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The Impact of Government Policy Responses to the COVID-19 Pandemic and Brexit on the UK Financial Market: A Behavioural Perspective

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At the height of the COVID-19 pandemic in the United Kingdom, the Governor of the Bank of England, while granting an interview, described the pandemic as an unprecedented economic emergency and said that the Bank could go as far as radical money-printing operations. In reaction, the UK financial market, particularly the FTSE 100 and pound sterling, witnessed record-breaking losses. Considering this evidence, we hypothesized that the emotions and moods of investors towards the financial market might have been impacted by the information they obtained from frequent government policy announcements. Furthermore, we proposed that the United Kingdom's final exit from the European Union (Brexit), which coincided with the pandemic, could have worsened the outlook of the UK financial market, as investors began to diversify their portfolios. Consequently, we examined the impact of government's policy announcements on investors' reactions to the concurrence of the COVID-19 pandemic and Brexit. Our findings reveal that the psychology of investors during the pandemic was significantly shaped by frequent policy announcements, which in turn affected overall market behaviour.

Introduction

With more than 300 million confirmed cases and about 6 million related deaths (as at December 2021), the damaging impact of the COVID-19 pandemic has literally been experienced by almost every nook and cranny of the world (WHO, 2020). Research shows that the pandemic disrupted nations significantly, albeit rather differently, as both public and private entities had to either shut down operations or downsize their workforce (Petzer, 2020). Across global financial markets, the effects of the COVID-19 pandemic on investors' wealth also took diverse shapes. Zhang, Hu and Ji (2020) observed that stock markets in Europe, Asia and North America were severely hit by the pandemic, while stock markets in Africa were mildly impacted (Topcu and Gulal, 2020). Essentially, the cost of the pandemic to countries varies with the level of exposure of their financial system to external shocks, and the immediate policy response(s) to cushion the effects. Despite the considerable country-wide variations in social and economic restrictions during the pandemic, global stock markets plummeted by almost 30% in value (World Bank, 2020), thus raising concerns over what factors influenced the behaviour of financial markets during the COVID-19 pandemic.

We propose that government's frequent policy announcements could be significant determinants. Hence, we analyse the impact of these announcements on investors' reactions to the concurrence of both Brexit and the COVID-19 pandemic in the United Kingdom. Our choice of the UK market is, first, not unconnected to the global statistics and report on the pandemic. According to the Coronavirus Resource Center at John Hopkins University (JHU, 2021), as at the end of 2021, the United Kingdom had the highest number of confirmed COVID-19 cases (about 12 million) and the highest death toll (more than 150,000) in Europe. Furthermore, our motivation for using the UK market stems from the recent relationship between the European Union and the United Kingdom. According to the UK Office of National Statistics (ONS, 2021), as an economic bloc, the European Union is the United Kingdom's largest trading partner; the final exit of the United Kingdom from the bloc, at a time when the COVID-19 pandemic was intensely ravaging all sectors, could only be double jeopardy for the UK economy, hence another motivation for our research.

Sakariyahu *et al.* (2021) note that markets react differently to bad and good news. The behaviour of every stock market is a response to shocks from both internal and external environments. Thus, understanding factors that drive market behaviour, particularly during a pandemic, is a critical aspect of investment and economic analyses. First, to an investor, in the quest to limit risks associated with the prevalence of the pandemic, an accurate measure of market behaviour provides insights into the appropriate diversification strategies that can be used to hedge long-term exposures. Second, during a global pandemic, financial assets become vulnerable to investors' sentiments occasioned by broad uncertainties; thus, estimating how financial markets react to the attitudes of investors, in a crisis period, assists firms to mitigate against potential downside risk associated with investment decisions (Berger, Dew-Becker and Giglio, 2020; Jurado, Ludvigson and Ng, 2015). Furthermore, considering that investors in the UK market were concerned with the magnitude of the impact of Brexit on their portfolios, and considering its concurrence with the pandemic, this study comes at a propitious time, as the world awaits yet another episode of the pandemic. We therefore address pertinent issues surrounding the behaviour of financial markets, with a view to providing valuable information to policymakers, regulators and investors.

Our study provides the following findings. First, prior evidence on the impact of the COVID-19 pandemic on financial markets focuses directly on the capital market using returns and volatility (Ambros *et al.*, 2021; Li, 2021; Prabheesh, 2020). Although the capital market plays a crucial role in providing long-term finance to government and firms; notwithstanding, the importance of the currency market in financing domestic and foreign trade – as well as maintaining financial stability within an economy – cannot be downplayed. Moreover, currency markets across the globe also came under severe stress during the global pandemic. In this study, we examined the impact of the pandemic on both the capital and currency markets and found that the pandemic had significant varying effects on both markets. Second, in sharp contrast to previous research on the pandemic, our study uses investor sentiments to explain how government policy responses permeate the financial market. Research shows that asset prices in the financial markets tend to drift from their equilibrium levels in the presence of investor sentiments (Smales, 2017). Thus, using new sentiment measures and a unique set of data, we found that investors relied on government policy announcements to make decisions, which in turn affected the outcomes of the market during the pandemic. Third, we created a new pandemic index as well as a government response index, and independently tested these indices on the market data. Last, we provide new evidence showing that the systematic risk of sectors within the UK stock market changed significantly during the pandemic, and that Brexit played a major role in influencing the outcomes of some of the sectors.

Through the lens of behavioural finance, this study explores whether UK government policies during the pandemic affected the performance of the financial market. Distinct from previous studies, our salient contributions to the literature are as follows. First, a quick scan through the literature shows that this is the first study examining the connection between investor sentiments and market performance during the pandemic. Considering that our findings confirm significant association between the duo, this study therefore offers crucial policy insights to key stakeholders in academia, government and industry. While many studies on

Table 1. Result of pandemic and GPR indices

Variables	Comp. 1	Comp. 2	Comp. 3	Comp. 4	Comp. 5	KMO
Panel A: Pandemic variables						
DIR	0.2655	0.4831	−0.2230	−0.5501	0.6047	0.5193
DFR	0.4901	0.4255	0.2797	0.3342	−0.4012	0.5911
BRR	0.4210	−0.1977	−0.2312	0.3049	0.4122	0.5312
IGR	−0.6544	−0.3316	0.3164	0.3301	0.2356	0.5900
VR	0.5715	−0.3326	−0.3196	0.348	0.2422	0.5097
Eigenvalue	1.6465	1.0278	0.3278	0.4012	0.3481	–
Varianceprop	0.3566	0.1984	0.1118	0.1342	0.1990	–
Overall KMO	–	–	–	–	–	0.5847
Panel B: GPR variables						
GRI	0.5015	0.3148	−0.3022	−0.5051	0.4407	0.5319
CHI	0.4155	0.4509	0.2901	0.3455	−0.4100	0.5122
SI	0.4122	−0.1709	−0.3224	0.4009	0.3226	0.5213
ESI	−0.5467	−0.3622	0.3145	0.3019	0.2562	0.5033
ROI	0.5152	−0.2633	−0.3601	0.3221	0.2214	0.5700
Eigenvalue	1.4522	1.2110	0.2833	0.4211	0.3155	–
Varianceprop	0.2090	0.3573	0.1360	0.1977	0.1000	–
Overall KMO	–	–	–	–	–	0.5768

This table shows the output of the pandemic and GPR indices. Panel A documents the output for the pandemic variables, while panel B represents that of the GPR variables. KMO stands for the Kaiser–Meyer–Olkin, which is a measure of variance among variables with common variance.

the pandemic generally focus on broad market performance, our study specifically contributes to the extant literature by illuminating how investors responded to frequent government policies. Second, we explore the medium through which investors influence market performance by separating government policies on the pandemic and those on Brexit. We find that the former has a more significant impact on the UK market than the latter during our sampled period. Our study, through a diffusion process, thus extends the current literature on the implications of both the pandemic and Brexit on global financial markets. Third, we investigate the interaction between investor sentiment and the UK financial market at sectoral levels and find significant bidirectional causality. While studies in the literature have revealed conflicting outcomes between sentiments and market outcomes, our findings shed further light on this relationship. Last, we contribute to the literature by testing the validity of the prospect or loss-aversion theory. This theory explains investors' reaction to different investment situations with an unknown probability of outcomes, and that investors consider returns to be the primary goal of investments. We suppose that an increase in uncertainties around the market will discourage investors from the financial market and consequently affect overall market performance. Given our findings, we provide evidence that supports this theory, thus extending similar studies in the literature that validate the theory.

