THE PENNSYLVANIA STATE UNIVERSITY
SCHREYER HONORS COLLEGE

DEPARTMENT OF FINANCE

The Impact of the Covid-19 Stimulus Checks on Retail Investor Investment Behavior

ANDREW HOFF
SPRING 2023

A thesis
submitted in partial fulfillment
of the requirements
for a baccalaureate degree
in Finance
with honors in Finance

Reviewed and approved* by the following:

Samuel Bonsall
Professor of Accounting
Thesis Supervisor

Brain Davis
Professor of Finance
Honors Adviser

* Electronic approvals are on file.

ABSTRACT

This paper sets out to explore the investment behavior of retail investors following the exogenous shocks to their liquidity associated with the Covid-19 stimulus checks. To investigate their behavior, this study has pulled daily aggregate retail investor trading data from January 1st to May 1st of the years 2018, 2019, 2020, 2021, and 2022 to establish if there was a statistically significant change in their behavior shortly following the disbursal of the stimulus checks. To categorize their investment behavior, this paper will analyze the sum total of buy and sell volume across a random selection of growth and value stocks. This study will treat each stimulus check as its own case study. The timing, disbursal period, and broader market and global factors are different for each check. This opens up room to additionally discuss the potential implications of factors not controlled by the study as they might affect investor behavior.

TABLE OF CONTENTS

LIST OF TABLES

ACKNOWLEDGEMENTS

I would like to thank everyone who made this possible. I would like to give special thanks to my thesis supervisor, Samuel Bonsall IV. Thank you for the invaluable resource you have been in helping me shape the methodology of this study. I don't know that I could have put this together without all those evening meetings. I would also like to thank my honors advisor, Bryan Davis, for the help and support he has given me. Thank you for helping me workshop the direction for my thesis. I would like to thank my academic advisor, Melissa Paloskey, for helping me manage my Smeal academic requirements as well as my class scheduling. I would like to thank Hans Schmidt for encouraging me to apply to Schreyer following my departure from Brandywine and for helping me prepare my materials. One final thanks to my parents who have supported me throughout my college career.

INTRODUCTION

With the suppression of the American economy caused by the outbreak of Covid-19 came a series of stimulus checks disbursed to Americans in hopes of mitigating the ongoing economic slowing. The first set of stimulus checks came in March 2020, the second, in January 2021, and the third, in March 2021. All these checks carried different nominal values and were received amidst variable social and economic conditions due to the tumultuous environment that the pandemic created. As such, to determine the impacts that these checks, or influxes of liquidity, had on retail investor investment decision-making, each instance of stimulus disbursal must be studied independently. Additionally, due to the complexity of investor decision-making, more factors than just the influx of liquidity associated with the stimulus check will sway investor behavior; because of this, we will also discuss other factors and how they might play into investor decision-making. The goal of this paper is to observe how retail investor trading behavior changed following the issuance of the stimulus checks and discuss how these changes in liquidity may have resulted in observable changes in investment behavior, or how other factors may have had an influence.

LITERATURE REVIEW

This section sets out the discuss some of the salient research associated with investor behavior in a pandemic environment. Such research discusses the factors that affect investor behavior. This section will be organized into the effects of liquidity and broader pandemic factors. The pandemic factors will be further broken down into the movements of the market, what investor behavior looked like at the onset of the Covid-19 pandemic, and how retail investor trading can influence the markets. Due to the complexity of these factors and how they play into one another as well as into investor decision-making, a discussion of the interplay between these ideas will follow the outline of the relevant research. The niche topic that this paper sets out to explore has not been heavily researched and because of that, the ideas outlined will be tangential to the overarching topic rather than being directly pertinent. This paper set out to understand retail investor investment behavior during the Covid-19 pandemic following the influxes of liquidity associated with the Covid-19 stimulus checks. To begin understanding this complex idea, this section will set out to lay the groundwork of completed research as a foundation on which to build greater understanding.

Retail investor liquidity

The most widely agreed upon and well-researched instances of liquidity affecting retail investor investment decisions are the turn-of-month and turn-of-year effects. The turn-of-year effect is also known as the “January Effect.” These effects both manifest as increases in stock returns and likely result from investors’ increased liquidity at the end of the month, caused by the standardization of the payment system in America and at the end of the year, likely resulting from the increase in liquidity associated with year-end bonuses or cash receipts.

Delving deeper into these ideas requires an understanding of how these theories were formed. There were at one point, two hypotheses attempting to explain the surge in stock performance in January. The first, Branch (1977) suggests that this January Effect is caused by year-end tax-loss selling and repurchasing[1]. The idea is that by selling a losing position, one can turn that loss into a tax gain in an effort to avoid taxes. Thereafter, one can repurchase the stock. This is known as a “wash sale.” Branch’s argument was that these “wash sales,” specifically the repurchasing in January, caused the surge in stock prices in January resulting in the aptly named, January Effect.

Many researchers believed that the year-end tax-loss selling was insufficient in explaining the January Effect; Ogden (1990) explores the January Effect as well as the Turn-of-Month Effect using empirical data[2]. He hypothesizes that both the Turn-of-Month Effect and January Effect are caused, at least in part, by the standardization of the payment system in America and the subsequent cash receipts on a monthly and annual basis. The magnitude of aggregate liquidity associated with the receipt of these regular payments directly impacts the amplitude of the surge that the market experiences at these intervals. As such, because liquid profits are affected by monetary policy, so too should the surges in the market be affected.

