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The effects of prior trading performance have on risk-taking of subsequent trading – The house money effect

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I hereby declare that this PhD dissertation is my original work
and it has been written by me in its entirety.
I have duly acknowledged all the sources of information
which have been used in this dissertation.

This PhD dissertation has also not been submitted for any degree
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Lenz TAN Koon Bin
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Abstract

This study tests for house money effect on 2,030 non-professional FX investors trading through an Australian Financial Service provider. The results indicate that, in general, investors display a positive relationship between prior gains and the change in subsequent weekly risk-taking - the house money effect. The results also suggest that astute investors display a stronger house money effect than mediocre investors following prior gains. In comparison, mediocre investors display a stronger disposition effect following prior losses than astute investors. The study further reveals that investors who initially demonstrated the house money effect became more prone to the disposition effect during stressful market conditions, as during the onset of the COVID-19 crisis.

Concurring with Odean's (1998) findings, the results of consequent tests demonstrate that for winners that were sold, the average excess returns holding the trade increased markedly, whilst for losing trades that were unsold, the losses escalated exponentially as the days passed. This further extends the belief that the disposition effect is detrimental to investing and that the house money effect is not as reckless as widely perceived.

The house money effect is also found to be more evident in Scalpers (shorter-term traders) than Day and Swing traders (longer term traders), and the house money effect seems to dissipate over time or Scalpers are predisposed to this form of investor bias.

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To God be the glory.

1. Introduction

Understanding investors' psychology, biases, and behaviours continue to intrigue researchers. One premise of these theories is that, in general, investors act rationally. However, the events that unfolded in the financial markets in January 2021 revealed a myriad of behaviours that are not always rational. What happened to GameStop, an ailing video game retailer, is nothing but astounding - the share price rose about 8,000% over six months during a global pandemic. The emotional ride of excitement, euphoria (FOMO), denial, fear, panic and capitulation never ceases to grip investors.

The phrase *"Let your profits run and cut your losses quickly"* has been the investors' mantra for decades, if not centuries. This essentially encourages the house money effect while cautioning against the disposition effect. Although investors knew what they ought to do, did they do as they said? Many investors succumb to the disposition effect (DPE) – the propensity to sell winners (risk-aversion during gains) and hang on to losers (risk-seeking in losses). Some investors exhibited the house money effect (HME), increasing their positions and taking on disproportionate amounts of risk (risk-seeking) when they experienced prior gains. Others became overconfident that led to active and excessive trading (Odean, 1999), or developed a strong belief that one is correct and compelled the investor to hang on or add to losing positions. Some are sensation seekers and this group is prone to overconfidence - trades more frequently, actively and unconventionally (Brown et al., 2018). Barber and Odean (2000) found that the 20% of investors who trade most actively earn an annual return net of trading costs of 11.4%. Buy-and-hold investors - 20% who trade least actively - earn 18.5% net of costs. Investors who trade the most perform the worst (Barber and Odean (2000)). And, men are more prone to overconfidence than women, trade more and perform worse than women (Barber and Odean (2001) and (Barber & Odean, 2013)).

But do investors predominantly display DPE or HME? Or could HME and DPE coexist together (Duxbury et al., 2015)? Past research from Kahneman & Tversky's 1984 work on 'Choices, Values and Frames' concluded that when a person experiences monetary gains, he is likely to become risk-averse (play it safe). On the other hand, when a person suffers losses, he becomes risk-seeking (doubling bets). The data in this study would allow the researcher to study the investing/trading behaviour empirically, particularly how an investor would behave after experiencing prior gains or losses. This study presents another facet of behaviour finance on non-professional investors trading the foreign exchange markets.

Forex as a suitable instrument of study

The foreign exchange (FX) market is a suitable instrument of study as it is the world's largest market with deep liquidity. Trillions of dollars are traded each day, reducing the risk of potential price manipulation. It operates 24 hours a day, five days a week. It is a fast-paced, volatile environment and trades are usually closed out within hours, if not within a few days. In addition, FX is a leveraged instrument, magnifying investors' gains and losses. It is not uncommon for broking houses to offer leverage of 30:1 and more, enabling investors to gain exposure with a fraction of the capital deposited. For example, if investors have access to a 30:1 margin, they can potentially execute a $300,000 trade with just $10,000 in margin. Thus, investors are exposed to the exuberances and capitulations of winning and losing large amounts of money in quick successions. Lastly, trading FX allows investors to short sell a currency, taking advantage of speculative opportunities and market inefficiencies on both rising and falling underlying currencies.

However, it must be noted that FX and equities can behave very differently. Stocks are usually associated with mid to longer-term investing and trading, while FX is better associated with hedging, shorter-term trading, and speculating. FX is more volatile and comparable with futures contracts, so it may not be an appropriate or direct comparison with stocks. Also, while investors generally hold to a longer-term view, traders or speculators have shorter-term views. Investors may focus on the intrinsic value of the financial instrument; traders may focus more on the direction of the instrument. Thus, the types of instruments and strategies affect the behaviour of investors.

I obtained trading data of 2,030 non-professional FX investors trading through an Australian Financial Services provider. With the unique investor-level dataset, which permits observation of individual decisions, I established that prior gains correlate positively with subsequent changes in weekly risk-taking (ρ = 0.906). Trading frequency (ρ = 0.323) has a smaller correlation, while Capital (ρ = 0.014) and Experience (ρ = 0.028) have little correlation. To remove variable biases, I control for time fixed effects (*t*-statistic = 12.26) and trader fixed effects (*t*-statistic = 15.36) independently and simultaneously (*t*-statistic = 14.54) prior gain remains significant to the change in weekly risk-taking.

Testing for the disposition effect (DPE) and the house money effect (HME), I found that investors in the sample generally display HME ($\beta = 0.02$) [β or HME is the slope coefficient from the regression of the change in risk-taking from period t-1 to period t on the gain in the previous period (t-1)]. Further separating the investors by their performance, i.e. Top 1/3 performers – astute investors; middle 1/3 performers – average investors; Bottom 1/3 performers – mediocre investors, I tested if HME would persist. The studies reveal that amongst the three types of investors, the astute investors display the highest HME ($\beta = 0.1357$) and are least affected by DPE, i.e. seem better able to regulate their risk exposures when experiencing prior losses. This is as opposed to the average and mediocre investors that tend to display DPE when experiencing prior losses. In addition, the average investors display a higher level of DPE than HME, while the mediocre investors display similar traits; their gains and losses are more extreme. This supports that HME may not be as detrimental to investing as widely perceived. Nevertheless, the results agree with Odean (1998) that DPE is damaging to the investors' performance.

To study if HME persists over time, an event study was conducted to see if HME persists when the markets go through uncertainty or are under stress. The opportunity availed itself through the onset of the COVID-19 crisis when the markets plummeted and subsequently recovered. This study observed that investors who traded before and through the crisis, during the periods between Jan 2017 and Jun 2020, demonstrated HME (β = 0.02). Compared with investors who traded between 24 February and 23 March 2020, when the financial markets represented by the broad S&P500 fell to a low, these investors exhibited DPE (β = -0.021). or reduced HME (β = 0.008 to 0.027, respectively) during stressful market conditions. When the markets subsequent recover between 24 March and June 2020, HME was again observed (β = 0.088).

Returning to the mantra, *"Let your profits run and cut your losses quickly"*, I revisited Odean's (1998) work. Odean found that the average excess return on winning stocks sold continues to increase in value even into the second year, while the average excess return on paper losses of losing stocks unsold continues to fall one year after the sale before turning up in the second year. I conducted a similar analysis of the FX data, albeit with a shorter time frame of T+1 day, T+3 days, and T+5 days, and found similar outcomes. For winners that were sold, the average excess returns holding the trade for T+1, T+3 and T+5 are 0.944, 1.805 and 2.188, respectively — indicating that when a trade was held for a longer period, the returns increased markedly. For losers that were unsold, the average excess returns holding the losing positions for T+1, T+3, and T+5 are -16.07, -7.44 and -16.27, respectively. For losing trades that were unsold, the losses escalate exponentially as the day passes. This further extends the belief that DPE is detrimental to investing and that HME is not as reckless a technique as widely perceived. Results from the study reiterate the adage to hold on to winning trades and, in this study, for two more days and realise losing trades soonest.

Although numerous studies have been conducted and several theories established, the outcomes of these studies continue to reveal more insights from the investors' geographical location; US (Odean, 1998), Finland (Grinblatt & Keloharju, 2001), type of investors (Huang & Chan, 2014), demographic segmentation and financial instruments deployed; futures contracts (Frino et al., 2008), stocks (Odean, 1998). The investor-level transaction data and FX instrument used in this study provide another facet and perspective to the study of behavioural finance in the area of HME and DPE. It is noted that much of the existing research is based on equities and investors collectively. A distinction could also be drawn between investors and traders and their strategies.

2. Data & Methodology

2.1 Data

The data for this study comprises foreign exchange transactions conducted through the Australian (Sydney-based) Financial Services provider, PsyQuation, from 24 January 2011 to 8 July 2020. There were 825,564 trades executed by 2,030 investors. Due to personal data protection requirements, the investors' demographics and other unique characteristics, such as investor age and gender, were not made available to the researcher for this study.

Although the investors' personal details were not known, the assigned Trader ID, the initial capital of the accounts, the number of years the trading account was opened, currency pair/instrument traded, transaction opening & closing prices, transactional opening & closing date/time, transaction size/position, and net profit/loss of transaction, are provided. Due to data limitations, the researcher could not calculate the dynamic returns of the trades. PsyQuation's mission is to identify and develop trading talent; we can assume most traders using this platform are retail investors or non-professional traders.

From the dataset, the average experience of these investors since account opening is 0.91 years, and their average capital or account size is USD 4,088. The average performance and risk taken by the investors per week are USD 2,511.61 and 1,356.97, respectively. The investor performance of the top 90 percentile per week is USD 2,599.79, while the bottom 10% recorded a loss of USD 825.78. The risk taken per week of the top 90 percentile is 910.47, and the bottom 10% percentile is 2.58. Risk-taking is computed using a variance-covariance matrix of the traded currency pairs multiplied by the transactions' quantity.

The summary statistics on the trading activity of investors are provided in Table 1.

[Insert Table 1 here]

The top-ten traded FX pairs by trade value are GBPJPY, USDJPY, EURJPY, AUDJPY, NZDJPY, EURUSD, CADJPY, GBPUSD, CHFJPY, and USDCAD.

The top-ten FX pairs contribute 99% of the total value of all trading values. The three most profitable FX pairs are EURUSD, GBPUSD and USDJPY, amounting to more than USD 4.3 billion.

[Insert Table 2 here]

The correlation between the dependent variable - weekly change in risk-taking and the independent variables - prior gain, trading frequency, experience and capital is provided in Table 3. The prior gains correlate positively with subsequent changes in weekly risk-taking ($\rho = 0.906$). This indicates that a gain from an earlier investment could positively increase the amount of risk taken on the subsequent trade. Trading frequency ($\rho = 0.323$) has a smaller correlation, while Capital ($\rho = 0.014$) and Experience ($\rho = 0.028$) have little correlation with the weekly change in risk-taking.

[Insert Table 3 here]

2.2 Methodology

This research attempts to understand the relationship between the effects between the increase and decrease of risk appetite due to prior gains or losses. Notably, prior gains increase the appetite for subsequent risk-taking. This is also known as the house money effect, β.

$$\Delta WkRT_{i,t} = \beta\ G_{i,t-1} + \varepsilon_{i,t}$$

- $\Delta WkRT_{i,t}$ is the change in risk-taking from period t-1 to period t, for i^{th} trader observation
- $G_{i,t-1}$ is the gain from the previous period t-1 (prior gain), for i^{th} trader observation
- β is the house money effect [the slope coefficient from the regression of the change in risk-taking from period t-1 to period t on the gain in the previous period (t-1)]

Note: Non-consecutive weekly trades (trades that do not compute $\Delta WkRT_{i,t}$) shall be excluded from the analyses.

This study tests the effects of prior gain on the subsequent trader risk appetite. Particularly, prior trading gains increase the risk-taking of subsequent trading, and trading losses reduce the subsequent trading risk-taking.

