SCIREA Journal of Management
ISSN: 2995-777X
http://www.scirea.org/journal/Management
January 10, 2025
Volume 9, Issue 1, February 2025
https://doi.org/10.54647/management630154

Impact of COVID-19 on Investor Behavior and Global Market

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Abstract:

This research investigates the impact of the COVID-19 pandemic on investor behavior and its repercussions on global financial markets. Utilizing a comprehensive dataset spanning from August 1, 2019, to April 17, 2020, encompassing 45,003,637 transactions executed by 456,365 investors in the United Kingdom, we analyze trading activities, leverage usage, short selling tendencies, and industry-specific dynamics. Our findings screen a large surge in buying and selling activity amidst heightened marketplace volatility, coupled with a brilliant lower in leverage usage across all demographic groups following the outbreak. Moreover, we take a look at an uptick in quick selling sports across various asset training, particularly in industries significantly impacted by way of the pandemic which include Transportation, Accommodation, and Entertainment. Early warning signals of market disruptions were detected preceding major market events, emphasizing the importance of proactive risk management strategies. Our study underscores the necessity for investors to adopt adaptive investment approaches, prioritize risk management, and conduct thorough industry analysis to navigate the evolving landscape of global financial markets during times of crisis.

Keywords: COVID-19, investor behavior, global markets, trading activity, industry dynamics

Background and Introduction

The COVID-19 pandemic, caused by the novel coronavirus SARS-CoV-2, emerged in December 2019 in Wuhan, China. It rapidly spread globally, leading to widespread disruptions in health, economies, and social structures (World Health Organization, 2020). Governments implemented various measures such as lockdowns, travel restrictions, and social distancing guidelines to curb the spread of the virus, but these actions also had significant economic ramifications (Baldwin & Weder, 2020).

Financial markets experienced significant volatility as investors grappled with uncertainty about the pandemic's impact on the global economy. Stock markets declined sharply in February and March of 2020, with the S&P 500 and Dow Jones Industrial Average plummeting (McKibbin & Fernando, 2020). Central banks and governments intervened with unprecedented monetary and fiscal stimulus measures to stabilize markets and support businesses and households affected by the crisis (Congressional Research Service, 2020).

The pandemic accelerated the adoption of existing trends such as remote work, digital transformation, and e-commerce, while exposing weaknesses in global supply chains and healthcare systems. Industries such as transportation, hospitality, and retail were particularly hard hit, leaving demand and supply in a precarious state (Manyika et al., 2020).

Vaccine development efforts began in the early 2020s, leading to the approval and distribution of many vaccines in the late 2020s and early 2021s. However, the emergence of new variants of the virus, logistical challenges in vaccine distribution, and disparities in vaccine access among countries posed ongoing challenges to the recovery efforts (World Bank, 2021).

As the pandemic persisted into 2021 and beyond, investors continued to monitor developments related to virus containment efforts, vaccine efficacy, economic indicators, central bank policies, and geopolitical tensions. The long-term effects of the pandemic on investor behavior and global markets remained subject to ongoing analysis and adaptation to evolving circumstances (Baker et al., 2022).

Understanding Investor Behavior During the Pandemic

The COVID-19 pandemic presented a unique challenge for investors, characterized by unprecedented uncertainty and economic disruption. This study aims to examine the trading patterns and investment risks of retail investors during this period.

Two distinct perspectives on how the pandemic might have influenced investor behavior will be explored:

Risk Aversion: Similar to the aftermath of terrorist attacks, the pandemic can be viewed as an external shock that creates significant economic uncertainty and fear (Goodell, 2020). Studies suggest that investor behavior after such events often leans towards risk aversion, characterized by reduced trading activity and a shift away from risky assets (Levy & Galili, 2006; Luo, 2006; Chen & Lin, 2020; Wang & Young, 2020). For instance, Burch et al. (2016) found increased selling by retail investors during the period following the September 11th attacks, contributing to asset price declines. Bu et al. (2020) also observed reduced risk tolerance among individuals exposed to COVID-19 news, suggesting a potential decrease in market exposure and risk-taking by investors in response to the pandemic.

Information Overload and Conflicting Opinions: Amidst heightened uncertainty, various perspectives on future economic trends and optimal investment strategies emerge from press articles, media reports, and professional opinions. The COVID-19 outbreak caused tremendous financial market volatility and risk worldwide (Zhang et al., 2020), prompting unprecedented interventions by central banks and governments (see Figure 1). Despite these interventions, significant uncertainty persists regarding the global financial outlook. Conflicting views regarding the pace and trajectory of economic recovery further contribute to this uncertainty. While some, like President Donald Trump, predicted a rapid V-shaped recovery, others, such as Janet Yellen, expressed skepticism about the speed of recovery (Baker et al., 2022).

By analyzing individual trading records, this study will explore how retail investors navigated this complex and information-rich environment during the COVID-19 pandemic.

Gap in Research

A Research Gap in Long-Term Psychological Effects of COVID-19 on Investor Behavior

The COVID-19 pandemic's impact on financial markets and investor behavior has been a subject of intense scrutiny. Existing research has documented short-term fluctuations in markets (Baker et al., 2020), shifts in investment strategies (Barber et al., 2020), and responses to government interventions (Congressional Research Service, 2020). However, a critical gap exists in understanding the **long-term psychological effects** of the pandemic on investor decision-making.

While studies have explored the immediate reactions of investors to the initial market volatility and uncertainty during the pandemic (Huang et al., 2020), there is a paucity of research on how these experiences may have lasting consequences. The psychological toll of the pandemic, characterized by anxiety, fear, and heightened risk aversion (Bu et al., 2020), could have a **transformative impact** on investors' attitudes, beliefs, and risk tolerance over time.