The remainder of this paper is structured as follows. The next section provides a literature review of past studies to support the formulation of our hypotheses. The third section provides details on the data collection process and source. The fourth section presents the empirical model; we present our findings in the fifth section and the sixth section concludes the paper, stating the significance of the main findings and outlining avenues for future research.

Theoretical framework

Several theories have been formulated in the finance and economics literature to validate the linkage between investor sentiments and stock market behaviours. Using *adaptive expectation theory*, Tinbergen (1939) showed that irrational investors formulate opinions about the future behaviour of financial markets based on past and trending events in such markets. The theory

Table 2. Summary statistics for the variables

Variables	Mean	SD	Min	Max	Skewness	Kurtosis	J-B
Panel A: Dependent variables							
FTSE	0.004	1.40	−10.87	9.05	−0.93	15.21	33.14
£/$	0.005	0.57	−4.09	2.95	−0.54	9.44	9.25
£/€	0.003	0.47	−3.62	1.67	−1.05	10.50	13.16
Panel B: Sentiment variables							
TSS	0.40	0.36	−0.19	2.98	−0.65	2.50	22.34
GPA	0.21	0.15	−0.33	1.47	−0.25	1.36	26.49
Panel C: Pandemic variables							
DIR	0.00028	0.00035	0.00	0.0028	2.80	16.37	18.27
DFR	46.93	248.27	−100.00	4666.67	11.28	18.79	19.78
BRR	0.34	0.42	−0.26	0.69	−0.58	3.57	24.71
IGR	0.19	2.33	−0.16	5.08	0.11	2.59	4.87
VR	0.0027	0.0033	0.00	0.0156	1.0401	3.3187	33.62
Panel D: Brexit variable							
BOT	−8.67	3.45	−12.45	5.60	3.44	5.02	5.46
Panel E: GPR variables							
GRI	2.20	2.17	2.06	3.45	0.08	2.75	3.12
CHI	3.26	3.17	1.95	5.17	0.26	1.66	23.55
SI	0.33	1.64	0.04	1.07	0.25	2.44	5.02
ESI	1.36	2.11	1.28	2.19	1.54	2.03	7.09
ROI	1.33	0.81	0.62	3.48	6.10	4.18	13.59

Table 3. Unit root test of variance

	Level			Differenced		
Variables	ADF	PP	KPSS	ADF	PP	KPSS
FTSE	−2.30	−1.44	1.47	−19.22	−20.12	0.23
£/$	−1.05	−2.26	1.70	−18.25	−21.44	0.79
£/€	−1.45	−1.56	1.79	−18.33	−25.26	0.38
TSS	−2.60	−1.77	1.85	−29.31	−27.24	0.54
GPA	−2.02	−1.22	1.87	−24.56	−29.12	0.47
DIR	−2.08	−2.13	1.22	−20.17	−19.31	0.29
DFR	−2.36	−2.91	1.35	−17.29	−22.47	0.33
BRR	−1.74	−2.05	1.89	−19.22	−28.11	1.56
IGR	−1.43	−1.67	1.15	−20.19	−19.56	0.31
VR	−2.01	−3.55	0.29	−18.25	−22.13	0.29
BOT	−2.05	−2.33	1.01	−22.20	−38.19	0.38
GRI	−1.46	−1.05	1.07	−28.53	−28.03	0.21
CHI	−1.55	−2.20	1.57	−21.38	−38.18	0.53
SI	−1.72	−2.01	1.33	−28.19	−34.02	0.43
ESI	−1.90	−2.14	1.06	−21.38	−32.10	0.39
ROI	−1.37	−2.22	1.56	−28.30	−23.19	0.29

suggests that current market behaviour is a function of the past and can transmit into the future. Although this is an illogical belief in finance,[1] the evidence of such behavioural patterns, nevertheless, still holds sway in some markets. Simon (1955) proposed the bounded-rational theory. The theory

[1]Based on random walk theory in finance, past trends in a stock market cannot be used to explain future behaviour of the market, because changes in the prices of stocks are random and independent of each other.

Table 4. GLM estimates using TSS

Variables	FTSE	£/$	£/€	FTSE	£/$	£/€	FTSE	£/$	£/€
TSS	−0.067*	0.012*	−0.081***	−1.327	−1.062	−1.308**	−0.35	−0.04*	−0.091**
	(0.512)	(0.410)	(0.139)	(0.145)	(0.80)	(0.245)	(0.201)	(0.135)	(0.022)
DIR	0.209**	−0.437*	0.387***	–	–	–	−0.416*	0.148	0.179*
	(0.13)	(0.218)	(0.231)	–	–	–	(0.255)	(0.105)	(0.102)
DFR	−0.378*	−0.854	−0.481*	–	–	–	−0.197	0.235*	−0.109
	(0.112)	(0.320)	(0.223)	–	–	–	(0.114)	(0.441)	(0.254)
BRR	0.01	0.14	1.324**	–	–	–	−0.134*	−0.195	0.348*
	(0.119)	(0.107)	(0.436)	–	–	–	(0.009)	(0.021)	(0.190)
IGR	−0.542*	−0.352**	0.082**	–	–	–	0.182*	−0.459	−0.665*
	(0.210)	(0.125)	(0.118)	–	–	–	(0.017)	(0.102)	(0.330)
VR	0.672**	0.435*	0.441*	–	–	–	0.661*	0.450**	0.889
	−(0.320)	(0.232)	(0.198)	–	–	–	(0.218)	(0.201)	(0118)
Balance of trade	–	–	–	−0.550	−1.014**	−1.143*	−0.267*	0.784**	−0.661*
	–	–	–	(0.211)	(0.143)	(0.203)	(0.117)	(0.225)	(0.185)
GRI	−0.230*	0.567**	−0.651	−0.339	0.588	−0.755	0.385	−0.664	−0.775***
	(0.119)	(0.235)	(0.204)	(0.331)	(1.273)	(1.355)	(0.114)	(0.167)	(0.119)
CHI	0.192	−0.229*	−0.342**	0.221	−0.438	−1.455	0.176	−0.443*	−0.513
	(0.051)	(0.082)	(0.113)	(0.009)	(0.241)	(0.127)	(0.221)	(0.128)	(0.223)
SI	0.267	−0.221	−0.420*	0.647*	−0.692	−1.403	0.334*	−0.190	−0.440
	(0.105)	(0.011)	(0.213)	(0223)	(0.009)	(0.37)	(0.115)	(0.1)	(0.112)
ESI	0.321	0.621	0.392	0.366	0.427	0.520	0.228	0.335	0.409
	(0.05)	(0.02)	(0.02)	(0.04)	(0.05)	(0.02)	(0.06)	(0.04)	(0.05)
ROI	0.60	0.56	0.62	0.60	0.56	0.68	0.56	0.47	0.62
	(0.119)	(0.228)	(0.102)	(0.231)	(0.225)	(0.202)	(0.061)	(0.124)	(0.005)
R^2	0.65	0.61	0.46	0.55	0.66	0.63	0.53	0.48	0.44

*, ** and *** refer to 1%, 5% and 10% levels of significance, respectively.

explains the limitations on the capabilities of investors to process complex market situations, thus leading to misjudgement and erroneous decisions. According to the theory, investors always want to make rational decisions but given their limited knowledge of financial market operations, limited access to market information, insufficient time to make a choice and other factors (e.g. social, cultural and economic), they end up drawing irrational conclusions, thinking they have made the best decision. Such is evident in the case of panic buying, where investors suddenly begin to buy a security, given the fear that its price may rise later, but in fact it has become irrational to continue doing so.

