Research Paper

Impact of COVID-19 on retail traders

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List of Abbreviations

COVID-19	The Novel Coronavirus
FED	The U.S. Federal Reserve
QE	Quantitative Easing
ATH	All-time Highs
BLS	The U.S. Bureau of Labor Statistics
SEU	Subjective Expected Utility
FOMO	Fear of Missing Out
CAR	Cumulative Abnormal Returns
VAR	Vector Autoregression
OLS	Ordinary Least Squares
BSI	Buy-sell Imbalance
DJIA	Dow Jones Industrial Average
TNA	Total Net Asset
ESG	Environmental, Social and Governance
FE	Fixed Effects
NAICS	The North American Industry Classification System

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Abstract

The Novel Coronavirus (COVID-19) has played a major role in society since early 2020 and in consequence, there have been significant, often detrimental changes across all industries, sectors and to people's livelihoods. In this paper, the focus is placed on how individuals have adapted in the harsh environment where jobs have been lost and the ability to travel severely restricted due to strict quarantine regulations to online trading, and why the financial markets have been able to facilitate this transition. We attempt to explore whether the results shown by new traders are sustainable or whether due to uncertainty in economic policies, market climate and the impact the coronavirus had on select industries provided retail traders a rare profitable opportunity.

It is necessary to understand the significance and role the financial markets have had on the economy and with millions of novice day traders flooding the market, it has become crucial to explore the impact it could continue to have. There has been a record-breaking wave of new traders who have opened brokerage accounts since strict quarantine restrictions were introduced in Q1, 2020. With advancements and innovations in online brokerages, it's now become more accessible than ever for most individuals to start their day trading journey. The surge of retail traders has contributed to more than 20% of stock trades which has forced finance professionals to recognize these traders as a significant market component (Ponczek, 2020).

The financial markets have direct relationships with the global economy, with the condition of the economies playing a major role on how society functions. Deep understanding of this topic will not only provide possible indications of future directions of day traders in terms of volume, trend, outlook and significance but will also highlight potential risks of these behaviors. Failure to recognize flaws or to implement improvements could result in tremendous losses, which in turn could ruin lives of millions. Furthermore, as day traders have become an entity with a strong foothold in the financial market, a market disruption emanating from novice traders could have significant knock-on implications for listed companies, markets and the economy as a whole. However, if day traders continue to show profitable results, there's a possibility that we are at the start of a new era in finance, where a shift in institutional ideology and investment strategy must be reconsidered.

Chapter 1: Introduction

As COVID-19 spread from China to all corners of the world, equities plummeted and market volatility soared all across the world's financial markets. The impact COVID-19 had on the US financial market exceeded that of previous major crashes. From Figure 1, we can see that in March 2020 market volatility levels were higher than levels recorded in previous market crashes of early 1930s and 2008 (Baker et al., 2020). There have never been any recorded instances of disease outbreaks which have displayed comparable results in the financial markets to the extent of what COVID-19 has displayed.

The study of Barro et al., 2020 in the correlation between news and its effect on the financial markets conducted by the Becker Friedman Institute concluded that all previous disease outbreaks showed no major move in the US stock market that derived from news. For example, the Spanish Flu pandemic of 1918-20 killed 2% of the world's population, yet there was no observable impact the news had on market volatility. However, COVID-19 showed a different reaction. Both positive and negative news regarding COVID-19 caused significant moves in the U.S. stock market (Baker et al., 2020).

The full extent of the global economic impact of COVID-19 is still unclear at the time of writing, however financial markets have demonstrated extreme movements in response to the regulations and policies mandated. The wild and unexpected spread of the COVID-19 outbreak caused extreme volatilities in the financial markets which led to massive losses for investors in a short time (Zhang et al., 2020). The U.S. S&P 500 index fell 35%, UK's FTSE index dropped more than 10% on the 12th of March, biggest single-day drop since 1987. The Japanese stock market fell by more than 20% from its highs in December 2019. With the global financial markets seemingly in freefall, financial regulators took swift action by introducing new policy instruments into the market in at attempt to restore stability and confidence.

The U.S. Federal Reserve (FED) announced on the 15th of March that it would pursue a zero percent interest rate policy along with at least US$700 billion in quantitative easing (QE). Shortly after this announcement, over a period of just 8 days, the FED increased the QE policy budget to unlimited level, meaning that it could potentially use this policy tool without constraints. The new policies by the FED and other Central Banks help the markets to stabilize and then rebound and since their lows of March, all major US indices have reached their respective all-time highs (ATH).

The effects of the pandemic were not limited to stock market declines, and with other negative repercussions such as unemployment for millions of individuals (Pastor and Vorsatz, 2020) widely recorded. In the US, the official unemployment rate in May 2020 was at a staggering level of 13% (prior to the pandemic, unemployment in the US was at a respectably low level of 3.5%); however, due to the categorization and definition of employed and unemployed, the real rate is estimated at 17.9% (BLS, 2020). Only individuals who do not have a job and who are actively looking for one are counted as unemployed, whereas people who are employed even if temporarily absent with or without pay are seen as employed. If a person is unable to fit in the criteria of employed or unemployed, the person is classified as not in the labor force. A survey conducted by the U.S. Bureau of Labor Statistics concluded that there were 9 million people seeking employment, who were all classified as not part of the labor force in May. Furthermore, people of ages 25 to 54 represented nearly one fifth of those not in the labor force in April and May (BLS, 2020). Figure 2 shows the civilian unemployment rate in the U.S. between year 2000 and 2020.

An increase in number of positive cases heightened the fear of COVID-19 and the spread of pandemic news along with economic uncertainty in the digitally connected world has led the financial markets to an uncharted area (Baker et al., 2020). Though the financial markets have been extremely volatile, in Table 1, all major online brokers saw massive surges of new accounts in the first quarter of 2020 (Fitzgerald, 2020). The number of retail traders has gone up as unemployment increased and I believe it’s due to the easy access to stock markets through these online brokers.

New traders are also the attracted to the availability of different financial instruments that can be traded, plus the quarantine restrictions presented people the luxury of time that previously they did not have, and the COVID-19 market crash in March gave retail traders a rare opportunity for these (mostly) young inexperienced investors to buy stocks extremely cheaply. Online brokers have introduced simplified trading platforms that promote a game-like feeling for the users, with fast transaction times and also offer benefits such as low to no trading costs and higher permitted trading volumes (Khan et al., 2017). The advancements and innovations in the financial sector enabled retail traders to participate in the market to the extent where since the surge of new traders early 2020, now 20% of all stocks traded are estimated to be executed by retail traders (Bloomberg, 2020).

As we’ve seen above, retail traders have increased in numbers during the volatile markets, hoping to benefit from potential opportunities. However, participating in such volatile market conditions during the COVID-19 pandemic is extremely risky and can leave investors exposed to losses exceeding their individual risk tolerance. With improper use of financial instruments which amplifies both risk and reward, a single loss has the potential to wipe out a balance if strict risk management isn’t imposed.

What concerns me is that retail traders have outperformed the standard market benchmarks, which in turn promotes additional risk taking. Retail traders have outperformed the S&P500 and even the well-known Goldman Sachs S&P 500 ETF during the pandemic as we can see in Figure 3 (Ponczek and Ballentine 2020). I believe the reasoning can be attributed to several explanations: retail traders believe that they have higher personal risk tolerances than they actually do, plus they approach the market with strategies and trade stocks based on their own understanding of the market using technical, fundamental and sentiment analysis. Their understanding may be flawed.

However, an individual with a solid understanding of their own risk/reward tolerance and backed up by their own studies of the market is not enough to justify the idea that retail traders are better off than institutional traders, who have years of experience in the financial markets with complete understanding, ability to analyze market conditions and justify why they choose to participate in the market. Have the retail traders showcased the flaws of institutional traders or is their success simply due to the luck playing favorably towards the newcomers? While the retail group has shown impressive performance so far this year, I believe that they need to be protected from their own judgment and erroneous decisions during unforeseen market environment where even the well-informed institutional traders understand little of what’s truly going on.

A deeper dive into retail traders’ behavior during the pandemic will provide relevant insight on retail trader’s psychology and behavior during times of stress derived from extrinsic factors, as well as in normal situations. Not only will knowing the reasoning behind the actions of retail traders be beneficial for the further optimization in terms of market strategies, but it will also provide reasoning on why retail traders have shown great results compared to their professional peers in recent months.

There are areas that need further exploration to understand retail traders’ behavior. The first area involves behavioral finance, in the belief that the psychology of traders will depict a clearer image as to why success has been shown in favor of novice day traders against their professional counterparts. Secondly, we will examine how online brokers are adapting in the face of the pandemic and the boom in retail investors. Thirdly, we look at whether financial literacy is growing more popular and thus is positively impacting the new traders. There are then five questions to consider that we suggest will lead to a concrete assessment of the future market environment.

- Was luck the major factor for day traders’ success since the COVID-19 crash?
- Do retail investors have a superior stock picking ability based on technical, fundamental and sentiment analysis?
- Are retail traders overconfident in their approach and understanding of the market and thus take bigger risks than institutional traders?
- Do retail traders closely follow news and react to it? The news in this context generally comes from twitter and other platforms where ideas are shared by 'experts'.
- Retail traders now have access to more educational sources to learn about the financial market, how does this influence their thinking when it comes to trading?

Chapter 2. Literature Review

In this chapter, we are now going to consider how previous academic literature can helps us to answer the questions surrounding what has led to the success of retail traders since the start of the pandemic. There will be a focus on how retail traders approach online trading from their own psychological point as well as external factors that influence retail traders' psychology. The first point considered is behavioral finance which will introduce the basic understanding of how novice traders think. Points two and three than expand on the effects online brokerages and education have on retail traders.

2.1 Psychology

Traditionally, the understanding of the financial market uses models where agents display rationality. Rationality is defined with two meanings, first, when a person receives new information the information is then processed and the person's belief is updated in line with the information. Second, given a person's belief, their choices are made if it's normatively acceptable, meaning it's consistent with Savage's notion of Subjective Expected Utility (SEU) (Barberis and Thaler, 2003). However, based on the homo economicus model, irrationality causes retail traders to sway from rational behavior that's anticipated of them (Barberis and Thaler 2003).

In behavioral finance, irrationality is accounted for and in order to reach a more realistic understanding of financial behavior, and learnings from psychology are implemented (Camerer and Loewenstein, 2004). Financial attitudes can be defined as one's psychological tendency upon the valuation of established practices of financial management within various degrees of acceptance/non-acceptance (Parrotta and Johnson, 1998), or even be defined as a view, state of mind, or judgement (Pankow, 2012).

Based upon several studies in this subject, there is a concurrent conclusion which leads to various aspects of individuals' attitudes contribute to irrationality. Psychological characteristics such as self-control and optimism have strong influence over an individual's financial behavior (Stromback et al., 2017). Park and Sela (2017) came to the conclusion that individuals, based on their psychological reasoning, tend to avoid finance-related decisions if it's believed to be incompatible with their personal style of decision making. One example of a financial behavior that derives from psychological attributes is the 'ostrich-effect' which describes the ignorance an investor portrays when their investments are falling, by avoiding information on the investment (Olafsson and Pagel, 2017).

Psychological traits as mentioned above play a big role in an individual's behavior when it comes to the stock market. To expand on this area, it's necessary to understand how individuals form expectations. Based on the research conducted by Barberis and Thaler (2003), below are 7 beliefs that individuals express in the stock market.

Overconfidence. Evidence points to the fact that people are overconfident in their judgements. This can be expressed in two ways. First, the observation of the confidence level individuals assigned themselves have been too narrow. When individuals assigned 98% confidence interval on their estimates for example, showed the true quantity only 60%

of the time. Second, when it comes to estimating probabilities, individuals displayed poor performance. An event people think will surely occur have only occurred only 80% of the time. An event seen impossible have occurred around 20% of the time.

Optimism. The majority of people have displayed unrealistically optimistic views of their own abilities and capabilities. Research showed that over 90% of people believe they're above average when asked. People have also shown systematic planning misbelief meaning they anticipate tasks will be completed much sooner than when it actually does.

Representativeness. When people try to evaluate the probability between two data sets and its relation to one another, representative heuristic is used (heuristics are defined as mental shortcuts that allow an individual to make a decision, pass judgement, or solve a problem quickly with minimal effort (By Psychologytoday)). This means that people determine the probability between the two sets based on the degree which one set represents essential characteristics of the other. Representativeness heuristics can lead to several biases, the first of which is base rate neglect. Base rate neglect is illustrated as such, if a description of a person is provided and was asked whether that person belongs in statement A or statement B, most people assigned greater probability to the statement which the person's description 'sounds' like even if it's impossible.

