Journal of Behavioral and Experimental Finance 27 (2020) 100343

Contents lists available at ScienceDirect

Journal of Behavioral and Experimental Finance

journal homepage: www.elsevier.com/locate/jbef

COVID-19: Media coverage and financial markets behavior—A sectoral inquiry

Omair Haroon, Syed Aun R. Rizvi *

Suleman Dawood School of Business, Lahore University of Management Sciences (LUMS), Lahore, Pakistan

ARTICLE INFO

Article history:
Received 7 May 2020
Accepted 14 May 2020
Available online 15 May 2020

ABSTRACT

We analyze the relationship between sentiment generated by coronavirus-related news and volatility of equity markets. The ongoing coronavirus outbreak (COVID-19) resulted in unprecedented news coverage and outpouring of opinions in this age of swift propagation of information. Ensuing uncertainty in financial markets leads to heightened volatility in prices. We find that overwhelming panic generated by the news outlets are associated with increasing volatility in the equity markets. Our results for individual economic sectors demonstrate that panic-laden news contributed to a greater extent to volatility in the sectors perceived to be most affected by coronavirus outbreak.

1. Introduction

Recent Coronavirus (COVID-19) outbreak has garnered great attention from media outlets all around the world. Media reporting inclines heavily towards highlighting high impact events such as infectious disease outbreaks leading to public panic (e.g. Blendon et al., 2004; Mairal, 2011; Young et al., 2013). The news related to infectious diseases can cause alarm and influences investors' sentiments (e.g. Tetlock, 2007). The recent outbreak of COVID-19 has had an impact on almost all countries. The US market and similarly world markets have seen a decline of nearly 30% within the first quarter of 2020.

In times of unprecedented access to news and information, individuals (including investors) find it difficult to accurately assess the economic significance and impact of such information. Using evidence from psychology literature, Barberis et al. (1998) demonstrate that financial markets overreact to consistent pattern of news, even though statistically the weight put on such news should be low. Earlier studies revealed at best a weak or moderate relationship between quantum of news and activity (volume, volatility, prices) in financial markets (e.g. Mitchell and Mulherin, 1994; Berry and Howe, 1994). However, Ederington and Lee (1994), observe that scheduled macroeconomic news announcements explain a significant portion of the volatility in financial markets. Klibanoff et al. (1998) also find evidence of market overreaction to prominence of news in the context of closed end mutual funds. As the world became more connected and information flows became almost instantaneous, the use of computers and artificial intelligence for reading, interpreting and making financial decisions based on news became a viable trading strategy (Groß-Klußmann and Hautsch, 2011). There have also been studies finding news sentiment useful for asset allocation by portfolio managers (e.g. Uhl et al., 2015).

The asset pricing literature has delved into mood variables in trying to explain the market behavior (Tetlock, 2007; Kaplanski and Levy, 2010; Su et al., 2017 etc.). We extend this stream of literature with a specific bent on health crisis by exploring whether the media reporting of covid-19, panic amongst investors, and the global sentiment has played a role in the previously unseen volatility in the equity markets. Earlier literature argues that unbalanced reporting of healthcare crises leads to disjoint in actual versus perceived risks leading to over/under reaction of sentiment. (Vasterman et al., 2005; Mairal, 2011; Young et al., 2013 etc.). Furthermore this paper adds to the currently scant literature on understanding the stock market reaction to the covid-19 pandemic.

This paper extends literature on three dimensions. Firstly it adds to the evolving literature on market response to pandemics (See: Al-Awadhi et al., 2020; Zhang et al., 2020; Albulescu, 2020). Secondly we focus our analysis on sector level, adding to the heterogeneity literature in financial markets (See: Westerlund and Narayan, 2015; Bannigidadmath and Narayan, 2016; Phan et al., 2015a,b; Rizvi and Arshad, 2018). The overall message emanating from this literature suggests that sectors and stocks are heterogenous, and aggregated index level analysis assumes homogeneity in stock market return and volatility profiling. Third dimension of literature where this paper contributes is the impact of media coverage originated sentiment to panic in financial markets (See: Tetlock, 2007; Barberis et al., 1998; Uhl et al., 2015).