Tversky and Kahneman (1981) advanced the *prospect theory*; this is also referred to as the loss-aversion theory. The theory explains the reaction of investors to different investment situations with an unknown probability of outcomes. It suggests that investors typically go to the financial market for the primary purpose of making returns depending on the time horizon. Notwithstanding, based on the risk attitude, an investor would be psychologically distressed when losses are incurred compared to when gains are made. Hence, given two investment choices, prospect theory proposes that an investor would place more value on the prospect of perceived gains than losses. Black (1986) came up with the *theory of noise trading*. The theory raises concerns that a critical segment of the market are noise traders with little or no knowledge about the market. They rely on noise from the market (e.g. trade volume and price variation) to make investment decisions. According to this theory, such trading action invalidates the essence of market efficiency and could destabilize expected market patterns. Merton (1987) introduced the *investor recognition hypothesis*. This hypothesis explains how the constraints of information tend to limit the portfolio of assets an investor can hold at a particular time. The hypothesis rests on the fact that investors with incomplete information can only hold a limited number of assets with lower recognition in the market. Accordingly, such assets (with lower recognition) tend to

Table 5. GLM estimates using government policy announcements as alternative sentiment measure

Variables	FTSE	£/$	£/€	FTSE	£/$	£/€	FTSE	£/$	£/€
GPA	-0.19^{**}	-0.03^{*}	-0.02^{*}	-1.34^{*}	−1.23	−1.16	-021^{*}	-0.02^{**}	−0.15
	(0.23)	(0.11)	(0.32)	(0.15)	(0.09)	(0.51)	(0.16)	(0.19)	(0.06)
DIR	−0.25	-0.31^{*}	0.22	–	–	–	-0.26^{**}	0.18	0.29^{**}
	(0.32)	(0.20)	(0.13)	–	–	–	(0.26)	(0.12)	(0.02)
DFR	-0.24^{**}	-0.45^{*}	-0.18^{*}	–	–	–	−0.24	0.29^{**}	−0.15
	(0.24)	(0.30)	(0.35)	–	–	–	(0.42)	(0.13)	(0.20)
BRR	0.23^{*}	−0.12	1.20^{*}	–	–	–	-0.18^{**}	-0.23^{*}	0.31^{*}
	(0.12)	(0.07)	(0.60)	–	–	–	(0.11)	(0.01)	(0.20)
IGR	-0.25^{**}	-0.23^{*}	0.21	–	–	–	0.23^{*}	−0.54	−0.51
	(0.20)	(0.15)	(0.18)	–	–	–	(0.32)	(0.18)	(0.39)
VR	0.25^{*}	0.50^{*}	0.16^{*}	–	–	–	0.16^{*}	0.09^{**}	0.97
	−(0.33)	(0.12)	(0.80)	–	–	–	(0.30)	(0.12)	(0.50)
Balance of trade	–	–	–	−0.41	-1.09^{*}	-1.34^{*}	-0.71^{*}	0.44^{*}	-0.15^{*}
	–	–	–	(0.10)	(0.39)	(0.53)	(0.26)	(0.15)	(0.50)
GRI	-0.19^{**}	0.22^{*}	0.14	−0.20	0.11	−0.15	0.35^{*}	-0.42^{*}	-0.18^{*}
	(0.20)	(0.15)	(0.04)	(0.19)	(1.31)	(0.09)	(0.24)	(0.11)	(0.22)
CHI	0.21^{*}	-0.19^{*}	-0.27^{*}	0.01	−0.31	−1.09	0.12	−0.38	-0.36^{*}
	(0.03)	(0.02)	(0.10)	(0.19)	(0.11)	(0.13)	(0.16)	(0.11)	(0.07)
SI	0.17^{*}	−0.19	0.22^{*}	0.41^{*}	0.23	0.39	0.30^{*}	0.10	0.08^{*}
	(0.15)	(0.22)	(0.45)	(0.39)	(0.28)	(0.16)	(0.09)	(0.22)	(0.17)
ESI	0.15	0.23^{*}	0.20^{*}	0.11^{**}	0.20^{*}	0.09	0.18^{***}	0.52^{*}	0.18
	(0.23)	(0.18)	(0.35)	(0.14)	(0.25)	(0.16)	(0.20)	(0.17)	(0.22)
ROI	0.25^{**}	0.39^{*}	0.15	0.17^{***}	0.22	0.40^{*}	0.19	0.70	0.02
	(0.14)	(0.33)	(0.29)	(0.15)	(0.50)	(0.13)	(0.19)	(0.34)	(0.51)
R^2	0.52	0.41	0.60	0.50	0.38	0.39	0.61	0.33	0.56

*, ** and *** refer to 1%, 5% and 10% levels of significance, respectively.

compensate their holders with a risk premium and higher return.

Epstein (1999) also proposed the *ambiguity aversion theory*, also called the uncertainty aversion theory. From the name, the theory signifies that an investor would prefer to hold assets with a known risk or outcomes than to hold those with an unknown outcome. The theory further demonstrates that some investors avoid a particular stock or sector due to ambiguity of future outcomes. Further exploring this theory, Easley and O'Hara (2009) discovered that the non-participation of traders due to ambiguity aversion often distorts market performance. Ultimately, Shefrin and Statman (2000) proposed the *behavioural portfolio theory*. The theory is a total deviation from the classical finance theories that assume all investors are rational and thus always want to maximize returns. Instead, the behavioural portfolio theory believes that investors have different motives for going to the market and, based on a pyramid of investment goals, they create a portfolio that meets their multifarious expectations.

Empirical reviews

A considerable number of empirical studies have appeared in the literature examining the connection between the pandemic and financial markets. For instance, Yan and Qian (2020) examined the impact of COVID-19 on the consumer industry of the Chinese stock market using an event study approach. Adopting a constant mean return model to estimate the abnormal return rate, their study shows that the pandemic had a limited and short-term conditional effect on the consumer industry. They conclude that government intervention and policies have significant influence on limiting the impact of COVID-19 on the consumer industry. Narayan (2020) assessed the influence of the pandemic on exchange rate resistance to shocks using the ¥/$ rate. Applying ordinary least squares regression and an NP unit root model that considers structural breaks in levels, they observed that prior to the pandemic, the ¥/$ rate was non-stationary, but became stationary during the pandemic, thus suggesting that the pandemic led to

Table 6. Co-integration, VAR and VECM results using FTSE 100 as the dependent variable

Panel A: Co-integration results

Models	Null hypothesis	Trace statistics	p Value (0.05)	Max eigen value	p Value (0.05)
Model 1	Ho: r = 0	35.84*	11.20	22.15*	13.27
	Ho: r ≤ 1	28.04*	9.09	9.05*	8.27
	Ho: r ≤ 2	6.35	7.92	6.55*	5.13
	Ho: r ≤ 3	11.28*	5.23	2.10	3.32
Model 2	Ho: r = 0	28.54*	10.55	19.23*	11.07
	Ho: r ≤ 1	5.99	10.19	4.78	8.20
	Ho: r ≤ 2	20.50*	8.12	7.10*	6.33
	Ho: r ≤ 3	15.81*	7.39	3.08	4.10
Model 3	Ho: r = 0	25.46*	10.59	20.46*	15.70
	Ho: r ≤ 1	9.04	11.33	9.52*	5.76
	Ho: r ≤ 2	13.68	17.20	8.46	9.39
	Ho: r ≤ 3	9.85	15.60	8.04*	5.24
	Ho: r ≤ 4	8.30*	5.94	7.32	8.41

Panel B: VAR results

Models	Variables	AIC	SIC	HQ	LR
Model 1	FTSE	105.43	101.60	22.53	−23.71
	TSS	87.31	70.21	20.10	−21.16
	COVID-19	117.19	107.10	19.86	−23.85
	GPR	103.55	91.28	20.35	−21.32
Model 2	FTSE	92.31	87.16	22.30	−20.16
	TSS	89.25	81.11	20.77	−20.02
	BOT	97.92	85.78	20.18	−19.55
	GPR	95.17	90.81	22.51	−20.08
Model 3	FTSE	104.39	98.04	20.39	−19.78
	TSS	93.17	70.21	20.10	−20.01
	COVID-19	105.02	95.20	20.98	−20.51
	BOT	97.99	86.55	24.61	−23.85
	GPR	103.51	81.08	20.61	−21.92

Panel C: VECM results

Models	Variables	FTSE	TSS	COVID-19	BOT	GPR	ECT
Model 1	FTSE	–	−1.76*	−5.03*	–	2.38	−3.10*
	TSS	−3.61*	–	−2.09	–	2.89	−1.5*
	COVID-19	1.71	1.07	–	–	2.38*	−2.03
	GPR	3.51*	1.86	−2.59	–	–	−2.32
Model 2	FTSE	–	1.60*	–	−3.44*	3.80	−1.99*
	TSS	−1.87*	–	–	2.01	−1.88*	−2.02
	BOT	3.11	1.55*	–	–	3.64*	−4.39*
	GPR	5.30*	2.61	–	−1.90	–	−3.09*
Model 3	FTSE	–	3.07*	−1.80	4.14*	2.09	−3.19*
	TSS	−2.75*	–	−1.88	1.05*	−3.12*	−1.27
	COVID-19	3.74	−1.48	–	2.61	1.86	−1.02*
	BOT	1.51	−5.36	−2.33	–	3.43*	−3.41*
	GPR	3.50*	−6.10	−3.24	−2.03	–	−1.88*

