures of business uncertainty over the aggregate stock market volatility in a time-varying framework that captures varying business conditions like the unprecedented economic slump observed during the COVD-19 pandemic.

More specifically, with the U.S. stock market volatility reaching exceptionally high levels since 2020 (see Figure A1 in the Appendix of the paper over our monthly sample period of 2016M09-2021M07), the objective of our analysis is to predict the realized variance (*RV*) of the S&P500 index using the information content of the business expectations and uncertainty indexes proposed by Altig et al., (2020). As pointed out by Poon and Granger (2003) and Rapach et al., (2008), return volatility is a key component of asset valuation, hedging as well as portfolio optimization models. Inaccurate predictions of volatility may lead to mis-pricing in financial markets, over/under-hedged business risks and incorrect capital budgeting decisions, with significant implications on earnings and cash flows. To that end, monitoring, modeling and predicting stock market volatility is crucial not only for investors and corporate decision makers, but also for policy makers in their assessment of financial fundamentals and investor sentiment. Given the importance of explaining the variability of the equity market, which is now at comparable levels to those witnessed during the Global Financial Crisis, and the fact that stock market volatility is driven by the uncertainty factors that relate to the volatility of cash flows and the discount factor (Shiller, 1981a, b), it makes perfect sense for us to analyse the role of expectations and uncertainties of U.S. firms regarding employment and sales in predicting the future path of the *RV* of S&P500.

At this stage, we must emphasize that measuring stock market volatility using *RV*, which, in our case is captured by the sum of daily squared returns over a month (following Andersen and Bollerslev, 1998), provides an accurate, observable and unconditional metric of volatility (unlike generalized autoregressive conditional heteroscedasticity (GARCH) and stochastic volatility (SV) models), which is otherwise a latent process (McAleer and Medeiros, 2008). To the best of our knowledge, ours is the first paper to use these new metrics of subjective uncertainty at the firm-level for predicting (both in and out-of-sample) *RV* of U.S. stock returns. Given this, our paper adds to the already existing large literature on the modeling and predictability of U.S. stock returns volatility based on a wide array of models and predictors including those that are macroeconomic, financial, and behavioural in nature (see, Ben Nasr et al., (2016), Salisu et al., (2020), Liu and Gupta (2021) for detailed reviews), by considering the role of subjective expectations and uncertainties associated with firm-level decisions.

As far as the econometric framework is concerned, in addition to the standard Granger causality test, we primarily draw our predictive inferences from a time-varying parameter vector autoregressive (VAR) model-based causality test that has been recently proposed by Rossi and Wang (2019). The use of this model is important as it not only controls for regime-changes in the relationship between *RV* and the predictors (which we show to exist formally based on statistical tests), but it also allows us to date-stamp the periods for which predictability holds. If predictability is indeed time-varying, it would provide us with an indication as to whether the result is contingent on the expectations and uncertainties to cross specific thresholds, besides highlighting the effect on predictions during the highly uncertain period associated with the ongoing COVID-19 pandemic. Time-varying predictability is surely of greater value, relative to a one-shot evidence based on a constant parameter approach, to investors and policymakers in terms of making their respective decisions (Karmakar and Roy, 2021; Karmakar et al., 2021). Since in-sample predictability does not guarantee forecasting gains, and considering that the ultimate test of any predictive model (in terms of the econometric methodologies and predictors employed) is its out-of-sample performance (Campbell, 2008), we also conduct a forecasting exercise for *RV* over the Coronavirus period, i.e., 2020M1 to 2021M7 (given an in-sample of 2016M09-2019M12). Indeed, our results suggest that the predictive power of firm-level business uncertainty is concentrated during the early part of the sample associated with the U.S.-China trade war, and towards the end of our data coverage in the wake of the outbreak of the COVID-19 pandemic. The out-of-sample analysis further shows that subjective expectations and uncertainties associated with sales growth rates and employment produces statistically significant predictability gains as well. Our results suggest that subjective measures of business uncertainty at the firm-level indeed captures predictive information regarding aggregate stock market uncertainty which has important implications for investors and economic projections at the policy level. The rest of the paper is organized as follows: Section 2 outlines the data and methodology, while Section 3 presents the empirical findings, and Section 4 concludes.