> For example, if a person named Lina was described as '25 years old, single, bright and works at a bank. As a student she was concerned with issues of discrimination and social justice'. Upon receiving Lina's description, and asked which of "Lina works at a bank" (Statement A) and "Lina is a banker as well as a member in the feminist movement" (Statement B) is likely to be true, most people will choose statement B, however based on her description it's impossible. The explanation is simple, people chose statement B because Lina 'sounds' like what a feminist would be based on her description.

Second, sample size is often neglected. People have been observed to fail to take into account the size of the data set. These people tend to believe a small sample is as representative as a large sample. For example, six-coin tosses that result in three heads and three tails are equally representative as 1000 tosses that result in 500 heads and 500 tails; however, this is not necessarily true.

Conservatism. Unlike in representativeness where the base rate is underweighted, there are instances where the base rate is over emphasized relative to the sample evidence.

Belief perseverance. Evidence has shown that once people form an opinion, they tend to cling onto it too tightly for too long. This is because of two effects; firstly, people are reluctant to look for any evidence that contradicts their beliefs. Secondly, if a person does find evidence that contrasts with their beliefs, it will most likely be looked over with skepticism. Based on the belief perseverance, studies have found an effect known as confirmation bias. Confirmation bias is when people misinterpret any information that goes against their beliefs as being in their favor.

Anchoring. When forming estimates, individuals have a starting value that perhaps is arbitrary and then as they progress, the initial value is adjusted. Evidence points to the fact that most often, the adjustment is insufficient and people anchor too much on their initial point.

Availability biases. When assessing the probability of a given event, people often look for any relevant memories that can be used for an estimate. This bias highlight that even though this is a sensible approach, due to the fact that not all memories are as retrievable or share equal weight, biased estimates are produced.

Collective behavioral tendency known as herding is important to highlight. Herding is the tendency to behave by imitating the actions of others whilst neglecting their own beliefs or information (Shanta, 2018). Herding can be deemed both rational and irrational based on the individual's approach arriving to the decision of following others. Intentionally or unintentionally being the key determinant to assess the rationality. However, herding is widely regarded to be unintentional because of market characteristics such as uncertainty, lack of information, illiquidity and low volumes which effects the investor's psychological state. In a market that's showing the characteristics above, people lose trust in their own judgement and regard following others as a safe bet (Shanta, 2018).

2.2 Online Brokers

Robinhood, a well-known online broker, has revolutionized the decades old brokerage industry by introducing a platform that is both easy to use and accessible for nearly everyone. Robinhood was founded in 2013 and broke new ground in the online trading space, by eliminating trading fees, providing a simple user interface and offering users a game-like feeling with all of its features included in an app. All of these measures appealed strongly to the young generation of retail traders. At the time of Robinhood's launch, most other well-established brokerage firms charged around $10 per trade and their respective platforms offered more complex functionalities making it unappealing for newcomers.

All of these features, plus the attractive cost structure, including attractive rewards (such as one free stock) for new members, helped Robinhood to move away from other old-school brokerages and attract a new generation of trader. Robinhood's home screen lists trendy stocks, when touched – a green button pops up with the word "trade", encouraging people to take action immediately, using the subtle psychological technique of the fear of missing out (FOMO).
Robinhood began solely as a stock trading platform and as the firm grew, they added margin loans and options trading to expand their clients' experience. Whilst new traders are legally barred from trading options, they are given a multiple-choice questionnaire that once completed, they are then regarded as "coached" and become "sophisticated" users even though they still may have little experience in these new areas. (Popper, 2020)

It is an industry standard for brokers to offer commission-free trading nowadays, with the use of the business model called 'payment for order flow'. When an investor places a trade on a brokerage, the broker then sends the order to a high-speed trading firm which earns money on the small spread between what the investor is willing to pay and the price someone is willing to sell it for, the high-speed trading firms earn enough that they pay brokers for sending them new orders to fulfill. With wide adoption of free trading, retail brokers thus fixated on their volume of trades (Massa and Ponczek, 2020) (Figure 4).

With the goal in mind to attract young investors, trading giants such as Schwab began offering ‘slices’ which means people are able to purchase a fraction of a stock (Rockeman, 2020) and thus previous barriers to entry for retail investors were thus lowered. Providing investors with the ability to purchase fractions of a stock (meaning more diversified stock portfolios are now possible), people have had the opportunity to invest in securities that are priced higher than what their budgets would normally allow, meaning that even investors with relatively little capital could start investing little by little.

Since Robinhood’s debut in 2013 with the introduction of new innovative features, young and novice investors were picking up interest in the stock market (Massa and Ponczek, 2020). With it, other established brokerages have also had to adapt and implement features that resonated well with the younger generation. Besides the enticing features such as zero commissions, splits and leverage now feature widely in their offerings, however retail brokerages have been thought to lack the technological hardware capabilities to handle heavy transaction loads (volumes). In an industry where software and investment innovation create demand for the use of a particular broker, it’s necessary to have a secure and advanced technological back bone which won’t hinder the user’s experience in ways such as site outages and the inability to execute trades (Basak, 2020).

2.3 Financial Literacy

Looking at financial literacy, this is generally viewed as the focused consumer expertise in terms of how a person manages their financial affairs successfully (Alba and Hutchinson, 1987): It is also the degree to which a person understands key financial concepts and has the capabilities to manage their personal finances with correct implementations of their own short-term decision making, long term planning and adaptiveness in the changing economic conditions (Remund, 2010).

Many governments, businesses and NGOs created interventions to improve financial literacy in general amongst the public, in an effort to reduce self-inflicted losses in the stock market and to promote healthier financial life styles in areas such as savings. The cost of implementation of financial literacy in education has already cost billions of dollars (Fernandez et al., 2014), however studies have shown the variance in individual behavior was only around 0.1% and lower than average effects in low-income areas (Fernandez et al., 2014).

Financial literature can prove ineffective when individuals aren’t able to conceptualize principles or unable to practice material studied, before it becomes obsolete. In the field of finance, it’s also difficult to teach complete financial knowledge, as understanding can be hampered by unforeseen future events that both the teacher and student cannot know. There is also the factor of herding that sway ones thought process, the opinion of many unknowledgeable people outweighing the voice of source material from experts can cloud individual’s mind with biased advice. (Fernandez et al., 2014)

This research work is aimed at analyzing the behavior of retail traders and this assessment can be done with several approaches. Firstly, based on consumer behavior during uncertain times we can examine the possible direction of retail traders' involvement in the market in the future. Another method is to identify retail trading activity during COVID-19 and then to try and determine the factors that influence retail trading during this period. The final approach involves examining the influence online personalities and social forums have had on retail trading and determine what it might signify in the long term.

As retail traders are analyzed in depth from the three stages mentioned above, a comparison will be then made with the trading profile and habits of professional fund managers. The performance and behavior of fund managers during the early part of the pandemic will provide further insight into the behavior of retail traders by providing comparison between the professional and retail traders in areas including the nature of instruments traded and the trading patterns. By comparing each investor group, the bigger picture of market activity as a whole will be presented which can be used to suggest future performances of retail traders. We will also try and draw conclusion as to why professional investors have performed poorly during the pandemic so far, relative to retail traders.

3.1 Times of uncertainty

COVID-19 brought many unprecedented circumstances in people's general daily life and the global economy. The effects of policy tools along with consumer spending behavior during the pandemic have been studied by a number of researchers, however, the impact it has had on retail traders has been less documented and consequently is less-well understood. To assess retail traders, the overall condition of the market during the pandemic is compared to past large-scale event(s) that brought significant consequences on everyday life, raised public fear and economic uncertainty, and here, we consider events such as terrorist attacks or natural disasters. Large scale events in the past can provide possible future indications if compared to an event that have had a roughly parallel impact to COVID-19 (Goodell, 2020). The comparison can help us better understand future events and how retail trading might be influenced by these types of events.

To affectively compare past events to the COVID-19 pandemic, the events must share similar characteristics in terms of the impact it caused. For the purposes of this study, only major events such as terrorist attacks will be used, as to COVID-19's impact on affected industries or sectors is wide-spread, rather than contained to any particular region or industry and thus is more in line with the general effects of a terrorist attack.

In a similar vein, a past aircraft crash cannot be used draw inference about the entire airline industry, as the scope is too narrow and specific. Though it might seem comparable, the two events are on a different scale. Following an air crash disaster, people do lose interest in flying in the short-term out of fear, but Bosch et al., (1998) concluded that in such circumstances the airline responsible for the crash is the largest loser and alternative airlines gain customers. While it is true that the airline industry suffered tremendous losses due to the pandemic and there are no past events that share similar characteristics in terms of the shift in demand or the magnitude where all airlines globally felt the negative impact, we nonetheless need to analyze events that have effects that are more widely felt across regions and industries.

As previously mentioned, no event in history had similar global impact as COVID-19, making it challenging for direct comparisons to assess possible future outcomes. Therefore, rather than focusing on the magnitude of past events, the level of spillover an event had in the financial market is where we have focused our attention. The COVID-19 pandemic had global impact requiring that the chosen event for comparative purposes, would have had spillover effects on a global scale as well. Unlike the pandemic, terrorist attacks are disaster events that are localized in terms of location; however, similarities are displayed on the impact it has on the financial market due to the rampant change in public mood and perception internationally.

The September, 11 2001 terrorist attack will be studied in this paper owing to the more general nature and dispersion of the effects felt around the world. The September, 11 2001 terror attack's impact on the global financial market was considerable and the only past event with large scale spillover affects globally. This was unlike other terror events including the 2004 Madrid metro attack or the 2005 London underground attack (Figure 5), which had a relatively smaller and shorter-lasting impact on the global financial market. Brounen and Derwall (2010) compared the three-terror attacks above by the price reaction on eight global indices, by their event day cumulative abnormal returns (CAR), 6-day CAR and 11-day CAR. The results show that following 9/11 there was an immediate stock market reaction varying from -0.57% in the UK and -7.48% in Italy, on average immediately after the attack the eight indices averaged -3.86%, in the following week the aggregated CAR was -8.24% and the negative performance continued even in week two. Following the September 11, 2001 terror attack, research by Hon et al., (2004) shows the correlation coefficients between the stock markets of the United States' and 24 countries' using a vector autoregression (VAR) model.

3.2 Retail Trading Activity

Unlike any previous virus outbreaks such as the Spanish flu (1918-20) where the stock market didn't show any correlation between news releases and price movement. Baker et al., (2020) concluded that the impact COVID-19 had on the financial market was unforeseen, where any positive or negative news regarding COVID-19 would lead to significant moves in the US stock market. To illustrate, the data set from Ortmann et al., (2020) is used where data is taken directly from undisclosed, transaction-level brokerages, that offer an online trading platform for retail traders under a UK broker license. The data sample compromised all trades executed by investors on the brokerage scene between August 1, 2019 and April 17, 2020 along with the exact time-stamp, instrument of the trade, the number of long/short trades and the investor demographics. The data set also includes the details of the push notifications that inform investors of potential trade opportunities provided by the broker. In total 45,003,637 transactions executed by 456,365 investors were recorded in the data set. Not only was the data used composed of a large set of transaction and investors, it provided pre/post COVID-19 data, which is useful for comparing the situation before and after. Additionally, exact details such as demographics, instrument used, time and direction of the trades were also given.

The data concerning push notifications is appealing, and this is because Arnold et al., (2020) observed investor attention triggers on risk taking and concluded that such push notifications entice risk-taking for less experienced, young, male investors in particular. There has also been a link to increased risk taking when the attention trigger was for stocks that attracted more endogenous attention (this means attention is directed towards the stimulus voluntarily, by interpreting a cue). For example, when a push notification shows future estimates of a company's profits or activity to be good, then people will be inclined to take more risk when buying that company's stock.

In the study from a data set of a total of 243,617 active investors, Arnold et al., (2020) explored the relationship between attention triggers and subsequent trading, and it was noted that a push notification has been seen to increase an investor's long trading activity by 0.0047 trades on a given day which is drastically higher than the mean daily number of investors' long trades in stocks at 0.000153. For short selling, the correlation is similar to regular long trades, where push notifications increased investors' short trading intensity by 0.0094 on a given day compared to 0.000146 of the mean daily number of investors' short trades. Thus, with data on push notifications, we can begin to gather insights on retail traders' psychology and thus suggest better speculative situations for investors by providing necessary knowledge to strengthen their risk-management and decision-making skills.