Panel D: Diagnostics test

Variables	LM	ARCH	White	Ramsey
FTSE	19.12*	7.45*	1.09*	0.95*
TSS	8.32*	5.43*	1.98*	3.29*
COVID-19	5.60*	4.33*	4.08*	26.21*
BOT	11.35*	5.15*	3.69*	3.10*
GPR	8.93*	5.02*	6.28*	3.03*

Table 7. Robustness 1: Causality between TSS and market behaviour (Ret = returns, Volt = volatility and Vol = volume) before and during the pandemic era

	Pre-pandemic			During pandemic		
Variables	TSS≈ Ret	TSS≈Volt	TSS≈ Vol	TSS≈ Ret	TSS≈Volt	TSS≈ Vol
FTSE	2.4*	1.11	0.3	1.7*	0.35*	9.2*
	0.6	2.16	1.45*	3.2**	2.01	2.45**
Oil and gas	0.2	0.33*	0.13	0.22*	0.32	11.09
	1.01	2.19	1.01*	1.09***	1.36	1.22
Basic materials	0.45*	0.65	1.90**	0.23**	1.02	6.45
	0.33	0.48*	1.45	0.15	1.27**	4.03
Industrials	0.21	1.33	1.32	0.67*	2.34*	1.30*
	0.16*	0.91**	0.41	0.50**	0.89***	0.45
Consumer goods	0.18	1.33*	0.19	1.33	0.49	1.09
	0.05	0.47	1.10*	0.20	0.16	0.28
Healthcare	0.33	0.15	1.10	1.36**	1.48*	0.32***
	0.18*	0.24	1.06	1.22*	1.02*	2.15**
Consumer services	0.11	1.06	0.06	2.14**	0.34*	0.23*
	0.23	0.14*	0.30	1.28***	1.55**	1.01**
Telecoms	1.08	0.22	0.43	0.19	1.81*	1.25*
	0.23*	1.09	0.02*	0.08	0.92*	1.60*
Utilities	2.28*	0.35	0.39	0.88*	0.12	1.09
	1.67	1.23	1.07	0.11*	1.53*	1.22*
Financials	0.33*	1.08*	0.19*	0.35*	1.04*	0.35*
	0.12*	0.23	1.12	1.13*	1.11*	0.19*
Technology	0.15*	1.48	1.57	12.04**	1.08*	1.02*
	0.76	0.35	1.23	9.67*	0.89***	1.65**

*, ** and *** refer to 1%, 5% and 10% levels of significance, respectively.

Table 8. Robustness 2: Causality between GPA and market behaviour (Ret = returns, Volt = volatility and Vol = volume) before and during the pandemic era

	Pre-pandemic			During pandemic		
Variables	TSS≈ Ret	TSS≈Volt	TSS≈ Vol	TSS≈ Ret	TSS≈Volt	TSS≈ Vol
FTSE	0.54	0.45	0.65*	1.25***	0.76**	0.85*
	0.75	0.26	0.19	0.67*	1.10***	0.56**
Oil and gas	0.45	0.23	0.37	0.44*	0.32*	0.21**
	0.31**	0.50	0.10**	0.58*	0.25	0.17*
Basic materials	0.10	0.22	0.13	0.02	0.35*	0.16
	0.32*	0.15*	0.17	0.19**	0.10*	0.03*
Industrials	0.15	0.09*	0.11	1.04*	0.90**	1.10***
	0.08	0.28	0.04*	0.67**	0.35*	0.78*
Consumer goods	0.54	0.30	0.21	0.87**	0.66*	0.72*
	0.21	0.17	0.08	0.70*	0.50**	0.31*
Healthcare	0.30*	1.12	0.18	1.34*	0.65*	0.21*
	0.16	0.02	0.21	1.78*	0.32***	0.43**
Consumer services	0.21	0.13*	0.01	0.08	0.10*	0.12**
	0.17	0.16	1.09	0.19**	0.23*	0.22*
Telecoms	0.33*	0.43	0.33	0.29*	0.14*	0.33**
	0.19	0.22	0.16	0.20*	0.10***	0.09***
Utilities	0.11	0.25	0.12	0.32**	0.18*	0.08**
	0.03	0.08*	0.01	0.16***	0.09*	0.23*
Financials	0.02	0.14	0.21	0.91*	0.15**	0.03*
	0.90*	0.32	0.08	0.35*	0.21*	0.80*
Technology	0.13*	0.44*	0.11	0.28***	0.14*	0.11*
	0.01	0.76*	0.36	0.09*	0.02*	0.50**

*, ** and *** refer to 1%, 5% and 10% levels of significance, respectively.

Table 9. Robustness 3: Sectorial analysis of short-term systematic risk (β) before and during the pandemic

Variables	Pre-pandemic era (β)	Pandemic era (β)	t-Stats
Oil and gas	0.63	1.85	22.09*
Basic materials	0.32	0.91	18.12**
Industrials	0.11	1.04	11.16*
Consumer goods	1.04	0.82	−2.65*
Healthcare	0.46	0.67	20.33***
Consumer services	0.35	0.04	−3.78*
Telecoms	0.87	0.93	14.67*
Utilities	0.35	0.51	11.03**
Financials	1.08	1.94	25.19**
Technology	0.55	0.70	16.08***

*, ** and *** refer to 1%, 5% and 10% levels of significance, respectively.

Table 10. Robustness 4: Introducing the lagged values of the dependent variables with main regressors

Variables	FTSE	£/$	£/€	FTSE	£/$	£/€	FTSE	£/$	£/€
$FTSE_{t-1}$	0.258**	–	–	0.375**	–	–	0.520*		
	(0.110)	–	–	(0.056)	–	–	(0.180)		
£/$ $_{t-1}$	–	0.269*	–	–	0.620*		–	0.455**	
	–	(0.155)	–	–	(0.133)		–	(0.101)	
£/€ $_{t-1}$			0.461**			0.355*			0.221**
			(0.121)			(0.110)			(0.200)
TSS	−0.157	0.126**	−0.119*	−0.264	−0.325	−0.311**	−0.251	−0.241*	−0.221**
	(0.225)	(0.136)	(0.220)	(0.241)	(0.080)	(0.125)	(0.109)	(0.122)	(0.099)
DIR	0.221*	−0.350*	0.221	–	–	–	−0.219**	0.237	0.227*
	(0.335)	(0.156)	(0.012)	–	–	–	(0.150)	(0.111)	(0.032)
DFR	−0.321*	−0.305	−0.126*	–	–	–	−0.219	0.152*	−0.195
	(0.126)	(0.201)	(0.230)	–	–	–	(0.144)	(0.201)	(0.223)
BRR	0.209*	0.311	0.240**	–	–	–	−0.145*	−0.150	0.332*
	(0.015)	(0.177)	(0.223)	–	–	–	(0.091)	(0.211)	(0.055)
IGR	−0.235*	−0.321	0.026**	–	–	–	0.233*	−0.343	−0.531*
	(0.122)	(0.105)	(0.018)	–	–	–	(0.011)	(0.112)	(0.030)
VR	0.255*	0.211*	0.292*	–	–	–	0.155*	0.204**	0.202
	(0.036)	(0.122)	(0.109)	–	–	–	(0.018)	(0.132)	(0.210)
Balance of trade	–	–	–	−0.032	−0.046**	−0.322*	−0.155	0.140	−0.133*
	–	–	–	(0.191)	(0.130)	(0.053)	(0.227)	(0.225)	(0.110)
GRI	−0.204*	0.101	−0.112*	−0.051	0.018**	−0.150	0.132	−0.114	−0.157**
	(0.001)	(0.150)	(0.042)	(0.120)	(0.344)	(0.126)	(0.140)	(0.155)	(0.120)
CHI	0.210*	−0.321*	−0.305	−0.219	0.152*	−1.455	0.176	0.211*	0.292*
	(0.051)	(0.126)	(0.201)	(0.144)	(0.201)	(0.127)	(0.221)	(0.122)	(0.109)
SI	−0.19**	0.22*	0.14	0.372*	−0.265	−0.311	0.240*	−0.108	−0.113
	(0.120)	(0.110)	(0.040)	(0.321)	(0.156)	(0.032)	(0.121)	(0.101)	(0.129)
ESI	0.233	0.215*	0.326	0.231*	0.255	−0.155*	0.522*	0.314	0.359**
	(0.129)	(0.022)	(0.035)	(0.039)	(0.125)	(0.108)	(0.215)	(0.124)	(0.025)
ROI	0.323*	0.250**	0.442***	0.330	0.256*	0.220	0.126*	0.337	0.255*
	(0.089)	(0.124)	(0.032)	(0.139)	(0.251)	(0.033)	(0.011)	(0.104)	(0.052)
R^2	0.21	0.33	0.41	0.25	0.46	0.32	0.34	0.29	0.36

a transitory shock on the exchange rate. Sharma (2020) explored the commonality in volatility of Asian economies during the pandemic.

