The Foundations of Behavioral Finance: A Case Study of Robinhood Users and the Impact of Biases in Financial Markets

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Abstract

Financial markets play a vital role in economies around the world. They facilitate the interactivity between those who are in need of capital and those with capital to invest. While its own separate entity, the stock market is correlated with the economy in various ways in which one may significantly impact the other on a regular basis. Thus, investors and firms participating in markets have much power in influencing the economy. Human behavior is prone to biases that are not accounted for in standard finance theory but is the subject of behavioral economics by utilizing psychology and sociology to aid in analyzing such behavior. The primary aim of this study is to examine some of the cognitive biases investors are typically exposed to and practice when making their financial decisions. Such discussions of cognitive errors are accompanied by a case study of Robinhood users. Observing a real world scenario regarding financial irrationality may be helpful in amplifying the foundations of behavioral finance. Additionally, four econometric tests were run to support test specific predictions made by behavioral finance models. All findings were in favor of behavioral finance, displaying evidence of cognitive biases in investor behavior while also rejecting elements of standard finance theory.

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1. Introduction

In his 1936 book *The General Theory of Employment, Interest and Money,* John Maynard Keynes juxtaposed stock market equilibrium to that of a popular newspaper competition of the time. The contest was simple; competitors were asked to choose the six prettiest faces from one hundred photographs with the winner being the one whose choices came closest to the average preferences of all other competitors (Keynes, 1936). According to Keynes, the only way a person would be able to win such a competition is not whether they pick the faces they think are the prettiest, but rather base their choices on what they think others are likely to think are the prettiest. This idea can even go a step further in that it would be in the best interest of the contestant to pick faces that one thinks others are most likely to think others think are the prettiest. The stock market works in a similar manner: one does not pick a firm that is most likely to succeed in the long run, but rather pick one that will most likely have the highest market value in the short run (Akerlof and Shiller, 2010). This was what Keynes essentially meant by “animal spirits” in that human emotion acts as a driving force for financial decision-making during uncertain and volatile periods in the market. These “animal spirits” help to explain the irrationality of human behavior and how individuals arrive at their financial decisions.

In accordance with such “animal spirits”, behavioral finance is sought to try and understand the market implications of investor psychological traits. While behavioral finance has yet to reach a complete and coherent comprehension of human behavior in financial markets, there has been an extraordinary amount of progress made in the field over the past few decades. During this time, there has been an increasing amount of research being done in understanding how psychology can help explain stock market anomalies, speculative market bubbles, and crashes. Behavioral finance also helps to clarify some of the speculative behavior of investors and explain why traders often take advantage of arbitrage opportunities. According to Shefrin (2002), “One investor’s mistakes can become another investor’s profits”. Observing the behavioral traits of investors may aid in clarifying why such arbitrage opportunities arise in the first place. Oftentimes, individuals depart from optimal judgment when making decisions in financial markets. Thus, behavioral finance helps to enhance our understanding of such cognitive errors by incorporating aspects of human behavior into financial models.

Interestingly enough, as the field of behavioral finance has grown in scope over the years, investor trading has drastically changed as well. While the 1990s provoked the use of online trading and lower commission fees, in more recent memory, the fintech brokerage Robinhood has brought about increasingly new changes to the way individuals invest in the stock market. The Robinhood platform is remarkably convenient and simple to operate to the point where nearly anyone over the age of 18 with a social security number can place a trade with the click of a button. With this, however, arises a problem in which uneducated individuals, with no prior experience or knowledge about financial markets, are making investment decisions with real money. Consequently, the trading platform may assist in magnifying the strength of cognitive biases in investor behavior. This is paired with the fact that modern-day investors often utilize social media platforms as an alternative to traditional news sources in receiving their financial headlines. For instance, Reddit’s WallStreetBets community is full of everyday retail investors who often make it a point that their posts do not constitute as financial advice, yet the subreddit has had a number of instances where they have profoundly affected the value of certain stocks' prices (Buz and de Melo, 2021).

This project serves as an exploration and introduction into the field of behavioral finance by observing a number of cognitive biases investors are most susceptible to practicing during their decision-making process. This paper also aims to bring awareness to not only investors and institutions, but perhaps to market regulators as well. In regards to Robinhood, the platform will be mentioned throughout this paper to better highlight and understand the goal and importance of behavioral finance. To better display the relationship between Robinhood investors, the stock market, and social media, this paper also strives to demonstrate causality between Robinhood users, stock prices, and WallStreetBets. Additionally, this research aims to debunk standard finance's theory on the volatilities of stock prices and dividend payouts. This paper will substitute such inadequate claims with proper, behavioral alternatives. Lastly, this paper tests for two cognitive biases which are mentioned in Chapter 3. These are loss aversion bias and the overconfidence heuristic. The primary objective of this particular trial is not to simply display whether or not loss aversion and overconfidence is present in financial markets, but rather observe the impact such biases have on the economic and financial performance of firms in the sample. This was done as a means of demonstrating the impact such cognitive errors have on businesses. In short, the tests run in this paper aim to: illustrate a causal relationship between Robinhood, social media, and the stock market; invalidate one particular aspect of standard finance by examining it in contrast to behavioral finance; inspect how certain cognitive biases impact firm performance. Before engaging with the data and methodology used in this research, the succeeding chapters will look to discuss the role of Robinhood and social media in financial markets (Chapter 2) and will then offer a literature review regarding the essence of behavioral finance and an in-depth analysis concerning several different cognitive errors practiced by investors (Chapter 3).

2. Background

This chapter will be looking at the growth of smartphones, Robinhood, and social media over time and how each entity comes together to impact and influence the role of the other in financial markets.

2.1 The Growth of Smartphones, Robinhood, and Social Media

2.1.1 Proliferation of Smartphones

Since the emergence of smartphones and their increasing popularity over the past decade, individuals are granted the ability to participate in nearly any activity they choose, which includes investing. By the end of 2020, nearly 46% of the world owned a smartphone with an estimated 6.4-billion smartphone subscriptions in circulation (O'Dea, 2021). In a study conducted by Choi and Lee (2012), it was found that the interface design, the presentation of information, and visual display attributes contribute to positive satisfaction from users interacting with their smartphones. While the amount of smartphone owners has greatly risen, so has their dependency and reliance on such devices. Gutiérrez et al. (2016) found that cell-phone addiction is very common amongst most smartphone owners. These individuals often demonstrate excessive use, dependence, and craving of their smartphones. If most smartphone users exhibit addictive engagement with their devices and the number of mobile phone users keeps growing at a steady rate, then it may be implied that an increase in mobile trading is inevitable. In the world of finance, simplicity alongside technological advancements has dramatically changed how modern-day investors make their financial decisions, especially compared to the investors of the 1980s and 1990s. The arrival and rise of Robinhood is one example of this and is explained in greater detail throughout this chapter.

2.1.2 Evolution of Robinhood

It all started in April 2013 when Vladimir Tenev and Baiju Bhatt would change the world of financial markets forever. The two Stanford grads were ultimately working towards the same goal in regard to the financial sector: provide everyone who wanted to invest in the stock market an opportunity to do so, not just those who were wealthy. Up to this point, many online brokerages not only charged a fee for every purchase, but also required account minimums that ranged anywhere from \$500 to \$2000 which was not entirely appealing to a demographic of young, less wealthy investors (Touryalai, 2014). Leading up to the release of the Robinhood app, Tenev stated that the millennial demographic has interests in trading but felt unable to do so because of fees and minimum account balances typically needed in order to invest (Huang, 2015). During its beta, Robinhood saw 50% of users who made a trade come back every day and at least 90% came back every week (Constine, 2014). Move forward to 2015 and roughly 80% of Robinhood's demographic fell into this "Millennial" demographic (Huang, 2015).

Since then, the company has only grown in value and popularity. From just \$2.9 million in revenue during their first year in the industry, Robinhood has seen its annual earnings grow all the way to \$959 million in 2020 (Curry, 2022). This of course has been a result of the rapid growth in usership over the past six years. In Robinhood's first year open to the public, roughly 500,000 users were trading on the platform (Curry, 2022). This number has grown all the way to 22.5 million as of 2021. It is important to note the largest increase in usership on a year-to-year basis was 9.5 million from 2020 to 2021, the same period as the arrival of the COVID-19 pandemic and the infamous GameStop short squeeze.

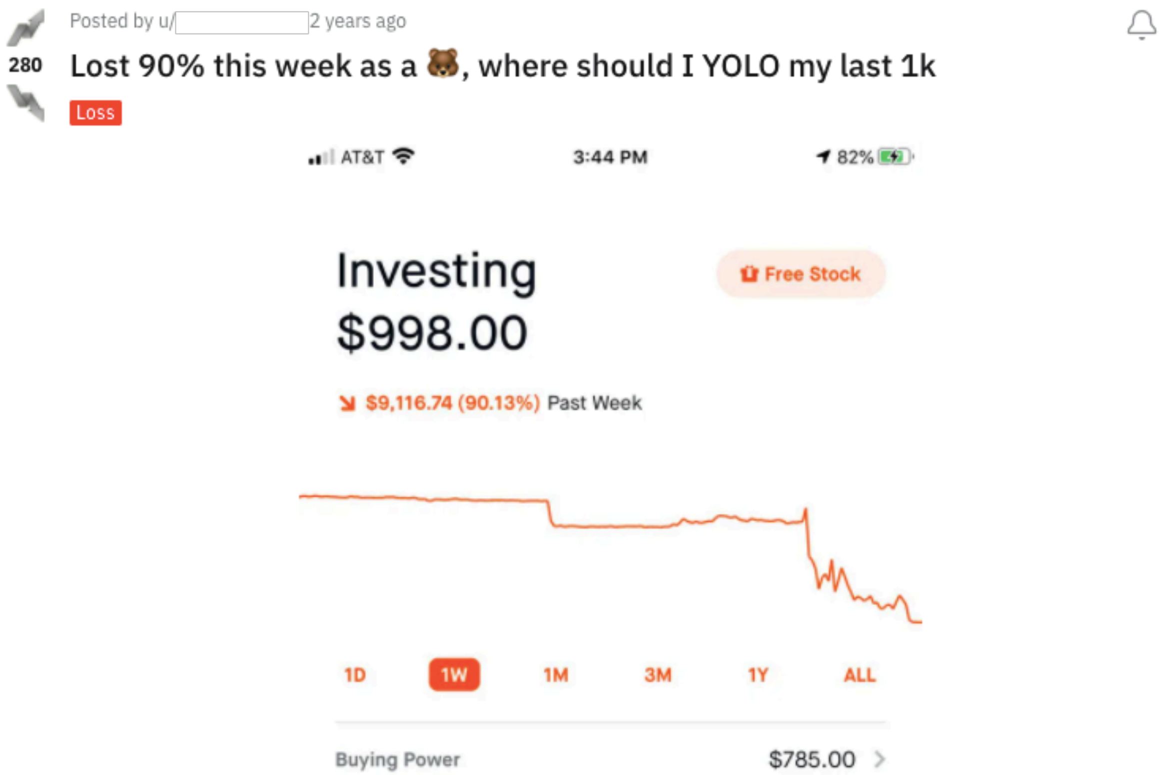
While Robinhood has helped tear down barriers for everyday people to enter the financial sector, the company has also had its fair share of controversies. For instance, in early March of 2020 Robinhood suffered system-wide outages that happened to take place at the same time as the largest daily point gain in Dow Jones' history (Verhage, 2020). They were even accused of failing to fully disclose the fact they were selling users' orders to high-frequency trading firms in which they were eventually fined for (Michaels and Osipovich, 2020). The list goes on and on, demonstrating that the Robinhood platform is far from perfect.

2.1.3 Social Media

Throughout the history of financial markets, investors have consistently relied on varying news sources to aid their investment decisions. Before the rise of social media, financial news would often be published in either newsletters or would come from financial news networks as a means of informing investors of company earnings reports, the outlook of future returns in the stock market, or the current state of the economy. Investors would then base their investment decisions not only on stock fundamentals, but also from such news headlines. However, social media has changed the way both individuals and investors perceive information. Granted, social media platforms have been around for nearly two decades, but it hasn't been until the last ten years it has seen the most development in not only the number of platforms available, but also in the participation on said platforms. Visiting sites such as Facebook and Twitter have become a daily routine for most people around the world and while social media may positively affect education, businesses, and society in some capacity, these applications are also at the root of many obstructive issues.

For many Robinhood and modern-day investors, the name WallStreetBets may sound familiar. The WallStreetBets subreddit (subreddit refers to a community on the Reddit platform) was first created in 2012 yet exploded into popularity during the heightened period of the pandemic in 2020. During this spell, the community grew to have a total of over one million members despite the fact it was not until 2017 when WallStreetBets hit 100,000 members. Jamie Rogozinski, creator of the subreddit, stated that the community was created as a place for people to talk about high-risk trades in “an unapologetic way” in order for investors to make short-term money with their disposable income (Asarch, 2021). During its early years, the subreddit was home to users such as Martin Shkreli, a former WallSreetBets bigwig who is currently serving a seven-year sentence for securities fraud.

The emergence of the term “YOLO” – “you only live once” – was soon popularized on most posts found on WallStreetBets and was typically used to demonstrate a gambling-like mentality to investing. The intention of investing manically and in a risky manner is still very much a part of the culture on the subreddit today. Most recently – and perhaps most famously – the community made headlines for what it did in January 2021. WallStreetBets members rose from fewer than two million at the start of January 2021 to more than 11 million after GameStop shares went flying (Banerji and McCabe, 2022). GME stock was originally valued at $40, but after members of the WallStreetBets community teamed together to push up the price, the stock was then valued at $492 (Asarch, 2021).



"Lost 90% this week as a [bear], where should I YOLO my last 1k" (WallStreetBets): This particular WallStreetBets user is poking fun at themselves for losing roughly $9,000 on Robinhood over the course of a week. This is just a small sample of the irrational and preposterous behavior practiced by WallStreetBets and Robinhood users.

2.2 The Relationship Between Smartphones, Robinhood, and Social Media

2.2.1 Accessibility to Trading

When Robinhood emerged onto the scene in 2013, the goal of the online discount brokerage was to democratize trading for all, primarily individuals who were rejected by traditional brokerages due to their unattractive customer margins. The primary proposition was a simple one: offer a highly engaging, intuitive, and visually compelling app interface that offers zero-commission trades (Tan, 2021). While not the first online trading platform, Robinhood paved the way for some of the more well known brokerages to not only reduce their commissions, but to make commission-free trading the industry norm (Tan, 2021).

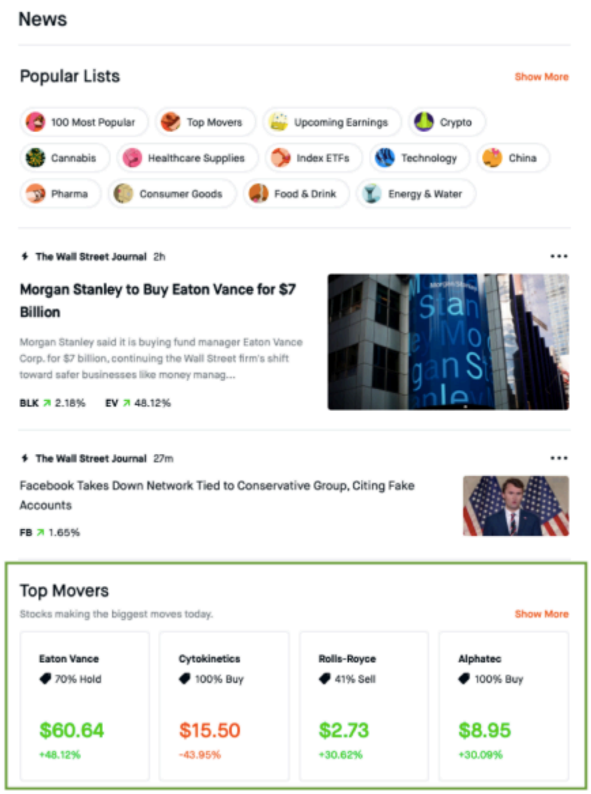
However, these "free" trades are not entirely free. Despite the fact Robinhood has established itself as a zero-commissions trade company, they still make money from other types of revenue streams, such as *Robinhood Gold*. This $5 a month subscription is a premium plan that includes larger instant deposits, access to professional market research, along with the access to margin trading (Tan, 2021). Despite this, Robinhood has still made the base platform available to all that are willing to deposit funds for investing. If you want some of the additional features Robinhood offers however, then a fee is required.

2.2.1.1 Robinhood's App Interface

Robinhood not only offers easier access to investment opportunities, but the app itself makes it simple for individuals to follow along with financial markets without having a true grasp of trading fundamentals. To fully encapsulate the essence of trading on Robinhood, Ingram (2019) had described the platform best: "The app has elements of fun, echoing in subtle ways the congratulatory elements of smartphone games that spur users to keep playing. Financial professionals say those elements encourage people — many of them young and inexperienced — to celebrate day-trading and develop risky habits that will cost users money over time."

Interface design plays a crucial role in not only presenting the functions of the Robinhood app, but also introducing the world of financial markets to millennials around the world in a way that is visually appealing (Tan, 2021). One designer of the app stated that the company is focused on making a design that's "friendly, that's inviting, that [does not] intimidate you, [and] that is not condescending" (Jacobs, 2018). The app is absent of clunky dashboards and clutters of information, capturing a minimalistic design. The Robinhood app also includes the use of vibrant colors with the company's emblematic bright green to help stand out to younger generations. Tan (2021) claims that this attractive-looking platform is an enabler of financial democratization in its own way as these virtual trading spaces are easy to navigate, are interactive, and are intuitive. Even the swipe-up gesture that confirms a stock transaction has been completed adds to the decentralization the platform already offers as it generates a sense of familiarity for millennials.

Nevertheless, the Robinhood app is not without its drawbacks. Many critics often compare the app to the highly addictive mobile game *Candy Crush* (Tan, 2021). As previously mentioned, users are rewarded with confetti when initiating their partnership with financial markets for the first time. Investors are also remunerated with a free stock if they successfully refer somebody to Robinhood. These users pick this free stock by scratching an on-screen lottery ticket to see which company they will be investing in. Elements such as these cause critics to consistently compare modern-day investing to that of mobile gaming and casino-style games.



Screenshot of Robinhood User Interface (Barber et al., 2020): This figure is an image taken directly from the "News" section on the Robinhood app. Users are presented with "Popular" lists to choose from and are also explicitly shown the top four stocks with the highest absolute return from the market close of the previous day. These stocks are better known as the "Top Movers" of the day.

2.2.2 How Smartphones, Robinhood, and Social Media Has Changed Financial Markets

2.2.2.1 Volume of Trading

According to Steib (2021), trading volume has increased roughly 300% over the past 50 years. With reduced barriers to enter the financial sector thanks to Robinhood, it goes without saying that an increase in both trading and participants was certain. This is clear to see with the 4,400% increase in the company's usership just over the span of six years. As mentioned earlier, once other major brokerages such as Charles Schwab and E-Trade saw the success of Robinhood, they had to make changes to no longer charge commission for stocks, ETF's, and options trades which has allowed for even more investors to start trading.

Nowadays, the NYSE, by far the world's largest stock exchange, represents less than 2% of the trading volume for NYSE listed companies (Steib, 2021). Hence, it's been noted that the trading volume on Robinhood has been large enough to impact the integrity of the financial system all by itself (Pasztor, 2021). This trend is unlikely to go away thanks to platforms like Robinhood continuously drawing in new investors to the market. Additionally, if Robinhood were to keep elements of gamification on their platform, then usership should only grow further (Steib, 2021).

COVID-19 has also had a significant impact on the volume of trading. As the world seemed to shut down in late February 2020, with college students returning home, nearly every American getting laid off from their jobs, and the circulation of unknown answers to uncertain events, the world was stuck at home. With Robinhood's easy to signup service and zero upfront costs, millions tried their hand at investing for the first time. This was suggested by the 125% increase in usership on the platform from 2019 to 2021 (Curry, 2021). During this interval however, the stock market was as unpredictable as ever due to worldwide lockdowns. In addition to the Dow Jones losing nearly 37% over the course of a month, Americans were met with stimulus checks just months later to help fund their trading expenditures (Steib, 2021). According to a survey conducted by *Betterment*, 91% of individuals said they had received a stimulus check to which about 46% mentioned they put some of their stimulant funds into the stock market (Friedman, 2021). Additionally, 70% of those who invested their stimulus check used at least half of the funds for investing. According to Steib (2021), people were paying much closer attention to their investments during the pandemic as well. JMP Securities Brokerages data showed that in 2020 most brokerages saw nearly double the amount of daily website visits compared to normal.