---

[1] Branch, B., & Chang, K. (1990). Low Price Stocks and the January Effect. *Quarterly Journal of Business and Economics*, *29*(3), 90–118. http://www.jstor.org/stable/40472999

[2] OGDEN, J. O. S. E. P. H. P. (1990). Turn-of-month evaluations of liquid profits and stock returns: A common explanation for the monthly and January effects. *The Journal of Finance*, *45*(4), 1259–1272. https://doi.org/10.1111/j.1540-6261.1990.tb02435.x

In Ogden’s study, he found that both the turn-of-month and turn-of-year stock returns were affected by monetary policy. In the easy, or less stringent periods (as defined by the difference in the Fed Funds rate and that of the short-term treasury bills), there was a statistically significant surge in stock performance on a monthly and annual basis. This points to the fact that retail investor investment behavior is affected by their liquidity.

Another interesting and salient piece of research demonstrating an association between retail investor liquidity and investment spending is Meng’s “Two Essays on Lottery-type Stock.”[3] For his analysis, he focuses mainly on retail investor investment behavior, specifically at the turn of the month, as it pertains to lottery-type stocks. He defines lottery-type stocks as stocks with low prices and high idiosyncratic volatility and skewness. His claim is that the demographics of those who are more likely to gamble and buy lottery tickets will also invest in these lottery-type stocks. He defines this demographic as those who tend to be poorer, less educated, urban, Catholic, and belong to minority groups.[4] This demographic suffers from having a lower income and likely limited savings; as such, their liquidity, or investable capital, shifts greatly at the turn of the month with the receipt of payment.

Meng is able to highlight this by doing the following: he shows that Lottery-type stocks significantly outperform non-lottery-type stocks by about 3 basis points per day on average. He then demonstrates that this effect is pronounced for lottery stocks in areas where local investors fit the lottery stock investor demographic. This points to the outperformance of lottery stocks

---

[3] Meng, Y., & Pantzalis, C. (2016). Monthly cyclicality in retail investors' liquidity and lottery-type stocks at the turn of the Month. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2820724

[4] KUMAR, A. L. O. K. (2009). Who gambles in the stock market? *The Journal of Finance*, *64*(4), 1889–1933. https://doi.org/10.1111/j.1540-6261.2009.01483.x

being driven by the local investors' desire to gamble. He is then able to empirically confirm the link between these changes in liquidity and the superior performance of lottery-type stocks by using household-level investment data showing that liquidity-constrained investors buy more lottery-type stocks at the turn of the month and "use the county-level change in mortality rate as a proxy for the change in local investors' personal liquidity position and document it is a driver of lottery-type stocks' ToM effect." Meng is able to demonstrate this trend and use it to such effect that he created a portfolio to capitalize on the monthly changes in value that outperformed by 13% annually.

Meng's analysis, while centered around a niche demographic of investors and stocks, demonstrates the notion that retail investor liquidity is a factor in retail investor investment decisions.

Pandemic factors

To understand the relationship between the pandemic, the market, and retail investors we must understand all of them individually and then the interplay between them:

Market Volatility

A paper written by Scott R Baker, discusses the behavior of the stock market at the onset of the Covid-19 pandemic.[5] Daily stock market jumps were the first method of analysis. From

[5] Baker, S. R., Bloom, N., Davis, S. J., Kost, K., Sammon, M., & Viratyosin, T. (2020). The unprecedented stock market reaction to COVID-19. *The Review of Asset Pricing Studies*, *10*(4), 742–758. https://doi.org/10.1093/rapstu/raaa008

January 2nd, 1994 to February 21st, 2020 there were 1,116 daily jumps, up or down, greater than 2.5%. These jumps, while only making up 3.5% of all trading days during that period, made up 47% of squared daily return variation in that timeframe. This points toward the significance of the role of such jumps in guiding overall market movement.

In the article’s analysis, the jumps were also characterized by their explanation presented in the next day’s news. Some of these categories included macroeconomic news, government spending, monetary policy, etc. One of the key findings of this further characterization was that none of these jumps were explained by referencing an infectious disease outbreak or the policy response associated despite 23 of these jumps being during the period of the Spanish Flu.

All of this shows that never have we seen the market make daily jumps up or down in response to a disease. This means that in the past, diseases had little impact on market behavior or investor outlook. Establishing this trend over the 120 years leading up to Covid makes the events following the onset of Covid particularly conspicuous.

Using the same analysis criteria as the period January 2nd, 1994 to February 21st, 2020, on the period February 24th, 2020 to April 30, 2020, Baker found that there were 27 jumps, 13.4 of which were attributed directly to the economic fallout of the pandemic and 10.4 of which were attributed to the policy response to the pandemic. This makes clear the unprecedented effects that Covid has had on the stock market.

The second piece of Baker’s analysis was the contribution of Covid-19 to the overall U.S. stock market volatility. Baker found that the impacts of the early phase of Covid were similar to those of other infectious disease outbreaks in the past 35 years. This quickly changed. By February, Covid was dominating the newspaper coverage of volatility and economic policy. By March, Covid received attention in more than 90% of all newspaper discussions of market volatility and policy uncertainty. This shows that Covid has undeniably had an unprecedented influence on market volatility and as we know this manifested, at least in the beginning, in a very negative direction.

Retail Investor Trading

A study conducted by Ortmann examines the changes in retail investor behavior following the onset of the Covid-19 pandemic by analyzing it as if it were a terrorist attack.[6] "It is an exogenous shock, that has drastic consequences on everyday life, raises public fear, and causes great (economic) uncertainty." Generally, investor behavior in the aftermath of a terrorist attack causes more risk aversion and a reduction in trading intensity.

Following 9/11, retail investor selling caused a precipitous decline in asset prices. We have seen a similar trend with Covid. Additionally, much like terrorist attacks, Covid brought about an increase in uncertainty that was compounded by the media. The media painted a torn picture of what the financial future would look like causing risk aversion and the subsequent downturn in the markets similar to those of terrorist attacks.

Ortmann claims that this torn image was created by press articles, media reports, and expert opinions and informed these investors' opinions of the market thus negatively influencing their trading. Using transaction-level brokerage data on retail investor trading, Ortmann found that investors increased their average weekly trading by 13.9% as the number of cases doubled.