3. Empirical Results

3.1 Correlation between prior gains and future risk-taking

Using the unique investor-level data obtained from the Australian Financial Services provider, I found that investors generally display HME (Table 5 Column 1). This supports the findings of Hsu & Chow (2013) that an increase in risk-taking correlates with prior gains. However, do investors with more robust past performance display anything different from investors with weaker past performance? Thus, I separated the investors by their performance, i.e. top 1/3 performers – astute investors; middle 1/3 – average investors; bottom 1/3 performers – mediocre investors, and further tested if the HME persists.

The change in risk-taking of the traders is measured weekly against the gains or losses acquired from the previous week. Non-consecutive weekly trades were excluded from the analyses. The investors were sorted into three groups – astute, average, and mediocre investors - to maintain a sizeable sample per group. The average investor group could also be useful to avoid the inadvertent crossing over of the astute and mediocre groups. The data was first sorted by trading performance (Gain) in the respective years. Trading performance of the astute investors (top 1/3 performers), average investors (middle 1/3 performers) and the mediocre investors (bottom 1/3 performers) in the preceding year (say 2016) were tabulated in respective categories, and the investors' IDs were recorded. The trading details, e.g. prior gains, change in weekly risk-taking, etc., are collected for the following year (2017). This is repeated for the years 2017, 2018, 2019 and 2020. The collected data for the astute investors (top 1/3 performers) for 2017, 2018, 2019 and 2020 were pooled together and regressed with their respective changes in weekly risk-taking. Correspondingly, the data for the average (middle 1/3) and mediocre investors (bottom 1/3 performers) for 2017, 2018, 2019, and 2020 were also pooled and regressed with the respective change in weekly risk-taking.

The results are presented in the binned scatter plots depicted in Figure 1a.

[Insert Figure 1a here]

The figures indicate a positive correlation between prior trading gains, or HME leads to a subsequent increase in weekly risk-taking for the astute and mediocre investors. Although the average investors display a mildly negative relationship, the results are not significant, with *t*-statistic and P-value at 0.6114 and 0.5423, respectively. The same results were plotted non-linearly and are presented in the binned scatter plots depicted in Figure 1b. It is interesting to note that the losses do not necessarily lead to a rise in risk-taking for the astute investors, as displayed in the average and mediocre investors. Thus, while the average and mediocre investors might display an increased level of risk-taking after prior gains, both display DPE or the increase in weekly risk-taking when they experience losses, but more so for the mediocre investors, which is damaging to their performances. This is consistent with the findings of Duxbury et al. (2015) that the DPE and HME do coexist. The seeming ability of the astute investors to control their emotions during losses may indicate the reasons for their excellent performance.

[Insert Figure 1b here]

3.2 Good performance leads to HME, or does HME leads to good performance?

An initial assumption was that astute investors or the top performers do better due to the house money effect (HME) – measured by Beta (β). HME is the propensity of an investor to take on more risk after experiencing a prior gain. However, how does one ascertain if good performance leads to HME or HME (taking on greater risks) leads to good performance?

Thus, I regressed the 2016 data, sorted by Beta, and recorded the investor IDs of the top 1/3 in Beta (more HME prone), middle 1/3 in Beta (mid HME prone) and bottom 1/3 in Beta (less HME prone). With the investor IDs, I extracted their ∆WkRT, prior Gains and the necessary details. This is repeated for 2017 through 2019, and the ∆WkRT and prior Gains for 2017 to 2020 were pooled together for further analyses.

The results are presented in the binned scatter plots depicted in Figure 2.

[Insert Figure 2 here]

In addition, I compared the two groups of investors by their trading performance and disposition to the house money effect (HME) in Table 4. The groups were segregated into degrees of their inclinations, i.e. investors who are astute investors, average investors and mediocre investors, versus investors who are more HME prone, middle HME prone and less HME prone. Their β (risk-taking) and average P&L were tabulated for comparison and analysis.

To compute the left side of the table, the 2016 data was sorted by investor performance and separated into three groups - astute investors (top 1/3 performers), average investors (middle 1/3 performers) and mediocre investors (bottom 1/3 performers). The investor IDs were recorded, and their 2017 transaction details were extracted. This process was repeated for 2017 through 2019, and the ΔWkRT and Gains for 2017 to 2020 were pooled together for further analyses on β (Refer to Figure 6a for illustration).

For the right side of the table, the 2017 data was sorted by investor performance and separated into three groups - more HME prone (top 1/3), mid HME prone (middle 1/3) and less HME prone (bottom 1/3), and their IDs were recorded. With the investor IDs, I extracted the ΔWkRT and Gains for 2016. This is repeated for 2018 through 2020, and the ΔWkRT and prior Gains for 2017 to 2019 were pooled together for further analyses on β (Refer to Figure 6b for illustration).

[Insert Table 4 here]

The results from Table 4, and observations from Figures 1a & 2 show consistency between the astute investors and the more HME prone investors - both groups of investors display positive HME (β) and strong gains. The astute investors and the more HME prone investors displayed β values of 0.0226 and 0.0835, respectively. Similarly, their average P&L are $6,846.27 and $17,710.13, respectively. The average investors and the mid-HME prone displayed a lower but positive relationship between risk-taking and gain with β values of 0.0413 and 0.0213, respectively. The Mediocre investors showed a very low β of 0.0188, while the less HME-prone investors showed a negative β of 0.0001, which is not statistically significant. The *t*-statistic and P-values for less HME prone investors are -0.0284 and 0.9774, respectively. With the performance of the astute and the more HME prone investors being broadly similar, one might deduce that HME is a positive trait amongst successful investors.

3.3 Time Fixed Effects and Trader Fixed Effects

Earlier, we established that the change in risk-taking was found to be correlated with gains (Table 3). I tested this relationship by regressing the change in weekly risk-taking with other independent variables, e.g. prior gain, trading frequency, experience and capital; the correlation between ΔWkRT and prior gain, i.e. HME, is positive and significant. The independent variables were selected due to the perceived connections; for example, the prior performance of the investor encourages higher frequency in trading, a more experienced investor performs better, and a successful investor has a larger capital base. Besides capital, gain, trading frequency and experience were found to be positively correlated to ΔWkRT. The negative correlation between capital and ΔWkRT might indicate that a larger capital base does not always lead to an increase in weekly risk-taking. To remove variable biases, I control for time and trader fixed effects independently. The results remain similar, investors display HME, and prior gain is found to be a significant variable of ΔWkRT.

Controlling both time and trader behaviour simultaneously, HME continues to be evident, with prior gain remaining significant. Due to the minimum opening amount to open the trading account, and investors usually start at that similar amount, the independent variable – capital, was omitted due to collinearity when the time and fixed effect studies were performed.

The results are presented in Table 5.

[Insert Table 5 here]

3.4 Market Uncertainty & Volatility

From the previous analyses, it seems that the astute investor performs better due to HME and possesses the ability to control their trading behaviours – increasing risk-taking on winners and reducing risk-taking on losers. Does this behaviour persist in all circumstances, like during uncertain and stressful markets? To study this, I conducted an event study between 24 February and 8 June 2020, from the onset of the COVID-19 crisis when the markets plummeted to when the markets recovered to pre-crisis levels.

Similar tests were conducted on the previously assigned investors – all investors, astute, average, and mediocre investors - who participated during these periods over the onset of COVID-19. The event window was selected between the periods 24 February and 8 June 2020, when the financial markets represented by the broad S&P500 fell to a low on 23 March and later recovered to pre-pandemic levels.

As before, the ∆WkRT and prior gains were recorded for four groups - all investors, astute investors, average investors, and mediocre investors that traded during the event window. The data was recorded and regressed for periods P1 and P2. P1 is from 24 February to 23 March 2020, when the financial markets were falling, and P2 is between 23 March and 8 June 2020, when the financial markets were cautiously improving.

[Insert Figure 7 here]

The study found that the investors who initially displayed HME had become more prone to the disposition effect during P1 when market conditions were stressful, uncertain or volatile. This is consistent with the findings by the authors of Limited Attention, Marital Events and Hedge Funds (Lu et al., 2016), who argued that marital events are deeply personal events that can be stressful and distract fund managers from their investment activities. Consequently, the fund managers make poorer investment decisions and exercise less investment discipline. In particular, fund managers who are tying the knot or undergoing divorce tend to be susceptible to the disposition effect.

As a whole, all investors in the sample - the astute, average and mediocre investors - displayed HME (β from 0.019 to 0.041) from Jan 2017 to Jun 2020 period. However, during market uncertainty, P1, the same investors displayed DPE (β = -0.021). In P2, when the market was cautiously improving, all investors reverted back to HME (β = 0.088).

The results in Table 5 indicate that during P1, the astute, average and mediocre investors, although still mildly displaying HME, have their readings markedly reduced by 0.012, 0.014 and 0.011, respectively. This corroborates with the earlier authors (Lu et al., 2016), who found that investors tend to make poorer investment decisions during stressful times or market uncertainties, exercise less investment discipline, and are susceptible to the disposition effect.

Why is β positive for the Astute, Average, and Mediocre investors while β is negative for All investors (β = -0.021) during P1?

1,084 investors recorded successive weekly trades between January 2017 and June 2020. Through this period, all trader types displayed HME (+ve β), as demonstrated in Figure 1a. However, during P1, investors who usually display HME begin to display DPE (β = -0.021), confirming that investors tend to take profits sooner and delay realising losses during market uncertainty and volatility. In P2, when the market was cautiously improving, all investors reverted back to HME (β = 0.088).

Nonetheless, this is not observed by the individual trader groups – astute, average, mediocre investors, which continue to display HME (β from 0.019 to 0.041). Delving deeper, it is noted that, on average, less than half of the 1,084 investors traded during P1 & P2. The drop in participation could be due to the avoidance of trading during these uncertain periods, or arguably, only the more experienced or those investors who believe they are skilful dare venture to trade during this perilous time. The number of astute, average, mediocre investors who traded in P1 is 48%, 47% and 45%, respectively. During P2, the number of astute, average, and mediocre investors is 45%, 45% and 47%, respectively. The number of individuals who traded during these periods is also fewer, 686(34%) and 1,583(78%) for P1 and P2, respectively. This is opposed to the 2030 investors who traded between 2017 and 2020. Thus, this may not be representative of all investors who would otherwise trade during regular periods.

[Insert Figures 3, 4 & 5 here]

[Insert Table 6 & 7 here]

3.5 Does hanging on to winners and cutting losses short make the investor more money?

Reference to Odean's (1998) work, where the author compares stocks that were sold for a profit (winning stock sold) and to stocks that could be, but are not, sold for a loss (paper losses). Odean measured the returns over the 84, 252 and 504 trading days after the sale of a realised winner and subsequent to days on which sales of other stocks take place in the portfolio of a paper loser. 84 trading days were selected as it was the approximate median in the sample holding period; 254 trading days represent one year and 504 trading days represent two years. He found that the average excess return on winning stocks sold continues to increase in value even into the second year. In contrast, the average excess return on paper losses continues to fall one year after the sale before turning up in the second year. Thus, it is better off holding to winners and cutting losses.

Analogous to Odean’s Ex Post Returns technique, I applied a similar concept to the dataset with some adjustments. The trades in the dataset consist of closed trades, and the P&L of each trade was recorded. Thus, winning (positive return) trades can be readily identified. For the losers that were unsold, more efforts were required to identify these trades. Losing (negative return) trades with the exact entry times, but different closing times (>1 day) were first identified. These trades indicate a position that was opened and partially closed when losses mount. The unsold or ‘leftover’ position was left to be closed at a later time. After the initial position was closed with losses, the quantity of the unsold positions was noted. The excess returns of these trades were collected and aggregated using the closing prices of trade date (T) plus ‘X’ number of days, e.g. investor’s average holding period. As before, the sample period is from Jan 2017 to Jun 2020.

From the dataset, it was found that the median, average and maximum periods of the FX trades are 1 hr 45mins, 1 day 6 hrs and 3 days, respectively. Due to the limitations of collecting the precise prices of each transaction plus a prescribed delayed period, some adjustments were made. The excess returns were collected from closing prices of trade date (T) plus 1 day or T+1 day (average period), T+3 days (max period) and T+5 (1 week). As the traded instrument is FX, a fast-moving market, the selected periods are seen as appropriate.