* Corresponding author.
E-mail addresses: omair.haroon@lums.edu.pk (O. Haroon), aun.raza@lums.edu.pk (S.A.R. Rizvi).

https://doi.org/10.1016/j.jbef.2020.100343

Table 1a
Description of Data.
Source: Ravenpack Finance[a].

Panic index	The Coronavirus Panic Index measures the level of news chatter that makes reference to panic or hysteria and coronavirus. Values range between 0 and 100 where a value of 7.00 indicates that 7 percent of all news globally is talking about panic and COVID-19. The higher the index value, the more references to panic found in the media.
Sentiment index	The Coronavirus Sentiment Index measures the level of sentiment across all entities mentioned in the news alongside the coronavirus. The index ranges between −100 and 100 where a value of 100 is the most positive sentiment, −100 is the most negative, and 0 is neutral.
Media coverage	The Coronavirus Media Coverage Index calculates the percentage of all news sources covering the topic of the novel coronavirus. Values range between 0 and 100 where a value of 60.00 means that 60 percent of all sampled news providers are currently covering stories about the COVID-19.

[a]RavenPack curates and accumulates real-time news from more than 19,000 global news sources. Panic index is created to represent the percentage of total news items for the day that mention 'panic' or 'fear' in coronavirus-related news. Panic index has been a leading indicator of coronavirus cases worldwide.

Table 1b
Description of Sectoral Indices Data.
Source: DataStream.

Code	Sector	Code	Sector
uti	Utilities	Auto	Automobiles
bm	Basic Materials	Oil	Oil & Gas
cgd	Consumer Goods	Tech	Technology
fin	Financial Services	Chem	Chemicals
csv	Consumer Services	Hotel	Hotels
health	HealthCare	Media	Media
pharm	Pharmaceuticals and Bio	Retail	Retail
tele	Telecom	Delvr	Delivery Services
indu	Industrial	Food	Food & beverages
tran	Transportation	Insu	Life Insurance
air	Airlines	Travel	Travel & Leisure
bank	Banks		

2. Data

We have used the benchmark indices for world and US and used 23 sectoral indices for US from Dow Jones. The reason for using the Dow Jones indices is for standardization in calculation of index price as highlighted by Rizvi et al. (2018).

Our sample period runs from 1 January 2020 till 30 April 2020 for the benchmark indices. This is owing to the limited availability of the data as well as just before the stimulus packages were announced by the US government in supporting the market. Daily returns are calculated using the equation $r_t = ln(P_t) - ln(P_{t-1})$. Here, r_t and P_t denote daily return and price at the business day t respectively.

For measuring the sentiment, panic in investors, and media coverage, following the works of Subhramanyam (2019), Ding et al. (2019) and Rogone et al. (2020), we use the Ravenpack finance for Panic Index, Global Sentiment Index and Media Coverage. Ravenpack aggregates news from hundreds of different news sources and creates daily index of level of hysteria inducing news (Panic), general sentiment of the news for the day based on an artificial intelligence index (Sentiment) and the quantity of coronavirus news as compared to other news (Media Coverage). Details of the index and their calculation description is provided in Table 1a. Fig. 1 plots these indices for a visual representation since the start of the year.

3. Methodology

To understand the volatility of the Stock market, we rely on Exponential GARCH models which have been extensively used in studying the volatility of stock markets in finance literature. Yu and Hassan (2008), Rizvi and Arshad (2018) etc. have relied on asymmetric GARCH model developed by Nelson (1991) suggesting a better fit of EGARCH model for volatilities. The EGARCH model presides over other models with its ability to allow for a more stable optimization of routines, and no parameter constraints.

$$\ln \sigma_{j,t}^2 = \omega_t + \beta_j \ln(\sigma_{j,t-1}^2) + \gamma \frac{\varepsilon_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|\varepsilon_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] \quad (1)$$

Where $\sigma_{j,t}^2$ denotes the conditional variance since it is a one-period ahead estimate for the variance calculated on any past relevant information. ω_t symbolizes a conditional density function. The α consideration represents a symmetric effect of the model, i.e. the GARCH effect. β calculates the perseverance in conditional volatility irrespective of market movements. Furthermore, the parameter γ measures the leveraging effect.

