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Retail Investors and Moving Averages: What is There to Learn?

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ABSTRACT

The existing body of literature demonstrates that market participants use signals drawn from technical analysis strategies as a reason to trade. We use retail user holdings data from the US market to contribute insights on how investors trade key moving average signals. Our findings confirm that retail users do use moving average signals as a reason to change their portfolio holdings. We find that the contrarian behavior disposed by retail investors is prevalent in how retail investors trade between buy signals and sell signals. In addition, there exist a difference in the asset selection by retail investors between buy signals and sell signals on moving average strategies. Our paper is first to find that retail investors are late to trade moving average signals, trade moving average signals in the after-hours market, and trade on the signals generated by exchange-traded fund assets.

KEY WORDS: Technical analysis, Momentum, Retail Investors

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SECTION A: Introduction

Financial markets are composed of many investors, who all hold different expectations of future asset prices. For the most part, market participants rely on fundamental analysis and technical analysis to base their opinions. Fundamental analysis relies on the expectations of discounted future cashflows to build a share price valuation. In contrast, technical analysis uses historic asset prices to predict future asset prices. Both applied methodologies are extremely different as they use different information sets that occur in different time frames. Fundamental analysis is forward looking while technical analysis is backward looking. The market efficient hypothesis stipulates the use of past information cannot be used to outperform the market. According to this theory, agents cannot use technical analysis decision rules to outperform the market. Many findings in the literature suggest that technical analysis cannot be used to outperform the buy and hold strategy. Dolvin (2014) finds that the returns of moving average strategies do not beat a simple buy and hold strategy. However, he finds that moving average strategies present more efficient portfolios due to their higher Sharpe ratios. This gives reason to believe that applying technical analysis strategies to asset prices is favorable as it lowers overall portfolio risk. In addition, the existing literature finds that market participants use technical analysis when deciding on portfolio allocations. A questionnaire presented to fund managers revealed that 87% of participants apply some form of technical analysis when making decisions to trade (Menkhoff, 2010). The efficiency and market application of technical analysis gives reason to believe that it is a prevalent topic in our current financial markets.

The increasing use of technology in our society has made it ever easier for retail investors to access financial markets. The rise of online trading platforms allows unsophisticated investors access to financial markets at low cost. In addition, the increased negative awareness towards high trading fees has enhanced the shift from brokerage accounts to online trading platforms. The existing body of literature has evolved to develop insights on the tendencies of retail investors as they trade financial securities. This area of the literature is fairly limited since access to retail data is not easily available. The rise of the Robinhood online trading platform has increased the availability of retail investor data. Using this new and unique retail data, our study provides insights on how investors trade on technical analysis signals. More specifically, our study is focused on the use of moving average signals due it’s wide use in the exiting literature and relative simplicity. Fritz & Weinhardt (2015) confirm that the aggregate volume activity among retail investors increases up to 11% on moving average signals derived from speculative products in Germany. Our unique retail user holdings data have allowed us to contribute towards existing findings in the literature. First, we confirm that retail investors in US markets trade on moving average signals. Second, our findings suggest that retail investors *in aggregate* trade on moving average signals. Existing findings in the literature use volume to measure activity surrounding key moving average signals. Our approach uses changes in retail user holdings to give each investor equal weighting, thus giving a better aggregate representation of retail investor activity.

Many findings on the behavior of retail investors suggest that they adopt contrarian tendencies when selecting assets in their portfolios. Thus, they are more likely to sell good performing assets and purchase bad performing assets. Boehmer et al. (2019) finds that retail investors display contrarian tendencies for periods up to 6 months. Our unique data on retail user holdings confirms that retail investors are contrarian. In addition, we test if contrarian tendencies are prevalent in how retail investors trade moving average signals. The use of changes in retail user holdings allow us to test this hypothesis since we can make interpretations on the direction of activity. The use of a volume metric only captures the magnitude of the activity and not the direction. Furthermore, existing literature has categorized retail investors of being holders of assets that are large, liquid and volatile (Boehmer, 2019). We confirm these findings regarding the asset selection choices of retail investors using our unique database. In addition, we test to see if there exist a difference in the assets that retail investors use to trade moving average signals compared to aggregate assets held by retail investors.

Throughout his paper on the activity surrounding moving average signals, Etheber (2014) revealed that investors try to time the market when trading moving average signals. He finds that there is an increase in volume activity in the days leading up to the signal. In addition, he finds that volume activity peaks on the day of the signal and that volume activity remains persistently higher in the days following the signals. Our unique Robinhood stock database from the US market are used to confirm the findings by Etheber (2014). We are able to contribute to this analysis by studying the changes in retail user holdings on the days leading up to and following a moving average signal. We expect a difference in market timing behavior since retail investors behave differently than other market participants. In addition, we study retail activity in the after-hours market to uncover if and how retail investors trade moving average signals in that market. This question has never been overlooked in the existing literature.

Our study uses changes in retail user holdings across 2241 common shares and 1787 exchange-traded funds occurring between May 4, 2018 and December 31, 2019. The sample period is limited by the short existence of the Robinhood trading platform. We use changes in retail user holdings to gather insights on how retail investors use moving average signals to trade equities and exchange-traded fund. Our paper is the first to address if retail investors use moving average signals to trade diversified portfolios, such as exchange-traded funds. There is reason to believe that investors would trade on exchange-traded funds due to their higher disposed profitability, lower standard deviation, and higher Sharpe ratios in relation to individual common share assets (Ahmad et al., 2018). We find that retail investors in US markets use common share asset moving average signals as reason to trade. In addition, our results suggest that investors trade on the moving average signals of exchange traded funds. The level of activity on moving average signals increases as the lag lengths used to calculate the indicator increases. When comparing the activity across sell signals and buy signals, we find clear evidence of the contrarian behavior of retail investors. Retail investors increase their holdings on sell signals more than they do on buy signals. Thus, retail investors purchase more on signals that have had recent poor performance than they do for signals that had recent good performance. This finding is of contribution to the exiting literature and is only possible due to our unique data on retail user holdings. The timing behavior of retail investors surrounding key moving average signals suggest that retail investors are late to trade moving average signals. The changes in retail user holdings is positive and peaks on the day following the day of the signal. We find differences in the assets that investors use to trade between buy signals compared to sell signals when aggregating activity into firm fundamental metric quantiles. Retail investors use buy signals to trade small, illiquid, and volatile assets while sell signals are used to trade large, liquid, and volatile stocks. Lastly, we find that retail investors use the after-hours market to trade moving average signals.

