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Return predictability of popular stocks among zero-commission traders under limits-to-arbitrage

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Abstract:

I examine stock returns following large increases in stock holdings among users of the Robinhood trading platform over time and the effects under proxies for limits-to-arbitrage. I use publicly available data on the stock holdings of Robinhood users between May 2018 and July 2020. Stocks in the top percentile of percentage increases in stock holdings over a day are associated with significantly negative (risk-adjusted) returns compared to those with small changes in stock holdings in the subsequent five trading days using a Carhart (1997) four-factor model. Over longer periods, I find some weak evidence of outperformance by the same stocks. The short-term effect is limited to stocks with high limits-to-arbitrage. Proxies for high limits-to-arbitrage include low market capitalization, high effective bid-ask spreads, low institutional ownership, and high idiosyncratic volatility.

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1. Introduction

What started as a small discussion on a Reddit discussion forum would soon turn into one of the best-known stock frenzies in the last decade, going so far as to a house representative of Michigan accusing the CEO of the zero-commission trading platform Robinhood of "[gaslighting] the American people" in a subsequently prompted congressional hearing (Badkar, Platt & Politi, 2021). In late January of 2021, Gamestop Corp. experienced an increase in its market valuation by nearly 400% (Li, 2021). This increase in its share price was not due to some sudden positive change in its fundamentals. In fact, prominent hedge funds were betting on its share price to fall even further (Li, 2021). Instead, small retail traders attempted to bid up the stock price enough for hedge funds to be forced to terminate their position, thereby prompting a "short-squeeze" (Li, 2021). Unfortunately, for these retail investors, the stock would also experience significant negative returns in the subsequent week (Li, 2021).

The fact that retail traders' investment decisions are not always driven by the fundamentals of an asset is nothing new. Cosemans and Frehen (2021) find that investors purchasing stocks with salient past returns likely induce overpricing, leading to lower subsequent returns. Barber and Odean (2008) find that investors are easily swayed by attention-inducing events such as abnormally high trading volume or extreme stock returns. Furthermore, Seasholes and Wu (2007) argue that retail investors on the Shanghai stock exchange narrow their consideration set by being particularly keen on buying stocks that had previously reached their upper daily price limits and find that such stocks would subsequently experience significantly negative returns. Furthermore, Barber, Odean, and Zhu (2009) document that stocks heavily purchased by individual investors experience subsequently lower returns in the following trading weeks, implying potential mispricing. More recently, Barber, Huang, Odean, and Schwarz (2020) find that users of the Robinhood trading platform are swayed to heavily purchase stocks related to attention-inducing events, leading stocks to experience subsequently negative abnormal returns. Additionally, previous literature has found that mispricing among stocks is greater under limits-to-arbitrage (Nagel, 2005; Mashruwala, Raipogal & Shevilin, 2006; Barber et al., 2009; Stambaugh, Yu & Yuan, 2015; Barber et al., 2020; Cosemans & Frehen, 2021). As an example, Stambaugh et al. (2015) find that overpriced stocks with high idiosyncratic volatility experience lower subsequent returns than their low idiosyncratic volatility counterparts.

The findings of the abovementioned articles, among many others prompt the question:

What are the consequences of large relative increases in stock ownership among Robinhood users on asset prices over time and how do limits-to-arbitrage influence these results?

Using a Carhart (1997) four-factor model, I find that stocks belonging to the 100th percentile of daily percentage increases in stock ownership among users of the Robinhood platform experience significantly negative subsequent (risk-adjusted) returns of -20.98% annually over a five-trading day holding period. These results persist when comparing the results to the 1st percentile of daily percentage increases in stock holdings using a long-short portfolio. I find weak evidence of outperformance by the 100th percentile group for the medium- (40 to 60 trading days) and longer-term (120 trading days). I then sort stocks belonging to the 100th percentile of daily percentage increases in stock ownership into high and low limits-to-arbitrage portfolios as proxied by market capitalization, the effective bid-ask spread, institutional ownership, and idiosyncratic volatility. I find that the negative return phenomenon of the 100th percentile stocks over the subsequent five trading days is limited to stocks with high limits-to-arbitrage. Over the medium to longer-run no consistent outperformance by the high compared to the low limits-to-arbitrage portfolios is found. Overall, the findings are in line with Seasholes and Wu (2007) and Barber et al. (2009; 2020) who show that large increases in popularity of stocks among retail investors are associated with negative subsequent returns in the subsequent days and weeks. The findings also provide weak evidence that over the longer-run these popular stocks may actually outperform, though it is unclear whether Robinhood investors will benefit from this phenomenon. Lastly, the results under limits-to-arbitrage agree with both theoretical literature (Pontiff, 1996; Shleifer & Vishny, 1997) and empirical literature (Nagel, 2005; Mashruwala et al., 2006; Barber et al., 2009; 2020; Stambaugh et al., 2015; Cosemans & Frehen, 2021) that mispricing is greater among stocks with higher limits-to-arbitrage.

While retail traders have been extensively studied in the past, (see Barber and Odean (2008), Barber et al. (2009), Seasholes and Wu (2007) among many others) the existence of a new dataset documenting the hourly stock holdings of users of the Robinhood trading platform allows for a more in depth analysis of this decade's group of retail traders and their investment decisions. Though Barber et al. (2020) also look at stock returns following large increases in stock holdings among Robinhood users using an event time analysis, this paper studies Robinhood users in a cross-sectional setting over shorter and longer periods using a Carhart (1997) four-factor model and in addition examines whether subsequent returns are stronger under various proxies for limits-to-arbitrage. Therefore, this paper adds to existing literature of retail traders by using a more extensive factor model to determine the risk-adjusted returns of stocks following such events, compared to the one-factor model in a cumulative abnormal return analysis used by Barber et al. (2020) and it adds to the literature of mispricing under limits-to-arbitrage by providing an additional perspective from the actions of today's retail traders. Lastly, by also examining returns over longer periods new insights are provided on how stocks with large sudden changes in popularity behave over an extended time horizon.

Additionally, this paper is socially relevant as studying the behavior of retail traders of a prominent zero-commission platform provides further understanding of how particularly young, and potentially inexperienced investors (Eaton, Green, Roseman & Wu, 2021) behave in the now prominent zero-commission trading environment and the potential dangers involved with participating in smaller but possibly similar events to the one of Gamestop in January of 2021.

The rest of the paper is organized in the following way: Section 2 discusses previous literature covering the behavior of retail traders and their impact on the financial market, limits-to-arbitrage in relation to asset-mispricing, and the Robinhood trading platform. Section 3 develops the sub-questions to answer the main research question. Section 4 provides the data, descriptive statistics, and the methodology. Section 5 shows the results of stock portfolios with large percentage changes in stock ownership, in addition to the results under proxies for limits-to-arbitrage. Section 6 discusses the results shown in section 5. Lastly, section 7 concludes on this paper and mentions several limitations as well as suggestions for further research.

2. Literature Review

2.1 Individual Investor Behavior and Return Predictability

Looking back at previous literature, both theoretical and empirical analyses have been conducted to analyze the effects of small individual investors. In this sub-section, I will review recent literature on the trading behavior of individual investors and consequential return predictability.

Cosemans and Frehen (2021) empirically investigate the implications of salience theory. The theory asserts that investors are particularly drawn to stocks with more salient past returns, thereby exerting a demand-driven price pressure which may push a stock's market valuation beyond its fundamentals (Cosemans & Frehen, 2021). The authors find, using a salience measure, that stocks with especially memorable high past returns experience subsequently lower returns, whereas stocks with particularly salient low past returns experience subsequently higher returns, in line with investor-induced mispricing.

Barber and Odean (2008) analyze the impact of attention-inducing events on the investing behavior of individual traders and large institutional traders. Attention-grabbing events include news, extreme stock returns, and abnormally high trading volume. The underlying theory behind Barber and Odean's (2008) analysis is that individual investors are more swayed to act on attention-grabbing events than institutional investors. Additionally, the authors suggest that buying rather than selling behavior of individual investors is more amplified during such events as the choice set for selling stocks (their own portfolio) is much smaller than their choice set for buying stocks (the entire stock universe). Barber and Odean (2008) subsequently find that individual investors show greater buy-sell imbalances following high-attention events than institutional investors, with investors at large discount brokerages engaging in nearly twice as many buys as sales of stocks receiving significant attention. This consequently implies that small traders are more swayed by such news and that these news have a greater impact on their purchasing rather than selling behavior.

Seasholes and Wu (2007) document that attention-grabbing events, proxied by stocks hitting the daily price limits in the Shanghai Stock Exchange narrow the consideration set of investors, thereby easing their investment choice by limiting the range of stocks from which they choose their investments. The authors examine the buy-sell imbalances of those stocks and find that individual investors are net buyers of stocks having hit the upper price limit on the previous trading day. Seasholes and Wu (2007) find that stocks associated with attention-grabbing events observe on average both negative raw returns and risk-adjusted returns over the subsequent five trading days, consistent with the hypothesis of individual investors driving up prices beyond their fundamental values in consequence of attention-inducing events.

Barber, Odean and Zhu (2009) further investigate individual investor-related market activity by examining buyer-or-seller-initiated trades over longer and shorter holding periods. In their analysis of value-weighted portfolios, based on the magnitude of purchases of individual investors, Barber et al. (2009) observe that portfolios of heavy previous buys exhibit significantly positive abnormal returns of a Frama-French-type four-factor model in the subsequent week. Nevertheless, using weekly Fama-Macbeth regressions, the authors also document price reversals several weeks after the initial period of strong purchases by individual investors, in line with the idea of investor sentiment pushing asset prices beyond their fundamentals.

As this paper intends to do, more recent literature more explicitly examines retail traders by observing the stock holdings of users of the zero-commission trading platform, Robinhood. Welch (2020) is one of the first authors to do so, using a dataset containing data on aggregate stock holdings of Robinhood users. He finds that, especially during the Covid-19 market downturn, Robinhood users increased their investments regardless of the market condition. Furthermore, using a portfolio weighted by the stock holdings of these investors, Welch (2020) finds that in aggregate, during the period of mid-2018 to mid-2020, Robinhood investors outperformed the market and a six-factor model significantly. Additionally, he finds that Robinhood investors are especially keen on investing in stocks with a high (dollar) trading-volume in the previous trading year.

Barber, Huang, Odean and Schwarz (2020) study the impact of the zero-commission brokerage on trading behavior of individual investors and asset prices on the stock market for large increases in Robinhood stock holdings. They find that Robinhood users are predictably swayed by attention-grabbing events, such as the top-movers feature of the trading app in which stocks with the largest absolute gains are displayed, thus providing additional evidence of such investors being less driven by the fundamentals of an asset and more by the assets' abilities to prey on the cognitive biases of individual investors. Additionally, in an event time analysis, Barber et al. (2020) estimate the abnormal returns, calculated as the stock return minus the value weighted CRSP index of the top 0.5% of stock purchases per day for stocks with at least a 100-user holding increase over that period. The authors find that while abnormal returns are near zero prior to the herding event, the event day experiences large positive abnormal returns followed by subsequent negative abnormal returns of -3.5% over the succeeding five trading days. Furthermore, the authors find the magnitude of subsequent price reversals to be correlated with the magnitude of the herding event.

The idea of individual investors of zero-commission brokers having a sizeable influence on the financial markets is further promoted by an additional working paper by Eaton, Green, Roseman and Wu (2021), who examine the impact of outages of the Robinhood platform on market quality - as proxied by various derivations of the bid-ask spread in addition to return volatility - by comparing these variables to similar periods in the previous trading week. Eaton et al. (2021) find that periods of platform outages – periods during which trading for Robinhood users is limited or non-existent – are associated with significantly narrower spreads quoted by high frequency traders with Robinhood order flow arrangements. Additionally, the authors find that return volatility is also significantly lower during such platform outages. Furthermore, to strengthen the notion of Robinhood investors' at times potentially naïve trading activities, Eaton et al. (2021) investigate the sophistication of Robinhood traders relative to retail traders of other platforms and find that Robinhood investors in particular visit the FAQ page of Robinhood much more frequently than other retail investors visiting their corresponding FAQ pages.