2.2.2.2 Quality of Trading

While Robinhood may have established itself as the hero for young and side-hustling traders – much like the legendary heroic outlaw to whom the company is named after –the financial sector may view the trading platform a bit differently. James Pasztor, an investor that has been a part of the financial services industry for nearly 40 years, set out to see whether Robinhood is truly the "hero" everyone has made the company out to be or if the platform plays the role of the "villain" in the financial industry. Pasztor (2021) started in the field during the 1980s and states that back then there was a much clearer line between investing and speculating. Pasztor (2021) remarks that speculation is more closely related to gambling and over the past decade, there has been an accelerating increase in the amount of wagers being placed. This is exactly the type of environment Robinhood investors thrive in. Robinhood is in the business of making money on transactions and has no relation to wealth management or financial advice, thus investors should steer clear of solely relying on the basic analytics the Robinhood app presents to its users (Pasztor, 2021).

Examining the role smartphones have on investment returns, it was found that newer technologies are associated with a decrease in an investor's portfolio efficiency. This implies that the inclusion of such technology demonstrates a change in investor behavior. By analyzing data from two German retail banks, both of which also have trading applications for mobile devices, Kalda et al. (2021) compared the trades executed by a specific investor depending on whether a trade was made on a smartphone or on a computer. The authors found that smartphone investments were typically the ones with high volatility and positive skewness. They also found that the probability individuals were investing in a lottery-type stock (asset with below median prices and above median volatility) increased by 67% for smartphone traders. These smartphone investors were also the ones that chased past returns, as shown by an increased probability of buying an asset in the top decile of past performance. Lastly, Kalda et al. (2021) noted some reasons as to why smartphone investors were more apt to making such investment decisions relative to individuals trading on their computers. One major element was that smartphone users tend to frequently trade after-hours. Trading after-hours implies there may be less trading volume for some stocks, making it more of a challenge for an investor to execute their trades. The opportunity to trade after-hours is much more noticeable for smartphone traders to take part in due to their device's accessibility. However, the main reason the participation in after-hours trading is greater for smartphone users is given by the fact that these investors are typically System 1 decision-makers.

So what exactly are Robinhood investors looking for when they log onto the app to trade? In a study conducted by Barber et al. (2020), Robinhood data was analyzed in order to demonstrate that fintech users participate in a larger percentage of attention-induced trading in comparison to other retail investors. Firstly, an attention-induced stock is one that is receiving the most "attention", such as a drastic change in price or recent herd behavior towards it. According to Barber et al. (2020), "Half of Robinhood users are first-time investors, who are unlikely to have developed their own clear criteria for buying a stock”. With this, such investors rely on the statistics presented to them by Robinhood. However, the app only displays a list of stocks that is surrounded by complex-free and somewhat pointless information. The authors found that besides basic market information, Robinhood only provides five charting indicators while TD Ameritrade, on the other hand, provides 489. This does not tend to help first-time investors distinguish a risky investment from a safe one. Additionally, the Robinhood app simplifies the act of placing trades, which leads to escalated trading numbers. Lastly, Barber et al. (2020) claim Robinhood users to be the ones who are usually purchasing attention-driven stocks. The authors state that the top 0.5% of stocks bought by Robinhood users each day typically experience negative average returns of approximately 5% over the next month. Additionally, they also find that in times of extreme herding, negative average returns are around 20%. Between the simplified information displays on the Robinhood app and the average inexperience level of the traders operating the platform, such a combination typically exacerbates such attention-induced trading.

During the pandemic, the same risky behavior was even more apparent. Once COVID-19 spread worldwide and markets became extremely volatile, evidence showed that Robinhood usership was positively correlated with such volatile markets (Fatah, 2021). COVID-19’s volatile market period not only attracted activity from existing investors, but also encouraged new investors to join. It should be noted that a majority of investors placed their first ever trade order during a period of some of the highest volatility the stock market has ever seen. In their portfolio analysis of Robinhood investors, it was discovered that their returns were typically low relative to the risk they bear, which is primarily due to the excessive amount of highly volatile stocks they hold. These stocks hardly contribute any returns and therefore reduce overall portfolio performance (Fatah, 2021).

While Robinhood has influenced users to take more risks and "live on the edge" so to speak, it can also be said that the role of social media has had just as notable of an impact on the quality of trading as the Robinhood app itself. Bukovina (2016) notes the existence of the parallel between social media platforms and retail investors. Such a relationship holds two economic interpretations: information demand and market sentiment. Information demand is the idea that retail investors utilize investment guidance from forums on social media platforms or on Google search engines as a publicly available source of information. The reason these investors tend to rely on these types of sources is because they often have limited access to professional databases such as Bloomberg (Bukovina, 2016). This may suggest that social media democratizes the flow of information in financial markets. In regards to market sentiment, such attitudes are based on the reaction of society towards existing information. Financially speaking, sentiment refers to the attitude and emotions of traders. These emotions may be in reference to the performance of a particular firm or to the stock market as a whole.

One of the most recent and most prominent displays of the influence social media has on financial markets was the "meme stock" phenomenon that took place during the early part of 2021. To define a "meme stock", these are shares of a particular company that has gained a "cult-like" following online and on social media outlets. Online communities such as WallStreetBets build publicity on Reddit and attempt (and sometimes succeed) in influencing the price of a company's shares. The value of a meme stock is rooted in social sentiment rather than core financial indicators used by corporations and professional investors.

In the case of meme stocks, social media is seen as a "coordination device" in which investors synchronize on buying signals on such platforms and ultimately affect stock price and trading volumes (Costola et al., 2021). Although social media platforms pose risks to financial markets by interfering with prices and trading volumes, plenty of investors on WallStreetBets see such events as opportunities for arbitrage. In a study conducted by Buz and de Melo (2021), a portfolio of the most popular WallStreetBets' stocks was created to which the authors found that over the course of a year the portfolio grew 480%, significantly outperforming the S&P 500. The authors acknowledge the potential detriment investors could face if their trading strategies are heavily influenced by posts on WallStreetBets, but also note that with high risk comes high reward. In short, taking investment advice from the subreddit may help to significantly increase profits if one is willing to bear the additional risk.

In conclusion, the combination of smartphones, Robinhood, and social media jointly influence financial markets and individual investors in various ways. While nearly anyone in today's world can become an investor thanks in part to both the increase in smartphones and the emergence of Robinhood, this may not always yield optimal returns due to either the lack of proper knowledge about the stock market or because they are heavily influenced by the design of the trading platforms themselves. It may even be that these investors seek trading advice from public forums as a means of gathering financial information. Regardless of what influences these investors, Robinhood traders and members of WallStreetBets tend to bear the most risk. The following chapter will be examining behavioral finance along with various cognitive biases typically practiced by investors.

3. Literature Review

This chapter will primarily focus on the emergence and elements of behavioral finance and the psychological factors that surround the decision-making process of investors. While this paper is not testing for every cognitive bias mentioned in this section, it is important to shed light on such irrationality in order to better understand the cognitive errors investors are most susceptible to all while enhancing the insight of behavioral finance as a whole. The first section of this paper will inspect standard finance together with the infamous efficient market hypothesis. The second section will examine the emergence and foundations of behavioral finance while the third section analyzes the most relevant, and most likely to occur, cognitive errors investors are most prone to conducting.

3.1 Standard Finance

Before delving into behavioral finance, it is important to observe standard financial theory as well as some of the shortcomings surrounding its viewpoint on investor behavior. Standard finance theory is built upon very few building blocks such as the fact that individuals are thought to be rational and markets are to be efficient (Statman, 2014). Simply put, standard finance is an extraordinarily broad view of financial markets.

We can start by first, and most importantly, defining a "rational" investor. Miller and Modigliani (1961) describe rational investors as ones that prefer more wealth to less and will be indifferent as to whether this increased wealth comes in the form of cash payments or market value in their investments. Furthermore, rational investors are immune to an entire range of cognitive errors, biases, and misleading emotions that may alter investment behavior. These individuals have complete self-control over their set of choices, always stick to their investment strategies, and are never tempted to invest in the numerous risky assets presented to them in the market. Rational investors care only about wealth and the utilitarian benefit of their investments, completely separating themselves from their roles as consumers (Miller and Modigliani, 1961). Statman (2014) uses the case of gun manufacturers and the impact they have on a rational investor's decision-making ability. For instance, an investor may object to the harm caused by gun violence, but because they are "rational", they invest in the stock of gun manufacturers if it would yield higher returns relative to other investments, disregarding their initial feelings towards firearms. This idea that all investors think in this way is irrational in itself. While it is clear to see the issues surrounding this concept of rationality in financial markets, it would be too simple to leave it at that. The next subsection will be dedicated to Efficient Markets Hypothesis, a foundational underpinning to standard finance in its entirety as it strives to expound upon this notion of rationality in the behavior of financial market agents.

3.1.1 Efficient Market Hypothesis

Before there was implementation of psychological and behavioral elements to understanding the way people invest their money, the Efficient Market Hypothesis (EMH) was widely accepted by financial economists and analysts alike. The main idea behind the hypothesis is that financial markets are extremely efficient in reflecting information about individual stocks and the market as a whole (Malkiel, 2003). When information arises, EMH asserts that such news spreads quickly throughout the market and is immediately incorporated into the price of a security. Neither technical analysis (the study of past prices in an attempt to predict future ones) nor fundamental analysis (the practice in which an investor observes various types of financial information, such as company earnings, in an attempt to find undervalued stocks) is practiced under EMH (Malkiel, 2003). The reason being is that both types of analysis would enable investors to achieve returns greater than what could be obtained from holding a completely random stock. Under EMH, opportunities for arbitrage are unfeasible. EMH acknowledges that if information is immediately reflected in the price of a security, then tomorrow's price change will reflect only tomorrow's news and would be completely independent of the price change that occurred today. Price changes must be unpredictable and random because news is by definition unpredictable (Malkiel, 2003). This is representative of the well-known idea of a "random walk" that is typically found throughout financial literature. Seeing prices fully reflect all known information, this must mean that uninformed investors obtain a rate of return that is the same as that of an expert. EMH expresses that an investor is unable to achieve above-average returns without accepting above-average risks.

By the end of the 20th century, many behavioral economists along with various studies had displayed markets were ultimately inefficient. Grossman and Stiglitz declared that markets were unable to be considered efficient if there is a cost of information to investors (Degutis and Novickytė, 2014). Later on, economist Robert Shiller claimed that excess volatility in stock prices must be a key contradiction to EMH. The results of Shiller's (2003) study found that the actual volatility of a security's price was higher than calculated from fundamental information. Thus, Shiller (2003) believed excess volatility to be attributed to investors' psychological behavior.

While behavioral economists have begun to believe stock prices are predictable on the account of past stock price patterns, Burton Malkiel – to whom a great deal of financial research has been dedicated to EMH and its critics – has research particularly centered on the idea that the market is very much susceptible to mistakes and that psychological factors can influence securities' prices, but in the end the true value of the asset wins. Malkiel (2003) argues that while market pricing is not always perfect, the market itself is certainly not inefficient. Markets can be considered efficient even when investors and market participants are irrational. Furthermore, the market is still considered to be efficient even when stock prices display greater volatility than can be explained by investment fundamentals. Despite this, it is impossible for the market to be perfectly efficient.

Malkiel (2003) finds that as long as stock markets exist, there will be a portion of participants that will make mistakes and demonstrate irrationality. These irrationalities ultimately lead to pricing irregularities and even predictable patterns in the pricing of securities from time to time, thus making markets inefficient. Despite this inefficiency, Malkiel (2003) believes that the market is still incredibly efficient in its usage of financial information. For instance, De Bondt and Thaler (1985) find that when investors overreact to company announcements, such reactions are ultimately reflected in a stock's price. Notwithstanding, the reliability and legitimacy of EMH still fails in explaining excess volatility in stock prices, investor overreaction, asset bubbles, etc. (Degutis and Novickytė, 2014).

3.2 Behavioral Finance

This section will analyze the emergence and evolution of behavioral finance in mainstream financial practices along with some of the foundational elements of the field.

3.2.1 The Emergence of Behavioral Finance

In 1841, a Scottish journalist by the name of Charles Mackay published *Extraordinary Popular Delusions And The Madness Of Crowd,* an infamous study observing the development of herd-like mentality amongst individuals, to what reasons people tend to seek popular opinions and beliefs, and why being misled by some of these more favorable ideas often leads to undesirable outcomes. In *Volume I* of Mackay's study, which was primarily centered on the development of economic bubbles, attention was drawn to the renowned "Tulip Mania". In Europe throughout the 16th century, tulips began to gain popularity once the uses for these flowers became known. Tulips typically have standard color petals, however, once a virus infects them they begin to exhibit varying dye patterns. Similar to how the rich today collect beautiful pieces of art at extraordinary prices, the wealthy of the 16th century began to collect and display these rare tulips (Harford, 2020). With the increasing prices of these tulips, the highest price for a single bulb was 5,200 guilders, or 20 times the annual income of a skilled worker today (Harford, 2020). While exchanges were continuing on for a brief period of time, trading ultimately failed as buyers did not have the money to pay for the tulips and sellers did not have enough bulbs to sell, ultimately causing the bubble to burst. Needless to say, the moral of the story was that it's in our human nature to be speculative, particularly if an arbitrage opportunity arises. If enough people join, then the amount of speculative individuals rises causing some very interesting phenomena. That's exactly what Mackay set out to explore: why do individuals tend to behave in such a risky manner?

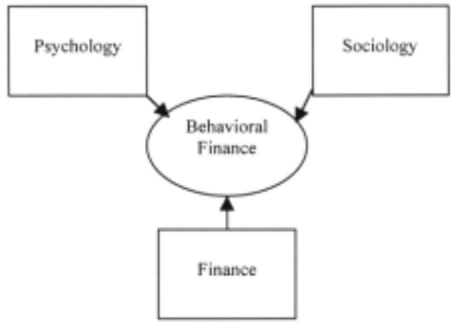
Nearly 70 years after Mackay's book, George Charles Selden published the *Psychology Of The Stock Market,* a book with a primary focus on the dependency of mental attitudes of investors and their effects on prices within the stock market. In the 1912 classic, Selden set out to demonstrate what really influences the behavior of financial markets. Selden (1912) notices that investor psychology plays a pivotal role in the movement of the market and individual stocks. Thus, it was important that such tendencies be exposed.

Once again, almost another 40 years went by before University of Oregon Business Professor O.K. Burrell produced the first-ever integration of psychological and financial research in a 1951 article titled "Possibility of an Experimental Approach to Investment Studies" (Olsen, 1998). Oregon Finance Professor W. Scott Bauman followed this study up 16 years later with a publication of his own. Both Burrell and Bauman were calling for a new area of financial research that emphasized the melding of quantitative investment models with information from the more traditional behavioral approaches (Olsen, 1998). Despite the emergence of such academic papers and research, interest in behavioral finance would take a hiatus until the later half of the 1980s. According to Olsen (1998), there were two reasons for the renewed interest in behavioral finance. The first was that existing standard theories were inadequate and inapplicable in fundamental ways. The second cause for the reemergence was in part thanks to the development of Kahneman and Tversky's (1979) prospect theory. Prospect theory ultimately presented a model of decision-making that was an alternative to expected utility theory with more-realistic behavioral assumptions in which gains and losses are valued differently.

In short, behavioral finance's emergence came in the wake of empirical findings that challenged EMH. While these psychological developments are fairly new relative to standard finance theory, it does not take away from the fact that EMH has reigned supreme over the financial world for far too long. All of the emerging research on behavioral finance over the past 70 years has led to a very important question posed by Shiller (2003) in rebuttal to EMH: how can stock prices represent the optimal forecast of present value if the price responds only to objective information about it? This question will be analyzed in more detail later in this chapter.

3.2.2 The Foundations of Behavioral Finance

By integrating the fields of finance, psychology, and sociology, behavioral finance is a construct that's used to better understand the manners and practices of investors. This area of behavioral economics helps to explain why and how investors behave the way they do while also attributing explanations to stock market anomalies, bubbles, and crashes. Essentially, behavioral finance aids in delineating how both sociological and psychological factors influence the decision-making process of investors, a group of shareholders, and larger financial institutions (Ricciardi and Simon, 2000). Before moving any further, it is key that proper definitions are created for each of the structural elements of behavioral finance seen in the figure below. Firstly, finance is, of course, concerned with asset valuation and investment decisions and includes acquiring, investing, and managing resources (Ricciardi and Simon, 2000). Psychology is the study of human behavior and mental processes. Psychology also determines how such decision-making procedures are affected by an individual's physical and mental state along with the influence of external environmental factors (Ricciardi and Simon, 2000). Lastly, sociology is the study of human social behavior in a group-oriented atmosphere, focusing primarily on the influence of social relationships on an individual's behavior.



The Foundations of Behavioral Finance (Ricciardi and Simon, 2000): Traditional finance is still the centerpiece of behavioral finance, but now psychological and sociological elements are integrated into the model.

The reason it is important to examine investor conduct stems from the fact that, oftentimes, their disorderly and irrational behavior may lead to bubbles and crashes that can cause disruption, misery, and even loss of livelihoods for individuals who may or may not have been involved. A better understanding into the world of behavioral finance may be able to prevent, or in at least some way mitigate, these undesirable phenomena.

Behavioral finance is part of science that is rooted in psychology with a primary mission to understand and predict financial market implications that stem from the decision-making processes of investors (Olsen, 1998). More so, behavioral finance helps to explain finance and investing from a human perspective. Despite implementing behavioral aspects, behavioral finance does not reject some of the more economic concepts. Some key elements behavioral finance establishes in regards to the decision-making process are as follows: investors' preferences are formed during the decision process itself; their decision-making process is adaptive; these investors seek satisfaction rather than optimal solutions (Olsen, 1998). All of these are not accounted for in standard finance as they are not represented in any measures and may be why financial markets are often susceptible to crashes and bubbles.

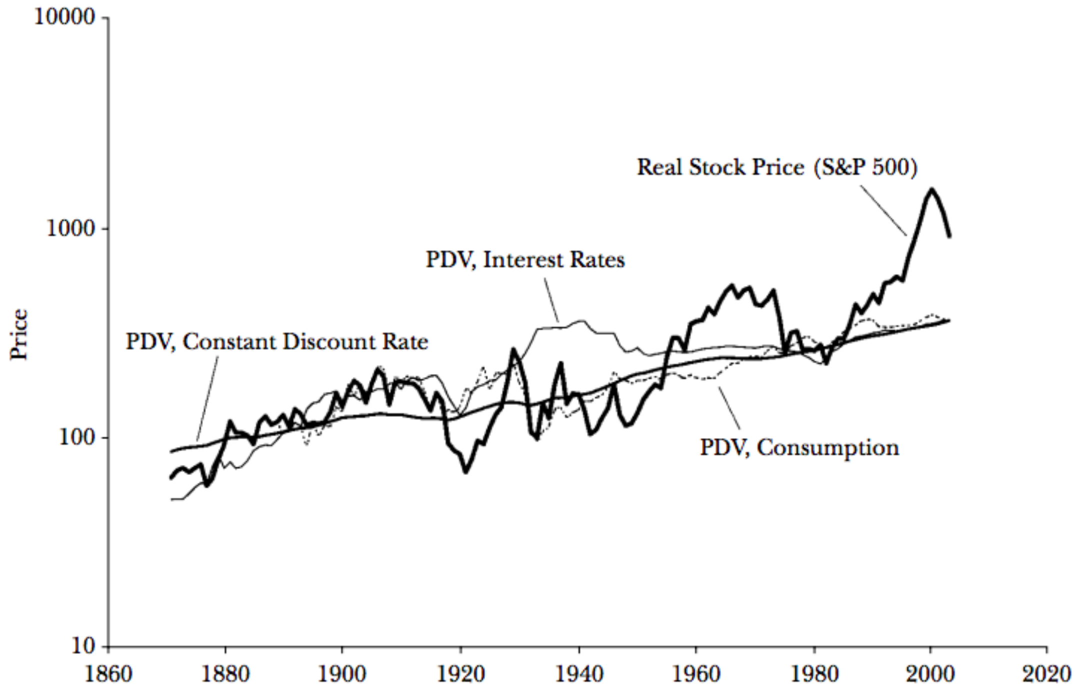
One of the most important assumptions of behavioral finance is that the information structure, as well as the characteristics of market participants, influences an investor's decision (Baker and Nofsinger, 2010). Rather than relying on a computer and the abundance of mathematical approaches to predicting earnings, behavioral investors utilize the human brain. The brain is the only human organ susceptible to shortcuts and emotional filters in which investors employ to help them make their financial decisions. These processes often influence people to act irrationally and violate traditional financial concepts. Ultimately, these suboptimal financial decisions come with ramifications for market efficiency and performance (Baker and Nofsinger, 2010). According to Baker and Nofsinger (2010), the original attraction for a behavioral finance field was that market prices did not seem to be fair and truly representative. While standard finance argues that an investor's irrationality does not affect market prices (this is because when prices deviate from fundamental value, rational investors would exploit the mispriced asset for personal gain), behavioral finance notes that there are numerous limitations of arbitrage that prevent rational investors from correcting price deviations.