---

[6] Baker, S. R., Bloom, N., Davis, S. J., Kost, K., Sammon, M., & Viratyosin, T. (2020). The unprecedented stock market reaction to COVID-19. *The Review of Asset Pricing Studies*, *10*(4), 742–758. https://doi.org/10.1093/rapstu/raaa008

This trading was accompanied by a significant increase in short selling and a decreased use of leverage after the 9.99% drop in the DOW on March 12.

While other factors could be influencing investor behavior, it seems to be clear that the media played a large part in shaping retail investor sentiment and associated action. Baker's analysis drives to illustrate the unprecedented nature of both the market's reaction to Covid as well as media coverage of it. Baker, in a way, studies the two events independently of one another, noting that never before has an infectious disease caused such havoc on financial markets nor has a disease been covered in the financial media the way Covid has. Baker never draws the conclusion that the two are intertwined, but the relationship between them is hinted at.

Conversely, in Ortmann's study, she ties together the media's influence on capital markets and investor sentiment. She points more concretely to the correlation between the media's influence and investor sentiment. These ideas together create the Covid narrative: Covid received a massive amount of financial media attention. The split media opinions informed investors' views. Investors then held differing views on the direction of the market. These differing perspectives then drove trade both upward and downward generating massive volatility. Despite these differing perspectives, the market trended downward as a whole driven by short selling.

Retail Investor Impact

The remaining question is whether or not retail investors have the power to shape the market's direction. A study by Kumar, based on an analysis of 1.85 million buy and sell transactions made by over 60,000 retail investors, discusses the effect that retail investor trading has on the broader market.[7]

The first component of Kumar's analysis was the evaluation of how correlated aggregate retail investor trading activities are. This is an important component because if retail investors don't aggregately trade in similar directions on similar stocks, then their trades are effectively noise. In other words, they will not have sufficient direction volume to shape trends.

As part of this analysis, Kumar used data on 62,387 households that trade stocks. Their portfolios summed to 2.18 billion. Each investor had an average of four portfolios with an average size of $35,629. The average monthly turnover rate is 6.59% with an average of 9 trades per year.

In addition to retail investor data, quarterly institutional ownership data from companies with more than 100 million dollars under management or common stock position of more than 10,000 shares or $200,000 was gathered to calculate quarterly institutional ownership for each stock.

Using this data, Kumar was able to ascertain that there is a positive correlation between non-overlapping stock portfolios as well as non-overlapping investor groups. This means that aggregately, retail investors tend to trade in the same direction, meaning that their impact has the potential to be more than noise. This means that the notion that retail investors could affect market trends is plausible.

---

[7] Kumar, A., & Lee, C. M. C. (2005). Retail investor sentiment and return Comovements. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.502843

The second component is retail investor sentiment shifts and stock return. Now that retail investors are known to trade in the same direction, the question remains of how much impact they have on changing market trends, especially in the shadow of large institutions.

Kumar finds that with a change in retail investor sentiment comes a directional change in line with the change in sentiment for small stocks, value stocks, stocks with low institutional ownership, and stocks with low prices. This shows that retail investor sentiment has the ability to affect the market.

Literature review discussion:

In summary, this literature review has been broken into the effects of liquidity and the pandemic effects on retail investor decision-making. Being that these two areas are niche topics, the amount of material that was directly salient to this discussion was limited. Despite this, creating an understanding of the effect of an increase in retail investor liquidity on decision-making was possible through the documentation of the turn-of-the-month and turn-of-the-year effects and Meng's research into retail investors' behavior with influxes of liquidity.

The turn-of-month and turn-of-year effects illustrate that investors, upon receiving payment, have the propensity to use a portion of it for investing behavior. Meng's research, while pertaining more directly to lottery-type stocks and gambling behavior, further reinforces the notion that an influx of liquidity for a retail investor is correlated to investment action soon thereafter. It is this behavior that creates swells in the market every month and year.

Furthermore, this literature review was able to examine the effect that the pandemic environment had on the broader market, the effect of the pandemic on retail investors, and retail investors' effect on the market.

Baker's research illustrated that Covid has had an unprecedented impact on both the media's discussion of market changes and the market itself. Baker showed that Covid was the first infectious disease outbreak that was covered by the media in reference to its effects on the market and the market's projectability. At the same time, no infectious disease has ever had such strong effects on market volatility. The media's coverage and the market effects go hand in hand. In many ways, the relationship between them is analogous to the question of the chicken and the egg; the media seems to be the precursor to market volatility, but market volatility certainly increases market coverage. Furthering this idea of media coverage's effect on investor sentiment was Ortmann in her study of retail investor trading in lieu of the pandemic. She found that retail investors were largely pessimistic, making selling, or short trades. This coupled with the observed increased trading frequency shows that retail investors, largely, were pushing down on the market due to the media's influence. The lingering question was whether retail investors have the power to influence the markets and a study by Kumar showed that they do, but mainly in stocks with low institutional investor presence.

All of this illustrates the complexity of the market environment during Covid. The media affected the market and retail investors, the market affected retail investors, liquidity affects retail investor decision-making, retail investors affect the market, and the market affects the media. This literature review has illustrated the importance of understanding and observing retail investor behavior during the pandemic, and further, following the stimulus checks. There is a multitude of factors that play into the observed trends and the purpose of this study is to shed light upon one more facet of the market during the pandemic. Understanding the behavior of retail investors following the influxes of liquidity associated with the Covid-19 stimulus checks is another data point that can help the field of finance unravel the enigmatic behavior of the market and by extension, its participants.

METHOD OF ANALYSIS

This study seeks to explore the extent to which the Covid-19 Stimulus checks affected retail investor behavior.