To test this, I compared the aggregate gain/loss when the investor held a winning or losing trade for another day, 3 days and a week after a trade was closed. When a trade is closed on trade date (T), the new comparison price (or the new price) will be the daily closing prices on T+1, T+3 and T+5 trading days. The results do not include transaction costs. The new comparison prices were extracted from Bloomberg and not from the Financial Services provider where the original trades were conducted.

To calculate the increase of gain/loss for a long position,

[(new closing price-opening price)/opening price] x Quantity

To calculate the increase of gain/loss for a short position,

[(opening price – new closing price)/opening price)] x Quantity

The results for the winning trades are aggregated and divided by the number of winning trades. Similarly, the results for the losing trades are aggregated and divided by the number of losing trades.

[Insert Table 8 here]

The results show that for winners that were sold, the average excess returns holding the trade for T+1, T+3 and T+5, are 0.944, 1.805 and 2.188, respectively — indicating that when a trade was held for a more extended period, the returns increase markedly. For losers that were unsold, the average excess returns holding the trade for T+1, T+3 and T+5, are -16.07, -7.44 and -16.27, respectively. The relatively fewer loser unsold trades – 59 trades – might have allowed a few large losing trades to move the average excess returns lower. For losing trades that were unsold, the losses escalate exponentially as the day passes. These results are consistent with Odean's (1998) finding and confirm that selling winners too soon reduces profits and holding on to losers increases losses, concurring that the disposition effect is detrimental to investing/trading.

3.6 Automated/Semi-automated Trading Platforms

It is noted that there were 59 losers unsold trades recorded in the Ex Post Returns study, which pales in comparison with the 538,648 winners sold recorded. The markedly fewer losers unsold trades could be due to the sophisticated and volatile environment of the FX market. To deal with the volatile environment, the FX trading platforms come with more complex tools to help investors react more quickly, and investors have become more acquainted with executing trades using these features in fast markets. Trading stops (stop-loss) and limit orders (profit-take) are often used to aid investors in entering and exiting trades expeditiously and without subjectivity. In the dataset of 256,524 losing trades, there were only 59 losers unsold – losing trades that were not quickly closed (sold >1 day later). This indicates that DPE could have been curtailed due to such sophisticated platforms.

This might be possible reason FX participants were less likely to extend their losing trades and thus limit DPE, as discussed in Fischbacher et al. (2017).

3.7 Trading strategies and durations – Scalpers, Day and Swing Traders

While some investors prefer to buy and hold for a longer term for more sizeable profits, others prefer to take smaller profits periodically. The discrepancy in trade duration could be attributed to the strategies and instruments used. Stocks are usually associated with mid to longer-term investing and trading, while FX is better associated with hedging, shorter-term trading, and speculating. FX is more volatile and comparable with futures, so it may not always be an appropriate or direct comparison with stocks. While investors generally hold to a longer-term view, traders or speculators have shorter-term views. Investors may focus on the intrinsic value of an instrument; traders may focus more on the directional trend of the instrument. Thus, FX participants may not always behave rationally. It is noted that in the study of Technical Analysis, price action moves in a ‘zig-zag’ fashion. In the short term, like the T+1 day used in the earlier study, the results could have been recorded when prices were retreating from the ensuing direction. Thus, the timing could also be another factor to be considered. In addition, market participants use numerous strategies. Popular strategies include Scalping, Day trading, and Swing trading for shorter-term trading.

Scalpers take advantage of small intraday price moves as small as five pips per trade, and the trade duration could vary from a few seconds to a few minutes. Scalpers tend to trade frequently and focus on one or a few specific liquid markets, e.g. only scalping EUR/USD. Day or Intraday traders generally do not hold positions overnight and prefer to close them before the session ends. Their trading durations vary from a few minutes to a few hours, and they may hold multiple open positions simultaneously. Swing traders hold open positions for several days. Investors who deploy such strategies require patience and fortitude, as they may sometimes have to hold on to paper losses for a period.

Table 9 shows the trade statistics by duration classified under three trading strategies – Scalping, Day (Intraday) trading, and Swing trading. As a comparison, the average duration and performance of all traders combined are 5 hrs 56 mins, and they recorded a gain of 6.18.

[Insert Table 9 here]

In this next study, an investor that holds a trade for five minutes or less is classified as scalping. Five minutes were arbitrarily selected. An investor who holds a trade for >5mins to ≤1 day is considered a Day trading, and an investor who holds a trade beyond a day is engaged in Swing trading. Table 9 shows that about 14% of the trades performed between 2017 to 2020 were scalping, and they performed 54% (9.53) better than the average trader (6.18). The majority (80%) of the trades were by day trading, gaining 4% (6.43) more than the average trader. Almost 6% of the trades were performed by swing trading. This trading style performed worst, recording losses of 4.40 and performing 171% worse than the average trader.

Hence, to withstand the ‘pain’ of holding a losing trade, position rightsizing is paramount to ride out the losses and allow time for the losing trades to break even and turn profitable. Invariably, most FX trades usually begin with the intention for a ‘quick buck’, i.e. a quick scalp. When profits were not forthcoming or losses arose, the quick scalp became an intraday trade; when the losses mounted, the trade could become a swing trade.

Next, I classified the traders by the strategies they have adopted for the majority of their trades – Scalpers, Day and Swing traders. For example, if the majority of a trader’s transaction duration is conducted >5mins to ≤1 day, the trader will be classified as a Day trader. Similarly, for Day traders (>5mins to ≤1 day) and Swing traders (>1 day).

As with earlier studies on HME, as depicted in Table 5, OLS regressions were performed on these three categories of traders – Scalpers, Day and Swing traders. The results in Table 10 show that HME is more prevalent in Scalpers (β = 0.2255) and less for Day (β = 0.0127) and Swing (β = 0.0001) traders. The results seem to indicate that HME dissipates over time (Hsu & Chow, 2013).

One possible explanation is that the Scalper has not integrated the winning as part of the trader's own and decided to risk it for more sizeable gains. Scalpers could also be momentum traders initiating larger or more trades in the direction of the previous winning trade or breakout. It may also suggest that Scalpers are predisposed to this form of bias – specific to investor type (O'Connell & Teo, 2009). Possibly, Scalpers enjoy large trades on quick successions. On the other hand, the Day and Swing traders, having more time to process their trades and take stock of their positions, may be less influenced by the HME.

[Insert Table 10 here]

The results from Table 10 also reveal that the observations for Scalpers and Swing traders are relatively few compared with the Day traders. Although the number of observations is statistically sufficient, a validation exercise was performed. A similar test was conducted, but this time, the investors were separated into three groups: Group 1 (Scalps + Day trades), Group 2 (Day trades) and Group 3 (Day + Swing trades). The classification of trading strategies remains the same – Scalps (≤5mins), Day (>5mins to ≤1 day), and Swing trades (>1 day).

The results show that Group 1 - Scalpers + Day traders displayed the highest house money effect (β = 0.1424), followed by Group 2 – Day traders (β =

0.0239) and Group 3 – Day + Swing traders ($\beta = 0.0104$). This is consistent with the earlier results in Table 10 that HME is more prevalent in Scalpers.

[Insert Table 11 here]

4. Conclusion

In this study, I found that prior gain is positively correlated and a significant variable to the subsequent increase or decrease in the change in weekly risk-taking. To remove variable biases, I control for time and trader fixed effects independently – the results remain similar. Controlling both time and trader behaviour simultaneously, prior gain continues to remain significant to the change in weekly risk-taking.

In general, investors in the sample demonstrate the house money effect, taking on higher risks after experiencing prior gains. The segregation of traders into three groups – astute, average and mediocre investors – provided more insights into investor behaviours. I observed that although the astute investors exhibit the house money effect during gains, they are the only group that possesses more discipline and the ability to reduce their risk exposure when experiencing prior losses. In contrast to the astute investors, the average investors display a higher disposition effect than the house money effect. The mediocre investors display a lower house money effect during gains and disposition effect during losses. Although the mediocre investors display similar traits to the average investors their gains and losses are more extreme.

Observing that the house money effect is a profitable trait found in astute investors, the house money effect may not be detrimental to investing as generally perceived. On the other hand, the disposition effect is damaging to investing, as seen in the mediocre investors' lacklustre performance.

Modelling Odean's Ex Post Returns technique shows that for winners that were sold, the average excess return holding the trade for T+1, T+3 and T+5 days are -0.944, 1.805 and 2.188, respectively — indicating that when a trade was held for a more extended period, the returns increase markedly. For losers that were unsold, the average excess return holding the trade for T+1, T+3 and T+5 days are -16.07, -7.44 and -16.27, respectively. For losing trades that were unsold, the losses escalate exponentially as each day passes.

Fortunately, there are fewer unsold losing trades in the sample. With FX brokers providing more sophisticated trading platforms and retail investors becoming more acquainted with using them, I posit that the use of stop-loss features could be a reason unsold losing trades are fewer. Thus, DPE was curtailed, and further losses were limited.

The study also shows through the onset of the COVID-19 crisis, when the market is volatile and uncertain, investors who demonstrate the house money effect before the crisis exhibit DPE or reduced HME during stressful market conditions due to external circumstances that affect their normal emotional state.

Finally, whilst studying the strategies and duration of the traders, the results in Table 10 show that HME seems to be more prevalent in Scalpers ($\beta = 0.2255$) and less for Day ($\beta = 0.0127$) and Swing ($\beta = 0.001$) traders. It seems to indicate that HME does dissipate over time.

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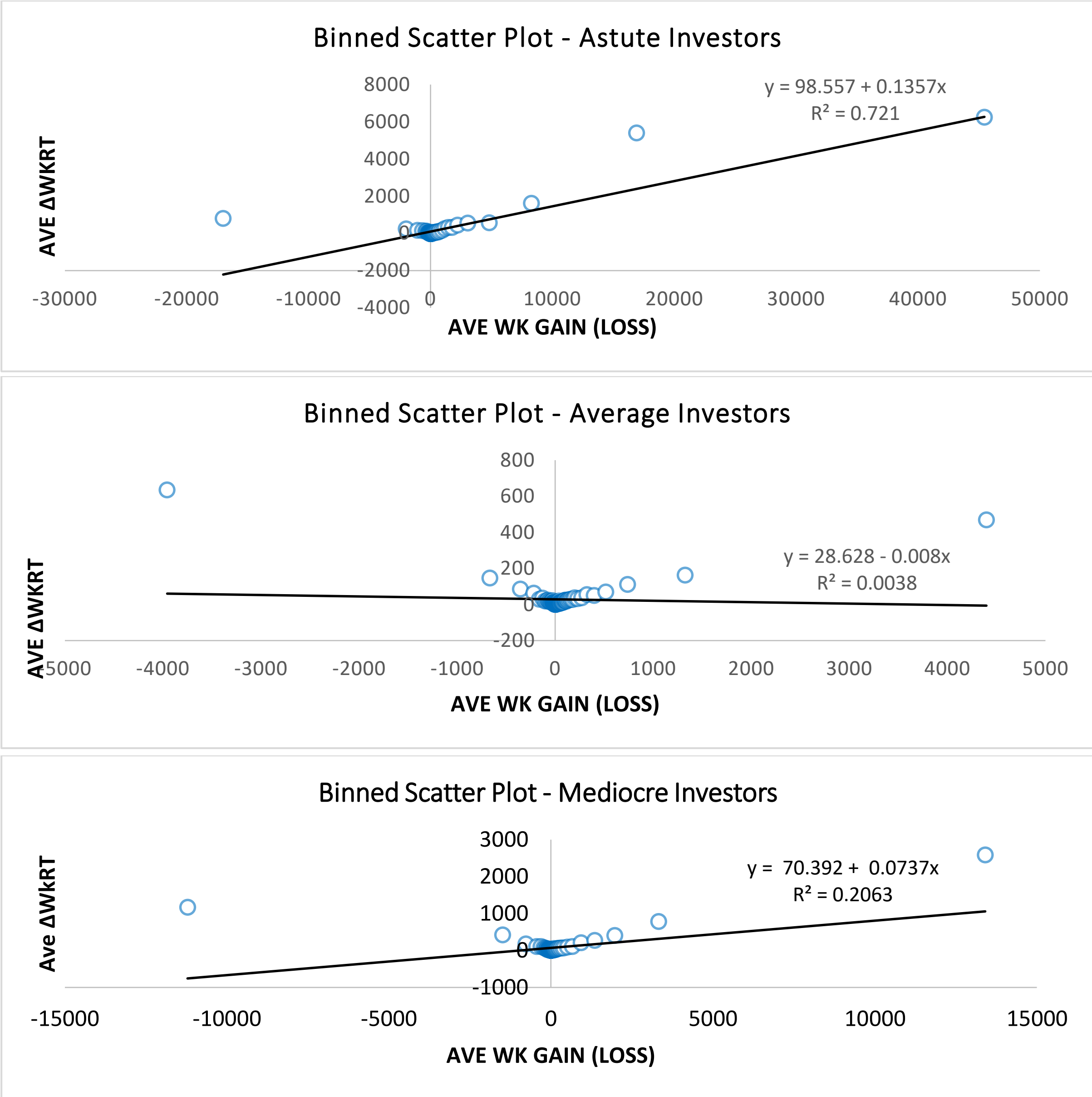
Figure 1a