3.2.3 From Efficient Markets Theory to Behavioral Finance

While it has been previously mentioned that behavioral finance's reemergence was not until the later half of the 1980s, Shiller (2003) points to the fact that the entirety of the decade challenged the consistency of the EMH model. Shiller (2003) asked whether stocks show excess volatility relative to what would be predicted by the efficient markets model. If most of the volatility in the stock market went unexplained, then this would cast down upon the basis of the entire EMH. Shiller (2003) notes that the evidence surrounding excess volatility imply that such price changes occur for no fundamental reason at all, perhaps by the "animal spirits" mentioned in the introductory chapter of this project.

The EMH model asserts that the price of a share equals the mathematical expectation of the present value for actual dividends accruing to that share. This present value is unknown and is forecasted in which the price is equal to the optimal forecast of it. According to Shiller (2003), the forecast error used in the efficient markets model must be uncorrelated with any information variable available at time *t*, otherwise it would not be the equilibrium price. Seeing the current price of a share serves as a piece of information at time *t*, both the forecast error and current price of a stock are uncorrelated. Since the variance of the sum of two uncorrelated variables is the sum of their variances, the variance of a dividend payment should be equal to the variance of a share's price plus the variance of the forecast error under EMH. However, Shiller (2003) finds that this is not the case.

Shiller (2003) found that for each year since 1871, the present value subsequent to that year of the real dividends paid on the Standard & Poor's Composite Stock Price Index, and discounted by a constant real discount rate, behaves as a stable trend. In contrast however, the Standard & Poor's Composite Stock Price Index itself gyrates wildly up and down around this dividend trend (see figure below).



Real Stock Prices and Present Values of Subsequent Real Dividends (Shiller, 2003): It is clear to notice how the "Real Stock Price" line vastly moves up and down around the "Constant Discount Rate" trend.

Shiller (2003) finds that the stability of the present value through time suggests there is excess volatility in the stock market relative to the implied volatility by the efficient markets model. This violates EMH belief that the volatility of dividends should be the same as the volatility of share prices. This idea will be discussed and further tested in Section 2 of the Methodology chapter.

3.3 Cognitive Biases

This section will be discussing some of the most popular biases that investors are susceptible to. The two heuristics this paper will be analyzing and testing for is loss aversion and overconfidence. While these are the only two biases this project will be explicitly testing for in the later chapters of this paper, it is still extremely critical to discuss the various types of financial cognitive errors as a means of elaborating behavioral finance's importance in financial literature.

3.3.1 Heuristics

Although Herbert Simon first introduced the concept of heuristics during the 1950s, it wasn't until Tversky and Kahneman ultimately developed the study of such biases in human decision-making in more detail during the 1970s and 1980s. According to Tversky and Kahneman (1974), many decisions are based on beliefs concerning the likelihood of uncertain events. The primary question Tversky and Kahneman (1974) were trying to answer was how do people assess the probability of an uncertain event occurring or the value of an uncertain quantity? They found that people often rely on a number of heuristics to reduce the complex tasks of assessing probabilities and predicting values. While making the most optimal decision is preferred, individuals are often limited by both the amount of time they have in making such choices and the amount of information that's presented to them. Essentially, heuristics help to make this process easier. While these heuristics are seen as useful, they frequently introduce errors to an individual's decision-making procedure (Tversky and Kahneman, 1974).

In reference to financial markets, investor behavior and investment strategies based on heuristics may give rise to stock market anomalies which not only impacts individual investment performance, but also the performance of others. Individual investors are apt to utilizing heuristics in situations of uncertainty due to the fact they often fail to determine the probability of an event accurately occurring (Gilovich et al., 2002). This is in reference to whether they will see profits from their investments. The proceeding subsections will center on several of the most commonly used heuristics in investment strategies.

3.3.1.1 Overconfidence Heuristic

Overconfidence exists when an individual is very confident of their knowledge and abilities. Simply put, it's a psychological bias that reflects optimism. Overconfidence has been a longstanding theme in the world of psychology and in 1977, Fischhoff, Slovic, and Lichtenstein set out to examine and exhibit its presence in individuals' decision-making abilities (Ricciardi and Simon, 2000). For their study, a group of participants were asked to respond to a set of standard questions in which the answers were definitive. With each question they answered, the participants would assign a score of confidence as to whether or not they believed their answer to be correct. Fischhoff, Slovic, and Lichtenstein found that individuals had a tendency to display a significant amount of overconfidence in their ratings. For instance, individuals who answered 10 percent of questions wrong predicted with a 100 percent degree of confidence that their answers were correct.

Relative to financial markets, studies have defined an overconfident investor as one who overestimates their own capacities to generate information and data that will be used to help build their forecasts (Bouteska and Regaieg, 2018). An overconfident investor is one who privileges their own information compared to the public information available to all investors. Thus, these types of investors believe they achieve success by trusting their own ideas and intuitions rather than on the reliance of others (Bouteska and Regaieg, 2018). It has been found that overconfident investors typically practice excessive trading as a means to obtain higher returns and commonly overreact to changes in stock prices despite the fact current stock prices cannot serve as a measure of future prices. (Abdin et al., 2017). These investors also tend to underreact to publicly available information. It has also been noted that overconfidence is the most poignant of all investor heuristics in that such behavior of focusing on price changes, along with over- and under-reactions to such price changes and financial news, helps to generate fundamental anomalies and shocks that impact the market (Abdin et al., 2017).

Additionally, overconfident investors look for familiar patterns in their past trading experiences. Individuals, especially traders, inherit the ability to either forget or fail to learn from past trading errors and poor investment decisions, further adding to their overconfidence dilemma (Ricciardi and Simon, 2000). Seeing overconfident investors primarily use their own beliefs and instincts as a proxy for making investment decisions, they believe they can always beat the market, an entity that is nearly impossible to defeat.

3.3.1.2 Representativeness Heuristic

The representativeness heuristic will be the second mental shortcut discussed in this section. Tversky and Kahneman discovered the representativeness heuristic during the 1970s and it shows how individuals typically cling to results that are more representative of the evidence that’s presented before them. Simply put, we typically base our decision of how likely a certain event will occur in the future on how similar it is to an existing mental prototype. Tversky and Kahneman found that people are usually concerned with “what is the probability that event A originates from process B?” In this case, if A happens to be highly representative of B, then the probability that A originates from B is judged to be high (Yazdipour and Constand, 2010). The problem that arises here is that such similarities should not impact the judgment of probability. According to Yazdipour and Constand (2010), the representativeness heuristic is a "built-in feature of the brain" that produces rapid probability judgments rather than a consciously adopted procedure. Individuals may deem the chances of a particular event to occur to be "normal" based on previous occurrences. However, this is far from the case.

In relation to finance, investors use past trends of a representative stock to make investment decisions, ignoring the many stock fundamentals that ought-to be observed. For instance, if an investor has bought and sold Apple stock twice over the past six months, and during their holding period they saw the stock's value increase dramatically, an investor practicing representativeness may purchase Apple stock once again simply based on its past performance of when they held the stock, even if its current performance has been poor. Thus, the representativeness heuristic distances investors from the fundamental elements surrounding stock performance and ignores such rudimentary components in order to keep watch of "hot" stocks (Abdin et al., 2017). These investors use past history to buy these hot stocks and avoid ones they believe to be poor. Pompian (2012) finds that investors base their decisions on limited statistical data and overweight the importance of past history and previous trends to construct their investment choices.

3.3.1.3 Availability Heuristic

According to Tversky and Kahneman (1973), availability refers to the ease with which an individual can bring to mind instances of an event that has previously taken place. Oftentimes, individuals disproportionately recall events they've observed in their lives either due to the fact that a specific episode has recently occurred or because that person has an emotional connection to such an incident. According to Yazdipour and Constand (2010), the more noteworthy an event is for a person, the more likely that memory will be recalled. Not all memories are equally retrievable or available, which leads to errors in an individual's judgment (Yazdipour and Constand, 2010). When presented with a moment of decision-making, easily recalled events or situations may spring to the forefront of a person's mind.

There is also the case in which excessive media coverage and the drama surrounding an event, such as the consistent coverage regarding a type of death, may also cause such episodes to be ingrained into an individual's memory (Lichtenstein et al., 1978). For instance, people who watch the news may become convinced that homicide occurs more than suicide simply because of the persistent news coverage regarding the matter. Thus, an individual might judge such events as more probable to occur than others, overestimating the probability similar events will take place in the future.

In the realm of finance, investors tend to rely on their previous experiences in the market as a basis for their next investment. For instance Shiller (1998) found that an investor's attention to investment categories, such as whether choosing between stocks and bonds may be affected by alternating waves of public attention or inattention. Barber and Odean (2007) also found that investors primarily consider investing in stocks that have recently: been in the news; been experiencing high, abnormal trading volume; or has displayed high, one-day returns. It has also been found that the availability heuristic influences the behavior of market analysts as well. Lee et al. (2008) find that when the economy is expanding, analysts' forecasts of a firm's long-term growth in earnings per share tend to be relatively optimistic. Contrastingly, when the economy is contracting, analysts' general outlook on a company's long-term growth is relatively pessimistic. Such findings are consistent with the availability heuristic in that forecasters overweight the current state of the economy in making predictions about a firm's long-term growth (Kliger and Kudryavtsev, 2010).

3.3.1.4 Anchoring Heuristic

The notion of anchoring was first introduced by Paul Slovic in 1955, although the anchoring-and-adjustment heuristic was not fully established until 1974 when Tversky and Kahneman published their groundbreaking work surrounding judgment under uncertainty (Furnham and Chu Boo, 2011). The idea surrounding the anchoring heuristic is that individuals will make judgments that are biased towards an initially presented value, or a starting point. In Tversky and Kahneman's (1974) initial study, participants were asked to provide an estimation of the percentage of African countries belonging to the United Nations. This percentage was with reference to a range of randomly arbitrary numbers that ranged from 0 to 100 and were generated by spinning a wheel. Participants were then asked to consider whether the actual answer was higher or lower than the reference value presented before the absolute judgment was made. Tversky and Kahneman (1974) found that participants' answers were significantly biased towards the randomly generated number produced from spinning the wheel. For instance, if a participant spun a 10, then their estimate was close to and around 10. When the random number was high, then the participants' median estimate was notably larger.

In a study conducted by Northcraft and Neale (1987), real estate agents were asked to analyze a given property. The researchers assigned list prices while the participating agents were asked to estimate: the purchase price of the property; the appraised value of the property; lowest acceptable offer. The participating agents were split into two groups with list prices being higher for one group than the other. The anchoring heuristic was seen to be strongly present in this scenario as the agents placed their forecasts close to the start value depending on which group they belonged to (Peña and Gómez-Mejía, 2020). According to Shiller (1998), anchoring is closely related to representativeness in the world of finance. Investors tend to rely on recent experiences and are overly optimistic when the market is trending upward and extraordinarily pessimistic in times of a downtrend. Given a current situation, an investor will adjust the desired stock price they want to buy at to one that's most representative of a previous stock's price, generally one they made a profit on. In this case, that previous stock's price serves as an anchor to gauge the price an investor should buy at (Abdin et al., 2017).

3.3.2 Framing Effects

Framing is known as the process where an individual's choice, given a set of options, is influenced by the way these alternatives are presented rather than by the substance of said choices (Plous, 1993). The information displayed to someone is deemed more or less attractive based on what exactly is being highlighted to the individual. One study conducted by Tversky and Kahneman (1981) presented participants with a scenario in which an unknown disease was spreading across the U.S. The respondents were then asked to decide on a plan with a rate of success bound to each plan. In Program A, it was stated that 200 individuals would be saved while in Program C, 400 people would die (both plans were out of 600 individuals). Tversky and Kahneman found that fewer participants chose Program C despite the fact it's the same risk-averse alternative as Program A. Ritter (2003) provides a real-world example of framing. Even though survival probabilities added with mortality rates come out to equal 100 percent, doctors have been documented in making different medical recommendations if evidence is presented to them in terms of either "survival probabilities" or "mortality rates". Thus, framing is extremely important in making choices in everyday scenarios.

In the financial world, governments are perceptive in encouraging individuals to make better provision for retirement through long-term savings and choice of investment funds. In a study conducted by Diacon and Hasseldine (2007), the authors found that people tend to struggle with long-term decision making as they are unaware of how much to save or what funds to invest in. They also found that roughly half of these individuals rely on past performance despite numerous amounts of research showing past investment performance to be a substandard indicator of predicting future returns. In many instances, past performance charts are provided to these individuals with the formatting of such charts significantly impacting the choice of funds to invest in. Additionally, these charts altered how risk was perceived. For instance, when equity fund performance was expressed as a percentage annual yield (the real rate of return on an investment for that year) opposed to an index of fund value (one that measures changes from a base year to the present year), respondents displayed heightened risk perceptions (Diacon and Hasseldine, 2007). These individuals were uncertain of what their future returns, strongly believing they might lose all of their money. These risk perceptions were a result of the way these values were framed to them. If the annual yield happened to be bad that year, an individual might get nervous and believe they are not making an adequate enough return on their investment. On the contrary, if the index of the fund's value displayed how much money has been made over the years, or at least compared to a specific year, then the investor's perception of risk may decrease significantly.

3.3.3 Loss Aversion Bias

First explored by Kahneman and Tversky (1979), loss aversion proved to be a core element of prospect theory, being described as a bias that reflects pessimism in individuals. Loss aversion bias suggests the value function for an individual is steeper for losses rather than for gains (Schmidt and Traub, 2002). Thus, Kahneman and Tversky find losses and the feeling one gets from such misfortune is much greater than the pleasure associated with gaining the same amount.

According to Bouteska and Regaieg (2018), investors performing loss aversion make decisions based on gains rather than losses in an attempt to avoid the risk linked to loss. Therefore, it is clear that the effect of a loss on an investor's behavior is more impactful than the effect of a gain. When an investor is immensely sensitive to loss, they seek to avoid it by any means necessary, impacting their decision-making process and ultimately altering their investment strategies. In a study carried out by Thaler and Johnson (1990), the authors found that the degree of an investor's loss aversion is dependent on whether past results were negative or positive. For instance, if an investor realizes past results as gains, then they become weakly averse to losses. Conversely, when they have previously experienced a loss, then they become strongly averse to future losses. Loss aversion forces investors to hold losing investments in hopes they will rise and will not have to trade at loss. In contrast, loss aversion prompts investors to sell their profitable stocks because they fear losing the profits they have made from holding a particular security. Also, individuals tend to find losses coming after prior gains to be less painful than recurring losses due to the fact that these losses were softened by earlier gains.

Framing effects are also an important component of loss aversion. When gains and losses are taken as changes in total wealth, this is defined as being “broadly” framed (Barberis and Huang, 2001). When investors refer to changes in their stock portfolio or the stocks they own, this is defined as “narrow” framing. When one stock from an investor’s portfolio performs poorly under “narrow” framing, they may feel a sense of regret (we will observe the theory of regret in the upcoming sections) in buying that stock in the first place. As each stock is associated with its own unique decision, gains and losses give rise to a distinct utility that is based on either the regret or the euphoria about the initial buying decision (Barberis and Huang, 2001). While observing gains and losses in total wealth is more relevant, investors tend to focus too much on the profits or costs of a particular stock or portfolio simply because information about such gain or loss is more accessible to notice.

In reference to large institutional investors, O'Connell and Teo (2009) find that institutions aggressively reduce risk following losses and moderately increase risk following gains. Given the fact that institutional investors manage other people's money with past performance records typically being available to the public, they are more likely to derive utility from past performance and practice loss aversion compared to retail investors. In the real estate market, Genesove and Mayer (2001) found that loss aversion determines seller behavior. More specifically, the authors suggest that loss aversion is able to help explain a seller’s choice of list price in the Boston area. After a boom, housing prices fall meaning they have a market value well below the price paid by its current owner. Unit owners that are loss averse have an incentive to reduce the effect of such loss by deciding on a limit price that exceeds the level they would set in the absence of a loss (Genesove and Mayer, 2001). For instance, Genesove and Mayer (2001) found that sellers whose unit's expected selling price fell below their original purchase price set an asking price that exceeded the asking price of other sellers in the market. In turn, a higher ask price corresponds with such housing units spending more time on the market.

3.3.4 Financial Cognitive Dissonance

Nearly 65 years ago, Leon Festinger published *A Theory of Cognitive Dissonance* (1957). This theory of cognitive dissonance was built on the premise that pairs of cognitions, or elements of knowledge, can either be relevant or irrelevant to one another (Harmon-Jones and Mills, 2019). If relevant to one another, the two cognitions may be considered dissonant if the opposite of one cognition follows the other. Dissonance, or the presence of being psychologically uncomfortable, stimulates an individual to reduce such discomfort. According to Harmon-Jones and Mills (2019), the greater the magnitude of the dissonance, the greater pressure there is to reduce it.

Festinger (1957) created a scenario that helps to better illustrate cognitive dissonance. This real world situation follows a habitual smoker that learns smoking damages one's health. This person experiences dissonance because the knowledge that smoking negatively impacts health is dissonant with the cognition that they continue to smoke. The smoker is left with two choices in order to reduce dissonance. The first option they have is to stop smoking, which is consonant with the cognition that smoking damages health. The second way they can reduce dissonance is by changing their cognition about the effects of smoking on their health. This individual may start to assume smoking does not have harmful effects on health and might look for some positives in smoking (for instance, believing it releases tension and relieves stress).

In relation to the world of finance, studies have shown that investors with under-performing securities are unwilling to admit they have made a bad investment decision (Ricciardi and Simon, 2000). Despite the poor performance of such securities, they still hold on to these sub-par investments. Why? Well, this gives them a reason to not admit they have made a poor financial choice (Ricciardi and Simon, 2000). For example, during the rise of Internet companies in the 1990s, many investors were using a financial criteria sheet that evaluated companies using various profitability measures. However, because these companies had no financial track record and had made little revenue, this meant such measures of financial profitability could not have been applied. As a result, investors began to change their investment styles to fit their previous decisions of investing in these Internet companies. These investors were the ones that led to the speculative “DotCom” bubble of 2000 to burst in which many of these Internet stocks decreased nearly 70% from their all-time highs (Ricciardi and Simon, 2000).

In a study conducted by Kessler (2010) regarding the global financial crisis of 2008, it was found that a case could be made that financial cognitive dissonance was the driving force behind the recession. When low interest rates and low lending standards fueled a housing price bubble, this motivated millions of Americans to borrow beyond what they could afford to spend, which included houses. Banks and subprime lenders then went on to sell these mortgages on the secondary market to which firms bought and resold to investors as mortgage-backed securities. Many were convinced that the 2008 financial crisis was primarily a result of the deregulation of financial markets. Kessler (2010) states that "believers in laissez-faire" (BLF as they are referred to) happened to demonstrate cognitive dissonance during this time. Kessler (2010) found that these BLF, most of whom were popular and influential during the time of the global financial crisis, would often deal with problems surrounding the financial catastrophe with statements that backed their laissez-faire beliefs. However, it became well aware that the government should have assisted from the start. Despite the clear evidence surrounding the problems caused by deregulation, BLF would continuously deny the facts, evidently demonstrating cognitive dissonance about the market.

3.3.5 Regret Theory

According to the *American Psychological Association,* regret theory is a model of decision-making in which people's fear of regretting poor choices either enhances or deters their behavior in situations involving uncertainty. Regret has two distinct functions here: the desire to have chosen differently and accusing oneself for believing an error in judgment was made. Regret is an emotion caused by comparing a given outcome with the state of forgone choice (Bell, 1982). Despite all this, regret can be a useful emotion to express as it can signal possible improvements of future actions in forthcoming scenarios (Bleichrodt and Wakker, 2015). Despite some of the benefits of being regretful, having a great deal of alternatives to choose from can actually inhibit decision-making and in turn reduce welfare in many situations (Irons and Hepburn, 2007). For instance, if an individual suffers regret from unexplored options that turn out to be better than their choice, then they start to anticipate regret which may begin to continuously affect their overall well-being and decision-making abilities. According to Irons and Hepburn (2007), the sequential search model has demonstrated that having an excess of options may cause an individual who continuously regrets their decisions to completely stop participating in decision-making altogether, where no research is performed and none of the specified possibilities are chosen.

For investors, there is a tendency to avoid selling securities if the price has gone down. This is done as a means of avoiding the feeling of regret in making the wrong investment choice along with the irritation of marking it down as a loss (Simon and Ricciardi, 2000). Investors may also follow the crowd and purchase hot stocks, allowing them to more easily rationalize their choice if the commodity significantly declines. In this case, investors experience lessened regret and anxiety due to the fact a large group of individuals have also lost money on that same mediocre investment (Simon and Ricciardi, 2000). A study by Michenaud and Solnik (2008) finds that regret is experienced if the outcome and returns of the rejected choice are still "visible" to the investor. Accordingly, investors anticipate an ensuing experience of regret and incorporate it into their objective function.