2. Data and Methodology

The stock price data we use for our analysis corresponds to the closing values of the daily S&P500 index, and is obtained from the FRED database of the Federal Reserve Bank of St. Louis.[1] The

[1] The data is downloadable from: https://fred.stlouisfed.org/series/SP500.

stock price data is converted into log returns in percentage, i.e., the first-difference of the natural logarithm of the price multiplied by 100, and then *RV* is computed as the sum of daily squared returns over a month. Our monthly predictors namely, expectations and uncertainties of Sales Revenue Growth and Employment Growth, are derived from the Atlanta Fed/Chicago Booth/Stanford Survey of Business Uncertainty (SBU),[2] as designed by the Federal Reserve Bank of Atlanta in partnership with Professor Steven J. Davis of the University of Chicago Booth School of Business and Professor Nicholas A. Bloom of Stanford University. The core survey questions elicit five-point subjective probability distributions over each firm's own future sales growth and employment. The look-ahead horizon is four quarters or twelve months, depending on the outcome variable. Survey respondents freely select five support points and then assign probabilities to each. This approach affords great flexibility for the respondent, allowing for high or low expected growth, uncertain or predictable outlooks, and negative or positive skew in the distribution over future outcomes. Using the subjective probability distributions, the survey measures expected future outcomes and the uncertainty surrounding those outcomes for each firm. For further technical details, the reader is referred to Altig et al., (2020). Based on data availability of the predictors, our analysis covers the monthly period of September, 2016 (2016M09) to July, 2021 (2021M07).

Table A1 in the Appendix of the paper provides the summary statistics of the variables. We observe the highest (lowest) means in the case of Employment Growth Uncertainty (Employment Growth Expectations), while Sales Revenue Growth Expectations (Employment Growth Uncertainty) commands the highest (lowest) standard deviation among the predictors. Moreover, all variables barring the expectations of employment growth, are found to be non-normal. Also Figure A1 plots the data, and as can be seen, uncertainties associated with sales and employment growth has jumped up following the outbreak of the COVID-19 pandemic, as has the *RV* of the S&P500. We also observe that expectations of sales growth turned negative during this period, while employment growth became very volatile since the onset of 2020. Understandably, preliminary analysis of the data plots seems to suggest a relationship between stock market volatility and the subjective measures of business expectations and uncertainties, in particular during the period of the ongoing Coronavirus pandemic.

In terms of the main econometric model used in this paper, we rely on the approach by Rossi and Wang (2019) to analyze the time-varying impact of the expectations and uncertainties of sales and employment on *RV*. Due to the existence of structural breaks, which we detect statistically, this approach tends to provide a more reliable inference on predictability rather than a constant parameter Granger causality method.

Formally, we consider the following VAR model with time-varying parameters:

$$y_t = \Psi_{1,t} y_{t-1} + \Psi_{2,t} y_{t-2} + \cdots + \Psi_{p,t} y_{t-p} + \varepsilon_t \tag{1}$$

where $\Psi_{j,t}$, $j = 1, \ldots p$ are functions of time varying coefficient matrices, $y_t = [y_{1,t}, y_{2,t}, \ldots, y_{n,t}]'$ is an $(n \times 1)$ vector and the idiosyncratic shocks ε_t are assumed to be heteroscedastic and serially correlated.

The variables included in our VAR constitutes of two endogenous variables[3] namely, *RV* and *Xj*, *j*=1,…4, in a bivariate set-up, with *X* including expectations and uncertainties of Sales Revenue

[2] The data is available for download from: https://www.atlantafed.org/research/surveys/business-uncertainty?panel=1.

[3] Given the evidences provided by Mumtaz and Theodoridis (2020) and Ludvigson et al., (forthcoming) that U.S. uncertainty could be endogenous, the usage of the VAR framework is more appropriate relative to a predictive

Growth, and the same for Employment Growth. We test the null hypothesis that *Xj* does not Granger cause *RV* for all *t* where the null hypothesis is $H_0: \phi_t = 0 \text{ for all } t = 1,2, \ldots, T$, given that ϕ_t is appropriate subset of $vec\ (\Psi_{1,t}, \Psi_{2,t}, \ldots, \Psi_{p,t})$. To this end, Rossi and Wang (2019) suggest four alternative test statistics namely: the exponential Wald (*ExpW*), mean Wald (*MeanW*), Nyblom (*Nyblom*) and Quandt Likelihood Ratio (*SupLR*) tests. Based on the Schwarz Information Criterion (SIC), the VAR model is estimated using 1 lag. We use an end-point trimming of 5% in the bivariate set-up.