To answer this question, I had to observe retail investor trading activity in the periods following the issuance of the stimulus checks and compare the trading activity in those periods to similar periods in years unaffected. To accomplish this, I pulled retail investor trading data from January 1st to May 1st of the years 2018, 2019, 2020,2021, and 2022. The intra-year period - January 1st to May 1st- encompasses the intra-year periods that the checks were issued. The five-year period includes the years that the checks were disbursed but also provides control years for the retail investor trading during the test periods to be compared against.

Now, with the approach established, the sourcing of the data is what is next immediately salient along with the measures employed to determine its significance.

All the data used for this analysis was pulled from the University of Pennsylvania's Wharton Research Data Services (WRDS) website. From their database, I used three specific services: Intraday indicators by WRDS, The Center for Research in Security Prices (CRSP), and Compustat – Capital IQ.

Compustat – Capital IQ was employed to index all publicly traded companies from 2018 to 2023 and their market-to-book value ratio. From there, they were segmented into the top and bottom 33% by market-to-book value ratios by year. Only companies that remained in their upper or lower 33% market-to book-ratio for all 5 years were eligible to be chosen. A subset of roughly 100 companies from both the upper and lower 33%, that met the previous requirements, were chosen at random. The 100 companies from the upper 33% were designated as “Value” stocks and the 100 from the lower 33% as “Growth” stocks.

After the subset of both growth and value stocks were selected - totaling roughly 200 - they were inputted into WRDS’s Millisecond Intraday Indicators over the date ranges January 1st to the May 1st for the years 2018, 2019, 2020, 2021, and 2022. This outputted retail investor daily total trading volume for the subset of 200 stocks across all five years.

Now, to standardize the sum of retail investor trading between different stocks, the number of shares outstanding would have to be used to calculate percent turnover as to be able to compare trading volumes between different stocks. To accomplish this, the same set of previously selected stocks was inputted into CRSP to tie the number of shares outstanding, in a given period, to the sum of retail investor trading in that same period. By doing this, daily trading activity was quantified as percent turnover rather than sheer sum so that stocks with different numbers of shares outstanding could be effectively compared.

After daily percent turnover was calculated for every stock, it was then used to create a weekly average turnover by stock by year. The weeks were standardized across years by using the first seven-day period beginning on January 1st of every year as week 1 and then the subsequent weeks were further 7-day increments. This was done to make the weeks represent the exact same periods in time, rather than the same days of the week, across the 5-year interval. The days of the week are less relevant than their timing within the year for the purposes of this study.

Case Breakdown

At this stage, the data consisted of stocks broken into 18-week periods with the average weekly percent turnover for each listed across all five years. So, to determine if there was a significant change in trading activity following the disbursal of the stimulus checks, a change must be observed between the test weeks and control weeks. To do this, each of the three checks was analyzed separately as three different cases.

Check #1

The first check was for roughly $1,200 and was disbursed from early April through April 15th, 2020. This period corresponds roughly with weeks 14-16 and to allow for time to invest the check, but without making the period too broad, the study period for the first check was weeks 14-17.

Check #2

The second check was roughly $600 and was disbursed from December 29th to January 15th, 2021. This time period corresponds to weeks 1-2. To give an adequate window of observation that would likely encapsulate spending but without being too broad, the study period for the second check was weeks 1-4.

Check #3

The third stimulus check was $1,400 and was disbursed primarily the weekend of March 13/14th 2021, but from their payments were sent out weekly until the end of the year. For sake of consistency, the study period for the third check was weeks 7-10.

Statistical Measures

The data at this stage is organized by week -weeks 1-4, 7-10, and 14-17- and each week has the percent turnover of the same 100 stocks listed across all five years -2018, 2019, 2020, 2021, 2022.

To determine if the stimulus checks had a statistically significant impact on retail investor trading, a paired T-test was used to compare the weekly percent turnover of every stock in the test year and the average percent turnover of the same stocks across the four control years.

FINDINGS

The criteria for a statistically significant change in trading volume for a given period is that the t stat is greater than the t critical two-tail value. If this is the case, it shows that the difference between the test and control means is large enough that we can be 95% confident that the difference is due to more than chance.

With that said, the study reveals that for the value stocks weeks 14, 15, 16, and 17 had a statistically significant change in trading volume **(see table 1.0)**. Additionally, among growth stocks, weeks 2 and 17 had a statistically significant change in trading volume **(see table 1.1)**.

These changes indicate that, following the disbursal of the first stimulus check, the volume of value stocks traded by retail investors significantly increased during all four observed weeks. The trading volume of growth stocks over that same period was normal except for the 4^{th} week – week 17. Apart from the first stimulus check, the only other instance of a significant change in retail investor trading volume was in week 2, following the second stimulus check.

