Copenhagen Business School
HANDELSHØJSKOLEN

The Rise of the Online Investor During COVID-19

A Behavioural Finance Analysis into Retail Investor Sentiment

Master's Thesis – MSc in Finance & Strategic Management
Copenhagen Business School, August 3rd, 2020
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Student Number: 116707
Number of Standard Pages: 54 /Number of Characters: 90546

Abstract

This thesis aims to examine whether U.S. financial markets experience waves of irrational market sentiment during large macroeconomic shocks to the economy. Large scale shocks to the economy, such as the dot.com bubble, are notorious for their breeches of market efficiency. As a result of COVID-19, we are currently in the middle of one of the most profound shocks in modern history; this offers a unique setting to analyse the workings of financial markets.

The goal will be achieved through a study based on behavioural finance that will concentrate on a possible source of the market sentiment – noise traders. Behavioural finance is a response to the limitations of neoclassical theory; thus, the critical assumptions of rational theory will be examined to contextualise this study. In particular, the thesis will analyse how noise traders have reacted to this crisis and whether as a group display signs of unusually high risk-seeking behaviour and irrationality. To further contextualise the study, the key actors and events that influenced the development of the current situation will be discussed.

The analysis will concentrate on breaking down the investment behaviour of noise traders through their choice of investments, identifying their risk profile and propensity to speculate. This will be done through a liquidity analysis on Robinhood investors' most bought long stock positions, creating a Robinhood portfolio. The liquidity analysis is inspired by the work of Baker, Stein & Wurglers' (2004,2006) work on market sentiment; they employed the share-turnover ratio to asses market liquidity and use high-levels of liquidity as a proxy for market sentiment.

The analysis finds that during the development of the COVID-19 pandemic share-turnover in the Robinhood portfolio increases. The share-turnover moves from 0.94% before the pandemic to 2.24% during the pandemic, a sign of heightened market sentiment. In addition to a heightened sentiment, the share-turnover ratio had significant explanatory power for price changes in the Robinhood portfolio and an S&P 500 ETF used as a benchmark when applied selectively to the period before and after the Pandemic. Lastly, the Robinhood portfolio showed that Robinhood investors have a risk-seeking behaviour as the Robinhood portfolio had a Beta of 1.56.

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1) Introduction

1.1) Context and Objectives

The most talked-about topic in 2020 has without question been COVID-19; it has affected the day to day lives of most people around the world and raised many concerns. With concerns come questions, be it COVID-19's impact on health, employment, person-to-person interaction or the economy and financial markets.

In the topics of the economy and financial markets, the pandemic has caused a plethora of new problems as well as exacerbating old ones. Most businesses have been affected in a never before seen way as a result of voluntary or government-mandated adjustments. These adjustments ranged from the complete shutdown in business activity and remote work policies to restrictions on commercial activity. The measures taken to fight the spread of COVID-19 have had a profound impact on company's' bottom lines as demand for many products and services has been affected, causing an increase in debt and a downward revision of growth expectations.

Naturally, the changes in the business landscape have spilt over to financial markets, with indices around the world suffering staggering losses and stock market volatility spiralling. As a result of the extreme market conditions, the stock market has become a focal talking point by news outlets and ignited interest in it by society at large. With most activities and forms of entertainments restricted, individuals have found new interests to occupy their time, one of these new interests is an online investment.

Online investment has become more accessible than ever before; a competitive industry ecosystem has arisen, and old barriers to investing have been demolished. Online investment apps now offer commission-free investment in a user-friendly format directly from users' phones. As a result, online investment companies have all seen a remarkable surge in new users and daily trades (Charles Schwab quarterly earnings, 2020). The growth in the online investment industry raises questions and concerns as a new group of market actors may bring with them a distinctive investment profile. An investment profile that may not fit with conventional, rational models of investor behaviour.

One would traditionally assume that the behaviour of a group of mostly inexperienced investors cannot affect the behemoth that is the U.S. stock market; but what if the group in question is composed of millions of members that invest in concert at a time of peak market uncertainty? The paper will attempt to answer by providing answers to these three questions:

1) Did the U.S. Financial markets experience a wave of sentiment during COVID-19?
2) Does sentiment (measured by share-turnover) help explain price changes during this period?
3) Are Robinhood investors rational investors?

1.2) Relevance

Research on the impact of COVID-19 on financial markets is scarce, and there is considerable room for advancement because of its novelty; this is particularly true for behavioural finance. Behavioural finance research thrives under unusual market conditions; it offers alternative explanations when rational models fail. For instance, Robert Shiller's ¨Irrational Exuberance¨ published at the peak of the dot.com boom in the year 2000, offered insight about pricing during that period that rational theory could not.

The COVID-19 crisis can give us a helpful perspective on the financial markets' reaction to rare economic shocks. For during these rare events, market-participant behaviour is more likely to deviate from the norm and features of behavioural finance are amplified, as is the case with the market sentiment. Studying the association of retail investors under extraneous circumstances to market sentiment will hopefully aid in the development of better models for times of market unrest, in which this work can provide an insight in retail investor behaviour.

1.3) Organisation of the Paper

Section 2 will be a literature review that will cover neoclassical theories on the concepts of rational, utility maximising investors (2.1) and the efficient market hypothesis (2.2). After establishing rational theory, the paper will offer an alternative set of theories showing the presence of both rational and irrational investors in a market setting, the combination of which allows there to be occasional irrationality in the markets in the form of sentiment (2.3).

Behavioural finance theory is used to explain the presence of irrational investors and markets (2.4); the focal point is the framing concept introduced by Kahneman & Tversky (1979) Prospect theory. The next section adds to the explanatory power of prospect theory by introducing other behavioural finance work like the Saliency theory (2.5). Behavioural finance is then contrasted with rational theory (2.6). Lastly, the credibility of behavioural finance is examined to illustrate its virtues and weaknesses (2.7).

Section 3 will start by describing how COVID-19 developed (3.1) followed by a description of how financial markets reacted (3.2). Next, the role of the federal reserve is discussed (3.3), followed by a summary of U.S. Government actions that have affected financial markets (3.4).

Section 4 covers the analysis of the thesis. Firstly, the methodology and tools will be explained (4.1) followed by the limitations and constraints (4.2). The next section serves to introduce and analyse the characteristics of Robinhood investors (4.3). An analysis is then performed through the share-turnover ratio on the 50 most popular Robinhood stocks (4.4) after the analysis is complete, the results will be discussed (4.5). Lastly, a more in-depth analysis is done by breaking down the most popular companies by industries and analysing the risks and rationale behind the investments.

Section 5 will entail a discussion about the results obtained and how they can help to answer the questions set up for this thesis (5.1). Lastly, recommendations and observations for future research are given (5.3), followed by the concluding remarks.

2 Literature Review

2.1) Expected Utility Theory

Traces of the expected utility hypothesis have observed throughout history in different forms, a notable example being Daniel Bernoulli's Saint Petersburg paradox in the late 18th century. By the mid 20th century, expected utility took a great leap forward as a result of the book "Theory of Games and Economic Behaviour." (Neumann and Morgestern 1944). This book serves as the basis for much of the work done on market rationality.

Expected utility theory weights the gain of outcomes within a game of choice to rank the choices by desirability. The concept of utility represents the satisfaction derived from an action or asset. The expected utility theory assumes that individuals will always attempt to maximise their gains. The most important axioms of expected utility theory are the following (Neumann & Morgestern 1944):

Completeness: if an agent prefers prospect A over prospect B and prospect B over prospect C, then that agent will always have a preference for A > C.

Transitivity: if an agent has to choose between two alternative prospects, a rational agent will not judge by their similarities, only by their differences. Suppose an agent has to choose between prospects A+C or B+C, as long as A>B the agent will always choose A+C.

Independence: if prospect A is preferred over prospect B, and a third prospect is added to the considerations, prospect C, a rational agent will still prefer A over B.

Continuity: if an agent prefers prospect A over prospect B and prospect B over prospect C, there is an exact probability of each prospect occurring that will make the agent indifferent in their choice of prospects. Continuity prevents there being discontinuous preferences.

If an agent complies with the axioms stated, he qualifies as a rational decision-maker, and as such, always chooses the optimal choice. Moreover, not only are rational agents rational, but they are also assumed to be knowledgeable.

The concept of a rational decision-maker is vital in the development of this thesis as there cannot be a market sentiment if financial markets are exclusively composed of knowledgeable, rational agents. However, there are many examples of expected utility axioms being infringed by investors, especially under unusual market conditions. For instance, there is evidence that closed-end funds can be less valuable than the sum of their investments, a clear violation of these principles. If fund A is composed of a bundle of securities B, B should not be more valuable than A; likewise, when a conglomerate owns several companies, these affiliate companies should not be worth more than the parent company (Shiller 2000).

While developing the expected utility theory, Neumann and Morgestern set out to:

"find the mathematically complete principles of which define rational behaviour for participants in a social economy, and derive from them the general characteristics of that behaviour" Theory of Games and Economic Behaviour, page 31

The authors had a good reason to generalise behaviour into a rational framework; it made the data adopt a stackable and divisible format, facilitating their mathematical modelling. Expected utility theory uses linear probability weights, represented by outcome X and probability P, when there is a set of outcomes and probabilities denoted as x1,p1. As more prospects are added with known probabilities the following is the case $\sum x1,p1 \ldots xn,pn$ where $\sum p=1$, This simplification is very useful to organise models.

Throughout Neumann & Morgenstern's book, economics is compared to physics and other natural sciences. Albeit, this stance comes at a cost, it discounts the diversity in human behaviour. To their credit, the trade-off has advanced the fields of economics and finance immensely; their work has in part helped establish a robust economic literature. At the same time, the rational agent assumption has caused models to ignore the nuances of human decision-making, these nuances, if decoded and included in traditionally rational models could enhance the veracity of these theories.

The issue is that unlike physics or chemistry, financial markets are much less exact, and one cannot control every variable. Unlike the case in objective sciences, the participants in financial markets are not mere observers; they are also an influence on the result. The hedge fund manager George Soros (in-line with the work of financial scholars) names the feedback loop between market participants and the markets Reflexivity (The Alchemy of Finance 1987). Reflexivity consists of a feedback loop in which market participants interact with the market in such ways that their actions influence not only security prices but other market participants perception on said prices, thereby distorting the objective value of the stock (Grunberg & Modigliani 1954).

Investment in financial markets revolves around decision-making under risk. In a setting with risk involved, expected utility relies on three main tenants outlined effectively by Kahneman & Tversky (1979): firstly, expectation which is the total utility of a given prospect. Secondly, asset integration which refers to whether adding the utility of a given prospect to market participants' current assets increases the participants' utility. Lastly, risk aversion, investors are risk-averse and prefer a certain outcome over an uncertain one with the same probability under ceteris paribus, this is represented by a concave utility function over an individual's wealth level.

2.2 Efficient Market Hypothesis

The efficient market hypothesis (EMH) relies on security prices that reflect all available information. Proponents of the EMH generally do not claim markets are hyper-rational. Instead, they claim that markets take a semi-efficient form (Fama 1991); that is, security prices are priced efficiently up to the point where the marginal cost of acquiring more information cancels out the marginal gain from using that information. However, the semi-efficient version, most models still rely on the assumption of a highly rational investor.

EMH basis security valuation on fundamental analysis; fundamental analysis states that a security's price at any point in time depends on business factors like sales, innovation and competition. When new information about a company's fundamentals becomes available, the value of the company is swiftly adjusted to reflect the new information. There is one more factor that influences a company's value, and that is macroeconomic events such as war or changes in interest rates which brings another type of uncertainty in the pricing of securities. The EMH assumes that all available information is reflected in the security price at all times and that extraordinary profits cannot occur over long periods resulting in a ¨random walk¨ pattern in financial markets (Fama 1965).

Sharpe (1964) proposed a factor model named the Capital Asset Pricing Model (CAPM) as a result of Marokwitz (1952) Portfolio theory work. This work helps investors assess the risk-return relationship of expected stock returns. The CAPM relies on the assumption that the risk premium of an asset is dependent on the amount of risk it adds to an investor's total portfolio. The return for any given security is based on the amount of risk required to hold it, so the higher the expected return, the higher the risk. The way risk and return are measured is through the covariance of a stock's past returns with an index, the S&P 500 for example. The expected return E(r), of stock i, is then equal to the following:

$$(1)\ E(ri)=\frac{Cov(Ri,Rm)}{\sigma^2 m}*E(rm)$$

In this model, all investments should have the same risk-reward ratio; if that were not the case, investors would sell the companies with subpar risk-reward ratio and purchase the ones with an excess reward to risk ratio, correcting any imbalances. The only difference in portfolio returns for investors, according to the CAPM is determined by their willingness to hold risk. An individual's level of risk tolerance is measured by A, so that:

$$(2)\ E(r) = U+ 0.5*A*\sigma\^{}2$$

The issue for assessing risk-tolerance through the A factor is that it is quite hard to map without having either the portfolio composition of an investor or an answered questionnaire or both (Bodie, Kane & Marcus 2014). Lastly, the CAPM introduces the concept of alpha, which is the difference between the actual return and the hypothetical return, in the long-term, if the efficient market view is correct, alpha should have an average value of 0.

