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SOCIAL MEDIA SENTIMENT AND STOCK MARKET VOLATILITY: EVIDENCE FROM THE US HI-TECH COMPANIES

Anupam Dutta[A]

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ABSTRACT

Purpose: This study aims to investigate the effects of social media sentiment, measured by Twitter-based uncertainty index, on the stock market volatility of the US technology companies.

Design/methodology/approach: Methodologically, we employ the quantile regression model. Our findings reveal that the volatility of Amazon, Apple, Google and IBM stocks are sensitive to the variations in twitter-based economic and market uncertainties (i.e., TEU and TMU indexes).

Findings: We observe significant influences at both lower and upper quantiles. Thus, for both high and low volatility regimes, the information on twitter-based uncertainty indexes can be used to predict the market volatility of these leading hi-tech companies. Moreover, TEU and TMU indexes exert positive effects on the stock price implied volatility implying that the variance of these technology firms experiences an upward trend as the social media uncertainty rises.

Originality/value: While numerous studies have focused on the influence of social media (e.g., Facebook, twitter etc.) on investment strategies, the impact of twitter sentiments on the risk linked to hi-tech firms remains understudied. Hence, investors participating in the technology sectors could use our findings for managing portfolio risk.

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SENTIMENTO DAS MÍDIAS SOCIAIS E VOLATILIDADE NO MERCADO DE AÇÕES: EVIDÊNCIAS DAS EMPRESAS DE ALTA TECNOLOGIA DOS EUA

RESUMO
Objetivo: Este estudo tem como objetivo investigar os efeitos do sentimento de mídia social, medido pelo índice de incerteza baseado no Twitter, na volatilidade do mercado de ações das empresas de tecnologia dos EUA.
Projeto/Metodologia/Abordagem: Metodologicamente, empregamos o modelo de regressão quântico. As nossas conclusões revelam que a volatilidade das ações da Amazon, Apple, Google e IBM é sensível às variações das incertezas econômicas e de mercado baseadas no twitter (ou seja, os índices TEU e TMU).
Constatações: Observamos influências significativas em quantis inferiores e superiores. Assim, tanto para os regimes de alta e baixa volatilidade, as informações sobre índices de incerteza baseados no twitter podem ser usadas para prever a volatilidade do mercado dessas empresas líderes em alta tecnologia. Além disso, os índices TEU e TMU exercem efeitos positivos sobre a volatilidade implícita nos preços das ações, o que implica que a variância destas empresas de tecnologia registra uma tendência ascendente à medida que aumenta a incerteza das redes sociais.
Originalidade/valor: Embora numerosos estudos tenham focado na influência das mídias sociais (por exemplo, Facebook, twitter etc.) nas estratégias de investimento, o impacto dos sentimentos do twitter no risco ligado a empresas de alta tecnologia continua subestudado. Por conseguinte, os investidores que participam nos setores das tecnologias podem utilizar as nossas conclusões para gerir o risco de carteira.

Palavras-chave: Incerteza Baseada no Twitter, Inovação Tecnológica, Indústria de Alta Tecnologia dos EUA, Volatilidade Implícita no Mercado de Ações, Mídias Sociais.

[A] *PhD in Economics and Business Administration. University of Vaasa. Finland. E-mail: adutta@uwasa.fi*

SENTIMIENTO EN LOS MEDIOS SOCIALES Y VOLATILIDAD EN EL MERCADO DE VALORES: EVIDENCIA DE LAS EMPRESAS DE ALTA TECNOLOGÍA DE ESTADOS UNIDOS

ABSTRACTO
Propósito: Este estudio tiene como objetivo investigar los efectos del sentimiento de los medios sociales, medido por el índice de incertidumbre basado en Twitter, sobre la volatilidad del mercado de valores de las empresas tecnológicas de Estados Unidos.
Diseño/Metodología/Enfoque: Metodológicamente, empleamos el modelo de regresión cuantil. Nuestros hallazgos revelan que la volatilidad de las acciones de Amazon, Apple, Google e IBM son sensibles a las variaciones en las incertidumbres económicas y de mercado basadas en Twitter (es decir, los índices TEU y TMU).
Hallazgos: Observamos influencias significativas tanto en cuantiles inferiores como superiores. Por lo tanto, para los regímenes de alta y baja volatilidad, la información sobre los índices de incertidumbre basados en Twitter se puede utilizar para predecir la volatilidad del mercado de estas empresas líderes de alta tecnología. Además, los índices TEU y TMU ejercen efectos positivos sobre la volatilidad implícita de los precios de las acciones, lo que implica que la varianza de estas empresas tecnológicas experimenta una tendencia al alza a medida que aumenta la incertidumbre en los medios sociales.
Originalidad/Valor: Aunque numerosos estudios se han centrado en la influencia de los medios sociales (por ejemplo, Facebook, Twitter, etc.) en las estrategias de inversión, el impacto de los sentimientos de Twitter en el riesgo vinculado a las empresas de alta tecnología sigue siendo poco estudiado. Por lo tanto, los inversores que participan en los sectores tecnológicos podrían utilizar nuestros hallazgos para gestionar el riesgo de la cartera.

Palabras clave: Incertidumbre Basada en Twitter, Innovación Tecnológica, La Industria de Alta Tecnología de EE. UU., Volatilidad Implícita en el Mercado de Valores, Medios Sociales.