The rest of the paper is separated in the following sections. Section B presents the literature review used to derive the proposed research topic. Section C explains the data, and section D highlights the methodology applied in deriving moving average signals. Section E presents key descriptive statistics to confirm existing literature findings. Sections F to I present insights uncovering how retail investors trade moving average signals. Section J summarize the findings and section K presents the appendix containing key tables and graphs.

SECTION B: LITERATURE REVIEW

Our paper contributes to the area of literature pertaining to the use of technical analysis trading strategies by retail investors, a group of market participants. The relevant literature can be divided among the participation of retail investors in the market, the profitability and use of momentum strategies, application of technical analysis by market users, and the factors affecting the profitability of technical analysis.

SECTION B.1: PARTICIPATION OF RETAIL INVESTORS

The existing body of literature only contains a handful of contributions regarding retail investor behavior as this data is rare. Our research uses the new Robintrack database derived from the Robinhood trading platform. The database presents the cumulative count of users holding a specific stock. This data enables us to study and understand the overall behavior of retail investors in North American stock markets. Existing literature on the subject of retail investor behavior shows the type of stock characteristics individual investors pay attention too. Using individual investor activity data from a brokerage firm, Gargano and Rossi (2018) demonstrate that retail investors pay attention to stocks that have high research and development costs, high market to book ratios, high market capitalization, as well as high leverage. These characteristics also represent the stocks that retail investors hold in their portfolios. Using individual investor accounts, Boehmer et al. (2020) demonstrates that retail investors tend to purchase aggressively in firms that are large, have high turnover, high volatility, and show signs of growth. Etheber et al. (2014) uses activity from a German discount brokerage to add that retail investors tend to trade on stocks that are young, volatile, large and have momentum. This section of the literature provides an understanding of the desirable firm characteristics that an investor considers when purchasing stocks for their portfolios. The existing body of literature concludes that retail investor asset choices mainly consist of firms that are large and display traits of uncertainty with potential to achieve high growth.

SECTION B.2: PROFITABILTY AND USE OF MOMENTUM STRATEGIES

Many findings suggest that the momentum anomaly, which has been widely researched and used in financial research, can deliver positive and abnormal returns. The momentum strategy, first documented by Jegadeesh and Titman (1993), consists of ranking stocks according to a certain metric system. In their case, stocks are ranked according to previous period returns. The long portfolio consists of the top percentile in performing stocks while the short portfolio is made up of the lowest percentile in performing stocks. As the portfolios are formed, the investor purchases the long portfolio and sells the short portfolio. Jegadeesh and Titman (1993) are able to produce positive and significant returns for all of the studied portfolios based on different lag performance horizons and different holding periods. Their findings demonstrate that the strategy using the past 12-month lag performance horizon and holding the portfolios for the next 3 months yields the most significant and positive returns (Jegadeesh and Titman, 1993). Further studies on the topic of momentum tested these findings in other international markets and included assumptions for transaction costs. Agyei-Ampomah (2007) studied this momentum-based strategy in the United Kingdom using previous asset returns as the metric criteria. After including assumptions for transaction costs, his findings suggest that transaction costs limit profits of momentum strategies in the shorter horizons but are still able to achieve profitability when longer holding periods are used (Agyei-Ampomah, 2007). In addition, Agyei-Ampomah (2007) finds that the “winner” and “loser” portfolios mostly consist of illiquid stocks with small market capitalization. These findings suggest that profitability from momentum-based strategies is best when performed on small illiquid stocks.

The momentum anomaly triggered further research to find new possible anomalies that use the long-short portfolio concept. Chen (2003) uses fundamental firm characteristics such as firm size, book to market ratio, and dividend yield as the metric criteria to form the long and short portfolios. His findings suggest that portfolios formed on firm specific characteristics can be used to predict future returns for longer periods of time since these characteristics are more stable across time (Chen, 2013). Other creative market anomalies that have been found, such as some based on technical analysis metrics. Park (2010) uses the moving average ratio (MAR) between the short-term and long-term moving average to form his portfolios. Findings from this anomaly suggest that the MAR has predictive power on several different moving average combinations of different lag lengths. Lastly, George and Hwang (2004) show that ranking portfolios based on the ratio between the current stock price and the 52-week high has predictive power on future returns.