Using a sample of five developed economies – China, Japan, Hong Kong, Singapore and South Korea – the study specifically explores the contagion effect, that is, whether market volatility at regional level can transmit into individual countries. Using daily data of the sampled countries, they observe that there is a spill-over in volatility from the Asian regional markets to the specific countries, and this was more prevalent during the

COVID-19 pandemic. In similar research, Ambros *et al.* (2021) assessed the impact of changes in the number of COVID-19 cases on the volatility of eight different stock markets using 30 min tick returns. They show that changes in the pandemic figures do not have a significant impact on the returns of the market, however, there is strong evidence of impact on market volatility. Iyke (2020) observed that the pandemic has a positive and significant impact on economic policy uncertainties (EPUs) in five leading Asian economies, examining the impact of the pandemic and government interventions on stock market returns of 20 OECD countries.

Using a panel regression model with robust standard errors, Yang and Deng (2021) also find that there is a significant negative relationship between the number of confirmed cases and market returns. Li (2021) explored the media effect of daily COVID-19 cases on China's stock market volatility. Using a nonlinear autoregressive distributed lag (NARDL) model, the study reveals that positive shocks to media attention on COVID-19 have a significant impact on stock price volatility in China – more than the direct impact of the pandemic. Prabheesh (2020) examined the dynamics of foreign portfolio investment and stock market returns in India during the pandemic. Utilizing daily data and the Toda and Yamamoto Granger causality test, they find a unidirectional causality between foreign portfolio investment flows and stock returns, thus concluding that the pandemic disrupted India's economy. Explaining the effect of the pandemic on the SP index using a structural vector autoregression model, Yilmazkuday (2021) observed that an increase in the number of COVID-19 cases results in a reduction in the S&P 500 index.

In a recent study, Liu, Shahab and Hoque (2022) examine the impact of public trust in government in combating COVID-19. Using data for 178 countries between 20 March 2020 and 8 April 2020, they show that public trust and support in government policy measures play a critical role in winning over the pandemic. Empirically, they find a positive association between increase in composite government response measures and public trust and belief in government. They conclude, however, that such an impact is subject to individual countries' legal systems, quality of welfare services, preparedness and prompt response to the socio-economic needs of citizens and institutional quality. Ataullah, Le and Wood (2022) also investigate the role of institutional investors during the pandemic. They explain how COVID-19 permeates institutional investors to influence firms' dividend policies and share buyback decisions. Using attention-based theories and hand-collected data of firms in the United Kingdom, the study applies a simple model to estimate the probability of a dividend reduction by firms based on institutional ownership. They show that firms with large institutional owners actively engage with their managers; hence, they are more likely to influence managers to retain earnings than pay dividends, as this would help to mitigate the effects of business uncertainties during the pandemic and enhance long-term growth.

Clearly, another wave of uncertainty that hovers around the UK economy is that of Brexit. A myriad of empirical studies in the literature has expressed serious concerns on the implications of Brexit on the global market. For instance, employing an event study on 107 logistic companies from the United Kingdom and Continental European countries, Schiereck and Tielmann (2016) provide evidence suggesting that Brexit had an overall negative value effect on the share price of companies both in the United Kingdom and Europe. However, the magnitude of impact is worse for UK companies than their European counterparts. Specifically, they show that UK companies suffered an abnormal return of over 10% compared to companies in Europe, whose abnormal returns were around 1%. Highlighting the implications of Brexit, Cumming and Zahra (2016) note that Brexit will create a future of massive uncertainties in the global market as the relationship between the United Kingdom and the rest of the world has to be redefined. Specifically, their study highlights the impact of Brexit on immigration, technology, entrepreneurship, international business and international finance. They reveal that Brexit is expected to have dire consequences on the UK economy and the business climate may take years to stabilize.

Wright *et al.* (2016) reveal that Brexit creates threats and problems for both private equity (PE) firms and their portfolio companies. They opine that the EU market may put in place tighter regulations and scrutiny for UK PE firms, thus making their activities less attractive to potential investors in the European Union and creating setbacks for their growth. Consequently, it will be difficult for

UK PE firms to access funds from the EU market as this may further diminish the United Kingdom's leading position in PE. In a similar study, Kellard *et al.* (2022) reveal how UK PE firms behave in the face of Brexit and economic uncertainties. Employing a dataset of PE targets and non-targets over the 2010–2019 period, they show that UK PE activities such as growth and expansion have been negatively impacted by Brexit-induced uncertainties. They therefore urge policymakers to quickly resolve such uncertainties surrounding Brexit.

In sum, studies on COVID-19 and market outcomes are numerous, as well as those on Brexit. Intriguingly, despite the array of studies documenting the impact of the pandemic on market outcomes, none has investigated the direction of sentiments. We therefore fill in the research vacuum by focusing attention on the role of investor sentiments on the behaviour of financial markets during the pandemic.

Hypothesis development

COVID-19, government responses and market outcomes

The pandemic has shown the importance of effective communication and how it formed the basis for crucial decision-making by both governments and citizens. Essentially, in a pandemic, there is an increase in levels of uncertainty and risk within the economy, particularly in the financial market. Hence, timely information not only saves lives, but also livelihoods. Investment decisions during pandemics are predicated on periodic pronouncements from government and its officials (Liu, Shahab and Hoque, 2022). Meanwhile, governments are privy to more sensitive information than citizens and in a bid to avoid public misconception and provocations, less sensitive statements are usually released for public consumption (Adolph *et al.*, 2021). The information asymmetry, alongside general uncertainties and restriction of social gatherings and movements, limits people's ability to make rational decisions. With a looming fiscal disaster and people's means of livelihood already in danger, investors need accurate information from government to make decisions that would protect their investments and social wellbeing. While emotions, fear and panic are common drivers of decision-making during an outbreak (Liu, Shahab and Hoque, 2022), the effectiveness of government's periodic pronouncements can play a moderating role. Some studies have demonstrated the importance of effective information dissemination during a pandemic. For instance, Reddy and Gupta (2020) explain how poor communication from government can jeopardize the safety of physicians, healthcare workers and vulnerable populations. Also, Ataguba and Ataguba (2020) describe effective crisis and risk communication by government as the foundation to building trust, credibility, honesty, transparency and accountability. Consequently, we derive our hypothesis as follows:

H1: Government periodic announcements shaped investment decisions towards the financial market.

COVID-19, investor sentiments and market outcomes

The COVID-19 pandemic and its widespread effects on economic agents (households, firms and governments) created massive disruptions across global financial markets. In the United Kingdom, the financial market experienced significant losses in March 2020 when the risk of the pandemic became heightened, as both the capital and currency markets withstood pressures from the concurrence of the pandemic and Brexit. Essentially, the FTSE 100 experienced its highest loss (since 1985) during the pandemic, although it later regained the losses and has since continued to rise. Likewise, the £/$ daily exchange rate recorded huge losses at the start of the pandemic but has also returned to its pre-pandemic average. The quick return of the UK financial market to its pre-pandemic era can be attributed to the immediate monetary policy actions of the Bank of England, as well as the government policy initiatives designed to insulate the UK economy from systemic collapse. Although these moves appear to be a universal approach, one still wonders why some markets manifest greater stress and are yet to recover. Evidence from the African and Asian markets, for example, points clearly to such stress; some markets within these regions still struggle to return to their pre-pandemic prices. This raises important questions as to whether those markets were better prepared for the pandemic, or whether a case of negative sentiments from investors took a toll on the markets. To this end, we construct the following hypothesis:

H2: Investor sentiments during the pandemic impacted the UK financial market.