2.2 The limits-to-arbitrage

The extent to which mispricing of stocks can take place depends on the magnitude of limits-to-arbitrage of an asset. Thus, in this sub-section I am reviewing past literature focusing on the impact of theoretical implications of limits-to-arbitrage and empirically documented factors impacting return predictability in consequence of these limits.

Shleifer and Vishny (1997) argue in their theoretical paper that mispricing may continue to persist and thus not as easily be eliminated due to costs associated with arbitrage. In their theoretical performance-based arbitrage model, the authors suggest that arbitrageurs acting on behalf of principals may have to prematurely terminate or even forego engaging in a mispricing-correcting position due to arbitrage-related holding costs associated with their investments (Shleifer & Vishny, 1997).

Pontiff (1996) in his research on arbitraging off value-deviations of closed-end funds suggests that investors face two forms of costs when engaging in price arbitrage. The first is transaction costs – costs incurred every time a position is initiated or terminated –, such as bid-ask spreads, thereby reducing the profitability of arbitrage, whereas the second form is holding costs – costs incurred during the period in which the position is maintained – such as risk exposure. In the latter case, arbitrageurs are affected in ways pointed out by Shleifer and Vishny (1997).

As an example of arbitrage risks affecting the extent of mispricing, Stambaugh, Yu, and Yuan (2015) investigate the relationship between asset mispricing and idiosyncratic volatility, representing a holding cost that deters rational investors from engaging in price-correcting arbitrage. Using a unique mispricing measure based on 11 empirically documented asset return anomalies to identify possible mispricing, the authors find that stocks with high potential mispricing and high idiosyncratic volatility, proxied by the standard deviation of the previous month's benchmark-adjusted returns, experience larger negative risk-adjusted returns compared to potentially overpriced stocks with low-idiosyncratic risk. Stambaugh et al.'s (2015) findings thus provide further evidence of limits-to-arbitrage impacting the magnitude of mispricing following asset valuations above fundamental value as illustrated by large subsequent price drops.

Similarly, Barber et al. (2009) find that stocks with high idiosyncratic volatility – proxied by the standard deviation of the firm's excess returns over the market's excess returns – that have been heavily bought by individual investors experience significantly lower subsequent risk-adjusted returns compared to their heavily bought low idiosyncratic volatility counterparts.

Furthermore, Mashruwala, Rajpogal and Shevlin (2006), in their investigation on the persistence of the accrual anomaly under limits-to-arbitrage, find that mispricing due to investors underweighting (overweighting) cash flows (accruals) when establishing beliefs about subsequent earnings is stronger for stocks with higher arbitrage risk, such as idiosyncratic volatility, but also for stocks with higher transaction costs, as proxied in their paper by low stock prices.

Moreover, the type of investors bearing majority ownership of a stock's shares may also affect the extent to which misvaluation can take place. Nagel (2005), explores the relationship between institutional ownership of assets and stock anomalies resulting in mispricing and finds that the magnitude of return predictability for these anomalies is positively related to institutional ownership, even after controlling for the negative relationship between size and stock ownership. In particular, he argues that both the level of sophistication of investors holding a stock and stock loan supply influences the extent to which stocks can become mispriced (Nagel, 2005). In the latter case, a lower stock loan supply would imply larger fees associated with borrowing a stock, thus making it less appealing for arbitrageurs to engage in price-correcting trading strategies (Nagel, 2005).

Additionally, Cosemans and Frehen (2021) find that their investigated cross-sectional return relationship for highly salient stocks is greater under high limits-to-arbitrage, as measured by high idiosyncratic volatility, low institutional ownership and low analyst coverage, with the effect being greatest for stocks with high idiosyncratic volatility.

3. Sub-question development

In this section, I develop sub-questions based on the theoretical and empirical findings discussed in Section 2 with which the main research question is answered. In total, three sub-questions are developed.

3.1 Sub-question one

Cosemans and Frehen (2021) find that stocks with salient positive returns experience subsequently lower returns. The empirical findings of Barber and Odean (2008), Seasholes and Wu (2007) and Barber et al. (2020) show that individual investors are easily swayed by attention-grabbing events and despite the investors' individual nature they act collectively as shown by greater buy-sell imbalances or large changes in stock holdings for Robinhood investors. In consequence of such events, during which individual investors collectively trade the affected stock, stocks initially experience positive returns, followed by significantly negative abnormal returns in the subsequent trading days and weeks (Seasholes & Wu, 2007; Barber et al., 2009; 2020), in line with the idea of individual investors pushing asset prices beyond fundamental justifications. Additionally, Eaton et al. (2021) provide further indications that Robinhood users in particular are potentially more naïve about the stock market than their peers at other retail trading platforms, making it potentially more likely that such investors may induce prices to increase unjustifiably.

Thus, based on these abovementioned findings, the first sub-question states the following:

Are large positive changes in stock ownership among Robinhood investors associated with subsequently lower returns?

3.2 Sub-question two

Several papers find that short attention-inducing events lead to subsequently lower returns over the coming trading weeks. Seasholes and Wu (2007) find that following attention-inducing events during which stocks hit the price ceiling of the Shanghai Stock Exchange, the returns of affected stocks are subsequently negative during the succeeding trading week. Similarly, Barber et al. (2020) examine the subsequent returns of stocks over 20 trading days and find that two thirds of stocks of their attention measure have negative cumulative returns during that period. Furthermore, Barber et al. (2009) document that portfolios based on heavy buys by individual investors first experience large positive abnormal returns followed by a reversal several weeks after the event.

Considering these findings and to better understand both the long-term implications of large short-term changes in stock holdings among individual investors, the second sub-question states:

What is the price impact of stocks experiencing large changes in stock ownership among Robinhood traders over time?

3.3 Sub-question three

Lastly, Shleifer and Vishny (1997) argue that mispricing is more prevalent among stocks with higher limits-to-arbitrage. Pontiff (1996) further makes a distinction between holding costs and transaction costs when discussing such limits. Stambaugh et al. (2015) and Barber et al. (2009) both find that potentially overpriced stocks with high idiosyncratic volatility experience larger negative risk-adjusted returns compared to those with low idiosyncratic volatility. Furthermore, Mashruwala et al. (2006) document that mispricing for a return anomaly is stronger among stocks with greater idiosyncratic volatility or transaction costs. Nagel (2005) assesses that return predictability for stock anomalies is greater for stocks with low institutional ownership, making it harder for arbitrageurs to correct mispricing. Finally, Cosemans and Frehen (2021) find that mispricing among salient stocks is greater for stocks with high idiosyncratic volatility, low analyst coverage and low institutional ownership.

Considering the abovementioned theoretical implications and findings regarding limits-to-arbitrage and their relationship to stock mispricing, the third sub-question states:

Are large changes in stock ownership among Robinhood traders associated with lower subsequent returns for stocks with greater limits-to-arbitrage?

4. Data, Descriptive Statistics and Methods:

This section discusses the data used in this paper, descriptive statistics around the different portfolios that are analyzed, and the methods based on which the portfolios are formed. This procedure holds for each sub-section.

4.1 Robintrack Data

The dataset with which holding changes among Robinhood investors are analyzed stems from the Robintrack website (https://robintrack.net) . The website compiles stock holding data from the Robinhood trading platform on an approximately hourly basis between May 2nd, 2018 and

August 13th, 2020, after which it discontinued sharing its user data with the public. In particular, the dataset from Robintrack displays cross-sectional information on how many users hold each particular stock on the Robinhood platform every hour. As an example, on August 1st, 2019 at 12:43pm ET, 165,231 Robinhood users held a positive position in the Tesla stock. Due to the Center for Research in Security Prices (CRSP) only providing data up to December 31st , 2020, and given the aim of this paper being to also examine the long-term effects of user changes on asset prices, the sample of Robinhood data used in this paper ends on July 13th, 2020 (120 trading days prior to December 31st ,2020).

Figure 1 Total user holdings between May 2018 and August 2020

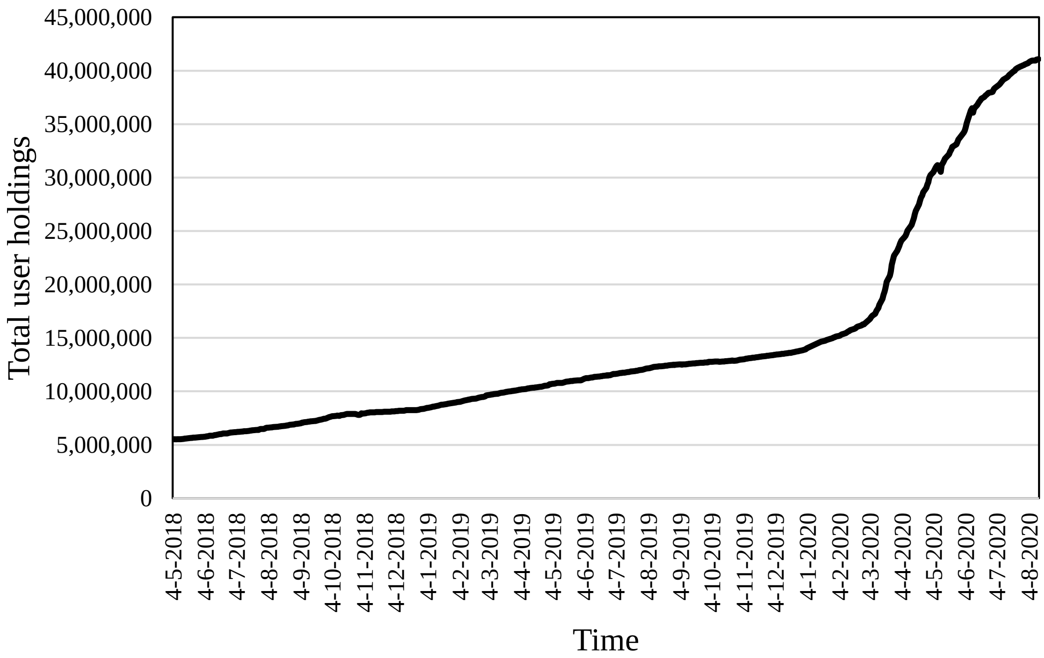

Figure 1 shows the progression of user holdings among Robinhood investors between May 4th, 2018 and August 13th, 2020. The trading platform experiences an initially steady, continuous gain in user holdings between the initiation of the Robintrack dataset in May of 2018 until early March of 2020. Following the start of the COVID-19 pandemic, the number of user holdings more than doubles from 16,923,278 in March 5th, 2020 to more than 41 million on August 13th, 2020, when Robinhood ceased its information sharing policy regarding its users' stock holdings.

4.2 Percentage user changes

Since this paper examines daily percentage changes in user stock holdings, daily holding data for each day is calculated at the end of each trading day at approximately 16:45pm ET. Stocks which do not have any user holding data after the closing of regular trading hours are excluded from the analysis for that particular day so that each day only stocks with the full magnitude of daily percentage user changes are analyzed.

Daily percentage user changes are calculated as the percentage change in daily stock holdings by Robinhood investors until approximately market closing. Thus, throughout this paper percentage holding changes for stock i at trading day t is calculated as follows:

$$Percentage\ user\ change_{i,t} = \frac{(User\ holdings_{i,t} - User\ holdings_{i,t-1})}{User\ holdings_{i,t-1}}$$

Table 4.1 Percentage user changes for Robinhood users

Percentage user change	**Mean**	**Median**	**Std. Dev.**	**Min.**	**Max.**	**Obs.**
Full sample	0.006	0.000	0.331	-1.000	331.758	3,595,970
10th decile	0.093	0.037	1.042	0.007	331.758	358,677
1st decile	-0.040	-0.024	-0.039	-1.000	-0.005	360,454
100th percentile	0.535	0.250	3.30	0.065	331.758	35,020
1st percentile	-0.148	-0.108	0.131	-1.000	-0.047	37,060

Note: Std. Dev refers to the standard deviation of the daily percentage user changes; Min. refers to the lowest percentage user change; Max. refers to the largest percentage user change; Obs. refers to the total number of percentage user changes observed; the sample period is between May 4th, 2018 and July 13th, 2020; Full sample refers to the full Robinhood sample; 10th decile refers to the 10th decile of daily percentage user changes; 1st decile refers to the 1st decile of daily percentage user changes; 100th percentile refers to the 100th percentile of daily percentage user changes; 1st percentile refers to the 1st percentile of daily percentage user changes.