Binned Scatter Plot – Astute, Average, Mediocre Investors (Linear)

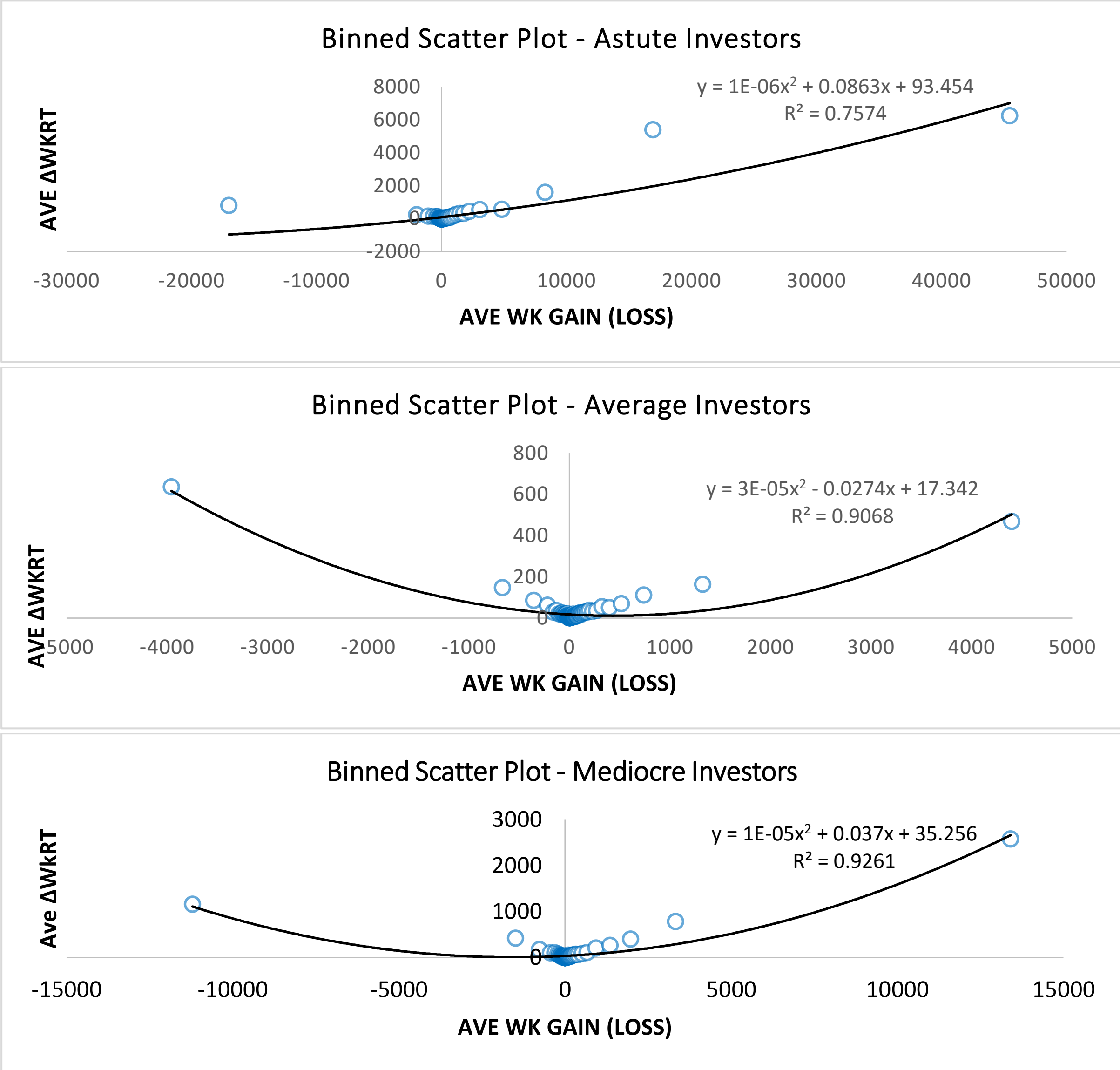


Note. Binned scatter plots (linear) of the Change in Weekly Risk-Taking (ΔWkRT) against Average Gains (week). The investors were sorted into three groups – astute, average, and mediocre investors. The data was first sorted by trading performance (Gain) in the respective years. The trading performance of the astute investors (top 1/3 performers), average investors (middle 1/3 performers) and the mediocre investors (bottom 1/3 performers) in the preceding year (say 2016) were tabulated and the investors' 2017 details were recorded. This is repeated through the sample period, for the years 2017 to 2020; the data were then pooled and regressed. The lines represent the best fit lines through the scatter plots.

Results for the Binned Scatter Plot – Average Investors are not significant, with a *t*-statistic of -0.6114 and a P-value of 0.5423.

Figure 1b

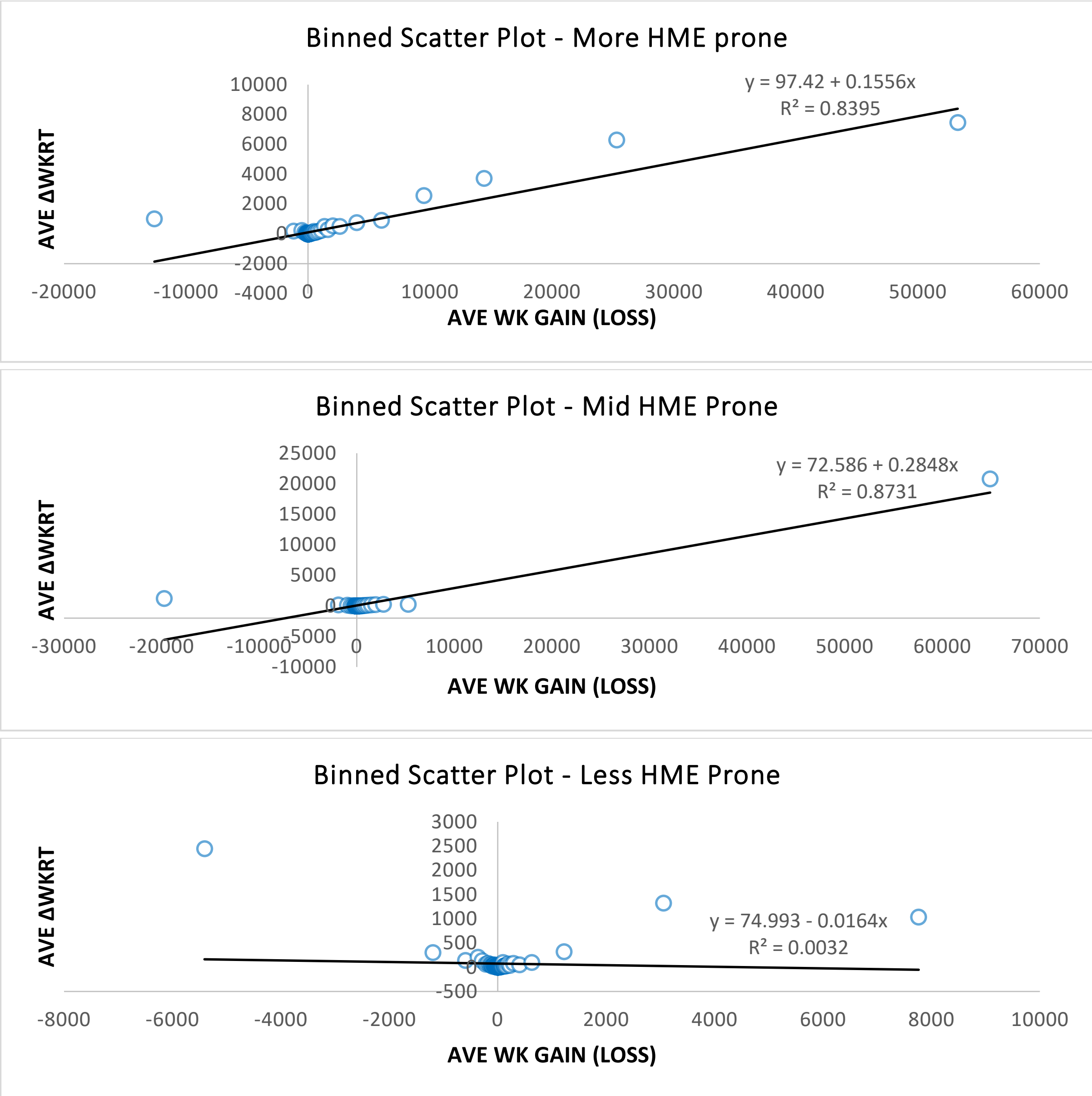
Binned Scatter Plot – Astute, Average, Mediocre Investors (Non-linear)



Note. Binned scatter plots (non-linear) of the Change in Weekly Risk-Taking (ΔWkRT) against Average Gains (week). The investors were sorted into three groups – astute, average, and mediocre investors. The data was first sorted by trading performance (Gain) in the respective years. The trading performance of the astute investors (top 1/3 performers), average investors (middle 1/3 performers) and the mediocre investors (bottom 1/3 performers) in the preceding year (say 2016) were tabulated and the investors' 2017 details were recorded. This is repeated through the sample period, for the years 2017 to 2020; the data were then pooled and regressed.

Figure 2

Binned Scatter Plot – More, Mid, Less HME Prone Investors



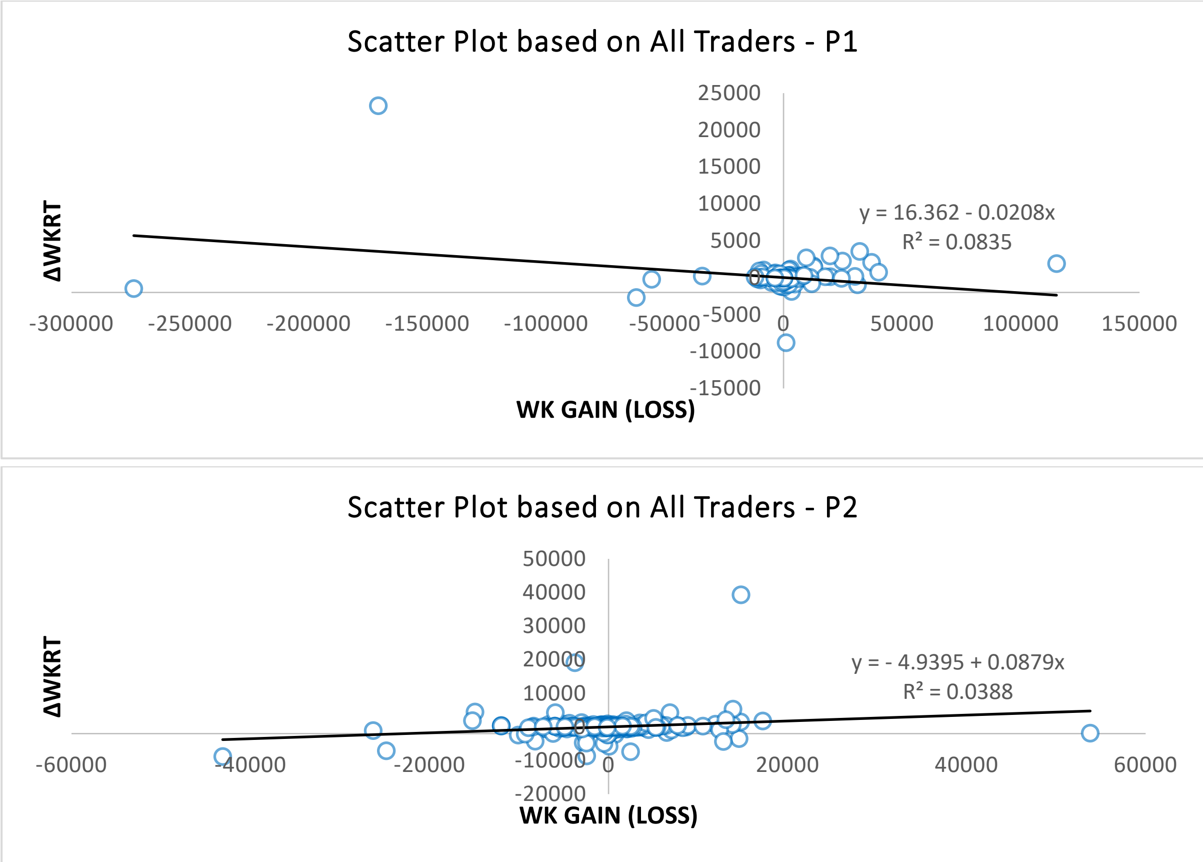
Note. Binned scatter plots (linear) of the Change in Weekly Risk-Taking (ΔWkRT) against Average Gains (week). The lines represent the best fit lines through the scatter plots. The sample period is between January 2017 and July 2020.