This is furthered with utilizing the Ordinary Least Square Regressions in multiple models to explore the question, of how much sentiment, panic and media coverage has influenced the market volatility in the covid-19 crisis. Table 1b describes the various industrial sectors we used for analysis.

4. Empirical analysis

The descriptive statistics for the market return and EGARCH volatility are provided in Table 2, and they suggest huge variation year to date. The magnitude of the spread requires a further inquiry.

Table 3 presents the results of regression of the market volatility with the sentiment, and media panic. The results show that Panic Index is positively associated with world index volatility, depicting a relationship between media induced panic and increased sense of uncertainty in financial markets. Negative sentiment in the news communications is associated with increasing volatility in returns in the US market, confirming findings from Su et al. (2017). However, interestingly higher coverage of coronavirus related news is associated with lower volatility in World markets. Donadelli et al. (2017) discuss the possible impact of media coverage of infectious diseases reaching similar conclusions.

The analysis of association between COVID-19 related news and volatility in various industrial sectors of US equities markets suggest that panic induced by COVID-19 related news is positively associated with volatilities in indices of several industrial sectors. Specifically, the association is strongest for Transportation, Automobiles & Components, Energy and Travel & Leisure industries.

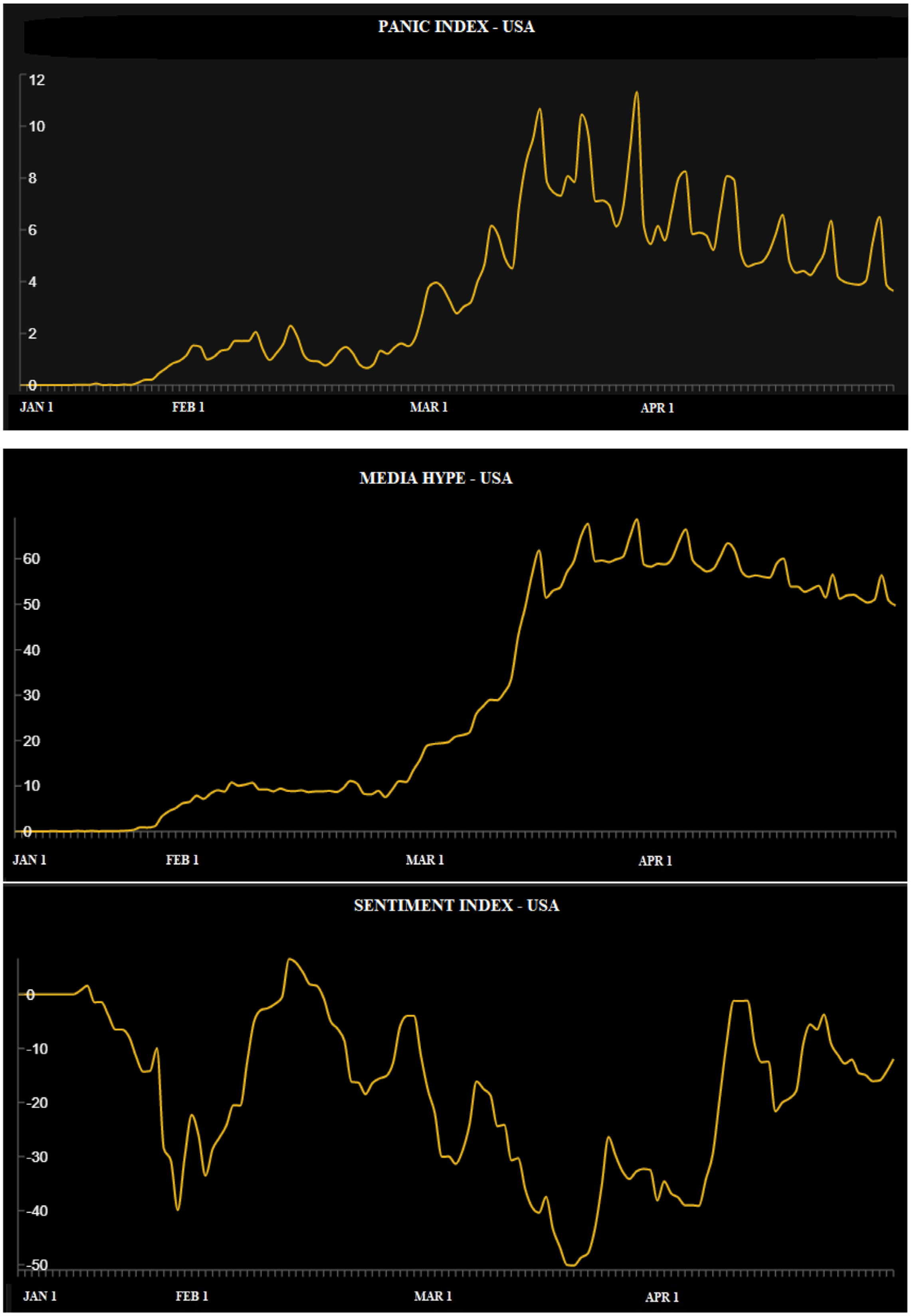

Fig. 1. Indices performance from start of year.