The relation between investors' trading activity and COVID-19 is studied with an ordinary least squares (OLS) regression analysis. Multiple variables are used to proxy investors' trading activity. Trading intensity denotes the number of trades in a given week and a value of 0 is given for investors who didn't trade in a given week. Leverage (borrowed capital used to enlarge the potential return of an investment) is a variable that depicts pure risk-taking. A short sale is a dummy variable that is valued at 1 if a trade is in a short position and 0 if it isn't. Abnormal net deposit indicates the number of deposits minus the number of withdrawals on a given day, divided by the average net deposits prior to COVID-19. Abnormal first deposits show the number of deposits by investors who opened a new account on a given day (for trading purposes), divided by the average first deposits prior to COVID-19. Buy-sell imbalances (BSI) are the difference between long and short positions. Abnormal trading volume in an industry illustrates the trading volume on a day (t) divided by the average trading volume in that industry over the last six months.

The impact of the pandemic is assessed with several variables. COVID-19 will denote the logarithm of the number of COVID-19 cases plus one. 'Dow drop' is a dummy variable that's valued at 1 on March 13th which is the day after the Dow and FTSE recorded extreme losses; the variable is 0 otherwise. On the 12th of March, the Dow Jones Industrial Average (DJIA) fell a total of 9.9% and the FTSE dropped more than 10%, which became its worst trading day since 1987.

Three more dummy variables were then used to define various stages of the outbreak. The first stage was between Jan. 23 to Feb. 22, this was when China first introduced the lockdown and investors globally began to start to become aware of the severity of the virus, as the lockdown in China posed a major threat to supply chains all over the world. The second stage was between Feb. 23 to Mar. 22, where the virus at this point in time had reached Europe, and Italy was amongst the first European nations to order a lockdown. The third stage was between Mar. 23 to Apr. 17 when the UK ordered a lockdown, and by this stage, the majority of countries globally had also already issued a state of lockdown. (Figure 6)

3.3 Impact of social media on retail traders

It's evident that social media has become a significant platform where individuals gather information and begin to form their investment opinions. For example, Bitcoin, a cryptocurrency that traded for US$0.06 in July 2010 rose to US$19,700 in December 2017, prior to falling back. Within only few months the price of Bitcoin fell to US$5,000 and part of the reasoning for the rise and fall in its price, could be due to the effect social media played – the social media networks were full of chat on the potential of this crypto, it's benefits and pitfalls.

In 2011, Bitcoin gained traction through a viral video uploaded on WeUseCoins which in retrospect was the catalyst that jumpstarted the cryptocurrency by amassing a total of 6.4 million views at the time. According to Mai et al., (2018), Bitcoin's performance and volume of transactions was due to the circulation of user generated content through social media. It would be difficult to image a traditional investment research report being as widely seen or read, when distributed through conventional channels. As seen from the example of Bitcoin where the relevancy of social media is highlighted, the effect social media has on individual's have become a vital aspect to further expand our understanding of retail traders' behavior.

To evaluate the relation between social media and trading, five sources that have relevance to the financial markets will be examined to determine the effects they all have with respect to trading activity and herding behavior. Based on the research conducted by Bizzi and Labban (2019), below are the five sources.

Social trading platforms. These are trading platforms such as Seeking Alpha, Wikifolio and eToro. Social trading platforms offer individuals the possibility to copy trading decisions of others opposed to following investment recommendations from institutional investors. With increased usage of social media, people are more likely to find out about social trading platforms which can in turn increase the likelihood of trading due to the false perception of easiness in online trading and accessibility these platforms portray to new users. These platforms also intensify herding behavior as people copy other traders who seem successful and obtain results faster than through trading and investing through traditional fund management channels

Bloggers. Financials bloggers are individuals who provide information concerning trading, whether it be recommendations or future outlooks, which then impact the followers' trading decisions (Saxton and Anker, 2013). Bloggers are also perceived as credible and thus are thought to provide reliable trading signals, which in turn strongly influence the followers' trading decisions (Luo et al., 2017). Not only do bloggers seem trustworthy and credible providers of trading information in the eyes of the followers, Harjoto et al., (2009) concluded that people perceive bloggers to have information that is exclusive to them, such as rumors or leaks that others don’t know. This also influences trading activity of those following a particular blogger.

As people spend more time online, and given the ease at which information is accessible in today’s technology age, the chances of discovering a blogger are fairly high and thus the chances of people engaging in online trading due to discovering a blogger, also increase. To attract more people, bloggers put out large amounts of posts and have become thought of as important sources trading information (Fotak, 2017), but people are also attracted to the opinions of well-known bloggers. There is thus a vicious circle that intensifies herding behavior because bloggers influence other bloggers which then influence the follower’s final trading decisions.

Influencers. Unlike bloggers who are known for the information they provide; influencers don’t necessarily have a website or blog where people come to gather information that otherwise they wouldn’t find. Influencers differ from bloggers as they are people who are at the center of attention and sought after by many, rather than a person who guides others in their field of expertise. Shalev and Morwitz (2011) believe social media celebrities influence individuals who would like to be associated or identified with them through comments and opinions. Kylie Jenner can be used as an example: Snapchat’s stock plummeted suddenly and lost US$1.3 billion due to what many believe was caused by her comment on twitter, criticizing the company.

Kupfer et al., (2018) regard influencers today as powerful human brands that can positively or negatively impact the performance of companies that are associated with them, such as in the Kylie Jenner example above. Besides celebrities, around 40% of financial advisers are believed to want to promote their own personal image as thought leaders and influencer on social media platforms (Putnam Investments, 2015). With the increase of social media usage, people are directly exposed to more influencers and ultimately, this can lead to increased herding behavior. Pelster and Gonzalez (2016) believe individuals tend to blindly follow influencers’ opinions and recommendations rather than coming to a decision, rationally on their own.

Social network contacts. Personal contacts on social media platforms influence trading behavior as Mudholkar and Uttawar (2015) argue that contacts on social media platforms are able to share their trading decisions through posts in order to exchange information with others which encourages trading. When information is received from friends or social contacts, it’s regarded as trustworthy and people usually value word to mouth communication from people they know more than information from experts (Garcia, 2013).

Psychologically, people often imitate each other’s decisions when there’s an affective relationship (Kilduff, 1990). This means that a contact on social media that posts their trading activity or encourages others in engaging in the stock market, those who view it might be enticed and feel the desire to trade in a similar way. In addition to the encouragement that people get from posts related to trading, there is the Fear Of Missing Out (FOMO) that can strongly influence an individual’s trading decisions. This is where individuals engage in trades that they otherwise wouldn’t have, in order to reduce their anxiety that stems from missing out on the reward that they perceive their friends are gaining (Clor-Proell et al., 2019). With the increase in the usage of social media, people are influenced more by their contacts, thus increasing the likelihood of trading themselves, if they believe that their contacts are trading and thus, they could miss out. These perceptions also serve to increase in herd behavior.

Online trading publishers. These are media publishers on social media platforms that are specialized in sharing online trading related information. Unlike traditional news outlets such as the Wall Street Journal, which require paid subscriptions for most of the investment-related information, online trading publishers offer news in timely manner, constant updates and are easily accessible (and are often free).

Online trading publishers are specialized in the financial market and mainly target individuals who are self-directed online traders. With increased usage of social media, people are more likely to be exposed to these publishers and thus are encouraged to trade because the information on trading publishers becomes appealing due to the sensationalism and extreme opinions expressed, which then lead to positive/negative views.

To attract followers, social media publishers can deliberately share fake news that appeals to people. Allcott and Gentzkow (2017) asserted that social media is the perfect medium to spread deliberate fake news because content can be shared without third-party filtering, fact checking or editorial judgement. Furthermore, fake news spreads rapidly on social media because individuals are less reluctant to judge the information rationally when they see themselves as part of the social group (Jun et al., 2017). This applies especially younger followers who trust online sources more than older members of society (Warner-Søderholm et al., 2018). As news implodes and becomes viral, it can lead to greater herding behavior.

To illustrate this point, the data Bizzi and Labban (2019) gathered is used, where a random sample of 286 Americans, without any exclusion criteria besides adult age are represented. Each person was asked the amount of time they typically spend on social media each day and how likely were they to engage in online trading. To assess herding behavior, if people were going to engage in online trading, they were asked how they reached their trading decision, whether by following choices others make when trading, blindly following choices others make when trading or looking at choices others made.

Then to assess the strength of the five sources of influence, people were first asked in general, how likely they were to consider the opinion of the following people on social media, with the following options: bloggers, influencers, social media friends/contacts, people who write articles on social media, and online news publishers. Second, to see the influence the five sources have on trading, people were asked: “if you would ever do online trading, how likely are you to consider the opinion of the following people on social media?”, with the following options: bloggers, influencers, social media friends/contacts, people who write articles about trading on social media, and people who use social trading platforms. The questions were answered with 5-point Likert scales and the results of this study then displayed the effect of social media on individual’s investment decisions based on personal traits such as daily social media exposure.

3.4 Mutual Funds during COVID-19

With the unprecedent conditions in the global economy, we also turned our attention to the professional side of the financial markets, in order to find out how large funds are investing their capital and what their clients are seeking from those funds. With record declines in indices and sharp incline in unemployment rate as the pandemic took hold, we want to assess whether mutual funds provided investors with a suitable hedge against the pandemic, through the active investment management strategies they employed.

To assess this matter, the paper by Pastor and Vorsatz (2020) from the National Bureau of Economic Research was studied. The S&P 500 and FTSE 100 indices were used as benchmarks against which to assess mutual funds' performance. The data sample contained 4292 U.S. actively managed equity mutual funds and as of January 31, 2020 the data represented US$4.9 trillion of total net assets (TNA). There is the use of other metrics as well, including the sustainability rating from Morningstar, as it's now considered one of the strongest predictors of performance.

Morningstar's sustainability rating is assigned between one and five globes, Morningstar gives sustainability "globes" to each fund: the more globes a fund has, the higher its sustainability rating. Another metric used is the fund's star rating from Morningstar. The star rating assigned as of January 31, 2020 is used to predict performance between February 20 and April 30, 2020 and like the Morningstar globe rating, the more stars a fund has, signifies better performance.

The use of sustainability and performance ratings provide information on how funds perform relative to their investments and reflect their clients' sentiment and outlook. A popular perspective on sustainability issues such as environmental concerns, are seen as "luxury goods" where only investors who've already met their basic needs are interested in such investments. However, during the COVID-19 crisis investors viewed sustainability as a necessity rather than luxury investment opportunities. This meant that pure performance was not the sole determinant of stock selection for funds and Morningstar's sustainability rating was an important variable in studying funds' behavior during the pandemic. This is also in line with the general move towards sustainability being more prominently on the agenda of investors, when selecting portfolio investments.

The findings of this study will give an appropriate understanding of funds' investment selection during the pandemic and future outlooks in areas including their clients' view on the financial market which is used to identify the distinctions between retail traders and professionals.

Morningstar sustainability ratings are given based on the fund's holding's on environment, social and governance (ESG) issues relative to the fund's peer group (i.e., Morningstar Global Category). Morningstar uses company level ESG scores from Sustainalytics to evaluate each fund's asset weighted average unmanaged ESG risk exposure. Then, each fund is given 1-5 globes based on their scores, funds with 5 globes being the most sustainable, whereas funds with 1 globe are the least sustainable in terms of the investments they contain.

Morningstar star ratings are calculated by computing each fund's risk adjusted performance over the past three, five and ten years relative to the fund's peer group. Then the results over the three periods are averaged out and based on the final results, 1-5 stars are given out where 5 stars indicate best performing funds. Other metrics used are exclusions and growth investment style. Certain funds employ exclusions in their investments. This means that a fund can exclude any stocks of firms that don't fit with their views (and hence reflect the current investment agenda of a broad spectrum of investors). For example, tobacco companies or gun manufacturers can be excluded by certain firms who find these investments as unacceptable. For another example, the growth investment style focuses on companies that show strong earnings growth.