3. Empirical Findings

In Table 1, to analyze the predictive ability of expectations and uncertainties of Sales Revenue Growth and Employment Growth on *RV* in a bivariate set-up, we first started with the standard constant parameter Granger causality test and found that none of the predictors, i.e., *Xj*'s, Granger causes *RV* at the conventional 5% level of significance. Note that, weak (at the 10% level of significance) predictive effect is detected only in the case of causality running from the Employment Growth Expectations to the aggregate stock market volatility. However, based on the powerful *UDmax* and *WDmax* tests of Bai and Perron (2003), used to detect 1 to *M* structural breaks in the *RV* equation of the four VAR(1) models, allowing for heterogeneous error distributions across the breaks and 5% trimming, yielded 5 (2018M01, 2018M09, 2019M08, 2020M04, 2020M12); 3 (2019M07, 2020M03, 2020M11); 5 (2018M02, 2018M10, 2019M08, 2020M04, 2020M12), and; 4 (2018M01, 2019M08, 2020M04, 2020M12) breaks under *Xj*, *j*=1,…4, respectively. In general, the break points are found to correspond to the dramatic escalation of trade policy tensions under the Trump Administration, and the coronavirus pandemic of 2020.

Given this evidence of instability, the results from the constant parameter model is not robust, and hence to obtain reliable inference, we look at the *ExpW*, *MeanW*, *Nyblom*, and *SupLR* tests of Rossi and Wang (2019) based on the time-varying VAR, results of which are also reported in Table 1. As can be seen, the null hypotheses of no-Granger causality from including the expectations and uncertainties of sales revenue and employment (i.e., X*j*, *j*=1,…4) to *RV* are overwhelmingly rejected at the highest possible level of significance across all the four tests (barring the *Nyblom* test statistic for Sales Revenue Growth Expectations), and the four predictors considered by turn.[4, 5] In other words, the predictive ability of including *Xj*, *j*=1,…4 for *RV* is in fact time-varying and exceptionally strong, even though virtually no evidence of predictability is observed from the constant parameter model.[6]

regression model. In fact, we did detect strong evidence (mostly at the 1% level) of time-varying causal feedbacks from *RV* to the four predictors, detailed results of which are available upon request from the authors.

[4] As reported in Table A1 in the Appendix of the paper, our findings of strong evidence of time-varying predictability continues to hold even from the smoothed versions (based on three-month lagged moving averages) of the four main predictors of our concern. In addition, *RV* is also found to be highly predictable by Expected Sales and Job Reallocation, and some discontinued predictors namely, expectations and uncertainties of Investment Rate and Businesses, with the data also derived from the work of Altig et al., (2020).

[5] In Table A1, we also depict strong predictability emanating from uncertainties and expectations of Sales Revenue Growth for *RV* (sum of daily squared log-returns in percentage over a month) of the FTSE100 of the United Kingdom (UK), i.e., international evidence. Note that, the data on predictors are derived from the Decision Maker Panel (DMP), available for download at: https://decisionmakerpanel.co.uk/. The DMP was set up in August 2016 by the Bank of England, Stanford University and the University of Nottingham. It provides direct insight into business expectations and uncertainty, for example due to COVID-19 and Brexit. The panel draws information from Financial Officers in UK companies operating in a broad range of industries, and is designed to be representative of the population of UK businesses. The closing prices of daily FTSE100 stock index data in turn is obtained from the Wall Street Journal at: https://www.wsj.com/market-data/quotes/index/UK/UKX/historical-prices.

[6] The time-varying response of the RV for uncertainties associated with growths of sales revenue and employment is consistently positive throughout the sample period, with a massive peak following the outbreaks of the COVID-19 pandemic. As far as the expectations are concerned, strong negative impacts on RV are observed during the

[INSERT TABLE 1]