Table 4.1 shows that, for the full sample, nearly 3.6 million percentage user changes in the entire Robinhood universe between May 2018 and July 2020 are considered in this paper. The mean percentage user change in the sample is relatively low at 0.6%, while the median percentage user change is zero. Thus, a large noticeable portion of daily percentage user changes is relatively small or close to zero, in line with the idea of individual traders limiting their consideration set of the stock universe to stocks that grab their attention (Barber & Odean, 2008; Seasholes & Wu, 2007). Despite the relatively low average daily user change, the sample sees considerable variation with a standard deviation of percentage user changes of 33.12%.

4.3 Percentile Portfolio sorts

To analyze the first sub-question, at the end of each trading day, each stock is sorted into a percentile group based on its percentage user changes relative to all the other asset's percentage user changes over the contemporaneous trading day. The top percentile group contains stocks with the greatest percentage user changes, whereas the bottom percentile group contains stocks with the smallest or most negative percentage user changes.

After, the returns of stocks belonging to the top percentile and bottom percentile of daily percentage user changes are examined and compared through a long-short portfolio to further investigate whether the results found are unique to the specific percentile sorts.

The reason for not imposing a coarser sorting criterion, such as sorting stocks into deciles based on daily percentage user changes is due to the median percentage user change of the top decile in Table 4.1 being relatively small. The median percentage user change for the top and bottom deciles are 3.7% and -2.4%, respectively. In both cases it is very unlikely that such user changes are bound to indicate a large change in trader sentiment regarding the asset. In contrast, the median percentage user change for the top and bottom percentile portfolios are 25% and -10%, respectively, which are more likely to represent reactions by investors to attention-inducing events as outlined in Seasholes and Wu (2007), Barber and Odean (2008) and Barber et al. (2009; 2020). Additionally, Barber et al. (2020) impose an even more stringent criterion for their cumulative abnormal return analysis by only examining stocks belonging to the top 0.5% of percentage user changes with an increase in users of at least 100. Nevertheless the 10th and 1st decile return results of daily percentage user changes are examined and reported in the appendix.

Table 4.2 Daily number of stocks added to the 100th and 1st percentile groups

Portfolio sorts	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Obs.**
100th percentile	64.78	6.14	50	74	35,020
1st percentile	68.51	6.09	57	82	37,060

Note: Std. Dev refers to the standard deviation of the daily number of stocks added to each portfolio sort; Min. refers to the lowest number of daily stocks added to the each portfolio sort; Max. refers to the largest number of daily stocks added to each portfolio sort; Obs. refers to the total number of stocks added during the sample period; the sample period is between May 4th, 2018 and July 13th, 2020; 100th percentile refers to stocks belonging to the 100th percentile of daily percentage user changes; 1st percentile refers to stocks belonging to the 1st percentile of daily percentage user changes.

Table 4.2 shows the number of stocks that are part of the daily calculated percentile groups. The number of stocks of each group depends on the number of stocks available for trade in the Robinhood universe, leading to some deviations at time. On average, close to 65 stocks are part of the percentile groups each day, leading to a total of 35,020 and 37,060 additions the top and bottom percentile groups, respectively, during the sample period.

Each day, stocks belonging to their respective percentile groups are added to a portfolio and held for the intended holding period. Thus, each trading day, new stock positions are initiated and old ones, conditional on them having been held for the intended holding period of the corresponding portfolio, are terminated. Furthermore, to determine a potential difference in portfolio performance between stocks of the top and bottom percentiles of daily percentage user changes, long-short portfolios are formed, in which stocks in the 100th percentile portfolios have a long position, while stocks in the 1st percentile portfolios are given a short position. The resulting portfolios yield a time-series of daily portfolio data for approximately two and a half years.

4.4 Limits-to-arbitrage sorts

Lam and Wei (2011) in their paper on the asset growth anomaly, mention several aspects of limits-to-arbitrage, among which are high potential transaction costs, low shareholder sophistication and high arbitrage risk. To capture these characteristics and to analyze the impact of large user changes on asset prices under limits-to-arbitrage, three proxies in addition to market capitalization are analyzed: the effective bid-ask spread (BIDASK), institutional ownership (IO), and idiosyncratic volatility (IVOL).

In general, each trading day, stocks belonging to the top percentile of overall daily percentage user changes and to the top or bottom quintile of each proxy of limits-to-arbitrage are identified.

Then, at the end of each trading day new stock positions of stocks belonging to both the current trading day's daily top percentile group and the daily top or bottom quintile of the corresponding proxy of limits-to-arbitrage group are initiated, while old positions, conditional of them having been held for the intended holding period of the corresponding portfolio, are terminated. To compare the portfolio performance of high and low limits-to-arbitrage, long-short portfolios are formed, in which portfolios with high limits-to-arbitrage take a long position, while portfolios with low limits-to-arbitrage take a short position.

Table 4.3 Quantified proxies for limits-to-arbitrage of each limits-to-arbitrage portfolio sort between May 4th, 2018 and July 13th, 2020

Portfolio sorts	**Mean**	**Median**	**Std. Dev.**	**Min.**	**Max.**	**Obs.**
Low market capitalization ($)	149mn	72mn	176mn	0.088mn	898mn	26,615
High market capitalization ($)	15,700mn	9,090mn	24,100mn	3,270mn	469,000mn	1,781
High BIDASK (%)	2.29	1.30	3.07	0.33	103.59	11,059
Low BIDASK (%)	0.01	0.00	0.01	0.00	0.11	6,889
Low IO (%)	2.15	0.00	3.78	0.00	16.68	11,880
High IO (%)	92.96	93.85	6.65	71.17	100.00	6,554
High IVOL (%)	7.34	5.40	7.50	2.31	201.92	10,098
Low IVOL (%)	0.62	0.45	0.70	0.00	5.39	8,048

Note: Std. Dev refers to the standard deviation of the values of each proxy of limits-to-arbitrage of the limits-to-arbitrage sorts; Min. refers to the lowest value of each proxy of limits-to-arbitrage of the limits-to-arbitrage sorts; Max. refers to the largest value of each proxy of limits-to-arbitrage of the limits-to-arbitrage sorts; Obs. refers to the total number of observations during the Robinhood sample period of this paper; the sample period of the portfolios is between May 4th, 2018 and July 13th, 2020; Low market capitalization refers to the market capitalization of stocks in the 100th percentile group of daily percentage user changes and the bottom 20% of the market's market capitalization using NYSE breakpoints; High market capitalization refers to stocks in the 100th percentile group of daily percentage user changes and the top 40% of the market's market capitalization using NYSE breakpoints; the values of Low market capitalization and High market capitalization are shown in millions of dollars; High BIDASK refers to the effective bid-ask spread of stocks in the 100th percentile group of daily percentage user changes and the 5th quintile of the effective bid-ask spread; Low BIDASK refers to the effective bid-ask spread of stocks in the 100th percentile group of daily percentage user changes and the 1st quintile of the effective bid-ask spread; the values of High BIDASK and Low BIDASK are shown in percent; Low IO refers to stocks in the 100th percentile group of daily percentage user changes and the 1st quintile of institutional ownership; High IO refers to stocks in the 100th percentile group of daily percentage user changes and the 5th quintile of institutional ownership; the values of Low IO and High IO are shown in percent; High IVOL refers to the idiosyncratic volatility of stocks in the 100th percentile group of daily percentage user changes and the 5th quintile of idiosyncratic volatility; Low IVOL refers to the idiosyncratic volatility of stocks in the 100th percentile group of daily percentage user changes and the 1st quintile of idiosyncratic volatility; High IVOL and Low IVOL are shown in percent; the sample period used to calculate Low market capitalization and High market capitalization is between April 2018 and June 2020; the sample period used to calculate High BIDASK and Low BIDASK and High IVOL and Low IVOL is between April 6th, 2018 and July 12th,2020; the sample period used to calculate Low IO and High IO is between March 30th, 2018 and March 31st, 2020.

Table 4.4 Daily number of stocks added to each limits-to-arbitrage portfolio sort between May 4th, 2018 and July 13th, 2020

Portfolio sorts	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Share of top percentile**	**Obs.**
Low market capitalization	49.44	7.77	31	70	0.76	26,649
High Market capitalization	3.22	2.16	1	11	0.05	1,780
Very high market capitalization	0.97	1.01	0	5	0.01	533
High BIDASK	24.15	5.86	9	49	0.37	13,007
Low BIDASK	14.59	3.77	4	24	0.23	7,926
Low IO	22.33	14.07	6	74	0.34	11,880
High IO	12.07	5.17	2	28	0.19	6,554
High IVOL	18.75	5.28	5	39	0.29	10,098
Low IVOL	15.09	5.80	4	37	0.23	8,048

Note: Std. Dev refers to the standard deviation of the daily number of stocks added to each limits-to-arbitrage portfolio sort; Min. refers to the lowest number of daily stocks added to each limits-to-arbitrage portfolio sort; Max. refers to the largest number of daily stocks added to each limits-to-arbitrage portfolio sort; Share of top percentile is the ratio of Mean of each limits-to-arbitrage sort and the total number of stocks added daily to the 100th percentile portfolio sort; Obs. refers to the total number of stocks added during the sample period; the sample period is between May 4th, 2018 and July 13th, 2020; Low market capitalization refers to stocks in the 100th percentile group of daily percentage user changes and the bottom 20% of the market's market capitalization using NYSE breakpoints; High market capitalization refers to stocks in the 100th percentile group of daily percentage user changes and the top 40% of the market's market capitalization using NYSE breakpoints; Very high market capitalization refers to tocks in the 100th percentile group of daily percentage user changes and the top 20% of the market's market capitalization using NYSE breakpoints; High BIDASK refers to stocks in the 100th percentile group of daily percentage user changes and the 5th quintile of the effective bid-ask spread; Low BIDASK refers to stocks in the 100th percentile group of daily percentage user changes and the 1st quintile of the effective bid-ask spread; Low IO refers to stocks in the 100th percentile group of daily percentage user changes and the 1st quintile of institutional ownership; High IO refers to stocks in the 100th percentile group of daily percentage user changes and the 5th quintile of institutional ownership; High IVOL refers to stocks in the 100th percentile group of daily percentage user changes and the 5th quintile of idiosyncratic volatility; Low IVOL refers to stocks in the 100th percentile group of daily percentage user changes and the 1st quintile of idiosyncratic volatility.

4.4.1 Market Capitalization

The data for each stock's monthly market capitalization is retrieved from the CRSP database. Monthly market capitalization is calculated as the product of the monthly shares outstanding and the stock's corresponding stock price, defined as the closing price or the average of the bid and ask price if the closing price is unavailable. Price data that is recorded as negative by CRSP to indicate that the price data is the average of the bid and ask price is made positive.

To determine, to which market capitalization quintile each stock belonging to the daily 100th percentile group belongs, monthly NYSE breakpoint data is obtained from Kenneth French's data library.

To then investigate whether subsequent returns for stocks with small or large market capitalization following large purchasing events by Robinhood investors differ, stocks belonging to the top percentile of daily percentage user changes are grouped into size portfolios based on the previous month's NYSE breakpoints and the stocks' previous month's market capitalizations. The reason for using the previous month's rather than the current month's market capitalization is to explicitly prevent the conflation of two potential phenomena related to large user changes: If large user changes do in fact impact or are associated with changes in prices, stocks belonging to the smallest market capitalization group prior to the event day may experience large enough price increases to subsequently belong to a different market capitalization group. This could negatively impact the results as some stocks with the greatest price increases might no longer be part of the small market capitalization group in the data of the event month.