1 INTRODUCTION

The influence of social media (Facebook, Twitter, etc.) on investment strategies has recently received considerable attention from researchers and academics (Rao and Srivastava, 2014; Li et al., 2014; Nguyen et al., 2015; Mao et al., 2015; Pagolu et al., 2016; Ho et al., 2017). Given that investors often share information on various assets using Facebook or X, social networking services could play a key role in predicting financial market returns. Nguyen et al. (2015), for example, provide empirical evidence that mood information from social media has significant predictive contents for stock market data. Several recent studies (Ho et al., 2017 and Teti et al., 2019) also reach similar conclusions.

The main purpose of this paper is to investigate the predictive power of social media for stock price volatility of the US technology firms. In doing so, we contribute to the existing literature in several aspects. First, based on our knowledge, this is the initial attempt to use the information content of twitter uncertainty indexes, recently developed by Baker et al. (2020), for the purpose of predicting stock market volatility. Baker et al. (2020) have constructed two different indexes: Twitter-based Economic Uncertainty (TEU) Index and Twitter-based Market Uncertainty (TMU) Index. The use of these indexes is particularly beneficial for studying equity price movements given that they are constructed on the basis of keywords related to equity markets such as 'equities', 'equity', 'equity-holder', 'equity-holders', 'finance', 'financeable', 'financed', 'finances', 'financial', 'financially', 'financials', 'financier', 'financiers', 'financing', 'financings', 'investment', 'investments', 'investor', 'investors', 'invests', 'market', 'markets', 'trader', 'traders', 'trades', 'trading', and 'tradings'.

Second, while earlier studies are mainly focused on the influence of social media on stock returns, the impact of social networking services on equity market volatility remains understudied. Understanding the volatility of equity prices is crucial given that it plays a pivotal role in portfolio allocation, risk management, asset pricing and investment decisions. Accordingly, market participants require sound knowledge on stock market risk and its forecasting. Note that the US technology industry attracts the investors due to the fact that the hi-tech stocks perform better than the other sectoral equity markets. For instance, the Dow Jones US Technology Index has increased 103% over the last five years compared to the 59% growth observed in the Dow Jones industrial average (DJIA) index. However, these stocks can be highly volatile as well given that a hi-tech company might become obsolete overnight if its rival firm brings significant innovation to the market. Nevertheless, the literature studying the dynamics of the relationship between social media and volatility pattern of technology stocks is scarce. To fill this vacuum in the exiting literature, we examine the relationship between Twitter-based uncertainty and the volatility of a number of innovative firms in the US technology companies.

Third, a strand of literature has utilized the information on Arca Tech 100 index (PSE) when investigating the risk linked to technology firms (Sadorsky, 2012; Bondia et al., 2016). Contrasting to prior literature, we consider using the firm-specific volatility indexes for different hi-tech companies: Amazon, Apple, Google and IBM. Chicago Board Options Exchange (CBOE) has launched the implied volatility indexes (VIX) for these firms in January, 2010. The application of these indexes could be beneficial as we can directly compare the effects of twitter-based uncertainty on the risk of these leading technology companies.

This paper proceeds as follows. The following section consists of a brief review of relevant literature. Section 3 describes the data, while Section 4 outlines the methodology. Results are presented in Section 5. We conclude in Section 6.

2 RELATED LITERATURE

A number of articles have evidenced a significant connection between social media and stock market returns. Siganos et al. (2014), for example, utilize the Facebook's Gross National

Happiness Index to measure the effect of Facebook's daily sentiment on global stock markets. The authors find that the Facebook sentiment has a positive influence on international capital markets. Rao and Srivastava (2014) also document a high positive correlation between Twitter sentiments and equity returns. Moreover, Nofer and Hinz (2015) show that Twitter sentiments can be used to predict the German capital market. Using a standard event study methodology, Ranco et al. (2015) report that Twitter sentiments can lead to significant abnormal returns in the Dow Jones Industrial Average (DJIA) index.

In addition, Nguyen et al. (2015) find that the information publicized in social media has superior forecasting power compared to historical stock prices. Moreover, Sul et al. (2016) find that Twitter sentiments have substantial impacts on the future stock returns of the S&P 500 firms. Employing the latent space model, Sun et al. (2016) show that the information content of social media can predict the S&P 500 index better than the baseline regression approach. Ho et al. (2017) also find a significant relationship between social media sentiments and the US equity indexes. The authors further document that such linkage tends to vary over time. A recent study by Bartov et al. (2018) reveals that individual tweets could help market participants to successfully predict firm-level earnings and equity prices. More recently, Teti et al. (2019) find that Twitter sentiments can predict the US equity market.

Notably, our study is close to the work of Teti et al. (2019) who also investigate the linkage between twitter and stock prices of the US technology firms. We extend their work in several ways. First, while Teti et al. (2019) are focused on stock returns, we examine how the volatility of technology stocks responds to the information publicized in social media. Second, we have used the newly constructed twitter-based uncertainty indexes to predict firm-specific volatility of the leading hi-tech companies. Third, employing quantile regression (QR) process, we assess the impact of twitter uncertainty indexes on the stock price volatility of technology firms under varied market conditions.

3 DATA

The data on twitter-based uncertainty are available from the website of Economic Policy Uncertainty (http://www.policyuncertainty.com/index.html). In addition, the volatility indexes of Amazon, Apple, Google and IBM are retrieved from the website of CBOE (http://www.cboe.com/products/vix-index-volatility/volatility-indexes). Our sample period ranges from June 2011 to December 2022. In sum, we have 2917 daily observations.

Table 1 reports the summary statistics of different indexes used in this study. Of the two uncertainty indexes, TMU is more volatile than TEU. In addition, both series are positively skewed. Among the volatility indexes, on the other hand, only Apple is positively skewed. It is also observed that each of the series under consideration is leptokurtic as the kurtosis is significantly higher than 3. We further note that none of these indexes satisfies the normality assumption as evidenced by the Jarque-Bera test. Finally, the ADF and PP tests confirm the stationarity condition for each index.