Table 1.0 *Statistical Findings by Week Among Value Stocks*

Week 1	*Variable 1*	*Variable 2*	*Week 7*	*Variable 1*	*Variable 2*	*Week 14*	*Variable 1*	*Variable 2*
Mean	0.000545	0.000539	Mean	0.000551	0.000624	Mean	0.000767	0.000447
Variance	4.97E-07	3.8E-07	Variance	7.81E-07	8.03E-07	Variance	3.32E-06	2.97E-07
Observations	114	114	Observations	114	114	Observations	115	115
Pearson Correlation	0.77453		Pearson Correlation	0.324721		Pearson Correlation	0.517914	
Hypothesized Mean Difference	0		Hypothesized Mean Difference	0		Hypothesized Mean Difference	0	
df	113		df	113		df	114	
t Stat	0.136263		t Stat	-0.74896		t Stat	2.132063	
P(T<=t) one-tail	0.445928		P(T<=t) one-tail	0.227718		P(T<=t) one-tail	0.017574	
t Critical one-tail	1.65845		t Critical one-tail	1.65845		t Critical one-tail	1.65833	
P(T<=t) two-tail	0.891856		P(T<=t) two-tail	0.455436		P(T<=t) two-tail	0.035148	
t Critical two-tail	1.98118		t Critical two-tail	1.98118		t Critical two-tail	1.980992	
Week 2	*Variable 1*	*Variable 2*	*Week 8*	*Variable 1*	*Variable 2*	*Week 15*	*Variable 1*	*Variable 2*
Mean	0.000489	0.000573	Mean	0.001387	0.000681	Mean	0.000734	0.000503
Variance	3.24E-07	4.85E-07	Variance	7.75E-05	1.34E-06	Variance	2.14E-06	5.31E-07
Observations	114	114	Observations	114	114	Observations	115	115
Pearson Correlation	0.577825		Pearson Correlation	0.078118		Pearson Correlation	0.5458	
Hypothesized Mean Difference	0		Hypothesized Mean Difference	0		Hypothesized Mean Difference	0	
df	113		df	113		df	114	
t Stat	-1.51836		t Stat	0.857838		t Stat	2.023018	
P(T<=t) one-tail	0.065858		P(T<=t) one-tail	0.196399		P(T<=t) one-tail	0.022706	
t Critical one-tail	1.65845		t Critical one-tail	1.65845		t Critical one-tail	1.65833	
P(T<=t) two-tail	0.131717		P(T<=t) two-tail	0.392798		P(T<=t) two-tail	0.045411	
t Critical two-tail	1.98118		t Critical two-tail	1.98118		t Critical two-tail	1.980992	
Week 3	*Variable 1*	*Variable 2*	*Week 9*	*Variable 1*	*Variable 2*	*Week 16*	*Variable 1*	*Variable 2*
Mean	0.000508	0.000543	Mean	0.000841	0.000664	Mean	0.0008	0.000473
Variance	7.25E-07	3.59E-07	Variance	4.39E-06	7.38E-07	Variance	2.85E-06	2.73E-07
Observations	114	114	Observations	114	114	Observations	115	115
Pearson Correlation	0.607914		Pearson Correlation	0.38183		Pearson Correlation	0.519526	
Hypothesized Mean Difference	0		Hypothesized Mean Difference	0		Hypothesized Mean Difference	0	
df	113		df	113		df	114	
t Stat	-0.55732		t Stat	0.971719		t Stat	2.36175	
P(T<=t) one-tail	0.289204		P(T<=t) one-tail	0.166633		P(T<=t) one-tail	0.009943	
t Critical one-tail	1.65845		t Critical one-tail	1.65845		t Critical one-tail	1.65833	
P(T<=t) two-tail	0.578409		P(T<=t) two-tail	0.333266		P(T<=t) two-tail	0.019885	
t Critical two-tail	1.98118		t Critical two-tail	1.98118		t Critical two-tail	1.980992	
Week 4	*Variable 1*	*Variable 2*	*Week 10*	*Variable 1*	*Variable 2*	*Week 17*	*Variable 1*	*Variable 2*
Mean	0.000625	0.000741	Mean	0.000551	0.000608	Mean	0.000717	0.000456
Variance	1.81E-06	1.73E-06	Variance	1.08E-06	6.44E-07	Variance	1.94E-06	2.15E-07
Observations	114	114	Observations	114	114	Observations	115	115
Pearson Correlation	0.692739		Pearson Correlation	0.302508		Pearson Correlation	0.621617	
Hypothesized Mean Difference	0		Hypothesized Mean Difference	0		Hypothesized Mean Difference	0	
df	113		df	113		df	114	
t Stat	-1.18304		t Stat	-0.54578		t Stat	2.406476	
P(T<=t) one-tail	0.119638		P(T<=t) one-tail	0.293148		P(T<=t) one-tail	0.008857	
t Critical one-tail	1.65845		t Critical one-tail	1.65845		t Critical one-tail	1.65833	
P(T<=t) two-tail	0.239276		P(T<=t) two-tail	0.586296		P(T<=t) two-tail	0.017714	
t Critical two-tail	1.98118		t Critical two-tail	1.98118		t Critical two-tail	1.980992	