3.3.6 Herd Behavior

Deemed to be the most socially interdependent species in the world, humans are often susceptible to the manifestation of herd behavior. Kameda and Hastie (2015) refer to herding as the alignment of thoughts and behaviors of individuals belonging to a group. Herding does not emerge through coordination determined by a central authority, but rather from the interactions between agents. One reason heading occurs may stem from the fact humans are often known to reproduce others' emotions in themselves. According to Kameda and Hastie (2015), when a receiver interacts with a sender, they will perceive the emotional expressions of the sender. Once the emotional expression of the sender is realized, they will then transfer the perceived expression to their bodily expression. Facial mimicry such as this is an instinctive, reflex-like process. Mimicry may also stem from "mirror neurons" in our brains that allows us to mirror others' actions and emotions (Kameda and Hastie, 2015). In a study conducted by Giacomo Rizzolatti during the latter half of the 1980s, it was found that while observing the electrical activity in the brain of a monkey, it was found that the neurons fired when it observed the same actions performed by another monkey (Kameda and Hastie, 2015). This implied that mirror neurons allow us to learn through imitation. Additionally, herd behavior may take place as a result of various social norms. Herbert Simon believed this concept to embody people's tendency to depend on others' suggestions, recommendations, and information through varying social channels (Kameda and Hastie, 2015).

In financial markets, an investor participates in herd behavior when they have knowledge of others investing in a particular security. This will essentially influence and change their decision from not investing to investing in a particular asset. Bikhchandani and Sharma (2000) note one reason as to why investors may participate in such behavior is that others may know something about the predicted return of an investment that you do not. It may also be the case that investors have an intrinsic preference for conformity.

Two of the most common types of herding in financial markets are reputation-based and compensation-based herding. Firstly, reputation-based herding is the idea that if an investment manager is uncertain in their ability to pick the right stock, conformity with other investment professionals is seen as an alternative. This is done as a means of alleviating some uncertainty (Bikhchandani and Sharma, 2000). The investment manager who was able to make an investment decision is referred to as the sender. If the sender has properly done their research, they will produce informative signals. The manager who is basing their decisions on the behavior of others will simply be nothing more than pure noise, amplifying signals without adding any informative messaging to others. In regards to compensation-based herding, this form arises when an investment manager's compensation is dependent upon the performance of others (Bikhchandani and Sharma, 2000). These other investment professionals are known as a benchmark. If the benchmark's performance is considered to have been good as of late, then the agent is inclined to imitate the strategies of the benchmark, as there is an incentive to perform on par relative with the other investors.

As much effort as there's been in trying to support the idea that herding can be considered "rational", herd behavior usually creates "information cascades" to which market participants transmit false information, in turn causing negative externalities (Stracca, 2004). An example of a negative externality is when a polluter makes a decision based solely on the profit opportunity from production. This polluting producer does not account for the indirect costs of those harmed by their contamination (Helbling, 2020). Some of these indirect costs include decreased quality of life and higher health care costs. According to Helbling (2020), because the producer does not bear these indirect costs, it can be said that these social costs outweigh the private costs for the producer. In finance, information cascades are derived from two important features: path dependency and fragility (Stracca, 2004). Essentially, path dependency refers to how information is passed along throughout these cascades. If this information happens to be shallow, this can ultimately impact the fragility of the market. A herd that is based on very little information will send small shocks through the market causing a strong, destabilizing impact (Stracca, 2004).

3.3.6.1 Conformity Bias

Conformity bias ultimately serves as an extension of herd behavior. Conformity bias can be interpreted as the tendency of going along with group norms, displaying a lack of agency (Padlia, 2014). In a study conducted by Solomon Asch (1951), eight individuals were placed in a room where seven of them agreed in advance what their response to a certain question would be. The real participant was unaware this was happening and assumed that the other seven individuals were all participants as well. This specific participant would be the last to respond to each question. Every question asked had a clear, obvious answer (they had to see which line most closely resembled the target line). Asch found that in over 12 trials, roughly 75% of participants conformed at least once and in the control group where there was no pressure to conform, less than 1% of participants gave the wrong answer. The implication here is that while participants believed the answer given by everyone else was wrong, they still conformed to the other participants' choices because they either wanted to fit in with the group or because they felt the group was better informed than them.

3.3.6.2 The Fear of Missing Out (FOMO)

The fear of missing out, most commonly referred to as FOMO, arises from an abundance of choices in regards to social events and activities that is banded with uncertainty over the best choice (Milyavskaya et al., 2018). Unlike regret theory, FOMO can be experienced despite believing one has made the best available decision. For instance, when a college student decides to go on a date rather than to a fraternity party, they still might wonder what they missed at the party despite still enjoying their date (Milyavskaya et al., 2018). Social media tends to play a serious role in the study of FOMO as it provides easy access to real-time information about activities and events happening across various social networks (Prybylski et al., 2013). Individuals with high-levels of FOMO may find participation on social media platforms appealing as it has the ability to highlight opportunities to connect with others more easily. Despite the fact that individuals can now readily chat and meet, time is a limited resource which means people have to miss out on a substantial amount of other experiences made noticeable by social media (Prybylski et al., 2013). In a study conducted by Prybylski et al. (2013), the authors examined the role FOMO played in the lives of first-year college students. The participants were asked a series of questions in regard to their social lives and found students who attained high levels of FOMO frequently check social media platforms, such as inspecting their phone right after they wake up, before they sleep, or during meals. Prybylski et al. (2013) found that these same students would even check text messages and emails while operating a motor vehicle.

With people nowadays having higher levels of FOMO due to the heavy presence of social media, such a phenomenon may lead to herd behavior. According to Hershfield

(2020), if there are a group of investors who think tech stocks are on the rise because of their performance over the past few years along with the fact that they have seen other investors make substantial earnings from investing in these tech stocks, they may fear missing out on potential future gains. This is exactly what happened during the GameStop short squeeze of 2021. Costola et al. (2021) noted as trade volumes of the stock increased, more investors noticed the “buying meme stocks” signals on social media, particularly on WallStreetBets. Driven by FOMO, even more serious traders who do not usually engage with WallStreetBets started buying these stocks as well.

3.3.6.3 Herd Behavior on Robinhood and WallStreetBets

Just like any financial market around the world, the Robinhood platform is also home to herd behavior amongst its users. Knowing Robinhood has attracted many young, inexperienced investors, Nijboer (2021) set out to observe the increase in the volume of trading on the platform during COVID-19. Nijboer (2021) found that herd behavior on Robinhood is related with the user experience the platform provides. With the game-like atmosphere the app offers to its users, entry to the world of finance on Robinhood is extremely captivating. Nijboer (2021) notes that these individuals primarily invest in what is brought to their attention by the platform. Securities included in the “Top Movers” and “Most Popular” lists cause Robinhood users to primarily invest in these stocks. This exhibits Robinhood users to prefer higher priced securities with a feedback loop being created between stock prices and herding on the platform.

While users on Robinhood look for some of the most volatile and highly priced securities the app presents to them, WallStreetBets can be considered to be even more prominent in generating herd behavior. Sahlberg (2021) examined the GameStop short squeeze of 2021 in order to inspect the cause of herd behavior on WallStreetBets. FOMO was inferred to be one of the key factors behind the herding episode in January 2021. Sahlberg (2021) found there to be a strong indication that these Reddit users are much more likely to post their positive experiences from being in the stock market on WallStreetBets as opposed to their negative ones. When other users see the earnings of their social media peers, they too desire to start investing in that particular security as well. Similarly to investment managers in the previously mentioned compensation-based herding, Robinhood users who view their fellow traders successes on Reddit are inclined to imitate the strategies of this “benchmark”. However, the issue here is that WallStreetBets primarily contains content that is opinionated and the least bit factual (Sahlberg, 2021).

In analyzing the GameStop short squeeze further, Allen et al. (2021) observed the number of mentions of a particular stock on WallStreetBets and found they are closely associated with changes in that same stock’s price. The authors’ note short squeezes of the past have not been formed in quite this way before. The reason for this occurrence was due to the rising popularity of social media platforms over the past few years. Information on securities trading in the market, which starts on social media, is entirely separated from the news sources employed by professional stock market analysts to which they were unlikely to anticipate this short-squeeze event (Allen et al., 2021).

4. Methodology

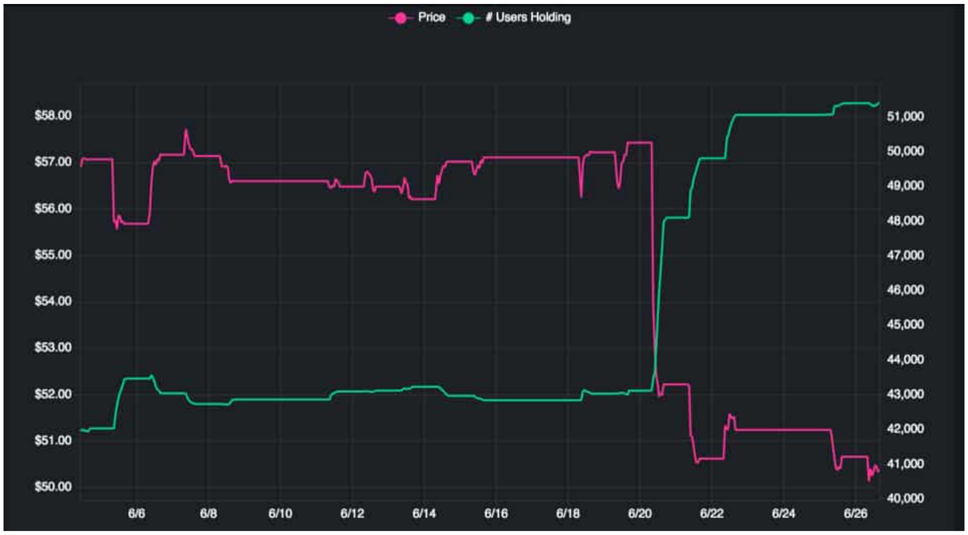
In an effort to analyze the behavioral traits of Robinhood users along with some of the biases investors are often susceptible to, this paper will be utilizing four separate econometric models and tests. I begin by testing for Granger causality amongst Robinhood investors, an important statistical concept that investigates patterns of correlation based on prediction. The second hypothesis aims to make a comparative analysis between the variances of a company's stock price and dividend price. The third hypothesis will analyze the impact loss aversion bias has on a firm's economic performance. Lastly, this project's final hypothesis attempts to examine the influence investor overconfidence has on the market performance of a company.

4.1 Testing for Granger Causality

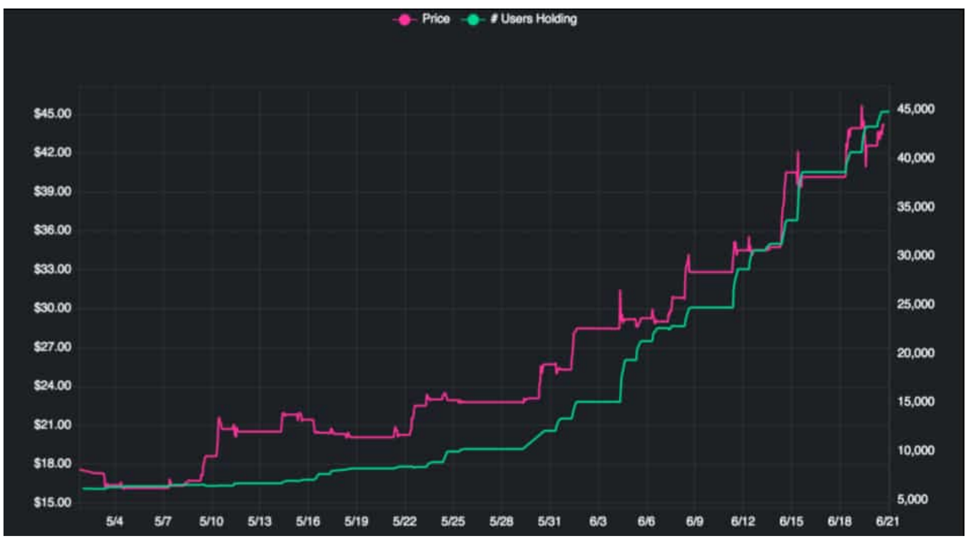
The first section of this chapter will be discussing whether the number of Robinhood users (*USERS*) holding a particular stock is influenced by a handful of different variables. There are three explanatory variables being analyzed for Granger causality: the closing price of a company's stock (*CLOSE*), the number of mentions of a particular stock on WallStreetBets (*MENTIONS*), and the market sentiment surrounding the discussions of a firm's stock on the subreddit (*SENTIMENT*). Before working through the methodology, model, and procedure, it is important to discuss what Granger causality is and how it relates to the investment strategies of Robinhood users.

Essentially, Granger causality is a statistical concept centered on the idea of prediction. To elaborate, it is a hypothesis test in establishing whether one time series is a factor in offering useful information for forecasting the data of another time series. One way to better explain this concept is with an example. Let's say that there is a rich city and a poor city, and each city has the ability to export a certain amount of goods each year. Given this scenario, the poor city wishes to break free from their financial struggles and attempts to do so by observing the strategies of the rich city, mainly in regards to exporting goods. In year one, the rich city exports, for instance, 500 goods. If the poorer city decides to follow the exporting strategies of the rich city, then one would assume that the poor city will export 500 goods in year two. If in year two the rich city decides to export 250 goods, then the poor city will export 250 goods in year three. So on and so forth. In this paper's case however, panel data is used instead of time-series data. The primary difference is that time-series focuses on a single firm at various time intervals while panel data centers on numerous firms during multiple time periods.

The procedure of determining the existence of causality is to test for significant effects of past values of x on the present value of y (Lopez and Weber, 2017). In this section, the dependent variable will remain constant throughout. The response variable in this case is $USERS$. *USERS* data is extracted from the *Robintrack* database, which was shut down in August 2020 because "the data [was being used] in ways that could mischaracterize the company as pandering to day traders" (Roberts, 2020). According to the *Robintrack* database, charts could be generated from the data in order to demonstrate the relationship between price and the number of Robinhood users holding a certain stock at a given time (which was a proxy for popularity). The purpose of using such data was to view trends and help in planning investments accordingly if one were using the Robinhood platform.



Traders buying the dip in SBUX (Robintrack): The above graph visually represents the concept of traders "buying the dip". This term simply refers to investors purchasing an asset after its price has decreased. Here, we see a lagged response from Robinhood traders in which more users purchase SBUX stock after its price has fallen.



Traders going full FOMO on IQ (Robintrack): The concept of FOMO was previously mentioned at the end of Chapter 3. Here, it is on full display in which the number of Robinhood users holding slightly lags behind the increase in the price of *IQ* stock. Robinhood users observe the price of the security continuously rising and feel that they will miss out on higher returns if they decide not to invest, hence the lag following the price hike.

Additionally, there will be three independent variables that will be used in order to test for Granger causality. The first is a stock's closing price, or $CLOSE$. The purpose of utilizing this predictor is to display sort of what is shown in the graphs above in that there is a relationship between the price of a firm's stock and the number of Robinhood users holding that same security. If this is the case in which the *USERS* time-series can be significantly predicted by observing the lagged values of the *CLOSE* time-series, it can be said that the *CLOSE* time-series "Granger causes" the *USERS* time-series. *CLOSE* data was retrieved from *Yahoo Finance.*

The second control variable that will be applied is the number of mentions of a particular stock on WallStreetBets on a given day. This is referred to as *MENTIONS* in the model. This data was extracted from *Quiver Quantitative* in which the database tracked how often users mentioned a particular stock on the subreddit. Using *MENTIONS* is an important variable to consider in the case of testing for Granger causality as a change in the number of mentions on the subreddit may lead to a change in the number of Robinhood users holding a particular stock. If this is the case, then such causality may explicitly demonstrate that the use of social media plays a serious role in offering financial information to Robinhood users.

The final input variable analyzed in testing for Granger causality is investor sentiment, or *SENTIMENT.* Data regarding investor sentiment was also selected from the *Quiver Quantitative* database. This variable measures the sentiment of the discussions taking place on WallStreetBets. Sentiment was calculated using the VADER method (a model used for text sentiment analysis that is sensitive to both polarity and intensity of emotion) which returns a score between -1 and 1, depending on the estimated negativity or positivity surrounding each post.

This paper utilizes the Dumitrescu and Hurlin (2012) procedure in testing for Granger causality in panel data. The Dumitrescu and Hurlin (2012) analysis tests whether past values of *x* are significant predictors of the current value of *y* in which the underlying regression between, for instance, closing price (CLOSE) and Robinhood users (*USERS*) would look something like this:

$$USERS_{i,t} = \alpha_i + \sum_{k=1}^{K} \gamma_{ik}\, USERS_{i,t-k} + \sum_{k=1}^{K} \beta_{ik}\, CLOSE_{i,t-k} + \varepsilon_{i,t}$$

Here, $USERS_{i,t}$ and $CLOSE_{i,t}$ are the observations of two stationary variables for firm *i* in period *t*. The lag order is represented by *K,* in which it is assumed to be identical for all companies in the sample. If the null hypothesis of the Dumitrescu and Hurlin (2012) is rejected, it is safe to assume that causality from *CLOSE* to *USERS* exists. The other predictor variables have models set up in a similar fashion.

4.2 Testing for Differences in Stock and Dividend Variances

In this section, the primary aim is to observe whether stock returns and dividends share equal volatilities, an important notion of standard finance theory and EMH. The hypothesis that stock returns and dividends should have differing volatilities was motivated by Shiller (2003) and Yang's (2019) research. Referencing back to Shiller (2003), it was found that the volatility of dividends was different when compared to the volatility of share prices. This happens to violate a key assumption of EMH. According to Yang (2019), stock return volatility has one extremely noteworthy feature. This is that volatility levels are much higher than those levels of dividend payments. As dividend payments come as periodic payments to the owners of a company's stock, most investors typically enjoy receiving such payments as they represent further return on their investments. The main draw to companies offering dividends is that they provide steady returns over time. In contrast, a company's stock itself will rise and fall in the market. Fundamentally, investing in firms that offer dividend payments are seen as much safer assets due to the fact they constitute as investments with guaranteed payouts.

Yang (2019) describes this concept in which stock prices generate higher volatility relative to dividend payouts as "the excess volatility puzzle". Yang (2019) also notes that loss aversion can help to explain this puzzle. Loss aversion generates a time-varying risk aversion in which individuals become more risk averse after hearing bad news and react inversely to good news. This section will directly quote Yang's (2019) example to better exhibit how a standard finance model with constant risk aversion demonstrates the exact same volatilities for stock prices and dividends. Let's say, for instance, a particular stock was trading at a price of $33.67 per share with a $1.00 dividend payment. This stock has an equal chance of either increasing by 7% or decreasing by 5%. Thus, the average dividend growth rate would be $\mu_D = 0.5 * (7\% - 5\%)$, or 1%. The volatility of the dividend growth rate would then be $\sigma_D = 0.5 * (7\% + 5\%)$, or 6%. According to Yang (2019), a traditional model only considers constant risk aversion which, in turn, asserts there to be a constant discount rate. Yang's (2019) illustration goes on to utilize a standard textbook Gordon model (a model used to dictate an investment's intrinsic value based on a future series of dividends growing at a constant rate) to determine the stock's price. The formula is as follows:

$$price\ of\ stock = \frac{(1 + dividend\ growth\ rate\mu_D) * current\ dividend}{discount\ rate - average\ dividend\ growth\ rate\ \mu_D}$$

Supposing the discount growth rate is 4% and that the dividend news for the year is good (meaning the stock's underlying firm issues a dividend of \$1.07), the standard Gordon formula assumes the stock price to rise to $\frac{(1+1\%)\$1.07}{4\%-1\%} = \$36.07$. The return for this stock, given that the dividend news for the year is good, is $r_u = \frac{\$36.02+\$1.07}{\$33.67} - 1 \approx 10\%$. Now, assuming the dividend news for the year is bad, dividend payments drop to \$0.95. When applying the Gordon formula once more, the stock price drops to $\frac{(1+1\%)\$0.95}{4\%-1\%} = \$31.98$. Given this scenario, stock return comes out to be $r_d = \frac{\$31.98+\$0.95}{\$33.67} - 1 \approx -2\%$. Given the returns for when there is both good and bad news, we can now calculate return volatility to be $0.5 * (r_u - r_d) = 6\%$. Thus, standard theory predicts that stock return volatility will be the same as the volatility of a company's dividend growth rate.

Contrary to these conventional beliefs, behavioral finance asserts that once risk attitudes become time varying, the results provided will be inconsistent with the volatility outcomes generated by the standard model. According to Yang (2019), with good news, a typical investor becomes less risk averse. When the news is good, the discount rate is said to be 3.5%. In this same scenario, when bad news arises, an investor becomes more risk averse and thus the discount rate rises to 4.5%. If this is the year a company is doing well, and in turn issuing a dividend payment of \$1.07, the stock prices rises to $\frac{(1+1\%)\$1.07}{3.5\%-1\%} = \$43.23$. Accordingly, the stock return will be $r_u = \frac{\$43.23+\$1.07}{\$33.67} - 1 \approx 36\%$.