Brexit, government responses and market outcomes

The future of the UK economy due to its exit from the European Union (Brexit) is obscure and seemingly unpredictable. Brexit has unleashed significant changes in the political, economic and social dynamics of the United Kingdom. While the effect of these changes may not be immediately felt, it has the potential to reconfigure UK relationships with the rest of the world. More so, the internal political wranglings in the United Kingdom with regard to Brexit are a serious source of concern for prospective and current investors. On the one hand, part of the United Kingdom (Scotland) is signalling interest in gaining independence; on the other hand, there is a rising challenge as to the Northern Ireland borders. In the face of these controversies, it is nevertheless believed that the benefits of Brexit far outweigh its drawbacks. For instance, with the right policies in place, Brexit is intended to create even and unfettered opportunities for talent and businesses across the globe. Although, in the interim, existing multinational companies may have to seek refuge in other EU countries to take advantage of economies of scale and avoid EU sanctions; there is, however, a possibility, in the long run, that new businesses will emerge, given that a set of independent and favourable policies will be implemented to ease the cost of doing business in the United Kingdom. The erstwhile trading tariffs and regulations imposed by the European Union would be abolished to ease and facilitate the transfer of skills, innovation, funds and technology.

Sadly, the official exit of the United Kingdom from the European Union coincided with the COVID-19 pandemic, creating more risks for an already destabilized economy. Due to government policy measures on social restrictions and movements, the production of goods and services sharply declined; the demand for UK products also dropped and the government resorted to *radical money printing* to assist businesses and cushion the effects. This pushed inflation up and the UK financial market, particularly the pound sterling, lost huge value, thus further harming local businesses and multinational setups. The coincidence of the pandemic and Brexit, coupled with political and currency instabilities, heightened the risks of investment as potential investors would have to delay entry into the UK market or ultimately consider alternative business environments. This might eventually relinquish the UK position of global financial hub. Among the G7 nations, the United Kingdom is the most heavily dependent on foreign direct investment (Loewendahl, 2016); the consequences of an ineffective government response can aggravate the fragile conditions of the UK economy. Hence, we hypothesize that:

H3: The concurrence of Brexit and the pandemic has a significant impact on the UK financial market.

Methodology

The first confirmed COVID-19 case in the United Kingdom was announced on 23 January 2020, the official Brexit date was 31 January 2020 and the final lifting of COVID-19 restrictions took place on 19 July 2021. Thus, our market data cover the daily period from 2 January 2020 to 31 December 2021. Our data consist of five sets of variables: financial market variables, sentiment variables, pandemic variables, Brexit variables and government policy measures.

Financial market variables

Our variables for the financial market are categorized into capital market data, represented by FTSE 100 daily returns, and currency market data, represented by returns on £/$ and £/€ daily exchange rates, obtained from Refinitiv DataStream and Yahoo Finance.

Sentiment variables

A plenitude of proxies has been documented for sentiments in the literature (Baker and Wurgler, 2006; Jiang *et al.*, 2019; Sakariyahu *et al.*, 2021), of which many are indirectly observed. In the absence of absolute measures, we use the Twitter sentiment score (TSS) and government policy announcements (GPA) as proxies for investor sentiments. We test these proxies independently on market data. We hypothesize that given the social restrictions imposed during the COVID-19 pandemic, the daily announcements by government officials and the varying levels of redundancy across the workforce, increased use of social media as a source of reliable information could have influenced investors' attention, shaped emotions and moods towards the financial market and consequently expanded the proportion of irrational trading to well-informed trading. Following the methodological approach of Kearney and Liu (2014) and Oliveira, Cortez and Areal (2016), we use the finance-related lexicon of Loughran and McDonald (2011) to measure the textual tone of our sentiment variables (TSS and GPA). The TSS is calculated as the number of negative words minus the number of positive words in a tweet, scaled by the total word count. For the GPA, it is calculated as the number of negative announcements minus the number of positive announcements, scaled by the total official announcements in a day.

For instance, a reduction in the number of daily deaths or cases would be classified as a positive announcement for that day, while the closure of schools or the announcement of stricter measures is categorized as a negative announcement:

$$TSS = \left[\sum_{n=i}^{m} NW - \sum_{n=i}^{m} PW \right] / \sum_{n=i}^{m} TW \quad (1)$$

$$GPA = \left[\sum_{n=i}^{m} NA - \sum_{n=i}^{m} PA \right] / \sum_{n=i}^{m} TA \quad (2)$$

where NW, PW and TW represent negative words, positive words and total words in a particular tweet, respectively. Similarly, NA, PA and TA represent negative announcements, positive announcements and total announcements made by government officials in a single day, respectively. If the output of TSS or GPA is positive, it suggests that there are more negative words/announcements than positive ones.

It is pertinent to mention that some criteria were used to extract the sentiment tweets. First, we extract tweets that mention both COVID-19 and the FTSE 100 in a single tweet; second, we extract tweets that mention both Brexit and the FTSE 100. Lastly, we extract tweets that mention COVID-19, Brexit and the FTSE 100 in a single tweet. We repeat the same process for the currency market variables (£/$ and £/€). In the case of government policy announcements, we use the pandemic timeline put together by the Institute for Government (UK) (IfG, 2021) on their website, showing formal public announcements by government officials daily.

COVID-19 pandemic variables

Our COVID-19 pandemic variables are: (i) the daily infection rate (DIR) per capita, calculated as the daily number of confirmed COVID-19 cases divided by the entire population; (ii) the daily fatality rate (DFR), obtained as a percentage change in the daily number of deaths of people whose death certificate mentioned COVID-19 as one of the causes;[2] (iii) the basic reproductive rate (BRR), which is the expected number of COVID-19 cases in a population where all or some individuals have been infected; (iv) the infection growth rate (IGR), which captures how quickly the number of COVID-19 infections changes daily; and (v) the vaccination rate (VR) per capita, which captures the doses of vaccines administered divided by the entire population. Our pandemic data were sourced from the UK Health Security Agency, Statista and the Johns Hopkins University Coronavirus Resource Center.[3]

Brexit variables

We presume that Brexit-induced policy reforms might aggravate the vulnerability of the UK market to the pandemic, given the concurrence of both events. We proxy Brexit with the percentage change in balance of trade, calculated as the difference between the exports to and imports from the European Union. We obtain data from the UK Office of National Statistics.

[2]At first, we used daily fatality rate per capita but the output was insignificant, hence we decided to use percentage change which gives a more reliable result.

[3]It is essential to mention that some of the data were transformed from their natural form into a more convenient structure. For instance, the IGR data is stated on the government website (https://coronavirus.data.gov.uk/) as intervals or range; instead, we use the average of the interval for our analysis. Also, the DFR and DIR were transformed into their natural logarithm to properly align with the numeric features of other variables.

Government policy responses

Government policy responses (GPR) to the pandemic are used as instrumental variables in this study. They include overall government response index (GRI), containment and health index (CHI), stringency index (SI), economic support index (ESI) and risk of openness index (ROI). Our GPR data were sourced from the Oxford COVID-19 Government Response Tracker (OxCGRT) as compiled and updated by Hale *et al.* (2021).