Small market capitalization stocks are defined as stocks belonging to the bottom 20% of the market's market capitalization, whereas large stocks are defined as belonging to the top 40% of the market's market capitalization. The mean market capitalization for small market capitalization stocks that are in the 100th percentile of daily percentage user changes is \$141 million compared to \$15.7 billion for large market capitalization stocks as seen in Table 4.3. The reason for not imposing a more stringent definition on large capitalization stocks (such as only examining the top 20% instead of the top 40%) is due to few very large stocks experiencing large percentage user changes in a day. Making such an imposition would result in an average of less than one stock per day being added to the portfolio (see Table 4.4). As seen in Table 4.4, 76% of stocks belonging to the top percentile of daily percentage user changes also belong to the bottom quintile of the market's market capitalization, in contrast to 5% for large market capitalization stocks (as defined in this paper). Furthermore, for small capitalization stocks, on average, nearly 50 stocks are added per day to their portfolios, whereas only three are added to the large market capitalization portfolios per day.

4.4.2 Effective Bid-Ask spread (BIDASK)

Data for the effective bid-ask spread is obtained by using the daily extract with time window tool offered by the CRSP database using the stocks' permanent identification numbers provided by CRSP.

The effective bid-ask spread (BIDASK) is then calculated in the same way as in Lam and Wei (2011), after which the 20-day arithmetic time series average is taken per day. Thus, BIDASK is calculated as the following:

$$BIDASK = \frac{\sum_{t=-1}^{-20} \frac{2x \left| Price - \frac{(Ask + Bid)}{2} \right|}{Price}}{20}$$

with the price being the closing price of the average of the bid and ask price if the closing price is not available. The reason for estimating BIDASK over a relatively short period of time is both to maintain consistency with the estimation of other limits-to-arbitrage proxies, such as idiosyncratic volatility (sub-section 4.4.4) and due to the event taking place over a single trading day instead of a longer period of time. After calculating BIDASK, quintiles based on BIDASK of the entire Robinhood universe per day are estimated.

To then investigate whether returns of stocks with large user changes differ for stocks of different effective bid-ask spreads, stocks belonging to the top percentile of daily percentage user changes and to the top quintile or bottom quintile of BIDASK are added to separate portfolios and subsequently analyzed. The average 20-day mean effective bid-ask spread for the top quintile portfolios is 2.29% compared to 0.01% for the bottom quintile portfolios as seen in Table 4.3. As shown in Table 4.4, on average, 37% of stocks belonging to the top percentile of daily percentage user changes are part of the top quintile of daily BIDASK, while only 23% are part of the bottom quintile of daily BIDASK. Each day, on average, 24.15 stocks are added to the top BIDASK quintile portfolios, compared to 14.59 stocks for the bottom quintile portfolios of daily BIDASK.

4.4.3 Institutional Ownership (IO)

Institutional ownership data is retrieved from the Thomson Institutional Holdings (13F) database. The 13F database consists of quarterly information on institutional stock holdings such as those of hedge funds. In particular, investment managers, exercising discretion over investments $100 million or more in fair value on the last trading day prior to the end of the quarter are mandated by the Security Exchange Commission to make a filing of their stock holdings within 45 days after the end of the calendar quarter. To correct for incorrect share adjustments due to splits if the report is filed late as also pointed out by Nagel (2005) (i.e. when the report date – the date on which the stock holdings are recorded – and the file date – the date on which the report is filed – are different) the shares documented by institutions are adjusted using the CRSP adjustment factor on the date of the filing.

Data on the number of shares outstanding on the report date or the last trading date prior to the report date are also retrieved from the CRSP database. Shares outstanding are subsequently adjusted using the CRSP adjustment factor. Like Nagel (2005), stocks which are on CRSP but do not have any reported institutional holdings are set to have zero institutional stock holdings.

Institutional ownership (IO) per stock per quarter is then defined as the ratio of the adjusted sum of all institutional share holdings and the adjusted number of shares outstanding. Afterwards, each quarter, stocks are sorted into quintiles based on IO. As done in Lewellen (2011), IOs for which the values calculated are above one are set to one (though omitting this adjustment does not change the portfolio allocations).

To then subsequently analyze a potential difference in price impact of large percentage user changes between stocks with low IO and stocks with high IO, each day, stocks in the top percentile group of daily percentage user changes belonging to the top or bottom quintile of the previous quarter's IO are added to separate portfolios. The reason for using the previous quarter's IO rather than the contemporaneous quarter's IO when sorting on the event day is again due to a conflation of phenomena: Large user changes may result in irrational price changes which may influence the level of stock holdings institutional investors want to have in the relevant stocks.

Table 4.3 shows that the average IO for the bottom quintile portfolios is 2.15% compared to 92.96% for the top quintile portfolios. Furthermore, Table 4.4 shows that 34% of stocks belonging to the top percentile of daily percentage user changes have low IO, compared to only 19% for stocks with high IO. Moreover, each day, on average, 22.33 stocks are added to the low IO portfolios, while 12.07 stocks are added to the high IO portfolios.

4.4.4 Idiosyncratic Volatility (IVOL)

Factor data to estimate idiosyncratic volatility (IVOL) is retrieved from the CRSP database. Return data for each stock is obtained using the event time window tool provided by the CRSP database using a stock's permanent identification number provided by CRSP.

In the spirits of Ang, Hodrick, Xing and Zhang (2006), daily IVOL per stock is calculated as the standard deviation of the residual of daily excess returns, benchmarked on the Carhart (1997) four-factor model, of the stock's preceding 20 trading days (see sub-section 4.6 for more information on the Carhart (1997) four-factor model).

The four-factor model is chosen for estimating a stock's IVOL to maintain consistency with the model used in estimating the risk-adjusted returns of the portfolios, as is detailed in sub-section 4.6. Idiosyncratic volatility is thus defined as the following:

$$IVOL = \sqrt{\frac{\sum_{t=-1}^{-20}(\varepsilon_t - \bar{\varepsilon})^2}{20 - 1}}$$

with ε_t being the daily error term over the Carhart (1997) four-factor model.

Each day, stocks are grouped into quintiles based on their daily estimated IVOL of the previous 20 trading days relative to the IVOL of the sample's stock universe. Stocks belonging to the top percentile group of daily percentage user changes and to the top or bottom quintile of IVOL are added to separate portfolios and subsequently analyzed.

Table 4.3 shows that the average IVOL of the top quintile portfolios is 7.34% compared to 0.62% for the bottom IVOL quintile portfolios. Table 4.4 illustrates that 29% of stocks belonging to the top percentile of daily percentage user changes exhibit high IVOL, whereas only 23% of the 100th percentile stocks exhibit low IVOL. Consequently, each day, on average, 18.75 stocks are added to the high IVOL portfolios and 15.09 stocks are added to the low IVOL portfolios.

4.5 Holding Periods

To investigate sub-question two, the portfolios mentioned in sections 4.3 and 4.4 are analyzed over the short-run and longer-run. Each portfolio is held for five trading days, ten trading days, 15 trading days, 20 trading days, 40 trading days, 60 trading days, 80 trading days, 100 trading days, and 120 trading days. Thus, initially portfolio performance is evaluated weekly up until approximately one trading month, after which the portfolios are analyzed on an approximately monthly basis up until approximately six trading months.

This enables me to both determine the time it takes to correct potential mispricing related to large percentage user changes and investigate possible differences in short-term and longer-term price impacts.

4.6 Return calculation

Holding return data, which are inclusive of dividends, are retrieved from the CRSP database using the daily extract with time window tool. It may be the case that Robinhood investors are keen on collectively making large purchases of stocks with subsequent dividend payments, which tend to depress stock prices following payout. Consequently, dividends are included in the portfolio return analysis to offset the negative price effect associated with stock prices following dividend payments since excluding dividends from the return calculation could otherwise negatively bias the return results of the portfolios.

Factor data to estimate the risk-adjusted returns of the portfolios outlined in sub-section 4.3-4.4 are retrieved from the CRSP database.

To evaluate returns following large user changes over the periods discussed in section 4.5, both annualized equally-weighted and value-weighted cumulative raw returns and risk-adjusted returns are estimated. In general, the daily returns of each portfolio can be portrayed as the following:

$$R_{pt} = \sum_{i=1}^{N} w_{it} R_{it}$$

with R_{pt} being defined as the portfolio return at time t, w_{it} being defined as a particular weight attached to stock i's return, R_{it}, at time t.

For the equally-weighted stock portfolios, the weight of stock i at time t, w_{it} , is defined as the following:

$$w_{it} = \frac{1}{N}$$

with N being the total number of stocks held in the portfolio at time t.

For the value-weighted stock portfolios, the weight of stock i at time t, w_{it} , is defined as the following:

$$w_{it} = \frac{V_i^0}{\sum_{i=1}^{N} V_i^0}$$

with V_i^0 being the closing price of a share of stock i on the day on which it is identified as belonging to the top percentile of daily percentage user changes.

The annualized cumulative raw portfolio returns are calculated as the following:

$$Annualized\ Cumulative\ Return = \left(\prod_{t=1}^{T}(1 + R_{pt})\right)^{1/\frac{T}{250}} - 1$$

with R_{pt} being the equally-weighted or value-weighted portfolio return at time t.

The risk-adjusted return of each portfolio is the intercept of a Carhart (1997) four-factor type model used in Barber et al. (2008), which includes the market, size, value, and the momentum factor. Thus, the alphas, defined as the risk-adjusted returns measured at daily frequency, for each portfolio are the intercepts of the following model:

$$\left(R_{pt} - R_{ft}\right) = \alpha + \beta\left(R_{mt} - R_{ft}\right) + \text{s}SMB_t + vVMG_t + \omega WML_t + \varepsilon_t$$

with R_{pt} being the equally-weighted or value-weighted portfolio return, R_{ft} being the risk-free rate proxied by the one-month treasury bill, SMB_t being size factor, VMG_t being the value factor, and WML_t being the momentum factor; all at time t.

The market risk factor ($R_{mt} - R_{ft}$) intends to capture the market risk associated with the portfolio. The size factor (*SMB*) intends to capture the size anomaly, in which small market capitalization stocks tend to outperform large market capitalization stocks (Fama & French, 1993). The value factor (*VMG)* hopes to capture the risk-factor associated with stocks with high book-to-market ratios outperforming the market (Fama & French, 1993). Lastly, the momentum factor (*WML*) intends to capture return reversals as discussed in Jegadeesh and Titman (1993).

The risk-adjusted returns are then annualized by multiplying them by 250, which approximates one trading year.

5. Portfolio Returns

In this section I discuss both the raw and risk-adjusted portfolio returns of the percentile sorts in sub-section 5.1 and the limits-to-arbitrage sorts in sub-section 5.2, over the holding periods outlined in sub-section 4.5, thereby answering the sub-questions developed in section 3.

5.1 Percentile sorts

First, sub-question one is assessed, which asks whether large changes in stock holdings among Robinhood investors are associated with subsequent returns. By discussing sub-question one, sub-question two, which asks about the price impact of these large user changes over time, is also answered for the percentile sorts.

Annualized Cumulative Returns

Panel A of Table 5.1 shows the equally-weighted and value-weighted annualized cumulative returns of the 100th percentile and 1st percentile portfolios of daily percentage user changes, and the long-short portfolios for holding periods between five to 120 trading days. In general, neither the returns of the 100th percentile portfolios nor the 1st percentile portfolios, for any holding period, significantly differ from zero for both the equally-weighted and value-weighted portfolios. Still, for a holding period of five days, the equally-weighted portfolio has an annualized cumulative return of nearly -21%, compared to the 1st percentile portfolio with an annualized return of only -3%, though neither returns are significant at conventional levels.

However, when examining the long-short portfolios in which the 100th percentile portfolios take a long position and the 1st percentile portfolios take a short position, the returns in the very short-run (five trading days), the medium run (40-60 trading days), and the longer-run (100-120 trading days) are significantly different from zero for the equally-weighted portfolios. In the five trading days following the event day, the top percentile portfolio significantly underperforms the bottom percentile portfolio by -18.03 percentage points (PP) on an annual basis at the five percent significance level. Over the medium-run, however, the top percentile portfolios significantly outperform the bottom percentile portfolios at the 10% level by approximately 7PP, annually. Lastly, for a holding period of approximately five to six trading months, the top percentile portfolios again significantly outperform the bottom percentile portfolios by close to 7PP annually, at the five percent level.

The returns of the top percentile sorts of the value-weighted portfolios, in contrast, do not significantly outperform the bottom percentile value-weighted portfolios for any of the tested holding periods.