Next, assuming the news for this year is bad and, consequently, dividend payments fall to \$0.95, a firm's predicted stock price drops to $\frac{(1+1\%)\$0.95}{4.5\%-1\%} = \$27.41$ and the total stock return becomes $r_d = \frac{\$27.41+\$0.95}{\$33.67} - 1 \approx -16\%$. Given the two varying stock returns, both of which are based on the disposition of company news, return volatility is now $0.5 * (r_u - r_d) = 24\%$. This is indeed greater than the dividend volatility of 6% produced under the standard finance model.

In accordance with this idea of volatility and loss aversion presented by Yang (2019), this paper will be finding and comparing the variances of a company's stock price and dividend payouts. If the variance of the *CLOSE* variable is larger than the variance of the *DIVIDEND* variable, then the assumption is that the behavioral finance approach checks out. Thus, this paper predicts:

$$\sigma^2 CLOSE \succ \sigma^2 DIVIDEND.$$

Two separate regressions will be run between a stock's closing price (*CLOSE*) and a firm's ticker (*TICKER*) and between a stock's dividend payout (*DIVIDEND*) and a firm's ticker (*TICKER*). This will help demonstrate that each closing price and dividend payout belong to a specific firm in the sample. The residuals of the *CLOSE* and *DIVIDENDS* variables are then run through a variance-comparison test. Data regarding dividend history came from the *Nasdaq* database.

4.3 Testing for the Impact of Loss Aversion

The methodology of testing for both the impact of loss aversion and overconfidence biases was inspired by Bouteska and Regaieg's (2018) research. In their study, Bouteska and Regaieg (2018) found both loss aversion and overconfidence to significantly impact a firm's economic and market performances. The implication is that investor sentiment and company performance are strongly correlated. The chief objective of their study was to demonstrate how the significance of investor biases impacts how a firm operates. The loss aversion model in this paper tests for the impact such cognitive error has on a firm's economic performance. The overconfidence model discussed in the following section will examine the impact investor overestimation has on a company's market performance.

To start, Bouteska and Regaieg (2018) utilized a panel fixed-effects model in their research as a means of demonstrating the relationship between loss aversion and economic performance. Fixed-effects assume that an entity may be manipulating the explanatory variables of a model to which the effect of time-invariant characteristics are removed (Torres-Reyna, 2007). Applying a fixed-effects regression to the loss aversion model in Bouteska and Regaieg's (2018) study makes sense because the authors wish to observe the results of economic performance across different sectors (i.e. the industry sector, service sector, etc.). While this paper looks to do the same and separates firms by sector, it may be more beneficial to apply random-effects. The rationale behind the random-effects model is that the variation across entities is assumed to be random and uncorrelated with the independent variables included in the model (Torres-Reyna, 2007). While the random-effects model is foreseen to be the ideal model for use in this section, a Hausman test was run to check whether fixed- or random-effects is appropriate.

In building Bouteska and Regaieg's (2018) loss aversion model, the response variable *ROA,* or return on assets for a company, is identified to be the economic performance measure of a firm. Essentially, *ROA* is the ratio between a firm's net income and total assets. *ROA* was selected by Bouteska and Regaieg (2018) as it is frequently used as a proxy of firm economic performance in financial literature. Furthermore, *ROA* exhibits how profitable a company's assets are in generating revenue. Return on assets can implicitly measure management performance and may also inform investors on how much a firm can recover from the value of its resources. Quarterly *ROA* data for each company observed in the dataset was extracted from the *MacroTrends* database.

The first independent variable in the loss aversion model is *SIZE,* which ultimately communicates the magnitude of a company. Asset turnover ratio was used as a proxy of firm size. Firm turnover ratio is essentially the amount of assets a business replaces in relation to its sales. A company's turnover ratio may serve as a satisfactory indicator of efficiency, or how well a business applies its assets as a means of generating revenue. Generally, for larger firms, a good turnover ratio lies anywhere between 0.25 and 0.5. For instance, if a company possesses a ratio of 0.5, it can be said that each dollar of that firm's assets brings about 50 cents worth of sales. Data regarding a firm's asset turnover ratio was taken from the *CSIMarket* database.

The second explanatory variable of Bouteska and Regaieg's (2018) loss aversion model is *MCAP,* or market capitalization. *MCAP* takes note of the total market value of a firm's shares outstanding. Essentially, it measures the value of a company set by the market (Henricks, 2019). *MCAP* often serves as an important indicator for investors to notice rather than simply looking at a company's share price. A firm with a high share price may be less valuable than a company that has a lower share price but more shares outstanding. Market cap data was gathered from *Yahoo Finance.*

The last control variable in Bouteska and Regaieg's (2018) loss aversion model is *LA,* or the loss aversion variable. In this case, the proxy for *LA* was the percentage variation of transaction volume. Ultimately, transaction volume of a firm is the total number of shares of a stock being traded throughout the market. According to Gomes

(2003), loss-averse investors tend to generate a significant degree of trading volume. Gomes (2003) finds that when loss-averse investors are following a portfolio insurance strategy (essentially a hedging method utilized by loss-averse investors to limit losses), then trading volume is positively correlated with stock return volatility. It has also been mentioned in Genesove and Mayer (2001) that loss aversion helps to explain why trading volume falls when prices decline. Investors perceive low prices as lower returns, or losses, to which trading volume significantly declines during such periods. Data regarding company trading volume was extracted from *Yahoo Finance.* Given each of the variables previously mentioned, the loss aversion model is as follows:

$$ROA_{i,t} = \beta_1 SIZE_{i,t} + \beta_2 MCAP_{i,t} + \beta_3 LA_{i,t} + \alpha + u_{i,t} + \varepsilon_{i,t}$$

According to Bouteska and Regaieg's (2018) loss aversion hypothesis, the prediction is that the coefficient of the *LA* variable will be significant. This suggests that loss aversion bias practiced by investors impacts a firm's *ROA.* The more investors are loss averse, the more the performance indicator *ROA* will be negatively influenced. In accordance with Bouteska and Regaieg's (2018) study, every firm in this sample will be categorized into specific sectors. A firm will either be placed into the *Industrial* sector, the *Service* sector, or into the *Both* category. In the case of this paper, a company that is in the business of manufacturing products, for instance *Boeing* (BA) which builds and sells airplanes, rockets, etc., will be classified as being a part of the *Industrial* sector. *American Airlines* (AAL) on the other hand does not manufacture aircrafts, but rather provides air transport services for traveling passengers and cargo. Therefore, the company is classified as being part of the sample's *Service* sector. It is important to note that a company that does not physically produce goods but produces entertainments, such as original movies in the case of *Netflix* (NFLX), are classified as *Service* industry firms. Lastly, a company such as *Disney* (DIS) is thought to be a part of both the *Industrial* sector and *Service* sector seeing the company produces toys and apparel while also providing guest services at their theme parks around the world. Thus, firm's that fall under this category are associated with *Both* sectors in the sample.

4.4 Testing for the Impact of Overconfidence

Once again, the model found in this section will be based on the work of Bouteska and Regaieg (2018). According to the authors, overconfidence bias will significantly impact the market performance of a firm. This paper hopes to reproduce their findings in seeing if overconfidence bias positively or negatively influences a company's market performance.

Firstly, we have the response variable, *Tobin's Q,* which serves as an indicator of stock market performance. The *Tobin's Q* ratio is simply the ratio between a firm's stock market value and the value of its fixed capital replacement. The goal of this ratio is to demonstrate the relationship between market valuation (stock price) and the intrinsic value (replacement costs) of a company. For the most part, *Tobin's Q* is a simple concept to interpret. The premise behind the ratio is that a firm should be worth the same value as their assets. When the *Tobin's Q* of a firm is less than 1, it can be said that that particular company is undervalued. Contrarily, a *Tobin's Q* greater than 1 exhibits an overvalued company, one that is estimated to be worth more than the cost of its assets. *Tobin's Q* data was extracted from the *Ycharts* database.

The first control variable in Bouteska and Regaieg's (2018) overconfidence model is *SIZE* and is again represented by a firm's asset turnover ratio. The second independent variable in the model is *NE,* or a company's net earnings. A company's net income is derived from the difference between firm revenues and costs. *NE* may serve as a useful measure for investors as it is typically important to know how much revenue exceeds the costs of a firm. *NE* data for the companies in the sample was obtained from *MacroTrends*.

The final control variable used in Bouteska and Regaieg's (2018) overconfidence model is the *OC* variable. The percentage change of shares held by shareholders serves as a proxy for *OC*. Shares outstanding refers to all the shares of a firm that have been authorized, issued and purchased by investors. Bouteska and Regaieg (2018) note that extraordinary events in society and throughout the market, such as a war or inflation, may alter the overconfidence levels of an investor. Thus, when a change in a firm's shares outstanding occurs, either increasing or decreasing in a remarkable manner, it reflects a reaction in investor confidence levels. For instance, when there is a positive change in the number of shares outstanding, this may signify overconfidence, especially during a period when a firm has a low *Tobin's Q* and low *NE.* Data regarding a firm's shares outstanding was also provided by the *MacroTrends* database. Thus, the overconfidence model is as such:

$$Tobin's\ Q_{i,t} = \beta_1 SIZE_{i,t} + \beta_2 NE_{i,t} + \beta_3 OC_{i,t} + \alpha + u_{i,t} + \varepsilon_{i,t}$$

Once again, firms will be separated based on sector in which the primary goal is to replicate Bouteska and Regaieg's (2018) results, or at the very minimum examine whether investor overconfidence has the ability to either negatively or positively impact a firm's market performance in some manner.

4.5 The Sample

The sample set chosen for this paper was inspired by an article published by Natasha Dailey (2021) discussing the 50 most popular stocks among retail investors trading on Robinhood. This paper observes 31 of these companies. The primary reason for not using all 50 firms is due to the fact that some companies lacked sufficient data. These firms are listed below in Table 1. The sample period ranges from August 1, 2018 until August 13, 2020. This time period was chosen because this was the span in which the *Robintrack* was still running.

Table 1: List of Firms in Sample

Name of Firm	Firm Ticker
Apple	AAPL
Amazon.com	AMZN
Boeing Co	BA
Alibaba	BABA
Bank of America	BAC
Carnival Corp	CCL
Delta Airlines	DAL
Walt Disney Co	DIS
Meta Platforms	FB
FuelCell Energy	FCEL
General Electric	GE
General Motors	GM
GameStop Corp	GME
GoPro Inc	GPRO
Coca-Cola Co	KO
Moderna Inc	MRNA
Microsoft Corp	MSFT
Netflix Inc	NFLX
Nio Inc	NIO
Nokia Oyj	NOK
Nvidia Corp	NVDA
Pfizer Inc	PFE
Plug Power Inc	PLUG
Starbucks Inc	SBUX
Snap Inc	SNAP
Tesla Inc	TSLA
Twitter Inc	TWTR
United Airlines	UAL
Uber Inc	UBER
Workhorse Inc	WKHS

5. Results

This chapter will be presenting the results from the Granger causality and variance-ratio tests. Additionally, the outcomes of both panel regressions will be discussed in detail. Descriptive and summary statistics belonging to each section can be found in the Appendix.

5.1 Granger Causality Results

5.1.1 Descriptive Statistics

Before examining the results produced under the Granger causality test, it is important to note some of the descriptive statistics regarding the variables mentioned in the first section of Chapter 4. Appendix Table A1 displays the 31 companies used in this sample along with the total observations, average, standard deviation, minimum, and maximum number of *USERS, MENTIONS, SENTIMENT,* and *CLOSE* for each firm over the sample period. There are a couple key takeaways from the statistics found in this table. The first is that the company with the largest average number of Robinhood users over the sample period was AAPL (257,561.00) while the company with the lowest average number of users was PFE (38,768). The firm with the highest average number of mentions on WallStreetBets was TSLA (106.129) while the firm with the lowest average number of mentions was GRPO (1.697581). Lastly, the company with the highest average closing price over the sample period was AMZN ($1952.194) while the firm with the lowest average closing price belonged to PLUG ($3.151). Moving on to Appendix Table A2, this figure exhibits all the same summary statistics found in Table A1, but this time for all observations in the sample, being not split by firm. On average, there were roughly 129,241 Robinhood users investing in a particular stock across all firms at a given time. The mean closing prices for all of the stocks in the sample came out to $138.002. The average number of mentions on WallStreetBets for all firms in the dataset was about 30.97 with the average market sentiment of such discussions on WallStreetBets equaling to .053.

5.1.2 Granger Causality Analysis

Table 2: Dumitrescu & Hurlin Granger non-causality test results [NumberofUsers, ClosingPrice]
Lag order: 1 W-bar = 61.7943 Z-bar = 239.3472 (p-value* = 0.0000, 95% critical value = 0.1772) Z-bar tilde = 238.2047 (p-value* = 0.0000, 95% critical value = 0.1870) H0: ClosingPrice does not Granger-cause NumberofUsers. H1: ClosingPrice does Granger-cause NumberofUsers for at least one panelvar (FirmTicker). *p-values computed using 1 bootstrap replications.

Table 3: Dumitrescu & Hurlin Granger non-causality test results [NumberofUsers, Mentions]
Lag order: 1 W-bar = 144.1406 Z-bar = 563.5450 (p-value* = 0.0000, 95% critical value = 1.3447) Z-bar tilde = 560.8693 (p-value* = 0.0000, 95% critical value = 1.3489) H0: Mentions does not Granger-cause NumberofUsers. H1: Mentions does Granger-cause NumberofUsers for at least one panelvar (FirmTicker). *p-values computed using 1 bootstrap replications.

Table 4: Dumitrescu & Hurlin Granger non-causality test results [NumberofUsers, Sentiment]
Lag order: 1 W-bar = 0.5041 Z-bar = -1.9525 (p-value* = 0.0000, 95% critical value = 0.4383) Z-bar tilde = -1.9538 (p-value* = 0.0000, 95% critical value = 0.4256) H0: Sentiment does not Granger-cause NumberofUsers. H1: Sentiment does Granger-cause NumberofUsers for at least one panelvar (FirmTicker). *p-values computed using 1 bootstrap replications.

To start by observing Table 2, these are the results regarding whether or not a firm's closing price (*CLOSE*) Granger-causes the number of Robinhood users holding that same company's stock (*USERS*). The most important statistic to observe from the results is the value produced by Z-bar. Seeing the *p*-value of the Z-bar statistic was zero and that the Z-bar value itself was significantly larger than the 95% critical value, it is safe to reject the null hypothesis (*H0*) and accept the alternative, concluding that a stock's price effects the number of Robinhood users. Table 3 offers the results regarding Granger causality between *USERS* and *MENTIONS.* Once again, the *p*-value of the Z-bar statistic was zero and the value of the Z-bar statistic itself was significantly larger than the 95% critical value generated from the bootstrap procedure. Thus, it is inferred that the number of mentions regarding a particular stock on the WallStreetBets subreddit Granger-causes the number of Robinhood users holding that same stock. Lastly, this section looked to examine whether the market sentiment surrounding the discussions happening on WallStreetBets ultimately impacted the number of Robinhood users holding. In Table 4, the *p*-value of the Z-bar statistic was once again zero. Also, the value of the Z-bar statistic happened to be larger than the 95% critical value once more (the Z-bar statistic is in absolute terms). Therefore, we reject the null hypothesis and presume that market sentiment, in regards to investor outlook on WallStreetBets, Granger-causes the number of Robinhood users holding the discussed stock.

To briefly recap this section's findings, all of the results found in the Dumitrescu & Hurlin (2012) Granger non-causality tests suggest that the closing price of a stock (*CLOSE*), the number of mentions of a stock on WallStreetBets (*MENTIONS*), and the market sentiment of a stock being discussed on WallStreetBets (*SENTIMENT*) all influence and Granger-cause the number of Robinhood users holding that particular stock (*USERS*). These results suggest Robinhood users tend to observe such factors when planning to invest in a company and may use such variables as proxies for performance. Whether or not this is the most satisfactory way of constructing an optimal investment strategy is still up for debate.

There are also a few implications in relation to behavioral finance that arise from these results. Firstly, they suggest that Robinhood users are susceptible to herd behavior and furthermore, conformity bias and FOMO. Given the fact a change in *USERS* is Granger-caused by *MENTIONS* and *SENTIMENT,* this may suggest Robinhood investors tend to closely follow the sentiment of posts on WallStreetBets. Based on such sentiment, Robinhood users then make their decision on whether to buy or sell a particular security mentioned on the subreddit. The results also imply the use of the representativeness heuristics during their decision-making process. Investors using past trends of a stock to make investment decisions is a clear indication of an investor practicing the representativeness heuristic, which is exactly what is displayed in Table 2.

5.2 Results of Stock-Dividend Variance Comparison

5.2.1 Descriptive Statistics

Before engaging with the regression and variance-ratio results, it is important to briefly discuss some of the descriptive statistics surrounding the closing prices and dividend amounts of the companies in the sample. Starting with Appendix Table A3, out of the 31 companies in the sample only 15 offered dividend payments. From August 1, 2018 to August 13, 2020, a firm, on average, had about 6.5 dividend distribution periods. Over the sample duration, AMZN had the highest average stock price at $1961.60 and FCEL had the highest average dividend payout at $1.96. FCEL also held the lowest average stock price over the sample at an average price of $1.81 while the lowest average dividend payout belonged to GE ($0.03). Lastly, AMZN was the firm with the highest standard deviation (380.525) in stock price and FCEL had the lowest (.734). In regards to Appendix Table A4, something to note is that throughout the entire sample, the average closing price for all firms was $138.00 while the average dividend amount for the 15 companies offering such payments was $0.46.

5.2.2 Regression and Variance-Ratio Analysis

Table 5: Regression results [ClosingPrice] by FirmTicker

ClosingPrice	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Ticker Symbol of C~	0	.	.	.	.	.	
AAPL	32.813	4.726	6.94	0	23.55	42.075	***
AMZN	1934.019	4.726	409.23	0	1924.757	1943.282	***
BA	284.792	4.726	60.26	0	275.53	294.055	***
BABA	156.205	4.726	33.05	0	146.942	165.467	***
BAC	.706	4.726	0.15	.881	-8.556	9.969	
CCL	14.352	4.814	2.98	.003	4.917	23.787	***
DAL	21.524	4.726	4.55	0	12.262	30.787	***
DIS	95.718	4.726	20.25	0	86.456	104.981	***
FB	157.429	4.726	33.31	0	148.166	166.691	***
FCEL	-25.763	6.373	-4.04	0	-38.254	-13.272	***
GE	48.405	4.726	10.24	0	39.143	57.668	***
GM	6.233	4.726	1.32	.187	-3.03	15.495	
GME	-19.882	4.777	-4.16	0	-29.245	-10.518	***
GPRO	-22.589	4.726	-4.78	0	-31.852	-13.327	***
KO	21.987	4.726	4.65	0	12.725	31.25	***
MRNA	2.04	5.088	0.40	.689	-7.933	12.013	
MSFT	113.471	4.726	24.01	0	104.208	122.734	***
NFLX	325.135	4.726	68.80	0	315.872	334.398	***
NIO	-22.491	4.795	-4.69	0	-31.89	-13.092	***
NOK	-22.749	4.726	-4.81	0	-32.012	-13.486	***
NVDA	29.175	4.726	6.17	0	19.912	38.438	***
PFE	10.928	4.726	2.31	.021	1.666	20.191	**
PLUG	-24.398	4.726	-5.16	0	-33.66	-15.135	***
SBUX	48.022	4.726	10.16	0	38.759	57.285	***
SNAP	-14.103	4.726	-2.98	.003	-23.365	-4.84	***
TSLA	65.244	4.726	13.81	0	55.982	74.507	***
TWTR	6.169	4.726	1.31	.192	-3.094	15.431	
UAL	46.306	4.726	9.80	0	37.044	55.569	***

UBER	6.211	5.4	1.15	.25	-4.372	16.794	
WKHS	-21.575	4.726	-4.57	0	-30.838	-12.313	***
Constant	27.577	3.342	8.25	0	21.027	34.127	***

Mean dependent var	138.002	SD dependent var	359.337
Overall r-squared	0.957	Number of obs	14825
Chi-square	327328.262	Prob > chi2	0.000
R-squared within	0.000	R-squared between	1.000

*** *p*<. 01, ** *p*<. 05, * *p*<. 1*

Table 6: Regression results [Dividends] by FirmTicker

Dividends	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Ticker Symbol of C~	0	.	.	.	.	.	
AAPL	.672	.025	26.50	0	.623	.722	***
CCL	.065	.025	2.56	.01	.015	.115	**
DAL	.4	.026	15.26	0	.349	.451	***
DIS	.271	.026	10.36	0	.22	.323	***
FB	.78	.034	23.05	0	.714	.846	***
FCEL	1.86	.026	70.96	0	1.809	1.911	***
GE	-.074	.026	-2.83	.005	-.126	-.023	***
GPRO	.28	.034	8.27	0	.214	.346	***
KO	.28	.026	10.68	0	.229	.331	***
MRNA	.3	.026	11.45	0	.249	.351	***
MSFT	.374	.025	14.73	0	.324	.423	***
PFE	-.055	.039	-1.40	.162	-.132	.022	
PLUG	.26	.025	10.24	0	.21	.31	***
SBUX	.059	.025	2.31	.021	.009	.108	**
UBER	.279	.025	10.98	0	.229	.328	***
Constant	.1	.019	5.40	0	.064	.136	***

Mean dependent var	0.462	SD dependent var	0.455
Overall r-squared	0.990	Number of obs	105
Chi-square	8875.816	Prob > chi2	0.000
R-squared within	0.000	R-squared between	1.000

*** *p*<. 01, ** *p*<. 05, * *p*<. 1*

Table 7: Variance ratio test

Variable	Obs	Mean	Std.	err.	Std.
residu~CP	14,825	0.000	0.614	74.723	-1.203
residu~DV	105	0.000	0.004	0.045	-0.009
Combined	14,930	0.000	0.609	74.460	-1.194

H0: ratio = 1   Degrees of freedom = 14824, 104

Ha: ratio < 1	Ha: ratio! = 1	Ha: ratio > 1
Pr (F < f) = 1.0000	2*Pr (F > f) = 0.0000	Pr (F > f) = 0.0000

Table 5 displays the results from the regression model between a firm's ticker and that same company's closing price. Given the results of the *R*-squared in this regression, it can be said that a firm's ticker symbol can explain roughly 95% of the variation in the closing prices of a stock in the dataset. Observing Table 6, the results found that a firm's ticker symbol accounted for nearly 99% of the variation in the payouts of dividends. The *R*-squared values of both of these regressions are not surprising as, clearly, both the price of a stock and dividend payouts are directly correlated to the company they belong to.