Table 1.1 *Statistical Findings by Week Among Growth Stocks*

Week 1	*Variable 1*	*Variable 2*	*Week 7*	*Variable 1*	*Variable 2*	*Week 14*	*Variable 1*	*Variable 2*
Mean	0.003745	0.002051	Mean	0.004629	0.001626	Mean	0.003471	0.000973
Variance	0.00025	8.7E-05	Variance	0.00034	5.44E-05	Variance	0.000301	4.3E-06
Observations	94	94	Observations	94	94	Observations	93	93
Pearson Correlation	0.206696		Pearson Correlation	0.596714		Pearson Correlation	0.814053	
Hypothesized Mean Difference	0		Hypothesized Mean Difference	0		Hypothesized Mean Difference	0	
df	93		df	93		df	92	
t Stat	0.988403		t Stat	1.911282		t Stat	1.534086	
P(T<=t) one-tail	0.16276		P(T<=t) one-tail	0.029524		P(T<=t) one-tail	0.06422	
t Critical one-tail	1.661404		t Critical one-tail	1.661404		t Critical one-tail	1.661585	
P(T<=t) two-tail	0.32552		P(T<=t) two-tail	0.059048		P(T<=t) two-tail	0.12844	
t Critical two-tail	1.985802		t Critical two-tail	1.985802		t Critical two-tail	1.986086	
Week 2	*Variable 1*	*Variable 2*	*Week 8*	*Variable 1*	*Variable 2*	*Week 15*	*Variable 1*	*Variable 2*
Mean	0.002488	0.001178	Mean	0.002393	0.001122	Mean	0.010661	0.00091
Variance	4.86E-05	8.13E-06	Variance	5.88E-05	4.99E-06	Variance	0.005762	3.59E-06
Observations	94	94	Observations	94	94	Observations	93	93
Pearson Correlation	0.911199		Pearson Correlation	0.577915		Pearson Correlation	0.143344	
Hypothesized Mean Difference	0		Hypothesized Mean Difference	0		Hypothesized Mean Difference	0	
df	93		df	93		df	92	
t Stat	2.804998		t Stat	1.857615		t Stat	1.242877	
P(T<=t) one-tail	0.003063		P(T<=t) one-tail	0.033194		P(T<=t) one-tail	0.108536	
t Critical one-tail	1.661404		t Critical one-tail	1.661404		t Critical one-tail	1.661585	
P(T<=t) two-tail	0.006127		P(T<=t) two-tail	0.066388		P(T<=t) two-tail	0.217071	
t Critical two-tail	1.985802		t Critical two-tail	1.985802		t Critical two-tail	1.986086	
Week 3	*Variable 1*	*Variable 2*	*Week 9*	*Variable 1*	*Variable 2*	*Week 16*	*Variable 1*	*Variable 2*
Mean	0.00325	0.000998	Mean	0.002511	0.001154	Mean	0.005211	0.000926
Variance	0.0002	4.91E-06	Variance	6.76E-05	7.1E-06	Variance	0.000511	3.02E-06
Observations	94	94	Observations	94	94	Observations	93	93
Pearson Correlation	0.274923		Pearson Correlation	0.358521		Pearson Correlation	0.770855	
Hypothesized Mean Difference	0		Hypothesized Mean Difference	0		Hypothesized Mean Difference	0	
df	93		df	93		df	92	
t Stat	1.593199		t Stat	1.713237		t Stat	1.939853	
P(T<=t) one-tail	0.057254		P(T<=t) one-tail	0.045		P(T<=t) one-tail	0.02773	
t Critical one-tail	1.661404		t Critical one-tail	1.661404		t Critical one-tail	1.661585	
P(T<=t) two-tail	0.114509		P(T<=t) two-tail	0.090001		P(T<=t) two-tail	0.055461	
t Critical two-tail	1.985802		t Critical two-tail	1.985802		t Critical two-tail	1.986086	
Week 4	*Variable 1*	*Variable 2*	*Wee 10*	*Variable 1*	*Variable 2*	*Week 17*	*Variable 1*	*Variable 2*
Mean	0.006744	0.000951	Mean	0.001945	0.002874	Mean	0.002325	0.000773
Variance	0.00094	4.34E-06	Variance	2.53E-05	0.000146	Variance	4.14E-05	1.47E-06
Observations	94	94	Observations	94	94	Observations	93	93
Pearson Correlation	0.560837		Pearson Correlation	0.437432		Pearson Correlation	0.722836	
Hypothesized Mean Difference	0		Hypothesized Mean Difference	0		Hypothesized Mean Difference	0	
df	93		df	93		df	92	
t Stat	1.901585		t Stat	-0.82931		t Stat	2.662087	
P(T<=t) one-tail	0.030161		P(T<=t) one-tail	0.204527		P(T<=t) one-tail	0.004583	
t Critical one-tail	1.661404		t Critical one-tail	1.661404		t Critical one-tail	1.661585	
P(T<=t) two-tail	0.060321		P(T<=t) two-tail	0.409054		P(T<=t) two-tail	0.009166	
t Critical two-tail	1.985802		t Critical two-tail	1.985802		t Critical two-tail	1.986086	

DISCUSSION

The implications of this study are unclear. The findings referenced above seem to point loosely toward a relationship between an influx in retail investor liquidity and an uptick in investment spending, but I don't feel as though the results point toward a definite or, much less, a causal relationship. There are many other factors that could have contributed to the observed trends and the trends that were observed, were not consistent across all stimulus receipts. This discussion will serve to foster a better understanding of what other factors – aside from liquidity – could have bearing on the observed results and of the flaws that are present in the methodology of this study.

Other Factors

With the complexity of investor decision making comes a number of factors that play into making investment decisions. This study has observed the volume of retail investor trading during targeted intervals in hopes of observing a statistically significant deviations from the average turnover in non-liquidity-affected years. Due to the observational nature of this study, claiming causation, even if results were statistically significant in all weeks, would be a stretch. With the way this study is configured, it doesn't control for some of the other factors that affect retail investor sentiment other than liquidity and because of this fact, the potential impact of such factors must be considered. The two largest factors that deserve discussion are the nature of the checks – their size, when they were sent within the observation period, and to whom they were sent – and the economic climate/market conditions when the checks were received.

Nature of checks

The first check was the product of the CAREs Act where eligible adults received a check with a nominal value of $1,200. The eligibility criteria demanded that recipients be tax-paying citizens with adjusted gross income below $75,000 for an individual and $150,000 for couples. Tens of millions of Americans received their deposits by Wednesday, April 15 2020 and many more in the following week.[8]

The second check was a $900 billion package titled the "Coronavirus Response and Relief Supplemental Appropriations Act of 2021." The act paid out one check of up to $600, but households were also able to claim an additional $600 for children 16 or under. The act stipulated that earnings under $75,000 would receive the full $600 while a decreasing amount was paid out to those earning more with a salary cap of $87,000. Payments were issued from 29 December 2020 through 15 January 2021.[9]

The third check was the product of the $1.9tn American Rescue Plan. The check came with a nominal value of $1,400 and couples filing jointly could receive up to $2,800. What made this check unique was that dependents were eligible for an additional payment of $1,400 per dependent and there was no limit to the number of dependents that could be claimed. Many Americans received their payments on the 13th of March 2021, but payments continued to be sent out weekly until the end of the year. This check was also limited by the same income cutoffs as the others.[10]

Now, if we use this information to inform our findings, a few things become apparent. The first, and most glaring, is that these checks were only received by those making less than $75,000 individually and $150,000 jointly. Intuition would say that those who received the checks are less likely to invest the

---

[8] AliciaAdamczyk. (2021, January 12). *The first coronavirus stimulus checks were deposited this week-here's when you can expect yours*. CNBC. Retrieved March 20, 2023, from https://www.cnbc.com/2020/04/13/first-coronavirus-stimulus-checks-deposited.html