Next, Table 2 exhibits the correlations among all the indexes. These numbers suggest that all the correlations are positive and statistically significant at 1% level. It is thus evident that when uncertainty rises, the volatility of technology firms also upsurges. Figure 1, which depicts the VIX series (a) and twitter indexes (b), also shows that the volatility of technology firms upsurges with the increase in TEU and TMU indexes. For instance, all these variables experience a significant escalation amid the COVID-19 pandemic period.

4 METHODOLOGY

This paper uses the quantile regression (QR) model to gauge the effects of twitter-based uncertainty on the volatility of technology stocks. Notably, the QR process not only offers a thorough investigation during the low and high risk periods for the equity market but also provides estimates which remain robust to outliers, heteroskedasticity, and skewness (Xiao et al., 2019).

The QR approach, developed by Koenkar and Bassett (1978), gains immense popularity among the researchers and academics due to the fact that unlike the ordinary least squares regression, it estimates the rates of change in different quantiles of the distribution for a dependent variable (Reboredo and Uddin, 2016; Xiao et al., 2018; Das and Dutta, 2019; Xiao et al., 2019). Since one of our objectives is to explore the connection between twitter and the volatility of hi-tech stocks under diverse market conditions, we employ the QR approach.
We frame this process as follows:

$$Q_{VOL_t}(\tau|VOL_{t-1}, \Delta X_{t-1}) = \varphi(\tau) + \lambda(\tau)VOL_{t-1} + \theta(\tau)\Delta X_{t-1} \quad (1)$$

Following Koenkar and Bassett (1978), $Q_{VOL_t}(\tau|VOL_{t-1}, \Delta X_{t-1})$ signifies the τ conditional quantile of VOL_t, the volatility series of technology stocks at time *t*. Besides, $\varphi(\tau)$

measures the unobserved impact in the quantile model, while ΔX_t indicates the first-order difference for TEU/TMU index at time t.

Now for a given τ, the following equation is estimated by minimizing the weighted absolute deviation:

$$arg \min_{\varphi(\tau),\lambda(\tau)+\theta(\tau)} \sum_{t=1}^{T} \rho_\tau \left(VOL_t - \varphi(\tau) - \lambda(\tau)VOL_{t-1} - \theta(\tau)\Delta X_{t-1}\right) \quad (2)$$

where,

$\rho_\tau(u) = u(\tau - I(u < 0))$ and I(·) refers to the indication function.

For a positive and statistically significant $\theta(\tau)$, we conclude that an upturn in the twitter uncertainty index causes an increase in the risk level of technology stocks. For a negative $\theta(\tau)$, on the other hand, we report a reverse association between these indexes.

Several quantiles (τ = 0.05, 0.10, 0.30, 0.50, 0.70, 0.90, 0.95) are considered in our estimation process. Lower quantiles (i.e. 0.05, 0.10, 0.30) imply low volatility regimes, while higher quantiles (i.e. 0.70, 0.90, 0.95) indicate high volatility regimes. Estimating the twitter-volatility linkage at these quantiles would examine the effect of twitter uncertainty index on the risk level of technology stocks under various market states.

5 EMPIRICAL RESULTS

Tables 3-6 demonstrate the findings of our quantile regression analyses. We present these results in two panels: Panel A includes the estimates for TEU index, whereas Panel B does the same for TMU index. Table 3 demonstrates that both TEU and TMU exert significant impacts on the implied volatility of Amazon company. Notably, no significant linkage is found at lower quantiles. In particular, the effects of TEU appear to be significant during the periods of high uncertainty as evidenced by the estimates at upper quantiles of 0.70, 0.90 and 0.95). Thus, volatility significantly transmits from TEU to Amazon during the high volatility state of stock prices. For the TMU index, we observe significant influences at both lower and upper quantiles. Thus, when stock prices experience bearish or bullish periods, the information on twitter-based market uncertainty index can be used to predict the equity market volatility. These findings simply indicate that information publicized in social media could have some predictive power for stock market volatility when market becomes uncertain. It is also noteworthy that the impact of TMU index is mostly higher than that of the TEU index. For instance, the impacts of TMU and TEU are 0.0030 and 0.0013 respectively at the upper quantile of 0.90. In addition, the stock price volatility reacts to its own past values and these estimates seem to be negative and significant mainly at the lower quantiles. These results indicate that the estimates of such impacts tend to be insignificant amid the bearish periods.

Moving to the estimates of Table 4, we find similar impacts of uncertainty measures on the risk levels of Apple stock. Hence, we find no significant association between TEU and Apple volatility series during the low volatility periods. That is, no significant effect is observed at lower quantiles (0.05, 0.010 and 0.30). Therefore, the TEU index transmits the risk to the Apple stock during the volatile periods (i.e., when financial markets experience a downturn). The findings also suggest that these impacts tend to increase at higher quantiles. Consistent with earlier findings reported in Table 3, we notice significant influences of TMU index at both lower and upper quantiles. It is further observed that the estimates of own lagged values for the Apple VIX are insignificant at upper quantiles.

Table 5 reveals that the volatility of Google company also reacts to different uncertainty indexes. We also report that the influence of TMU index is higher relative to that of TMU index at extreme upper quantile. For instance, the impacts of TMU and TEU indexes amount to 0.0007 and 0.0033, respectively at the upper quantile of 0.95. We also observe that the TMU index impacts the volatility of Google stock at both lower and upper quantiles. This result is in line with that documented in Tables 3 and 4. Unlike the Amazon and Apple companies, the TEU index exerts a significant effect on the volatility of Google at lower quantile as well (see the result for $\tau = 0.10$). These results suggest that twitter uncertainty indexes have certain explanatory power for the volatility of technology stocks. It is further observed that the volatility of Google stock can be predicted by its own past values during both bearish and bullish periods.