Once both of these regressions were run, residuals were obtained in order to test the equality of variances between *CLOSE* and *DIVIDEND* data. Remember, standard finance predicts that the variance of a stock's return is equal to the volatility of dividend payouts. The reason for this is because investors in the standard model do not react to good or bad news about a firm. According to Yang (2019), behavioral finance accounts for such investor reactions in which traders will alter their discount rates based on the type of news they hear. If the variance of the closing price residuals were to be equal to the variance of the dividend payout residuals, we would then accept the standard finance hypothesis. The main draw to companies offering dividends is that they provide steady returns over time, while stocks are simultaneously rising and falling in the market. The implication is that the standard model assumes an investor to treat the volatility of both stock prices and dividends to be the same in which they would be indifferent between choosing to invest in a company that offers dividends and one that does not. Behavioral finance on the other hand insists that investors modify their discount rates in reaction to varying types of financial news. In turn, the volatility between dividends and stock returns will differ. This was essentially the aim of the variance ratio test: to see if the behavioral approach, $\sigma^2 CLOSE > \sigma^2 DIVIDEND$, is correct in debunking standard finance theory and EMH.

In Table 7, when running the variance-ratio test "*H0*: ratio = 1" represented the null hypothesis, or the prediction that the variances of the two sets of residuals will be equal to one another. This is the hypothesis of the standard model. Given the *p*-value for this hypothesis is zero, it is safe to say we can reject the null. We can reject the hypothesis that the variances of a stock's closing price and a firm's dividends are identical and accept the alternative in which the two investments offer differing variances. This goes back to the point made under behavioral finance in which a risk-averse investor bases their decisions off of financial news and more importantly, risk. We can assume that an investor practicing risk-aversion will ultimately want to refrain from investing in riskier securities, for instance stocks, as they display much higher levels of volatility (which essentially conveys higher levels of risk). They rather favor purchasing safer assets, such as investing in companies that offer dividends, as there are much lower levels of volatility (which infers lower levels of risk).

5.3 The Impact of Loss Aversion

5.3.1 Descriptive Statistics

Prior to interpreting the results from the panel regression, it would be helpful to discuss some key descriptive statistics regarding the variables used during this analysis. Observing Appendix Table A5, the firm with the highest positive average *ROA* belonged to NVDA (.231) while PLUG possessed the highest negative average *ROA* throughout the sample period (-2.245). The firm with the highest average percentage variation of transaction volume (*LA*) was NIO (262.214) while the companies with the highest average turnover ratio (*SIZE*) and market cap (*MCAP*) were GME and MSFT respectively. Moving to Table A6, the mean *ROA* of all companies in the sample from August 1, 2018 to August 13, 2020 was approximately -0.149 meaning, on average, most firms are not able to utilize their assets sufficiently enough to generate a profitable return. The average asset turnover ratio of all firms in the dataset came out to .667 while the average percentage variation in transaction volume for all companies in the sample was 48.6%.

5.3.2 Random-Effects Regression Analysis

Table 8: Hausman specification test [Loss Aversion]

	Coef.
Chi-square test value	1.923
P-value	.75

Table 9: Random-effects regression results [ROA, SIZE, MCAP, LA]

ROA	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
SIZE	.239	.213	1.12	.263	-.18	.657	
MCAP	0	0	1.33	.185	0	0	
LA Industrial	-.005	.001	-3.86	0	-.008	-.003	***
LA Service	0	.001	0.27	.784	-.001	.001	
LA Both	0	.003	0.04	.965	-.005	.005	
Constant	-.327	.184	-1.78	.075	-.687	.033	*

Mean dependent var	-0.161	SD dependent var	1.297
Overall r-squared	0.111	Number of obs	184
Chi-square	.	Prob > chi2	.
R-squared within	0.051	R-squared between	0.242

*** *p*<.01, ** *p*<.05, * *p*<.1

In testing for whether the results of the fixed- or random-effects model would be more applicable to observe, the Hausman specification results found the *p*-value to be 0.7500, demonstrating insignificance and thus implying that the random-effects model should be used in analyzing regression results (as seen in Table 8). Table 9 displays the panel regression results for when random-effects are in place. To start, the *R*-squared found in

Table 9 suggests that the loss aversion model is able to explain roughly 11% of the variation in the *ROA* of firms in this sample. Examining the coefficients of each predictor variable, only one appeared to be statistically significant, and that was the percentage variation in transaction volume of *Industrial* sector companies, or, the level of loss aversion practiced by traders investing in *Industrial* sector firms.

The correlation coefficient between *Industrial* sector loss aversion and a firm's return on assets was roughly -0.05, or for a 1% increase in the variation of an industrial firm's transaction volume, that same firm's return on assets decreased by about 5%. Generally, the higher a company's *ROA*, the better that firm's economic performance is. In relation to Bouteska and Regaieg's (2018) study, the results from this paper were able to partially replicate those found in their research. This analysis was able to demonstrate that loss aversion negatively affects a firm's asset returns (*ROA*) and even more so, it illustrated that this impact was statistically significant within the *Industry* sector. Unlike Bouteska and Regaieg's (2018) findings however, the results in this paper was not able to demonstrate a statistically significant relationship between *ROA* and *LA* in the *Service* sector or for firms that were identified to be a part of *Both* sectors. One reason for this may be chalked up to insufficient-data bias as the sample used in Bouteska and Regaieg's (2018) research was significantly larger than the one used in this project. The amount of firms in this paper's *Industrial* sector also happened to be larger than the amount of companies found in the other two sectors. In turn, insufficient-data bias may not have allowed for the kind of confidence needed to produce the desired outcomes of this model. Despite not being the most ideal end result, this test was at the very least able to demonstrate some sort of relationship between a firm's economic performance indicator, in this case return on assets, and loss aversion bias. In conclusion, the negative impact of loss aversion on the *ROA* of *Industrial* firms demonstrates that the more an investor is loss-averse on whether to invest in a firm, the lower that company's economic performance will be. More precisely, *ROA* of industrial firms evolves with the loss aversion of investors, occurring in opposite directions.

5.4 The Impact of Overconfidence

5.4.1 Descriptive Statistics

Before investigating the results from this panel regression, it is important to briefly discuss some descriptive statistics regarding the dependent and independent variables of the overconfidence model mentioned at the end of Chapter 4. To start, the firms with the highest average Tobin's Q, asset turnover ratio (proxy for firm size), net earnings, and positive percentage change of shares outstanding (proxy for overconfidence) were NFLX, GME, AAPL, and NIO respectively as seen in Table A7. Moving on to Appendix Table A8, the summary statistics exhibit that on average, Tobin's Q for all firms included in the sample was roughly 2.43. Typically, a Tobin's Q over 1 suggests that a firm is worth more than the costs of its assets, or more specifically, their values are overestimated. Thus, it is clear that a large portion of the firms in this sample is overvalued. Next, it is important to mention that on average, the percentage change in shares outstanding was about 2.5% for all firms in the dataset. The average net earnings for the 31 firms in the sample were about $1.7 billion while the mean asset turnover ratio for all companies was 0.702.

5.4.2 Fixed-Effects Regression Analysis

Table 10: Hausman specification test [Overconfidence]

	Coef.
Chi-square test value	14.749
P-value	.0053

Table 11: Fixed-effects regression results [TobinsQ, SIZE, NEUSD, OC]

TobinsQ	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
SIZE	-.06	1.566	-0.04	.969	-3.157	3.037	
NEUSD	0	0	0.04	.964	0	0	
OC Industrial	-.294	.04	-7.32	0	-.374	-.215	***
OC Service	-.002	.023	-0.07	.948	-.048	.045	
OC Both	.003	.082	0.04	.968	-.159	.166	
Constant	2.683	1.076	2.49	.014	.554	4.811	**

Mean dependent var	2.474	SD dependent var	2.929
R-squared	0.282	Number of obs	170
F-test	10.745	Prob > F	0.000
Akaike crit. (AIC)	632.985	Bayesian crit. (BIC)	648.664

**** p<.01, ** p<.05, * p<.1*

According to Bouteska and Regaieg (2018), the hypothesis surrounding the overconfidence model, as seen in Chapter 4, predicts that the coefficient of the *OC* variable will be significant. The purpose of the model is to examine whether overconfidence bias has an effect on the market performance of U.S. companies. It is important to note that when running the Hausman specification test this time, it was suggested that the fixed-effects panel regression results were the optimal values for analysis (seen in Table 10). The first thing to notice in Table 11 is the *R*-squared for the overconfidence regression model. It was found that the overconfidence model accounted for about 28% of the variation in a company's market value relative to its assets' replacement cost, better known as Tobin's Q.

Looking at the *p*-value for overconfidence by sector, it was once again apparent that the only sector (and only control variable for that matter) to demonstrate statistical significance was the *OC* of individuals investing in firms that belong to the *Industry* sector. The *OC Industrial* variable had a coefficient of -0.294, meaning a 1% increase in the variation of an industrial firm's shares outstanding would decrease the Tobin's Q for that company by approximately 29.4%.

To compare these results with those of Bouteska and Regaieg (2018), the authors found that the impact of overconfidence on a firm's Tobin's Q can be either positive or negative depending on which sector the company belonged to. Seeing this project was only able to discover the impact of overconfidence in the *Industrial* sector, it would be impractical to make assumptions about the impact of overconfidence bias on the *Service* sector. Furthermore, Bouteska and Regaieg's (2018) research found the percentage change in a firm's shares outstanding to positively impact the market valuation of the *Industrial* sector companies in their sample. However, this paper finds the relationship between investor overconfidence and *Industrial* firms' Tobin's Q to be negative, contrary to the authors' findings. Thus, it is concluded that the market performance of a firm is negatively impacted by investor overconfidence, at least in the *Industry* sector. Once again, these differing results may be a consequence of insufficient-data bias as there were much fewer firms being analyzed in this project's sample than in the one utilized by Bouteska and Regaieg (2018).

6. Discussion

From Robinhood traders to institutional investors, any market participant is susceptible to cognitive error. It has been found that such behavioral biases have been a primary cause of the stock market's long running history with anomalies, bubbles, and crashes. While standard finance theory has been the most widely accepted and used financial doctrine for quite some time, primarily because of the theory's simple ideology regarding price prediction and rationality amongst investors, it neither gives credence to investor irrationality nor assists to justify investor behavior. With the emergence and support of behavioral finance, such illogical conduct carried out by investors in the market is exposed and analyzed to better understand why these individuals behave in such a manner.

This project first discussed Robinhood investors and the role of social media in order to display the high volume of irrationality in this particular group of investors. By first examining the Robinhood platform and the users on it, this helped to demonstrate some of the problematic behavior that has taken place in financial markets. These issues were addressed as a means to display irrationality and imply that, undoubtedly, a number of psychological biases are present in investor behavior. The implication of analyzing such studies and narratives regarding Robinhood and social media was to further demonstrate the demand for behavioral finance as a means of helping address the immensely problematic behavior of such investors. Numerous reports and studies have noted Robinhood users to be young and inexperienced. In turn, these investors often make use of social media and basic analytics provided by Robinhood to form their investment strategies. Consequently, their financial decisions are hindered by the use of social media and the Robinhood platform itself. Such studies established the need to analyze not only

Robinhood users, but all investors participating in the market from the perspective of behavioral finance.

Following this paper's discussion of Robinhood, the field of behavioral finance was examined further in order to increase understanding of its goal and how it holds up next to standard finance theory. Much financial literature has indicated the major gripe with standard finance is its assertion that investors are completely rational when making financial decisions. Furthermore, the Efficient Market Hypothesis assumes markets to be extremely efficient in reflecting information about individual stocks and the market as a whole. EMH, however, has been disproved in a number of studies by behavioral economists. Ultimately, EMH fails to explain excess volatility in stock prices, investor overreaction, and various stock market anomalies. In contrast, behavioral finance accounts for such irrationalities across markets by applying psychology and sociology to the financial field. Behavioral finance takes into consideration a number of different cognitive biases, such as varying heuristics, framing effects, and herd behavior as a means of explaining such irrationalities.

In the methodology portion of this study, Granger-causality was applied to see if stock prices, stock mentions on WallStreetBets, and the market sentiment around the discussions on the subreddit had any impact on the number of Robinhood users holding a particular stock. The results displayed each control variable to Granger-cause the number of Robinhood users holding the stock of a particular company. The outcomes of the Granger-causality tests offered a handful of behavioral implications. It was found that the results may have aided in displaying herd behavior, or, furthermore, conformity bias and

FOMO amongst Robinhood users. Additionally, the results may have implied the use of the representativeness heuristic amidst Robinhood users.

This project also tested for dividend variance in a comparative analysis against stock price variance as a means of disproving standard finance theory. According to Shiller (2003), the volatility of dividends should be the same as the volatility of share prices under EMH. Yang (2019) added that under standard finance theory, such rational investors have constant risk aversion. This is grounded in the fact that investors in standard finance do not react to good or bad news, having a continuous discount rate no matter what. In behavioral finance, investors are prone to practicing loss aversion in which their discount rates change based on their sentiment towards the type of news they receive. According to Yang (2019), when discount rates vary, the volatility of stock prices increases much more dramatically in relation to the volatility of dividends. This paper found Shiller (2003) and Yang's (2019) findings to be accurate. The results in Chapter 5 demonstrated the volatility of dividends to be significantly lower than the volatility of stock prices.

Lastly, loss aversion and overconfidence proxies were utilized in testing for the impact such biases had on both the economic and market performance of firms. Unfortunately, this paper was unable to replicate the exact findings of Bouteska and Regaieg (2018). The results in this research was only able to demonstrate that loss aversion negatively affects a firm's return on assets in the industry sector and that overconfidence negatively impacts Tobin's Q for industry sector companies. These varying results compared to the findings of Bouteska and Regaieg (2018) may be due to insufficient-data bias as the sample used in this study was significantly smaller than the sample size in Bouteska and Regaieg's (2018) research. However, these results at the very least happened to display some sort of relationship between loss aversion and overconfidence and the economic and market performances of a firm.

In conclusion, this paper aim was to bring awareness to not only investors and institutions, but perhaps to market regulators as well. While it isn't entirely realistic that financial governance can halt the biases of investors all together, it may help in assisting what decisions to make in regulating the market. While the irrationally and illogical investment decisions of Robinhood and social media investors has been the most recent instance of senseless stock market behavior, it certainly won't be the last. Irrationality has been a long, withstanding feature of stock market participation that has been around well before the emergence of Robinhood and will be around long after it is gone (in the case it ever gets shut down). As investors, having an understanding of our "animal spirits" may help to benefit our future investment decisions and may aid in mitigating the development of future bubbles and crashes in the market.

Appendix

Table A1: Summary statistics [NumberofUsers, Mentions, Sentiment, ClosingPrice] by FirmTicker
Ticker Symbol of Company:

	N	Mean	SD	Min	Median	Max
AAL						
NumberofUsers	727	111962.84	215207.46	4926	9662	659935
Sentiment	297	.024	.262	-.91	.006	.869
Mentions	297	39.983	92.575	1	11	886
ClosingPrice	501	27.577	9.114	9.04	29.95	43.6
AAPL						
NumberofUsers	727	258377.28	102258.65	154460	226379	718187
Sentiment	688	.074	.183	-.93	.057	.923
Mentions	688	45.408	83.596	1	21	851
ClosingPrice	501	60.39	16.313	35.547	54.972	115.01
AMZN						
NumberofUsers	727	136666.64	67703.855	86984	116872	427679
Sentiment	675	.062	.194	-.893	.051	.915
Mentions	675	43.994	93.809	1	16	942
ClosingPrice	501	1961.596	380.525	1343.96	1847.75	3225
BA						
NumberofUsers	727	80766.029	105303.88	16309	36603	339829
Sentiment	568	.03	.204	-.844	.018	.898
Mentions	568	71.887	157.538	1	14	1312
ClosingPrice	501	312.369	86.366	95.01	347.48	440.62
BABA						
NumberofUsers	727	130095	40048.326	77293	120587	256324
Sentiment	552	.039	.262	-.936	.017	.975
Mentions	552	20.143	54.424	1	4.5	550
ClosingPrice	501	183.782	28.007	130.6	178.5	265.68
BAC						
NumberofUsers	727	141018.56	85282.17	78134	104563	361718
Sentiment	518	.074	.27	-.988	.059	.938
Mentions	518	13.116	27.086	1	5	332
ClosingPrice	501	28.283	3.517	18.08	28.53	35.64
CCL						
NumberofUsers	677	93719.594	177804.09	1377	3151	502941
Sentiment	214	.058	.187	-.631	.035	.956
Mentions	214	36.813	45.897	1	21	259
ClosingPrice	466	41.929	16.241	7.97	46.435	67.17
DAL						
NumberofUsers	727	107006.31	195852.88	8126	14368	599395
Sentiment	297	.088	.253	-.964	.065	.922
Mentions	297	22.199	35.413	1	9	271
ClosingPrice	501	49.101	12.545	19.19	54.8	63.16

DIS						
NumberofUsers	727	213775.08	178815.95	64085	153492	630757
Sentiment	570	.036	.201	-.767	.028	.919
Mentions	570	46.737	93.242	1	16	807
ClosingPrice	501	123.295	14.444	85.76	117.79	151.64
FB						
NumberofUsers	727	163037.31	30533.795	125080	156997	253391
Sentiment	651	.03	.214	-.915	.022	.906
Mentions	651	36.555	96.655	1	11	1082
ClosingPrice	501	185.005	28.509	124.06	183.55	268.44
FCEL						
NumberofUsers	278	55085.367	19637.381	18553	58411	82180
Sentiment	67	.161	.3	-.542	.077	.955
Mentions	67	5.403	18.818	1	1	151
ClosingPrice	190	1.814	.734	.261	1.955	3.37
GE						
NumberofUsers	727	349805.77	206835.23	151542	276429	862741
Sentiment	573	.036	.248	-.956	.023	.914
Mentions	573	15.928	25.444	1	8	213
ClosingPrice	501	75.982	16.014	43.92	76.56	108.53
GM						
NumberofUsers	727	46467.715	39953.859	21432	26038	136476
Sentiment	387	.038	.337	-.923	.002	.978
Mentions	387	6.279	12.791	1	3	149
ClosingPrice	501	33.81	5.594	16.8	35.75	40.88
GME						
NumberofUsers	698	16409.673	9777.631	6386	12978	35000
Sentiment	338	.067	.317	-.866	.028	.882
Mentions	338	10.888	39.545	1	3	601
ClosingPrice	480	7.695	4.141	2.8	5.63	17.04
GPRO						
NumberofUsers	727	240030.74	119564.82	120776	184844	494277
Sentiment	175	.063	.385	-.916	0	.9
Mentions	175	2.034	2.277	1	1	18
ClosingPrice	501	4.988	1.173	2.01	4.91	7.55
KO						
NumberofUsers	727	68909.336	56761.777	20697	46230	217371
Sentiment	411	.075	.315	-.916	.043	.983
Mentions	411	6.518	9.85	1	3	86
ClosingPrice	501	49.564	4.134	37.56	48.48	60.13
MRNA						
NumberofUsers	550	56120.629	88980.559	1620	5539.5	342422
Sentiment	175	.061	.223	-.889	.048	.778
Mentions	175	27.663	62.258	1	7	361
ClosingPrice	380	29.617	19.656	12.26	20.645	94.85
MSFT						
NumberofUsers	727	256096.05	119499.18	135884	217734	654414