Cross-sectional regressions models are used to analyze fund performance pre and during the COVID-19 pandemic. The performance during the crisis is based on the timeline between February 20 and April 30, 2020. Pre crisis performance is based on the timeline between October 1, 2019 to January 31, 2020. The dependent variable for both pre and during COVID-19 is the FTSU/Russel benchmark with adjusted performance. Performances during both the periods are calculated using simple returns, expressed in annualized percentage terms. The variables used are sustainability, exclusions, growth investment styles and the Morningstar star rating. The parameters and controls used are:

- Global category fixed effects (FE) that are based on the Morningstar Global Category variable.
- Fund-level controls which include the log of the fund's age in days, the log of the fund's total net assets (TNA) [January 31, 2020 for during, September 30, 2019 for pre]. Turnover ratio as of January 2020 (during) and September 2019 (pre). Net expense ratio as of January 2020 (during) and September 2019 (pre). Net cash position in percent of TNA as of January 2020 (during) and September 2019 (pre). Morningstar medal rating as of January 2020 (during) and September 2019 (pre).
- Industry controls which include the fund's net position in percent of TNA in the following industries: basic materials, communication services, consumer cyclical, consumer defensive, energy, financial services, healthcare, industrial, real estate, technology, and utilities.

With the results gathered in this section, institutional investors' approach on the market is determined along with the explanation of their underperformance relative to benchmarks like the S&P 500. Along with previously studied areas such as trading psychology, the final conclusion can be derived on the possible behavior institutional traders have had during the COVID-19 pandemic.

Retail investors make quick decisions, looking at what the rest of the pack is doing, loving the gamification aspect but not really understand what they are doing and certainly giving no thought to managing risk, whereas institution investors, bound by mandates which are in turn derived from a longer-term investment approach, stick to their established investment strategy and thus could find themselves missing out of a sector or company stock that is being bid up by social media hype. Also, institutional investors look not only at performance, but also risk management of the portfolio, which helps them navigate the uncertainty. The new day traders, would not really be aware or sophisticated enough to use proper portfolio hedging tools and strategies, thus while markets rally, they have a false sense of security, but the true test will be when markets correct.

Chapter 4. Findings

4.1 Times of Uncertainty

The findings from the correlation coefficients estimated with the VAR model (Table 2) are as follows. In column 8, we can see the evidence of contagion as there are six countries that have experienced significant increase in correlation with the U.S. stock market three months after the September 11, 2001 attack. Column 9 shows us that majority of the countries showed significant correlation to the U.S. stock market even six months after the terror attack. Column 5 shows us that in following the terror attack, all 24 countries had the lowest volatility levels three months after September 11. From the results, we see that the stock market variance is highest right after the terror event occurred.

4.2 Retail Trader Behavior

From Figure 7 (A) we can observe the investors' investment trends during the early part of the pandemic in detail. There was a significant increase in trading intensity for indices between February 23, and March 23, which then started to decrease after March 23. Though not as extreme as index trading, there was also an increase in stock trading up until March 23 then intensity fades shortly after. Contracts for difference (CFD) trading on stocks unlike other instruments, have shown spikes three times since January 23, and March 23. We also observed a spike in crypto trading the day the Dow dropped on March 12.

In Figure 7 (B) there's a major decrease in the use of leverage for all asset classes shortly prior and after the drop in Dow between February 23 and March 23. In Figure 7 (C) we observe a spike in short sales using CFDs between February 23 and March 23, however there are no other clear trends for other asset classes. From this observation we can say that retail traders reacted cautiously when the market fell.

Table 3 Panel A shows us the trading intensity of investors, Model 1 depicts that there was a positive slope of a gradient 0.229 for the average weekly trading intensity as COVID-19 cases double, compared to the average trading intensity before the pandemic. Model 2 depicts the increase in trading intensity with a positive slope of a gradient 3.5557 after the 9.99% drop in the Dow, compared to the average trading intensity pre pandemic. Model 3 depicts the trading intensity between February 23, to March 22 is the largest increase in trading intensity. Model 4 depicts the increase in trading activity driven by male investors. Model 5 depicts the increase in trading activity by older investors. Table 3 Panel B shows the trading intensity based on the asset class. During the pandemic, investors' trading intensity increased for stock and index asset classes at 0.0363 and 0.1813 respectively. For CFDs, gold and cryptocurrencies there's no observable significant changes. Similarly, Panel C depicts that new positions opened increased for stock and index trading with 0.0195 and 0.0910 increase respectively.

Table 3 Panel D shows us the use of leverage by investors, Model 1 depicts 0.3 decrease in average of the use of leverage, compared to the average leverage usage before the pandemic. Model 2 depicts the decrease in the use of leverage by a negative slope of a gradient -1.7197 or 172% after the 9.99% drop in the Dow. Model 3 depicts the decrease in the use of leverage between March 23, to April 17 to be the largest decrease in leverage usage at -2.9917. Model 4 depicts the use of leverage by male investors where an increase of 0.0146 was seen. Model 5 depicts the increase in leverage usage by oldest and youngest investor groups was highest amongst all other investor age group at an increase of 0.0040 and 0.0033 respectively. Table 3 Panel E shows the use of leverage by asset classes. Where CFDs, index and gold all show declines in the use of leverage, however crypto assets saw an increase at 0.0045.

Table 3 Panel F shows the increase in short sales taken by investors after the outbreak of COVID-19. On average, a 2% increase in investor tendency to short was recorded compared to their level of tendency before the pandemic. There is a significant increase in short sales when the Dow dropped as seen in Model 2, at 0.0158. From Model 3, we can see the increase in short sales occurred between January 23 to April, 17. Amongst all the age groups, younger investors displayed the most amount of short selling as seen on Model 5. Table 3 panel G shows the increase in short sales by asset classes, and all asset classes show an increase.

Table 4 shows us that on average, investors have added additional funds to their trading accounts. Model 1 shows the increase in abnormal net deposits by 0.41 as COVID-19 cases doubled. Model 2 and 3 shows the increase in additional deposits by both new and established investors.

Figure 8 shows the BSI over time. On average investors have taken long positions for stocks and as the pandemic took place, investors increased the tendency to take long positions on stocks. The BSI for gold and index positions on average are both neutral, hovering around zero. Cryptocurrencies displayed two spikes in long positions near February 23, and March 23. CFD stock positions had a trend for shorts up until around March 23, which then displayed strong long positions since.

Figure 9 shows the trading volume and the fraction of short sales jointly for stock trading and CFDs on stocks on five industries with the largest changes in the two variables. From industries based on the North American Industry Classification System (NAICS), industries that showed the highest abnormal trading volume were Transit and Ground Passenger Transportation, Motion Picture and Sound Recording Industries, Accommodation, Water Transportation, and Air Transportation. The five industries that showed the highest short selling were Motion Picture and Sound Recording Industries, Accommodation, Air Transportation, Supportive Activities for Transportation, and Administrative and Support Services (includes travel related companies like TripAdvisor, Expedia, etc.). Trading volume started to increase from January 23, to February 23, with Accommodation and Water Transportation industries being the first to experience abnormal trading volume. We noticed that around the start of February, prior to massive spikes in short selling in March, industries impacted by the pandemic had already seen an increase in short selling.

4.3 Influence of Social Media

The results from Table 5 shows us that heavy social media users have a likelihood of 63% of considering online trading, compared to 55% of light social media users. Furthermore:

The effects seen from herding behavior are as follows:

- 78% of heavy social media users were likely to follow choices others made when trading online, against 54% for light social media users.
- 4% of light social media users would blindly follow choices others made, when trading online. This was against 26% for heavy social media users.
- Compared to light social media users, heavy social media users were 440% (4.4x) more likely to follow others blindly when trading online.
- Compared to light social media users, heavy social media users were 64% more likely to look at choices others made in trading decisions, rather than trying to understand future cash flow or company fundamentals for themselves.

Looking at the influence of social media in general, the following could be observed:

- 59% of heavy social media users were influenced by bloggers. 37% for light social media users.
- 45% of heavy social media users were influenced by influencers. 25% for light social media users.
- 89% of heavy social media users were influenced by their contacts/friends on social media. 69% for light social media users.
- Heavy social media users were 78% more likely to be influenced by individuals who post articles on social media than light social media users.
- Heavy social media users were 23% more likely to be influenced by online publishers than light social media users.

Turning to the influence of social media on online trading, we observed that:

- 50% of heavy social media users were influenced by trading bloggers, opposed to 29% for light social media users.
- 54% of heavy social media users were influenced by influencers. 25% for light social media users. Heavy social media users were 109% more likely to be influenced by influencers than light social media users.
- 69% of heavy social media users were influenced by friends or contacts on social media. 40% for light social media users.
- 89% of heavy social media users were influenced by people who wrote articles about trading on social media. The figure was 52% for light social media users.
- 91% of heavy social media users were influenced by individuals who use social trading platforms, against 62% for light social media users.

It is clear that social media and influencers active on the various social media platforms have a clear impact in determining how this new breed of retail trader thinks, believes and subsequently acts.

4.4 Mutual Funds’ performance

Table 6 shows fund performance during the COVID-19 pandemic. Depicted in column 1, funds classified as high sustainability outperformed other funds by 14.21% when the only control used was the global category FE. When more controls were added, though the slope of performance for high sustainability decreases, we can see that funds with high sustainability ratings still outperform others by 9.76% when all controls were included.

In column 2, we see that funds that employed exclusions have outperformed same style funds who didn't employ exclusions by 8.61%, when the only control used was the global category FE; as more controls were used, we see that performance fades. In column 3, we see that one additional star led to an increase of 5.78% in performance, which is significant because it indicates that a five-star fund on average will outperform a one-star fund by 23.1% in a given year (all other factors being equal, although future performance cannot be guaranteed). In column 4, we see that growth-styled funds outperformed non growth funds by 12.43%.

Table 7 shows fund performance before the COVID-19 pandemic. We see that amongst all the variables, only the growth variable function was a positive performance indicator. Sustainability, exclusions and star ratings all showed insignificant or negative performance results which leads us to understand that the three variables above only functioned as a performance indicator during the crisis.

Figure 10 shows the average fund performance compared to the S&P 500 index during the pandemic. Between February 19, and March 23, the S&P 500 dropped 34% in value, before gaining roughly 30% again by the end of April, 2020. The graph shows us that on average, active funds shared a similar trend with the S&P 500 during the crisis, however overall, funds underperformed the index significantly. On April 15th, the S&P 500 had a performance level of roughly 85 whereas in contrast, the average active fund had a performance level of 80.

Chapter 5. Conclusion, Limitations, and Recommendations

Due to COVID-19 restrictions, individuals had an opportunity to start trading in the stock market, that previously, they did not have. Along with a surge in new traders, retail traders in fact showed many successes in terms of the increase in the value of their traded portfolios. We wanted to know whether retail traders were lucky, or if they were great stock pickers, or whether financial psychology played a role in their success, and how their successes (based on their behaviors and how they were influenced by social media), compared to their professional counterparts.

From the results gathered, it can be concluded that retail traders were in fact highly influenced and lacked rational decision making when deciding which stocks or financial instruments to trade, or how (which trading strategies to employ) to trade them. Not only was it evident that young, male investors were the ones that made up the majority of the new traders, they also took the biggest risks, having been influenced by external factors such as bloggers, influencers, trading pages on social media the most.

With increased time spent at home due to quarantine restrictions and the lack of other typical entertainment such as live sporting events to attend, or visiting casinos, individuals had more time to spend on social media which has shown to increase the likelihood of trading by being influenced by others. With this, the question of the role played by luck, stock selection, influences and psychology could be analyzed.

Retail traders also displayed several negative behavioral traits, including the taking of additional risk through the overconfidence bias that we believe derived from the social media bloggers and social media influencers (especially those with so-called celebrity status). The increased social media usage amplified herding behavior as most new retail investors lacked sufficient understanding of the financial markets and its tools to rationally make investment decisions. Therefore, due to increased exposure to trading related sources on social media, individuals with limited knowledge, viewed trading related sources as reliable and thus were likely to copy investment decisions they saw online, without trying to understand the deep reasoning behind those decision.

This reasoning also aligns with the study that any news related to COVID-19 showed an impact in the stock market. That being said, we believe that retail traders' stock selection was made from multiple confluences that ultimately lead investors to their decisions. The first element is derived by what others are trading at that time, another element is due to the lack of financial education, which gave a false perception of stocks and their associated risks. The general thinking seemed to be that stock prices were at their lowest, hence will go up from that point and can only continue to go up.