Annualized risk-adjusted returns

When adjusting for risk using the four-factor Carhart (1997) model more significant results are found. Panel B of Table 5.1 shows the annualized risk-adjusted returns for the equally-weighted and value-weighted portfolios. For the equally-weighted 100th percentile portfolios with a holding period of five trading days following a large increase in users, stocks experience an annualized negative risk-adjusted return measured at daily frequency of -20.08%, which is significant at the one percent level. Additionally, over approximately six trading months, stocks exhibit a positive risk-adjusted return of 5.92% annually, which is significant at the ten percent level. The bottom percentile portfolios of the equally-weighted portfolios, for any holding period, do not exhibit significant performance. The results of the long-short portfolios confirm that for a holding period of five trading days, the top percentile portfolio significantly underperforms the bottom percentile portfolio at an annual level by -17.24PP at the five percent significance level. For a holding period of two, three, and six trading months, the 100th percentile portfolio significantly outperforms the 1st percentile portfolio at the ten percent significance level by 5.84PP, 5.23PP, and 3.80PP on an annual level, respectively.

The annualized risk-adjusted returns of the value-weighted portfolios do not exhibit such patterns for any holding period. While the bottom percentile portfolio has an annualized risk-adjusted return of -7.60% for a holding period of 15 trading days, which is weakly significant at the ten percent level, its performance does not differ significantly from the top percentile portfolio in the long-short portfolio.

Table 5.1 Annualized cumulative and risk-adjusted returns of portfolios of stocks in the 100th and 1st percentile groups of daily percentage user changes between May 4th, 2018 and July 13th, 2020

	Equally-weighted portfolios			**Value-weighted portfolios**			
Holding period (days)	**100th percentile**	**1st percentile**	**Highest – Lowest**	**100th percentile**	**1st percentile**	**Highest - Lowest**	**Days observed**
			Panel A: Annualized cumulative returns				
120	0.1479	0.0746	0.0732**	0.1092	0.0909	0.0202	670
	(1.33)	(0.87)	(2.35)	(0.89)	(0.81)	(0.68)	
100	0.1166	0.0506	0.0676**	0.0828	0.0579	0.0269	650
	(1.07)	(0.62)	(2.10)	(0.72)	(0.58)	(0.83)	
80	0.0550	0.0052	0.0544	0.0293	0.0201	0.0132	630
	(0.60)	(0.18)	(1.60)	(0.38)	(0.32)	(0.40)	
60	0.0678	0.0006	0.0723*	0.0407	0.0187	0.0259	610
	(0.69)	(0.12)	(1.93)	(0.45)	(0.31)	(0.69)	
40	0.0504	-0.0143	0.0707*	0.0165	-0.0105	0.0314	590
	(0.55)	(-0.04)	(1.73)	(0.29)	(0.10)	(0.74)	
20	0.0335	-0.0005	0.0389	-0.0107	-0.0175	0.0138	570
	(0.41)	(0.10)	(0.75)	(0.13)	(0.02)	(0.28)	
15	-0.0266	-0.0279	0.0061	-0.0249	-0.0526	0.0367	565
	(-0.08)	(-0.22)	(0.17)	(0.05)	(-0.26)	(0.57)	
10	-0.0753	-0.0120	-0.0591	-0.0269	-0.0412	0.0231	560
	(-0.45)	(-0.04)	(-0.83)	(0.05)	(-0.18)	(0.35)	
5	-0.2098	-0.0312	-0.1803**	-0.0500	-0.0292	-0.0112	549
	(-1.53)	(-0.26)	(-2.25)	(-0.05)	(-0.11)	(0.03)	
			Panel B: Annualized risk-adjusted returns				
120	0.0592*	0.0212	0.0380*	-0.0009	0.0229	-0.0238	670
	(1.69)	(0.84)	(1.73)	(-0.03)	(0.80)	(-0.94)	
100	0.0457	0.0104	0.0353	-0.0135	0.0084	-0.0219	650
	(1.26)	(0.40)	(1.50)	(-0.39)	(0.28)	(-0.77)	
80	0.0195	-0.0113	0.0308	-0.0249	0.0033	-0.0282	630
	(0.52)	(-0.42)	(1.25)	(-0.66)	(0.10)	(-0.93)	
60	0.0370	-0.0153	0.0523*	-0.0009	0.0059	-0.0068	610
	(0.94)	(-0.61)	(1.89)	(-0.22)	(0.17)	(-0.44)	
40	0.0328	-0.0256	0.0584*	-0.0212	-0.0063	-0.0149	590
	(0.77)	(-0.97)	(1.83)	(-0.47)	(-0.17)	(-0.38)	
20	0.0122	-0.0240	0.0362	-0.0562	-0.0440	-0.0122	570
	(0.22)	(-0.78)	(0.74)	(-0.95)	(-1.19)	(-0.21)	
15	-0.0270	-0.0438	0.0168	-0.0513	-0.0760*	0.0247	565
	(-0.45)	(-1.36)	(0.32)	(-0.77)	(-1.83)	(0.38)	
10	-0.0670	-0.0254	-0.0416	-0.0422	-0.0559	0.0137	560
	(-0.97)	(-0.70)	(-0.68)	(-0.57)	(-1.22)	(0.17)	
5	-0.2008***	-0.0284	-0.1724**	-0.0374	-0.0546	0.0172	549
	(-2.34)	(-0.70)	(-2.09)	(-0.37)	(-0.91)	(0.16)	

Note: T-statistics shown in parentheses and are calculated prior to annualizing returns; t-statistics in Panel B are calculated using heteroskedasticity-robust standard errors; Panel A shows the annualized cumulative return of each portfolio; Panel B shows the risk-adjusted return of a Carhart (1997) four-factor model of each portfolio; return data stems from May 5th, 2018 until December 31st, 2020 latest; 100th percentile refers to stocks belonging to the 100th percentile group of daily percentage user changes; 1st percentile refers to stocks belonging to the 1st percentile group of daily percentage user changes; Highest-Lowest refers to a long-short portfolio which is the difference in returns between the 100th percentile portfolio and the 1st percentile portfolio; the returns of Highest-Lowest in Panel A are annualized after taking the cumulative product of the difference; Holding period indicates the number of trading days each stock in the portfolios is held; Days observed refers to the total number of trading days the portfolios are held; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2 Limits-to-arbitrage sorts

Second, sub-question three, which asks whether large user changes are associated with greater mispricing for stocks with higher limits-to-arbitrage, is assessed. By answering sub-question three, sub-question two, which inquires about the price impact over time following large percentage user changes, is answered simultaneously.

5.2.1 Market capitalization

Annualized cumulative returns

Panel A of Table 5.2 displays the equally-weighted and value-weighted portfolio returns of the low market capitalization and high market capitalization sorts for holding periods between five and 120 trading days. For the equally-weighted portfolios, at a holding period of five trading days, the low market capitalization portfolio exhibits annualized stock returns of -28.90%, which is significant at the one percent significance level. For longer holding periods, the returns are insignificantly different from zero. High market capitalization stocks do not experience significantly positive or negative returns for any of the tested holding periods. When examining the long-short portfolios, for a holding period of five trading days, the low market capitalization portfolio significantly underperforms the high market capitalization portfolio at the five percent significance level by -36.07PP annually. For any extended holding period no significant under- or outperformance by the low market capitalization portfolios is found.

For the value-weighted portfolios, with a holding period of five trading days, the return of the low market capitalization portfolio is significantly different from zero at the ten percent level and quantifies annually at -27.37%. For longer holding periods, no significant returns are found. The high market capitalization portfolios do not perform well for any holding period. Lastly, the long-short portfolios indicate that low market capitalization stocks do not outperform or underperform high market capitalization stocks for any holding period.

Annualized risk-adjusted returns

Panel B of Table 5.2 shows the equally-weighted and value-weighted portfolio returns of the low market capitalization and high market capitalization sorts for holding periods between five and 120 trading days. For the equally-weighted portfolios, in the short-run, the low market capitalization sorts exhibit negative risk-adjusted returns for a ten- and five-trading-day holding period of -13.78% and -35.04% on an annual level, respectively. The results are significant at the five and one percent level, respectively. High market capitalization stocks do not exhibit significantly positive or negative risk-adjusted returns during any holding period at any conventional significance level. The long-short portfolios confirm that low market capitalization stocks significantly underperform high market capitalization stocks at the one percent significance level during the first five subsequent trading days by -43.75PP on an annual basis. Outperformance or underperformance for longer holding periods is not found to be conventionally significant.

For the value-weighted portfolios, the low market capitalization portfolios with stock holding periods of ten and five trading days have qualitatively similar results to those of the equally-weighted portfolios, with annualized returns of -19.31% and -35.03%, respectively, which are significant at the five and one percent level, respectively. High market capitalization stocks do not exhibit significant risk-adjusted returns. Lastly, the value-weighted long-short portfolios do not experience significant risk-adjusted returns for any of the tested holding periods.

Table 5.2 Annualized cumulative and risk-adjusted returns of portfolios of stocks with high and low market capitalization of the 100th percentile group of daily percentage user changes between May 4th, 2018 and July 13th, 2020

	Equally-weighted portfolios			**Value-weighted portfolios**			
Holding period (days)	**Low market capitalization**	**High market capitalization**	**Low - High**	**Low market capitalization**	**High market capitalization**	**Low - High**	**Days observed**
				Panel A: Annualized cumulative returns			
120	0.1437	0.1741	-0.0541	0.1106	0.0946	0.0031	670
	(1.45)	(1.22)	(-0.56)	(0.97)	(0.81)	(0.14)	
100	0.1101	0.1382	-0.0566	0.0880	0.0757	-0.0018	650
	(1.14)	(0.99)	(-0.54)	(0.81)	(0.68)	(0.07)	
80	0.0471	0.0984	-0.0793	0.0129	0.0368	-0.0386	630
	(0.57)	(0.73)	(-0.69)	(0.27)	(0.43)	(-0.43)	
60	0.0557	0.1227	-0.1014	0.0477	0.0397	-0.0104	610
	(0.66)	(0.85)	(-0.81)	(0.52)	(0.44)	(-0.03)	
40	0.0335	0.0697	-0.0813	0.0360	0.0110	0.0047	590
	(0.45)	(0.58)	(-0.53)	(0.43)	(0.26)	(0.16)	
20	0.0153	0.0716	-0.1115	0.0554	-0.0236	0.0503	570
	(0.27)	(0.57)	(-0.60)	(0.52)	(0.06)	(0.51)	
15	-0.0482	-0.0145	-0.0982	-0.0366	-0.0422	-0.0263	565
	(-0.39)	(0.17)	(-0.47)	(-0.12)	(-0.04)	(-0.06)	
10	-0.1083	0.0345	-0.1990	-0.1435	-0.0180	-0.1610	560
	(-0.99)	(0.40)	(-1.13)	(-0.92)	(0.11)	(-1.08)	
5	-0.2880***	0.0158	-0.3607**	-0.2737*	-0.700	-0.2715	549
	(-2.81)	(0.33)	(-1.99)	(-1.71)	(-0.09)	(-1.29)	
				Panel B: Annualized risk-adjusted returns			
120	0.0617	0.0640	-0.0023	0.0110	-0.0224	0.0334	670
	(1.54)	(1.30)	(-0.04)	(0.26)	(-0.60)	(0.66)	
100	0.0433	0.0461	-0.0028	0.0074	-0.0332	0.0406	650
	(1.07)	(0.83)	(-0.05)	(0.17)	(-0.81)	(0.77)	
80	0.0077	0.0568	-0.0491	-0.0346	-0.0341	-0.0005	630
	(0.19)	(0.89)	(-0.73)	(-0.79)	(-0.78)	(-0.01)	
60	0.0166	0.1026	-0.0860	0.0020	-0.0279	0.0299	610
	(0.39)	(1.40)	(-1.12)	(0.04)	(-0.57)	(0.48)	
40	0.0035	0.0680	-0.0645	0.0018	-0.0447	0.0465	590
	(0.08)	(0.83)	(-0.74)	(0.03)	(-0.84)	(0.67)	
20	-0.0242	0.0737	-0.0979	0.0056	-0.0824	0.0880	570
	(-0.41)	(0.69)	(-0.86)	(0.06)	(-1.11)	(0.04)	
15	-0.0775	0.0110	-0.0885	-0.0841	-0.0879	0.0038	565
	(-1.34)	(0.10)	(-0.75)	(-1.18)	(-1.03)	(0.04)	
10	-0.1378**	0.0708	-0.2086	-0.1931**	-0.0534	-0.1397	560
	(-2.09)	(0.58)	(-1.63)	(-2.33)	(-0.58)	(-1.15)	
5	-0.3504***	0.0871	-0.4375***	-0.3503***	-0.0756	0.2747	549
	(-4.19)	(0.59)	(-2.62)	(-2.79)	(-0.51)	(-1.40)	