Sentiment	676	.078	.181	-.806	.065	.997
Mentions	676	74.624	146.428	1	23	1315
ClosingPrice	501	141.048	31.198	94.13	136.95	216.54
NFLX						
NumberofUsers	727	111022.35	26272.267	88446	104835	236520
Sentiment	613	.057	.258	-.852	.039	.988
Mentions	613	18.042	55.467	1	7	990
ClosingPrice	501	352.712	59.449	233.88	351.39	548.73
NIO						
NumberofUsers	686	100246.81	50465.88	6771	92964	281644
Sentiment	445	.029	.281	-.907	.003	.957
Mentions	445	6.515	53.014	0	0	884
ClosingPrice	473	5.086	2.901	1.32	4.14	14.98
NOK						
NumberofUsers	727	44851.868	34805.208	11029	31459	132703
Sentiment	286	.069	.295	-.91	.043	.832
Mentions	286	7.059	12.657	1	3	109
ClosingPrice	501	4.828	.938	2.42	5.06	6.57
NVDA						
NumberofUsers	727	97204.04	14116.198	77959	96646	156391
Sentiment	636	.067	.226	-.923	.056	.993
Mentions	636	19.494	32.464	1	9	443
ClosingPrice	501	56.752	19.509	31.77	51.697	114.43
PFE						
NumberofUsers	727	39063.757	35188.737	18418	26566	200415
Sentiment	255	.058	.326	-.912	.014	.997
Mentions	255	13.098	25.741	1	3	206
ClosingPrice	501	38.505	3.548	27.848	38.483	45.188
PLUG						
NumberofUsers	727	147675.41	99963.371	30837	118766	393817
Sentiment	186	.074	.323	-.823	.031	.934
Mentions	186	8.597	36.252	1	2	478
ClosingPrice	501	3.179	1.946	1.01	2.54	12.04
SBUX						
NumberofUsers	727	96430.333	49441.616	55030	82075	207256
Sentiment	524	.051	.259	-.861	.029	.937
Mentions	524	8.796	12.689	1	5	97
ClosingPrice	501	75.599	11.853	51.51	76	99.11
SNAP						
NumberofUsers	727	173868.39	73528.869	87923	155052	359472
Sentiment	611	.02	.239	-.869	.003	.997
Mentions	611	21.339	63.866	1	8	1202
ClosingPrice	501	13.474	4.794	4.99	13.78	26.41
TSLA						
NumberofUsers	727	161902.87	94858.987	75268	145982	563245
Sentiment	680	.055	.171	-.97	.049	.929
Mentions	680	114.515	264.003	1	21	2617

ClosingPrice	501	92.821	66.568	35.794	64.328	328.6
TWTR						
NumberofUsers	727	130038.46	42622.532	98919	112617	233405
Sentiment	467	.037	.324	-.946	.005	.983
Mentions	467	7.668	16.419	1	3	170
ClosingPrice	501	33.746	4.487	22	33.19	45.42
UAL						
NumberofUsers	727	54597.455	110098.27	2115	2316	341526
Sentiment	225	.049	.242	-.81	.024	.922
Mentions	225	15.533	23.879	1	8	193
ClosingPrice	501	73.883	23.327	19.92	84.64	96.7
UBER						
NumberofUsers	452	146311.96	58662.073	68551	117121	261998
Sentiment	335	.043	.31	-.944	.026	.96
Mentions	335	9.382	23.603	1	4	265
ClosingPrice	311	33.788	5.8	14.82	32.68	46.38
WKHS						
NumberofUsers	727	112190.33	50150.971	37139	120549	221671
Sentiment	154	.115	.376	-.913	.067	.997
Mentions	154	5.279	17.078	1	1	157
ClosingPrice	501	6.002	1.681	3.44	6.07	10.44

Table A2: Summary statistics [NumberofUsers, Mentions, Sentiment, ClosingPrice]

	N	Mean	SD	Min	Median	Max
NumberofUsers	21516	129241.2	127148.71	1377	103398	862741
Sentiment	13249	.053	.254	-.988	.037	.997
Mentions	13249	30.965	96.081	0	7	2617
ClosingPrice	14825	138.002	359.337	.261	44.16	3225

Table A3: Summary statistics [ClosingPrice, Dividends] by FirmTicker
Ticker Symbol of Company:

	N	Mean	SD	Min	p25	Median	p75	Max
AAL								
ClosingPrice	501	27.577	9.114	9.04	25.41	29.95	33.73	43.6
Dividends	7	.1	0	.1	.1	.1	.1	.1
AAPL								
ClosingPrice	501	60.39	16.313	35.547	49.48	54.972	70.005	115.01
Dividends	8	.772	.034	.73	.75	.77	.795	.82
AMZN								
ClosingPrice	501	1961.596	380.525	1343.96	1754.91	1847.75	1988.3	3225
Dividends	0	.	.	.	.	.	.	.

BA								
ClosingPrice	501	312.369	86.366	95.01	313.05	347.48	367.46	440.62
Dividends	0	.	.	.	.	.	.	.
BABA								
ClosingPrice	501	183.782	28.007	130.6	165.4	178.5	201.89	265.68
Dividends	0	.	.	.	.	.	.	.
BAC								
ClosingPrice	501	28.283	3.517	18.08	26.03	28.53	30.37	35.64
Dividends	0	.	.	.	.	.	.	.
CCL								
ClosingPrice	466	41.929	16.241	7.97	33.06	46.435	53.83	67.17
Dividends	8	.165	.016	.15	.15	.165	.18	.18
DAL								
ClosingPrice	501	49.101	12.545	19.19	47.96	54.8	57.66	63.16
Dividends	7	.5	0	.5	.5	.5	.5	.5
DIS								
ClosingPrice	501	123.295	14.444	85.76	112.21	117.79	136.06	151.64
Dividends	7	.371	.027	.35	.35	.35	.4	.4
FB								
ClosingPrice	501	185.005	28.509	124.06	165.55	183.55	200.87	268.44
Dividends	3	.88	0	.88	.88	.88	.88	.88
FCEL								
ClosingPrice	190	1.814	.734	.261	1.39	1.955	2.335	3.37
Dividends	7	1.96	.171	1.71	1.71	2.06	2.06	2.06
GE								
ClosingPrice	501	75.982	16.014	43.92	62.28	76.56	87.92	108.53
Dividends	7	.026	.042	.01	.01	.01	.01	.12
GM								
ClosingPrice	501	33.81	5.594	16.8	32	35.75	37.67	40.88
Dividends	0	.	.	.	.	.	.	.
GME								
ClosingPrice	480	7.695	4.141	2.8	4.335	5.63	11.315	17.04
Dividends	0	.	.	.	.	.	.	.
GPRO								
ClosingPrice	501	4.988	1.173	2.01	4.15	4.91	6.01	7.55
Dividends	3	.38	0	.38	.38	.38	.38	.38
KO								
ClosingPrice	501	49.564	4.134	37.56	46.19	48.48	53.3	60.13
Dividends	7	.38	0	.38	.38	.38	.38	.38
MRNA								
ClosingPrice	380	29.617	19.656	12.26	16.945	20.645	30.265	94.85

Dividends	7	.4	.008	.39	.39	.4	.41	.41
MSFT								
ClosingPrice	501	141.048	31.198	94.13	112.14	136.95	160.92	216.54
Dividends	8	.474	.033	.42	.46	.46	.51	.51
NFLX								
ClosingPrice	501	352.712	59.449	233.88	308.93	351.39	372.78	548.73
Dividends	0	.	.	.	.	.	.	.
NIO								
ClosingPrice	473	5.086	2.901	1.32	2.95	4.14	6.81	14.98
Dividends	0	.	.	.	.	.	.	.
NOK								
ClosingPrice	501	4.828	.938	2.42	4.05	5.06	5.55	6.57
Dividends	0	.	.	.	.	.	.	.
NVDA								
ClosingPrice	501	56.752	19.509	31.77	41.057	51.697	66.972	114.43
Dividends	0	.	.	.	.	.	.	.
PFE								
ClosingPrice	501	38.505	3.548	27.848	35.688	38.483	41.64	45.188
Dividends	2	.045	.007	.04	.04	.045	.05	.05
PLUG								
ClosingPrice	501	3.179	1.946	1.01	1.95	2.54	3.85	12.04
Dividends	8	.36	.015	.34	.35	.36	.37	.38
SBUX								
ClosingPrice	501	75.599	11.853	51.51	67.5	76	84.69	99.11
Dividends	8	.159	.004	.15	.16	.16	.16	.16
SNAP								
ClosingPrice	501	13.474	4.794	4.99	10.05	13.78	16.46	26.41
Dividends	0	.	.	.	.	.	.	.
TSLA								
ClosingPrice	501	92.821	66.568	35.794	51.636	64.328	109.44	328.6
Dividends	0	.	.	.	.	.	.	.
TWTR								
ClosingPrice	501	33.746	4.487	22	30.41	33.19	36.85	45.42
Dividends	0	.	.	.	.	.	.	.
UAL								
ClosingPrice	501	73.883	23.327	19.92	77.49	84.64	88.58	96.7
Dividends	0	.	.	.	.	.	.	.
UBER								
ClosingPrice	311	33.788	5.8	14.82	29.75	32.68	37.21	46.38
Dividends	8	.379	.026	.36	.36	.36	.41	.41

WKHS								
ClosingPrice	501	6.002	1.681	3.44	4.74	6.07	6.53	10.44
Dividends	0	.	.	.	.	.	.	.

Table A4: Summary statistics [ClosingPrice, Dividends]

	N	Mean	SD	Min	Median	Max
ClosingPrice	14825	138.002	359.337	.261	44.16	3225
Dividends	105	.462	.455	.01	.38	2.06

Table A5: Summary statistics [ROA, SIZE, MCAP, LA] by FirmTicker
Ticker Symbol of Company:

AAL

	N	Mean	SD	Min	Median	Max
ROA	6	.003	.033	-.057	.018	.028
SIZE	6	.765	.203	.37	.825	.92
MCAP	6	1.162e+10	5.138e+09	5.155e+09	1.205e+10	1.903e+10
LA	5	192.637	407.464	-14.565	6.104	919.97

AAPL

ROA	8	.165	.007	.159	.162	.177
SIZE	8	.761	.046	.71	.75	.83
MCAP	8	1.073e+12	2.557e+11	7.461e+11	1.043e+12	1.563e+12
LA	7	14.304	47.509	-31.811	-4.069	95.07

AMZN

ROA	8	.065	.009	.051	.064	.078
SIZE	8	1.505	.099	1.41	1.47	1.65
MCAP	8	9.572e+11	1.881e+11	7.375e+11	9.263e+11	1.382e+12
LA	7	10.394	56.574	-52.218	-9.07	104.098

BA

ROA	8	.036	.05	-.025	.036	.091
SIZE	8	.691	.21	.33	.735	.91
MCAP	8	1.752e+11	5.216e+10	8.416e+10	1.941e+11	2.153e+11
LA	7	103.108	187.701	-37.686	54.592	503.277

BABA

ROA	8	.118	.027	.083	.116	.154
SIZE	2	.585	.276	.39	.585	.78
MCAP	8	4.733e+11	7.733e+10	3.525e+11	4.566e+11	5.812e+11
LA	7	20.624	78.798	-54.66	6.68	181.65

BAC

ROA	8	.01	.002	.007	.011	.012
SIZE	8	.04	0	.04	.04	.04
MCAP	8	2.544e+11	4.290e+10	1.842e+11	2.654e+11	3.112e+11
LA	7	21.006	95.633	-61.48	-23.56	221.28

CCL						
ROA	8	.067	.011	.042	.07	.077
SIZE	7	.446	.039	.36	.46	.47
MCAP	8	3.250e+10	1.034e+10	1.231e+10	3.372e+10	4.304e+10
LA	6	203.126	491.27	-39.764	-2.505	1199.899
DAL						
ROA	8	.053	.044	-.054	.07	.076
SIZE	8	.73	.095	.51	.755	.81
MCAP	8	3.213e+10	8.877e+09	1.789e+10	3.611e+10	3.998e+10
LA	7	107.865	288.223	-44.162	8.209	757.037
DIS						
ROA	8	.07	.045	-.005	.07	.128
SIZE	8	.448	.101	.34	.405	.6
MCAP	8	2.062e+11	3.664e+10	1.645e+11	1.991e+11	2.576e+11
LA	7	42.905	121.608	-70.885	-1.641	280.709
FB						
ROA	8	.184	.032	.153	.17	.24
SIZE	8	.588	.018	.56	.585	.61
MCAP	8	5.115e+11	8.299e+10	3.741e+11	4.920e+11	6.471e+11
LA	7	15.033	72.939	-45.218	-19.046	164.163
FCEL						
ROA	3	-.286	.015	-.303	-.282	-.273
SIZE	3	.177	.012	.17	.17	.19
MCAP	3	4.295e+08	95654882	3.354e+08	4.263e+08	5.267e+08
LA	2	-19.861	13.63	-29.499	-19.861	-10.224
GE						
ROA	8	-.044	.032	-.1	-.038	-.01
SIZE	8	.36	.019	.34	.355	.39
MCAP	8	8.093e+10	1.481e+10	5.978e+10	8.254e+10	9.812e+10
LA	7	12.691	61.261	-55.234	-9.209	113.797
GM						
ROA	8	.026	.015	.004	.032	.04
SIZE	8	.688	.076	.52	.72	.75
MCAP	8	4.639e+10	9.085e+09	2.969e+10	4.937e+10	5.465e+10
LA	7	32.465	117.271	-33.877	-4.264	293.642
GME						
ROA	8	-.179	.054	-.283	-.162	-.125
SIZE	8	2	.067	1.9	2.005	2.08
MCAP	8	6.584e+08	4.644e+08	2.531e+08	4.311e+08	1.488e+09
LA	7	25.029	104.467	-46.976	-16.325	248.127
GPRO						
ROA	8	-.115	.081	-.279	-.099	-.02
SIZE	8	1.614	.139	1.37	1.625	1.77
MCAP	9	7.607e+08	1.985e+08	3.887e+08	7.422e+08	1.071e+09
LA	8	-1.954	49.445	-69.258	-.162	77.488
KO						
ROA	8	.037	.037	-.054	.048	.059

SIZE	8	.42	.035	.37	.425	.47
MCAP	8	2.085e+11	1.842e+10	1.900e+11	2.010e+11	2.369e+11
LA	7	32.433	86.792	-39.884	1.858	217.857
MRNA						
ROA	6	-.329	.088	-.484	-.305	-.223
SIZE	6	.032	.038	0	.015	.1
MCAP	6	9.954e+09	7.816e+09	4.817e+09	6.639e+09	2.525e+10
LA	5	131.212	188.67	-27.397	98.331	441.878
MSFT						
ROA	8	.139	.029	.074	.149	.163
SIZE	8	.492	.02	.46	.495	.52
MCAP	8	1.074e+12	2.404e+11	7.804e+11	1.044e+12	1.541e+12
LA	7	40.76	130.664	-55.971	-.201	323.67
NFLX						
ROA	8	.058	.011	.043	.056	.078
SIZE	8	.67	.016	.66	.66	.7
MCAP	8	1.526e+11	2.748e+10	1.169e+11	1.581e+11	2.007e+11
LA	7	17.499	82.493	-65.172	-2.297	152.137
NIO						
ROA	3	-.705	.268	-1	-.64	-.475
SIZE	2	.4	.198	.26	.4	.54
MCAP	4	5.394e+09	3.128e+09	1.668e+09	5.486e+09	8.936e+09
LA	3	262.214	321.591	-60.741	264.96	582.422
NOK						
ROA	8	-.006	.013	-.024	-.009	.016
SIZE	2	.83	.071	.78	.83	.88
MCAP	8	2.681e+10	5.361e+09	1.775e+10	2.815e+10	3.218e+10
LA	7	13.146	51.171	-37.682	-5.255	104.979
NVDA						
ROA	8	.231	.08	.166	.192	.381
SIZE	8	.769	.13	.64	.72	1.01
MCAP	8	1.422e+11	5.598e+10	8.711e+10	1.256e+11	2.620e+11
LA	7	-.7	42.891	-56.97	1.484	76.615
PFE						
ROA	8	.093	.024	.068	.089	.142
SIZE	8	.321	.016	.29	.325	.34
MCAP	9	2.194e+11	2.856e+10	1.812e+11	2.168e+11	2.583e+11
LA	8	17.046	51.464	-56.649	10.2	94.178
PLUG						
ROA	8	-2.245	5.732	-16.43	-.248	-.11
SIZE	8	.45	.067	.34	.45	.54
MCAP	8	8.948e+08	7.904e+08	2.718e+08	5.886e+08	2.733e+09
LA	7	112.216	148.151	-58.427	51.399	294.584
SBUX						
ROA	8	.158	.051	.052	.163	.234
SIZE	8	1.223	.136	.93	1.27	1.36
MCAP	8	9.019e+10	1.194e+10	7.668e+10	8.923e+10	1.047e+11

LA	7	40.418	154.894	-43.689	-14.265	388.489
SNAP						
ROA	8	-.359	.073	-.455	-.357	-.267
SIZE	8	.464	.058	.35	.485	.51
MCAP	8	1.858e+10	8.360e+09	7.261e+09	1.824e+10	3.438e+10
LA	7	3.222	46.305	-51.836	-13.012	79.044
TSLA						
ROA	8	-.028	.018	-.063	-.027	-.004
SIZE	8	.762	.062	.63	.775	.84
MCAP	8	7.595e+10	5.406e+10	3.982e+10	5.289e+10	2.008e+11
LA	7	8.008	53.561	-81.265	-4.8	73.094
TWTR						
ROA	8	.109	.09	-.098	.128	.216
SIZE	8	.304	.028	.26	.3	.34
MCAP	8	2.442e+10	3.877e+09	1.926e+10	2.427e+10	3.196e+10
LA	7	9.583	58.437	-47.656	-14.707	126.079
UAL						
ROA	8	.038	.03	-.031	.049	.058
SIZE	8	.835	.126	.55	.88	.93
MCAP	8	1.920e+10	6.421e+09	7.801e+09	2.228e+10	2.428e+10
LA	7	134.398	263.612	-35.235	23.515	698.995
UBER						
ROA	3	-.282	.053	-.333	-.285	-.228
SIZE	5	.46	.01	.45	.46	.47
MCAP	5	5.683e+10	1.238e+10	4.830e+10	5.191e+10	7.864e+10
LA	4	63.958	153.091	-82.478	57.51	223.291
WKHS						
ROA	8	-2.219	.877	-3.056	-2.494	-.629
SIZE	7	.086	.166	0	.02	.46
MCAP	8	3.045e+08	5.107e+08	30767053	1.591e+08	1.553e+09
LA	7	20.046	45.156	-36.669	25.562	87.573

Table A6: Summary statistics [ROA, SIZE, MCAP, LA]

	N	Mean	SD	Min	Median	Max
ROA	229	-.149	1.178	-16.43	.042	.381
SIZE	216	.667	.462	0	.565	2.08
MCAP	234	2.044e+11	3.186e+11	30767053	5.861e+10	1.563e+12
LA	202	48.597	159.826	-82.478	-.404	1199.899

Table A7: Summary statistics [TobinsQ, OC, NEUSD, SIZE] by FirmTicker
Company's stock ticker:

AAL

	N	Mean	SD	Min	Median	Max
TobinsQ	8	.735	.089	.613	.74	.915
OC	7	-1.038	1.885	-4.054	-.897	.866
NEUSD	8	-2.406e+08	1.189e+09	-2.241e+09	3.485e+08	6.620e+08
SIZE	6	.765	.203	.37	.825	.92

AAPL

	N	Mean	SD	Min	Median	Max
TobinsQ	8	3.313	.881	2.158	3.095	5.08
OC	7	-1.938	1.921	-4.535	-1.519	1.032
NEUSD	8	1.426e+10	4.467e+09	1.004e+10	1.262e+10	2.224e+10
SIZE	8	.761	.046	.71	.75	.83

AMZN

	N	Mean	SD	Min	Median	Max
TobinsQ	8	5.002	.886	4.152	4.805	6.956
OC	7	.227	.267	-.2	.199	.593
NEUSD	8	3.160e+09	9.513e+08	2.134e+09	2.955e+09	5.243e+09
SIZE	8	1.505	.099	1.41	1.47	1.65

BA

	N	Mean	SD	Min	Median	Max
TobinsQ	8	1.458	.462	.709	1.645	1.865
OC	7	-.342	1.189	-2.389	0	1.034
NEUSD	8	2.679e+08	2.342e+09	-2.942e+09	2.690e+08	3.422e+09
SIZE	8	.691	.21	.33	.735	.91