Although the findings on the momentum anomaly give sufficient reason for its use in the market, evidence suggests that not all market participants use momentum when making investment decisions. Boehmer et al. (2020) uses data from American markets to study the behavior of retail investors and find that retail investors demonstrate contrarian tendencies for time horizons up to 6 months. Retail investors tend to purchase poor performing securities and sell good performing securities, which is completely contrary to the momentum strategy. The contrarian behavior of retail investors has been documented in other international markets. Grinblatt and Keloharju (2002) use a unique Finnish database made up of several market participants to study momentum behavior. They find that foreign investors, mostly comprised of mutual funds, hedge funds, and foreign investment banks, display momentum behavior when purchasing and selling assets (Grinblatt and Keloharju, 2002). However, Finnish households comprised of retail investors display contrarian behavior for all studied horizons (Grinblatt and Keloharju, 2002). Kyrolainen and Perttunen (2003) follow up on these findings only using Finnish information technology stocks from a different time period. They find that household investors demonstrate contrarian tendencies even across high growth industries (Kyrolainen and Perttunen, 2003). Lastly, Dalt et al. (2018) find that retail investors display more contrarian tendencies towards common shares than on exchange-traded funds (ETF). The overall findings from this literature suggest that momentum trading strategies are profitable and should be applied by market participants. However, retail investors are contrarian, and go against the proven success of momentum strategies. We revisit these findings in our paper when observing the activity of retail investors surrounding key technical analysis signals.

SECTION B.3: APPLICATION OF TECHNICAL ANALYSIS BY MARKET PARTICIPANTS

The valuation of financial securities has been, for the most part, segregated among two different methodologies: fundamental analysis and technical analysis. The latter is widely criticized by the efficient market hypothesis with the notion that past asset prices cannot be used to predict future asset prices. The emergence of this theory has not stopped market participants, including retail investors, from using technical analysis as a form of decision-making criteria when purchasing and selling assets. Menkhoff (2010) conducted a survey on 692 fund managers across 5 countries and found that 87% of participants claimed to put some form of importance on technical analysis when making decisions. There are participants in the market who only use rule-based trading rules when making trading decisions. Nagel (2004) finds that 25% of the volume on the NYSE and AMEX exchange is from rule-based trading, with momentum strategies having the largest contribution. This suggests that technical analysis is applied in markets since technical analysis strategies purchased recently good performing stocks and sell recently poor performing stocks. Researchers have recently been analyzing why market participants decide to use technical analysis. Ebert and Hilpert (2019) find that the distribution of returns from simple technical analysis trading rules are rightly skewed, thus presenting “lottery-like” payoffs. While the payoffs are often small losses, the infrequent very large gains have attracted market participants to technical analysis. In addition, the increase in technology has allowed online trading platforms to offer more sophisticated graphical resources to its users, which has increased the amount of market participants using technical analysis (Hoffmann and Shefrin, 2012).

The field of technical analysis is extremely broad, with a wide selection of indicators to choose from when making trading decisions. Our study solely focuses on the moving average trading strategy due to its simplicity and wide use in the literature. A moving average is simply an average of previous asset prices over a fixed period of time. The moving average trading strategy uses current asset prices and the moving average indicator to form trading decisions. The signal is generated when asset prices crosses above or below the moving average indicator. Evidence from the current literature shows that retail investors volume increases by 35% on chart patterns and by 11% on moving average signals (Fritz and Weindhart, 2015). These results are consistent with those of Etheber et al. (2014) who claim that retail trading volume surges between 6% to 88% on a given signal. Our results could be different as we account for the unique characteristics of our Robinhood database, which will be outlined in the data component (section C) of our paper. In a separate paper, Etheber (2014) adds that trading activity increases by 25-55% on “buy” signals, while only increasing by 15-25% on “sell” signals. This finding can be explained by several factors, such as: investors refrain from shorting stocks; investors are unable to sell a stock on a sell signal, since they do not hold the stock; and by the disposition effect. The results regarding the application of technical analysis is sufficient to claim that investors use technical analysis trading strategies—even the simplest ones, like the moving average trading strategy.

SECTION B.4: FACTORS AFFECTING THE PROFITABILITY OF TECHNICAL ANALYSIS

Technical analysis is widely used in the financial markets, especially due to its simple ability to form decision rules. However, the body of literature surrounding the profitability of technical analysis has been mixed, with the general conclusion that profitability disappears when accounting for transaction costs. Brock et al. (1992) is one of the first to favor the profitability of technical analysis. They find that the difference in profits on simple trading strategies between "buy" signals and "sell" signals are positive and statistically significant on the Dow Jones index, between 1897 to 1986 (Brock et al., 1992). Even if the technical analysis strategy are profitable, it is possible that it won't beat the "buy and hold" strategy. Dolvin (2014) contributes to this statement arguing that moving average strategies cannot beat the "buy and hold" strategy but are still favorable because they provide a positive risk adjusted return. Thus, the returns from the moving average strategy are less volatile, produce a higher sharp ratio, and return a positive alpha value (Dolvin, 2014). The literature finds that the use of simple technical analysis strategies can be profitable and produce a positive risk adjusted performance, even though they may not outperform the "buy and hold" strategy.

The aforementioned studies on the overall profitability of technical analysis were applied to index-type securities. The body of literature has extended the study of technical analysis strategies towards securities from different asset classes and on securities with different characteristics. Marshall et al. (2009) argue that the profitability from simple trading rules, including the moving average strategy, is more profitable when applied to small and illiquid stocks. Bokari et al. (2005) finds a similar conclusion, arguing that technical analysis trading rules have higher predictability when the company size is smaller, but cannot conclude that profits are higher due to transaction costs. Since our database does not account for the very minimal transaction costs, we should find that small capitalization companies are more profitable. The profitability of technical analysis differs when applied to different asset classes. Ahmad et al. (2018) finds that returns from simple technical analysis trading strategies are more significant when applied to portfolios rather than individual stocks. Portfolios benefit from the diversification effect as it cancels out the noise from individual asset daily returns (Ahmad et al., 2018). Therefore, technical analysis strategies on exchange-traded funds should be more profitable since they represent *portfolios* of individual common stocks.