These industries have been identified in the popular press as being the hardest hit by the pandemic and related shut-downs (e.g. Suneson, 2020). The volatility in prices of industries such as Basic Materials, Consumer Goods, Industrial Goods, Banks, Technology, Hotels, Media, Delivery Services and Insurance were also correlated with panic-causing news. However, the extent of media coverage and news sentiment was not associated with volatility in prices of most industrial indices.

Table 2
Descriptive statistics for World and US benchmark indices.

	Returns				Volatility			
	Mean	St. Dev	Max	Min	Mean	St. Dev	Max	Min
World	−0.61%	2.71%	5.75%	−10.44%	0.07%	0.11%	0.48%	0.00%
USA	−0.44%	3.79%	10.76%	−13.84%	0.47%	2.56%	20.36%	0.00%
UTI	−0.23%	3.89%	12.68%	−11.75%	0.15%	0.27%	1.01%	0.00%
BM	−0.58%	3.73%	11.36%	−11.47%	0.19%	0.31%	1.29%	0.01%
CGD	−0.35%	3.19%	7.67%	−10.54%	0.10%	0.17%	0.86%	0.00%
CSV	−0.35%	3.13%	7.25%	−11.72%	1.12%	7.43%	59.06%	0.00%
FIN	−0.40%	4.36%	13.38%	−15.01%	0.21%	0.38%	2.09%	0.00%
HEALTH	−0.28%	3.05%	7.33%	−10.82%	1.71%	9.01%	64.48%	0.01%
PHARM	−0.25%	2.72%	6.75%	−8.42%	0.14%	0.38%	2.87%	0.01%
TELE	−0.31%	2.79%	7.90%	−8.57%	0.36%	1.72%	13.63%	0.00%
INDU	−0.49%	3.83%	11.39%	−13.32%	0.17%	0.28%	1.43%	0.00%
TRAN	−0.55%	3.81%	11.77%	−12.26%	0.13%	0.16%	0.55%	0.00%
AIR	−1.06%	5.93%	18.80%	−22.70%	4.82%	30.55%	242.15%	0.02%
BANK	−0.80%	4.94%	14.43%	−16.54%	0.25%	0.40%	1.51%	0.00%
AUTO	−0.29%	5.80%	16.91%	−17.88%	0.29%	0.25%	0.92%	0.02%
OIL	−1.20%	5.38%	14.87%	−23.18%	0.24%	0.30%	1.05%	0.00%
TECH	−0.25%	3.84%	10.70%	−14.60%	0.13%	0.18%	0.68%	0.00%
CHEM	−0.59%	3.85%	10.50%	−12.64%	0.24%	0.49%	2.48%	0.00%
HOTEL	−0.92%	4.29%	10.00%	−15.81%	0.19%	0.24%	0.95%	0.01%
MEDIA	−0.53%	3.51%	9.14%	−10.72%	0.15%	0.23%	1.13%	0.00%
RETAIL	−0.17%	2.91%	6.69%	−10.97%	0.10%	0.20%	1.11%	0.00%
DELVR	−0.31%	3.18%	8.68%	−10.23%	0.09%	0.10%	0.35%	0.00%
FOOD	−0.33%	3.10%	7.84%	−10.56%	0.09%	0.16%	0.69%	0.00%
INSU	−0.77%	5.46%	16.57%	−18.87%	0.27%	0.45%	2.23%	0.00%
TRAVEL	−0.74%	4.34%	14.32%	−15.48%	0.17%	0.23%	0.94%	0.00%