BABA

	N	Mean	SD	Min	Median	Max
TobinsQ	8	2.999	.321	2.705	2.935	3.605
OC	7	.609	1.118	-.533	.344	2.736
NEUSD	8	4.945e+09	3.086e+09	3.210e+08	4.412e+09	1.015e+10
SIZE	2	.585	.276	.39	.585	.78

BAC

	N	Mean	SD	Min	Median	Max
TobinsQ	8	.024	.048	-.07	.045	.059
OC	7	-2.069	2.571	-6.142	-2.165	.962
NEUSD	8	5.820e+09	1.595e+09	3.284e+09	6.725e+09	7.109e+09
SIZE	8	.04	0	.04	.04	.04

CCL

	N	Mean	SD	Min	Median	Max
TobinsQ	8	1.092	.261	.611	1.111	1.38
OC	7	.305	2.408	-2.113	-.288	5.409
NEUSD	8	4375000	1.948e+09	-4.374e+09	4.370e+08	1.780e+09
SIZE	7	.446	.039	.36	.46	.47

DAL

	N	Mean	SD	Min	Median	Max
TobinsQ	8	.846	.186	.533	.904	1.076
OC	7	-1.125	1.788	-3.89	-.613	.872
NEUSD	8	1.073e+08	2.441e+09	-5.717e+09	1.060e+09	1.495e+09
SIZE	8	.73	.095	.51	.755	.81

DIS

	N	Mean	SD	Min	Median	Max
TobinsQ	8	1.434	.322	1.052	1.417	1.963
OC	7	2.928	8.375	-8.159	-.055	18.022
NEUSD	8	1.403e+09	2.886e+09	-4.721e+09	1.934e+09	5.452e+09
SIZE	8	.448	.101	.34	.405	.6

GE						
TobinsQ	8	.371	.096	.238	.358	.53
OC	7	.092	.15	-.092	0	.276
NEUSD	8	-2.962e+09	9.223e+09	-2.281e+10	2.385e+08	6.156e+09
SIZE	8	.36	.019	.34	.355	.39
GM						
TobinsQ	8	.531	.052	.425	.557	.567
OC	7	.01	.31	-.556	.069	.349
NEUSD	8	1.315e+09	1.346e+09	-8.060e+08	2.056e+09	2.503e+09
SIZE	8	.688	.076	.52	.72	.75
GME						
TobinsQ	8	.188	.082	.098	.181	.366
OC	7	-5.536	11.941	-26.136	0	7.317
NEUSD	8	-1.780e+08	1.853e+08	-4.890e+08	-1.385e+08	21000000
SIZE	8	2	.067	1.9	2.005	2.08
GPRO						
TobinsQ	8	1.129	.345	.613	1.203	1.588
OC	7	.805	1.381	-.714	.69	2.878
NEUSD	8	-15500000	56145220	-75000000	-25500000	96000000
SIZE	8	1.614	.139	1.37	1.625	1.77
KO						
TobinsQ	8	2.71	.28	2.396	2.685	3.137
OC	7	.07	.214	-.208	.093	.372
NEUSD	8	2.028e+09	6.279e+08	8.700e+08	1.961e+09	2.775e+09
SIZE	8	.42	.035	.37	.425	.47
MSFT						
TobinsQ	8	3.696	.648	2.872	3.546	4.948
OC	7	-.153	.248	-.555	-.208	.116
NEUSD	8	1.044e+10	1.652e+09	8.420e+09	1.072e+10	1.319e+10
SIZE	8	.492	.02	.46	.495	.52
NFLX						
TobinsQ	8	5.478	.972	4.254	5.469	7.235
OC	7	.063	.211	-.221	0	.442
NEUSD	8	4.791e+08	2.215e+08	1.340e+08	4.950e+08	7.200e+08
SIZE	8	.67	.016	.66	.66	.7
NIO						
TobinsQ	8	2.173	.629	1.24	2.268	2.954
OC	5	.387	.918	-.773	.195	1.736
NEUSD	7	-4.963e+08	4.210e+08	-1.421e+09	-3.950e+08	-1.710e+08
SIZE	2	.4	.198	.26	.4	.54
NOK						
TobinsQ	8	.588	.115	.387	.642	.687
OC	7	.11	.295	-.32	.054	.554
NEUSD	8	16125000	3.408e+08	-5.070e+08	-500000	6.400e+08
SIZE	2	.83	.071	.78	.83	.88

NVDA						
TobinsQ	8	7.628	1.336	6.009	7.3	10.19
OC	7	.025	.708	-1.44	0	.647
NEUSD	8	7.664e+08	2.764e+08	3.940e+08	7.605e+08	1.230e+09
SIZE	8	.769	.13	.64	.72	1.01
PFE						
TobinsQ	8	1.442	.169	1.174	1.513	1.597
OC	7	-.891	1.433	-3.798	-.406	.46
NEUSD	8	3.355e+09	2.676e+09	-3.940e+08	3.687e+09	7.680e+09
SIZE	8	.321	.016	.29	.325	.34
PLUG						
TobinsQ	8	1.501	.55	.835	1.435	2.709
OC	7	5.809	10.252	0	2.597	28.692
NEUSD	8	-21375000	8943273.6	-37000000	-18000000	-9000000
SIZE	8	.45	.067	.34	.45	.54
SBUX						
TobinsQ	8	4.437	1.111	3.175	4.28	6.058
OC	7	-2.431	3.688	-10.179	-1.016	.818
NEUSD	8	6.115e+08	5.953e+08	-6.780e+08	7.585e+08	1.373e+09
SIZE	8	1.223	.136	.93	1.27	1.36
SNAP						
TobinsQ	4	5.492	1.219	4.108	5.391	7.077
OC	3	1.297	2.505	-1.292	1.473	3.709
NEUSD	4	-2.750e+08	48380437	-3.260e+08	-2.735e+08	-2.270e+08
SIZE	4	.5	.02	.47	.51	.51
TSLA						
TobinsQ	8	2.512	1.253	1.548	2.152	5.439
OC	7	2.319	5.511	-4.157	2.312	12.063
NEUSD	8	-36375000	3.424e+08	-7.100e+08	1.085e+08	3.110e+08
SIZE	8	.762	.062	.63	.775	.84
TWTR						
TobinsQ	8	1.758	.369	1.1	1.807	2.404
OC	7	.185	.699	-.636	.64	.9
NEUSD	8	1.406e+08	7.304e+08	-1.378e+09	1.550e+08	1.120e+09
SIZE	8	.304	.028	.26	.3	.34
UAL						
TobinsQ	8	.767	.137	.55	.818	.925
OC	7	.5	5.856	-4.231	-2.239	12.851
NEUSD	8	1.215e+08	1.133e+09	-1.704e+09	5.510e+08	1.052e+09
SIZE	8	.835	.126	.55	.88	.93
UBER						
TobinsQ	5	1.817	.393	1.482	1.646	2.406
OC	4	16.36	36.067	-26.588	19.506	53.015
NEUSD	5	-2.441e+09	1.728e+09	-5.236e+09	-1.775e+09	-1.096e+09
SIZE	5	.458	.008	.45	.46	.47
WKHS						
TobinsQ	8	8.325	8.664	3.35	4.687	29.29

OC	7	7.901	13.073	-10.714	8.696	31.25
NEUSD	8	-23000000	44442579	-1.310e+08	-8500000	5000000
SIZE	7	.086	.166	0	.02	.46

Table A8: Summary statistics [TobinsQ, OC, NEUSD, SIZE]

	N	Mean	SD	Min	Median	Max
TobinsQ	217	2.434	2.733	-.07	1.588	29.29
OC	187	.622	7.194	-26.588	0	53.015
NEUSD	216	1.617e+09	4.239e+09	-2.281e+10	4.555e+08	2.224e+10
SIZE	195	.702	.466	0	.63	2.08

Stata Do-File – Granger Causality

```
 // Convert date to STATA usable format //
format %tdMonth_dd,_CCYY Date


// Keep the variables that will be analyzed//
keep Date Ticker NumberofUsers Mentions Sentiment CloseLast
Volume LastChange


// Rename and label the  variables //
encode Ticker, gen(FirmTicker)
lab var FirmTicker "Ticker Symbol of Company"


ren CloseLast ClosingPrice
lab var ClosingPrice "Last Transacted Price of Security
Before Market Close"

lab var NumberofUsers "# of Robinhood users holding stock"

lab var Mentions "Number of mentions of stock on Reddit"

lab var Sentiment "Index of sentiment, -1 (bearish) to +1
(bullish)"

lab var Volume "Total # of shares exchanged between
buyers/sellers of a security during trading hours on given
day"

ren LastChange PCofClosingPrice
lab var PCofClosingPrice "Percentage change in closing
price"


// xtset declares the data in memory to be a panel. xtset
[panelvar] [timevar] //
xtset FirmTicker Date


// Test to see if all data is balanced //
spbalance


//Create summary stats//
```

```
bys FirmTicker: asdoc sum NumberofUsers Sentiment Mentions
ClosingPrice, stat(N mean sd min median max) replace

asdoc sum NumberofUsers Sentiment Mentions ClosingPrice,
stat(N mean sd min median max) replace


// Fill in missing values in data for ClosingPrice and
NumberofUsers//
replace ClosingPrice = ClosingPrice[_n-1] if
missing(ClosingPrice)

replace NumberofUsers = NumberofUsers[_n-1] if
missing(NumberofUsers)

tsfill

replace ClosingPrice = ClosingPrice[_n-1] if
missing(ClosingPrice)

replace NumberofUsers = NumberofUsers[_n-1] if
missing(NumberofUsers)


//Run Granger Causality to see if ClosingPrice does Granger-
cause lagNumberofUsers for at least one panelvar//
xtgcause NumberofUsers ClosingPrice, bootstrap lags(1)
breps(1)
//Seeing p-values are 0.0000 and Z-bar stat > than the 95%
critical value, we should reject H0 and conclude that
Granger causality exists//


//Replace missing value for Sentiment and Mentions//
replace Sentiment = Sentiment[_n-1] if missing(Sentiment)

replace Mentions = Mentions[_n-1] if missing(Mentions)

replace Mentions = 0 in 1

replace Mentions = 0 in 2

replace Mentions = 0 in 3

replace Mentions = 0 in 4

replace Mentions = 0 in 5
```

```
replace Mentions = 0 in 6

replace Mentions = 0 in 7

replace Sentiment = 0 in 1

replace Sentiment = 0 in 2

replace Sentiment = 0 in 3

replace Sentiment = 0 in 4

replace Sentiment = 0 in 5

replace Sentiment = 0 in 6

replace Sentiment = 0 in 7

// Run Granger causality test on number of mentions and
sentiment//

xtgcause NumberofUsers Mentions, bootstrap lags(1) breps(1)

xtgcause NumberofUsers Sentiment, bootstrap lags(1) breps(1)
```

Stata Do-File – Stock and Dividend Variances

```
// Convert date to STATA usable format //
format %tdMonth_dd,_CCYY Date


// Rename and label the variables //
keep Date Ticker CloseLast DividendAmount

ren CloseLast ClosingPrice
lab var ClosingPrice "Last Transacted Price of Security
Before Market Close"


// DividendAmount variables shows up as string. Must fix //
gen Dividends = real(DividendAmount)
drop DividendAmount
lab var Dividends "Dividend Payout"

// Create summary statistics //
bys FirmTicker: asdoc sum ClosingPrice Dividends, stat(N
mean sd min median max) replace

asdoc sum ClosingPrice Dividends, stat(N mean sd min median
max)


// Convert the Ticker string to  Stata usable format //
encode Ticker, gen(FirmTicker)
drop Ticker
lab var FirmTicker "Ticker Symbol of Company"


// xtset declares the data in memory to be a panel. xtset
[panelvar] [timevar] //
xtset FirmTicker Date


// Run regression between FirmTicker and ClosingPrice. [.i]
specifies that the firm's ticker is a categorical variable
//
xtreg ClosingPrice i.FirmTicker


// Following this regression, it is necessary to predict the
residuals of ClosePrice //
predict residualsClosePrice, e
```

```
// Must complete the same process with FirmTicker and
DividendPayout //
xtreg Dividends i.FirmTicker
predict residualsDividends, e


// Lastly, we perform tests on the equality of variances
between ClosePrice and Dividend//
sdtest residualsClosePrice == residualsDividends


// Create Regression and Variance-ratio tables //
asdoc reg ClosingPrice i.FirmTicker, replace

asdoc reg Dividends i.FirmTicker, replace

asdoc sdtest residualsClosePrice == residualsDividends,
replace
```

Stata Do-File – Loss Aversion Regression

```
// Convert date to STATA usable format //
format %tdMonth_dd,_CCYY Date


// Rename and label the  variables //
label var MarketCap "Total market value of firm's
outstanding shares"
ren MarketCap MCAP

label var ROA "Ratio between net income and total assets"


ren AssetTurnoverRatio SIZE
label var SIZE "Asset Turnover Ratio -> amount of assets a
firm replaces in relation to its sales"


// Convert the Ticker string to  Stata usable format //
encode Ticker, gen(FirmTicker)
lab var FirmTicker "Company's stock ticker"


drop H


// Create service variable //

gen service=0


// Identify which companies belong to the service sector//
replace service=1 if Ticker=="AAL"

replace service=1 if Ticker=="BABA"

replace service=1 if Ticker=="BAC"

replace service=1 if Ticker=="DAL"

replace service=1 if Ticker=="CCL"

replace service=1 if Ticker=="FB"

replace service=1 if Ticker=="GME"
```

```
replace service=1 if Ticker=="NFLX"

replace service=1 if Ticker=="SBUX"

replace service=1 if Ticker=="SNAP"

replace service=1 if Ticker=="TWTR"

replace service=1 if Ticker=="UAL"

replace service=1 if Ticker=="UBER"


// generate "both" variable; when a company belongs to both
the industrial and service sector//

gen bothsectors=0


// Identify which firms belong to both sectors//

replace bothsectors=1 if Ticker=="AMZN"

replace bothsectors=1 if Ticker=="DIS"

replace bothsectors=1 if Ticker=="NOK"

replace bothsectors=1 if Ticker=="MSFT"


// Generate and identify which firms in the sample belong to
the industrial sector//

gen indsutrialsector = 0

replace indsutrialsector=1 if Ticker=="BA"

replace indsutrialsector=1 if Ticker=="FCEL"

replace indsutrialsector=1 if Ticker=="GE"

replace indsutrialsector=1 if Ticker=="GM"

replace indsutrialsector=1 if Ticker=="GPRO"

replace indsutrialsector=1 if Ticker=="KO"
```

```
replace indsutrialsector=1 if Ticker=="AAPL"

replace indsutrialsector=1 if Ticker=="NIO"

replace indsutrialsector=1 if Ticker=="NVDA"

replace indsutrialsector=1 if Ticker=="PFE"

replace indsutrialsector=1 if Ticker=="PLUG"

replace indsutrialsector=1 if Ticker=="TSLA"

replace indsutrialsector=1 if Ticker=="WKHS"

//Generate Percentage variation of transaction volume, or
LA, variable //
bysort FirmTicker (Date): gen pchange=100*(Volume[_n]-
Volume[_n-1])/Volume[_n-1]
ren pchange LA
lab var LA "Percentage variation of transaction volume"


// Generate LA data based on sector//

gen LA_both = LA*bothsectors
gen LA_service = LA*service
gen LA_industrial = LA*indsutrialsector


// xtset declares the data in memory to be a panel. xtset
[panelvar] [timevar] //
xtset FirmTicker Date


// Firstly, we run a code that fits regression models to
panel data [xtreg]. [fe] accounts for a fixed effects model
//
xtreg ROA SIZE MCAP LA_industrial LA_service LA_both, fe


// We then store these estimates for later use //
estimates store fixed


// We then run a regression model thats fit to panel data
[xtreg] and random effects [re] //
xtreg ROA SIZE MCAP LA_industrial LA_service LA_both, re
```

```
// We also store these estimates for later use //
estimates store random


// To decide between fixed or random effects we run a
Hausman test where the null hypothesis is that the preferred
model is random effects compared to the fixed effects
model//
hausman fixed random


// Create summary statistics //
bys FirmTicker: asdoc sum ROA SIZE MCAP LA, stat(N mean sd
min p25 median p75 max) replace

asdoc sum ROA SIZE MCAP LA, stat(N mean sd min p25 median
p75 max) replace


//Create random-effects regression table displaying test
results//
asdoc xtreg ROA SIZE MCAP LA_service LA_both
LA_industrial,re replace
```

Stata Do-File – Overconfidence Regression

```
// Convert date to STATA usable format //
format %tdMonth_dd,_CCYY Date


// Rename and label the variables //
drop I J
lab var TobinsQ "Ratio between firm's stock market value and
its fixed capital replacement"


ren AssetTurnoverRatio SIZE
lab var SIZE "Asset Turnover Ratio -> amount of assets a
firm replaces in relation to its sales"


ren NetIncomeinmillionsUSD NEUSD
lab var NEUSD "Difference between firm's revenues and costs
in USD"
replace NEUSD = 1000000*NEUSD

ren Tiicker Ticker

// Create service variable //

gen service=0


// Identify which companies belong to the service sector//
replace service=1 if Ticker=="AAL"

replace service=1 if Ticker=="BABA"

replace service=1 if Ticker=="BAC"

replace service=1 if Ticker=="DAL"

replace service=1 if Ticker=="CCL"

replace service=1 if Ticker=="FB"

replace service=1 if Ticker=="GME"

replace service=1 if Ticker=="NFLX"

replace service=1 if Ticker=="SBUX"
```

```
replace service=1 if Ticker=="SNAP"

replace service=1 if Ticker=="TWTR"

replace service=1 if Ticker=="UAL"

replace service=1 if Ticker=="UBER"


// generate "both" variable; when a company belongs to both
the industrial and service sector//

gen bothsectors=0


// Identify which firms belong to both sectors//

replace bothsectors=1 if Ticker=="AMZN"

replace bothsectors=1 if Ticker=="DIS"

replace bothsectors=1 if Ticker=="NOK"

replace bothsectors=1 if Ticker=="MSFT"
// Manually add bothOC for AMZN //


// Generate and identify which firms in the sample belong to
the industrial sector//

gen indsutrialsector = 0

replace indsutrialsector=1 if Ticker=="BA"

replace indsutrialsector=1 if Ticker=="FCEL"

replace indsutrialsector=1 if Ticker=="GE"

replace indsutrialsector=1 if Ticker=="GM"

replace indsutrialsector=1 if Ticker=="GPRO"

replace indsutrialsector=1 if Ticker=="KO"

replace indsutrialsector=1 if Ticker=="AAPL"
```

```
replace indsutrialsector=1 if Ticker=="NIO"

replace indsutrialsector=1 if Ticker=="NVDA"

replace indsutrialsector=1 if Ticker=="PFE"

replace indsutrialsector=1 if Ticker=="PLUG"

replace indsutrialsector=1 if Ticker=="TSLA"

replace indsutrialsector=1 if Ticker=="WKHS"

//Destring Ticker//

encode Ticker, gen(FirmTicker)
lab var FirmTicker "Company's stock ticker"


// Creat OC variable //
replace SharesOutstandinginmillions =
1000000*SharesOutstandinginmillions
bysort FirmTicker (Date): gen
pchange=100*(SharesOutstandinginmillions[_n]-
SharesOutstandinginmillions[_n-
1])/SharesOutstandinginmillions[_n-1]
ren pchange OC
lab var OC "Percentage change in shares outstanding"


// xtset declares the data in memory to be a panel. xtset
[panelvar] [timevar] //
xtset FirmTicker Date


// Generate OC data based on sector//

gen OC_both = OC*bothsectors
gen OC_service = OC*service
gen OC_industrial = OC*indsutrialsector


// Firstly, we run a code that fits regression models to
panel data [xtreg]. [fe] accounts of a fixed effects model //
xtreg TobinsQ SIZE NE OC_industrial OC_service OC_both, fe


// We then store these estimates for later use //
```

```
estimates store fixed


// We then run a regression model thats fit to panel data
[xtreg] and random effects [re] //
xtreg TobinsQ SIZE NE OC_industrial OC_service OC_both, re


// We also store these estimates for later use //
estimates store random


// To decide between fixed or random effects we run a
Hausman test where the null hypothesis is that the preferred
model is random effects compared to the fixed effects
model//
hausman fixed random

// hausman test not working, try hausman fixed random,
sigmamore //
hausman fixed random, sigmamore
//Results suggest we should observe fe//

// Create summary statistics //
bys FirmTicker: asdoc sum TobinsQ OC NEUSD SIZE, stat(N mean
sd min p25 median p75 max) replace

asdoc sum TobinsQ OC NEUSD SIZE, stat(N mean sd min p25
median p75 max) replace


//Create fixed-effects regression table displaying test
results//
xtreg TobinsQ SIZE NE OC_industrial OC_service OC_both, fe
replace
```

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