Note: T-statistics are shown in parentheses and are calculated prior to annualizing returns; t-statistics in Panel B are calculated using heteroskedasticity-robust standard errors; Panel A shows the annualized cumulative return of each portfolio; Panel B shows the risk-adjusted return of a Carhart (1997) four-factor model of each portfolio; return data stems from May 5th, 2018 until December 31st, 2020 latest; Low market capitalization refers to stocks in the 100th percentile group of daily percentage user changes belonging to the bottom 20% of the previous month's total market capitalization using NYSE breakpoints; High market capitalization refers to stocks in the 100th percentile group of daily percentage user changes belonging to the top 40% of the previous month's total market capitalization using NYSE breakpoints; Low-High refers to a long-short portfolio which is the difference in returns between the Low market capitalization portfolio and the High market capitalization portfolio; the returns of Low-High in Panel A are annualized after taking the cumulative product of the difference; Holding period indicates the number of trading days each stock in the portfolios is held; Days observed refers to the total number of trading days the portfolios are held; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2.2 Effective bid-ask spread (BIDASK)

Annualized cumulative returns

Panel A of Table 5.3 displays the annualized cumulative returns for the BIDASK sorts for holding periods between five and 120 trading days. For the equally-weighted portfolios, with a holding period of approximately six trading months, the high BIDASK portfolio experiences significantly positive annualized returns of 21.70% at the ten percent significance level. Furthermore, for a holding period of five days, the high BIDASK portfolio experiences significantly negative returns at the one percent level of -48.05% annually. The high BIDASK portfolios do not exhibit significant returns for any other holding period. The low BIDASK portfolios do not exhibit any significant returns for any holding period. When comparing the high BIDASK to the low BIDASK portfolios, the high BIDASK portfolio significantly outperforms the low BIDASK portfolio at the ten percent level for a holding period of 100 trading days by 11.96PP annually. However, for a holding period of five trading days, the high BIDASK portfolio significantly underperforms the low BIDASK portfolio by -44.70PP annually at the one percent significance level.

For the value-weighted portfolios, neither the high BIDASK nor the low BIDASK portfolios individually experience significant returns at any of the holding periods at conventional significance levels. When comparing both portfolios, however, the high BIDASK portfolio significantly underperforms the low BIDASK portfolio with a ten-day holding period by -26.54PP annually at the ten percent significance level.

Annualized risk-adjusted returns

Panel B of Table 5.3 displays the annualized risk-adjusted returns for the BIDASK sorts with holding periods between five and 120 trading days. When looking at the equally-weighted portfolios, the high BIDASK portfolios with a holding period of ten and five days experience significantly negative annualized risk-adjusted returns of -24.83% and -64.62%, respectively, at the five and one percent significance level, respectively. For longer holding periods, the high BIDASK portfolios do not exhibit significant risk-adjusted returns at conventional significance levels. The low BIDASK portfolios do not experience any significant risk-adjusted returns for any of the tested holding periods. When comparing the performance of the high- and low BIDASK portfolios, the low BIDASK portfolio significantly underperforms the high BIDASK portfolio at the ten percent significance level by -23.43PP annually for a holding period of ten trading days. It also significantly underperforms the high BIDASK portfolio at the one percent significance level by -60.51PP annually for a holding period of five trading days.

When looking at the value-weighted portfolios, only the high BIDASK portfolio with a stock holding period of ten trading days experiences significant risk-adjusted returns at the five percent significance level of -25.70% annually. It does not experience any other significant risk-adjusted returns for any of the other tested holding periods. The low BIDASK portfolios do not exhibit any significant risk-adjusted returns for the tested holding periods. Lastly, when comparing the risk-adjusted performance of the low BIDASK and high BIDASK portfolios, no significant outperformance or underperformance by the low BIDASK portfolios is found for any holding period.

Table 5.3 Annualized cumulative and risk-adjusted returns of portfolios of stocks belonging to the 5th or 1st quintile of the effective bid-ask spread and the 100th percentile of daily percentage user changes between May 4th, 2018 and July 13th, 2020

	Equally-weighted portfolios			Value-weighted portfolios			
Holding period (days)	**High BIDASK**	**Low BIDASK**	**High – Low**	**High BIDASK**	**Low BIDASK**	**High – Low**	**Days observed**
			Panel A: Annualized cumulative returns				
120	0.2170*	0.1197	0.0935	0.0573	0.1014	-0.0458	670
	(1.68)	(1.39)	(1.40)	(0.57)	(0.86)	(-0.45)	
100	0.1923	0.0719	0.1196*	0.0495	0.0853	-0.0391	650
	(1.49)	(0.89)	(1.70)	(0.52)	(0.74)	(-0.35)	
80	0.0896	0.0413	0.0526	-0.0289	0.0251	-0.0606	630
	(0.81)	(0.55)	(0.80)	(0.02)	(0.36)	(-0.58)	
60	0.0858	0.0666	0.0233	0.0162	0.0465	-0.0378	610
	(0.78)	(0.81)	(0.40)	(0.29)	(0.49)	(-0.29)	
40	0.0678	0.0620	0.0083	-0.0157	0.0298	-0.0559	590
	(0.65)	(0.75)	(0.20)	(0.08)	(0.37)	(-0.44)	
20	0.0456	0.0399	0.0028	0.0056	0.0227	-0.0403	570
	(0.46)	(0.49)	(0.16)	(0.24)	(0.33)	(-0.05)	
15	-0.1051	0.0056	-0.1122	-0.1417	0.0180	-0.1807	565
	(-0.61)	(0.17)	(-0.99)	(-0.76)	(0.30)	(-1.26)	
10	-0.2092	-0.0206	-0.1946	-0.2328	0.0079	-0.2654*	560
	(-1.27)	(-0.06)	(-1.56)	(-1.24)	(0.26)	(-1.71)	
5	-0.4805***	-0.0719	-0.4470***	-0.2328	0.0230	-0.2873	549
	(-3.44)	(-0.43)	(-3.45)	(-0.95)	(0.35)	(-1.30)	
			Panel B: Annualized risk-adjusted returns				
120	0.1114	0.0487	0.0653	-0.0443	-0.0097	-0.0346	670
	(1.63)	(1.59)	(1.02)	(-0.61)	(-0.28)	(-0.46)	
100	0.1069	0.0145	0.0924	-0.0351	-0.0165	-0.0186	650
	(1.51)	(0.52)	(1.47)	(-0.46)	(-0.44)	(-0.23)	
80	0.0434	0.0082	0.0352	-0.0848	-0.0427	-0.0421	630
	(0.60)	(0.28)	(0.54)	(-1.05)	(-1.05)	(-0.50)	
60	0.0406	0.0346	0.0060	-0.0369	-0.0211	-0.0158	610
	(0.54)	(1.11)	(0.09)	(-0.44)	(-0.49)	(-0.18)	
40	0.0320	0.0386	-0.0066	-0.0541	-0.0333	-0.0208	590
	(0.39)	(1.09)	(-0.09)	(-0.60)	(-0.66)	(0.22)	
20	0.0028	0.0185	-0.0157	-0.0176	-0.0357	0.0181	570
	(0.02)	(0.35)	(-0.13)	(-0.11)	(-0.45)	(0.11)	
15	-0.1437	0.0033	-0.1467	-0.1716	-0.0239	-0.1477	565
	(-1.36)	(0.06)	(-1.43)	(-1.56)	(-0.26)	(-1.15)	
10	-0.2483**	-0.0140	-0.2343*	-0.2570**	-0.0119	-0.2451	560
	(-1.97)	(-0.24)	(-1.87)	(-2.02)	(-0.11)	(-1.57)	
5	-0.6462***	-0.0411	-0.6051***	-0.2363	0.0576	-0.2939	549
	(-4.32)	(-0.50)	(-3.75)	(-1.36)	(0.42)	(-1.37)	

Note: T-statistics are shown in parentheses and are calculated prior to annualizing returns; t-statistics in Panel B are calculated using heteroskedasticity-robust standard errors; Panel A shows the annualized cumulative return of each portfolio; Panel B shows the risk-adjusted return of a Carhart (1997) four-factor model of each portfolio; return data stems from May 5th, 2018 to December 31st, 2020 latest; High BIDASK refers to stocks in both the top quintile of the 20-trading-day moving average of daily effective bid-ask spreads and in the 100th percentile group of daily percentage user changes; Low BIDASK refers to stocks in both the bottom quintile of the 20-trading-day moving average of daily effective bid-ask spreads and in the 100th percentile group of daily percentage user changes; High-Low refers to a long-short portfolio which is the difference in returns between the High BIDASK portfolio and the Low BIDASK portfolio; the returns of High-Low in Panel A are annualized after taking the cumulative product of the difference; Holding period indicates the number of trading days each stock in the portfolios is held; Days observed refers to the total number of trading days the portfolios are held; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2.3 Institutional Ownership (IO)

Annualized cumulative returns

Panel A of Table 5.4 shows the annualized cumulative portfolio returns of the IO sorts for holding periods between five and 120 trading days. When examining the equally-weighted portfolios with a holding period of five trading days, stocks with low IO experience significantly negative returns at the one percent significance level of -42.76% annually. Over longer holding periods, however, the low IO portfolios do not experience significant returns. The high IO portfolios do not experience significant returns at any holding period. When comparing the low IO to the high IO portfolios, the low IO portfolio underperforms the high IO portfolio at a holding period of five days by -47.89PP annually, which is significant at the one percent significance level. For any other holding period, no under- or overperformance is found.

For the value-weighted portfolios, neither the low IO portfolios, nor the high IO portfolios exhibit any significant returns for any holding period. Furthermore, the low IO portfolios do not outperform the high IO portfolios for any holding period that is examined either.

Risk-adjusted returns

Panel B of Table 5.4 displays the annualized risk-adjusted returns of the IO sorts for holding periods of five to 120 trading days. For the equally-weighted portfolios, the low IO portfolio experiences significantly negative risk-adjusted returns during the first five trading days at the one percent significance level with an annualized risk-adjusted return of -53.55%. For holding periods longer than five trading days, the low IO portfolios do not exhibit significant risk-adjusted returns. Furthermore, the high IO portfolios do not experience significant risk-adjusted returns for any of the tested holding periods. When comparing the high IO portfolios to the low IO portfolios, the low IO portfolios significantly underperform the high IO portfolios with holding periods of ten and five trading days. For a holding period of ten trading days, the low IO portfolio significantly underperforms the high IO portfolio at the ten percent significance level by -25.02PP annually. At a five-trading-day holding period, the low IO portfolio significantly underperforms the high IO portfolio at the one percent significance level by -64.99PP annually. For the value-weighted portfolios, no significant risk-adjusted returns at conventional levels are found for neither the low IO portfolios nor the high IO portfolios for any holding period. When comparing both portfolios through a long-short strategy no under- or outperformance is found for any of the tested holding periods.