Looking at the numbers of Table 6, we notice that twitter sentiments seem to affect the volatility of IBM stock as well. Note that the outcomes of Table 6 match with those shown in Table 5. For instance, we observe significant influences of TEU and TMU indexes at both lower and upper quantiles. The findings also reveal that at the extreme upper quantile of 0.95, the volatility of IBM stock is more sensitive to the TEU index (0.0032) than to the TMU index (0.0015). It is further observed that the estimates of own lagged values for the IBM VIX are significant for both high and low volatility states.

In sum, the results of our empirical work indicate that volatility of the US technology firms is sensitive to the variations in twitter-based uncertainty indexes. Thus the findings confirm that information revealed in social media impacts the volatility of hi-tech firms. Figures 2-5, which depict the effects of twitter sentiments on the risk level of technology stocks at different quantiles, also support these results implying that TEU and TMU indexes have positive effects on the stock price implied volatility implying that volatility of the US technology firms experiences an upward trend as the social media uncertainties increase. Rao and Srivastava (2014) also document a high positive correlation between Twitter sentiments and stock indexes.

Our findings are in line with Nofer and Hinz (2015), Ranco et al. (2015), Sul et al. (2016), Ho et al. (2017), Bartov et al. (2018) and Teti et al. (2019). These articles also show that stock prices are sensitive to the information publicized in social media. Our study reports similar findings for the volatility of the US hi-tech stocks. Overall, the results indicate that twitter-based uncertainty indexes can be used to predict the US equity market volatility.

6 CONCLUSIONS

While a growing body of literature has focused on the influence of social media on equity returns, the impact of twitter sentiments on stock market volatility remains understudied. This paper conceals this gap in the current literature. In doing so, the effects of newly constructed twitter-based uncertainty indexes on the volatility of leading technology firms are explored. Employing the quantile regression model, we show that the volatility of Amazon, Apple, Google and IBM stocks are sensitive to the variations in twitter-based economic and market uncertainties (i.e., TEU and TMU indexes). We observe significant influences at both lower and upper quantiles. Thus, for both high and low volatility regimes, the information on twitter-based uncertainty indexes can be used to predict the market volatility of these leading hi-tech companies. Moreover, TEU and TMU indexes exert positive effects on the stock price implied volatility implying that the variance of these technology firms experiences an upward trend as the social media uncertainties increase.

The findings of this empirical research could have important implications to investors. As the results indicate that twitter-based uncertainty indexes can be used to predict the volatility of US technology stocks, market participants may exercise these outcomes to make proper asset allocation decisions. For instance, when the technology stocks are highly volatile, investors might use the information on twitter sentiments to estimate the market risk and rebalance their portfolios accordingly in order to maximize diversification benefits. This suggests that they should closely observe twitter sentiments on stock price movements, which could be useful for realizing the future market risk more precisely and taking appropriate asset-allocation decisions. Additionally, the findings could be used to formulate proper hedging policies amid the episodes of market downturn and thereby hinder the potential losses.

The use of twitter sentiments in forecasting stock market volatility is still an emerging area of empirical research. It is, therefore, difficult to completely understand the role of social media for predicting asset price movements. As investors, academics and companies are very keen to have further knowledge about this domain, future research could use more sophisticated econometric models to shed light on how information publicized in web media such as Facebook, twitter, WhatsApp etc. increases the likelihood of predicting the risk associated with technology stocks. For instance, copula-based quantile regressions can be employed to study the extreme tail dependency in lower and upper quantile levels.

Although the findings of our empirical investigation provide evidence that social media have emerged as a good tools for realizing stock market movements, traders should still make investment decisions based on fundamentals, keeping an eye open on twitter/Facebook sentiments. In sum, market participants should carefully monitor social media sentiments, but not use them as a key prediction tool.

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APPENDICES

Table 1

Summary statistics

	Mean	Std. Dev.	Skewness	Kurtosis	J-B test	ADF test	PP test
TEU	0.2761	104.65	4.03	250.87	6119814***	-20.29***	-294.26***
TMU	0.2669	153.22	2.98	84.52	664796.5***	-27.34***	-217.14***
Amazon	-0.0003	2.53	-1.45	18.37	24357.87***	-54.06***	-54.47***
Apple	0.0018	2.47	0.85	25.77	51904.95***	-62.17***	-17.48***
Google	0.0005	2.16	-0.14	23.63	42396.28***	-58.37***	-58.55***
IBM	0.0063	2.22	-0.01	27.11	57872.53***	-34.16***	-59.74***

Notes: First differences are considered for each index. ***p<0.01; **p<0.05; *p<0.10.

Table 2

Correlation matrix

	TEU	TMU	Amazon	Apple	Google	IBM
TEU	1					
TMU	0.52***	1				
Amazon	0.07***	0.13***	1			
Apple	0.08***	0.15***	0.53***	1		
Google	0.09***	0.16***	0.60***	0.59***	1	
IBM	0.08***	0.07***	0.37***	0.40***	0.46***	1

Notes: First differences are considered for all the indexes. ***p<0.01; **p<0.05; *p<0.10.