The profitability of technical analysis on portfolios can produce differing results when classified among different characteristics. Han et al. (2011) conclude that technical analysis trading rules on portfolios sorted by volatility can outperform the "buy and hold" strategy. Similar to what is said about individual common stocks, the profitability from technical analysis strategies increases when applied to illiquid exchange-traded funds (Huang, J. & Huang, Z., 2020). In addition, Shynkevich (2012) finds that returns from simple trading rules are significantly positive when applied to small capitalization portfolios. It is evident that the profitability derived from simple technical analysis rules increase when applied to small and illiquid assets, especially when applied to portfolio-type assets, such as exchange-traded funds. Lastly, the profitability from technical analysis strategies increases as the lag length of the moving average decreases (Han and Yang and Zhou, 2013 & Ahmad et al., 2018). One should thus expect a larger increase in retail holdings surrounding short-term moving averages due to the expected higher profitability.

SECTION B.5: RESEARCH PROPOSAL

Our paper will focus on gathering further insights on how retail investors trade on moving average signals as they appear in financial market. Market participants, including retail investors, have a desire to use technical analysis in financial markets. The positive profits and positive risk adjusted performance from technical analysis give reason for investors to use such rules when purchasing and selling securities. We test if market participants, including retail investors, trade on key moving average signals. Our literature suggest that retail investors display contrarian behavior in portfolio allocation decisions. We try to uncover if contrarian behavior affects how retail investors trade moving average signals. Furthermore, we see profitability increases when applied to small and less liquid common stocks and portfolios such as exchange-traded funds. These fundamental asset characteristics are contrary to what we see in the behavior of retail investors, who focus their attention and asset selection towards large liquid assets. We are interested to see if retail investors who trade on simple moving average signals try to trade on the assets that will give them the highest profits, or if they continue to trade on assets of high market capitalization that are liquid. In addition, our paper gathers contributing insights on the timing of moving average signals and determine if non-normal market hours are used to trade these signals.

Our proposed research topic is similar to that by Etheber et al. (2014) who study changes in volume around key moving average signals. However, our study is different to their study in numerous manners. First, our study focusses on a much larger database of retail investor activity from US markets rather than from German markets. The context for the retail investors is different, since they trade on different market exchanges from different continents. Second, our study focusses on the changes in number of investors holding the stock around key signals instead of the changes in volume balances. This provides a more accurate measure as to whether the investors trade on signals; the use of volume changes can be misleading because it can be controlled by a few investors. Third, our database provides investors with very minimal fees as well as the option to trade "fractional shares", which reduces the constraints placed on investors when purchasing securities. Fourth, the Robinhood trading platform allows for pre-market and after-market trading activity. This data gives us the ability to see if retail investors use additional market hours to trade key technical signals. Lastly, our paper will be the first to study the changes in retail activity around key technical analysis signals for exchange-traded funds.

SECTION C: DATA

Our paper develops an in-depth understanding on how retail investors behave around key technical analysis signals that arise from the moving average strategy. With the growth of technology and the migration towards the use innovative trading platforms, retail data has now become widely available to the public. Our recently available retail activity data is derived from the newly established fintech company Robinhood. Robinhood provides a mobile application platform for everyday investors to purchase stocks, exchange-traded funds, and options. The platform was first founded in April 2013 and available for public use in March 2015. This new innovative trading platform is very successful due to its ability to provide investors minimal transaction fees as they purchase and sell financial securities.

In addition to its low trading fees, Robinhood provides other unique benefits to its users. First, users of the platform have the ability to purchase financial products created by the Robinhood Company. This allows retail investors with low financial knowledge to purchase well-structured financial products with minimal effort. Second, investors have the ability to purchase fractional shares. Robinhood users can purchase expensive company shares even if they do not have the full dollar amount to purchase one full share of a listed security. This unique feature is a privilege to everyday investors and may impact our results on retail investor behavior when compared to the existing literature. Lastly, Robinhood gives its users access to the pre-market and after-market trading hours.

Although the platform brings many advantages to its users, it does present some drawbacks that will limit our study. The data provided by Robinhood does not present any information regarding the specific qualities of the retail investor. This information would be interesting because it would allow us to develop insights on which type of investors are acting on technical analysis signals. Moreover, the Robinhood trading platform does not allow investors to engage in short selling. We assume that investors are only able to enter long positions when trading moving average strategies.

Our primary data is obtained from the "Robintrack" public website, which is derived from the Robinhood trading platform. The Robinhood trading platform allows users to see the number of users that are currently holding a position in the asset of interest. On an hourly basis, the Robintrack platform keeps track of the retail user counts for each asset on the platform. The size of our database is limited since the Robinhood trading platform is still relatively new. Our first observation starts on May 4, 2018 and ends on December 31st, 2019. For the purposes of our study, we only keep the closing retail user holdings for each stock at the end of each market trading day. We select the first observation of each asset on each trading day that occurs after 4 p.m. Eastern Time (ET). In addition to these final daily close holdings, we compile the after-market stock holdings. The after-hours trading market takes place between 4p.m. and 6p.m. ET. To account for the close holdings in the after-hours market, we keep the first observation of each asset at each point in time occurring after 6 p.m. Although the Robinhood data allows for pre-market trading, this information is limited in the Robintrack database, and will therefore not be used in our analysis. The data provided by Robintrack is comprised of 8392 unique financial assets, ranging from common share assets to exchange-traded funds and Real Estate Investment Trust (REIT). In the initial gathering of the Robinhood data, we have eliminated any security that does not have any retail holdings throughout the studied period.