[9] English, A. S. (2022, March 17). *How much were the first, second and third stimulus checks and when were they sent out?* Diario AS. Retrieved March 20, 2023, from https://en.as.com/en/2022/03/17/latest_news/1647514558_032514.html

[10] English, A. S. (2022, March 17). *How much were the first, second and third stimulus checks and when were they sent out?* Diario AS. Retrieved March 20, 2023, from https://en.as.com/en/2022/03/17/latest_news/1647514558_032514.html

money because of their more limited comparable means to those who wouldn't receive the checks. That is to say that the demographics that are most likely to be investing in the first place were unaffected by the checks, meaning that these observations were based on a subset of individuals who had a comparatively decreased propensity to "participate in the study," i.e. invest. This means that the structure of the disbursal of the checks was limited to a subset of people that would use it to maintain their present quality of life rather than forgo that consumption to better position themselves later. I am sure that this was an intended consequence of the checks.

The other facet of consideration is the timing of the disbursal of the checks and the observed statistical increases in investment behaviors. To summarize, there were observed increases in trading, of statistical significance in weeks 14-17 for value stocks and weeks 2, 17 for growth stocks. Weeks 14-17 followed the first stimulus check and week 2 followed the second check. Looking first at the trends following the first stimulus check, there are one of two conclusions to draw. The first is that the increase in liquidity associated with the receipt of the first check did cause an increase in investment behavior, but that is undermined by the lack of similar changes following the other checks. The second is that these trends are the product of a factor other than liquidity; perhaps the market conditions or uncertainty caused by the pandemic. Which one, as stated previously, is unclear, but regardless of this trend's causation, it is interesting that whatever caused this change didn't affect the value stocks and growth stocks evenly. It seems as though the trading of the value stocks increased much more than the growth. I can't venture an explanation, especially with the lack of established directionality in trading, but it was a trend I thought was worth highlighting.

The only question remaining is what caused the increased trading among growth stocks following the second stimulus check. Week 2 took place in the early half of January 2021 and at that time. The best explanation I can venture is it could be selling following the storming of the Capitol Building on January 6th, 2021.

Economic climate/ market conditions

One of the other factors that likely affected investor behavior aside from the influxes of liquidity was the behavior of the market as well as broad economic sentiment. As referenced in the literature review, the beginning of the pandemic was characterized by financial news coverage of the pandemic that held largely pessimistic sentiment.

The finding from my analysis seem to align with what Ortmann found in her study. She found that investors increased their trading as cases increased and the majority of this trading was short. This indicates that these observed trends following the first stimulus check are unlikely due to the influx of liquidity and more to do with the direction of the market and pessimistic investor attitudes. Despite not having directionality associated with my observations, especially in lieu of Ortmann's research, it seems as though the increased in trading was in the selling direction, which isn't characteristic of investment behavior caused by increased liquidity.

Methodological Flaws

The final point of discussion is the potential flaws in my analysis of the retail investors' investment behavior. The first and more salient to the preceding topic of discussion is the lack of information regarding the directionality of the observed increases in trading volume. Typically, with an increase in liquidity comes an increase in purchasing; these are the conclusions of Meng and the idea behind the January effect. With that said it would have been useful to be able to determine the directionality of the retail investor trading so that a clearer relationship between the increase in volume and the preceding influx of liquidity. Ideally, what I would have hoped to see would have been a significant increase in buying following just after the receipt of the stimulus. With the current data configuration it is hard to attribute the increase in volume to an increase and buying and therefore due to the increased liquidity.

Furthermore, at different junctures during the analysis, I had to make discretionary decisions about how the data would be represented. One example is how I assigned the weeks; they were seven-day increments following January first rather than the organic calendar weeks. Another example is how I chose to average the turnover of the four control periods rather than performing t-tests against all other periods individually. Certainly, there are other discretionary examples, but the point is that if I had done things differently, the results could have been different. Considering that for many of the weeks, the t stat was just short of the critical value for significance, these decisions could have shifted some of the findings; however, I am confident that regardless of the numerical results of the statistical analysis, the conclusions would have remained roughly the same.

CONCLUSION

The behavior of the United States financial markets is a microcosm for the broader United States population. It encapsulates American fear, optimism, irrationality, risk tolerance, and its participation captures our preferences between present consumption and future return. All of this is to say that by observing the behavior of the market in such a turbulent time as the Covid-19 pandemic we can gain insight into the nature of the investor and by extension the American people. Certainly, an investor is not emblematic of the entire population; they generally fall into the higher income brackets, but it does still speak to human nature and behavior.

What we find through this exercise is that the Covid environment had an effect on retail investor trading. We have demonstrated that, at the onset of Covid, retail investor trading volume, especially among value stocks, significantly increased. This time frame roughly aligned with the receipt of the first stimulus check, but despite this, the attribution of this rise in trading is unclear. Other research indicates that the directionality of this increase is short, and because the directionality of my findings are unclear I am left to assume that they are in the short direction. If we are to assume that they are short, and that increases in trading volume caused by influxes of liquidity are mainly long, then it’s unlikely that the receipt of the stimulus checks is the cause of this increase in trading volume. This seems to be consistent with the lack of a statistically significant reaction to the other stimulus checks. A factor that could contribute to this pattern is the demographics that received the checks. Those who received the checks were members of a lower income bracket and as such are less likely to have surplus liquidity for investment activity.

Based on previously completed research and my findings, it seems as though, in the case of the Covid-19 pandemic, the largest driver of retail investor investment decision-making is the news and the economic/ market climate.