The CAPM is a one-factor model and may not be the best predictor of the risk-return relationship. Fama & French (1993) develop a three-factor model that uses two more proxies to explain company returns. According to Fama & French, the CAPM left out significant factors in the explanation of expected return. To make the expected return model more accurate, Fama and French add two factors that have proven to matter in estimating returns historically, these factors are the SMB, HML. The SMB is the small minus big factor, and it measures the return of a portfolio with smaller firms to that of a portfolio with large firms. Companies with smaller market capitalisation outperformed companies with higher market capitalisation. The HML stands for high minus low, which shows the difference between value stocks and growth stocks as low price to book stocks have a trend to overperform high price to book stocks. The following formula represents the 3-factor model:

$$(3)\ E(ri)= rf+\beta i(rm-rf)+\beta_{SMB}*SMB+\beta_{HML}*HML$$

In 2015 Fama and French added two more factors creating the F-F 5 factor model. In this model, they have added a factor for profitability denoted by RMW (with the assumption that companies with high operating profit outperform companies with low operating profit) and also the investment factor denoted by CMA (which accounts for companies with high asset growth underperforming companies with low asset growth). The adjusted equation is the following:

$$(4)\ E(ri)= rf+\beta i(rm-rf)+\beta_{SMB}*SMB+\beta_{HML}*HML+\beta_{RMV}*RMV+\beta_{CMA}*CMA$$

From the data presented by Fama & French in their 2015 paper, The F-F 5 factor model improves the explanatory power of the 3-factor model; this model will be used to attempt to explain the risk-return profile of Robinhood investors.

The Random Walk Theory (RWT) relies on well-defined markets with a sizeable number of rational participants who are profit-maximising and knowledgeable. In the RWT, all available information is exploited to avoid under-pricing or over-pricing of securities. Knowledgeable investors ensure that any anomalies in prices compete away through arbitrage. Arbitrage occurs when a security price does not reflect its intrinsic value. At this point, rational investors would invest in the opposite direction of whichever direction the security deviated from its intrinsic value.

In an uncertain world, it is impossible to determine the intrinsic value all of the time; prices fluctuate as expectations change, and corrections take place. This idea complies with a random pattern of uncertainty also described as Brownian motion (Brown 1827); a stochastic process for modelling random behaviour in data. By the conditions described, the stock market has no memory, and past returns serve no indication of future returns (Fama 1965). The notion that past returns cannot influence future returns is contested by behavioural finance by studies like the ones provided by Rozeff and Kinney (1976) who found that there was a seasonality in stock returns. Rozeff and Kinney found that during January, stocks averaged a much higher return than during the rest of the year.

Rational models are not infallible, colloquially speaking they can "break", evidence of this is observed during the 2008 financial crisis, where risk management models failed to account for the depth of the losses. When financial markets deviate from rational models, Fama (1991) tells us that it is impossible to tell whether the market is inefficient, or the model used was a ¨bad model¨. Fama attributes a lot of behavioural finance research to statistical tinkering or luck. A notable rebuttal by Fama was Debondt and Thaler's papers (1985, 1987) on irrationally high returns of underperforming "losers" and poor returns of overperforming "winners". Debondt & Thaler claim that the explanation to the variance in returns they found is an over-reaction by market participants, Fama disagrees and instead attributes it to statistical luck or the difference of risk-adjusted expected return between smaller companies and larger ones.

2.3) Speculative Investors and Market Sentiment

In a market that isn't entirely rational, there is a mix of at least two broad categories; rational investors and speculative noise traders. Noise traders are investors that invest less methodically than rational investors and are influenced by cognitive biases when making investment choices; this feature creates irrational sentiments in their portfolio choices.

The EMH would argue that informed, rational investors would offset irrational pessimism or optimism created by noise traders, thereby returning a security to its intrinsic value. Moreover, the presence of noise traders would be considered a temporary occurrence as rational agents would eventually drive them out. However, there is not that much evidence for this theory, in fact, the opposite may be true, De long & Shelifer (1990) show that even in market equilibrium "rational" investors exacerbate the speculative signals given off by noise traders. Moreover, even if rational investors identified a security mispricing to exploit, the price reversal could be hampered by an inflow of even more retail investors doubling down on the irrational investment. The inflow of further irrational investment would cause rational agents to liquidate their position to prevent further losses (Barberis, Shleifer & Vishny 1997), simply put: The market can stay irrational longer than a rational investor can stay solvent.

Using Kyle's 1985 model of market equilibrium with a relaxed assumption on insider traders' knowledge (superior knowledge instead of insider information), we can see an increase in market order volume by informed investors when noise traders become more active. Kyle's model shows that the more noise traders auction for a stock the more informed traders act, this is because noise traders act as a camouflage for the informed traders in the eyes of market makers who set the prices. Market makers are rational agents but cannot differentiate informed and noisy trades. Market makers cannot tell who is making an order because stock's price reflects all bids by both noisy and informed traders, this view is also corroborated by Black (1986) who displays the difficulty of differentiating noise trades and informed trades. The more trades that are enabled for informed traders by noise traders, the more they can extract extraordinary profit from the market at the expense of noise traders.

Kyle's model can help explain why more volume is traded when markets are composed of both noise-traders and informed investors. The model presents a volume maximising principle; when one group trades the other follows suit. During large shocks to the market, more noise traders enter the market. Aa result, market liquidity increases; a sign that sentiment becomes a more potent factor in the pricing of securities.

Market liquidity is a feature of the EMH. A market is "liquid" according to Black (1971) when:

i) There is a constant flow of bid and ask prices for an investor to buy and sell instantly.
ii) The difference between the bid-ask spread is small.

iii) When investors selling a large block of securities can do so without high unwinding costs (as long as it is done gradually)

Market liquidity is a mixed blessing, it enables rational theory to operate through rapid information absorption into security prices, but in excess, it can be a symptom of an increase in speculation and waves of investor sentiment that may not be entirely rational (Berkman and Koch 2008). Liquidity can be used as a proxy to measure market sentiment (Baker & Stein 2004 and Baker & Wurgler 2006). There are a few ways to calculate how liquid a market is, for the analysis section of this thesis it will be measured through the share-turnover ratio. The share turnover ratio shows how many times shares change hands as a proportion of the total shares outstanding in a company.

Wurgler and Baker (2006) define sentiments in respect to financial markets as an irrational propensity to speculate which drives the demand for particular securities higher or lower than they should be. The speculative features in noise-traders that causes market sentiment can be explained through behavioural finance theory. Nevertheless, finding significant empirical evidence to support the theory is complex. Wurgler and Baker believe that certain stocks appear to be more vulnerable to unsophisticated speculative investors. An example of an attractive security for a noise-trader is one that is young, unprofitable and has potential for high-growth.

Baker & Stein (2004) identify irrational investors that underreact to information of order flow and boost liquidity, and argue that when liquidity is high, it is a symptom of a strong presence of irrational investors. They organise their model in three periods; in the 3rd period, the stock pays a dividend of F+q+w where q and w are independent normally distributed variables unknown to investors. The independent variables maintain the expected risk premium constant in period 1 and 2. At time 2, Baker & Stein project an insider to trade based on private information of q, this action reveals information to informed investors who will quickly react to this signal.

Baker & Stein dichotomise the investors in their model into "smart" and "dumb", equivalent to informed investors and noise traders. They show that although both types of investors will read the market signals and act on them, noise traders will not take full advantage due to their misconstrued market framing. They propose a classification for market sentiment and market activity broken-down into three scenarios:

1) Under low investor sentiment only informed rational investors participate.
2) Under intermediate investor sentiment there is a mix between rational and noise traders.
3) Lastly, under high investor sentiment noisy traders compose the majority of the trade volume.

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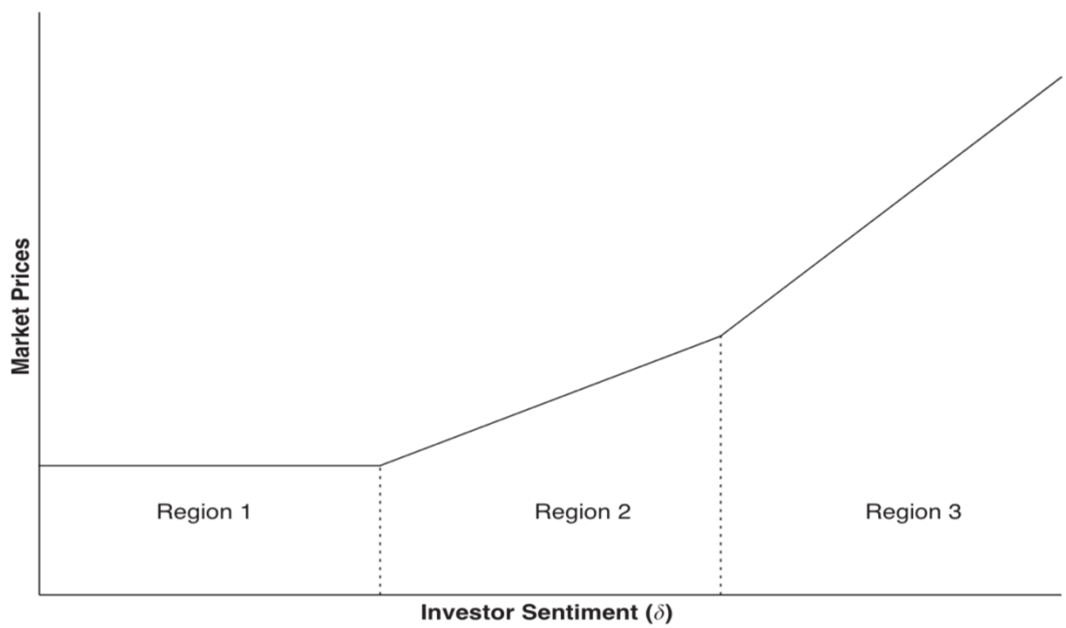

Figure 1: hypothetical increase in prices as more noisy traders crowd the market (Baker & Stein 2004)

For noise-traders to have a significant effect on security prices, their collective actions must be correlated (Burghardt 2010); do noise traders display herding behaviour? A way to find a herding effect in retail investors is through market order imbalances. Order imbalances show whether there is a disproportionate interest in a particular stock or group of stocks. In financial markets, there always is a seller for every buyer and so general order imbalances don't exist, so the study of order imbalances must be divided into subgroups of buyers and sellers, Kumar & Lee (2003) do precisely that. Using a large dataset of 1.85 million retail investors, Kumar & Lee show a strong correlation in trading decisions and evidence of investor sentiment affecting stock returns.

In 2020, herding behaviour among the group of retail investors has likely increased. The internet has provided many influential sources of stock market information such as Stocktwits, Weibo and Reddit that can exacerbate a uniform investment strategy for retail investors. Moreover, given the accessibility granted by the internet, these online investing communities boast of tens of millions of users, as will be shown in the analysis. For instance, Zhou, Xu & Zhao 2018 found that ¨experts¨ with large followings had a powerful effect on their followers. They used a Bayesian classifier of emotions to find that different types of investors react differently to new information, with the least experienced being the most sensitive.

2.4) Behavioural Finance I: Prospect Theoy

Although much of the initial work on rational theory dates back to the mid 20th century, it was essential to examine the source of expected utility and rational behaviour during decision making. As most behavioural finance, such as Kahneman and Tversky seminal paper on prospect theory (1979) directly rebuttal it. The impact of expected utility and rational behaviour in economics and finance is seen by the fact that a rebuttal to Neumann and Morgenstern's work was relevant in 1979, and even today, almost 80 years later.

Prospect theory is designed by Kahneman & Tverseky to be an alternative to expected utility theory. One of their main argument is that under a risky market environment, investors are susceptible to cognitive biases that will impede them from acting entirely rationally. They argue that the way individuals frame their decision-making process infringes upon the axioms of expected utility. Prospect theory does not assume the rationality of market participants and is a descriptive theory instead of a normative theory like the EMH. It serves to introduce some of the axiomatic principles of behavioural finance, which help explain why the market behaves irrationally and fails to comply with rational models on occasions, especially in times of market distress. Prospect theory is divided into a two-step process, described as an editing, or framing phase and an evaluation phase, which will be briefly discussed.

The framing phase consists of individuals gauging the decision-making subject matter, creating a simplistic deconstruction of all the perceived nuances in a given prospect. The framing phase encompasses a wide variety of processes that lead to irrational behaviour; an example would be coding. Coding refers to the way individuals perceive the importance of outcomes. Individuals perceive the attractiveness of outcomes relative to their wealth. Investors have different levels of wealth, so their utility functions aren't as easily stackable as expected utility might assume. Kahneman and Tversky also reference experiments that show that the coding process can be affected by the subject's expectations or the formulation of the prospect.

Another relevant example of framing would be the process of simplification, in this context simplification is a mental shortcut taken when assessing probabilities; the authors point towards individuals simplifying the odds of a given prospect through tools like mental accounting, which causes individuals to round the probability of an outcome to more easily understood iterations. For example, if there is an 89% chance of a prospect occurring, the decision-maker may round it up to 90%. As a result of mental accounting, when events with low probabilities do happen, they will have been under-represented in the minds of many investors resulting in them being overly exposed to losses. Essentially, low odds can be confused with there being no odds of a prospect materialising. This effect could help explain the lag in the western countries and markets to take action against the Coronavirus in its early stages. For it seemed unlikely to be a global pandemic during the first two months as very few cases had been reported in Europe and North America.

The framing phase results in an erroneous perception of the nuances present in different prospects, and so leads to irrational decisions when considering uncertain prospects like the ones present in financial markets.

The concept of framing is crucial in the process of explaining market sentiment. Under the umbrella of framing, we can incorporate many features of behavioural finance from different authors as they all have the same general effect: constructing an irrational decision-making framework for risky prospects. The heuristics present in framing are the type of cognitive biases that lead investors to have unreasonable sentiments about the market. Heuristics, as described by Kahneman & Tversky (1974), are in general, useful traits of the human psyche. They are mental shortcuts that help individuals deal with the limitations of their rationality and expedite everyday decision-making. The issue lies in the fact that heuristics are inherently vulnerable to biases. The three main heuristics discussed by Kahneman & Tversky (1974) are representativeness, anchoring and availability.