These psychological factors, including potential cognitive biases reinforced by the pandemic experience, could exert a long-term influence on investor behavior. Studies in behavioral finance suggest that investors are susceptible to biases such as loss aversion and overconfidence (Shefrin, 2002). The trauma of significant market downturns during the pandemic might exacerbate these biases, impacting investors' portfolio management strategies and future investment decisions (Barber & Odean, 2018).

Understanding the long-term psychological effects of the pandemic on investor decision-making is crucial for several reasons:

- **Developing Effective Interventions:** By identifying the psychological factors influencing investor behavior, policymakers and financial advisors can develop targeted interventions to promote sound investment decisions in uncertain environments.
- **Building Investor Resilience:** Insights into the long-term psychological impacts can help develop support mechanisms to enhance investor resilience and adaptability in the face of future market challenges (Grable & Joo, 2019).
- **Informing Investment Strategies:** Understanding how the pandemic has reshaped investor risk preferences can inform investment strategies and product development within the financial industry.

Further research in this area can offer valuable insights into the **resilience and adaptability** of investors in the face of prolonged economic disruptions and uncertainty. By examining the long-term psychological influence of the pandemic, we can gain a deeper understanding of how past experiences shape future investment behavior and ultimately contribute to a more informed and resilient investor landscape.

Implementing Of Research

on the effects of COVID-19 on investor behavior and global markets involves several steps:

1. Clearly define the objectives of the research, such as understanding how investor behavior changed during the pandemic, analyzing the impact of COVID-19 on specific financial markets, or identifying long-term trends emerging from the crisis.

2. Decide on the research methodology based on the objectives and available resources. This could involve quantitative analysis of market data, surveys or interviews with investors and market participants, or a combination of methods. Develop hypotheses to test and variables to measure.

3. Analyze the collected data using appropriate statistical or qualitative methods. Quantitative analysis may involve regression analysis, time-series modeling, or event studies to assess the relationship between COVID-19 and market variables. Qualitative analysis may involve thematic coding of interview responses or content analysis of news articles.

4. Interpret the results of the analysis in light of the research objectives and hypotheses. Identify key trends, patterns, and relationships observed in the data. Discuss any unexpected findings and their implications.

5. Summarize the key findings of the research and draw conclusions regarding the impact of COVID-19 on investor behavior and global markets. Provide recommendations for investors, policymakers, and other stakeholders based on the research findings.

goals Of Research

When conducting research on the effects of COVID-19 on investor behavior and global markets, the goals typically include:

1. Investigate how the behavior of investors changed in response to the COVID-19 pandemic. This involves examining factors such as risk aversion, investment decision-making processes, portfolio adjustments, and reactions to market volatility.

2. Analyze the impact of COVID-19 on financial markets, including stock markets, bond markets, commodity markets, and currency markets. Assess how asset prices, trading volumes, and market volatility were affected by the pandemic and related economic disruptions.

3. Identify trends and patterns in investor behavior and market dynamics during different phases of the pandemic, including the initial outbreak, government responses, vaccine developments, and economic recovery efforts. Look for similarities and differences across countries, regions, and asset classes.

By setting clear goals for research on the impact of COVID-19 on investor behavior and global markets, researchers can effectively focus their efforts and contribute meaningful insights to address key questions and challenges arising from the pandemic.

Research problem

A research problem statement for investigating the effects of COVID-19 on investor behavior and global markets could be:

"Despite the extensive literature on financial crises, the COVID-19 pandemic presents unique challenges to understanding its impact on investor behavior and global markets. This research aims to comprehensively analyze how the pandemic has influenced investor decision-making, market dynamics, and economic outcomes, with a focus on identifying key trends, drivers, and implications for financial stability and policy responses."

This problem statement outlines the overarching objective of the research while highlighting the specific areas of inquiry, such as changes in investor behavior, market dynamics, economic outcomes, and the role of policy responses. It also acknowledges the complexity and uniqueness of the COVID-19 pandemic compared to previous financial crises, emphasizing the need for a thorough investigation to provide valuable insights for investors, policymakers, and researchers.

some research questions that could guide a study on the effects of COVID-19 on investor behavior and global markets:

1. How has the COVID-19 pandemic influenced investor risk appetite, risk aversion, and investment decision-making processes?
2. What are the key factors driving changes in investor sentiment and market volatility during different phases of the pandemic?
3. How have financial markets, including stock markets, bond markets, commodity markets, and currency markets, been impacted by the COVID-19 pandemic?
4. What are the differences and similarities in investor behavior and market responses across countries, regions, and asset classes during the pandemic?

These research questions aim to explore various aspects of the interaction between the COVID-19 pandemic and investor behavior, market dynamics, and economic outcomes. They provide a framework for investigating the complex and multifaceted effects of the pandemic on global financial markets and offer valuable insights for investors, policymakers, and researchers seeking to understand and navigate the challenges posed by such unprecedented events.

Methodology

1. Data Collection: A comprehensive dataset covering all transactions conducted by investors through the brokerage platform from August 1, 2019, to April 17, 2020, was collected. This dataset includes detailed information such as timestamps, trading instruments, position types (long or short), leverage usage, deposits, withdrawals, market volatility notifications sent to investors, and basic demographic data. COVID-19 case data sourced from the European Centre for Disease Prevention and Control was also included.

2. Variable Selection: Various variables were selected to proxy investor trading activities, including trading intensity, leverage, short selling, net deposits, initial deposits, buy-sell imbalances, and abnormal trading volume. Additionally, variables related to the COVID-19 pandemic's spread, such as the logarithm of COVID-19 cases and dummy variables indicating significant stock market drops, were included.