Another element came from governmental stimulus packages, which gave investors another reason to buy stocks, as their future outlook looked reassuring against an implied government and central bank support of equity markets. The final element we believe that influenced stock selection was the impact COVID-19 had on particular large industries such as airlines, which experienced tremendous losses and were seen as an opportunity, given investors expect airlines to show growth again once the pandemic ends. In terms of luck, we believe that retail investors did benefit greatly from it, because their trading decisions were highly influenced by others. This means that if the investments didn't go according to the influencer who thought of it, there could be a tremendous loss. Not only do we believe luck was involved because of the influence social media has on investors, but if the government and central banks hadn't stepped in with multiple stimulus plans, the market wouldn't have recovered the way it did. These new day traders would have seen their luck dry up very quickly.

From the professional's perspective, new traders were making questionable actions within the last three months such as buying the dips of companies with fundamental flaws, engaging in the trading of high-volatility stocks and buying stocks that had lottery-like upside. Michael Krause, chief investment officer at Counterpoint Mutual Funds, said "Robinhood investors are making all the classic mistakes in the short term. May work for today's market, but not in the long-run if repeated." (Fitzgerald, 2020). Professional investors were extremely selective in their investments during the pandemic, by investing in stocks of companies that were deemed to be sustainable as well showing good performance, not simply because a security's price being low as in the case of retail investors. The professional investors in other words, stuck to their long-term strategic positioning, although this has cost them some element of short-term performance.

With retail traders outperforming large institutions, the noise trader risk theory (Shleifer and Vishny, 1997) can be used as a possible explanation to why that may be from a behavioral and theoretical standpoint. Professional portfolio managers often times exploit arbitrage opportunities meaning when a security's price is deemed under or overvalued then they will take action before the price is corrected. Noise risk theory is the risk that the mispricing of the security will in fact worsen in the short term if exploited. If stock X holds a fundamental value of $100 however pessimistic traders have dropped the price to $85, the portfolio manager will buy at $85 knowing stock X will reach its fundamental valuation.

However, the pessimistic investors who caused stock X to go down can become even more pessimistic, lowering the price further still. This means that the arbitrageurs can be forced to liquidate their positions prematurely, potentially causing steep losses. During the crash and its recovery phase, investors who lack the knowledge to assess the investment strategy might simply have evaluated the portfolio manager based on previous performance and returns. With extreme market movements and uncertainty, the mispricing opportunities that the arbitrageur exploits worsen then not only is it exposed to great losses in the short term but the portfolio manager is also risking clients withdrawing due to negative performance.

The limitations in this paper are that the data from the sample sets might not portray the average household. The data set for the effect of social media consisted of less than 300 people which could be unrepresentative of a large population. The data set on retail trading activity consists of a large sample set however, investors might select a brokerage service that's based on their own preferences, meaning the investors in the data set from the brokerage firm that supplied the information might represent a different perspective than from those who use another brokerage that offer different services such a different trading platform, different fees and so on.

Overall, we believe that the future of retail trading can be positive in the long term however in the short term, given the learning from the analysis of their behavior during the early stage of the pandemic, retail traders are likely to eventually be exposed to significant losses which could wipe out much of their early promising gains. As retail traders experience losses and understand the financial market more as they continue to trade, we believe that novice traders will begin to value the importance of psychological factors such as FOMO, social media's impact and other behavior traits that are hindering them from rational decision making.

With better understanding of their psychology and deeper knowledge of the financial markets, in the long term we believe retail traders to be able to show promising results. Improved financial literacy might also help retail investors better understand risk, and how to manage risk within the context of their portfolios. This will also help them shift towards a longer-term approach to investing, which should also make them less susceptible to the negative aspects of herding, FOMO and blindly following social media trends. Retail investors have performed well, but as a large part of this performance was due to circumstance, they cannot only rely on this going forward.

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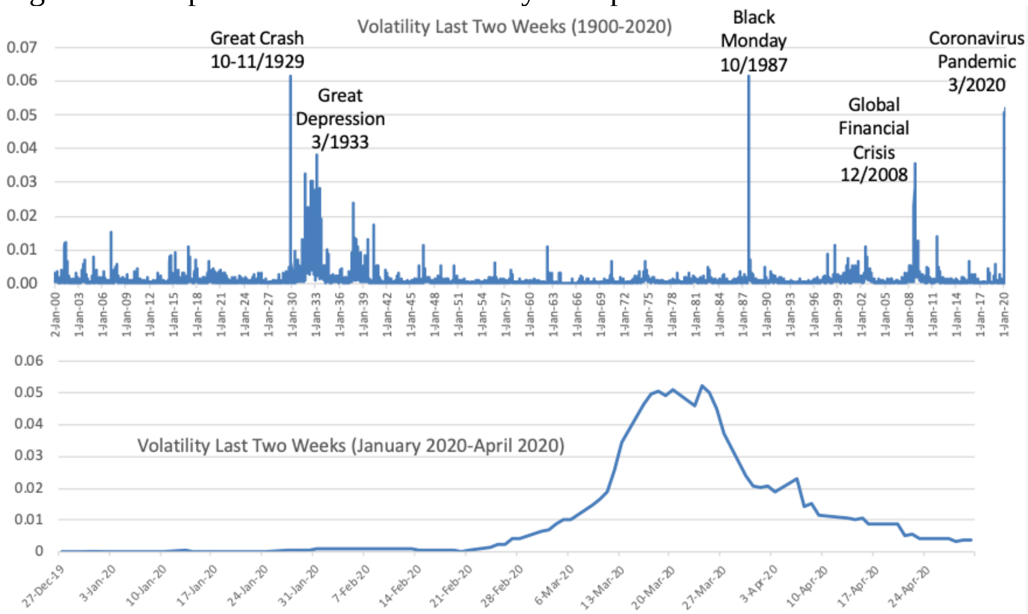
Appendix

Figure 1. Comparison of market volatility with past market crashes

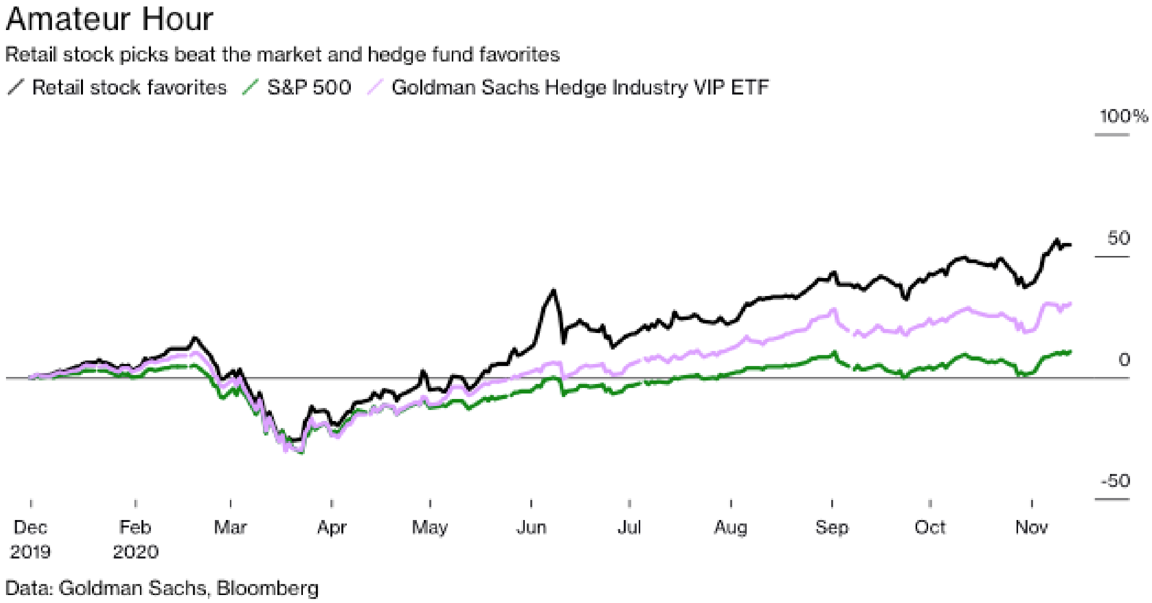


Source: https://bfi.uchicago.edu/wp-content/uploads/BFI_White-Paper_Davis_3.2020.pdf

Figure 2. U.S. Unemployment rate

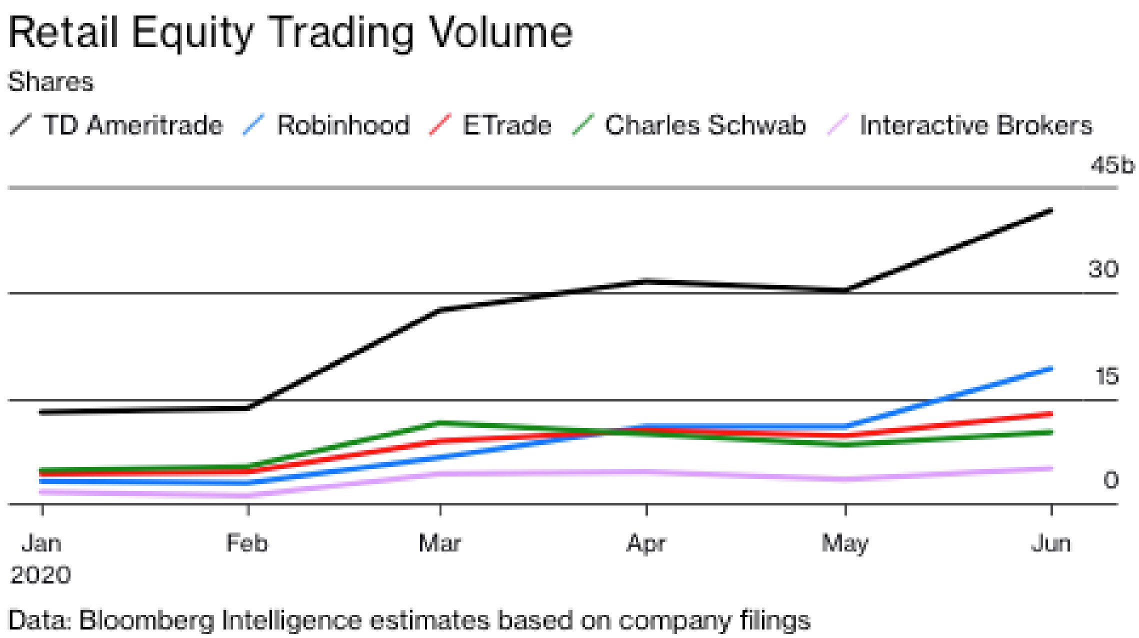
Source: https://www.bls.gov/charts/employment-situation/civilian-unemployment-rate.htm