Representativeness is broken-down into base rate neglect and sample size neglect. Sample size neglect is the propensity for investors to extrapolate from a sub-sample of data instead of assessing the whole sample. Base rate neglect is a substitute for research and causes investors to buy into companies they somewhat understand while at the same time ignoring what they do not understand, leaving out of their consideration important nuances that affect the risk of the investment.

Anchoring refers to the tendency of individuals to attach themselves to an arbitrary reference point. The initial position acts as an anchor for future considerations. The agent then chooses prospects that align with the reference point. An example of anchoring would be extrapolating future returns to be close to past returns assuming all conditions will stay the same.

Lastly, in the availability heuristic (Kahneman & Tversky 1973), events are judged by a mental recall from past experiences. Availability heuristics can take several forms. It can affect the way investors categorise new information by assigning it to a known category despite not necessarily being the same information. Availability can also manifest in forecasting expected values and returns; this will cause the forecasts to be inaccurate as individuals will use their incomplete but available information to make the forecasts. Lastly, investors may look for investment prospects that fit with the information they have at-hand, thereby engaging in limited research. For instance, Barbaris et al (2001) provide a study of an example of this heuristic at work; they find that many investors judge a particular stock based on the stocks past returns, which is what they can most easily recall, this does not guarantee the same returns though.

The evaluation phase consists of weighing the prospects designed in the framing phase and choosing the prospect with the highest perceived utility. The value is derived from the perceived desirability of the prospects which might not objectively be the most utile to them.

2.5) Behavioural Finance II: Saliency Theory

Bordalo et al. in their 2012 paper, developed saliency theory, in this theory, the authors find that individuals' level of risk-seeking or risk-averseness varies depending on what kind of "game" they play. They use the example of insurance versus the lottery, in which individuals are willing to play the lottery despite abysmal odds and a small prize (relative to the investment made and the odds of winning). What the theory proposes, in line with behavioural finance literature, is that individuals have limited cognitive capabilities; we can only concentrate on a subset of available data which prevents us from capturing the full picture of a situation.

Bordalos' theory narrates a similar story to that of Kahneman and Tversky's framing phase; individuals cannot comprehend all the nuances involved in a decision, so they misinterpret some of the data while ignoring other parts of it. To compound the saliency and framing effects, Gennaioli and Shleifer (2010) introduce local thinking, in the context of ignoring relevant data that is underrepresented, this is also related to Kahneman & Tversky's heuristics. For instance, the most popular financial news of the day may not be the most important one, but due to its spread and availability investors can overweigh it while underweighting less attention-grabbing but just as relevant news.

From a more macroeconomic perspective, Ito, Noda & Wada (2016) produce a non-Bayesian time series model on the evolution of the stock market to test its efficiency. Their results show that for vast lengths of time, the stock market is efficient, but it has irrational periods such as the 1958 crisis, in which extraordinary causes seem to lead to inefficiency. Their explanation for the irrationality found in their research is "sudden and abrupt changes in an individual's behaviour" in answer to extreme events. By all accounts, the 2020 pandemic would classify as an extreme and a cause for irrationality in financial markets.

2.6) Divergence Between Rational Theory and Behavioural Theory

Many behavioural phenomena violate the expected utility tenants. In Kahneman & Tversky's (1979) experiment, for instance, 80% of test subjects responded that they would rather have a guaranteed chance of winning 3000 than having an 80% probability chance of gaining 4000 dollars. Nevertheless, the expected utility is higher with the 4000 dollars choice; this is an example of the certainty effect and a violation of the substitution axiom of utility theory.

Interestingly, when instead of positive outcomes, people are asked between two adverse outcomes, a "reflection effect" takes place in which oddly enough makes participants become risk-seeking. The way the reflection effect is tested is, to use the previous example, instead of a certain chance of winning 3000 and a 0.8 chance of winning 4000, subjects are asked to choose between a sure chance of losing 3000 and an 0.8 chance of losing 4000, in this example 92% of the participants choose to gamble with the 0.8 chance of losing 4000, the suboptimal rational choice.

Kahneman and Tversky's theory is also ratified by Markowitz's early work in 1952 & 1959, who shows through a series of experiments that utility functions do not follow the principles established by rational theory. Subjects show different risk profiles depending on their level of wealth and framing of the quantities at stake. The utility of a gamble is determined how the outcomes affect the wealth reference point. This is demonstrated graphically by figure 2.

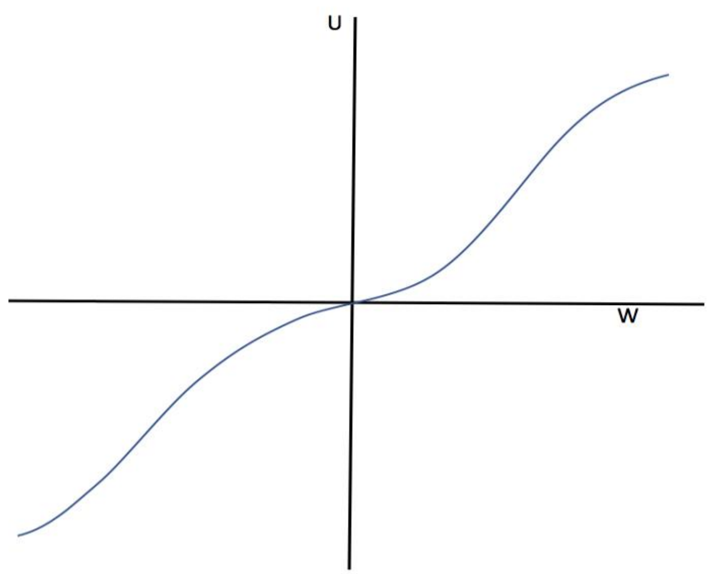

Figure 2: Utility as a function of wealth as shown by Markowitz (1959)

Figure 2 shows that for levels of wealth above the reference value, the curve is first concave and then convex, the opposite is true for losses. This shows a risk aversion for different distances from the wealth reference point, a violation of expected utility.

The findings By Markowitz. Kahneman & Tversky, illustrate an attitude towards risk attitude that can explain movements in the stock market under distress. This model can be superimposed on an investor's portfolio, which during a black swan event like the 2020 pandemic, losses 50%

of its value. In which case, Markowitz hypothesises that a moderate loser of the "Game" (in the Neumann sense) would want to cut their losses, but someone who loses what they consider a large sum would want to keep playing with increasingly riskier bets to get back to their wealth reference point. The change in risk-profile as a response to heavy losses can be described as the break-even effect; where individuals try to regain their loss until they are back to their previous wealth reference point (Kahneman & Tversky 1979). This kind of shift in reference can extend to the stock market following large movements such as the one caused by the pandemic; the wealth of many investors was affected. A shift in wealth can result in their reference points to lag and change the framing of their investment choices, leading to riskier investment prospects in order to ¨break-even¨.

2.7) Behavioural Finance Discussion

It must be said that a great deal of behavioural finance concentrates on developing theory from small to medium-sized samples. These experiments involve groups of individuals under a controlled environment, and the monetary stakes are low as opposed to macro-level studies with high monetary stakes.

There are several criticisms for experimental behavioural finance studies. One criticism is that results may change when subjects are faced with hypothetical decisions as opposed to decisions with real outcomes, some studies like Kahneman & Thaler's mug experiment (1990) address that and have real stakes, albeit relative low-value stakes (the lack of high-stakes studies is understandable as they are not financially feasible to run). A common criticism of low-value stakes is that if the stakes were higher, subjects would take it more seriously and become more rational. Thaler's rebuttal is that if the stakes were higher, it would be more likely that irrational choices were made as individuals have little practice with high-stakes decisions (Thaler 2016).

There is also plenty of papers studying the broader aspects of behavioural finance using large amounts of data from financial markets like Debondt & Thalers' 1985. Behavioural studies on financial markets can show issues with the EMH view of markets, but they can rarely attribute an empirically sound motive for these patterns of irrationality.

There seems to be a flaw in the unification of behavioural finance; studies on large samples using market data can identify a deviation in rationality but struggle to provide empirical evidence on why the behaviour occurs, meanwhile studies that isolate behavioural theories such as prospect theory isolate the behaviour but cannot strictly attribute market irrationality to the behaviour.

There is also a lack of consolidation within behavioural finance literature; for instance, the aforementioned break-even effect contradicts the ¨house-money¨ effect developed by Thaler & Johnson (1990). The house-money effect is an inter-temporal theory stating that past returns to investors affect their risk propensity in future periods. If an investor makes a profit in period 1, he will have a lower risk-aversion in period 2 as in gambling terms he is playing with ¨house-money¨, likewise if he losses in period 1 he is likely to become more risk-averse in period 2; this is the opposite of what Kahneman & Tversky find through their break-even effect.

3) Covid-19

3.1) Description of COVID-19

COVID-19, has been the most critical news socially, politically, and even culturally in 2020. It has had devastating effects on the economy and has catapulted volatility in the financial markets in an unprecedented way.

By most accounts, COVID-19 has been traced to the province of Wuhan in mainland China. It is believed that started in one of Wuhan's ¨wet markets¨ in early December of 2019. The Chinese authorities waited until December 31st to inform the World Health Organisation about what was happening. Even after the epidemic was announced, governments around the world had a dismissive approach for the first couple of months. It was not until February that serious consideration was given to the risks by western authorities.

This strand of the beta-coronavirus family was previously unknown and is believed to have mutated to jump species from bats to humans. It was not the first Coronavirus known to infect humans; in fact, the rise of COVID-19 marks the 7th Coronavirus to infect humans. Several epidemics have arisen from this family of viruses, Notably the MERS-CoV in 2012 and SARS-CoV in 2002. Although no other coronavirus has caused as much destruction as the current virus, the possibility of a large-scale spread was never off the table. The mortality rate varies among countries and age groups but is estimated to be between one and two per cent (albeit the real number of infected people is unknown, which may result in variability of the real statistic).

3.2) Market Reaction to COVID-19

As a result of government policy against the Coronavirus, security prices suffered immensely, as macroeconomic events account for an estimated 75% of market volatility (Corradi, Distaso, Mele 2013). Pandemics and epidemics have a history of influencing financial markets, but the most significant pandemics of the 20th century did not cause a reaction that was even close to the magnitude of COVID-19. For instance, neither the 1918 Spanish flue that killed an estimated 2% of the world population nor the Influenza pandemics of the late 1950s and 1960s (Baker et al., 2020) had nearly as much impact as COVID-19 despite their higher mortality rates.

A vital factor in the market's initial reaction was the general uncertainty given the lack of knowledge about how dangerous COVID-19 could be. When it was clear that COVID-19 was spreading to all nations, the Global economy declined precipitously. Although by the time U.S. markets reacted to COVID-19, there had been enough information available for some time which could have predicted a strong adverse reaction.

As a result of the spread, countries around the world went on lockdown. Individuals were not allowed to leave their homes for extended periods, and most economic activity either massively slowed down or shut down completely. Naturally, this warranted a sharp decline in financial markets worldwide. The S&P 500 lost 1148,75 points (33,92%) from February 19th to March 23rd, one of the largest and fastest declines ever, in the same period, the S&P 500 volatility index, the VIX went from 14,38 to a peak of 82,69, a 475,03% increase rivalling the volatility experienced in the 2008 financial crisis. However, miraculously, from March 23rd to June 8th, The S&P 500 experienced a 994,99 point rebound (44,47%) while the virus was still developing in the U.S., leaving experts baffled trying to explain such a rise before the dust had even settled.

Firstly, although the stock market lagged in its reaction, the drop itself conforms with an efficient market construct, market participants reacted appropriately to changes in expected cash flows, growth potential, and default potential among other changes to expectations. Prices were adjusted down due to the uncertainty and poor prospects ahead; for instance, the airline industry was essentially put on hold and suffered significant losses, with many airlines filing for bankruptcy like LATAM and Virgin Australia. Most companies suffered some degree of price decline except for a few that were benefited by COVID-19 like Zoom Video. The market reaction was not due to the spread or mortality by COVID-19 directly, but instead, it was a reaction to government policy.

In February, COVID-19 was vociferously covered by all media outlets, and the narrative espoused was extremely pessimistic. While media presents itself as arbiters of truth and detached observers concerning financial markets, in his 2001 article Shiller argues they are an essential part of market movements, as market events occur if there is herding effect in large amounts of investors, and the news can serve as a catalyser for herding. Media outlets are in constant competition to grab their readers' attention, more so now than ever when factoring the effects of the internet and social media.

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News about the economy and financial markets are attractive, as they are a daily source of exiting content, especially during COVID-19, as many sources of entertainment such as outdoor activities and sports broadcasts were cancelled. For retail investors, the stock market can play the role of a "big casino"; this should not be the case for informed, professional traders. However, Barber and Odean (2008) find that flashy headlines draw professional investors attention, providing them with what could be alarmist or over-the-top news that could influence their perception. Furthermore, previous pandemics hardly influenced the market, with the Spanish Flu failing to trigger a single fall of more than 2,5% in the markets (although the period did have a higher propensity for price swings) (Baker et al. 2020). What sets this pandemic apart is the advancements in information distribution. As a result, the news regarding the pandemic has spread much faster. However, the news alone cannot explain the economic shock to the stock market, albeit it can be one of the instigators of irrational market behaviour.