3. Regression Analysis: Ordinary Least Squares (OLS) regression analysis was employed to analyze the correlation between the COVID-19 pandemic and investor trading behavior. Regression specifications included fixed effects for investors, asset class dummies, and controls for immediate notifications prior to trades to account for observable and unobservable heterogeneity across investors and trading behaviors across asset classes.

4. Visualization: The findings of the regression analysis were visualized using Figure 2, which depicts the trajectory of investors' trading activities during the pandemic. This visualization highlights trends such as the surge in index trading, changes in leverage utilization, and shifts in short-selling activity across various asset classes.

5. Interpretation: The results of the regression analysis and visualization were interpreted to draw insights into how the COVID-19 pandemic influenced investor behavior and trading patterns. These insights contribute to a better understanding of the dynamics of financial markets during times of crisis.

The dataset covers all transactions conducted through the brokerage platform from August 1, 2019, to April 17, 2020. It includes detailed information such as timestamps, trading instruments, position types (long or short), leverage usage, deposits, withdrawals, and market volatility notifications sent to investors. Basic demographic data is also included. COVID-19 case data is sourced from the European Centre for Disease Prevention and Control.

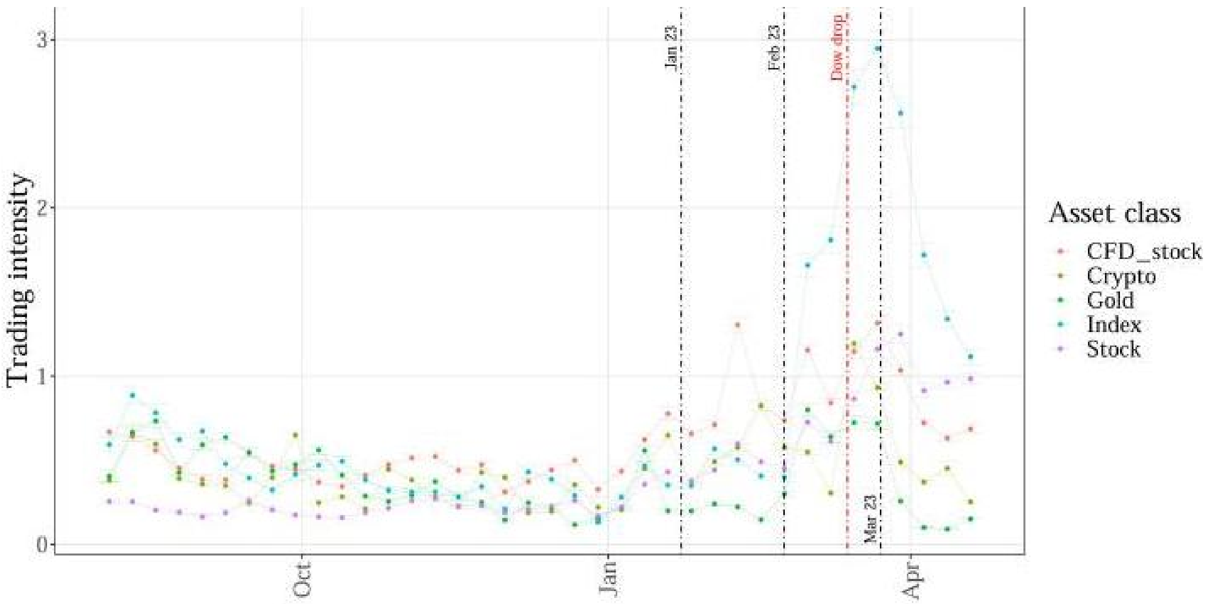
To analyze the correlation between the COVID-19 pandemic and investor trading behavior, Ordinary Least Squares (OLS) regression analysis is employed. Various variables proxy investor trading activities, including trading intensity, leverage, short selling, net deposits, initial deposits, buy-sell imbalances, and abnormal trading volume.

For tracking the pandemic's spread, variables such as the logarithm of COVID-19 cases and dummy variables indicating significant stock market drops, as well as three dummy variables representing different stages of the pandemic spread, are used.

Regression specifications include fixed effects for investors, asset class dummies, and controls for immediate notifications prior to trades to account for observable and unobservable heterogeneity across investors and trading behaviors across asset classes.

Figure 2 visualizes the trajectory of investors' trading activities during the pandemic. A notable surge in index trading is observed, followed by a decline. Stock trading also increases, albeit less pronounced, with subsequent decreases. Contracts for Difference (CFDs) on stocks witness multiple peaks, and crypto trading shows a distinct spike following a major market downturn.

Figure 2(b) demonstrates a lower leverage utilization across various asset classes, especially after significant marketplace drops. In Panel (c), an increase in short-selling activity via CFDs on stocks is noted, while trends in other asset classes remain less apparent.