Next in Figures 1 to 4, we present the whole sequence of the Wald statistics over time, which gives more information on when the Granger-causality occurs. As can be seen, from Figure 1, Sales Revenue Growth Expectations is found to consistently predict *RV* virtually over the entire sample period, with a brief exception towards the end of 2019. A similar predictability behaviour is also depicted by uncertainties involving Sales Revenue Growth (see Figure 2) and Employment Growth (see Figure 3), though in this case, the lack of causality on to *RV* is for a bit longer and covers mid- to end-2019. These phases are generally associated with strong expectations of Sales Revenue Growth and relatively lower uncertainties involving sales revenue and employment (see Figure A1). Compared to these 3 predictors, the causal effect of the Employment Growth Expectations is much more intermittent, with significant predictions only observed at the beginning of the sample period, over 2018 to 2019, and for a short-span following the outbreak of the Coronavirus pandemic in 2020 (see Figure 4). The causal pattern fluctuates just like the predictor itself (see Figure A1). In sum, our finding show that all the predictors provide evidence of time-varying predictability for *RV*, with the strongest impact (in terms of the sample-coverage of the significant test statistic) coming from the Sales Revenue Growth Expectations, followed by uncertainties associated with the growth rates of sales revenue and employment, and then finally, due to Employment Growth Expectations. In addition, given the information provided by relatively higher values of the test statistic, strong predictability is primarily concentrated during the height of the bitter trade battle involving the world's two largest economies namely, the U.S. and China, whereby tariffs worth of hundreds of billions of dollars on one another's goods were imposed, and since the onset of 2000, following the emergence of the COVID-19 pandemic.

[INSERT FIGURES 1 TO 4]

As it is well-known that in-sample predictability does not necessarily translate over an out-of-sample, we conducted a forecasting exercise, with the latter being a stricter test of predictability. In this regard, we use the recursively estimated VAR model, over the COVID-19 outbreak period of 2020M1 to 2021M7, with an in-sample of 2016M09 to 2019M12, to produce and compare one-step(month)-ahead forecasts for *RV* with and without the predictors. Table 2, reports the Mean Square Forecast Errors (MSFEs) for *RV* from the VAR(1) model with the four predictors relative to the same from the AR(1) model of RV, i.e., the case without the expectations and uncertainties-related variables. As can be seen, the Relative MSFEs are less than one in all the four cases, suggesting that the VAR(1) model of *RV* produces lower MSFEs than its AR(1) alternative, i.e., adding the predictors in fact reduces the forecasting errors associated with S&P500 volatility.[7] In general, consistent with the results of the time-varying Granger causality test, Sales Revenue Growth Expectations produces the strongest performance with a gain of 6.1884%, followed by the uncertainty of the same (5.2338%), and then uncertainties (5.7281%) and expectations (5.5228%) of Employment Growth. More importantly, using the *MSE-F* test of McCracken (2007), the forecasting gains derived from expectations and uncertainties of the growth rates of sales revenue and employment are statistically significant at the 5% level, relative to the nested AR(1) benchmark (which excludes the predictors).

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coronavirus period, when the values of these predictors were negative conveying bad news, and resulting in sharp increases in volatility due to the leverage effect. Complete details of these results are available upon request from the authors.

[7] A forecasting exercise based on a 50% in- and out-of-sample split also produced forecasting gains except under the case of Sales Revenue Growth Uncertainty. Complete details of these results are available upon request from the authors.

[INSERT TABLE 2]

Overall, our fundings indicate that the measures of subjective expectations and uncertainties associated with firm-level decisions on sales revenue and employment growth do carry strong evidence of both in- and out-of-sample time-varying predictability for the realized volatility of aggregate stock market returns, especially during periods of heightened uncertainty associated with the U.S.-China trade war and of course during the recent Coronavirus outbreak. Considering the evidence that monetary policy can affect stock market valuations via its effects on risk taking behaviour in financial markets (e.g. Rajan, 2006; Adrian and Shin, 2008; and Borio and Zhu, 2008), one can argue that the predictive power of subjective measures of uncertainty at the firm-level, particularly during periods of heightened uncertainty associated with the US-China trade relations and pandemic relief actions, could be driven by a discount rate channel in which uncertainty regarding governmental policies affects risk taking behaviour by investors and corporations alike, which in turn, contributes to the predictive relationship captured in our tests. Nevertheless, our findings clearly suggest that uncertainty regarding business conditions at the micro level can indeed propagate to the aggregate stock market, creating a predictive relationship between micro and macro level uncertainty proxies.