3.3) The Federal Reserve

A critical factor in the unfolding of the market reaction to COVID-19 has been the Federal Reserve of the United States of America (FED). The FED offers guidance that is then interpreted by market actors and can drastically change future market expectations. Table 1 shows an increase in its loans to banks, providing them with liquidity to theoretically stimulate the economy by providing funding to businesses and households.

Table 1. Loans to depository institutions and other loans, net
(in millions)

	March 31, 2020	December 31, 2019
Loans to depository institutions		
Primary, secondary, and seasonal credit	$ 49,087	$ 42
Other loans, net		
Money Market Mutual Fund Liquidity Facility	50,084	—
Primary Dealer Credit Facility	36,178	—
Total other loans, net	$ 86,262	$—
Total loans	**$135,349**	**$ 42**

Table 1: Federal Reserve first-quarter report of 2020

During the COVID-19 pandemic, the FED has not only provided liquidity to the economy through direct financing operations like quantitative easing but has also lowered the interest rate to 0 to bring down borrowing costs. Historically, when the FED has lowered rates, the economy has had a positive response with Financial markets soaring.

On March 15th (a Sunday) the FED made a release that was timed just before the sitting U.S. president's speech, in his speech Donald Trump was extremely pleased by the Fed's extraordinary announcement in which they unleashed an array of counter COVID-19 measures to help the economy recover. Counterintuitively, on March 16th, the S&P 500 index dropped by 11.98%, and the S&P 500 VIX rose 42.99%, the most significant per cent drop in the S&P in recent history as well as a monumental increase in fear shown by the VIX.

It cannot be said that the FED alone caused the 11,92% decline, but undoubtedly it played a key role given their importance in the U.S. financial system. A popular narrative was that if the FED was using most of its ammo, the situation was much worse than anticipated, and panic ensued. The announcement acted as confirmation bias, in the sense that it ratified the markets worst fears. As time went by and it became clear that the FED was going to save financial markets at all costs by statements like the following by the Chairman of the FED Jerome Powell:

"We will continue to use these powers forcefully, proactively, and aggressively until we are confident that we are solidly on the road to recovery. "– Jerome Powell April 9th, 2020.

Reactions to the FED announcements have returned to having a positive outlook. However, March 15th is a unique case that points towards an irrational element in the markets. The FED itself offered no actual data on the pandemic that was not already known to investors, and what they revealed during the speech was positive measures for businesses that were meant to aid the economy and appease market-actors. In a rational framework, this announcement should not have been followed by the most prominent one day drop in recent history.

A parallel can be made between FED announcements and aggregate company earnings announcement in that both actions warrant a revision of stock prices. These revisions are influenced by market sentiments (Mian & Sankaraguruswamy 2012), and so, given the prolific and consistent actions by the FED throughout the COVID-19 pandemic, mispricing could have occurred after FED announcements as it confirmed investors worst fears during the start and nudged towards a recovery afterwards.

3.3) The U.S Government

The U.S. government response, just like the European response was uncoordinated, different states implemented different measures at different times. The state by state reactions will not be covered, but it is relevant to mention that key states like California and New York imposed extreme lockdown measures that had a significant impact in the most influential parts of the American economy. The lockdowns are the most significant factor in explaining the market volatility as it directly affects future expectations on returns.

The U.S. government passed the CARES Act by bipartisan congressional support. The CARES Act consisted of a $2.3 trillion economic relief package, involving loans, grants and other forms of assistance. On top of the CARES Act, a separate $105 billion in unemployment and food assistance in the Families first Coronavirus Response Act.

The federal government also imposed travel restrictions for China as well as European countries which is quite damaging to specific industries, especially the airline industry. It is essential to mention government actions for two reasons. Firstly, it showcases the seriousness of the situation, a signal markets pick up on and secondly, it helps us in understanding the pause in business activity and the enormous influx of cheap or free money for individuals and businesses.

4) Analysis

4.1) Tools and Methodology

I will be using Finbox.io excel add-on to retrieve the daily volume of shares traded in order to calculate the share turnover ratio of each of the top 50 Robinhood stocks found on Robintrack.net; the share turnover ratio acts as a proxy for the market sentiment (Baker & Stein 2004). I also used Finbox to retrieve the 2-year beta for the selection of Robinhood Securities to assess their risk. Finbox has a partnership with Standard & Poors market intelligence; this provides an assurance of accurate and reliable data. Robintrack is not affiliated with Robinhood but sources all its data through Robinhood's public API.

The share-turnover ratio is a measure of a securities liquidity and can be used to approximate market sentiment. It is calculated by dividing the total number of shares traded by the average shares outstanding; this calculation can be done daily and can be graphed to show patterns in volume traded relative to shares outstanding.

I will be aggregating the results to form the Robinhood share-turnover portfolio; this is done to discern the overall market sentiment of the selected securities. I will also be using FRED to put together a graph to contrast my results with past share-turnover data from U.S. markets.

The data collected for the share-turnover ratio is from November 1st 2019 to July 15th 2020, this time-frame was selected to collect data before and after COVID-19 hit the U.S. in order to be able to contrast the periods. It encompasses a pre-COVID-19 quarter from November 1st to February 18th (approximate cut-off is required due to COVID-19 having a gradual onset), a quarter of extreme fear February 19th to March 23rd (from the peak of the S&P 500 to its lowest point) and a quarter showing the recovery period (which is still ongoing) from March 24th to July 15th. I use regression analysis jointly with the Fama-French 5 factor model to show whether the share-turnover ratio can explain the price changes in the stock market

The S&P 500 index ETF will be used as a benchmark. Furthermore, the 2-year beta is calculated separately from the Fama-French 5 factor model to have a consistent benchmark for risk for the industry analysis. This is done in orders to avoid issues with the short time frame and sample size of the analysis.

For the industry analysis section, I will be using different methodologies and tools to describe the risks of each industry. This is done to more accurately depict the sources of risk and their attraction for noise traders. To assess the risk of each industry in the Robinhood portfolio, I will be using the 2-year beta as a measure.

4.2) Limitations and Constraints

The study I present has a variety of limitations and constraints. Firstly, papers relating to behavioural finance and the coronavirus pandemic are scarce, it is a recent event, and accurate data that spans through adequate time frames are hard to come by.

Secondly, practical explanations to sentiment mostly come through surveys and experiments on a limited number of subjects, making it complicated to extrapolate to financial markets at large, given the size and multivariate nature of financial markets and their participants.

There are no perfect measures of market sentiment, so market liquidity (through the shares turnover ratio) is used as a proxy as previously done by Baker & Stein (2004) and Baker & Wugner (2006). Using the share-turnover ratio alone cannot tell us whether the sentiment is positive or negative (although the general direction is readily observable).

One of the companies in the Robinhood portfolio, NKLA, had its IPO on June 4th, to keep the data time-consistent this stock was replaced with the 51st most popular stock, SPCE.

Robinhood users are what would be categorised as retail investors (as mentioned by the CEO of Robinhood, at least half of the people using the platform have little to no experience). As so, they are used as a proxy for the whole group of retail investors, when Robinhood users are drawn to a stock, the assumption is that other retail investors do too. Furthermore, the data cannot tell us how much of the change in liquidity is due to retail investors, nor if there are subgroups of retail investors with entirely different characteristics.

I will be using the 2-year beta for the industries as opposed to the Fama-French 5 factors because of sample size constraints and availability of data. The 2-year beta will be used to assess the industry's relative risk to the S&P 500 ETF.

4.3) Robinhood Investors in the time of COVID-19

The 2020 pandemic has seen many businesses file for bankruptcy, such as Hertz Global Holdings Inc and JC Penney Company Inc, among many others. In normal circumstances, given the state of their balance sheets and low chance of recovery, these companies would be trading in losses in the stock market and eventually stop trading altogether unless a good restructuring strategy took place.

Nevertheless, a peculiar effect is taking place where these stocks are experiencing bewildering interest by investors, causing volatile swings in their price and volume traded.

Google trends can illustrate a general pattern of rising interest in the stock market. The graph shows that shocks to the market increase search volume, as shown by the 2008 peak and the 2020 peak (This does not serve as evidence of an increase in sentiment or investment)

Figure 3 can illustrate a general pattern of rising interest in the stock market. The graph shows that shocks to the market increase search volume, as shown by the 2008 peak and the 2020 peak (This does not serve as evidence of an increase in sentiment or investment)

Figure 3: Google Trends, Number of Searches for "Stock Market", X = Time Y= Proportion of Searches.

The volume of shares traded in general has seen a significant increase after the indexes bottomed, there has been a momentum of "buying the dip" which has catapulted many security prices to reach their highest valuation ever, all this while one of the worst economic and social shocks of all times took place.

There are several reasons to explain the market movements; the one that will be discussed is the influx of online retail investors led by easily accessible platforms like Robinhood, Charles Schwab, or T.D. Ameritrade.

Online investment applications enable vast amounts of people to invest in the stock market through their commission-free trading system, which used to be a considerable barrier for retail investors as the commission could quickly eat away at their profits. The removal of commissions also acts as an incentive to not only invest in financial markets but to do so often as there is no friction between buying and selling (daily volume for trading in online platforms is at an all-time high according to Charles Schwab Q1 earnings report). These platforms also make it easy to join and offer a user-friendly interface that makes trading in the financial markets as simple as possible.

Robinhood, in particular, has experienced enormous growth in users and by their admission, half of the users have no investment experience at all, with the other half having an undisclosed level of previous exposure the financial markets. Moreover, many online trading platforms experienced similar growths (Charles Schwab Q1 earnings report, 2020).

Robinhood's business model revolves around payments for order flow, in which brokerage companies pay Robinhood for the rights to determine the prices at which Robinhood trades are executed. Essentially, the more users buy and sell securities, the more money Robinhood makes, creating an incentive to encourage more trading on their platform. Robinhood has successfully exploited this incentive and added features that allegedly parallel gambling, which encourages risky behaviour by inexperienced users. In addition, Iancu & Maier (2016) found through surveys that retail investors believe they have the same or more information than institutional investors; this could lull users into a false sense of security.

There are many behavioural finance theories (Barber & Odean 2008, Gennaioli Shleifer et al. 2012) that points towards inexperienced investors attracted to attention-grabbing news about popular stocks while ignoring less "flashy" securities. This fact not only violates the axiomatic principles of the EMH but also causes markets to become more emotional and prone to waves of irrationality due to investor sentiment.

In the first quarter of 2020, most businesses reduce their growth expectations as a consequence of the global pandemic. However, Robinhood received a spike of 3 million new users making their total user count close to 13 million users (Vladimir Tenev, CEO of Robinhood 2020). The company has been growing steadily for the past five years, but this is the most significant total growth in users they have had. Furthermore, many Americans received an influx of time and disposable income ($1200 stimulus cheque), making it easier for them to invest.

According to research made by the company Alphacution (2020), the average Robinhood user has 4500 dollars in their account totalling an amount close to 60 billion dollars of available money with the purpose of investment. Robinhood only accounts for one online trading platform; the combined account balances of all trading platforms are in the hundreds of billions without counting other forms of retail investment.

4.4) Results and Initial Analysis of Results

In order to figure out whether the market had a heightened sentiment, I took the top 50 Robinhood stocks by popularity and applied a share-turnover ratio for the period of November 1st to July 15th. Below is the aggregate share turnover of the picks.

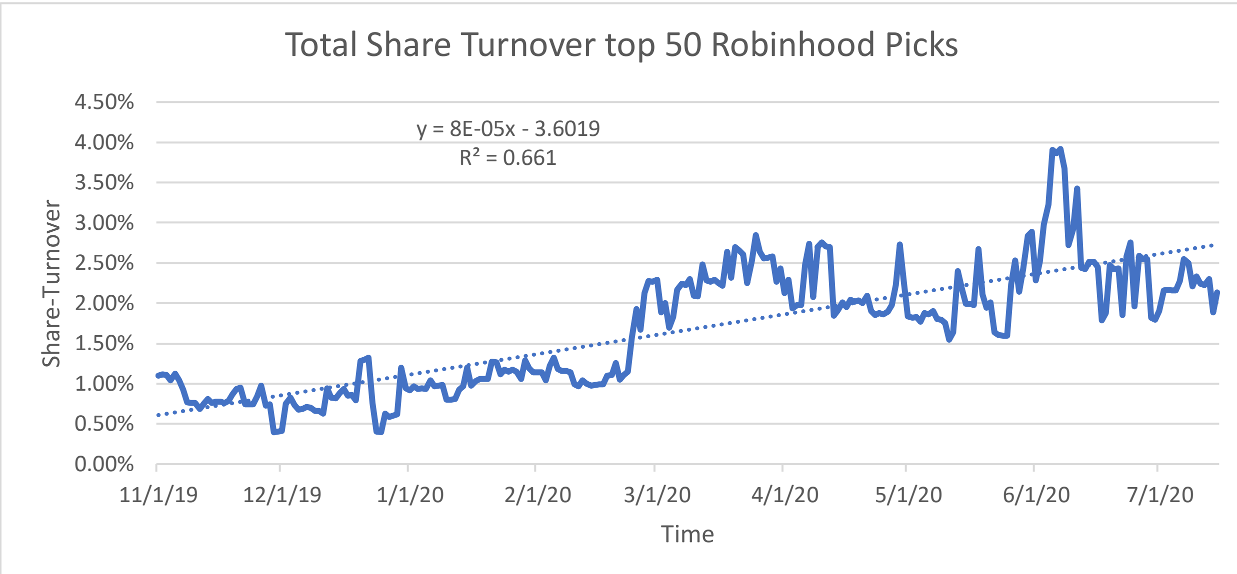


Figure 4: Total share-turnover for the Robinhood Portfolio from November 1st to July 15th

The results show a correlation of increasing liquidity within Robinhood's favourite picks as the pandemic took shape. From November 1st to February 23rd, the average share turnover was of 0.94%. After an initial drop in the U.S. markets on February 19th, a slight drop in volume can be seen until February 23rd, which could be initial fear, although the time period is too short to draw any valid conclusions. From the 23rd onwards, while the Down Jones, the S&P 500 and the NASDAQ composite were having their worst decline this century, the share volume went up and has remained at around 2.24%, more than double the pre-COVID period. In addition, the 2-year CAPM beta for the Robinhood portfolio which came out to be 1,56, 56% higher than the average S&P 500 company, showing an appetite for risk.