Figure 3. Retail traders outperform hedge funds



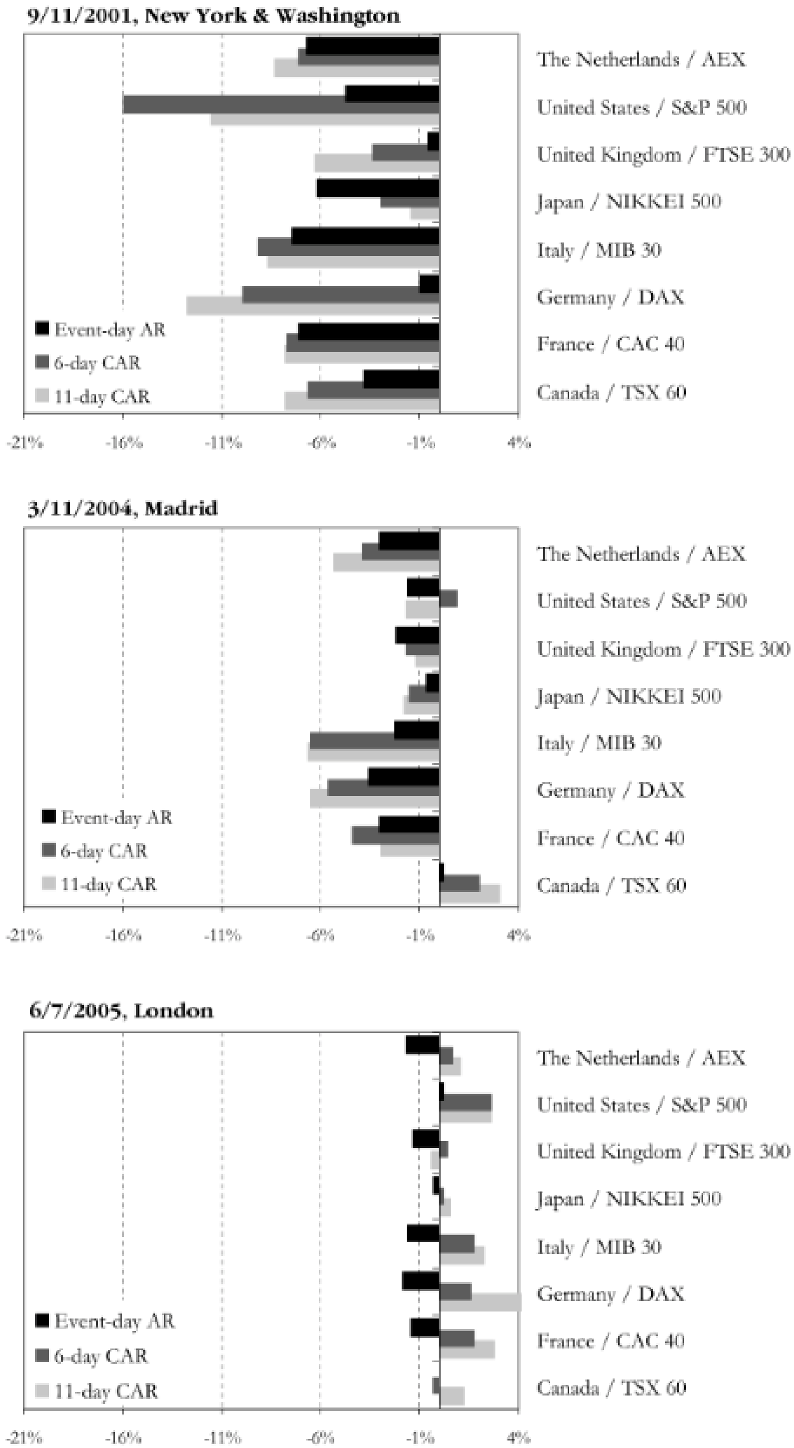
Source: https://www.bloomberg.com/news/articles/2020-11-14/got-lucky-got-it-right-how-newbie-stock-jocks-beat-the-market?utm_source=url_link

Figure 4. Retail equity trading volume



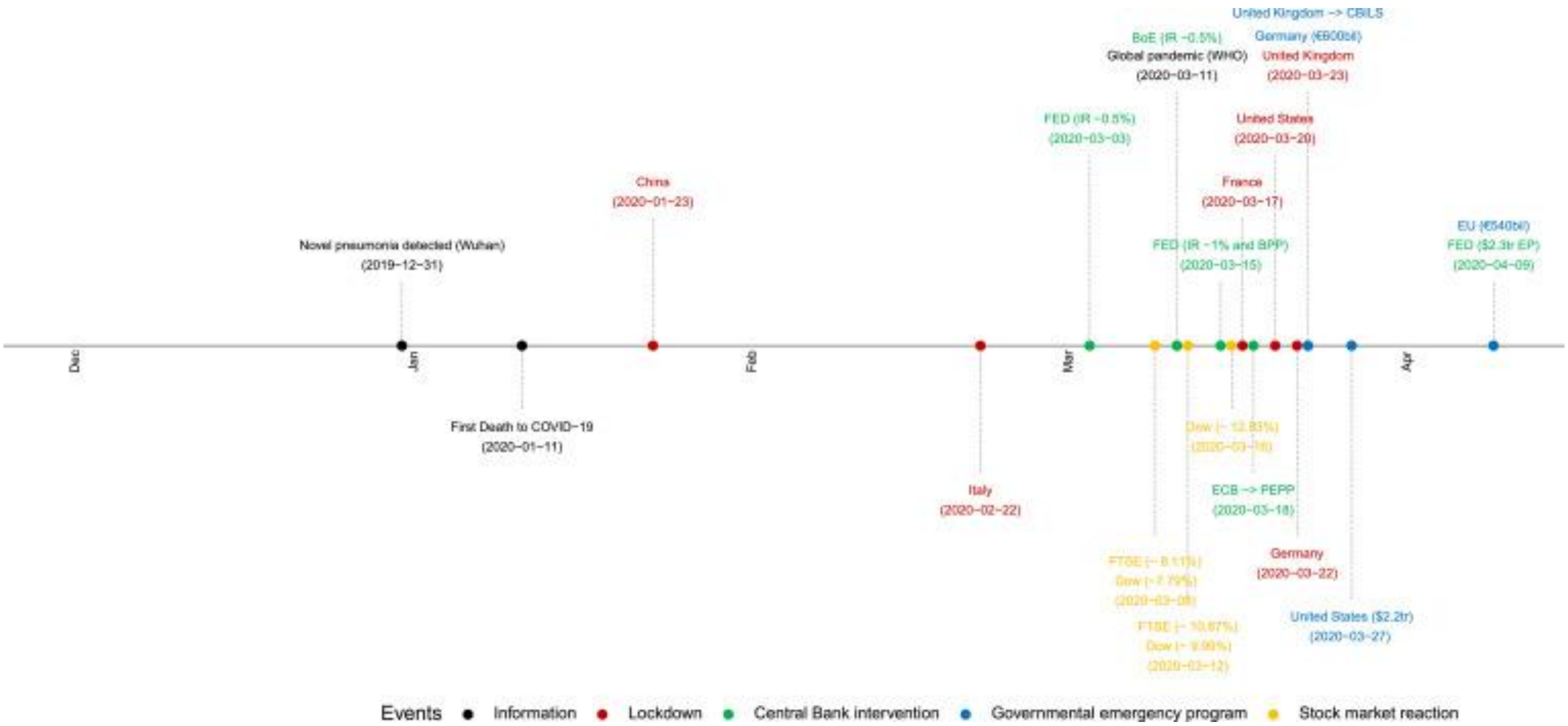
Source: https://www.bloomberg.com/news/features/2020-10-22/how-robinhood-s-addictive-app-made-trading-a-covid-pandemic-pastime

Figure 5. Impact of Sep. 11, 2001 terror attack compared to other terror attacks



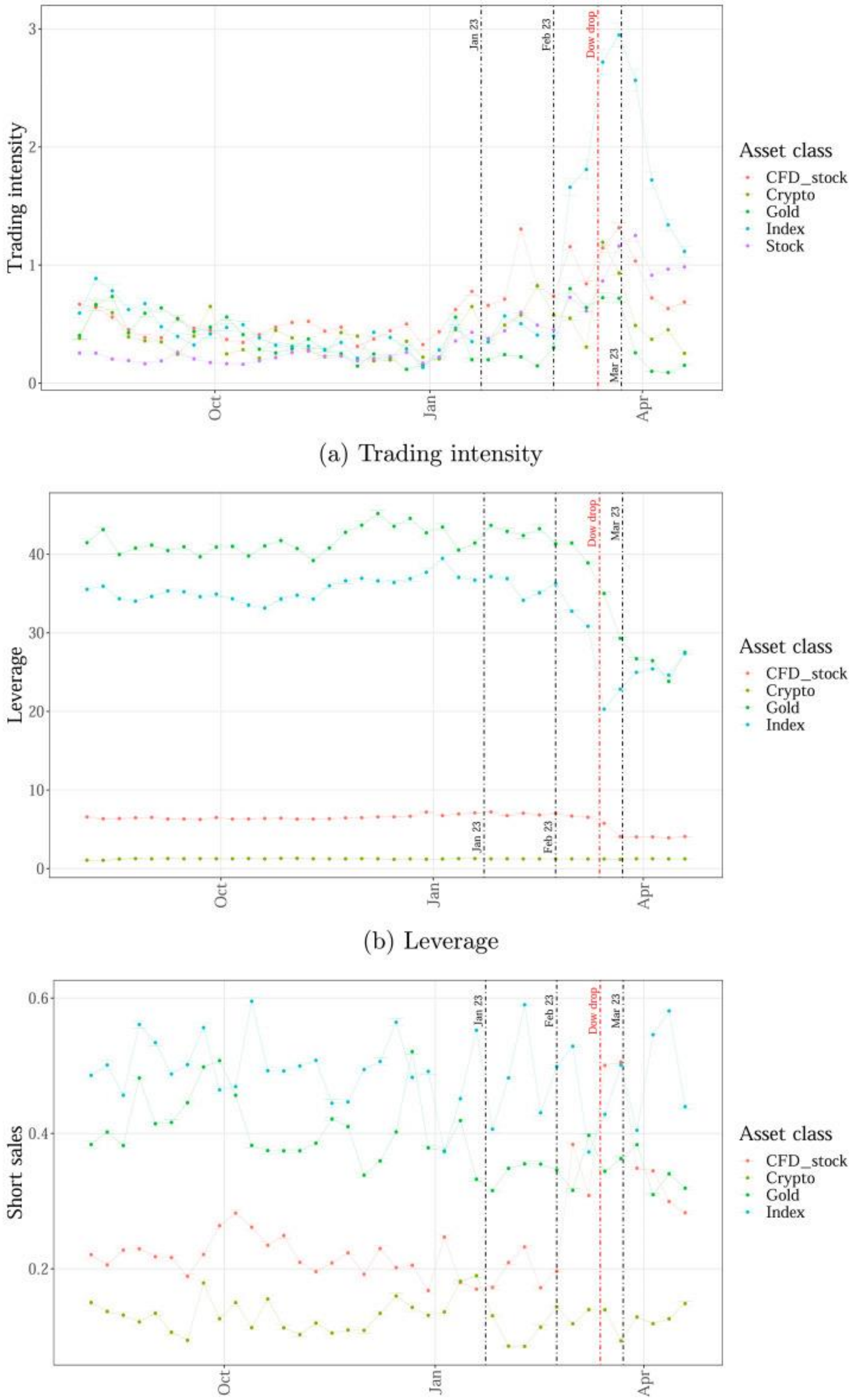
Source: https://onlinelibrary.wiley.com/doi/epdf/10.1111/j.1468-036X.2009.00502.x?saml_referrer