4. Conclusions

In this paper, we examine the predictability of the realized variance (*RV*, i.e., sum of daily squared log-returns over a month) of S&P500 based on information provided by expectations and uncertainties associated with the sales and employment growth rates at the firm-level, derived from a panel of surveys conducted on a large number of U.S. firms. Using monthly data over the period of September, 2016 to July, 2021, we find that standard Granger causality tests derived from constant parameter VAR models fail to detect any evidence of predictability from the firm-level predictors for *RV* at conventional levels of statistical significance. But we show that this result is not surprising, given the existence of regime changes in the predictive relationship, based on formal statistical tests of multiple structural breaks. In light of this finding, when we rely on a predictability test based on a time-varying parameter VAR model, which is robust to misspecification in the linear model due to breaks, we find strong evidence of time-variant predictability from all the four predictors. A particularly strong causal effect is derived from the expectations of Sales Revenue Growth, and the uncertainties associated with the growth rates of both sales revenue and employment, and during the two-ends of our sample period which corresponded to the U.S.-China trade war and the ongoing Coronavirus outbreak. With in-sample predictions not necessarily guaranteeing out-of-sample gains, we also conducted a formal forecasting exercise over January, 2020 to July, 2021, based on the training period of September, 2016 to December, 2019. The forecasts for *RV* generated based on a recursively estimated VAR model involving the predictors over the out-of-sample period is found to be statistically more accurate than those derived from an AR model of the same, indicating that business expectations and uncertainties at the firm-level have strong causal in- and out-of-sample time-varying effects on *RV* of the S&P500.

Our findings have important implications for portfolio managers and policy authorities. Recall that, when volatility is interpreted as uncertainty, it becomes a key input to investment decisions and portfolio choices. Investors can bear a certain level of risk, and a good forecast of volatility of asset prices over the investment-holding period is a good starting point for assessing investment risk. Further, volatility is the most important variable in the pricing of derivative securities, as to correctly price an option, one needs to have an accurate estimate for the volatility of the underlying asset from the current period to its expiration. Given this, as our results show, traders in the U.S.

equity market can use the information contained in expectations and uncertainties of sales revenue and employment growth rates in order to produce accurate forecasts of observable volatility. Moreover, financial risk management according to the Basel Accord also requires modeling and forecasting of volatility as a compulsory input to risk-management for financial institutions. So banks and trading houses can use forecasts of volatility based on these firm-level predictors derived from firms-based surveys in order to set aside reserve capital of at least three times that of Value-at-Risk (VaR), which in turn are readily available given volatility forecast, mean estimate and a normal distribution assumption for the changes in total asset value. Finally, financial market volatility, as witnessed during the recent outbreak of the COVID-19 pandemic, has had wide repercussions on the economy as a whole (Gupta et al., 2021), via its effect on real economic activity and public confidence. Hence, accurate forecasts of market volatility based on business expectations and uncertainties can serve as a measure for the vulnerability of financial markets and the economy, and can help policymakers design appropriate policies. Evidently, appropriate modeling and accurate forecasting of the process of volatility has ample implications for portfolio selection, the pricing of derivative securities and risk management.

As part of future research, it would be interesting to extend our analysis to the U.S. industry-level stock returns volatility predictions based on these metrics of business expectations and uncertainties, and to check, if the impacts are heterogeneous across sectors.

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Table 1. In-sample Tests of Predictability of S&P500 Realized Variance (*RV*)

Predictor (*X*)	Granger Causality	Rossi-Wang Causality			
	$\chi^2(1)$	*ExpW*	*MeanW*	*Nyblom*	*SupLR*
Sales Revenue Growth Expectations	0.0327	79.9971***	68.8771***	1.846	167.9038***
Sales Revenue Growth Uncertainty	0.0155	65.6796***	56.7007***	55.6788***	139.1011***
Employment Growth Expectations	3.6785*	20.7471***	12.2541***	247.4694***	49.3971***
Employment Growth Uncertainty	0.1051	97.5583***	39.5463***	29.5824***	203.0268***