The investors were sorted into three groups – more HME prone, mid HME prone, and less HME prone investors. The 2016 data was first regressed, sorted by Beta, and the investor IDs of the top 1/3 in Beta (more HME prone), middle 1/3 in Beta (mid HME prone) and bottom 1/3 in Beta (less HME prone) were recorded. With the investor IDs, I extracted their ΔWkRT, prior Gains and the necessary details for the following year. This is repeated through the sample period for the years 2017, 2018, 2019, 2020, and the ΔWkRT and prior Gains for 2017 to 2020 were pooled together for further analyses.

Results for the Binned Scatter Plot – Less HME Prone Investors are not significant, with a *t*-statistic of -0.5673 and a P-value of 0.5718.

Figure 3

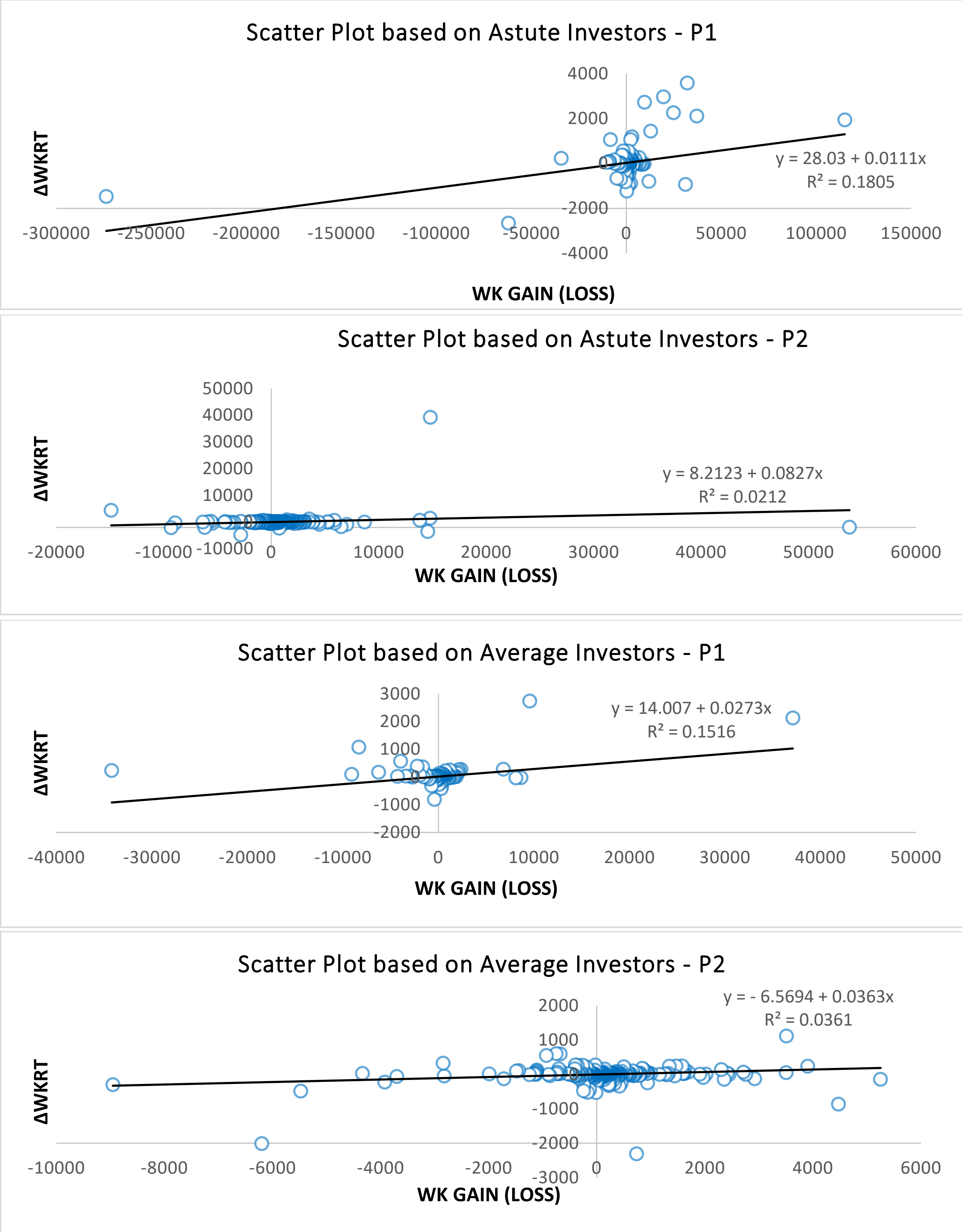
Uncertain and Volatile Market (Shocks) – P1 & P2

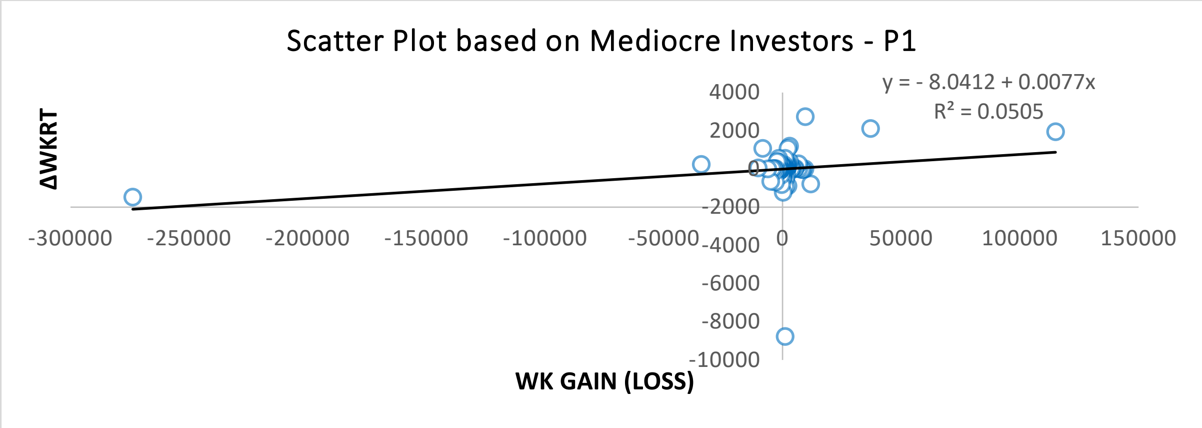


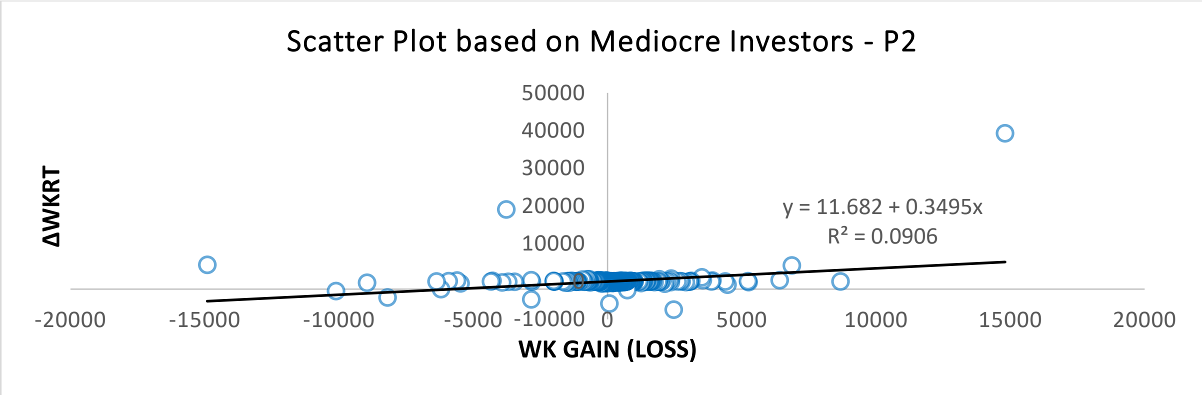
Note. Scatter plots (linear) of the Change in Weekly Risk-Taking (ΔWkRT) against Gains (Week) for all investors/traders who participated during the sample periods P1 and P2. P1 is the period between 24 February and 23 March 2020, when the markets plummeted due to the onset of COVID-19. P2 is the period between 23 March and 8 June 2020, when markets recover to pre-pandemic levels. The lines represent the best fit lines through the scatter plots.

Figure 4

Scatter Plots – Astute, Average, Mediocre Investors (P1 & P2)





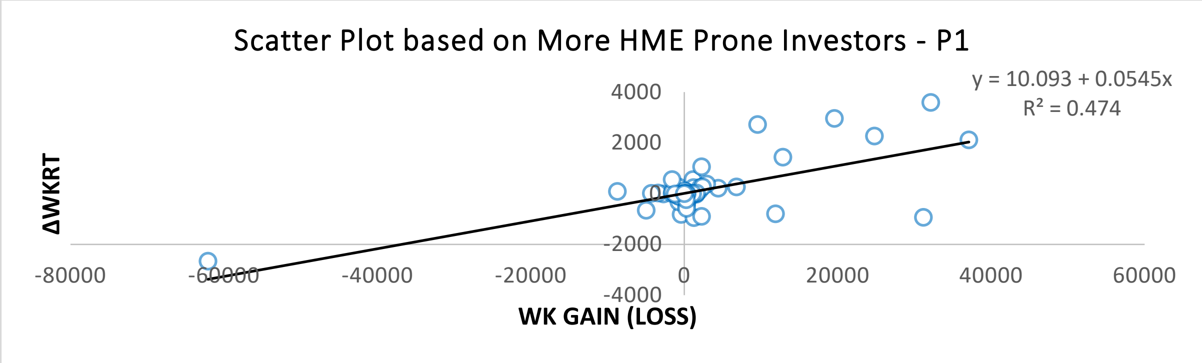


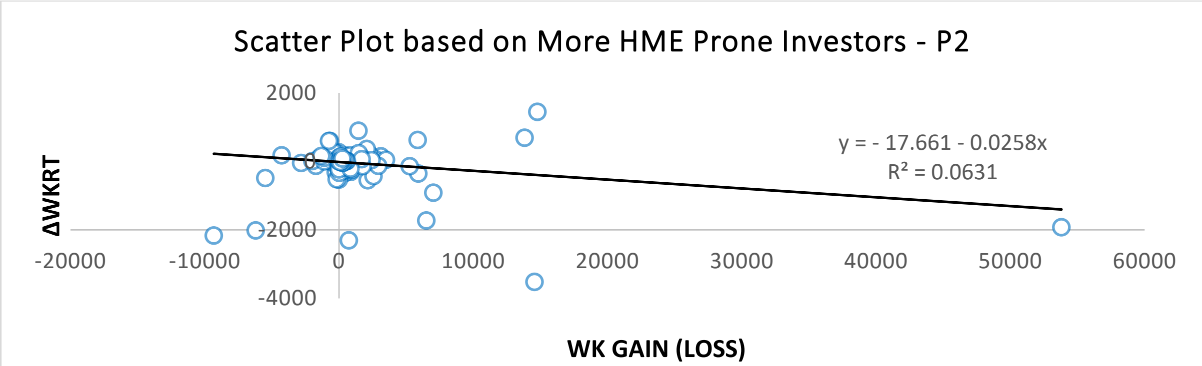
Note. Scatter plots (linear) of the Change in Weekly Risk-Taking (ΔWkRT) against Gains (Week) during the sample periods P1 and P2. P1 is the period between 24 February and 23 March 2020, when the markets plummeted due to the onset of COVID-19. P2 is the period between 23 March and 8 June 2020, when markets recover to pre-pandemic levels. The lines represent the best fit lines through the scatter plots.