Figure 6. Timeline of key events during the pandemic



Source: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7414361/

Figure 7. Retail traders' investment trends



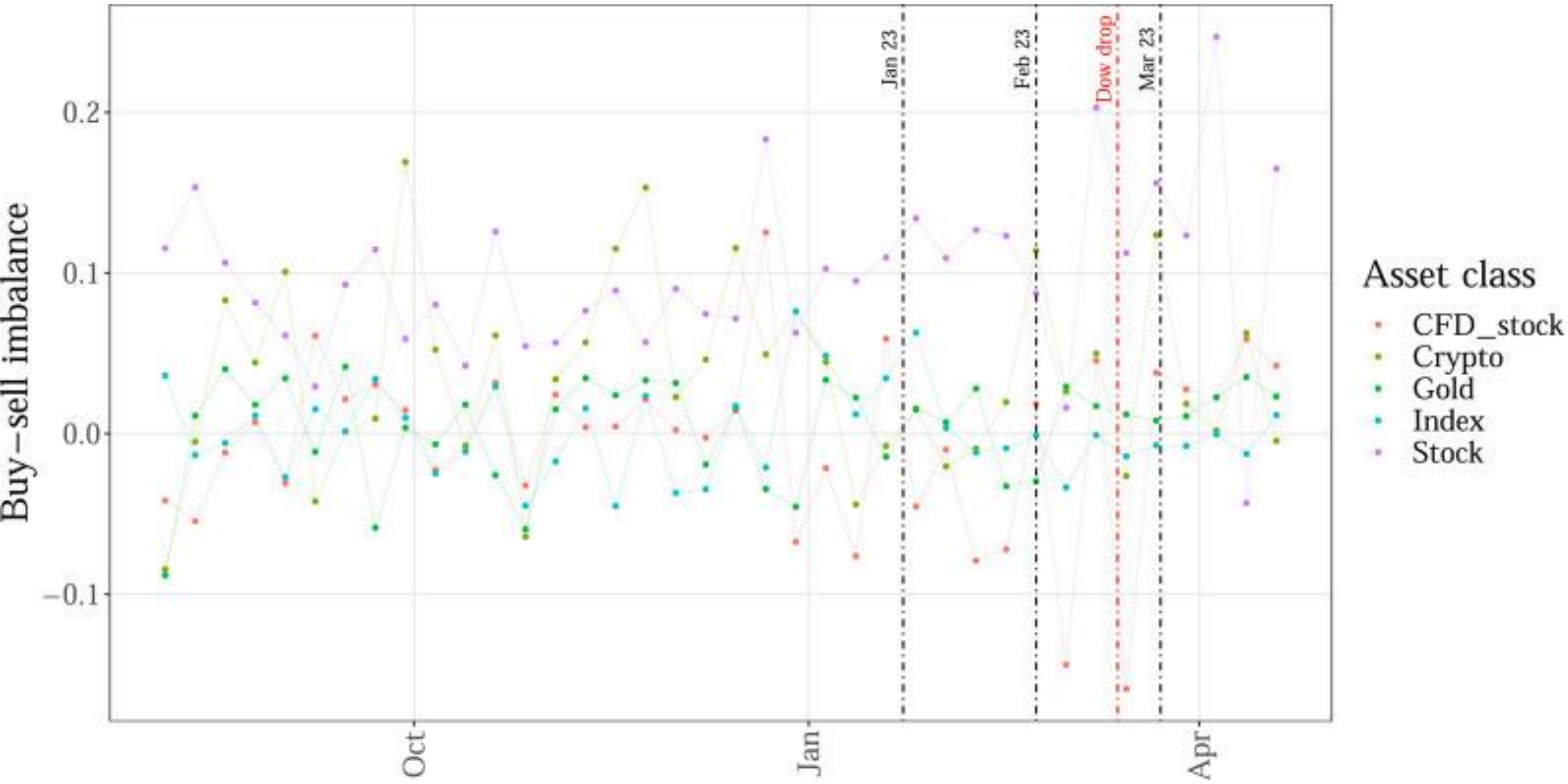
(a) Trading intensity

(b) Leverage

(c) Short sales

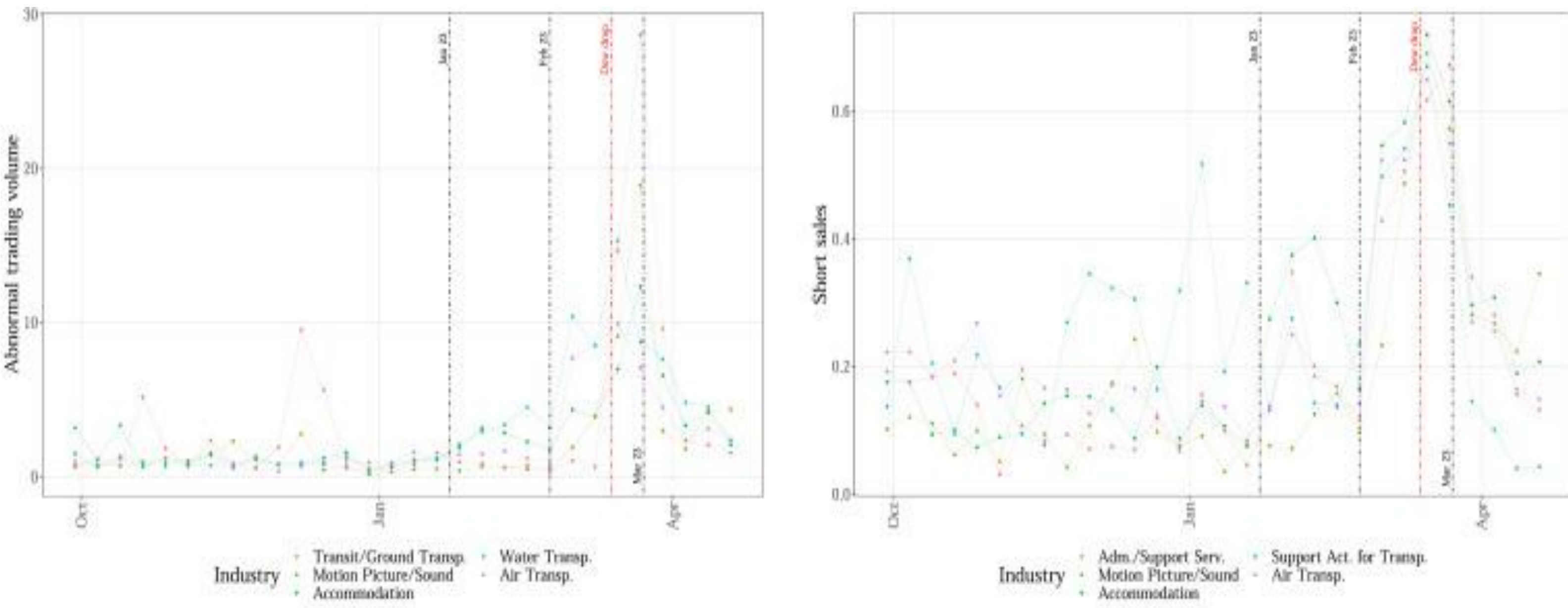
Source: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7414361/

Figure 8. BSI Overtime



Source: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7414361/

Figure 9. Trading volume and short sales in five industries during the pandemic

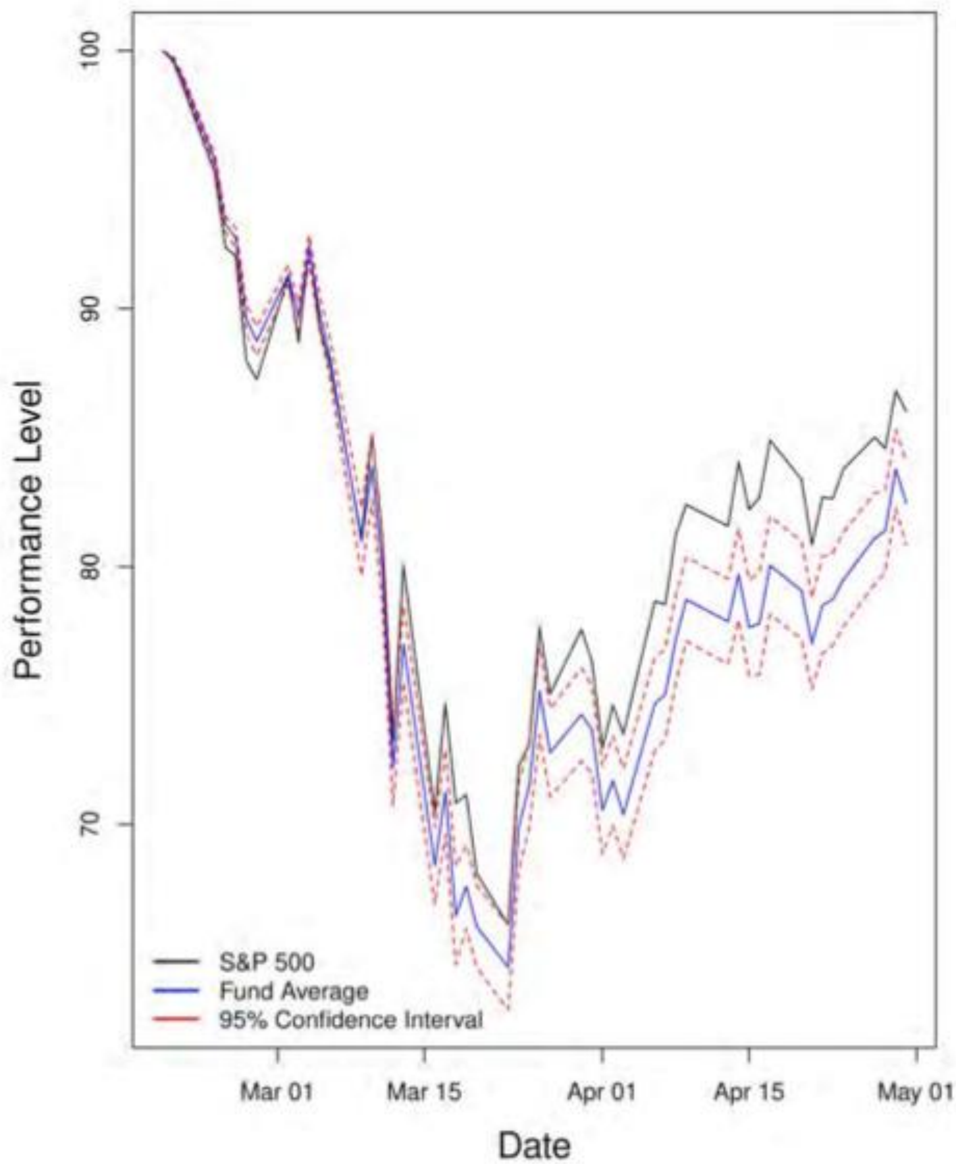


(a) Abnormal trading volume

(b) Fraction of short sales

Source: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7414361/

Figure 10. Average fund performance vs. S&P 500 index



Average Fund Performance vs. the S&P 500 During the Crisis. This figure plots the performance of the average active equity mutual fund against the S&P 500 in February 20 through April 30, 2020. Both price indices are initialized at 100 on February 19, 2020 and computed by compounding daily returns. The fund average is computed by adding the average difference between the fund price index and the S&P 500 price index to the S&P 500 price index. Standard errors are estimated for this difference and are clustered on the Morningstar Institutional Category. 95% confidence intervals are plotted in red.

Source: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7414361/

Table 1. Online brokers see a spike in new account during coronavirus

.	New accounts Q1 2020	New accounts Q1 2019	year-over-year increase
Charles Schwab	609,000	386,000	58%
TD Ameritrade	608,000	244,000	149%
Etrade	363,000	135,000	169%

Source: https://www.cnbc.com/2020/05/12/young-investors-pile-into-stocks-seeing-generational-buying-moment-instead-of-risk.html

Table 2. Results of the VAR correlation coefficient model on the impact of 9/11

Country	12-Month Pre-Attack (September 10, 2000, to September 10, 2001)		3-Month Post-Attack (September 11, 2001, to December 11, 2001)		6-Month Post-Attack (September 11, 2001, to March 11, 2002)		Contagion Test Statistic	
	ρ	σ	ρ	σ	ρ	σ	3-Month Post	6-Month Post
Australia	0.136	5.36E-05	0.2274	2.84E-05	0.1778	2.98E-05	0.6652	0.387
Belgium	0.3677	5.44E-05	0.3539	2.03E-05	0.3346	2.92E-05	0.1114	0.3399
Canada	0.7311	5.25E-05	0.8178	2.94E-05	0.7896	3.18E-05	1.5013	1.2572
Denmark	0.3471	5.40E-05	0.4105	2.49E-05	0.3544	3.15E-05	0.508	0.0749
Finland	0.4484	5.61E-05	0.2891	2.75E-05	0.368	3.34E-05	1.3021	0.8741
France	0.6098	5.46E-05	0.4362	6.34E-05	0.4963	3.10E-05	1.6963*	1.4837
Germany	0.6417	5.20E-05	0.5949	2.83E-05	0.6097	3.10E-05	0.5343	0.4769
Hong Kong	0.1626	5.04E-05	0.5623	2.09E-05	0.494	2.78E-05	3.1874***	3.2674***
Indonesia	−0.0494	5.16E-05	0.0063	2.61E-05	0.0975	3.12E-05	0.3844	1.291
Italy	0.4139	5.60E-05	0.4523	2.92E-05	0.4487	3.22E-05	0.3323	0.3863
Japan	0.123	5.58E-05	0.4364	2.10E-05	0.5444	2.93E-05	2.3125**	4.2716***
Korea	0.132	4.95E-05	0.5579	2.20E-05	0.3915	2.39E-05	3.3828***	2.4513***
Malaysia	0.0651	4.73E-05	0.052	2.39E-05	0.1499	2.99E-05	0.0872	0.76
Mexico	0.6596	4.84E-05	0.3999	2.81E-05	0.5395	3.49E-05	2.4743***	1.6483*
New Zealand	0.0872	5.46E-05	0.1884	2.61E-05	0.0606	3.31E-05	0.7158	0.2401
Philippines	−0.0221	4.80E-05	−0.1271	1.66E-05	−0.1072	2.10E-05	0.7168	0.7567
Portugal	0.4132	5.63E-05	0.2893	2.43E-05	0.2292	2.83E-05	0.9717	1.8694*
Singapore	0.2118	5.11E-05	0.122	2.95E-05	0.2173	3.14E-05	0.6398	0.0508
Spain	0.5133	5.60E-05	0.5287	2.84E-05	0.5108	3.36E-05	0.1488	0.0298
Sweden	0.6178	5.53E-05	0.4266	2.73E-05	0.4757	3.33E-05	1.8681*	1.8347*
Switzerland	0.4577	5.46E-05	0.5023	2.64E-05	0.424	3.07E-05	0.383	0.377
Taiwan	0.0549	4.79E-05	0.2798	1.92E-05	0.2068	2.69E-05	1.5397	1.3596
Thailand	0.0861	4.68E-05	−0.0180	2.32E-05	−0.0540	2.72E-05	0.7299	1.2314
United Kingdom	0.5825	5.39E-05	0.5524	2.66E-05	0.5621	3.08E-05	0.3036	0.2725
χ^2							295.803	335.077

VAR cross-market correlation coefficients (ρ) and variances (σ) between the United States and 24 other countries. The test statistics are derived from Fisher *z* transformations testing for the equality of pre–September 11 cross-market correlations with post–September 11 cross-market VAR estimates. χ^2tests null of no contagion across all economies.