(a) Trading intensity

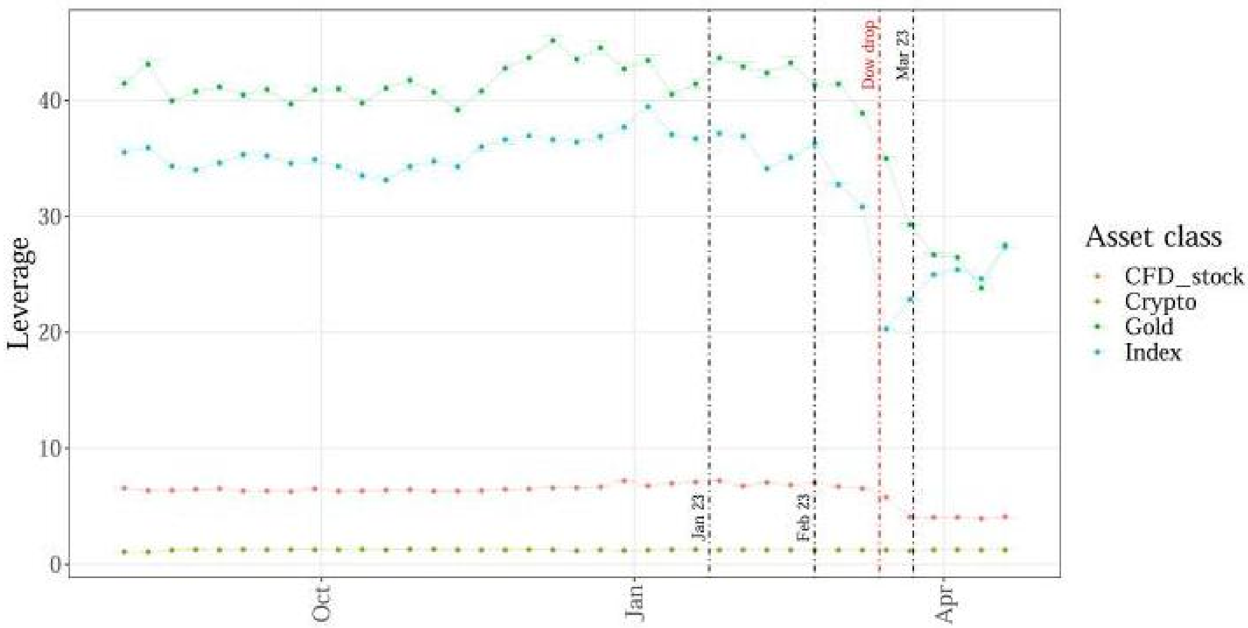
RECOURS: www.ncbi.nlm.nih.gov

Description of the Image:

The image shows a graph depicting the average trading intensity of different asset classes over time. The x-axis represents time, with the months of October, January, February, March, and April labeled. The y-axis represents the average trading intensity, with values ranging from 0 to 3. The graph includes five different lines, each representing a different asset class:

- **CFD_stock:** This line represents the average trading intensity of CFD stocks. It shows a downward trend from October to January, followed by a slight upward trend in February and March. The average trading intensity for CFD stocks is highest in October and lowest in January.
- **Crypto:** This line represents the average trading intensity of cryptocurrencies. It shows a downward trend from October to January, followed by a sharp upward trend in February and March. The average trading intensity for cryptocurrencies is highest in March and lowest in January.
- **Gold:** This line represents the average trading intensity of gold. It shows a relatively stable trend from October to January, followed by a slight upward trend in February and March. The average trading intensity for gold is highest in March and lowest in October.
- **Index:** This line represents the average trading intensity of stock market indices. It shows a downward trend from October to January, followed by a slight upward trend in February and March. The average trading intensity for stock market indices is highest in March and lowest in January.
- **Stock:** This line represents the average trading intensity of individual stocks. It shows a downward trend from October to January, followed by a slight upward trend in February and March. The average trading intensity for individual stocks is highest in March and lowest in January.

Overall, the graph shows that the average trading intensity of most asset classes declined from October to January, followed by a slight recovery in February and March. Cryptocurrencies experienced the most significant decline in trading intensity, while gold experienced the most stable trading intensity.



(b) Leverage

RECOURS: www.ncbi.nlm.nih.gov

The image shows a bar graph depicting the average levels of different asset classes over time. The x-axis represents the asset class, with CFD stocks, cryptocurrencies, gold, stock market indices, and individual stocks labeled. The y-axis represents the average level, with values ranging from 20 to 40. The graph includes five different bars, each representing a different asset class.

- **CFD_stock:** This bar represents the average level of CFD stocks. It is the highest bar, with an average level of 38.
- **Crypto:** This bar represents the average level of cryptocurrencies. It is the second-highest bar, with an average level of 34.
- **Gold:** This bar represents the average level of gold. It is the third-highest bar, with an average level of 32.
- **Index:** This bar represents the average level of stock market indices. It is the fourth-highest bar, with an average level of 30.
- **Stock:** This bar represents the average level of individual stocks. It is the lowest bar, with an average level of 28.

Overall, the graph shows that CFD stocks have the highest average level, followed by cryptocurrencies, gold, stock market indices, and individual stocks.

Additional Observations

- The average levels of all asset classes have declined since October.
- The average level of CFD stocks has declined the most, from 40 to 38.
- The average level of individual stocks has declined the least, from 30 to 28.