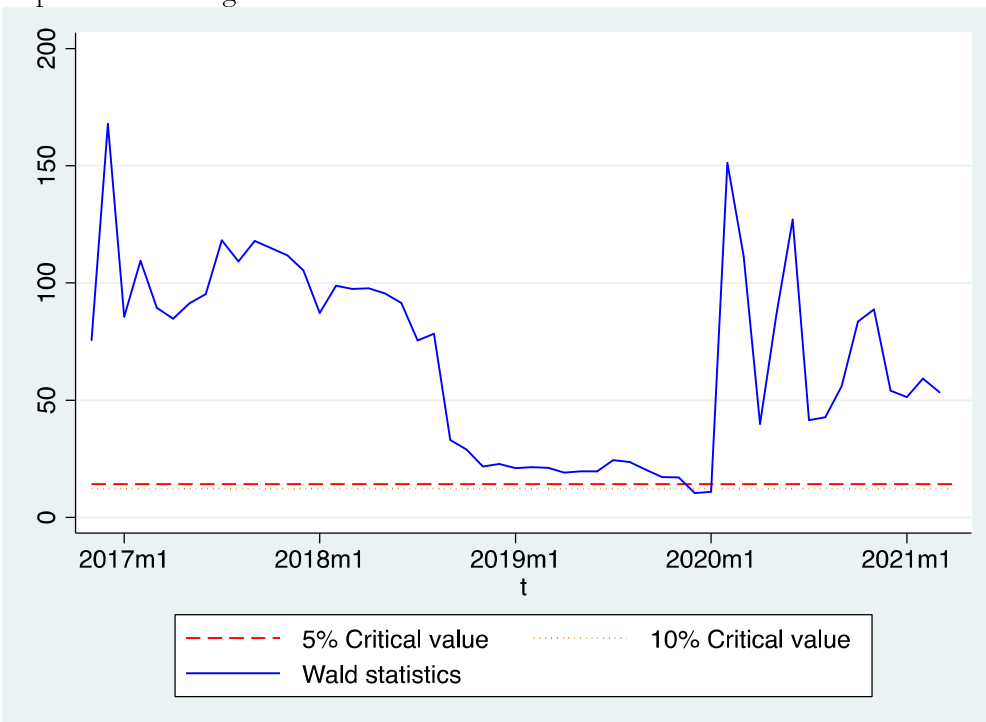
Note: *** and * indicates rejection of the null-hypothesis of no-Granger causality at 1% and 10% levels of significance respectively.

Table 2. Out-of-Sample Forecasting Performance of Predictors for S&P500 Realized Variance (*RV*) over 2020M01-2021M07

Predictor	Relative MSFE	*MSE-F* Test Statistic
Sales Revenue Growth Expectations	0.9381	1.2534**
Sales Revenue Growth Uncertainty	0.9417	1.1766**
Employment Growth Expectations	0.9477	1.0493**
Employment Growth Uncertainty	0.9427	1.1545**

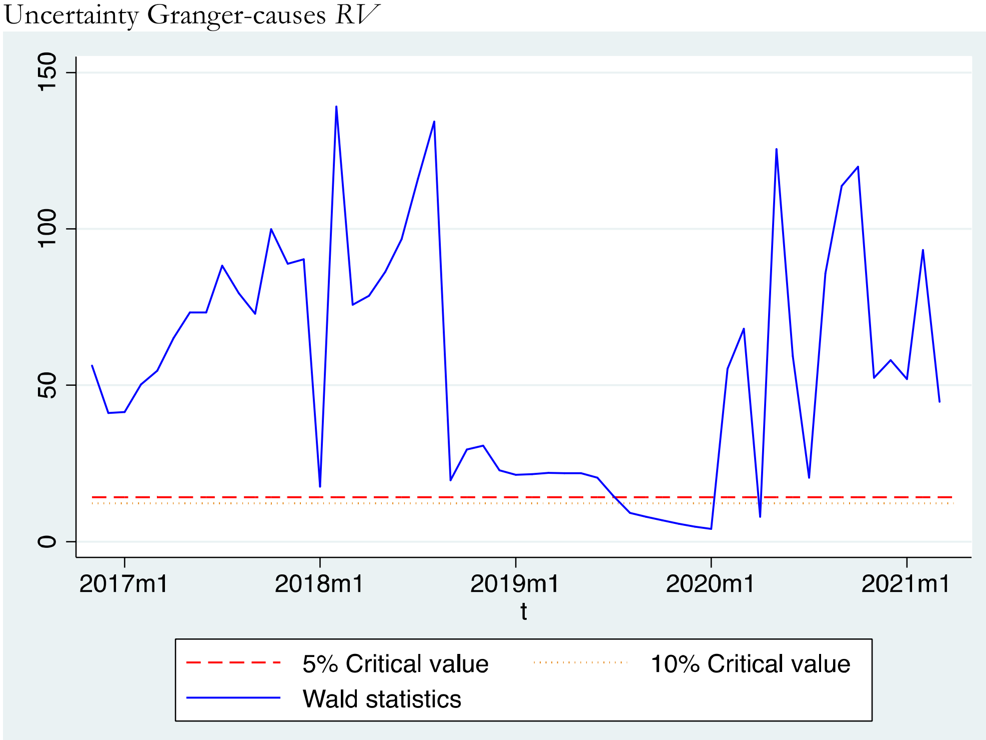
Note: Relative Mean Square Forecast Error (MSFE) corresponds to the MSFE of the VAR(1) model of *RV* with predictors relative to the AR(1) model of *RV*; ** indicates significance of the *MSE-F* test at the 5% level of significance, given the critical value of 1.0380.