Table 3

Risk Spillover from Twitter to Amazon

Quantiles →	Q(0.05)	Q(0.10)	Q(0.30)	Q(0.50)	Q(0.70)	Q(0.90)	Q(0.95)
Panel A: Effect of TEU							
Constant	**-3.2442**	**-1.9214**	**-0.5986**	0.0265	**0.6590**	**2.2180**	**3.3846**
VOL_{t-1}	**-0.1293**	**-0.0735**	-0.0218	-0.0157	-0.0173	-0.0275	-0.0455
ΔTEU_{t-1}	0.0031	0.0016	0.0011	0.0012	**0.0019**	**0.0013**	0.0018
Panel B: Effect of TMU							
Constant	**-3.2239**	**-1.9394**	**-0.5967**	0.0142	**0.6690**	**2.1623**	**3.3298**
VOL_{t-1}	**-0.1295**	**-0.0662**	-0.0149	-0.0150	-0.0153	0.0102	-0.0104
ΔTMU_{t-1}	**0.0027**	**0.0023**	**0.0011**	**0.0012**	**0.0014**	**0.0030**	0.0020

Notes: This table presents the QR results for the Amazon Company. 5% significance level (bold numbers) is considered.

Table 4

Risk Spillover from Twitter to Apple

Quantiles →	Q(0.05)	Q(0.10)	Q(0.30)	Q(0.50)	Q(0.70)	Q(0.90)	Q(0.95)
Panel A: Effect of TEU							
Constant	**-3.1281**	**-2.0720**	**-0.6570**	**-0.0597**	**0.6145**	**2.2425**	**3.3358**
VOL_{t-1}	**-0.2197**	**-0.1539**	**-0.0799**	-0.0447	0.0032	0.0803	0.0532
ΔTEU_{t-1}	0.0013	0.0004	0.0003	0.0007	**0.0010**	0.0033	**0.0042**
Panel B: Effect of TMU							
Constant	**-3.1118**	**-2.0822**	**-0.6600**	-0.0457	**0.6079**	**2.2085**	**3.3546**
VOL_{t-1}	**-0.2174**	**-0.1429**	**-0.0810**	-0.0440	-0.0027	-0.0669	-0.0597
ΔTMU_{t-1}	0.0016	**0.0009**	**0.0008**	**0.0010**	**0.0015**	**0.0026**	**0.0041**

Notes: This table presents the QR results for the Apple Company. 5% significance level (bold numbers) is considered.

Table 5

Risk Spillover from Twitter to Google

Quantiles →	Q(0.05)	Q(0.10)	Q(0.30)	Q(0.50)	Q(0.70)	Q(0.90)	Q(0.95)
Panel A: Effect of TEU							
Constant	**-2.6009**	**-1.6890**	**-0.5035**	0.0325	**0.6045**	**1.7980**	**2.8432**
VOL_{t-1}	**-0.1517**	**-0.0925**	**-0.0684**	**-0.0745**	**-0.0855**	**-0.1521**	**-0.2249**
ΔTEU_{t-1}	0.0016	**0.0014**	0.0009	0.0010	**0.0014**	0.0013	**0.0007**
Panel B: Effect of TMU							
Constant	**-2.6143**	**-1.6764**	**-0.5164**	0.0347	**0.5974**	**1.8283**	**2.8199**
VOL_{t-1}	**-0.1375**	**-0.1053**	**-0.0680**	**-0.0707**	**-0.0868**	**-0.1507**	**-0.2135**
ΔTMU_{t-1}	**0.0010**	**0.0013**	**0.0008**	**0.0009**	**0.0010**	**0.0029**	**0.0033**

Notes: This table presents the QR results for the Google Company. 5% significance level (bold numbers) is considered.

Table 6

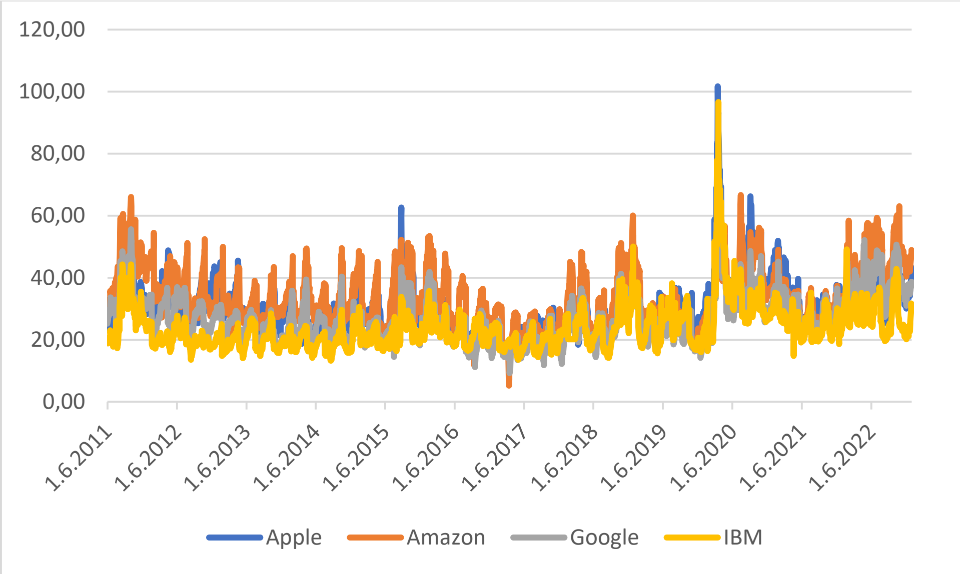
Risk Spillover from Twitter to IBM

Quantiles →	Q(0.05)	Q(0.10)	Q(0.30)	Q(0.50)	Q(0.70)	Q(0.90)	Q(0.95)
Panel A: Effect of TEU							
Constant	**-2.6566**	**-1.4575**	**-0.3876**	0.0169	**0.4944**	**1.5063**	**2.3453**
VOL_{t-1}	**-0.2191**	**-0.1245**	**-0.0737**	**-0.0665**	**-0.0866**	**-0.0845**	-0.0180
ΔTEU_{t-1}	**0.0018**	0.0014	0.0007	**0.0009**	**0.0015**	**0.0019**	**0.0032**
Panel B: Effect of TMU							
Constant	**-2.6072**	**-1.4331**	**-0.3902**	0.0160	**0.4831**	**1.4946**	**2.4338**
VOL_{t-1}	**-0.2218**	**-0.1184**	**-0.0797**	**-0.0624**	**-0.0838**	**0.1003**	-0.0579
ΔTMU_{t-1}	**0.0007**	0.0008	0.0004	**0.0005**	**0.0008**	0.0013	**0.0015**