Our study gathers asset security information from both CRSP and COMPUSTAT to compliment the Robinhood database. The CRSP database is used to gather information on the daily closing share price, the daily volume, and the asset share code. For the purposes of our study, we are only interested in assets that are classified as either common shares or exchange-traded funds. Thus, we only keep securities with share code 10 & 11 to reference common shares and share code 73 to represent exchange-traded funds. The closing price data from CRSP is used to develop the moving average trading strategies, and for the calculation of asset returns. Similarly, the closing price data and volume from CRSP are used to calculate firm-specific fundamental metrics, such as firm volatility and firm liquidity. Quarterly security data is acquired from COMPUSTAT to build additional firm fundamental metrics. Some of these metrics include firm size, firm market to book ratio, and firm research & development expenses. This information is gathered to build an understanding of the types of securities that retail investors like to hold in their portfolios. We eliminate any asset that does not have complete COMPUSTAT quarterly information. After merging all the data from Robintrack, CRPS, and COMPUSTAT, we end up with a database of 2241 stocks and 1787 exchange-traded funds. The database provides over 18 months of data, ranging from May 4, 2018, until December 31, 2019. Our database is limited to December 31, 2019, because this is the last date in which information from the CRSP database is available.

SECTION D: METHODOLOGY

The well-known market efficiency hypothesis stipulates that in a weak form efficient market, historic asset prices and information cannot be used by investors to generate returns that can outperform the market. This implies that any technical analysis trading rule derived from historic asset prices cannot outperform the market buy & hold strategy. The proven underperformance of technical analysis strategies has not prevented all classes of investors to use or make reference to technical analysis when making trading decisions. Investors continue to use technical analysis signals as a reason to trade financial securities.

The term *technical analysis* can be defined as the practice of using historic asset prices to form trading decision rules to predict the direction of unknown future asset prices. The field of technical analysis is very wide and holds many different forms of application. The first form of technical analysis, known as "charting," occurs when an investor tries to use reoccurring chart patterns to develop buy and sell signals. For example, investors will draw support and resistance lines on a stock chart and form trading decisions when prices surpass these key levels. The second form of technical analysis uses specific formulas on historic asset prices to calculate technical "indicators." Several well-known indicators used in practice and in the literature include: the Relative Strength Index (RSI), the Moving Average (MA), and the Moving Average

Convergence Divergence (MACD). The application of these indicators is stricter in comparison to charting, since chart patterns do not always replicate the exact same pattern.

For the purpose of our study, we focus on the technical analysis trading rules derived from one specific class of indicators—moving average (MA) indicators. There are several reasons to express why we have centered our attention on moving average signals. First, the moving average indicator is very simple to use and calculate. It is simply an average of historic asset prices of a certain time period, at a specific moment in time. Second, the moving average indicator has been widely studied in the existing body of literature. The unique information from Robintrack allows us to contribute new knowledge on existing findings. Third, the moving average indicator is well known in practice and tends to automatically appear on a stock chart. For example, when opening a stock chart, it is common to see the share price accompanied with the standard 200-day moving average. Lastly, several variations can be used to calculate a moving average, thus giving us much room for developing an in-depth analysis. Variations in the calculations of the moving average indicator includes changing the method of calculating the indicator, changing the way the indicator is used to generate signals, and changing the applied lag length of values for calculating the indicator. Further details on the different methodologies to deriving a moving average are explained in the following sections.

SECTION D.1: THE SIMPLE MOVING AVERAGE vs. THE EXPONENTIAL MOVING AVERAGE STRATEGY

Several variations using the same information can be used to calculate the moving average indicator value. The simple moving average (SMA) is the simplest form and the easiest moving average to calculate. The simple moving average is calculated by taking the average of the closing prices for a desired lag length period. For example, the 50-day simple moving average (SMA) consists of calculating the average closing price of a financial security over the last 50 observable asset prices. The value of the moving average indicator is adjusted daily. Other forms of the moving average have been studied in the literature and applied in the field. Dolvin (2014) studied the difference between the simple moving average (SMA), the exponential moving average (EMA), and the linear moving average (LMA). For the purposes of our study, we focus on the simple moving average and the exponential moving average for the following reasons. First, both moving average indicators presents several differences in the way they are calculated. The simple moving average uses an equal weighted approach, which gives each day in the calculation the same proportion. The exponential moving average provides more reference towards recent prices. Details on the difference in calculations between the simple moving average and the exponential average are presented later in this section of the paper. Second, exponential moving average is presented in addition to the simple moving average because it is used in the calculation of other well-known indicators. For example, the 12-day EMA and 26-day EMA are both used in the construction of the widely used Moving Average Convergence Divergence (MACD) indicator. We provide **GRAPH #1** to illustrate the difference between the simple moving average and the exponential moving average, in which both indicators are calculated using the same lag length period. GRAPH #1 demonstrates that when the share price of AAPL is increasing, the 50-day EMA (red line) is above the 50-day SMA (blue line). When AAPL share price is decreasing, the 50-day EMA (red line) is below the 50-day EMA (blue line). This demonstrates that the 50-day EMA is more responsive to the recent changes in security prices because it puts more emphasis on recent asset prices in its calculation. Dolvin (2014) claims that the increased weight on recent prices when calculating the exponential moving average allows to efficiently identify trend reversals, thus improving the alpha and Sharpe Ratio of a trading strategy. There exists a structural difference in the calculation process of these two indicators. The calculation of the simple moving average (SMA) consists of an equal weighted average of all selected observation. For example, the 5-day simple moving average is calculated as follows:

$$\textbf{SMA} = \frac{\sum_{s=0}^{\mathbf{N}} \mathbf{P}(-S)}{\mathbf{N}}$$

P = Closing Price of Security
P(-x) = Closing Price of Security "x" lag days ago
N = The Number of Observations (Our case = *5)

The calculation of the exponential moving average uses a weighted value approach, which gives recent observations more relevance. The formula to calculate the 5-day exponential moving average (EMA) is as follows:

$$\textbf{EMA} = \textbf{P} \times \textbf{K} + \textbf{EMA}(-1) \times (1 - \textbf{K})$$

$$\textbf{K} = 2 / (N + 1)$$

P = Closing Price of Security
P(-x) = Closing Price of Security "x" lag days ago
N = The Number of Observations (Our case = *5)
K = The Weighted Multiplier