Table 3
Regression results.

Dependent	World	USA	uti	bm	cgd	fin	csv	health	pharm	tele	indu	tran	air
Panic	0.067***	0.091**	0.127*	0.160**	0.0872**	0.186*	1.482	0.566	0.117	0.0798	0.151**	0.110***	6.3
	3.29	2.5	−2.61	−2.81	−2.69	−2.46	−0.84	−0.26	−1.34	−0.19	−2.84	−3.87	−0.88
Media Coverage	−0.056*	−0.076	−0.106	−0.14	−0.0724	−0.165	−1.68	−0.229	−0.114	0.0276	−0.128	−0.0916*	−7.097
	(1.79)	(1.36)	(−1.40)	(−1.58)	(−1.44)	(−1.40)	(−0.62)	(−0.07)	(−0.84)	−0.04	(−1.54)	(−2.08)	(−0.63)
Sentiment Index	−.070	−0.136*	−0.294**	−0.294*	−0.122	−0.282	−1.704	−1.744	−0.081	−0.204	−0.191	−0.0188	−8.064
	(1.55)	(1.68)	(−2.72)	(−2.32)	(−1.69)	(−1.68)	(−0.44)	(−0.37)	(−0.42)	(−0.22)	(−1.61)	(−0.30)	(−0.50)
Constant	0.550*	0.917***	1.680***	1.833***	0.837**	1.899**	13.63	9.461	0.853	1.094	1.364**	0.524*	61.07
	2.99	2.80	(3.85)	(3.58)	(2.88)	(2.80)	(0.87)	(0.49)	(1.09)	(0.30)	(2.85)	(2.06)	(0.95)
R^2	0.4346	0.3392	0.4238	0.4106	0.3698	0.3211	0.0338	0.0139	0.0852	0.0132	0.38	0.4561	0.038
Dependent	bank	auto	oil	tech	chem	hotel	media	retail	delvr	food	insu	travel	
Panic	0.236**	0.154***	0.189***	0.110**	0.230*	0.145**	0.125**	0.0847*	0.0601**	0.0777*	0.245**	0.145***	
	−3.17	−3.69	−3.9	−3.45	−2.23	−3.34	−2.93	−2.05	−3.26	−2.57	−2.89	−3.62	
Media Coverage	−0.216	−0.105	−0.145	−0.0946	−0.218	−0.121	−0.111	−0.0783	−0.0452	−0.0681	−0.208	−0.12	
	(−1.86)	(−1.62)	(−1.93)	(−1.90)	(−1.36)	(−1.79)	(−1.67)	(−1.22)	(−1.58)	(−1.45)	(−1.58)	(−1.93)	
Sentiment Index	−0.221	−0.0164	−0.125	−0.0598	−0.152	−0.12	−0.179	−0.168	0.0368	−0.152*	−0.26	−0.121	
	(−1.33)	(−0.18)	(−1.16)	(−0.84)	(−0.66)	(−1.25)	(−1.88)	(−1.83)	−0.9	(−2.27)	(−1.38)	(−1.37)	
Constant	1.873**	0.735	1.246**	0.696*	1.591	1.087**	1.237**	1.032**	0.102	0.928**	2.020*	1.064**	
	(2.80)	(1.96)	(2.87)	(2.43)	(1.72)	(2.78)	(3.23)	(2.79)	(0.61)	(3.43)	(2.65)	(2.97)	
R^2	0.3822	0.495	0.5209	0.4149	0.2114	0.4299	0.3933	0.2689	0.3719	0.3781	0.3724	0.473	