BIBLIOGRAPHY

AliciaAdamczyk. (2021, January 12). *The first coronavirus stimulus checks were deposited this week-here's when you can expect yours*. CNBC. Retrieved March 20, 2023, from https://www.cnbc.com/2020/04/13/first-coronavirus-stimulus-checks-deposited.html

Baker, S. R., Bloom, N., Davis, S. J., Kost, K., Sammon, M., & Viratyosin, T. (2020). The unprecedented stock market reaction to COVID-19. *The Review of Asset Pricing Studies*, *10*(4), 742–758. https://doi.org/10.1093/rapstu/raaa008

Branch, B., & Chang, K. (1990). Low Price Stocks and the January Effect. *Quarterly Journal of Business and Economics*, *29*(3), 90–118. http://www.jstor.org/stable/40472999

English, A. S. (2022, March 17). *How much were the first, second and third stimulus checks and when were they sent out?* Diario AS. Retrieved March 20, 2023, from https://en.as.com/en/2022/03/17/latest_news/1647514558_032514.html

KUMAR, A. L. O. K. (2009). Who gambles in the stock market? *The Journal of Finance, 64*(4), 1889–1933. https://doi.org/10.1111/j.1540-6261.2009.01483.x

Kumar, A., & Lee, C. M. C. (2005). Retail investor sentiment and return Comovements. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.502843

Meng, Y., & Pantzalis, C. (2016). Monthly cyclicality in retail investors' liquidity and lottery-type stocks at the turn of the Month. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2820724

Nagy, R. A., & Obenberger, R. W. (1994). Factors influencing individual investor behavior. *Financial Analysts Journal*, *50*(4), 63–68. https://doi.org/10.2469/faj.v50.n4.63

OGDEN, J. O. S. E. P. H. P. (1990). Turn-of-month evaluations of liquid profits and stock returns: A common explanation for the monthly and January effects. *The Journal of Finance*, *45*(4), 1259–1272. https://doi.org/10.1111/j.1540-6261.1990.tb02435.x

Ortmann, R., Pelster, M., & Wengerek, S. T. (2020). Covid-19 and investor behavior. *Finance Research Letters*, *37*, 101717. https://doi.org/10.1016/j.frl.2020.101717

Shive, S. (2007). An epidemic model of investor behavior. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.687410

Talwar, M., Talwar, S., Kaur, P., Tripathy, N., & Dhir, A. (2021). Has financial attitude impacted the trading activity of retail investors during the COVID-19 pandemic? *Journal of Retailing and Consumer Services*, *58*, 102341. https://doi.org/10.1016/j.jretconser.2020.102341

ACADEMIC VITA

ANDREW J. HOFF

a.hoff4471@gmail.com

EDUCATION

The Pennsylvania State University | Schreyer Honors College — **University Park, PA**
Smeal College of Business | Major in Finance, Minor in Economics — *Class of 2023*
GPA: Xxx /4.00

AWARDS AND RECOGNITION

- Featured in Smeal Magazine as an exemplary 2+2 student
- 2X Recipient of the Debby Vinokur-Kaminsky and Howard Kaminsky Honors Scholarship
- 2X Recipient of the Poole Family Honors Scholarship
- **Semi-finalist** 2021 Kohl's Case Competition
- Recipient of the Nicholas Altobello Honors Scholarship
- **2X Recipient** of the Frederik and Sonja Wenzel Honors Scholarship

PROFESSIONAL EXPERIENCE

Deloitte — **Philadelphia, PA**
Strategy Analyst — Sept 2022
- Incoming full-time Strategy Analyst for Deloitte Consulting.

Chatham Financial — **Kennett, PA**
Corporate Analyst Intern — *May 2022 – Aug 2022*
- Generated **recommendations** regarding **profit maximization** and **service diversification** based on a breakdown performed on **125M in revenues** over the course of the previous 5 years.
- Analyzed Chatham's competitive market to generate **differentiating strategies** concerning educational content and outreach.
- Partnered with 2 other Interns to benchmark **interest rate, foreign exchange, and commodity exposures** across **1,400** corporations ranging from **mid-sized to Fortune 500**.
- Presented findings from engagements to the **CEO**, Managing **Partners**, and **Global Head of Corporates**.

Maplezone Sports Village — **Aston, PA**
Assistant Facility Manager & Head of Advertising — *June 2020 – Sept 2021*
- Developed a framework for the company's **first sponsor outreach strategy** and generated recurring revenues that amounted to a **5% increase** in total annual revenue.
- Created proposal decks and organized meetings with **executive staff** to explore additional revenue opportunities.

LEADERSHIP EXPERIENCE

Assistance in Transition to University Park (ATUP) — **University Park, PA**
Vice President of External Affairs — *Aug 2022 – Present*
- ATUP's key spokesperson and in-house consultant.
- Oversaw **PR, marketing, and communication strategy** to facilitate the sustainable and projectable expansion of the organization.
- Held supervisory responsibility for the Directors of Marketing, Operations, and Commonwealth Liaisons.

Nittany Lion Consulting Group (NLCG) — **University Park, PA**
Engagement Manager — *Aug 2022 – Dec 2022*
- Guided and mentored **3 Associates** through an engagement with the Smeal College of Business to tailor recommendations regarding **best practices** for the **implementation** of experiential learning programs.
- Supervised the processes of **benchmarking, brainstorming, deliverable creation, delivery, and implementation.**

EXTRACURRICULAR INVOLVEMENT

TEDxPSU — **University Park, PA**
Speaker — *Feb 2023*
- Selected to be **1 of 10 speakers (1 of 2 students)** at one of the world's **most recognized** and **competitive** independently run TEDx conferences.
- Spoke about the opportunity cost of time and how the allocation of our time shapes our path through life.

Nittany Lion Consulting Group (NLCG) — **University Park, PA**
Associate & Finance Lead — *Jan 2022 – May 2022*
- Worked on a 10-week case for a nonprofit healthcare foundation in western Pennsylvania focusing on **organizational structure, internal and external communication, revenue growth, and business expansion.**

SKILLS AND CERTIFICATIONS

Proficient in Salesforce, Power BI, Microsoft Excel, Word, PowerPoint, Teams, OneNote, Outlook