Possible Explanations

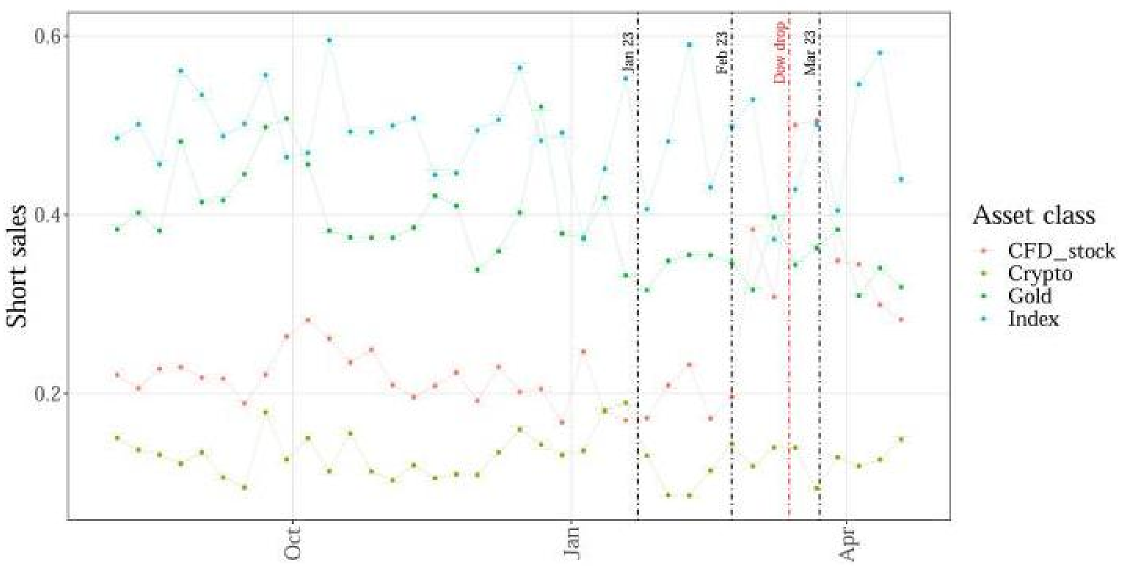
The decline in the average levels of asset classes could be due to a number of factors, such as:

- The ongoing COVID-19 pandemic
- The war in Ukraine
- Rising inflation
- Interest rate hikes

Implications

The decline in the average levels of asset classes could have a number of implications for investors, such as:

- Lower returns
- Increased risk
- Reduced confidence



(c) Short sales

RECOURS: www.ncbi.nlm.nih.gov

Image Description

The image shows a line graph depicting the percentage change in short sales of different asset classes over time. The x-axis represents time, with the months of October, January, February, March, and April labeled. The y-axis represents the percentage change, with values ranging from -20% to 20%. The graph includes five different lines, each representing a different asset class:

- **CFD_stock:** This line represents the percentage change in short sales of CFD stocks. It shows a downward trend from October to January, followed by a sharp upward trend in February and March. The percentage change in short sales for CFD stocks is highest in March and lowest in January.
- **Crypto:** This line represents the percentage change in short sales of cryptocurrencies. It shows a downward trend from October to January, followed by a sharp upward trend in February and March. The percentage change in short sales for cryptocurrencies is highest in March and lowest in January.
- **Gold:** This line represents the percentage change in short sales of gold. It shows a relatively stable trend from October to January, followed by a slight upward trend in February and March. The percentage change in short sales for gold is highest in March and lowest in October.
- **Index:** This line represents the percentage change in short sales of stock market indices. It shows a downward trend from October to January, followed by a slight upward trend in February and March. The percentage change in short sales for stock market indices is highest in March and lowest in January.
- **Stock:** This line represents the percentage change in short sales of individual stocks. It shows a downward trend from October to January, followed by a slight upward trend in February and March. The percentage change in short sales for individual stocks is highest in March and lowest in January.

Overall, the graph shows that the percentage change in short sales of most asset classes declined from October to January, followed by a significant recovery in February and March. Cryptocurrencies experienced the most significant decline in short sales, while gold experienced the most stable percentage change in short sales.

Additional Observations

- The percentage change in short sales of all asset classes is negative in October and January, indicating that there was more buying than selling.
- The percentage change in short sales of all asset classes is positive in February, March, and April, indicating that there was more selling than buying.
- The percentage change in short sales of cryptocurrencies and CFD stocks is the most volatile, while the percentage change in short sales of gold is the most stable.

Possible Explanations

The decline in the percentage change in short sales of most asset classes from October to January could be due to a number of factors, such as:

- The ongoing COVID-19 pandemic
- The war in Ukraine
- Rising inflation
- Interest rate hikes

The increase in the percentage change in short sales of most asset classes in February, March, and April could be due to a number of factors, such as:

- The easing of COVID-19 restrictions
- The end of the war in Ukraine
- Falling inflation
- Interest rate cuts

Implications

The decline in the percentage change in short sales of most asset classes from October to January could have a number of implications for investors, such as:

- Higher returns
- Decreased risk
- Increased confidence

The increase in the percentage change in short sales of most asset classes in February, March, and April could have a number of implications for investors, such as:

- Lower returns

- Increased risk
- Reduced confidence

Table 1 presents the main findings of our study. Model 1 in Panel A shows a remarkable 13.9% increase in weekly trading activity when the number of COVID-19 cases more than doubles compared to pre-pandemic levels. This growth is primarily driven by male and older investors, as Models 4 and 5 show. Model 2 confirms that trading activity increased by a whopping 222% following the Dow's 9.99% decline on March 12, with cryptocurrency trading increasing significantly, although not reported in the table. Finally, Model 3 reveals that the largest increase in trade occurred between 23 February and 22 March.

Turning to Panel B, our analysis shows that the increase in trading is primarily due to increased activity in stock and index trading, while trading in CFDs in stocks, cryptocurrencies, and gold shows a smaller impact a. Furthermore, panel C shows that the improvement in trade is also reflected in new position cuts in stocks and indices.