*,**,*** represents significance at 10%, 5% and 1% level respectively, corresponding t statistic of coefficients is reported.

In order to demonstrate that Panic Index and Media Coverage is related to spread of the disease across the globe and not sensationalism created by news outlets, we run an OLS regression of the number of reported Covid-19 cases and Covid-19 related deaths on these two indices (Table 4). We find that these indices are related to reports of increases in confirmed cases but not related deaths. Perhaps, it is the contagiousness of the disease and not related mortality that has been source of panic and coverage in the news media.

Table 4
Panic and media dependence on Covid-19.

Dependent variable	Panic index	Media coverage
Covid cases	0.7094	0.459466
	(0.042)**	(0.000)*
Covid deaths	−0.2064	−0.1777
	(0.544)	(0.164)
Constant	−5.526	0.1546
	(0.000)*	(0.740)
R-Squared	0.79237	0.896647

Values in parenthesis are *p*-value. *,**,*** represents significance at 1%, 5% and 10% confidence level.

5. Conclusion

In this information age, pandemics like the ongoing Coronavirus (COVID-19) outbreak causes media frenzy and a competition for updated 'breaking' news in media outlets. Participants in financial markets may not quickly and accurately assess the economic effect of such onslaught of news. We analyze the relationship between news coverage and ensuing generation of sentiments on volatility of financial markets. We find that panic spawned by the news outlets is associated with heightened volatility in financial markets around the world and this association is stronger for industries hardest hit by the events that unfolded during the pandemic. However, sentiment and quantum of media coverage had little to moderate association with volatility of prices. These results suggest that investor behavior in equity markets could be in line with predictions of Griffin and Tversky (1992).

References

Al-Awadhi, A.M., Al-Saifi, K., Al-Awadhi, A., Alhamadi, S., 2020. Death and contagious infectious diseases: Impact of the COVID-19 virus on stock market returns. J. Behav. Exp. Financ. 100326.

Albulescu, C., 2020. Coronavirus and financial volatility: 40 days of fasting and fear. arXiv preprint arXiv:2003.04005.

Bannigidadmath, D., Narayan, P.K., 2016. Stock return predictability and determinants of predictability and profit. Emerg. Mark. Rev. 26, 153–173.

Barberis, N., Shleifer, A., Vishny, R., 1998. A model of investor sentiment. J. Financ. Econ. 49 (3), 307–343.

Berry, T.D., Howe, K.M., 1994. Public information arrival. J. Finance 49 (4), 1331–1346.

Blendon, R.J., Benson, J.M., DesRoches, C.M., Raleigh, E., Taylor-Clark, K., 2004. The public's response to severe acute respiratory syndrome in Toronto and the United States. Clin. Infect. Dis. 38 (7), 925–931.

Ding, R., Zhou, H., Li, Y., 2019. Social media, financial reporting opacity, and return comovement: Evidence from seeking alpha. J. Financial Mark. 100511.

Donadelli, M., Kizys, R., Riedel, M., 2017. Dangerous infectious diseases: Bad news for main street, good news for Wall Street? J. Financial Mark. 35, 84–103.