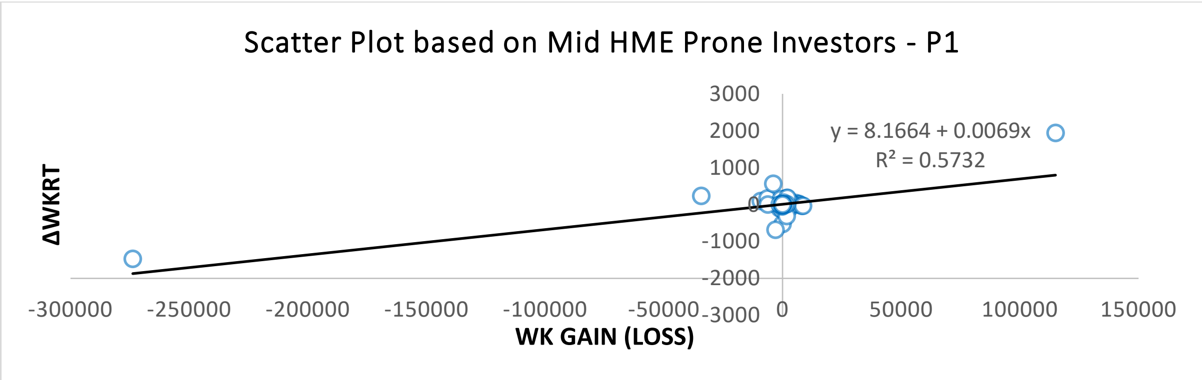
The investors were sorted into three groups – astute, average, and mediocre investors. The data was first sorted by trading performance (Gain) in the respective years. The trading performance of the astute investors (top 1/3 performers), average investors (middle 1/3 performers) and the mediocre investors (bottom 1/3 performers) in the preceding year (say 2016) were tabulated, and the investors' details were recorded for 2017. This is repeated through the sample period, for the years 2017 to 2020; the data were then pooled and regressed.

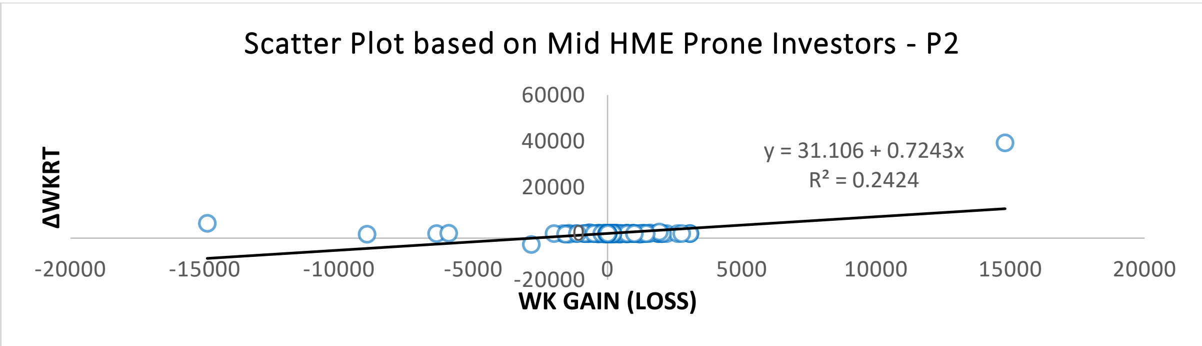
Figure 5

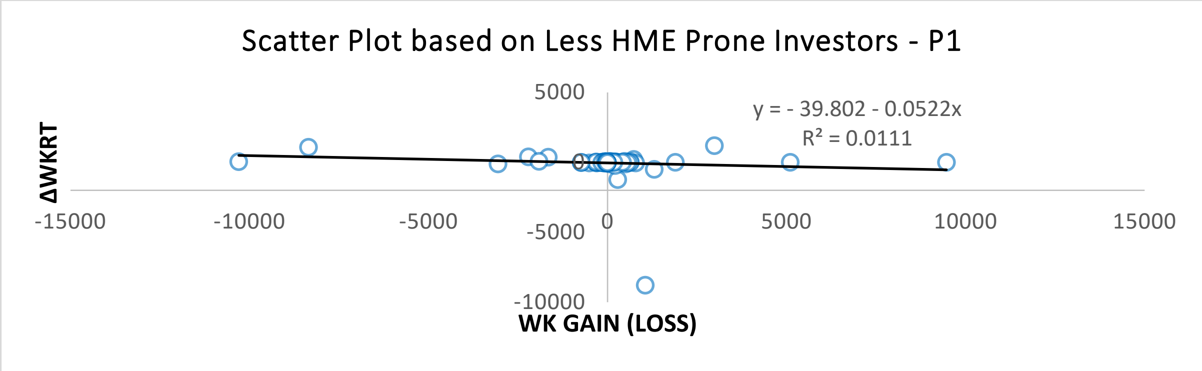
Scatter Plots – More, Mid, Less HME Prone Investors (P1 & P2)

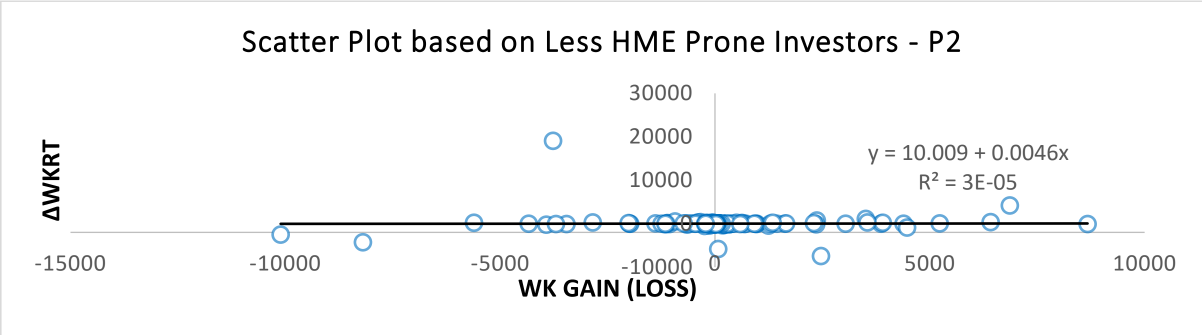












Note. Scatter plots (linear) of the Change in Weekly Risk-Taking (ΔWkRT) against Gains (Week) during the sample periods P1 and P2. P1 is the period between 24 February and 23 March 2020, when the markets plummeted due to the onset of COVID-19. P2 is the period between 23 March and 8 June 2020 when markets recover to pre-pandemic levels. The lines represent the best fit lines through the scatter plots.

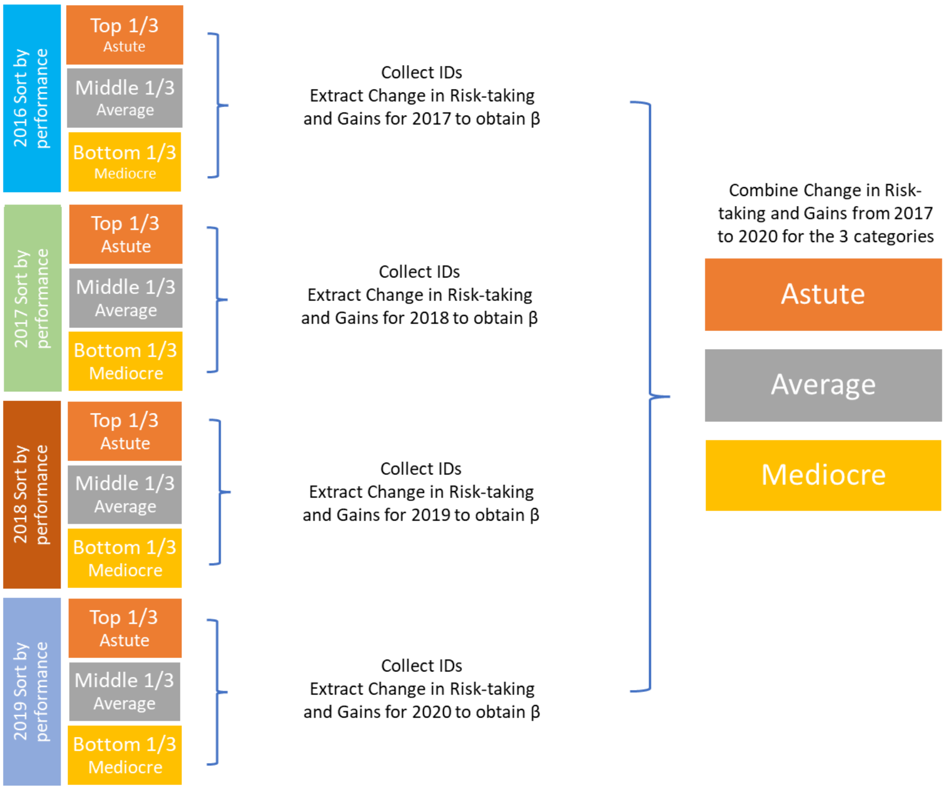
The investors were sorted into three groups – more HME prone, mid HME prone, and less HME prone investors. The 2016 data was first regressed, sorted by Beta, and the investor IDs of the top 1/3 in Beta (more HME prone), middle 1/3 in Beta (mid HME prone) and bottom 1/3 in Beta (less HME prone) were recorded. With the investor IDs, I extracted their ΔWkRT, prior Gains and the necessary details for the following year. This is repeated through the sample period for the years 2017, 2018, 2019, 2020, and the ΔWkRT and prior Gains for 2017 to 2020 were pooled together for further analyses.

Results for the Scatter Plot based on Less HME Prone Investors (P1) are not significant, with a *t*-statistic of -1.4554 and a P-value of 0.1472.

Results for the Scatter Plot based on Less HME Prone Investors (P2) are not significant, with a *t*-statistic of 0.1156 and a P-value of 0.9080.

Figure 6a

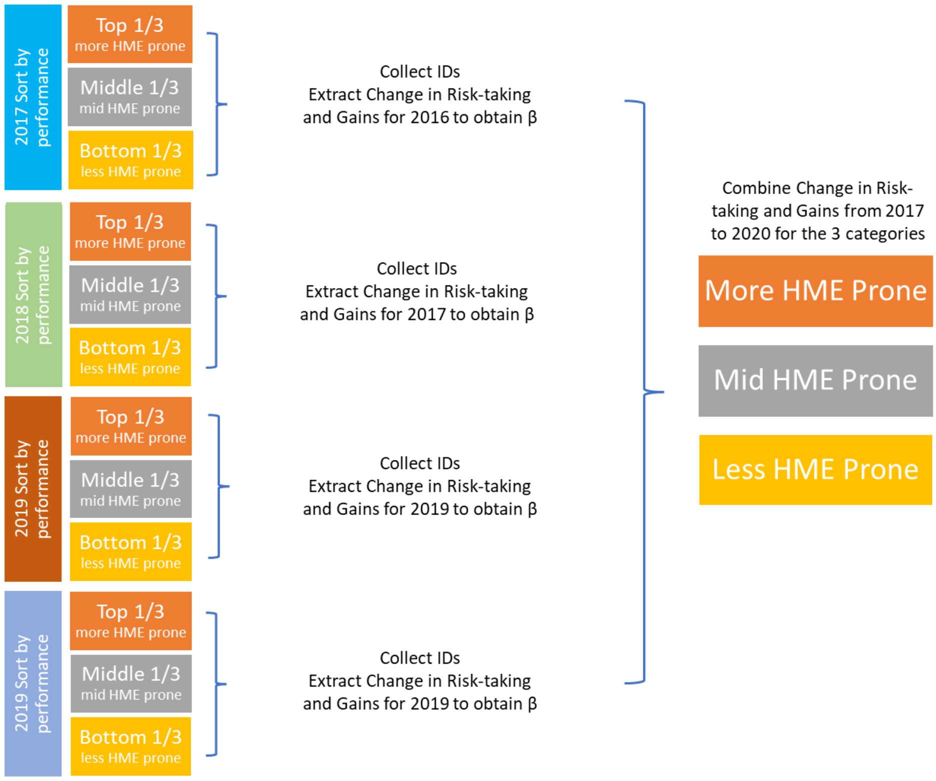
Prior Performance leads to HME



Note. Sort by 2016 P&L and extract IDs to obtain 2017 Beta.