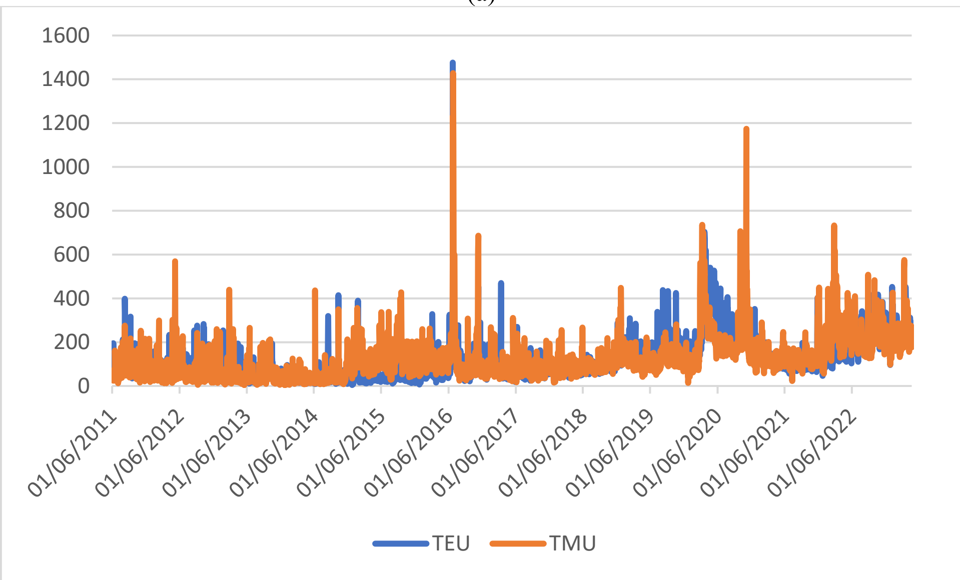
Notes: This table presents the QR results for the IBM Company. 5% significance level (bold numbers) is considered.

Figure 1

Time-series plots for different indexes



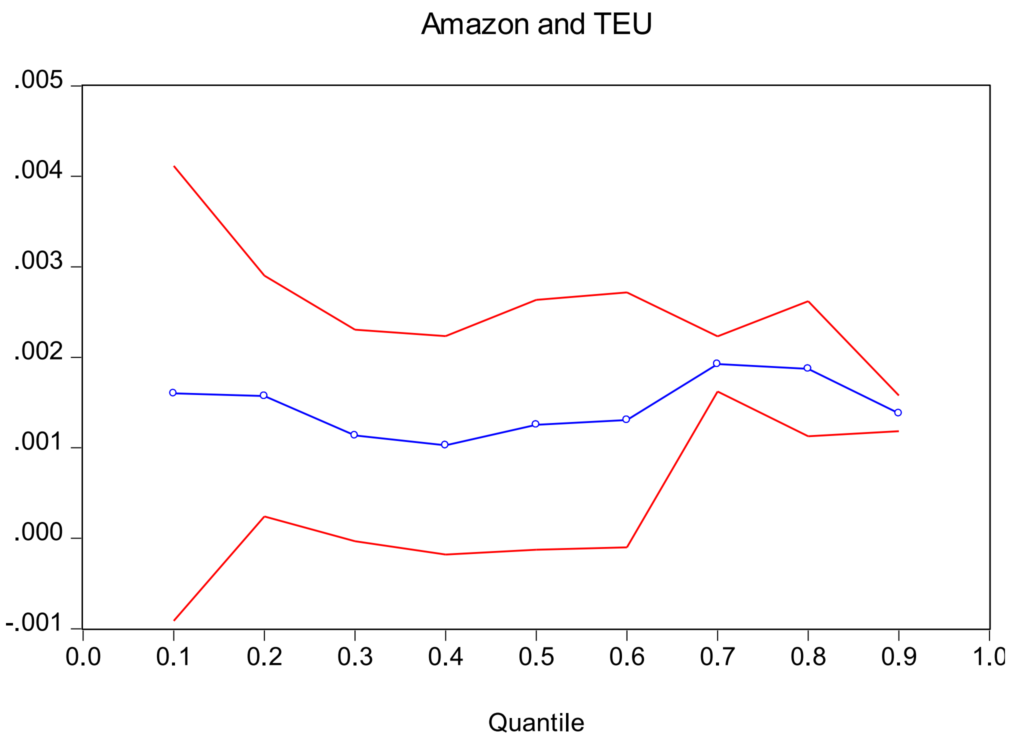
(a)



(b)