Empirical models

Given the nature of our data, we employ a generalized linear model (GLM) regression to estimate the models, with a view to overcoming endogeneity problems and possible issues of non-normal distribution. The GLM applies Poisson, gamma and binomial distributions for modelling (Nelder and Wedderburn, 1972) and specifies a link function between the response variable and a vector of predictor variables. Additionally, we investigate the causality among the variables using vector autoregression (VAR) and a vector error correction model (VECM). However, considering the time-series properties of our data, it is expedient to first examine the presence of unit roots (stationarity) in the series, as this is a vital condition for the use of VAR/VECM. In most cases, time-series variables are not stationary at levels, but become stationary when differenced. Besides, the nature of the unit root in the series explains the presence of cointegration, implying the possibility of long-run equilibrium. If the series are stationary, but not cointegrated, the VAR model is used; otherwise, the VECM is used. In testing for a unit root, we use the augmented Dickey–Fuller (ADF), Phillips–Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) stationarity tests. Essentially, the KPSS should produce a positive figure while the ADF and PP statistics should be negative for all variables. Consequently, we would reject the null hypothesis if the computed t-value for ADF and PP is more negative than the critical value. Furthermore, we conduct a residual diagnostic to check for serial correlation and heteroscedasticity (LM test) as well as stability (Ramsey test) of the models. GLM, VAR and VECM are modelled in the following equations:

$$\ln V_i = \alpha + \beta\,[\ln W_i] + \beta\,[\ln X_i] + \beta\,[\ln Y_i] + \beta\,[\ln Z_I] + \varepsilon_i \tag{3}$$

$$\ln V_i = \alpha + \sum_{n=i}^{m} \beta V_{t-n} + \sum_{n=i}^{m} \beta W_{t-n} + \sum_{n=i}^{m} \beta X_{t-n} + \sum_{n=i}^{m} \beta Y_{t-n} + \sum_{n=i}^{m} \beta Z_{t-n} + \varepsilon_i \tag{4}$$

$$\Delta \ln V_i = \alpha + \sum_{n=i}^{m} \beta \Delta V_{t-n} + \sum_{n=i}^{m} \beta \Delta W_{t-n} + \sum_{n=i}^{m} \beta \Delta X_{t-n} + \sum_{n=i}^{m} \beta \Delta Y_{t-n} + \sum_{n=i}^{m} \beta \Delta Z_{t-n} + \beta ECT_{i-n} + \varepsilon_i \tag{5}$$

where V_i denotes each of our dependent variables: FTSE 100 index, £/\$ and £/€. α is the intercept, β is the slope or coefficient, W_t is the sentiment variable (TSS), X_i denotes a vector of pandemic variables (DIR, DFR, BRR, IGR, VR), Y_i represents the Brexit variable (ln BOT),[4] Z_i denotes a vector of government policy responses (instrumental variables: GRI, CHI, SI, ESI, ROI) and ε_i is the error term. The coefficients of the differenced terms in the VECM explain the short-run dynamics, while ECT is the error correction term and represents the estimated residual from the cointegration regression. If ECT is significant, it suggests that the current outcomes are significantly determined by the past.

As an additional test, we construct pandemic and GPR indices using orthogonal dimensions without distorting the intrinsic properties of the observations. Following Baker and Wurgler (2006) and Chen and Sherif (2016), first we generate a pandemic index (PI) explaining the unique component in the pandemic variables:

$$PI = \beta_1\,(X_1) + \beta_2\,(X_2) + \beta_P\,(X_P) \tag{6}$$

While calculating the PI, we focus our attention on the highest variance to prevent potential bogus scores for the weights of β_1 and β_2, which could affect the variance of PI. Consequently, we restrict

[4]Although both the pandemic and Brexit happened concurrently, we deem it essential to not include the proxies for both models simultaneously in the main equations. This is, moreover, bearing in mind that during the pandemic, the sentiment from Brexit was relegated.

the weights to ensure that their sum of squares is 1:

$$\beta_{I1}^2 + \beta_{I2}^2 + \beta_{I3}^2 + \cdots + \beta_{IP}^2 = 1 \qquad (7)$$

In a similar pattern, the second index (GPR variables) is produced with an orthogonal transformation that prevents it from being correlated with the first index but it must produce the next greatest possible variance. The outcomes of the pandemic and GPR indices are shown in Table 1.

As a robustness check, we follow the methodological approach of Brown and Cliff (2004) and Chung, Hung and Yeh (2012) to investigate the causality between our sentiment proxies and stock market behaviour at the sectoral level and perform a sectoral analysis of short-term systematic risk (β) before and during the pandemic. To measure stock market behaviour, we use daily data on returns, volume and volatility of the FTSE 100 index and sectoral indices, based on the DataStream Industry Classification Benchmark (ICB). The Granger-causality equations are shown below:

$$R_t = \alpha_r + \sum_{i=i}^{k} \beta_{ri} R_{t-i} + \sum_{i=i}^{k} \delta_{ri} S_{t-i} + \varepsilon_{rt} \qquad (8)$$

$$V_t = \alpha_v + \sum_{i=i}^{k} \beta V_i V_{t-i} + \sum_{i=i}^{k} \delta V_i S_{t-i} + \varepsilon_{vt} \qquad (9)$$

$$D_t = \alpha_D + \sum_{i=i}^{k} \beta D_i D_{t-i} + \sum_{i=i}^{k} \delta D_i S_{t-i} + \varepsilon_{Dt} \qquad (10)$$

Equations (8)–(10) above represent the Granger-causality equations, where R_t, V_t and D_t denote daily returns, volume and volatility, for FTSE 100 and the sectors, respectively. S_{t-i} stands for the lagged value of sentiment indicators at time t, k represents the maximal lag and ε is the white-noise error term. Prior to estimating the model, it is essential to specify the number of lags because few or many lags may lead to misspecification. Essentially, few lags may imply variable omission and lead to bias in results, while many lags may cause large standard errors, thus affecting the precision of results. The modern rule of thumb is to allow the system to compute the appropriate maximum lag length by performing Wald tests using critical values.

Findings

Our discussion of the findings starts with the descriptive statistics shown in Table 2. This table describes the output of both dependent and independent variables. For the dependent variables, it is revealed that the average of returns for the FTSE 100, £/\$ and £/€ during the sampled period is less than 1% for each of the variables. This suggests that if an investor had invested £1000 in the UK financial market within the sampled period, such investor might not have earned a return of £1, on average, for each of the market variables. During the same period of pandemic, the results show that the highest loss on a single day for the FTSE 100, £/\$ and £/€ are about 11%, 4% and 4%, respectively. Surprisingly, these losses were the highest since 1985. A couple of factors can be attributed to this tragedy based on the timeline of the pandemic in the United Kingdom.

First, the record-breaking losses for the three variables occurred in the month of March 2020. Considering the data and timeline of events in March, the FTSE 100 plummeted on 12 March 2020, the same day that (i) the UK Chief Medical Officer announced that the risk of the pandemic in the United Kingdom had increased from moderate to high and (ii) Public Health England announced it would stop performing contact tracing due to infections overwhelming NHS capacity (ONS, 2021). We believe these announcements impacted investor sentiments as they began to sell off their financial assets, consequently transmitting negatively into the financial market.

In the case of £/\$ and £/€, the massive depreciation happened on 18 March 2020, the same day the Governor of the Bank of England, while granting an interview, labelled the pandemic an 'unprecedented economic emergency' and said that the Bank of England could go as far as radical money-printing operations. He further stated that 'the closing of borders, the reduction of internal movement, the measures that prevent people from going about their daily lives, with good reason, will affect the economy' (Ed, 2020). We opine that the Governor of the Bank of England is a critical stakeholder whose action or statement can

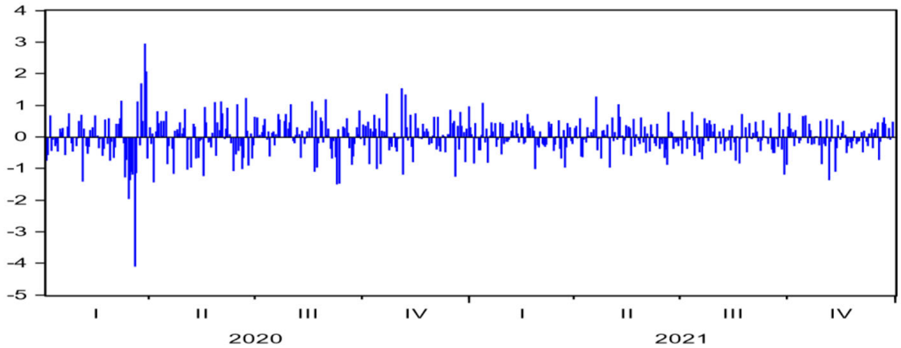

Figure 1. Graph of Ret-USD [Colour figure can be viewed at wileyonlinelibrary.com]

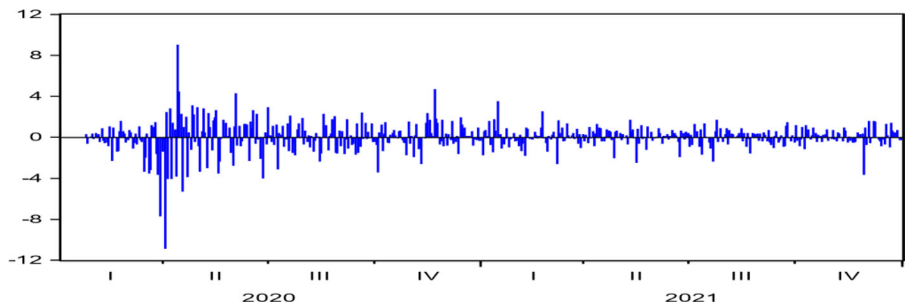

Figure 2. Graph of Ret-FTSE [Colour figure can be viewed at wileyonlinelibrary.com]