Table 5.4 Annualized cumulative and risk-adjusted returns of portfolios of stocks belonging to the 1st or 5th quintile of quarterly institutional ownership and the 100th percentile of daily percentage user changes between May 4th, 2018 and July 13th, 2020

	Equally-weighted portfolios			Value-weighted portfolios			
Holding period (days)	**Low IO**	**High IO**	**Low – High**	**Low IO**	**High IO**	**Low – High**	**Days observed**
			Panel A: Annualized cumulative returns				
120	0.1511	0.1130	-0.0012	0.0410	0.1061	-0.0869	670
	(1.55)	(0.94)	(-0.09)	(0.48)	(0.82)	(-1.02)	
100	0.1393	0.0678	0.0201	0.0281	0.0843	-0.0872	650
	(1.41)	(0.64)	(0.35)	(0.38)	(0.69)	(-0.94)	
80	0.0860	0.0483	0.0182	0.0171	0.0309	-0.0289	630
	(0.88)	(0.50)	(0.31)	(0.30)	(0.40)	(-0.18)	
60	0.0937	0.0511	-0.0073	0.0218	0.0053	-0.0309	610
	(0.99)	(0.51)	(0.05)	(0.33)	(0.26)	(-0.16)	
40	0.0554	0.0768	-0.0356	0.0232	0.0172	-0.0025	590
	(0.64)	(0.65)	(-0.18)	(0.33)	(0.32)	(0.13)	
20	0.0113	-0.0261	-0.0505	0.0126	-0.0748	0.0326	570
	(0.23)	(0.05)	(-0.18)	(0.27)	(-0.16)	(0.39)	
15	-0.0833	-0.0390	-0.0914	-0.0842	-0.1186	-0.0023	565
	(-0.56)	(-0.01)	(-1.13)	(-0.28)	(-0.39)	(0.16)	
10	-0.1788	-0.0118	-0.2188	-0.1015	-0.1088	-0.0387	560
	(-1.23)	(0.16)	(-1.13)	(-0.31)	(-0.32)	(-0.03)	
5	-0.4276***	0.0135	-0.4789***	-0.2752	-0.0708	-0.2644	549
	(-3.09)	(0.30)	(-2.58)	(-0.86)	(-0.09)	(-0.86)	
			Panel B: Annualized risk-adjusted returns				
120	0.0610	0.0148	0.0462	-0.0549	0.0000	-0.0549	670
	(1.08)	(0.40)	(0.61)	(-0.88)	(0.05)	(-0.92)	
100	0.0615	0.0026	0.0589	-0.0591	0.0109	-0.070	650
	(1.05)	(0.07)	(0.79)	(-0.88)	(0.21)	(-1.01)	
80	0.0326	0.0126	0.0200	-0.0381	-0.0071	-0.0310	630
	(0.53)	(0.29)	(0.54)	(-0.55)	(-0.12)	(-0.28)	
60	0.0472	0.0600	-0.0128	-0.0306	0.0201	-0.0507	610
	(0.69)	(1.37)	(-0.20)	(-0.38)	(0.32)	(-0.50)	
40	0.0223	0.0599	-0.0376	-0.0219	-0.0037	-0.0182	590
	(0.29)	(1.12)	(-0.27)	(-0.23)	(-0.05)	(-0.02)	
20	-0.0204	0.0034	-0.0238	-0.0266	-0.0686	0.042	570
	(-0.21)	(0.05)	(-0.53)	(-0.22)	(-0.83)	(0.28)	
15	-0.1032	0.0061	-0.1093	-0.0918	-0.1123	0.0205	565
	(-0.96)	(0.07)	(-0.84)	(-0.70)	(-1.28)	(0.12)	
10	-0.1964	0.0538	-0.2502*	-0.0872	-0.0980	0.0108	560
	(-1.57)	(0.54)	(-1.68)	(-0.58)	(-1.09)	(0.04)	
5	-0.5355***	0.1144	-0.6499***	-0.2259	-0.0049	-0.2210	549
	(-3.46)	(0.87)	(-3.23)	(-0.94)	(-0.04)	(-0.83)	

Note: T-statistics are shown in parentheses and are calculated prior to annualizing returns; t-statistics in Panel B are calculated using heteroskedasticity-robust standard errors; Panel A shows the annualized cumulative return of each portfolio; Panel B shows the risk-adjusted return of a Carhart (1997) four-factor model of each portfolio; return data stems from May 5th, 2018 to December 31st, 2020 latest; Low IO refers to stocks in the bottom quintile of the previous quarter's institutional ownership and the 100th percentile group of daily percentage user changes; High IO refers to stocks in both the top quintile of the previous quarter's institutional ownership and the 100th percentile group of daily percentage user changes; Low-High refers to a long-short portfolio which is the difference in returns between the Low IO portfolio and the High IO portfolio; the returns of Low-High in Panel A are annualized after taking the cumulative product of the difference; Holding period indicates the number of trading days each stock in the portfolios is held; Days observed refers to the total number of trading days the portfolios are held; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2.4 Idiosyncratic volatility (IVOL)

Annualized cumulative returns

Panel A of Table 5.5 displays the annualized cumulative returns of the IVOL sorts for holding periods between five and 120 trading days. For the equally-weighted portfolios, the high IVOL stocks show significantly negative returns at the one percent level in the first five trading days with an annualized return of -50.83%. Additionally, in the longer-run, for a holding period of approximately six trading months, the high IVOL portfolio shows significantly positive returns at the ten percent significance level of 26.50% annually. For any other holding periods, the returns are not significant. The low IVOL portfolios do not experience significant returns for any of the tested holding periods. When comparing the high IVOL portfolios to the low IVOL portfolios, the long-short portfolio with a holding period of ten trading days shows significantly negative returns at the ten percent level of -31.84PP annually. Furthermore, for a holding period of five trading days, the high IVOL portfolio underperforms the low IVOL portfolio by -52.56PP annually, which is significant at the one percent significance level.

The value-weighted portfolios show different results. The high IVOL portfolios do not experience any significant returns for any holding period. The low IVOL portfolios, in contrast, show significantly positive returns for holding periods of 15, 20, 40 and 80 trading days. For a holding period of 15 trading days, the portfolio experiences significantly positive returns at the ten percent level of 15.71% annually. For both 20 and 40 trading days, annualized returns are approximately 17% and are significant at the five percent significance level. Lastly, for a holding period of 80 trading days, the annualized return is 12.62% and is significant at the ten percent level. When comparing the portfolios using a long-short strategy, however, the returns between the high IVOL and low IVOL portfolios do not differ at any conventional significance level.

Annualized risk-adjusted returns

Panel B of Table 5.5 shows the annualized risk-adjusted returns of the IVOL sorts for holding periods between five and 120 trading days. When looking at the equally-weighted portfolios, the high IVOL portfolios with stock holding periods of five and ten trading days experience significantly negative risk-adjusted returns. For a holding period of ten trading days, the high IVOL portfolio sees significantly negative risk-adjusted returns at the ten percent significance level of -29.21% annually. For a holding period of five days it sees significantly negative risk-adjusted returns of -62.93% annually at the one percent significance level. For more extended holding periods, the high IVOL portfolios do not experience risk-adjusted returns that are significantly different from zero. The low IVOL portfolios, in contrast, exhibit significantly positive risk-adjusted returns at the ten and five percent significance level of 4.95% and 3.63% annually for holding periods of 120 and 40 trading days, respectively. When comparing the high IVOL portfolios to the low IVOL portfolios, the high IVOL portfolios underperform the low IVOL portfolios for holding periods of ten and five trading days. At 10 trading days, the long-short portfolio experiences significantly negative risk-adjusted returns at the five percent level of -33.55% annually, while for a holding period of five trading days it experiences significantly negative risk-adjusted returns of -68.42% annually.

For the value-weighted portfolios, the risk-adjusted returns are not significant for any of the holding periods tested. The risk-adjusted returns of the low IVOL portfolios are significantly positive for a holding period of 40 and 20 trading days. For a holding period of 40 trading days, the low IVOL portfolio experiences significantly positive risk-adjusted returns at the five percent level of 9.99% annually, while for a holding period of 20 days it experiences significantly positive risk-adjusted returns at the ten percent level of 9.75% annually. The risk-adjusted returns for the long-short portfolios, however, do not see any significant performance.

Table 5.5 Annualized cumulative and risk-adjusted returns of stocks belonging to the 5th or 1st quintile of idiosyncratic volatility and the 100th percentile of daily percentage user changes between May 4th, 2018 and July 13th, 2020

	Equally-weighted portfolios			Value-weighted portfolios			
Holding period (days)	**High IVOL**	**Low IVOL**	**High – Low**	**High IVOL**	**Low IVOL**	**High – Low**	**Days observed**
			Panel A: Annualized cumulative returns				
120	0.2650*	0.0942	0.1670	0.1731	0.1228	0.0608	670
	(1.73)	(1.55)	(1.38)	(1.04)	(1.62)	(0.57)	
100	0.2262	0.0700	0.1570	0.1593	0.1209	0.0503	650
	(1.48)	(1.19)	(1.35)	(0.95)	(1.57)	(0.51)	
80	0.0813	0.0449	0.0444	0.0160	0.1262*	-0.0843	630
	(0.68)	(0.79)	(0.50)	(0.37)	(1.65)	(-0.20)	
60	0.0929	0.0517	0.0480	0.0732	0.1185	-0.0270	610
	(0.73)	(0.93)	(0.51)	(0.59)	(1.54)	(0.12)	
40	0.0427	0.0613	-0.0150	-0.0630	0.1654**	-0.1860	590
	(0.45)	(1.13)	(0.09)	(0.04)	(2.06)	(-0.68)	
20	0.0017	0.0591	-0.0485	0.0659	0.1779**	-0.0866	570
	(0.23)	(1.10)	(-0.08)	(0.55)	(2.03)	(-0.01)	
15	-0.1655	0.0591	-0.2044	-0.0105	0.1571*	-0.1369	565
	(-0.71)	(1.02)	(-1.14)	(0.29)	(1.71)	(-0.26)	
10	-0.2801	0.0625	-0.3184*	-0.0451	0.1598	-0.1643	560
	(-1.32)	(1.12)	(-1.81)	(0.21)	(1.64)	(-0.32)	
5	-0.5083***	0.0418	-0.5256***	-0.1692	0.1318	-0.2537	549
	(-2.65)	(0.73)	(-3.07)	(-0.06)	(1.26)	(-0.44)	
			Panel B: Annualized risk-adjusted returns				
120	0.1163	0.0495**	0.0668	0.0252	0.0549	-0.0297	670
	(1.44)	(1.98)	(0.86)	(0.27)	(1.47)	(-0.30)	
100	0.1070	0.0298	0.0772	0.0362	0.0554	-0.0192	650
	(1.25)	(1.36)	(0.94)	(0.34)	(1.38)	(-0.18)	
80	0.0233	0.0172	0.0061	-0.0260	0.0672	-0.0932	630
	(0.26)	(0.78)	(0.07)	(-0.22)	(1.61)	(-0.77)	
60	0.0479	0.0236	0.0243	0.0566	0.0496	0.0007	610
	(0.50)	(1.09)	(0.26)	(0.45)	(1.14)	(0.05)	
40	0.0198	0.0363*	-0.0165	-0.0627	0.0999**	-0.1626	590
	(0.19)	(1.66)	(-0.16)	(-0.43)	(2.14)	(-1.06)	
20	-0.0092	0.0308	-0.040	0.0913	0.0975*	-0.0062	570
	(-0.06)	(1.26)	(-0.27)	(0.42)	(1.74)	(-0.03)	
15	-0.1662	0.0324	-0.1986	0.0452	0.0890	-0.0438	565
	(-1.14)	(1.30)	(-1.38)	(0.23)	(1.48)	(-0.21)	
10	-0.2921*	0.0434	-0.3355**	0.0377	0.1075	-0.0698	560
	(-1.73)	(1.08)	(-2.00)	(0.17)	(1.62)	(-0.31)	
5	-0.6293***	0.0549	-0.6842***	-0.0327	0.1252	0.1579	549
	(-3.06)	(1.08)	(-3.22)	(-0.11)	(1.58)	(-0.53)	

Note: T-statistics are shown in parentheses and are calculated prior to annualizing returns; t-statistics in Panel B are calculated using heteroskedasticity-robust standard errors; Panel A shows the annualized cumulative return of each portfolio; Panel B shows the risk-adjusted return of a Carhart (1997) four-factor model of each portfolio; return data stems from May 5th, 2018 to December 31st, 2020 latest; High IVOL refers to stocks in both the top quintile of the previous 20-trading days' idiosyncratic volatility and in the 100th percentile group of daily percentage user changes; Low IVOL refers to stocks in both the bottom quintile of the previous 20-trading days' idiosyncratic volatility and in the 100th percentile group of daily percentage user changes; High-Low refers to a long-short portfolio which is the difference in returns between the High IVOL portfolio and the Low IVOL portfolio; the returns of High-Low in Panel A are annualized after taking the cumulative product of the difference; Holding period indicates the number of trading days each stock in the portfolios is held; Days observed refers to the total number of trading days the portfolios are held; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6. Discussion

The results outlined in section 5 provide several implications regarding potential asset mispricing following large increases in stock holdings among Robinhood traders. First, stocks experiencing large percentage increases in ownership by Robinhood traders experience significantly lower (negative) returns over a holding period of five trading days compared to stocks with small or even negative changes in ownership. Even when adjusting for risk-factors and momentum, this result continues to hold, thereby providing further evidence to the findings of Seasholes and Wu (2007), Barber et al. (2009) and more recently Barber et al. (2020) that attention-inducing events lead to subsequently negative returns. Furthermore, the fact that significantly negative (risk-adjusted) returns are only found in the first five trading days immediately following the large change in users agrees with the findings of Seasholes and Wu (2007) in which price reversals also happen relatively swiftly. Additionally, the economic magnitude of these negative risk-adjusted returns in the short-run suggests that short-sellers quite heavily trade against these event-trades to achieve such a level of negative returns. Interestingly, when looking at a coarser measure of daily user changes such as deciles, the 10th decile of daily percentage user changes has significantly higher (risk-adjusted) returns than the 1st decile of daily percentage user changes for a holding period of ten to 15 days. Furthermore, no underperformance for a five-trading-day holding period is found, implying that the negative return results are unique to stocks with the largest daily percentage user changes (see Table 1 of the Appendix).