The exponential moving average makes a direct reference to the product of the current security price and the weighted multiplier “K.” When we increase the lag length (N) of the moving average, we decrease the “K” value and thus decrease the contribution of current price “P” to the calculation of the exponential moving average. In any case, the current price “P” will have nearly twice the representation in the exponential moving average then it will in the simple moving average. This can be seen in the formula of the weighted multiplier “K.” For example, suppose we compare the 5-day SMA to the 5-day EMA. In the 5-day SMA, the last closing price has a weighted representation of 20%. However, in the EMA, the last closing price will have a weighted representation of 33.3%. This difference in the calculation between the SMA and the EMA can be used to explain the behavior observed in GRAPH #1. The observable difference among both indicator methodologies gives us reason to believe that there exists a difference in how market participants respond to them.

SECTION D.2: THE SINGLE MOVING AVERAGE STRATETGY Vs. THE DOUBLE MOVING AVERAGE CROSSOVER STRATEGY

The different methodologies used in the calculation of the moving average indicator will generate different results. The same is true when considering the different methodologies in which a calculated moving average can be used to develop trading signals. The first trading signal generating methodology, based on moving average indicators, is the single moving average. This method was widely used by Brock et al. (1992), who was one of the first to argue in favor of the profitability of technical analysis trading rules. The single moving average methodology consists of developing trading rules using the closing price of a security and the selected moving average. When the price of a security closes above the selected moving average, a “BUY” signal is generated. This buy signal is held until the asset price closes below the selected moving average, thus forming a “SELL” signal. Our study will only focus on long moving average trade signals, since short selling is not permitted on the Robinhood trading platform. Emphasis is still be put towards sell signals to understand if these signals present an indication for retail investors to refrain from holding a security or selling a security they already own.

Our paper also studies the double moving average crossover methodology. Ebert & Hilbert (2013) widely used the double moving average crossover methodology in their paper when studying the utility derived from moving average strategies. The double moving average crossover methodology consists of 2 moving averages: a short-term moving average and a long-term moving average. The short-term moving average responds more quickly to recent changes in asset prices, since it holds a larger representative proportion on the recent price observations compared to the long-term moving average. In the double moving average crossover methodology, a "BUY" signal is generated when the short-term moving average pierces the long-term moving average from below. An investor will hold the long-term position until the short-term moving average pierces the long-term moving average from above, thus generating a "SELL" signal.

The presentation of findings in **GRAPH #2** illustrates some of the key differences between both moving average methodologies. Panel A presents an example of the single moving average methodology on AAPL security, while Panel B presents the double crossover moving average methodology on AAPL security. In each panel, we highlight a few moments in time in which "BUY" signals (in green writing) and "SELL" signals (in red writing) are generated to illustrate how each methodology can be used. The graph demonstrates some of the key differences between both methodologies. First, the single moving average methodology makes direct relation to the asset prices when making trading signals, while the double crossover moving average methodology only makes reference to the price indirectly through both moving averages. Second, more trading signals are generated from the single moving average methodology than there are in the double crossover moving average methodology. Our paper develops insightful findings by comparing the performance and investor activity between both signal generating methodologies.

SECTION D.3: FINAL SELECTED TRADING RULES FOR OUR STUDY

We can differentiate moving average strategies by changing the manner in which we calculate the indicator value. Our paper focuses on the simple moving average (SMA) and exponential moving average (EMA) approach. In addition, we can differentiate our strategies by changing the method in which we assign signals. We focus our attention toward the single moving average methodology and the double moving average crossover approach. When we put this all together, we end up with *four* different moving average trading methodologies:

1. Simple Moving Average (SMA) + Single Moving Average Method
2. Simple Moving Average (SMA) + Double Crossover Moving Average Method
3. Exponential Moving Average (EMA) + Single Moving Average Method
4. Exponential Moving Average (EMA) + Double Crossover Moving Average Method

For each of the four applied moving average trading methodologies, a series different lag length moving averages are included. The lag lengths used for the simple moving average methodology (SMA) include the 5-day, 10-day, 20-day, 50-day, 100-day, and 200-day. The choice for these moving averages were taken from various readings in the literature regarding moving average trading strategies. As for the exponential moving averages (EMA), we include the 5-day, 10-day, *12-day, 20-day, *26-day, 50-day, 100-day, and 200-day lag lengths. The 12-day and 26-day lag length's moving averages are added to the list of the exponential moving averages due to their use in the formation of the widely known Moving Average Convergence Divergence (MACD) indicator. This information will serve to see if retail investors trade other moving average indicators, such as the MACD. The aforementioned lag length values are used in the double moving average crossover trading strategy. Our proposed list of double moving average crossover strategies is formed using both simple moving average (SMA) values and exponential moving average (EMA) values. We developed a total of 27 different moving average trading decision rules to better understand the behavior of retail investors as these signals appear. **TABLE #2** presents the full list of all trading strategies studied over the course of our paper. The 27 trading strategies are divided among the four previously mentioned principle moving average trading methodologies.

SECTION E: DESCRIPTIVE STATISTICS

Our gathered findings from existing literature mainly focused on understanding the behavior of retail investors, momentum-based trading strategies, as well as profitability & the use of technical analysis. Using compiled data from Robintrack, CRPS, and COMPUSTAT, we try to develop a better understanding on the actions of retail investors. First, a combination of the retail user holdings data from Robintrack, and quarterly fundamental data from COMPUSTAT, and daily CRSP data are used to describe the types of assets retail investors hold in their portfolios (in aggregate). Second, using CRSP asset prices and Robintrack retail user holdings data, we determine whether retail investors demonstrate contrarian or momentum tendencies when selecting assets to hold in their portfolios. Third, CRSP daily asset price data is used to describe the return distribution across all different moving average methodology trading strategies. Lastly, we combine CRSP data with Robintrack retail user holdings data to determine whether retail investors use moving average signals as a reason to engage in financial markets. All of these areas of interest make a distinction between common share assets and exchange-traded fund assets. This following section of our paper tries to confirm some of the existing findings from our body of literature, while contributing additional knowledge when applicable.