Interestingly, the volume traded reached a peak of 3.92% during the height of the recovery, when the S&P had gone up 44.97% from its lowest point. The data seems to comply with the expectations of the representative heuristics theory. Market participants could observe a consistent rise across indexes with the addition of supporting positive data from the FED and news about reopening throughout this period. A noise trader influenced by representative heuristics would interpret this as a signal of more gains to come. As a result, an increase in volume as investors increase their exposure is to be expected. The increase in market volume for the selected stocks coincides with the increase in Robinhood users buying into these stocks.

To check the explanatory power of the pattern illustrated by figure 5, a linear regression was performed using the Fama-French 5 factor model adding share-turnover as a sixth factor (appendix). Neither the Alpha nor the Betas are sufficiently strong to prove share-turnover as a critical factor in the price changes from November 1st to June 15th, Yet If the timeline is split into a period of recovery from March 23rd to June 8th and a period of losses from November 1st to March 20th (period 1 and period 2) the share-turnover ratio becomes highly significant as shown by figure 5 and figure 6 The Share-Turnover factor has a coefficient of -1.43 with a T-stat of -5.94. in period 1 and 1.62 with a T-stat of 2.48 in period 2. Figure 5 shows that the only factor that has explanatory power is RM-RF during period 1. This leads me to believe that the Fama-French model has a stronger explanatory power for market returns during periods where there is no economic turmoil.

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0,5955414							
R Square	0,35466956							
Adjusted R Squar	0,31164753							
Standard Error	0,01263954							
Observations	97							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	6	0,00790217	0,00131703	8,24390588	4,0548E-07			
Residual	90	0,01437821	0,00015976					
Total	96	0,02228038						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0,0118485	0,00307031	3,85905402	0,00021379	0,00574879	0,01794822	0,00574879	0,01794822
RM-RF	-0,2241021	0,06125869	-3,6582901	0,00042738	-0,3458032	-0,102401	-0,3458032	-0,102401
SMB	0,12248188	0,17543279	0,69816982	0,486871	-0,226046	0,47100974	-0,226046	0,47100974
HML	-0,2539142	0,18320176	-1,3859812	0,16917717	-0,6178765	0,11004807	-0,6178765	0,11004807
RMV	0,3918608	0,39094602	1,0023399	0,31886679	-0,3848217	1,16854331	-0,3848217	1,16854331
CMA	0,11090171	0,4595723	0,24131505	0,80985988	-0,8021189	1,0239223	-0,8021189	1,0239223
Share-Turnover	-1,4288554	0,24062116	-5,9381952	5,328E-08	-1,9068913	-0,9508195	-1,9068913	-0,9508195

Figure 5: Fama-French 5 Factor Model Regression Results for Period 1 in the Robinhood Portfolio

SUMMARY OUTPUT

egression Statistics	
Multiple R	0,41424119
R Square	0,17159576
Adjusted R Squa	0,06584203
Standard Error	0,02023159
Observations	54

ANOVA

	df	SS	MS	F	Significance F
Regression	6	0,00398494	0,00066416	1,62259769	0,16192647
Residual	47	0,01923792	0,00040932		
Total	53	0,02322286			

	Coefficients	tandard Erroi	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	-0,0319789	0,01492301	-2,142923	0,03732755	-0,0620001	-0,0019576	-0,0620001	-0,0019576
RM-RF	-0,0503372	0,13085259	-0,384686	0,70220532	-0,3135786	0,2129043	-0,3135786	0,2129043
SMB	0,37409541	0,38287923	0,9770585	0,33354265	-0,3961583	1,14434907	-0,3961583	1,14434907
HML	-0,0210202	0,28001475	-0,0750684	0,94047893	-0,5843373	0,54229677	-0,5843373	0,54229677
RMV	-0,1710136	0,48772526	-0,350635	0,72742891	-1,1521902	0,8101631	-1,1521902	0,8101631
CMA	-0,599764	0,83826684	-0,715481	0,47785141	-2,2861393	1,08661138	-2,2861393	1,08661138
Share-Turnover	1,62512878	0,65587966	2,477785	0,0168702	0,3056691	2,94458846	0,3056691	2,94458846

Figure 6: Fama-French 5 Factor Model Regression Results for Period 2 on Robinhood Portfolio

The regression was also performed on the S&P 500 ETF to contrast with the Robinhood portfolio for the same time periods. The Share-turnover is significant for period 1 but not period 2 as shown by figure 7 and figure 8. The other notable difference is that with the larger sample size provided by the S&P 500 ETF, the Fama-French 5 factor model factors are more significant in explaining price changes, Especially the RM-RF beta.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,70264813
R Square	0,4937144
Adjusted R Squa	0,45996202
Standard Error	0,00808968
Observations	97

ANOVA

	df	SS	MS	F	Significance F
Regression	6	0,00574362	0,00095727	14,6275459	1,3738E-11
Residual	90	0,00588986	6,5443E-05		
Total	96	0,01163348			

	Coefficients	tandard Erroi	t Stat	P-value	Lower 95%	Upper 95%	Lower 95,0%	Upper 95,0%
Intercept	0,00877932	0,00196509	4,46763949	2,2927E-05	0,00487532	0,01268332	0,00487532	0,01268332
RM-RF	-0,2665738	0,0392074	-6,7990699	1,1183E-09	-0,3444662	-0,1886815	-0,3444662	-0,1886815
SMB	-0,0685143	0,11228223	-0,6101972	0,54326893	-0,2915826	0,15455395	-0,2915826	0,15455395
HML	0,04386551	0,11725461	0,37410481	0,70920626	-0,1890812	0,27681225	-0,1890812	0,27681225
RMV	-0,1577424	0,25021715	-0,6304221	0,53001594	-0,6548425	0,33935761	-0,6548425	0,33935761
CMA	0,40512729	0,29414002	1,37732803	0,17182666	-0,1792332	0,98948777	-0,1792332	0,98948777
Share-Turnover	-0,9354619	0,15400474	-6,0742414	2,9288E-08	-1,2414192	-0,6295046	-1,2414192	-0,6295046

Figure 7: Fama-French 5 Factor Model Regression Results for Period 1 of the S&P 500 ETF

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0,53827205
R Square	0,2897368
Adjusted R Squa	0,1990649
Standard Error	0,00921283
Observations	54

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	6	0,0016273	0,00027122	3,19544213	0,01030782
Residual	47	0,00398918	8,4876E-05		
Total	53	0,00561648			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	-0,0013516	0,00679546	-0,1989027	0,84319685	-0,0150223	0,01231907	-0,0150223	0,01231907
RM-RF	-0,2071392	0,05958612	-3,4763004	0,00110482	-0,3270111	-0,0872674	-0,3270111	-0,0872674
SMB	-0,1048046	0,17435105	-0,6011123	0,55065348	-0,4555536	0,24594452	-0,4555536	0,24594452
HML	0,33681698	0,12750983	2,6414981	0,01117235	0,08030028	0,59333367	0,08030028	0,59333367
RMV	-0,2770722	0,2220946	-1,2475415	0,21837935	-0,723869	0,16972447	-0,723869	0,16972447
CMA	-0,8250809	0,38172011	-2,1614812	0,03578413	-1,5930027	-0,057159	-1,5930027	-0,057159
Share-Turnover	0,2283656	0,29866678	0,76461668	0,44832198	-0,3724745	0,82920567	-0,3724745	0,82920567

Figure 8: Fama-French 5 Factor Model + Share-Turnover Regression Results for period 2 on S&P 500 ETF

As previously mentioned, there has been a significant increase in online investors, many of which have little experience. We can apply Kyle's model to explain the rise in share turnover, the increase in retail investors provides the opportunity for highly informed agents to exploit their information under cover of the chaotic environment.

Rational investors can amplify the sentiment created by retail investors, increasing the irrationality of the trading environment. This irrational trading environment fits in the intermediate level of investor sentiment as defined by Baker and Wurgler (2004) In this scenario there is a mix of rational and speculative investors in the market and securities may be overpriced.

Figure 9 shows the Nasdaq Composite index over the past 21 years and compares it to share turnover ratio for the same period. The share-turnover peaks leading up to or during economic shocks such as the 2000 dot.com bubble and the 2007-2008 financial crisis.

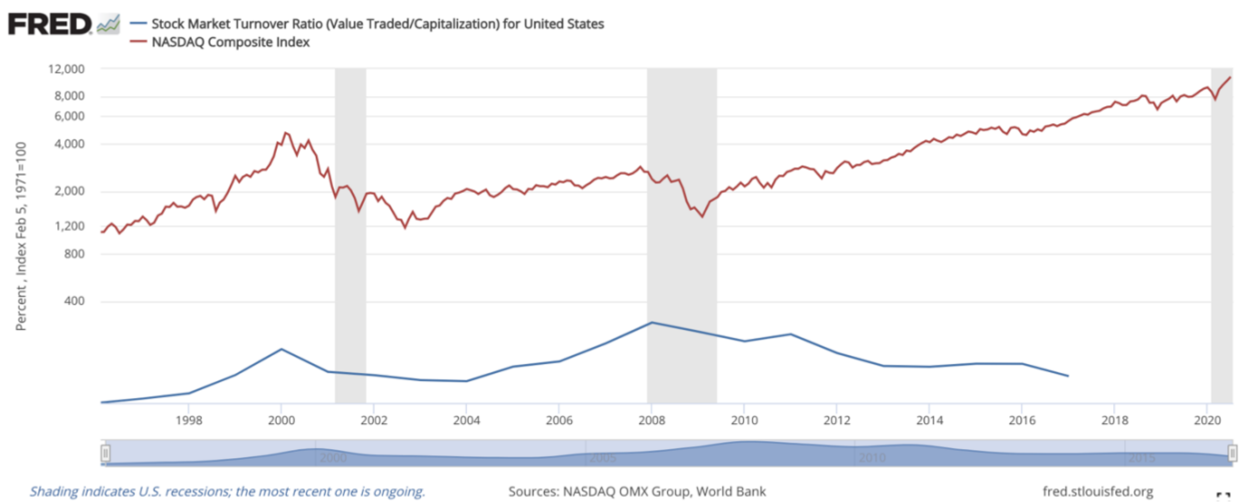


Figure 9: Stock Market Turnover-ratio for the U.S. Plotted Alongside Nasdaq Composite Index Returns for the Period of 1997-2020 Source: https://fred.stlouisfed.org/series/DDEM01USA156NWDB#0

Using the share turnover ratio as a proxy for sentiment, we can identify periods building up to a recession. When sentiment is high, investors are more inclined to speculate (Mian & Sankaraguruswamy 2012). The increase in speculation causes future returns to be extrapolated to be as positive as past returns (Kahneman & Tversky 1974).

4.5.a) Industry Analysis

Since the pandemic started, a clear growth pattern in interest for struggling businesses has been seen among Robinhood users. Within the top 5, most bought stocks in the past three months are two airlines (American Airlines and Delta Airlines) and a car manufacturing company (Ford Motor), industries that were hit the heaviest by the lockdown. What can also be seen is a high demand for bankrupt companies and companies that have had negative results, this pattern of purchases helps us establish that there is a demand for high-risk securities by Robinhood users, as shown by the distribution of 50 most popular Robinhood stocks as shown below.