Figure 6b

HME leads to Good Performance

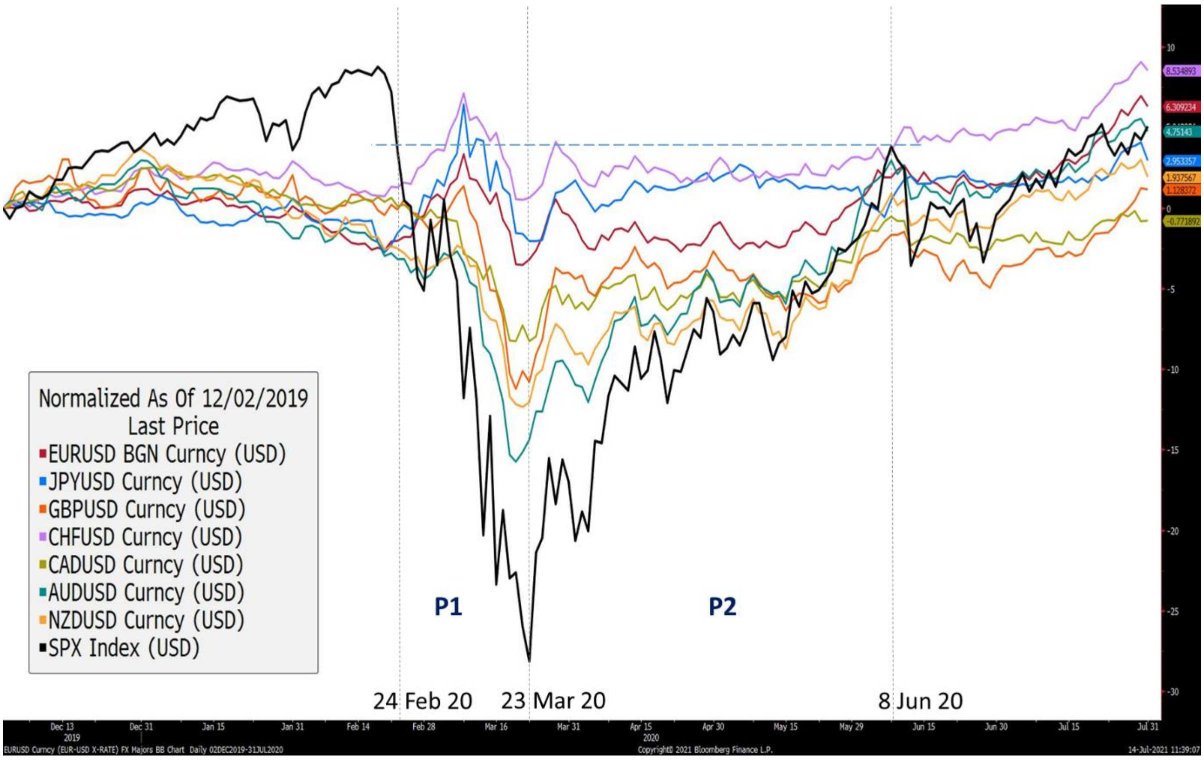


Note. Sort by 2017 P&L and extract IDs to obtain 2016 Beta

Figure 7

The S&P500 and FX majors

The chart depicts the movements of the S&P500 and the FX majors between 12 February 2019 and 31 July 2020. This period marks the selloff and subsequent recovery of the financial markets due to the COVID-19 crisis. P1 indicates the period between 24 February and 23 March 2020, when the S&P500 plummeted. P2 indicates the period between 23 March and 8 June 2020, when the S&P500 recovered to about the same level as pre-crisis.



P1: 24 February to 23 March 2020, P2: 23 March to 8 June 2020

Note. Data from Bloomberg, 2021.

Table 1
Summary statistics

This table provides the summary statistics of the trading activities of individual investors between 24 January 2011 and 8 July 2020. The data for this study comprises of foreign exchange trades conducted through the Australian Financial Services provider, PsyQuation. There were 825,564 trades executed by 2,030 non-professional/retail investors. The demographics and other personal details of the traders were not made available to the researcher of this study. Although the personal details of the traders were not known, the initial capital of the accounts and when they were first opened are known. PsyQuation's mission is to identify and develop trading talent; hence, we can assume the traders using this platform are non-professional traders, i.e. retail investors.

Summary Statistics	**NOBS**	**Mean**	**10%**	**25%**	**50%**	**75%**	**90%**	**Std Dev**
By Trades								
Risk/trade	825,564	3.337	0.001	0.006	0.163	0.768	3.197	29.961
Gains/trade/wk (USD)	825,564	6.18	-8.02	-0.71	0.83	4.47	19.52	409.670
By Trades								
Risk/trader	2,030	1,356.971	2.584	15.120	57.016	244.240	910.467	19,605.13
Gains/trader/wk (USD)	2,030	2,511.61	-825.78	-211.04	13.09	453.93	2,599.79	58,346.16

The average experience of these investors is 0.91 years, and their average capital or account size is USD 4,088. The average performance and risk taken by the investors per week are USD 2,511.61 and 1,356.97, respectively. The investor performance of the top 90 percentile per week is USD 2,599.79, while the bottom 10% recorded a loss of USD 825.78. The risk taken per week of the top 90 percentile is 910.467, and the bottom 10% percentile is 2.584. Risk-taking is computed using a variance-covariance matrix of the traded currency pairs multiplied by the transactions' quantity.

Table 2

The top 10 most traded FX pairs and top 10 most profitable FX pairs.

Transactional statistics of the trading activities by individual investors between 24 January 2011 and 8 July 2020. The total trade value for all 71 traded FX pairs between 24 January 2011 and 8 July 2020 is USD 3,832,132.79. The top 10 FX pairs contributed USD 3,778,036.27 in trade value. The top 3 most traded FX pairs are GBPJPY, USDJPY and EURJPY.

Top 10 most traded FX pairs by trade value

No	FX Pairs	Trade value (USD)	Net profit (USD)
1	GBPJPY	1,547,542.39	15,456.69
2	USDJPY	949,970.24	317,823.53
3	EURJPY	673,683.01	209,842.79
4	AUDJPY	172,127.01	64,943.52
5	NZDJPY	143,458.10	110,534.28
6	EURUSD	88,289.54	3,008,213.05
7	CADJPY	79,125.84	-21,937.96
8	GBPUSD	63,213.60	1,008,299.35
9	CHFJPY	47,259.74	13,054.08
10	USDCAD	13,366.79	247,630.85
	Total	**3,778,036.27**	**4,973,860.18**
	All trades	3,832,132.79	5,098,575.44
	%	99%	98%

Top 10 best performing FX pairs

No	FX Pairs	Net profit (USD)
1	EURUSD	3,008,213.05
2	GBPUSD	1,008,299.35
3	USDJPY	317,823.53
4	USDCAD	247,630.85
5	EURJPY	209,842.79
6	EURAUD	154,230.73
7	USDCHF	140,648.91
8	NZDJPY	110,534.28
9	AUDJPY	64,943.52
10	GBPNZD	62,942.90

The top 3 most profitable FX pairs are the EURUSD, GBPUSD, and USDJPY.

Table 3
Correlation table

This table shows the correlation between the change in weekly risk-taking **(**ΔWkRT), profit & loss (Gains), number of trades (Trading Freq), initial capital/account value (Capital), and trading experience (Experience).

	ΔWkRT	**Gains**	**Trading Freq**	**Acct Size**	**Experience**
ΔWkRT	-				
Gains	0.906	-			
Trading Freq	0.323	0.332	-		
Capital	0.014	0.003	0.181	-	
Experience	0.028	0.004	0.459	0.118	-

From the table, it can be seen that ΔWkRT is positively correlated with Gains.

Table 4

Prior Performance and HME

This table compares two groups of investors by their trading performance and disposition to the house money effect (HME or β). The groups were further sorted into degrees of their inclinations, i.e. investors who are astute traders, average traders and mediocre traders versus investors who are more HME prone, mid HME prone and less HME prone. Their β (risk-taking) and average P&L were tabulated for comparison and analysis.

Investor Groups	**β**	**Ave P&L**	**Investor Groups**	**β**	**Ave P&L**
Astute	0.0226	6,846.27	more-HME prone	0.0835	17,710.13
Average	0.0413	763.71	mid-HME prone	0.0213	396.75
Mediocre	0.0188	486.05	less-HME prone*	-0.0001	-387.05

* Statistically not significant

Note. To compute the left side of the table, the 2016 data was sorted by investor performance and separated into three groups - astute investors (top 1/3 performers), average investors (middle 1/3 performers) and mediocre investors (bottom 1/3 performers). The investor IDs were recorded, and their 2017 transaction details were extracted. This process was repeated for 2017 through 2019, and the ΔWkRT and Gains for 2017 to 2020 were pooled together for further analyses on β.

For the right side, the 2017 data was sorted by investor performance and separated into three groups - more HME prone (top 1/3), mid HME prone (middle 1/3) and less HME prone (bottom 1/3), and their IDs were recorded. With the investor IDs, I extracted the ΔWkRT and Gains for 2016. This is repeated for 2018 through 2020, and the ΔWkRT and prior Gains for 2017 to 2020 were pooled together for further analyses on β.

The results show little difference between the astute investors and the more HME prone investors - both groups of investors display positive HME (β) and strong gains. The astute investors and the more HME prone investors displayed β values of 0.0226 and 0.0835, respectively. Similarly, their average P&L are $6,846.27 and $17,710.13, respectively. The average investors and the mid-HME prone displayed a positive relationship between risk-taking and gain with β values of 0.0413 and 0.0213, respectively. The Mediocre investors showed a very low β of 0.0188, while the less-HME prone investors showed a negative β of 0.0001, which is not statistically significant. The *t*-statistic and P-values for less HME prone investors are -0.0284 and 0.9774, respectively. With the performance of the astute and the more HME prone investors being broadly similar, one might deduce that HME is a positive trait amongst successful investors.

Table 5

Regression Table

Columns 1 to 5 in this table report the results of OLS regressions of the dependent variable, Change in Weekly Risk-Taking (*ΔWkRT*), against the various independent variables. The independent variables include profit & loss (*Gains*), trading frequency (*Trading Freq*), trading experience (*Experience*), initial capital/account value (*Capital*). The OLS regressions also include dummy variables to control for time fixed effects and trader fixed effects. Column 1 reports the results of the OLS regression of Change in Weekly Risk-Taking (*ΔWkRT*) against prior Gains during the sample period from Jan 2017 to Jun 2020. Column 2 reports the results of the OLS regression of Change in Weekly Risk-Taking (*ΔWkRT*) against prior Gains, trading frequency (*Trading Freq*), trading experience (*Experience*), and initial capital/account value (*Capital*) during the sample period from Jan 2017 to Jun 2020. Controlling for time fixed effects, Column 3 reports the results of the OLS regression of Change in Weekly Risk-Taking (*ΔWkRT*) against prior Gains, trading frequency (*Trading Freq*), trading experience (*Experience*), and initial capital/account value (Capital) during the sample period from Jan 2017 to Jun 2020. Controlling for trader fixed effects, Column 4 reports the results of the OLS regression of Change in Weekly Risk-Taking (*ΔWkRT*) against prior Gains, trading frequency (*Trading Freq*), trading experience (*Experience*), and initial capital/account value (*Capital*) during the sample period from Jan 2017 to Jun 2020. Controlling for both time and trader fixed effects, Column 5 reports the results of the OLS regression of Change in Weekly Risk-Taking (*ΔWkRT*) against prior Gains, trading frequency (*Trading Freq*), trading experience (*Experience*), and initial capital/account value (*Capital*) during the sample period from Jan 2017 to Jun 2020.