Figure 1. Time-varying Wald statistics for the VAR(1) testing whether Sales Revenue Growth Expectations Granger-causes *RV*



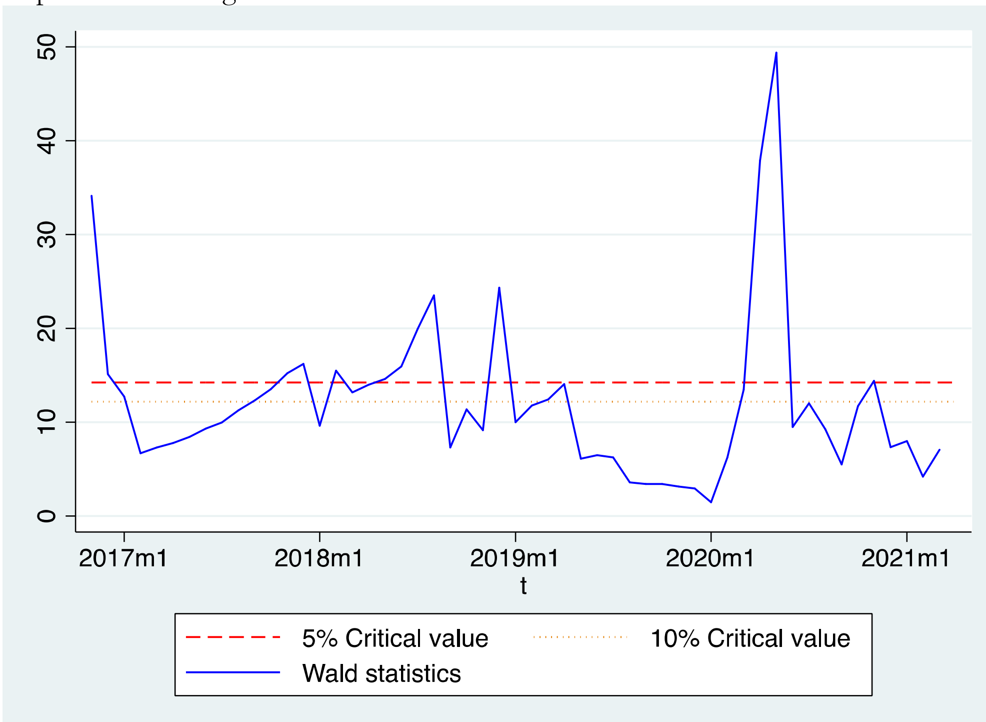
Note: *t*: corresponds to monthly data period; and the vertical axis measure the test statistic.

Figure 2. Time-varying Wald statistics for the VAR(1) testing whether Sales Revenue Growth Uncertainty Granger-causes *RV*



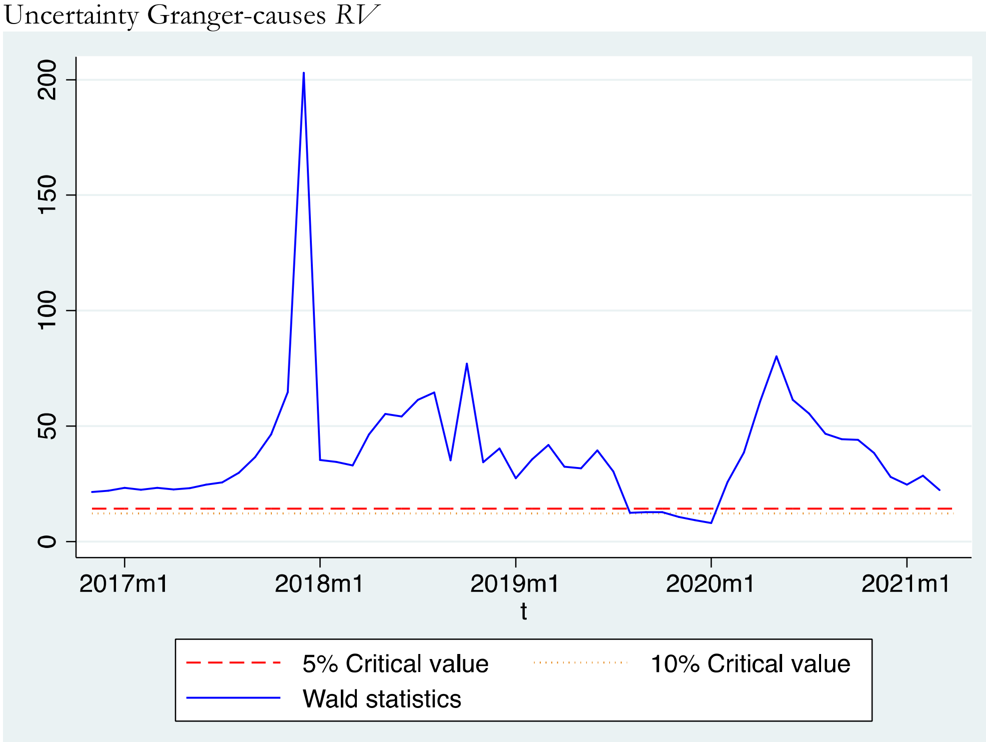
Note: See Notes to Figure 1.