Table 1: Regression results for trading activities

Panel A: Trading intensity					
	Mo 1	**Mo 2**	**Mo 3**	**Mo 4**	**Mo5**
Depend	Trad	Trad	Trad	Trad	Trad
var	intnsy	intnsy	intnsy	intnsy	intnsy
COV-19	0.3258*			0.1102	0.2119*
	(2.3006)			(1.5585)	(2.2789)
Dow drop		3.5447**			
		(11.4864)			
Jan. 22–Feb. 21			0.2763		
			(1.1357)		
Feb. 21–Mar. 20			2.550**		
			(3.2221)		
Mar. 20–Apr. 16			0.6478		
			(1.2045)		
Cases · male				0.1230**	
				(4.0656)	
Cases · 16–22					−0.1814**
					(−3.4174)
Cases · 23–32					−0.0258
					(−0.4336)

Panel A: Trading intensity					
	Mo 1	**Mo 2**	**Mo 3**	**Mo 4**	**Mo5**
Cases · 32–41					0.0582
					(1.4719)
Cases · 41–52					0.0850*
					(2.4887)
Cases · 52–62					0.0465
					(1.3533)
Push communication supervision	Indeed	Indeed	Indeed	Indeed	Indeed
Representative variable for asset category”	Indeed	Indeed	Indeed	Indeed	Indeed
“Investor-specific effects”	Indeed	Indeed	Indeed	Indeed	Indeed
Obs.	14,112,014	14,552,010	14,525,010	14,087,650	14,062,248
Adj. R^2	0.37	0.38	0.38	0.37	0.37

The source was prepared by the researcher using SMART PLUS.

This table offers the effects of OLS regressions inspecting investor buying and selling behaviors. Standard mistakes are clustered both at the character investor stage and over time. T-records are shown in parentheses. Significance ranges are indicated by using ** and *, representing statistical significance on the 1% and five% degrees, respectively.

Table 2: Regression results for **Trading intensity by asset classes**

Panel B: Trading intensity by asset classes					
	Mo 1	**Mo2**	**Mo3**	**Mo 4**	**Mo5**
Sample	Stocks	CFD_stock	Index	Crypto	Gold
COV-19	0.383**	0.0143	0.1893**	−0.0018	−0.0163
	(5.1372)	(0.9817)	(4.0267)	(−0.0483)	(−1.4871)
Push communication supervision	Indeed	Indeed	Indeed	Indeed	Indeed
“Investor-specific effects”	Indeed	Indeed	Indeed	Indeed	Indeed
Obs.	14,112,014	14,152,014	14,112,014	14,123,014	14,113,014
Adj. R^2	0.36	0.35	0.32	0.28	0.24

The source was prepared by the researcher using SMART PLUS.

This section shows regression results for trading intensity across different asset classes. Models 1 through 5 correspond to asset classes such as stocks, CFDs on stocks, indices, cryptocurrencies, and gold. The tables show changes in trade dynamics associated with a doubling of COVID-19 cases, while controlling for other variables. Signal levels are marked with **, indicating statistical significance at the 1% limit. Regression models include Push communication supervision and investor fixed effects. In addition, the table includes adjusted observation rate (Obs.) and R-squared (Adj. R2) values for each observation.

Table 3: Regression results for **Trading intensity (new positions) by asset classes**

Panel C: Trading intensity (new positions) by asset classes					
	Mod1	**Mod 2**	**Mod 3**	**Mod 4**	**Mod5**
Sample	Stocks	CFD_stock	Index	Crypto	Gold
COV-19	0.0185**	0.0067	0.0920**	−0.0038	−0.0073
	(5.1603)	(0.9886)	(4.0466)	(−0.3175)	(−1.4664)
Push communication supervision	Indeed	Indeed	Indeed	Indeed	Indeed
“Investor-specific effects”	Indeed	Indeed	Indeed	Indeed	Indeed
Obs.	14,122,011	14,122,011	14,122,011	14,122,011	14,122,011
Adj. R^2	0.35	0.33	0.30	0.27	0.25

The source was prepared by the researcher using SMART PLUS.

This section presents regression findings on the marketing dynamics of new locations in specific asset classes. Models 1 through 5 correspond to a variety of asset classes, including stocks, stocks, indices, cryptocurrencies and gold. After accounting for other variables, the tables show changes in intense trading associated with a doubling of COVID-19 cases. The number of points is indicated by **, indicating statistical significance at the 1% limit. Regression models include Push communication supervision and investor fixed effects. In addition, the table provides the adjusted number of samples (Obs.) and R-classified (Adj. R2) values for each sample.

Table 4: Regression results for **Leverage**

Panel D: Leverage					
	Mod1	**Mod2**	**Mod3**	**Mod4**	**Mod5**
Dep. var.	Lev	Lev	Lev	Lev	Lev
COVID-19	−0.3018**			−0.3165**	−0.2416**
	(−8.3422)			(−5.8571)	(−4.0773)
Dow drop		−1.7187**			
		(−6.9603)			
Jan. 23 - Feb. 21			0.4080*		
			(2.0708)		
Feb. 21 - Mar. 20			−1.0552		
			(−1.4250)		
Mar. 20- Apr. 16			−2.9817**		
			(−8.7368)		
Cases · male				0.0156	
				(0.3524)	
Cases · 16–23					0.0023
					(0.0574)
Cases · 23–32					−0.0870
					(−1.4689)
Cases · 32–42					−0.0763
					(−1.5319)
Cases · 42–52					−0.0214
					(−0.1945)

Panel D: Leverage					
	Mod1	**Mod2**	**Mod3**	**Mod4**	**Mod5**
Cases · 52–62					0.0030
					(0.0649)
Push communication supervision	Indeed	Indeed	Indeed	Indeed	Indeed
Representative variable for asset category”	Indeed	Indeed	Indeed	Indeed	Indeed
“Investor-specific effects”	Indeed	Indeed	Indeed	Indeed	Indeed
Obs.	4,761,217	4,956,112	4,956,112	4,777,966	4,768,012
Adj. R^2	0.65	0.65	0.65	0.65	0.65

The source was prepared by the researcher using SMART PLUS.