Figure 2

Impact of Twitter-based uncertainties on the implied volatility of Amazon



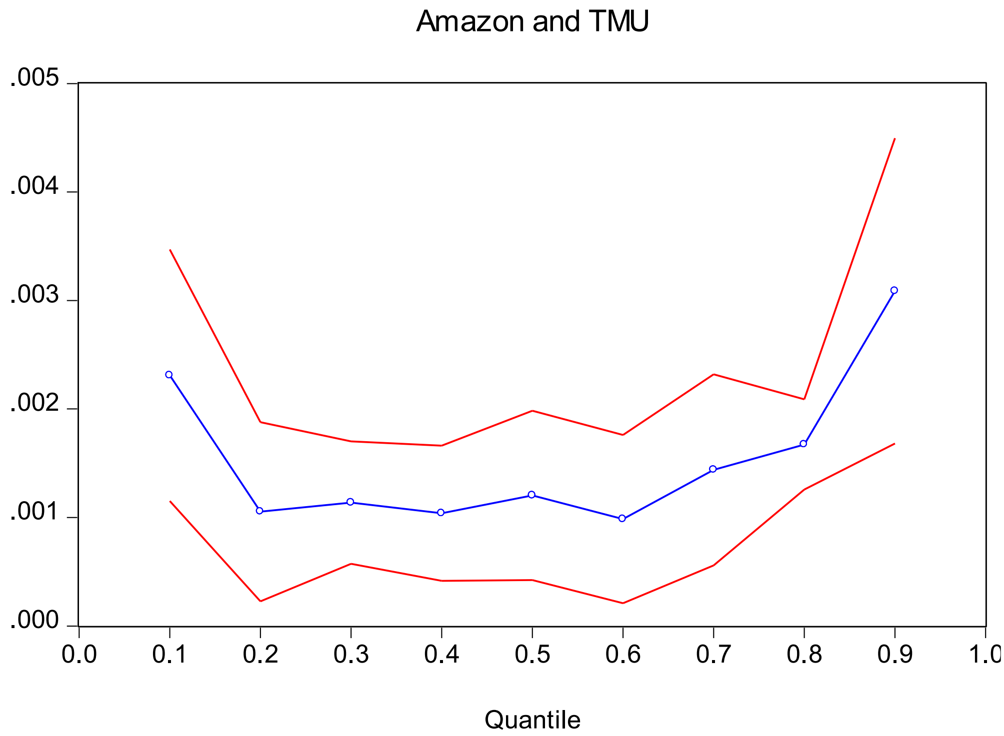


Figure 3

Impact of Twitter-based uncertainties on the implied volatility of Apple

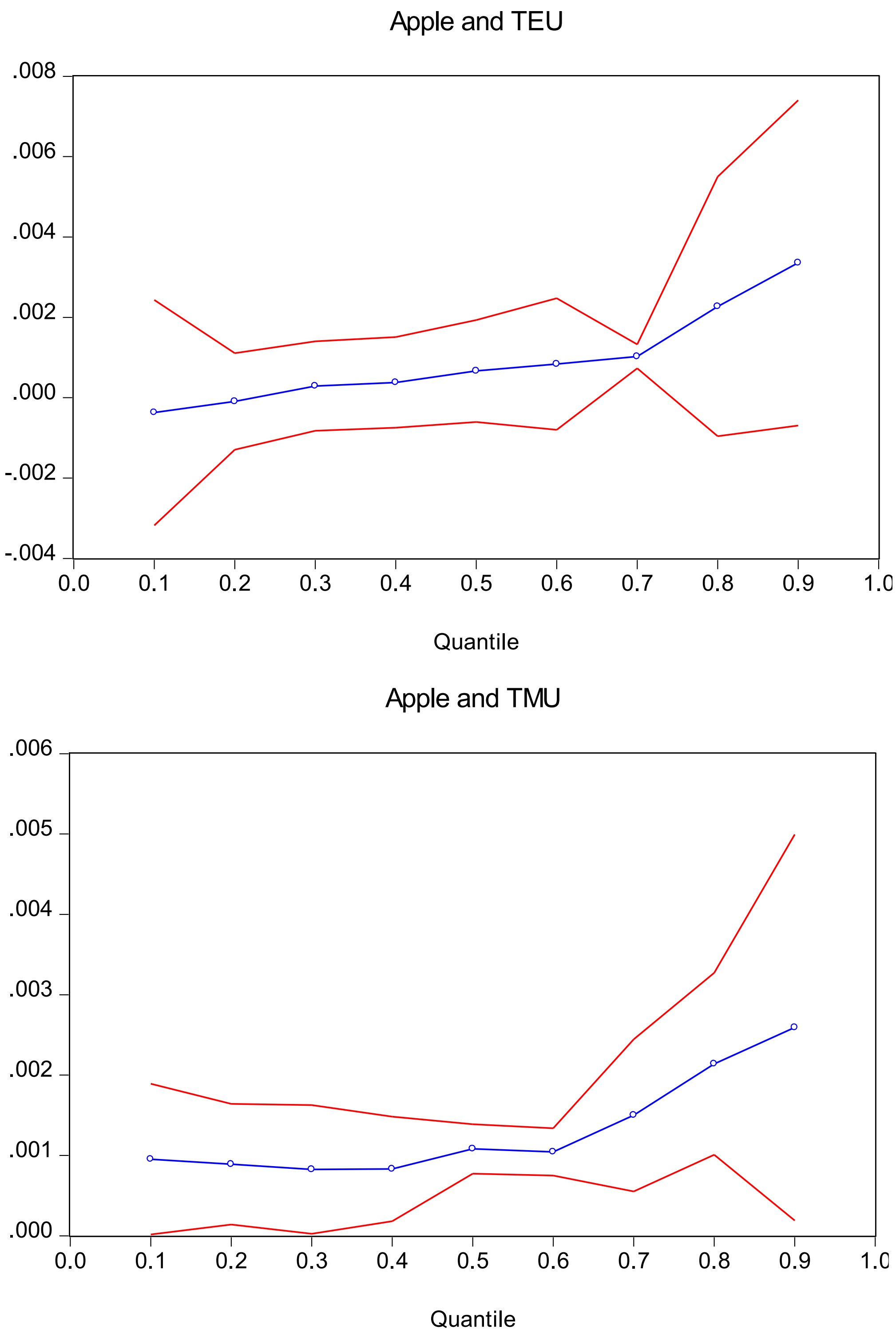
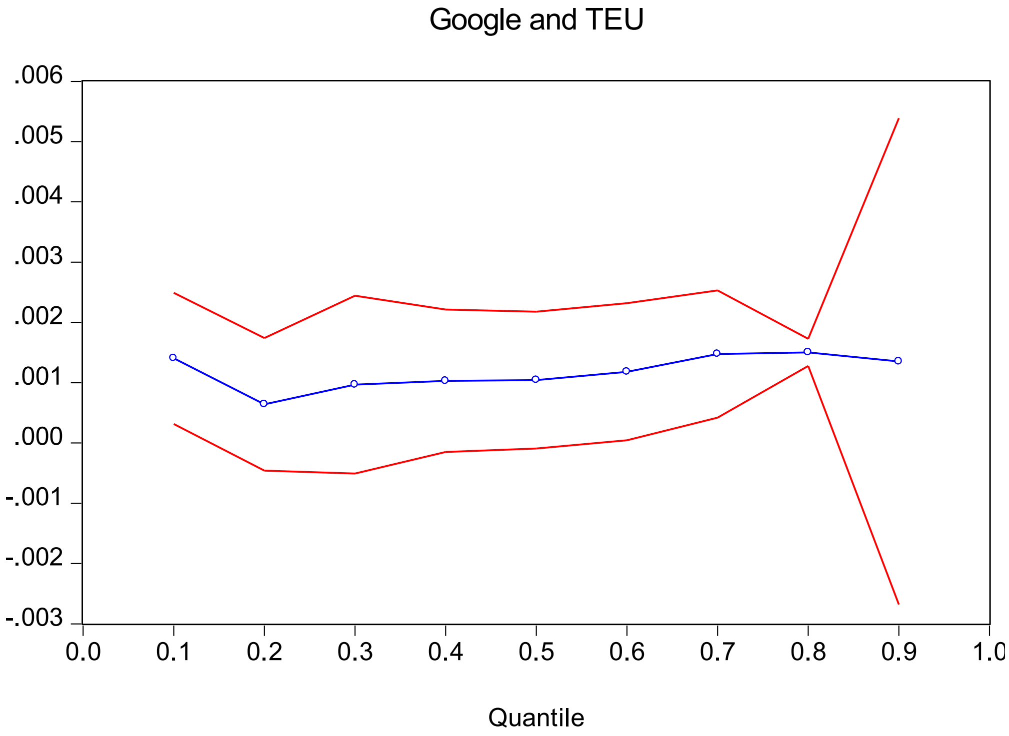