Figure 3. Time-varying Wald statistics for the VAR(1) testing whether Employment Growth Expectations Granger-causes *RV*



Note: See Notes to Figure 1.

Figure 4. Time-varying Wald statistics for the VAR(1) testing whether Employment Growth Uncertainty Granger-causes *RV*



Note: See Notes to Figure 1.

APPENDIX:

Table A1. Summary Statistics

	Variable				
Statistic	S&P500 Realized Variance (*RV*)	Sales Revenue Growth Expectations	Sales Revenue Growth Uncertainty	Employment Growth Expectations	Employment Growth Uncertainty
Mean	30.1315	4.1618	3.6223	1.6888	4.3555
Median	8.4651	4.3774	3.2008	1.6543	4.1108
Maximum	747.3868	6.5869	6.3146	3.6958	6.5332
Minimum	1.8641	-2.4152	2.3830	0.1088	3.5267
Std. Dev.	97.6563	1.6063	1.0315	0.8095	0.6929
Skewness	6.9055	-1.7889	1.1232	0.4165	1.2152
Kurtosis	51.0681	7.5425	2.9922	3.0082	3.8964
Jarque-Bera	6148.9910***	82.1943***	12.40634***	1.7058	16.4966***
Observations	59				

Table A1. Additional In-sample Tests of Predictability of S&P500 Realized Variance (*RV*)

Predictor (*X*)	Sample	Granger Causality	Rossi-Wang Causality			
		$\chi^2(1)$	*ExpW*	*MeanW*	*Nyblom*	*SupLR*
Sales Revenue Growth Expectations (Smoothed)	2016M12-2021M07	0.3577	184.8355***	60.9927***	23.3163***	377.4749***
Sales Revenue Growth Uncertainty (Smoothed)	2016M12-2021M07	0.0805	615.6218***	92.6806***	72.6037***	1239.0476***
Employment Growth Expectations (Smoothed)	2016M12-2021M07	0.0206	10.0879***	11.7213**	9.7493***	27.4952***
Employment Growth Uncertainty (Smoothed)	2016M12-2021M07	0.0257	53.9317***	40.1984***	75.6973***	115.6596***
Expected Sales Reallocation	2016M09-2021M07	0.0218	120.6597***	129.8633***	5.3841***	1782.2468***
Expected Job Reallocation	2016M09-2021M07	0.0373	459.6015***	130.8458***	2.6379*	927.1132***
Investment Rate Expectations	2015M01-2020M07	4.2952***	60.7788***	23.3489***	5728.8952***	129.7261***
Investment Rate Uncertainty	2015M01-2020M07	4.0007***	84.513***	31.3972***	4186.4941***	177.1945***
Business Expectations	2015M01-2020M07	0.132	41.5166***	61.9258***	31.9577***	2485.207***
Business Uncertainty	2015M01-2020M07	0.1693	66.9501***	42.1358***	10.2144***	142.0688***
Sales Revenue Growth Expectations of the UK	2016M09-2021M03	0.7415	192.1828***	26.8178***	44.5144***	392.1328***
Sales Revenue Growth Uncertainty of the UK	2016M09-2021M03	9.133***	154.9488***	53.4522***	793.0959***	317.665***

Note: ***, ** and * indicates rejection of the null hypothesis of no Granger causality at 1%, 5% and 10% levels of significance respectively.

Figure A1. Data plots