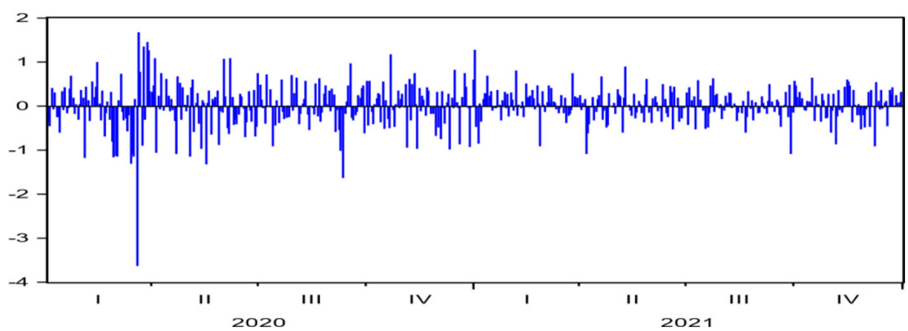

Figure 3. Graph of Ret-EUR [Colour figure can be viewed at wileyonlinelibrary.com]

influence investor sentiments towards the financial market.

Similarly, we observe that the three market variables FTSE 100, £/$ and £/€ made the highest daily gains of about 9%, 3% and 2%, respectively, as depicted in Figures 1–3. We also attribute these gains to the preceding events and announcements up to the day. For instance, the FTSE 100's gain occurred on 24 March 2020; although the highest daily COVID-19-related deaths in the United Kingdom were recorded on that day, we believe that the announcement of stricter COVID-19 measures, by the Prime Minister on 23 March 2020, could have been construed as positive news by investors. The other variables (£/$ and £/€) recorded their highest gains on the day (27 March 2020) the Prime Minister and his Health Secretary announced that they had tested positive for COVID-19. However, prior to that day, the government had announced that some self-employed people would be paid about 80% of their average historical monthly profits, to the tune of £2500 a month. This was with a view to cushioning the economic hardship imposed by the pandemic. We opine that this announcement, among other factors, led to the significant appreciation of the pound sterling the following day.

Turning attention to the sentiment variables, we observe that the TSS and GPA have positive mean values (0.40 and 0.21, respectively). This implies that, on average, there were more negative tweets/announcements than positive ones daily during the pandemic period. For the pandemic variables, the mean of daily infection rate (DIR) shows that about three out of 10,000 people tested positive for COVID-19 in the United Kingdom; the minimum of 0 implies that there were days of no positive cases and the maximum of 0.0028 indicates that there were days of about three out of 1000 residents reportedly testing positive. Our outputs for the vaccination rate (VR) and basic reproduction rate (BRR) are interpreted in similar fashion. The death fatality rate (DFR) is quoted as a percentage. The result shows that, on average, there was about a 47% increase in COVID-19-certified deaths. While some days recorded a 100% reduction (minimum) from the previous day's figures, there was about a 4667% increase reported on a particular day. We interpret the values for IGR and BOT like the death fatality rate, because they are both a percentage. Also included in the descriptive statistics are the results of skewness, kurtosis and Jarque–Bera (J-B) normality tests. The outputs show that many of the variables deviate from the normal distribution. The output of the unit root test (as shown in Table 3) shows stationarity of variables at level and/or first difference.

Table 4 shows the output of the GLM estimates for three different models. Model 1 has the TSS, pandemic variables and GPR variables as independent variables. Model 2 has the TSS, Brexit variable and GPR variables as independent variables, while model 3 combines them all as independent variables. Starting with model 1, the TSS (for the pandemic) is negatively related to the FTSE 100 index and £/€, and statistically significant at both the 5% and 10% levels, but positively related to £/$. The pandemic variables have mixed results while most of the GPR variables reveal positive signs. We also see similar patterns in model 2, and in model 3 when all the independent variables are included. The overall output suggests that as more negative sentiments were expressed on Twitter during the pandemic era, the financial market endured the consequences. This result is akin to the findings of Rao and Srivastava (2012) and Ranco *et al.* (2015), who also find a strong relationship between the sentiments expressed on Twitter and market returns.

According to behavioural finance theory, prices in the financial market reflect the optimism (or pessimism) of investors. Hence, we interpret the output of the pandemic variables to suggest that investors express pessimism by disposing their financial assets when the death toll and infection rates increase, whereas the market becomes bullish (optimistic) when there is an increase in COVID-19 vaccinations. For the Brexit Twitter sentiment score, the output in models 2 and 3 suggests that opinions expressed on Twitter in relation to Brexit have negative impacts on the variables of the financial market. The outputs further reveal that the Brexit variable itself (BOT) has a significant negative impact on the financial market variables, as shown in the second model. However, the variable produced mixed results when included in model 3. Intuitively, a deficit balance of trade between the United Kingdom and the European Union will decrease the value of pound sterling to the euro. The output of the second GLM estimate using government policy announcements (GPA), as shown in Table 5, also reveal identical patterns with those of TSS.

In Table 6, the output of the cointegration test for the FTSE 100 reveals that the variables are cointegrated at order one and a long-run equilibrium relationship may be present. Consequently, the output of the VECM (in Table 2) is used to explain the direction of causality. The output shows bidirectional causality between most of the variables, implying that an increase in one variable is likely to cause a similar impact in the other. The residual diagnostics also confirm stability of the models and absence of serial correlation. The outputs of cointegration, VAR and VECM for £/$ and £/€ are shown in the Appendix.

Table 7 shows the causality between the first proxy for investor sentiment (TSS) and market behaviour proxies (returns, volume and volatility). The output shows that prior to the pandemic, a unidirectional causality existed between the sentiment variable and the market proxies in most sectors. Meanwhile, a bidirectional causality is seen for these variables during the pandemic era. Our explanation for the symbiotic causality during the pandemic is such that investors react differently to good and bad information about the market and as the market continues to exhibit new trends, investors would immediately take positions to minimize losses. As investors respond to changes in the market, the market equally reacts to the attitude of its participants (investors).

We observe a similar trend of causality in Table 8, which has the second proxy for investor sentiment (GPA) and market behaviour. Interestingly, our estimates show similar causality patterns for the sectors and the FTSE 100.

Table 9 displays the short-term systematic risk difference in UK sectors. We observe that Brexit and the COVID-19 pandemic have led to an increase in the systematic risk of about eight sectors – oil and gas, basic materials, industrials, healthcare, telecoms, utilities, financials and technology – and a decline in systematic risk of two sectors – consumer goods and consumer services. We consider the changes in systematic risk of these sectors to be unsurprising, as they conform to the expectations of the Bank of England for the UK economy post-Brexit.

We perform an additional test to check the robustness of the findings. For example, we believe that asset prices in the financial market follow an autocorrelation pattern and to control for dynamic endogeneity, we introduce the lag values of the dependent variables into the main equation as regressors. The results are shown in Table 10 and suggest a high degree of similarity between past and current values. Essentially, the results indicate that current changes in the values of the dependent variable are contingent upon past values. We infer from these values that investors in the financial market during the crisis are likely to make continuous losses in a successive period given the momentum of uncertainties in the market. Our results reinforce the positions of prior studies such as Zhang, Hu and Ji (2020) and Liu, Shahab and Hoque (2022).

Conclusion

In recent times, investors in the United Kingdom have had to contend with the adversities of both Brexit and the COVID-19 pandemic. These Siamese twins, which have brought about sweeping changes in government policies and laws, have impacted investors' sentiments. While investors continue to grapple with the realities of the duo, we submit that the implications of Brexit for the UK economy are far-reaching, based on the foreign policy and trade reforms that continue to influence investors' sentiments towards the UK market. We also posit that pandemic-induced policies such as periodic announcements, social restrictions, benefits and taxes have also had their fair share of implications for the UK market due to the immediate and significant impact of these policies on the psychology of investors. Given the resurgence of the pandemic in some parts of the world, we urge the government to take serious caution in enacting policies that might have negative impacts on investor sentiments and may consequently exacerbate the already fragile and slowly recovering financial system.

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Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflict of interest

The authors declare that there is no conflict of interest.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section at the end of the article.