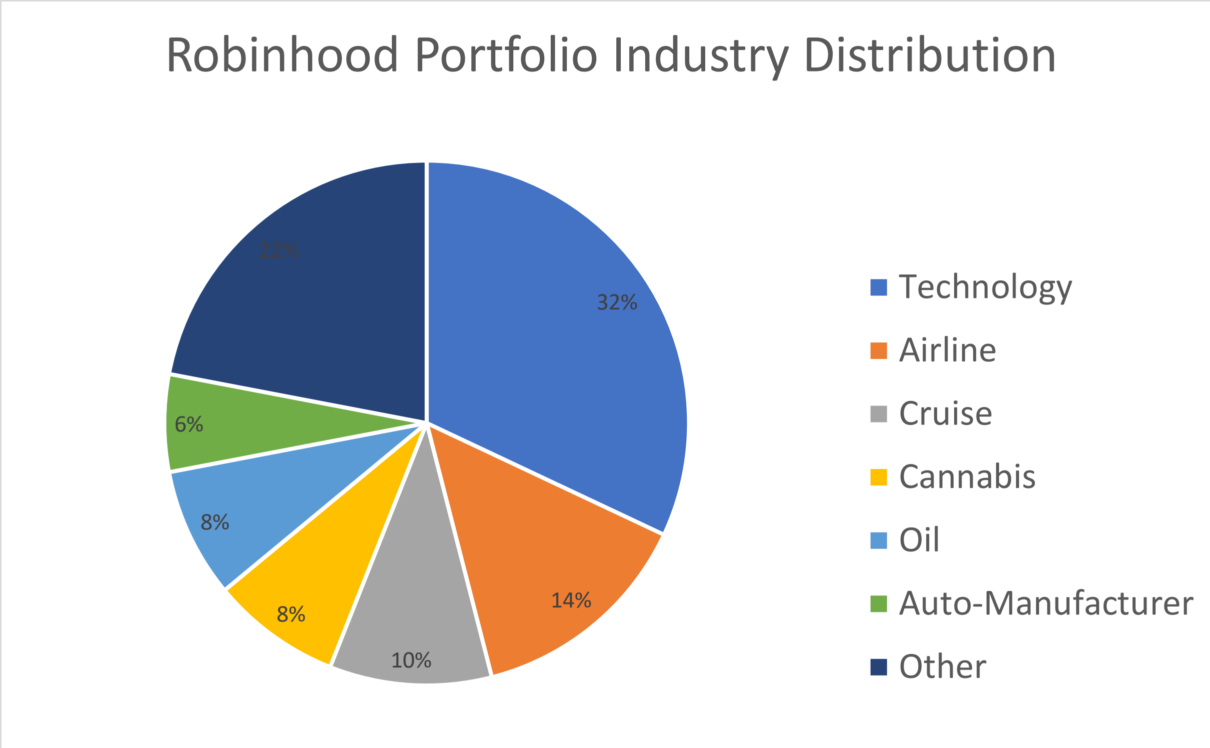


Figure 10: Robinhood´s top 50 picks by Industry

4.5.b) The Technology Industry

The Technology industry comprises 32% of Robinhood's top 50 and weathered COVID-19 well. The NASDAQ has a high concentration of technology companies that declined less than the S&P 500 from February 19th to March 23rd slowdown and then proceeded to rally up to 56% from its March to July. Many technology stocks fall into the category of high-growth potential and little to no profit with valuations at high-earnings multiples as described by Baker & Wurgler 2004. The propensity of tech stocks in the Robinhood portfolio could be because of availability heuristics since the average age of users is 31; many of the users know about or use the technologies provided by these stocks.

The average 2-year Beta of Robinhood tech stocks is surprisingly low, 0.98. For instance, Snapchat (SNAP), Robinhood's 15th most popular stock has never seen a positive net profit or positive EPS. In the past year alone, the price for SNAP has moved 82,8%; features of a volatile stock with significant upside and downside potential, like many other technology companies.

Since the start of the February sell-off on February 19th to July 15th, the number of Robinhood users owning Snapchat stock has increased from 192782 to 336594, a 174,6% increase.

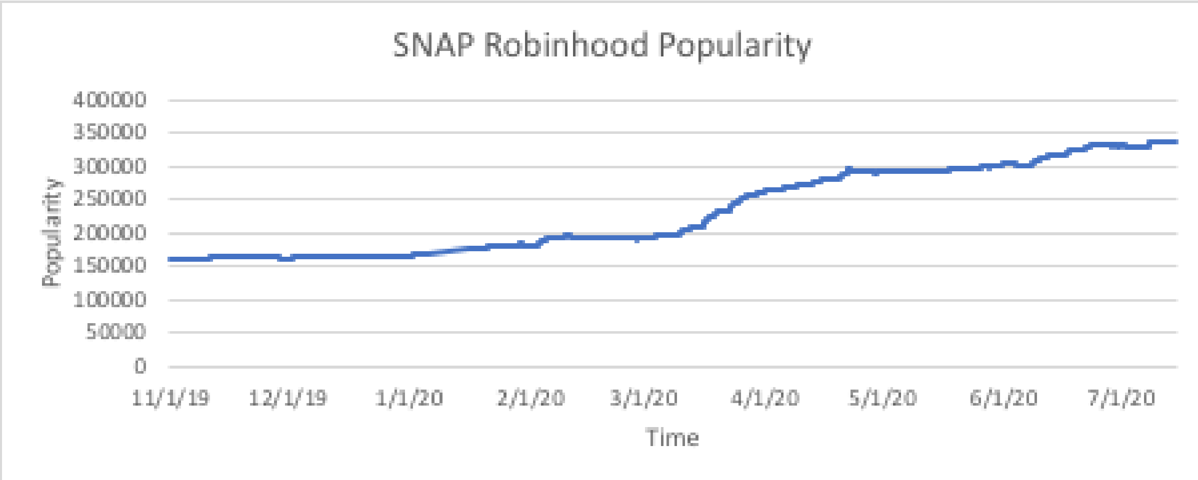


Figure 11: Number of New Robinhood ssers that own shares of SNAP

SNAP is an example of an outlier in the data, there isn't a smooth share turnover rise. Instead, what can be observed is short waves of volatility during certain time periods in which share turnover is magnified by an exponential amount.

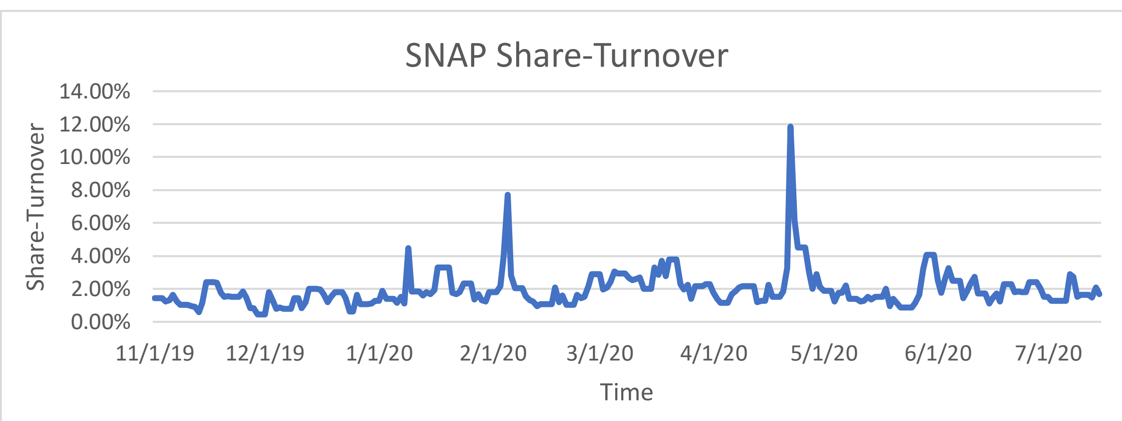


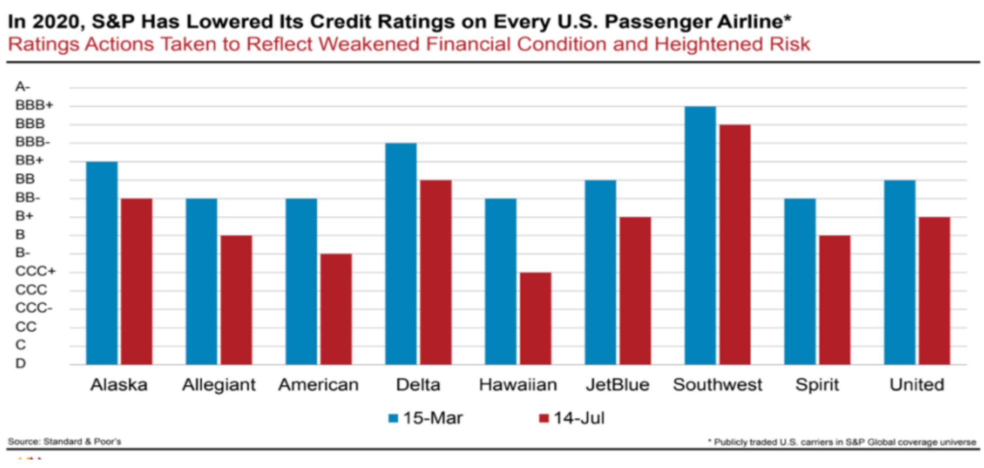
Figure 12: SNAP share-turnover Ratio

4.5.c) The Airline and Cruise Industries

The airline and cruise industries are arguably the most affected by COVID-19. Cruise activity was completely halted in most of the world, and air travel was severely restricted. 22% of the 50 most popular Robinhood stocks were either in the airline industry (14%) or the cruise industry (8%).

As of July 24th, four U.S. airlines have declared bankruptcy due to COVID-19, and several like Jet Blue and American Airlines are seeking strategic partnerships or Mergers. The Robinhood airline stocks 2-year beta 2.33, an extremely high number that shows a low risk-aversion. Goldman Sachs estimates that the expected volume of passengers for 2020 is going to be negative 56% and the forecasts for 2021 are negative -30%. Moreover, Airlines are burning through billions of dollars due to idle or empty planes and a decrease in revenue of 91% (ARC report 2020), this is reflected by their declining credit ratings as shown by figure 13, which indicates a higher risk of default.

Figure 13: Credit ratings for major U.S airlines. Source: Airlines.org through Standard & Poor's



Nevertheless, the airline industry is the second most popular industry in the top 50 Robinhood held companies. For instance, Delta Airlines, as seen on the graph below has seen its popularity exponentially increase from 18112 on February 19th to 582975 on July 15th, a 3200.19% increase to become Robinhoods' fifth most popular stock following American Airlines at number 3.

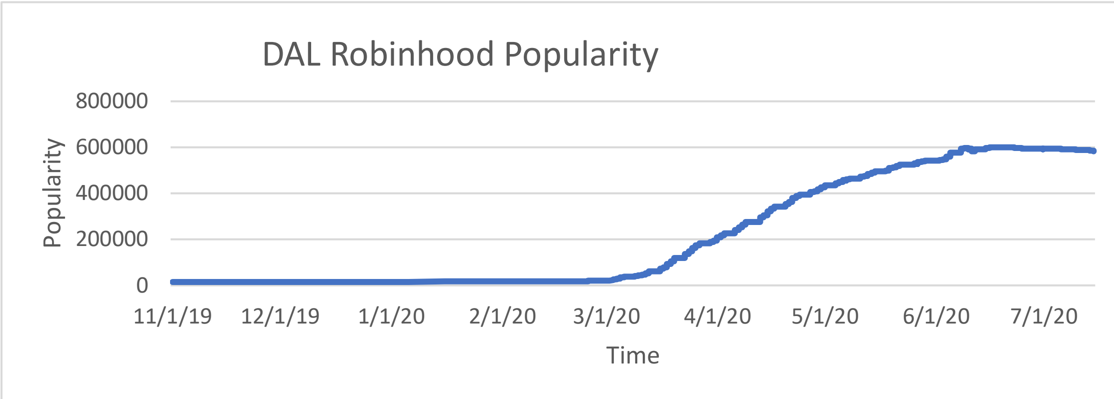


Figure 14: Number of new Robinhood users that own a share of DAL

At the same time, the number of shares traded of DAL stock went from less than 1% average to 7.7% from February 19th to July 15th. A pattern shared by the rest of the airline industry.

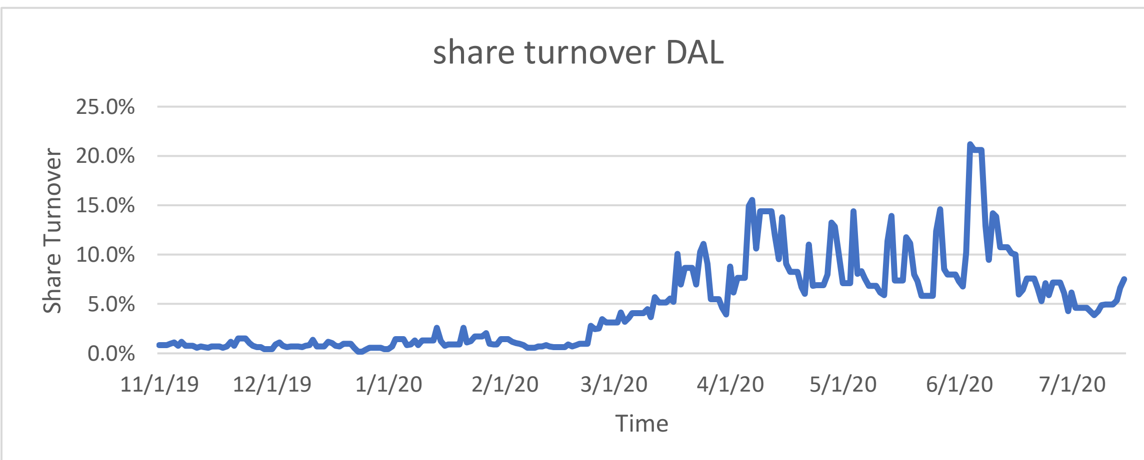


Figure 15: DAL Share-Turnover

The cruise industry had to shut down its commercial operations around the world. Even when they are able to resume operations, the demand for cruises is expected to be below pre-COVID levels for years. Moreover, cruise ships have received horrible P.R. due to the Diamond Princess cruise incident, which was covered worldwide; this particular cruise ship had 712 passengers' contract COVID-19. The Robinhood cruise stocks average beta of 2,54 this high number is indicative a strong risk-seeking behaviour.

Following the aforementioned trend, Robinhood investors find these hard-hit stocks very attractive, since COVID-19 started affecting the U.S. economy, Cruise ship stocks have seen an incredible rise in demand. For instance, Carnival Cruise Line (ticker CCL) is Robinhood's' ninth most popular stock. As can be seen, by the figure 16, the share ownership of CCL, just like the rest of cruise companies has increased in enormously. On February 19th, only 8718 users owned at least one share of this company, by July 15th the number of users owning CCL stock was 489673, a 5616.80% increase in just shy of 5 months.