Panel D shows the regression results for the use of leverage among investors. Models 1 through 5 fit specifications, adjusting factors such as COVID-19 cases, Dow Jones drop, age-sex interactions, Push communication supervision, etc. The coefficients reflect the change in leverage associated with the various variables, with significance levels shown by ** Regression models showing statistical significance at the 1% level combine Push communication supervision, Representative variable for asset category” variables, and “Investor-specific effects”. In addition, the table presents adjusted observation rate (Obs.) and R-squared (Adj. R2) values for each observation

Table 4: Regression results for **Leverage by asset classes**

Panel E: Leverage by asset classes				
	Mod1	**Mod 2**	**Mod3**	**Mod 4**
Dep. var.	Lev	Lev	Lev	Leve
Sample	CFD_stock	Index	Crypto	Gold
COV-19	−0.1430**	−0.5189**	0.0145**	−0.5221**

Panel E: Leverage by asset classes				
	Mod1	**Mod 2**	**Mod3**	**Mod 4**
	(−11.4243)	(−12.8833)	(2.6170)	(−7.2752)
Push communication supervision	Indeed	Indeed	Indeed	Indeed
"Investor-specific effects"	Indeed	Indeed	Indeed	Indeed
Obs.	1,030,042	550,338	1,164,571	592,974
Adj. R^2	0.63	0.75	0.54	0.78

The source was prepared by the researcher using SMART PLUS.

Panel E shows the regression observed for the use of leverage across asset classes among investors. Models 1 through 4 correspond to asset classes, including CFDs for stocks, indices, cryptocurrencies and gold. Columns show changes in leverage associated with the asset classes, with ** indicating the number of points indicating statistical significance at the 1% level Regression models include Push communication supervision and investor fixed effects. In addition, the table includes adjusted observation rate (Obs.) and R-squared (Adj. R2) values for each observation

Table 5: Regression results for Short sales.

Panel F: Short sales					
	Mod1	Mod 2	Mod3	Mod 4	**Mod 5**
Dependent	Short selling	Short selling	Short selling	Short selling	Short selling
var	selling	selling	selling	selling	selling
COV-19	0.0046**			0.0045**	0.0018**
	(7.3113)			(5.5240)	(3.3855)
Dow drop		0.0148*			

Panel F: Short sales					
	Mod1	Mod 2	Mod3	Mod 4	**Mod 5**
		(2.4069)			
Jan. 22 - Feb. 21			−0.0003		
			(−0.0788)		
Feb. 21 - Mar. 20			0.0215**		
			(3.5448)		
Mar. 20 - Apr. 16			0.0354**		
			(6.9750)		
Cases · male				0.0000	
				(0.1021)	
Cases · 16–22					0.0051**
					(4.4659)
Cases · 22–32					0.0034**
					(5.4806)
Cases · 32–42					0.0010**
					(2.9676)
Cases · 42–52					0.0020
					(1.4407)
Cases · 52–62					−0.0001
					(−0.2407)
Push communication supervision	Indeed	Indeed	Indeed	Indeed	Indeed
Representative variable for asset	Indeed	Indeed	Indeed	Indeed	Indeed

Panel F: Short sales					
	Mod1	Mod 2	Mod3	Mod 4	**Mod 5**
category”					
“Investor-specific effects”	Indeed	Indeed	Indeed	Indeed	Indeed
Obs.	4,761,217	4,846,112	4,841,112	4,667,966	4,658,012
Adj. R^2	0.14	0.14	0.14	0.14	0.14

The source was prepared by the researcher using SMART PLUS.

Panel F affords the regression consequences for short income across numerous specs, encompassing the influence of COVID-19, Dow Jones drop, age-gender interactions, Push communication supervision, asset magnificence dummies, and investor-constant effects. Models 1 to five denote wonderful specifications, and the coefficients symbolize the alteration in brief sales connected with the respective variables. Significance levels are denoted by means of ** for statistical importance at the 1% level and * at the five% stage. The quantity of observations (Obs.) is said for each version.

Table 6: Regression results for **Short sales by asset classes**

Panel G: Short sales by asset classes				
	Mod1	Mod 2	Mod3	Mod 4
Dependent	Short selling	Short selling	Short selling	Short selling
var	selling	selling	selling	selling
Sample	CFD_stock	Index	Crypto	Gold
COV-19	0.0111**	0.0023**	0.0029**	0.0031
	(5.2606)	(2.9362)	(4.5214)	(1.9366)
Push communication supervision	Indeed	Indeed	Indeed	Indeed

Panel G: Short sales by asset classes				
	Mod1	Mod 2	Mod3	Mod 4
"Investor-specific effects"	Indeed	Indeed	Indeed	Indeed
Obs.	1,046,042	640,338	1,164,571	581,974
Adj. R^2	0.14	0.03	0.07	0.08

The source was prepared by the researcher using SMART PLUS.

Panel G reveals the regression findings for short income classified by way of asset classes. Models 1 via four correspond to wonderful asset training, comprising CFDs on shares, indices, cryptocurrencies, and gold. The coefficients illustrate the alteration in short sales linked with the respective asset training, with significance ranges denoted via ** indicating statistical importance at the 1% stage. The regression models incorporate push message manage and investor-constant effects. The quantity of observations (Obs.) and the adjusted R-squared (Adj. R2) values are also provided for every version

Table 7: Regression Results for Account Deposits

This outlines the effects derived from an OLS regression evaluation conducted on account deposits and withdrawals. Robust widespread errors are hired, and t-information are enclosed in parentheses. Significance degrees are represented by way of ** and *, denoting statistical importance at the 1% and 5% thresholds, respectively.