*** Significant at the 1% level.

** Significant at the 5% level.

* Significant at the 10% level.

Source: https://onlinelibrary.wiley.com/doi/full/10.1111/j.1475-6803.2004.00079.x?saml_referrer

Table 3 Panel A. Retail trading intensity during the pandemic.

Panel A: Trading intensity					
	Model 1	Model 2	Model 3	Model 4	Model 5
Dependent variable	Trading intensity	Trading intensity	Trading intensity	Trading intensity	Trading intensity
COVID-19	0.2220*			0.1202	0.2129*
	(2.3004)			(1.5625)	(2.2849)
Dow drop		3.5557**			
		(11.4704)			
Jan. 23–Feb. 22			0.2763		
			(1.1377)		
Feb. 23–Mar. 22			2.7410**		
			(3.3521)		
Mar. 23–Apr. 17			0.6378		
			(1.2035)		
Cases · male				0.1130**	
				(4.0556)	
Cases · 18–24					−0.1714**
					(−3.4184)
Cases · 25–34					−0.0150
					(−0.4196)
Cases · 35–44					0.0542
					(1.4619)
Cases · 45–54					0.0950*
					(2.4387)
Cases · 55–64					0.0475
					(1.3193)
Push message control	Yes	Yes	Yes	Yes	Yes
Asset class dummy	Yes	Yes	Yes	Yes	Yes
Investor-fixed effects	Yes	Yes	Yes	Yes	Yes
Obs.	14,113,014	14,525,010	14,525,010	14,088,650	14,072,248
Adj. R^2	0.36	0.37	0.37	0.36	0.36

Regression results: trading activities. This table reports results from an OLS regression on the trading activities of investors. Standard errors are double-clustered at the individual investor level and over time; *t*-statistics are in parentheses. ** and * denote statistical significance at the 1% and 5% levels, respectively.

Source: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7414361/

Table 3 Panel B. Retail trading intensity by asset class during the pandemic

Panel B: Trading intensity by asset classes

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Sample	Stocks	CFD_stock	Index	Crypto	Gold
COVID-19	0.0363**	0.0142	0.1813**	−0.0008	−0.0165
	(5.1362)	(0.9807)	(4.0297)	(−0.0463)	(−1.4860)
Push message control	Yes	Yes	Yes	Yes	Yes
Investor-fixed effects	Yes	Yes	Yes	Yes	Yes
Obs.	14,113,014	14,113,014	14,113,014	14,113,014	14,113,014
Adj. R^2	0.37	0.34	0.3	0.27	0.23

Table 3 Panel C. Retail trading intensity (new positions) by asset class during the pandemic

Panel C: Trading intensity (new positions) by asset classes

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Sample	Stocks	CFD_stock	Index	Crypto	Gold
COVID-19	0.0195**	0.0068	0.0910**	−0.0028	−0.0083
	(5.1803)	(0.9776)	(4.0396)	(−0.3065)	(−1.4974)
Push message control	Yes	Yes	Yes	Yes	Yes
Investor-fixed effects	Yes	Yes	Yes	Yes	Yes
Obs.	14,113,011	14,113,011	14,113,011	14,113,011	14,113,011
Adj. R^2	0.37	0.33	0.3	0.28	0.23

Table 3 Panel D. Use of leverage during the pandemic

Panel D: Leverage					
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Dep. var.	Leverage	Leverage	Leverage	Leverage	Leverage
COVID-19	−0.3019**			−0.3155**	−0.2406**
	(−8.3412)			(−5.8471)	(−4.0663)
Dow drop		−1.7197**			
		(−6.9803)			
Jan. 23 - Feb. 22			0.4080*		
			(2.0808)		
Feb. 23 - Mar. 22			−1.0652		
			(−1.4160)		
Mar. 23 - Apr. 17			−2.9917**		
			(−8.9368)		
Cases · male				0.0146	
				(0.3624)	
Cases · 18–24					0.0033
					(0.0484)
Cases · 25–34					−0.0970
					(−1.5689)
Cases · 35–44					−0.0963
					(−1.6319)
Cases · 45–54					−0.0114
					(−0.1945)
Cases · 55–64					0.0040
					(0.0639)
Push message control	Yes	Yes	Yes	Yes	Yes
Asset class dummy	Yes	Yes	Yes	Yes	Yes
Investor-fixed effects	Yes	Yes	Yes	Yes	Yes
Obs.	4,771,217	4,946,112	4,946,112	4,767,966	4,758,012
Adj. R^2	0.64	0.64	0.64	0.64	0.64

Table 3 Panel E. Use of leverage by asset class

Panel E: Leverage by asset classes

	Model 1	**Model 2**	**Model 3**	**Model 4**
Dep. var.	Leverage	Leverage	Leverage	Leverage
Sample	CFD_stock	Index	Crypto	Gold
COVID-19	−0.1530**	−0.5289**	0.0045**	−0.5121**
	(−11.5243)	(−12.9833)	(2.7170)	(−7.3752)
Push message control	Yes	Yes	Yes	Yes
Investor-fixed effects	Yes	Yes	Yes	Yes
Obs.	1,040,042	650,338	1,174,571	591,974
Adj. R^2	0.64	0.76	0.55	0.79

Table 3 Panel F. Retail traders' short sales during the pandemic

Panel F: Short sales					
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Dependent variable	Short sales	Short sales	Short sales	Short sales	Short sales
COVID-19	0.0056**			0.0055**	0.0028**
	(7.3213)			(5.5340)	(3.3955)
Dow drop		0.0158*			
		(2.5069)			
Jan. 23 - Feb. 22			−0.0004		
			(−0.0798)		
Feb. 23 - Mar. 22			0.0315**		
			(3.5548)		
Mar. 23 - Apr. 17			0.0364**		
			(6.9650)		
Cases · male				0.0000	
				(0.1031)	
Cases · 18–24					0.0061**
					(4.4759)
Cases · 25–34					0.0044**
					(5.4906)
Cases · 35–44					0.0020**
					(2.9686)
Cases · 45–54					0.0010
					(1.4507)
Cases · 55–64					−0.0002
					(−0.2507)
Push message control	Yes	Yes	Yes	Yes	Yes
Asset class dummy	Yes	Yes	Yes	Yes	Yes
Investor-fixed effects	Yes	Yes	Yes	Yes	Yes
Obs.	4,771,217	4,946,112	4,946,112	4,767,966	4,758,012
Adj. R^2	0.15	0.15	0.15	0.15	0.15

Table 3 Panel G. Retail Traders' short sales by asset class

Panel G: Short sales by asset classes

	Model 1	**Model 2**	**Model 3**	**Model 4**
Dependent variable	Short sales	Short sales	Short sales	Short sales
Sample	CFD_stock	Index	Crypto	Gold
COVID-19	0.0112**	0.0033**	0.0039**	0.0041
	(5.2606)	(2.9362)	(4.5214)	(1.9366)
Push message control	Yes	Yes	Yes	Yes
Investor-fixed effects	Yes	Yes	Yes	Yes
Obs.	1,047,042	650,338	1,174,571	591,974
Adj. R^2	0.15	0.04	0.09	0.08

Table 4. Account deposits

Regression results: account deposits. This table reports results from an OLS regression on deposits and withdrawals. Standard errors are robust; *t* -statistics are in parentheses. ** and * denote statistical significance at the 1% and 5% levels, respectively.

	Model 1	**Model 2**	**Model 3**
Dependent variable	Abnorm. net deposits	Abnorm. net deposits	Abnorm. net deposits
Sample	Full sample	New investors	Established investors
(Intercept)	1.0611**	1.0007**	1.0532**
	(9.1315)	(32.0302)	(18.6130)
COVID-19	0.4132**	0.2825**	0.1373*
	(5.9015)	(12.0879)	(2.5400)
Obs.	261.0000	261.0000	261.0000
Adj. R^2	0.1900	0.5500	0.0400

Source: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7414361/

Table 5. Influence of social media

SOCIAL MEDIA USE

	OUTCOME	Light SM use	Heavy SM use	Diff.	Partial Correl	Statistical Strength
ONLINE TRADING	Likelihood to engage in online trading	55%	63%	+14%	.15	p =.009
ONLINE HERDING BEHAVIOR	Following the choices others make when trading online	54%	78%	+44%	.23	p =.000
	Blindly following the choices others make when trading online	4%	26%	+441%	.22	p =.000
	Looking at choices others make rather than trying to understand future cash flow	34%	56%	+64%	.24	p =.000
SOCIAL MEDIA INFLUENCE	Bloggers	37%	59%	+57%	.27	p =.000
	Influencers	25%	45%	+76%	.27	p =.000
	My social media friends and contacts	69%	89%	+28%	.36	p =.000
	People who write articles in social media	46%	82%	+78%	.32	p =.000
	Online news publishers	68%	84%	+23%	.25	p =.000
SOCIAL MEDIA INFLUENCE ON ONLINE TRADING	Bloggers	29%	50%	+69%	.24	p =.000
	Influencers	25%	54%	+109%	.29	p =.000
	My social media friends and contacts	40%	69%	+69%	.31	p =.000
	People who write articles in social media about online trading	52%	89%	+70%	.32	p =.000
	People who use social trading platforms.	62%	91%	+45%	.33	p =.000

Statistical Strength (*p-value*): Medium High .

Results of the partial correlations control for: (1) gender, (2) age, (3) years of tenure in current organization, (4) education level, (5) college business education, (6) number of books about business read.

Source: https://www.sciencedirect.com/science/article/pii/S0007681319300369?via=ihub

Table 6. Mutual funds' performance during the crisis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A. Benchmark-Adjusted Performance						
𝕀(4 or 5 Sustainability Globes)	14.21				11.51	8.61	9.76
	[4.85]				[3.22]	[2.26]	[2.60]
𝕀(Employs Exclusions)		8.61			5.47	2.03	2.79
		[3.26]			[2.44]	[1.05]	[1.24]
Star Rating			5.78		5.12	7.00	6.49
			[2.84]		[2.42]	[3.50]	[3.41]
𝕀(Growth Tilt)				12.43	7.24	9.39	5.15
				[2.35]	[1.16]	[1.70]	[0.75]
Global Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Level Controls	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	Yes
Observations	2,494	2,561	2,286	2,561	2,251	1,632	1,604
Adjusted R^2	0.06	0.05	0.06	0.06	0.06	0.12	0.15

Standard errors are clustered on the Morningstar Institutional Category, t-statistics are in brackets.

Source: Source: https://www.nber.org/system/files/working_papers/w27551/w27551.pdf

Table 7. Mutual funds' performance pre crisis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A. Benchmark-Adjusted Performance						
𝕀(4 or 5 Sustainability Globes)	−0.51				−1.99	−0.97	−2.58
	[−0.40]				[−1.25]	[−0.44]	[−1.29]
𝕀(Employs Exclusions)		−2.17			−0.81	−1.63	−1.59
		[−2.32]			[−0.73]	[−1.62]	[−1.54]
Star Rating			0.65		0.51	0.90	0.63
			[0.96]		[0.72]	[1.03]	[0.70]
𝕀(Growth Tilt)				5.69	6.29	6.35	3.90
				[3.96]	[3.68]	[3.06]	[1.37]
Global Category FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Level Controls	No	No	No	No	No	Yes	Yes
Industry Controls	No	No	No	No	No	No	Yes
Observations	2,515	2,601	2,313	2,601	2,262	1,614	1,586
Adjusted R^2	0.06	0.06	0.07	0.07	0.08	0.12	0.16

Standard errors are clustered on the Morningstar Institutional Category, t-statistics are in brackets.

Source: https://www.nber.org/system/files/working_papers/w27551/w27551.pdf