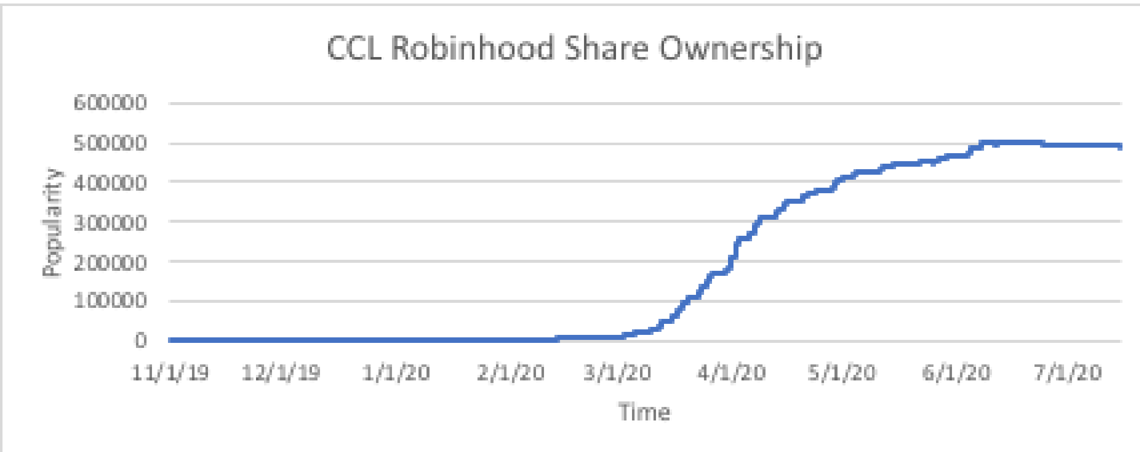


Figure 16: Number of Robinhood users that Own a Share of CCL

The stock price for CCL was $43.34 on February 19th and bottomed at 7.97 on April 2nd, a drop of 81,67% drop since then it has risen 119.32%. As can be seen, by figure 17, the share turnover for CCL was massively amplified during the COVID-19 period, an indication of speculative sentiment.

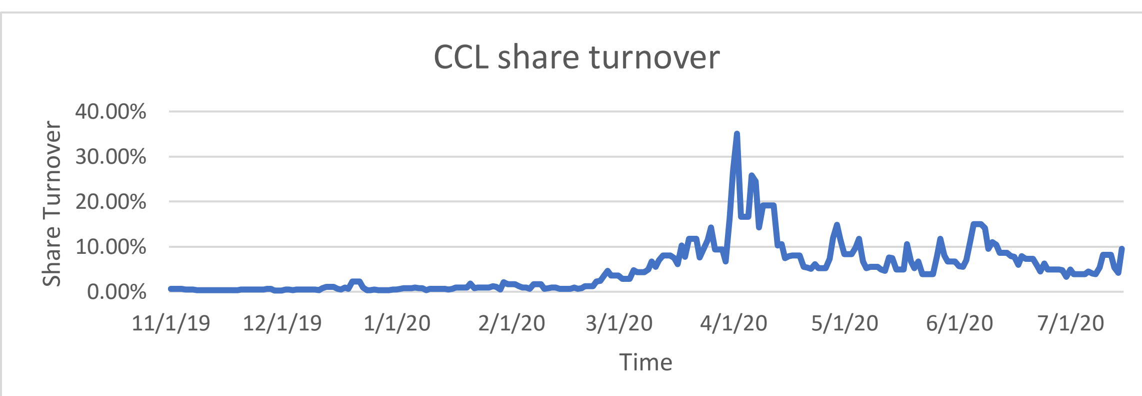


Figure 17: Share Turnover for CCL

4.5d) The Cannabis Industry

Within the top 50 Robinhood favourite picks there are four cannabis companies. The cannabis industry in the U.S. fits perfectly in Baker & Wurgler's definition of a speculative security. For instance, Aurora Cannabis has never had a positive free cash flow and only posted a profit once since 2014 (the earliest data there is on the company). The Cannabis industry is relatively new and is a result of U.S. governments more relaxed policy on the product. It is important to note that the Cannabis industry already experienced what could be seen as a bubble. From November 2018th to January of 2019th ACB grew over 300%. The whole industry experienced the same frenzy with companies like Tilray (TLRY) rising by over 700% in less than a month in the period of August to early September of 2018. The cannabis stocks held by Robinhood users have a beta of 1.35, showing a slight inclination towards risk.

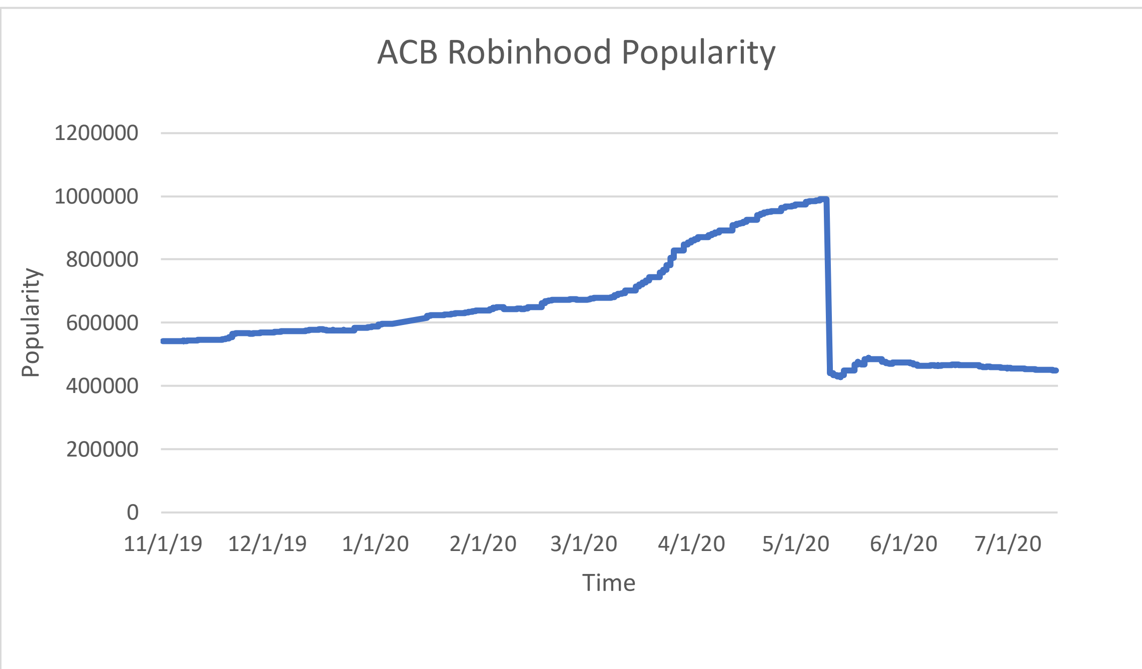


Figure 18: Number of new Robinhood users that own a share of ACB

Cannabis companies have been a Robinhood favourite for years. Even still, during the first half of 2020, there was an increase in popularity as illustrated by figure 17. What the popularity and share-turnover for ACB show is short periods of intense trading volume. This is due to reaction to price changes, at the time of the drop- n popularity and spike in share-turnover ACB´s price rose 194% that week.

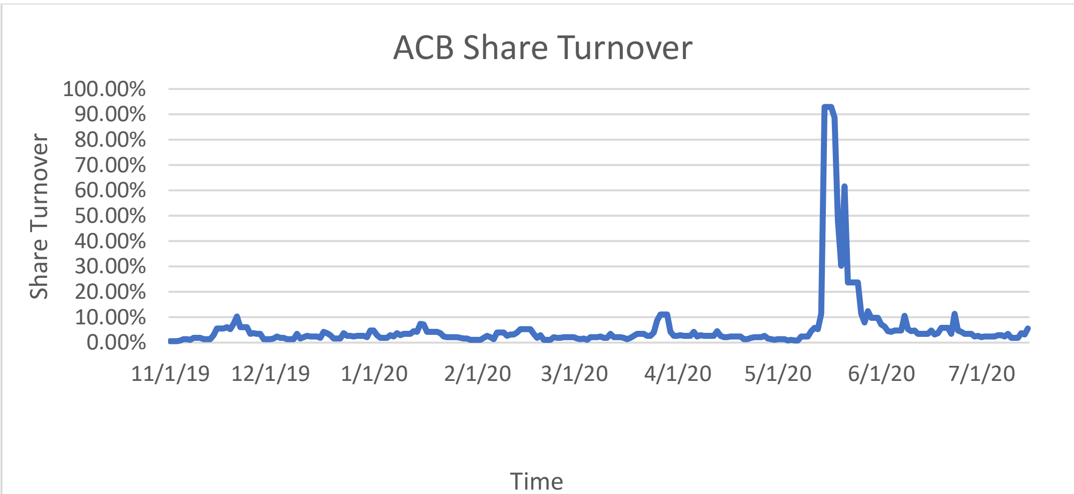


Figure 19: Share-turnover ACB

4.5.e) The Auto-Manufacturing Industry

A similar narrative can be seen with auto manufacturers, for although they do not fit with the prototype speculative stocks, it has been a very enticing industry to speculative retail investors. This is because COVID-19 heavily hit auto-manufacturing companies. Due to lockdowns, cars were not used as much, and citizens could not easily physically go and purchase new cars, so the rates of car purchases fell. The auto manufacturing industry further adds to the pattern of investing in the most damaged industries by COVID-19 found among retail investors. On February 19th the number of Robinhood users owning at least one Ford Motors stock was 372433, by July 15th, 2020 that number more almost tripled at 941682, a 252,8% increase. The beta for the auto-manufacturing stocks held by Robinhood users is 1.6 once again showing high-risk tolerance.

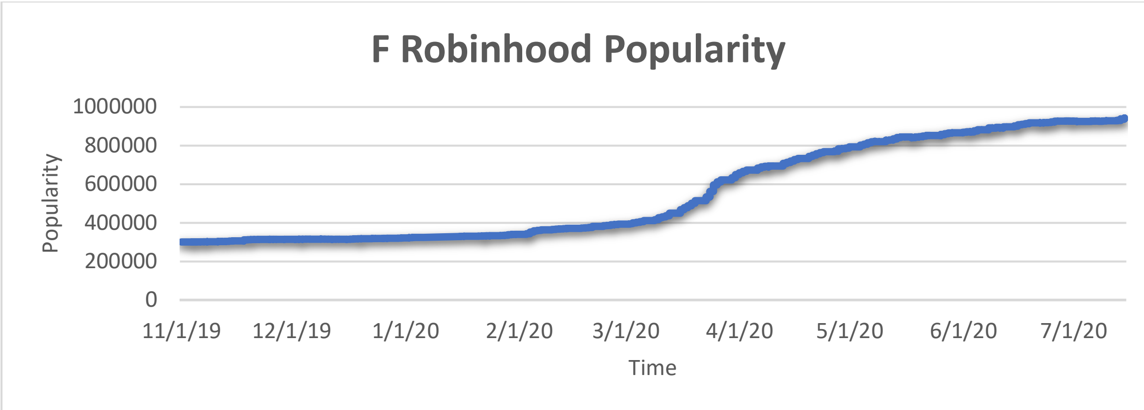


Figure 20: Number of Robinhood users that Own a Share of F

Ford Motors is Robinhood's most popular stock; the overall market share turnover-ratio in figure 21 demonstrates a significant rise in share-turnover over the observed period. However, the rise in ownership is not proportionally as high as other companies as it is Robinhood's most bought security.

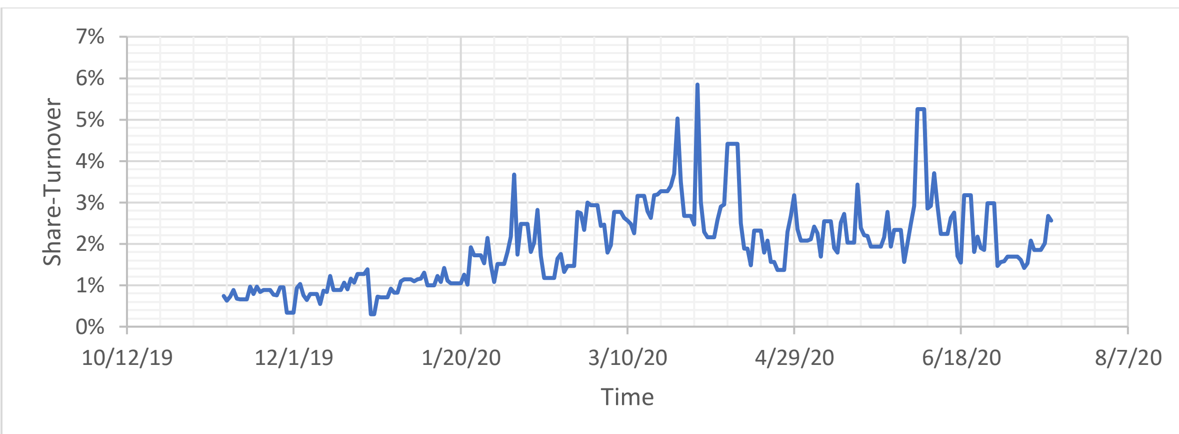


Figure 21: Share-Turnover for F

4.5.f) The Oil industry

It has been a turbulent year for oil companies, not only did COVID-19 halt demand, but Rusia and Saudi Arabia had disagreements on oil production, causing Saudi Arabia to increase the supply. The result was that oil prices plummeted. As can be expected, Robinhood users jumped on the opportunity and the demand for companies like Exxon or Marathon Oil Jumped. The Oil industry beta for the Robinhood companies is 3,07 the highest beta of any industry, once again demonstrating the appetite of Robinhood investors for risk. As shown below the share-turnover for XOM shows an increase in shares trading during the COVID-19 period, especially during the Saudi Arabia-Russia conflict.