Ederington, L.H., Lee, J.H., 1994. The response of the dollar/yen exchange rate to economic announcements. Financial Eng. Jpn. Mark. 1 (2), 111–128.

Griffin, D., Tversky, A., 1992. The weighing of evidence and the determinants of confidence. Cogn. Psychol. 24 (3), 411–435.

Groß-Klußmann, A., Hautsch, N., 2011. When machines read the news: Using automated text analytics to quantify high frequency news-implied market reactions. J. Empir. Financ. 18 (2), 321–340.

Kaplanski, G., Levy, H., 2010. Exploitable predictable irrationality: The FIFA world cup effect on the U.S. stock market. J. Financ. Quant. Anal. 45, 535–553.

Klibanoff, P., Lamont, O., Wizman, T.A., 1998. Investor reaction to salient news in closed-end country funds. J. Finance 53 (2), 673–699.

Mairal, G., 2011. The history and the narrative of risk in the media. Health Risk Soc. 13 (1), 65–79.

Mitchell, M.L., Mulherin, J.H., 1994. The impact of public information on the stock market. J. Finance 49 (3), 923–950.

Nelson, D.B., 1991. Conditional heteroskedasticity in asset returns: A new approach. Econometrica 59 (347–370).

Phan, D.H.B., Sharma, S., Narayan, P.K., 2015a. Intraday volatility interaction between the crude oil and equity markets. J. Int. Financ. Mark. Inst. Money 40, 1–13.

Phan, D.H.B., Sharma, S., Narayan, P.K., 2015b. Stock return forecasting: Some new evidence. Int. Rev. Financ. Anal. 40, 38–51.

Rizvi, S.A.R., Arshad, S., 2018. Understanding time-varying systematic risks in Islamic and conventional sectoral indices. Econ. Model. 70, 561–570.

Rizvi, S.A.R., Arshad, S., Alam, N., 2018. A tripartite inquiry into volatility-efficiency-integration nexus - case of emerging markets. Emerg. Mark. Rev 34, 143–161.

Rogone, L., Hyde, S., Zhang, S.S., 2020. News sentiment in the cryptocurrency market: An empirical comparison with Forex. Int. Rev. Financ. Anal. 69, 101462.

Su, Z., Fang, T., Yin, L., 2017. The role of news-based implied volatility among US financial markets. Econ. Lett. 157, 24–27.

Subrhamanyam, A., 2019. Big data in finance: Evidence and challenges. Borsa Istanbul Rev. 19 (4), 283–287.

Suneson, G., 2020. Industries hit hardest by coronavirus in the US include retail, transportation, and travel. USA Today Retreived from https://www.usatoday.com.

Tetlock, P.C., 2007. Giving content to investor sentiment: The role of media in the stock market. J. Financ. 62 (3), 1139–1168.

Uhl, M.W., Pedersen, M., Malitius, O., 2015. What's in the news? Using news sentiment momentum for tactical asset allocation. J. Portfolio Manag. 41 (2), 100–112.

Vasterman, P., Yzermans, J.C., Dirkzwager, A.J., 2005. The role of the media and media hypes in the aftermath of disasters. Epidemiol. Rev. 27, 107–114.

Westerlund, J., Narayan, P.K., 2015. Testing for predictability in conditionally heteroskedastic stock returns. J. Financ. Econ. 13, 342–375.

Young, M.E., King, N., Harper, S., Humphreys, K.R., 2013. The influence of popular media on perceptions of personal and population risk in possible disease outbreaks. Health Risk Soc. 15 (1), 103–114.

Yu, J., Hassan, M., 2008. Global and regional integration of the Middle East and North African (MENA) stock markets. Q. Rev. Econ. Finance 48, 482–504.

Zhang, D., Hu, M., Ji, Q., 2020. Financial markets under the global pandemic of COVID-19. Finance Res. Lett. 101528.