SECTION E.1: AGGREGATE HOLDINGS OF RETAIL INVESTORS

Using retail user holdings data from Robintrack, we describe at the aggregate level, which fundamental asset characteristics are of interest to retail investors. The general findings in our literature show that retail investors tend to favor stocks that are large, liquid, and present some form of uncertainty (Boehmer et al., 2002 & Gargano and Rossi, 2018). Our unique database presents many differences from other databases used in the existing literature to describe retail investor holdings. First, our database is comprised of a much larger retail base, allowing us to improve the aggregate description of the average retail investors. Findings by Gargano & Rossi (2018) use brokerage account data comprised of 11,000 users. Our end sample is significantly larger as it comprises of over 7 million retail users. Second, our large database is focused solely on retail users. Boehmer et al. (2002) applied a specific methodology to identify retail orders from institutional orders throughout a wholesaler brokerage firm database. For example, retail order balances were identified by the price improvement given by wholesaler brokers to retail investors (Boehmer et al., 2002). However, there still exists a possibility that the orders marked as “retail” may not actually be by a retail investor. Our database is unique and of advantage as it is comprises solely of retail users. Lastly, our data involves the count of users holding a stock at a specific moment in time. Each retail investor is given equal weighting in our analysis. Most of the existing literature uses volume order balances, which can limit findings as it gives more weight to large transactions.

We use COMPUSTAT quarterly fundamental data and CRSP daily data to develop some key fundamental metrics to address investor asset holding preferences. The selected metrics are consistent to those used by Boehmer et al. (2002) and Gardano & Rossi (2018). Some of these fundamental asset metrics include firm size, firm volatility, and firm liquidity. Due to the non-normal distribution of firms across most of the studied metrics, we take the natural log generate a more normal distribution. **GRAPH #3** presents a histogram of the distribution of firms by respective market capitalization. The values in Panel A are unadjusted, while the values in Panel B are adjusted using the natural logarithm. The distribution of firms by size (Panel A) is clearly skewed to the right, meaning our sample holds many small firms and a few extremely large firms. Therefore, our results would be heavily impacted by large outliers if this skew is to remain in the data. Taking the log of firm size (Panel B) gives the appearance that the distribution of firms is bell-shaped and normal. Many of our fundamental metrics suffer from this issue and therefore we apply log values when necessary. In addition, we separate the retail holdings and respective firm fundamental metrics data between common share assets and exchange-traded fund assets to uncover any possible differences across both asset types. Some of the metrics used to explain common shares may not be applied to exchange-traded funds, since the former are portfolios of stocks, rather than their own respective firms. For example, "profitability" and "research & development expenses" are used to explain common share holdings but cannot be used to explain exchange-traded fund holdings.

We use an ordinary least squares regression to explain the fundamental asset characteristics that are of interest to retail investors. Two separate regression analysis are conducted to account for differences between common shares and exchange-traded funds. The dependent variable in our regression model consists of the last observable retail holdings for each asset. The final retail users holding observations of each common share and exchange-traded fund asset are paired with the most recently calculated firm fundamental metrics. We provide a sufficiently large list of independent variables to explain the retail holdings. The **TABLE #3** provides a qualitative table of the name to each independent variable used in our regression model, as well as the COMPSUSTAT variable code names used to calculate the final fundamental metric.

Results from our ordinary least square regression are presented in **TABLE #4**. Several conclusions can be drawn from the interpretations of the regression results. First, retail investors are attracted to large assets as represented by the positive and significant coefficients for both common shares and exchange-traded funds. This finding is consistent with our selected literature. Second, retail investors like to purchase common shares that dispose high volatility and high research & development expenses, as presented by the positive and significant coefficients. These findings are consistent across the literature and capture the message that retail investors like to purchase stocks with a sense of uncertainty. Firms spending large lump sums of money towards research & development express a sense of uncertainty, since there is no guarantee that they will ever see this money again. Third, the regression output suggests that retail investors like to hold assets that are liquid. We have used 3 different measures to represent liquidity ("log liquidity," "log 1/close," "log volume") due to the varying approaches used in the existing literature. Details on the calculations to each liquidity metric is presented in TABLE #3. Of the 3 metrics, "log 1/close" and "log volume" were positive and significant across common shares and exchange-traded funds, suggesting retail investors hold liquid assets. The "log liquidity" metric across common shares had a negative coefficient sign. We believe this can be explained by the actual calculation of this metric. The "log liquidity" metric takes the sum of asset volume over the previous 1 month and divides it by the total shares outstanding. The coefficient regression output for "log liquidity" in TABLE #3 is negative and significant. This suggests that retail investors like to hold assets that have been relatively quiet over the past month. Retail investors may try to time the market by purchasing assets when they are quiet, with the hopes of holding the asset when significant material news arises. In addition, retail investors may be less likely to hold an asset that received a lot of attention over the previous month. In aggregate, we find liquidity to be an important metric for retail investors when selecting assets. Lastly, we find that retail investors tend to hold assets that have a high share price. These findings are of no surprise due to the ability of Robinhood traders to purchase fractional shares.