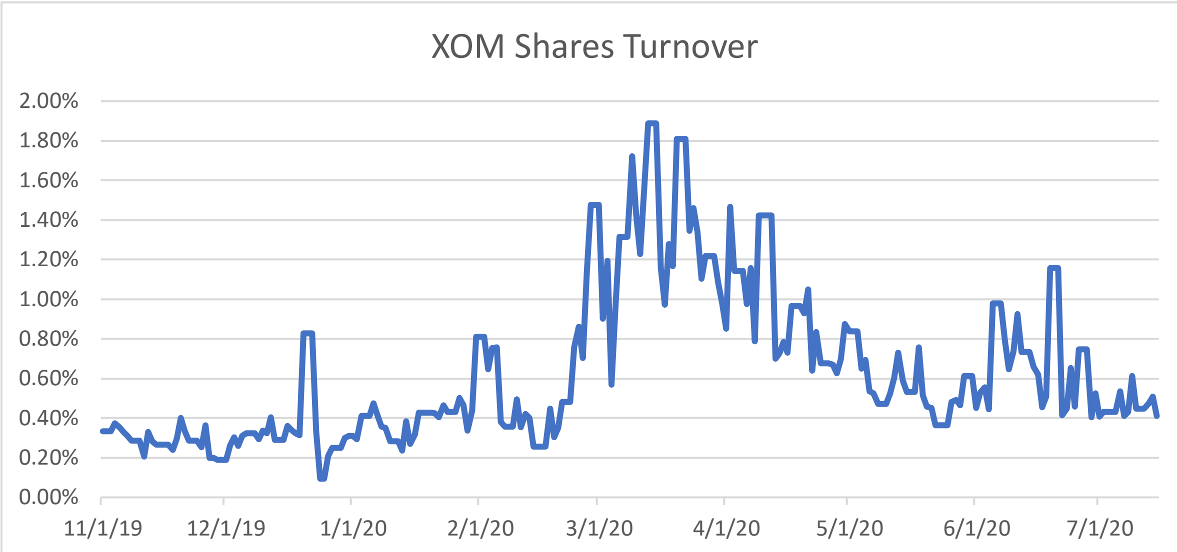


Figure 22: Share-turnover for XOM

4.6.a) Discussion

Did the U.S. Financial markets experience a wave of sentiment during COVID-19?

A correlation was established between the Robinhood portfolio and an increase in share-turnover as COVID-19 developed. The average liquidity pre-COVID-19 was 0.94%, during the COVID-19 period, that number jumped to 2.24%. The increase in liquidity helps us establish the presence of heightened market sentiment in U.S. financial markets. Albeit, the results cannot tell us what behaviour caused the sentiment or whether the sentiment is positive or negative.

Does sentiment (measured by share-turnover) help explain price changes during this period?

A regression analysis was done to see if the share-turnover in the Robinhood portfolio could explain prices. The T stat and the P value for the regression of the whole period were insignificant, negating the explanatory power of the share-turnover ratio and by proxy, sentiment.

However, if the regression is split into a recovery period and period of falling prices, the share-turnover becomes an essential component of price changes. During, the recovery rally from March 23rd to June 13th, the share-turnover has a significant alpha and beta values as shown by the T-stat and P-values. the same is true for the periods of November 1st to March 20th.

A regression analysis was also performed to test the predictive power of the share-turnover ratio on the wider market through the S&P 500 ETF price, the results are very similar in explanatory power to the ones performed on the Robinhood portfolio, it showed an effect on prices in the period before and after COVID-19 but the P value was insignificant for both periods together. There could be several reasons that explain why share-turnover was significant in separate periods. The most plausible explanation is that the share-turnover can proxy market sentiment but cannot distinguish the whether there is a positive or a negative market sentiment; this muddies the relationship between share-turnover and price.

Are Robinhood investors rational investors?

This study sheds light on the growing phenomenon of online retail investment and attempts to test their rationality. There is no conclusive data on whether Robinhood investors are inherently irrational but there are several indicators in the data that could show their irrationality.

In the industry analysis I highlighted Robinhood investors propensity to flock to distressed companies, showing a herding effect, albeit its potency cannot be determined.

What was illustrated about Robinhood investors is their appetite for risk, on average the Robinhood portfolio had a beta of 1.56. The 1.56 total beta was weighed down by the propensity of technology stocks in the portfolio which had a beta of 0.98. Although technology stocks seem not to carry that much risk, they fit the profile of a speculative company based on profitability and growth expectations (Baker & Wurgler 2004). Moreover, it's quite possible that the interest in technology is in great part due to availability heuristics. Robinhood investors, with an average

age of 31 are highly exposed to technology companies in their everyday lives. A similar case can be seen in the Cannabis industry, they are high-growth companies with little to no profit.

The rest of the industry break-down data shows a much higher risk-seeking attitude, with the Cruise, airline and oil industries having an average beta of 2.63. there have been some interesting theories that could help explain it. For instance, it could be the case that the general public is bored as a result of restrictions on entertainment and normal activities and perceive the stock market as a source of entertainment. Behavioural finance would suggest that money spent on entertainment would not be constraint to the same risk-profile.

Another possible influence on the American society is the avalanche of anecdotal rags to riches stories published in reputable news outlets as well as highlighted in online investment communities. Due to the speedy rally in the stock market that started in March, many first-time investors made small fortunes. The rags to riches stories make for an attractive narrative that may influence other retail investors, this complies with representative and availability heuristics.

Lastly, the U.S. $1200 cheque was designed to help those that had been affected by COVID-19, yet most Americans did not lose their job and in fact had less expenses than they normally would. As has been discussed in section 2, individuals do not adjust their wealth reference point right away due to anchoring mechanisms. As a result, a sudden influx of wealth may parallel the effects of the betting with ¨house money¨ effect described by Thaler & Johnson (1990) (this effect could also be exacerbated due to the lack of effort required to gain the extra wealth) which would increase their risk-seeking behaviour. An additional theory that explains irrationality due to an influx of cash is presented by Kahneman & Tversky (1979), hypothetically if the perceived the probability of doubling up or losing stood at 0.5,0.5 the gamble with the $1200 cheque could be perceived as (1200,0.5) (0,0.5) instead of (1200,0.5) (-1200,0.5); this would comply with the anchoring heuristic and explain low-levels of risk-averse behaviour.

4.6.b) Future Research and improvements

Several improvements could be made to the analysis presented; the analysis would benefit from multi-directional sentiment proxy to capture how different sentiments affect markets differently. Share-turnover is an indicator of sentiment, but it fails to tell us whether it's a bullish sentiment or a bearish sentiment. A crucial improvement would be to know not just whether a Robinhood user owns shares of a company but how many shares, and what proportion of their wealth is invested in each company. This would allow the data to more accurately depict their risk profile and sentiment. The study would also benefit from a larger sample of stocks as some industries were under-represented which reduced the accuracy of the results. It would also be useful to compare the share-turnover of the Robinhood portfolio with a share-turnover of the whole of the S&P 500 (this data was not available on FRED but will become available in the future), this would help determine whether the Robinhood Index is more emotional than the broader market.

From the results in the analysis section, it can be seen that the U.S. market has become much more emotional. It is the hope of this study to influence further research on online retail investors as the number of them is rapidly growing and much data can be extracted in future studies. An important addition to the analysis would be further isolation of different retail investors, for instance; are Robinhood users the norm or the exception to retail investing?

The literature could also be advanced by attempting further decipher Robinhood users decision-making process. Users that join Robinhood are asked questions by the app, if future research could tap into that data, they could attempt to find empirical evidence of behavioural finance theories such as representativeness at a market wide level.

5) Conclusion

In conclusion, the findings are in line with Baker & Wurgler's and Baker & Stein's work on sentiment. Retail investors appear to invest in companies that experience high-share turnover and are of high-growth potential. The Robinhood portfolio as a whole showed an increase in share-turnover during the economic shock caused by COVID-19 from 0.94% daily share-turnover to 2.24%. Moreover, a significant causal relationship was found between the Robinhood portfolio share-turnover and the changes in prices both in the S&P 500 ETF and the Robinhood portfolio when split into period 1 and 2. The beta of the Robinhood portfolio was 1.56, making The Robinhood portfolio considerably risker than the S&P 500. Due to the results, sentiment is likely affecting pricing considerations which would be an infringement of much of rational theory. With the work done, I hope to influence further research studying the relationship between noise-trader created sentiment and irrational pricing of securities.

Appendix

1	F	11	ACB	21	NIO	31	INO	41	MRO
2	GE	12	PLUG	22	HEXO	32	ZNGA	42	JBLU
3	AAL	13	AMZN	23	UBER	33	NFLX	43	MGM
4	DIS	14	NCLH	24	BABA	34	SAVE	44	GNUS
5	DAL	15	BAC	25	CGC	35	KO	45	OGI
6	AAPL	16	SNAP	26	FB	36	T	46	XOM
7	MSFT	17	FIT	27	RCL	37	TOPS	47	MFA
8	CCL	18	BA	28	TWTR	38	SBUX	48	GUSH
9	GPRO	19	UAL	29	AMD	39	APHA	49	USO
10	TSLA	20	MRNA	30	CRON	40	LUV	50	SPCE

List of top 50 Robinhood Stocks

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0,22939737							
R Square	0,05262315							
Adjusted R Squa	0,01447375							
Standard Error	0,01824245							
Observations	156							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	6	0,00275427	0,00045905	1,37939647	0,2264845			
Residual	149	0,04958525	0,00033279					
Total	155	0,05233953						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	-0,0026984	0,00346055	-0,7797721	0,43676191	-0,0095365	0,00413965	-0,0095365	0,00413965
RM-RF	-0,073954	0,06560013	-1,1273445	0,26140901	-0,2035807	0,05567277	-0,2035807	0,05567277
SMB	0,24207706	0,19621278	1,2337477	0,21923951	-0,145642	0,62979609	-0,145642	0,62979609
HML	0,10765167	0,16124903	0,66761126	0,50541447	-0,2109785	0,42628187	-0,2109785	0,42628187
RMV	0,25104171	0,32835181	0,76455101	0,4457481	-0,3977858	0,89986922	-0,3977858	0,89986922
CMA	0,12839189	0,47896315	0,26806214	0,78902223	-0,8180456	1,07482939	-0,8180456	1,07482939
Share-Turnover	0,10883238	0,19292804	0,56410865	0,57352832	-0,272396	0,49006073	-0,272396	0,49006073

Fama-French 5 Factor + Share-Turnover Model Regression: Results from 1st of November to 15th of June on total Robinhood Portfolio

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0,44438735							
R Square	0,19748011							
Adjusted R Squa	0,16404179							
Standard Error	0,01000989							
Observations	151							
ANOVA								
	df	*SS*	*MS*	*F*	*Significance F*			
Regression	6	0,0035505	0,00059175	5,905801	1,5546E-05			
Residual	144	0,01442851	0,0001002					
Total	150	0,01797901						
	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	0,00052399	0,00194683	0,26914792	0,78820111	-0,0033241	0,00437204	-0,0033241	0,00437204
RM-RF	-0,2058176	0,03657844	-5,6267445	9,2698E-08	-0,2781176	-0,1335175	-0,2781176	-0,1335175
SMB	-0,0605309	0,1088865	-0,5559079	0,57913657	-0,2757532	0,15469148	-0,2757532	0,15469148
HML	0,24279341	0,0902922	2,6889742	0,00801306	0,06432409	0,42126273	0,06432409	0,42126273
RMV	-0,0273293	0,18137201	-0,1506811	0,88043818	-0,3858247	0,33116607	-0,3858247	0,33116607
CMA	-0,02082	0,26507738	-0,0785433	0,93750496	-0,5447654	0,5031253	-0,5447654	0,5031253
Share-Turnover	-0,0195024	0,11102242	-0,1756616	0,86080658	-0,2389465	0,19994177	-0,2389465	0,19994177

Fama-French 5 Factor + Share-Turnover Model Regression: Results from 1st of November to 15th of June on S&P 500 ETF

SUMMARY OUTPUT	
Regression Statistics	
Multiple R	0,53827205
R Square	0,2897368
Adjusted R Squa	0,1990649
Standard Error	0,00921283
Observations	54

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	6	0,0016273	0,00027122	3,19544213	0,01030782
Residual	47	0,00398918	8,4876E-05		
Total	53	0,00561648			

	Coefficients	*Standard Erroi*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95,0%*	*Upper 95,0%*
Intercept	-0,0013516	0,00679546	-0,1989027	0,84319685	-0,0150223	0,01231907	-0,0150223	0,01231907
RM-RF	-0,2071392	0,05958612	-3,4763004	0,00110482	-0,3270111	-0,0872674	-0,3270111	-0,0872674
SMB	-0,1048046	0,17435105	-0,6011123	0,55065348	-0,4555536	0,24594452	-0,4555536	0,24594452
HML	0,33681698	0,12750983	2,6414981	0,01117235	0,08030028	0,59333367	0,08030028	0,59333367
RMV	-0,2770722	0,2220946	-1,2475415	0,21837935	-0,723869	0,16972447	-0,723869	0,16972447
CMA	-0,8250809	0,38172011	-2,1614812	0,03578413	-1,5930027	-0,057159	-1,5930027	-0,057159
Share-Turnover	0,2283656	0,29866678	0,76461668	0,44832198	-0,3724745	0,82920567	-0,3724745	0,82920567

Fama-French 5 Factor Model + Share-Turnover Regression: Results from 23rd of March to to 8thth of June on S&P 500 ETF

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