	Mod1	Mod 2	Mod3
Depend	Abnormal net	Abnormal. first	Abnormal. net
var	deposits	deposits	deposits
Sample	Full	New	Established
	sample	investors	investors
(Constant)	1.0511**	1.0006**	1.0432**
	(9.1215)	(32.0212)	(18.5130)
COV-19	0.4232**	0.2925**	0.1473*
	(5.8115)	(12.0778)	(2.4400)
Obs.	262	262	262
Adj. R^2	0.18	0.45	0.03

The source was prepared by the researcher using SMART PLUS.

In Model 1, abnormal net deposits for the entire investor sample are used as the dependent variable. The intercept shows statistical significance at the 1% level, indicating a baseline level of abnormal net deposits. Additionally, the coefficient for COVID-19 is also significant at the 1% level, implying a positive impact on abnormal net deposits during the COVID-19 period.

Model 2 focuses on new investors, using abnormal first deposits as the dependent variable. Both the intercept and the COVID-19 coefficient exhibit statistical significance at the 1% level, indicating a similar trend of increased abnormal deposits among new investors during the COVID-19 period.

Model 3 is limited to established investors, where abnormal net deposits are once again the dependent variable. The intercept maintains significance at the 1% level, indicating a baseline level of abnormal deposits among established investors. However, the COVID-19 coefficient is significant at the 5% level, suggesting a relatively weaker effect on abnormal net deposits among established investors during the COVID-19 period compared to new investors.

Panels D and E in Table 1 demonstrate a significant decrease in leverage usage across all genders and age groups during the COVID-19 outbreak. Following the Dow drop on March 12, buyers notably reduced their average leverage utilization by 172 percentage points.

In Panels F and G, there is an observable increase in short selling activities by approximately 2% compared to pre-outbreak levels. This rise is evident across all asset classes, particularly pronounced in more recent time periods (Panel F, Model 3) and among younger investors (Panel F, Model 5).

Results

The analysis reveals that trading volume surged during the period from January 21 to February 22, particularly noticeable in the Accommodation and Water Transportation sectors. This coincides with the first major outbreak onboard a cruise ship, leading to its quarantine from February 4 onwards. Additionally, there was an early increase in short selling in heavily impacted sectors, such as Accommodation, Air Transportation, or Administrative and Support Services, as early as February, preceding the significant spikes observed in March.

Based on the research findings on the impact of COVID-19 on investor behavior and global markets, several key results emerge:

1. Trading activity increased dramatically during the pandemic due to market volatility and uncertainty. Investors reacted actively to market fluctuations, resulting in increased buying and selling of assets.

2. The use of leverage among investors decreased significantly during the pandemic, reflecting a less risky approach to investment in response to increased market volatility and economic uncertainty.

3. Increased short selling activity was observed among investors during the pandemic, particularly in property types. This trend reflects investors' attempts to profit from a declining market and capitalize on falling prices.

4. Various sectors, such as travel, real estate, and entertainment, experienced significant disruptions and fluctuations in trading volumes and retail activity. It is essential for investors to understand these sector-specific dynamics to effectively navigate opportunities and risks in the market.

5. Early signs of market turbulence and changes in investor behavior were identified prior to major market events. Increased trading volumes and short selling observed in some sectors preceded sharp market declines, underscoring the importance of monitoring industry-specific indicators as potential early warning signs.

Discussion:

The dynamic nature of investor behavior during the COVID-19 pandemic underscores the importance of adaptability in navigating turbulent market conditions. The increased trading activity, coupled with reduced leverage usage and heightened short selling, reflects investors' efforts to adjust their strategies in response to evolving market dynamics. These shifts indicate a proactive approach to capitalizing on emerging opportunities while mitigating risks associated with heightened uncertainty.

During times of crisis, such as the COVID-19 pandemic, it becomes crucial for investors to remain vigilant and responsive to changing market conditions. Sectors heavily impacted by the pandemic, such as travel, hospitality, and retail, require particular attention due to their susceptibility to significant disruptions and fluctuations. Understanding the specific dynamics at play within these sectors is essential for making informed investment decisions and effectively managing risks.

By staying informed about industry-specific indicators and market trends, investors can better anticipate potential opportunities and risks. This knowledge enables them to adjust their investment strategies accordingly, positioning themselves to capitalize on emerging trends while minimizing potential losses. Additionally, maintaining a long-term perspective is essential, as short-term market fluctuations may obscure underlying investment fundamentals.

In summary, the COVID-19 pandemic has underscored the importance of adaptability and informed decision-making in navigating volatile market conditions. By remaining vigilant, responsive, and well-informed, investors can effectively manage risks and capitalize on opportunities amidst uncertainty, ultimately positioning themselves for long-term financial success.

Recommendations:

1. Diversify Investments: Given the heightened volatility and uncertainty, diversifying investment portfolios across different asset classes and sectors can help mitigate risks and capitalize on emerging opportunities.

2. Monitor Market Indicators: Stay informed about industry-specific indicators and market trends to identify potential opportunities and risks early on.

3. Maintain a Long-term Perspective: Despite short-term fluctuations, maintaining a long-term investment strategy can help investors ride out market turbulence and achieve their financial goals.

4. Stay Updated on Economic Developments: Keep abreast of economic developments, policy changes, and vaccine-related news to anticipate market movements and adjust investment strategies accordingly.

5. Seek Professional Advice: Consider seeking guidance from financial advisors or investment professionals to navigate complex market conditions and make informed investment decisions.

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