Dependent variable = *ΔWkRT*					
Independent variable	(1)	(2)	(3)	(4)	(5)
Gain	0.0189 (12.09)	0.0217 (13.11)	0.0204 (12.26)	0.0278 (15.36)	0.0265 (14.54)
Trading Freq		0.2264 (4.41)	0.2135 (4.14)	0.5422 (6.77)	0.5107 (6.34)
Experience		0.0142 (1.09)	0.0107 (0.78)	0.0179 (0.80)	-0.0049 (-0.02)
Capital		-0.0004 (-6.31)	-0.0004 (-5.89)	NA#	NA#
Time fixed effect	No	No	Yes	No	Yes
Trader fixed effect	No	No	No	Yes	Yes
R^2	0.0069	0.0095	0.0095	0.0073	0.0320
N	21,109	21,109	21,109	21,109	21,109

The *t*-statistics are in parentheses.

#omitted due to collinearity

Table 6

Uncertain or Stressful Market

This table reports the results of OLS regressions of the dependent variable, Change in Weekly Risk-Taking (ΔWkRT), against the independent variables, profit & loss (prior Gains). The sample period is from Jan 2017 to Jun 2020. P1 is between 24 February and 23 March 2020, when the market plummeted at the onset of the COVID-19 crisis. P2 was the period between 23 March and 8 June 2020 when the market recovered to the pre-crisis period.

The investors were previously sorted into three groups – astute, average, and mediocre investors. The data was first sorted by trading performance (Gain) in the respective years. The trading performance of the astute investors (top 1/3 performers), average investors (middle 1/3 performers) and the mediocre investors (bottom 1/3 performers) in the preceding year (say 2016) were tabulated, and the investors' details were recorded for 2017. This is repeated through the sample period, for the years 2017 to 2020; the data were then pooled and regressed.

DV = ΔWkRT **IV = Gain**	***Coeff***	***SE***	***t-Stat***	***P-value***
Jan 2017 – June 2020				
Astute Investors in prior year	0.023	0.003	8.959	0.000**
Average Investors in prior year	0.041	0.003	12.267	0.000**
Mediocre Investors in prior year	0.019	0.003	7.049	0.000**
COVID Market Shock - P1 & P2				
P1: 24 Feb - 23 Mar 2020, P2: 23 Mar - 8 Jun 2020				
All Investors who traded during P1	-0.021	0.002	-11.036	0.000**
All Investors who traded during P2	0.088	0.006	15.770	0.000**
Astute Investors in prior year - P1	0.011	0.001	9.362	0.000**
Astute Investors in prior year- P2	0.083	0.019	4.473	0.000**
Average Investors in prior year - P1	0.027	0.003	9.233	0.000**
Average Investors in prior year- P2	0.036	0.006	6.477	0.000**
Mediocre Investors in prior year- P1	0.008	0.002	5.150	0.000**
Mediocre Investors in prior year- P2	0.346	0.032	11.106	0.000**

$^{*}p<.05$

$^{**}p<.01$

Table 7
Number of investors who participated during P1 & P2

The sample period is from Jan 2017 to Jun 2020. P1 is the period between 24 February and 23 March 2020, when the market plummeted at the onset of the COVID-19 crisis. P2 was the period between 23 March and 8 June 2020 when the market recovered to the pre-crisis period.

No of investors by type (prior year) recorded at least 1 successive weekly trade

Year	Astute	Average	Mediocre	Sum by Year	Inds Traded*
2020 (from 2019)	225	276	306	807	506
2019 (from 2018)	49	63	58	170	113
2018 (from 2017)	19	20	23	62	47
2017 (from 2016)	11	15	19	45	35
Sum by type	**304**	**374**	**406**	**1,084**	**2,030**

No of investors who have recorded at least 1 successive weekly trade during P1 & P2

Period	Astute	Average	Mediocre	Sum by Period	Inds Traded*
P1	146(48%)	177(47%)	184(45%)	507(47%)	686(34%)
P2	138(45%)	167(45%)	189(47%)	494(46%)	1,583(78%)

% of investors who traded during P1 or P2 over the sum of investor type in parentheses.
*No of traders who traded during the period.

1,084 investors recorded successive weekly trades between the period Jan 2017 and Jun 2020. Through this period, all trader types displayed HME, as demonstrated in Figure 1a. However, during P1, investors who usually display HME begin to display DPE ($\beta = -0.021$), confirming that investors tend to take profits sooner and delay realising losses during market uncertainty and volatility. In P2, when the market was cautiously improving, all investors reverted back to HME ($\beta = 0.088$).

Nonetheless, this is not observed by the individual trader groups – astute, average, mediocre investors, which continue to display HME (β from 0.019 to 0.041). Delving deeper, it is noted that, on average, less than half of the 1,084 investors traded during P1 & P2 either avoid trading during these uncertain periods or arguably, only the more experienced or those investors who believe they are skilful dare venture to trade during this perilous time. The number of individuals traded during these periods is fewer, 686(34%) and 1,583(78%) for P1 and P2, respectively. Thus, this may not be representative of all investors who would otherwise trade during regular periods.

The results in Table 6 indicate that during P1, the astute, average and mediocre investors, although still mildly displaying HME, have their readings markedly reduced by 0.012, 0.014 and 0.011, respectively. This corroborates with the findings of authors Lu et al. (2016), who found that investors tend to make poorer investment decisions during stressful times or market uncertainties, exercise less investment discipline, and are susceptible to the disposition effect.

Table 8

Excess Average Returns Holding onto Winning & Losing Trades.

This table compares the aggregate gain/loss if the investor held on to winners that were sold and losers that were unsold for 1 day, 3 days and 5 days (a week) after a trade was closed. The sample period is from Jan 2017 to Jun 2020.

When a trade is closed on trade date (T), the new comparison price will be the daily closing prices on T+1, T+3 and T+5 trading days, respectively. The results do not include transaction costs. The new comparison prices were extracted from Bloomberg and not from the financial service provider.

To calculate the increase of gain/loss for a long position,
[(new closing price-opening price)/opening price)] x Quantity

To calculate the increase of gain/loss for a short position,
[(opening price – new closing price)/opening price] x Quantity

Data for winners sold were easily obtained as all the trades recorded were completed/closed trades. For losers unsold, more effort was required to extract losing trades from the same trader, instrument, type, and opening time. However, the closing time must be different from the initial/first trade and must be held for more than a day (the closing time and the opening time must be more than a day). Due to these requirements, the number of losers unsold trades found was fewer at 59. This could have allowed a few large losing unsold trades to lower the average excess return. In contrast, the number of winners sold is 538,648. The results were aggregated and divided by the number of winning trades.

Table 8 reports the excess average returns for the periods following the sale of winning trades sold and losing trades unsold. Three investment horizons are examined: T+1 (ave) trading day, T+3 (max) trading days, and T+5 trading days (one week).

	T+1 day	**T+3 days**	**T+5 days**
Average excess return on winners sold	0.944	1.805	2.188
Average excess return on losers unsold	-16.07	-7.44	-16.27
Difference in excess returns	17.014	9.245	18.458

For winners that were sold, the average excess returns holding the trade for T+1, T+3 and T+5 are 0.944, 1.805 and 2.188, respectively. Indicating that when a trade was held for a longer period, the returns increased markedly. For losers that were unsold, the average excess returns holding the trade for T+1, T+3 and T+5 are -16.07, -7.44 and -16.27, respectively. For losing trades that were unsold, the losses escalate exponentially as the day passes.

Table 9

Trade statistics by duration are classified under three trading strategies – Scalping, Day trading, and Swing trading.

All FX pairs	**All traders**		**Scalping ≤5mins**		**Day trading >5mins to ≤1 day**		**Swing trading >1 day**	
	USD	Duration*	USD	Duration*	USD	Duration*	USD	Duration*
Median	0.83	00:01:18	0.38	00:00:02	0.97	00:01:37	0.34	01:13:01
Mean	6.18	00:05:56	9.53	00:00:02	6.43	00:04:02	-4.40	01:19:00
Transactions	825,564		113,537		660,018		52,009	
Proportion	100%		14%		80%		6%	

*Duration in days:hours:minutes

Scalpers take advantage of small intraday price moves as small as five pips per trade, and the trade duration could vary from a few seconds to a few minutes. Scalpers tend to trade frequently and focus on one or a few specific liquid markets, e.g., only scalping EUR/USD. In this study, an investor that holds a trade for five minutes or less is classified as a scalper. Five minutes were arbitrarily selected, and about 14% of the dataset trades were contributed by Scalpers.

Day (Intraday) traders generally do not hold positions overnight and prefer to close them before the session ends. Their trading durations vary from minutes to a few hours, and they may have multiple open positions simultaneously. The majority (80%) of the trades performed between 2017 to 2020 were Day trades.

Swing traders hold open positions for several days. Investors who deploy such strategies require patience and fortitude, as they may sometimes have to hold on to paper losses for a period. In this study, traders who hold on to their positions for more than a day are classified as Swing traders, and these traders make up about 6% of the trades.

Table 10

The propensity of HME of Scalpers, Day (Intraday) and Swing traders.

This table reports the results of OLS regressions of the dependent variable, Change in Weekly Risk-Taking (ΔWkRT), against the independent variables, profit & loss (prior Gains). The sample period is from Jan 2017 to Jun 2020.

DV = ΔWkRT ***IV = Gain***	***Coeff***	***SE***	***t Stat***	***P-value***	***No of Traders***	***Observations***
Jan 2017 – June 2020						
Scalpers	0.2255	0.0093	24.249	0.000**	100	211
Day Traders	0.0127	0.0021	6.085	0.000**	1,574	13,687
Swing Traders	0.0001	0.0010	0.144	0.886	37	242

$*p<.05$

$**p<.01$

Note. The investors were sorted into three groups: Scalpers, Day, and Swing traders. The data was first sorted by trader ID for the identification of trading strategy – Scalpers (≤5mins), Day traders (>5mins to ≤1 day), and Swing traders (>1 day). For example, if the majority of a trader's transactions are conducted >5mins to ≤1 day, the trader will be classified as a Day trader.

The results show that Scalpers display the highest house money effect (*Coeff*), followed by the Day and Swing Traders. Results for the Swing Traders are not statistically significant, with a *t*-statistic of 0.144 and a P-value of 0.886.

One possible explanation is that the Scalper has not integrated the winning as part of the trader's own and decided to risk it for more sizeable gains. Scalpers could also be momentum traders initiating larger or more trades in the direction of the previous winning trade or breakout. It may also suggest that Scalpers are predisposed to this form of bias – they enjoy large trades on quick successions. On the other hand, the Day and Swing traders, having more time to process their trades and take stock of their positions, may be less influenced by the HME.

Table 11

The propensity of HME of Scalpers, Day (Intraday) and Swing traders – validation exercise.

This table reports the results of OLS regressions of the dependent variable, Change in Weekly Risk-Taking (ΔWkRT), against the independent variables, profit & loss (prior Gains). The sample period is from Jan 2017 to Jun 2020.

DV = ΔWkRT ***IV = Gain***	***Coeff***	***SE***	***t Stat***	***P-value***	***No of Traders***	***Observations***
Jan 2017 – June 2020						
Grp 1 (Scalpers+Day)	0.1424	0.0053	26.7502	0.000**	523	4228
Grp 2 (Day)	0.0239	0.0032	7.4631	0.000**	540	5511
Grp 3 (Day+Swing)	0.0104	0.0028	3.6688	0.002**	520	7032

**p<.05*

***p<.01*

Note. The investors were sorted into three groups: Group 1 (Scalpers + Day traders), Group 2 (Day traders) and Group 3 (Day + Swing traders). The classification of trading strategies is – Scalps (≤5mins), Day trades (>5mins to ≤1 day), and Swing trades (>1 day).

The results show that Group 1 - Scalpers + Day traders displayed the highest house money effect (0.1424), followed by Group 2 – Day traders (0.0239) and Group 3 – Day + Swing traders (0.0104). This is consistent with the results in Table 10 that HME is more prevalent in Scalpers.