Over the medium-term and longer-term, the same stocks of the 100th percentile portfolios seem to outperform stocks with small user changes by several percentage points annually, even after adjusting for risk-factors; though not to the same extent to which they underperformed those same stocks in the short-run. Despite this weak evidence of outperformance for the top percentile stocks, it remains questionable whether the same investors who rapidly invested in those stocks within one trading day maintain their position long enough to be able to profit off these potential long-run returns. Furthermore, the fact that 76% of the affected stocks are small market capitalization stocks (see Table 4.4) may make it more difficult to economically profit off these returns anyway.

A pattern that seems to repeat itself throughout the results is that only the equally-weighted and not the value-weighted portfolios experience this under- and overperformance. This is not surprising, given the fact that this paper also provides evidence that the negative returns in the subsequent five trading days are only prevalent among low market capitalization stocks and that these returns differ significantly from large market capitalization stocks as shown by the Low-High portfolio in Table 5.2. Unique to the low market capitalization sorts is that even for the value-weighted portfolios, the returns differ significantly from zero over five trading days, further indicating that small stocks seem to be the driver of negative returns in the short-run. Thus, the value-weighted portfolios overweigh the non-performing large stocks and underweigh the strongly affected small stocks. Similarly, Barber et al. (2020) find in their analysis that negative returns following large changes in Robinhood users are largely among stocks with low market capitalization. In general, the results for the value-weighted portfolios should be interpreted with caution, as a small number of large stocks (see Table 4.4) may be driving the results for these portfolios, thereby distorting the picture.

With regard to sub-question three, which asks whether stocks with high limits-to-arbitrage experience lower subsequent returns, the limits-to-arbitrage portfolios show that the negative returns in the five to ten trading days after the initial large increase in users is limited to stocks with high limits-to-arbitrage, whereas portfolios with low limits to arbitrage do not experience significant subsequent returns. Similar to Barber et al. (2009) and Stambaugh et al. (2015), stocks with greater IVOL experience lower subsequent returns compared to low IVOL stocks, with the price reversals happening in the first two weeks following a large change in users. The strong negative (risk-adjusted) returns of stocks with low IO compared to stocks with high IO provide further evidence to the suggestions of Nagel (2005) that the extent to which mispricing can occur depends on the sophistication of the shareholders holding the stocks. The fact that the negative-return phenomenon is especially prevalent for stocks with large bid-ask spreads also provides some evidence for Pontiff's (1996) take that transaction costs, such as the bid-ask spread, in addition to holding costs, such as IVOL, have an impact on arbitraging away mispricing. Evidence for medium and longer-term price impacts of stocks under limits-to-arbitrage is at the very most mixed with no clear indication of whether high or low limits-to-arbitrage portfolios perform at all or out- or underperform the risk factors and momentum. Additionally, any significant (risk-adjusted) returns dissipate when comparing the high to low limits-to-arbitrage results using the long-short portfolios. Thus, a significant difference in (risk-adjusted) returns for high limits-to-arbitrage stocks exists primarily in the five to ten trading days following the initial large increase in users' stock holdings.

Overall, the results of section 6 provide further evidence that individual investors, following investment-inducing circumstances, invest in stocks whose subsequent short-run returns are significantly negative, potentially implying a temporary deviation in prices from the assets' fundamental values. Additionally, it provides some weak evidence that the same stocks outperform in the longer-run, though it is not clear whether Robinhood investors benefit off this.

7. Conclusion

In conclusion, the main research question asked:

What are the consequences of large relative increases in stock ownership among Robinhood users on asset prices over time and how do limits-to-arbitrage influence these results?

The findings show that on average stocks belonging to the 100^{th} percentile of daily percentage user changes experience significantly negative (risk-adjusted) returns of up to -20.08% annually in the subsequent five to ten trading days and consistently underperform stocks in the 1^{st} percentile of daily percentage user changes by -17.24PP on average using the risk-adjusted returns of a Carhart (1997) four-factor model. Over longer periods, stocks with the greatest positive percentage user changes perform well, even after adjusting for risk factors and momentum. Furthermore, it is shown that the negative subsequent returns in the five to ten trading days are limited to stocks with high limits-to-arbitrage as proxied by low market capitalization, high effective bid-ask spreads, low institutional ownership, and high idiosyncratic volatility; though over medium to longer periods no consistent pattern of under- or outperformance is found for the limits-to-arbitrage sorts.

While zero-commission trading platforms to the likes of Robinhood may have simplified the way in which investors can trade and have allowed a previously less participatory group of individuals to become more involved in the stock market, the results show that, when focusing on the temporarily most popular stocks, the potentially naïve trading behavior of these investors (Eaton et al., 2021) may at times be detrimental to their investments with potentially large subsequent losses, especially for less established, more volatile stocks. This may be especially true for investors with shorter holding periods, given that that is when the severe underperformance takes place.

Nevertheless, the findings should be interpreted with caution. First the percentage user change variable is only a rough estimate of changes in popularity as it only shows how many users own a certain stock but not the magnitude of each individual investor's position. Thus, some changes may have a large (small) relative increase in users but a relatively small (large) increase in the magnitude of individual investment positions. Additionally, the user changes are also influenced by the fact that new Robinhood users get a free share of a stock using a virtual scratch-off lottery card (Welch, 2020), which may at times inflate the daily percentage user change variables of certain stocks. Furthermore, in the market capitalization sorts, only very few large market capitalization stocks are part of the daily 100^{th} percentile group, making it difficult to compare the small to large capitalization sorts. Lastly, the sample period consists of only two and a half years from May 2018 to July 2020, making it potentially more likely that the results are in part driven by events specific to that sample period (such as the COVID-19 pandemic).

As a suggestion for further research, given some evidence of longer-run outperformance of stocks with large changes in popularity, it may be useful to investigate the investment horizon of traders like the ones of Robinhood to see whether these investors may actually profit of the positive longer-run results. Additionally, it would be interesting to quantify the actual economic losses that investors of these highly popular stocks would incur in the short-run once the bid-ask spreads have been considered.

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Appendix:

Appendix Table 1 Annualized cumulative and risk-adjusted returns of portfolios of stocks in the 10th and 1st decile groups of daily percentage user changes between May 4th, 2018 and July 13th, 2020

	Equally-weighted portfolios			**Value-weighted portfolios**			
Holding period (days)	**10th Decile**	**1st Decile**	**Highest – Lowest**	**10th Decile**	**1st Decile**	**Highest – Lowest**	**Days observed**
			Panel A: Annualized cumulative returns				
120	0.1442	0.1308	0.0133	0.1131	0.1178	-0.0021	670
	(1.16)	(1.10)	(0.84)	(0.90)	(0.96)	(-0.03)	
100	0.1218	0.1030	0.0187	0.1009	0.0963	0.0070	650
	(0.99)	(0.90)	(1.03)	(0.81)	(0.81)	(0.24)	
80	0.0668	0.0485	0.0197	0.0524	0.0559	0.0007	630
	(0.63)	(0.52)	(0.89)	(0.52)	(0.55)	(0.07)	
60	0.0788	0.0415	0.0389	0.0837	0.0466	0.0405	610
	(0.69)	(0.46)	(1.53)	(0.68)	(0.49)	(0.98)	
40	0.0746	0.0285	0.0485*	0.0880	0.0273	0.0639	590
	(0.65)	(0.37)	(1.72)	(0.70)	(0.36)	(1.40)	
20	0.0782	0.0549	0.0258	0.0682	0.0363	0.0364	570
	(0.66)	(0.54)	(0.81)	(0.58)	(0.41)	(0.72)	
15	0.0719	0.0356	0.0391	0.0597	0.0287	0.0365	565
	(0.62)	(0.41)	(1.05)	(0.53)	(0.36)	(0.67)	
10	0.0595	0.0353	0.0290	0.0469	0.0298	0.0252	560
	(0.54)	(0.41)	(0.72)	(0.46)	(0.37)	(0.44)	
5	0.0385	0.0155	0.0275	0.0151	0.0311	-0.0074	549
	(0.41)	(0.27)	(0.58)	(0.29)	(0.37)	(-0.01)	
			Panel B: Annualized risk-adjusted returns				
120	0.0649**	0.0490*	0.0159	-0.0038	0.0088	-0.0126	670
	(2.16)	(1.76)	(1.17)	(-0.13)	(0.42)	(-0.47)	
100	0.0620**	0.0406	0.0214	-0.0024	0.0014	-0.0038	650
	(1.96)	(1.42)	(1.38)	(-0.07)	(0.06)	(-0.12)	
80	0.0514	0.0245	0.0269	-0.0118	-0.0013	-0.0105	630
	(1.53)	(0.85)	(1.46)	(-0.34)	(-0.06)	(-0.30)	
60	0.0724**	0.0218	0.0506**	0.0190	-0.0111	0.0301	610
	(2.09)	(0.76)	(2.48)	(0.51)	(-0.50)	(0.77)	
40	0.0833**	0.0198	0.0635***	0.0343	-0.0237	0.0580	590
	(2.23)	(0.68)	(2.71)	(0.83)	(-1.08)	(1.38)	
20	0.0723*	0.0251	0.0472	0.0092	-0.0379*	0.0471	570
	(1.79)	(0.90)	(1.62)	(0.21)	(-1.75)	(0.98)	
15	0.0878**	0.0194	0.0684**	0.0158	-0.0413*	0.0571	565
	(2.00)	(0.69)	(1.99)	(0.34)	(-1.81)	(1.08)	
10	0.0900*	0.0222	0.0678*	0.0191	-0.0359	0.0550	560
	(1.93)	(0.80)	(1.79)	(0.39)	(1.47)	(0.97)	
5	0.0926*	0.0164	0.0762	0.0099	-0.0310	0.0409	549
	(1.69)	(0.58)	(1.56)	(0.19)	(-1.03)	(0.65)	

Note: T-statistics shown in parentheses and are calculated prior to annualizing returns; t-statistics in Panel B are calculated using heteroskedasticity-robust standard errors; Panel A shows the annualized cumulative return of each portfolio; Panel B shows the risk-adjusted return of a Carhart (1997) four-factor model of each portfolio; return data stems from May 5th, 2018 until December 31st, 2020 latest; 10th decile refers to stocks belonging to the 10th decile group of daily percentage user changes; 1st decile refers to stocks belonging to the 1st decile group of daily percentage user changes; Highest-Lowest refers to a long-short portfolio which is the difference in returns between the 10th decile portfolio and the 1st decile portfolio; the returns of Highest-Lowest in Panel A are annualized after taking the cumulative product of the difference; Holding period indicates the number of trading days each stock in the portfolios is held; Days observed refers to the total number of trading days the portfolios are held; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.