Figure 4

Impact of Twitter-based uncertainties on the implied volatility of Google



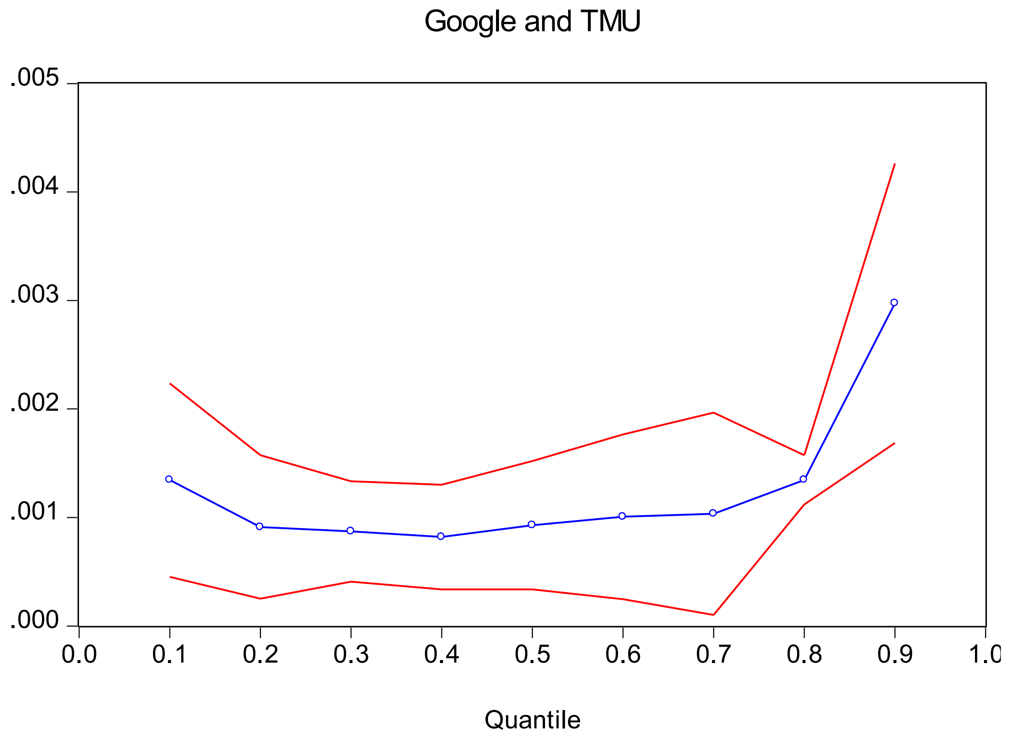


Figure 5

Impact of Twitter-based uncertainties on the implied volatility of IBM