We accompany our regressing output table with a detailed bar graph founded on the same information to uncover additional insights on retail investor asset choices. For each independent variable used in our ordinary least squares regression, we chronologically rank all the firms from smallest to largest. Across all fundamental metrics, firms are placed into 4 quantile groups based on the following percentile rankings:

- **QUANTILE #1:** 0 – 24th PERCENTILE GROUP

- **QUANTILE #2:** 25^{TH} – 49^{TH} PERCENTILE GROUP
- **QUANTILE #3:** 50^{TH} – 74^{TH} PERCENTILE GROUP
- **QUANTILE #4:** 75^{TH} – 100^{TH} PERCENTILE GROUP

We take the average retail user holding counts for each quantile group allocated to each independent variable. This information is conveyed in **GRAPH #4** and uncovers additional interesting facts on retail investor asset choices. For example, the regression output table demonstrated that retail investors prefer to hold assets that have a high share price. Findings in GRAPH #4 demonstrate that retail investors are also attracted to firms with small share prices. The average retail user count for the quantile group #1 is nearly the same as that quantile group #2. This is of surprise since Robinhood users can purchase fractional shares of higher-priced assets. In addition to asset price, GRAPH #4 provides additional information to describe asset volatility. The regression output from TABLE #4 demonstrates that retail investors prefer assets of high volatility. GRAPH #4 reveals that, for both common shares and exchange-funds, quantile group #4 does not hold the highest average count in retail user holdings. Although retail investors are attracted to volatility, they tend to stay away from assets that present extreme forms of volatility. Lastly, our regression results did not find the "log market to book ratio" to be a positive and significant variable. The "log market to book ratio" in GRAPH #4 appears to show that as firms increase in market to book ratio, there is an increase in the average retail holdings across quantile groups. These findings may be impacted by a few extreme stocks with high retail holdings, giving the impression that retail holdings increase as the market to book ratio increases.

Our regression output table and bar graph present findings to describe retail holdings that are consistent to the existing literature. Retail investors tend to hold common shares and exchange-traded funds that are large in size, have liquidity, and present some form of uncertainty through high volatility.

SECTION E.2: RETAIL INVESTORS: MOMENUTM OR CONTRARIAN BEHAVIOR?

The use of momentum-based strategies when purchasing and selling securities is widely studied in the literature and has proven in some cases to outperform the simple buy and hold strategy. Additional research on retail activity finds that retail investors display contrarian behavior when deciding to purchase or sell stocks. Grinbhatt & Keloharju (2000) find that domestic investors in Finland display contrarian behavior. The data from their study is gathered from the Finnish Central Securities Depository (FCSD), which holds transaction data on practically all publicly traded Finnish stocks. Boehmer et al. (2002) found retail investors to display contrarian behavior for periods up to 6 months in North American markets. Our unique database allows us to extend on the existing knowledge of retail investor contrarian behavior. The aforementioned literature uses observed retail order transactions to describe contrarian behavior. Our study is unique as it uses the changes in aggregate retail user holdings count across all asset, giving each investor equal weighting in all calculations. Results will not be impacted by the actions of large investors. For example, one very large contrarian market order could dominate several small momentum-based market transactions and aggregate all investors as being contrarian.

We first apply an ordinary least squares regression to examine the contrarian or momentum-based behavior of retail investors. The daily log difference in retail user holdings is used as the dependent variable. This dependent variable is regressed on 5 different lag period asset returns:

- Previous Day Return
- Previous Week Return (not including the "Previous Day Return")
- Previous Month Return (not including the "Previous Week Return")
- Previous 3 Month Return (not including the "Previous Month Return")
- Previous 6 Month Return (not including the "Previous 3 Month Return")

The data used in this regression comes from a large panel data. Each asset at each date in time holds a value for each of the 5 aforementioned independent variables. This will cause much autocorrelations in the regression output because at each day, we re-calculate the 5 independent variables, where the only new added data point is the additional asset return from the new day. As a result, we adopt the Newey-West HAC standard errors adjustment to account for any specific heteroscedasticity and autocorrelation in the regression error terms. Further, our panel of data contains observations for each date in time across several different securities. We include security fixed effects to control for all variables that are constant across time, but that will vary across entities. In addition, we include a date fixed effect to account for variables that are constant across all entities, but that change over time.

The regression output table in **TABLE #5** makes the distinction between common share assets and exchange-traded fund assets to uncover any possible differences. The overall consensus from our regression suggest that retail investors display contrarian behavior when purchasing and selling assets. We break down the results by comparing different lag period asset returns across common shares and exchange-traded funds. First, retail investors display significant contrarian behavior for both common shares and exchange-traded funds following the previous 1-day return. For example, retail investors tend to purchase assets that had a negative return in the previous day. Second, consistent to the findings by Boehmer et al. (2002), we find that retail investors display contrarian behavior for periods up to 6 months. Retail investors are more likely to purchase assets that experienced a poor performance in the previous 6 months. In addition, retail investors display contrarian behavior for periods up to 6 months across exchange-traded funds.

We accompany our regression table with a simple graph to uncover additional information on the contrarian behavior of retail investors. In our selected literature, we discovered that retail investors display less contrarian behavior when trading exchange-traded funds than when they trade common shares (Dalt et al., 2019). The P-values in our regression results in TABLE #5 are more significant for exchange-traded funds than for common shares. However, this does not signal that retail investors are more contrarian towards exchange-traded funds than they are towards common shares. We can affirm with higher confidence that retail investors display contrarian behavior towards exchange-traded funds than we can affirm retail investors are contrarian towards common shares. The **GRAPH #5** displays the average change in retail holdings to the average change in asset returns across different lag periods. We only use the last observable day of each asset in formulating this graph. GRAPH #5 affirms that contrarian behavior is strongest in common shares than it is in exchange-traded funds. At each moment in time on GRAPH #5**,** the average asset returns for common shares (Panel A) is always lower than those of exchange-traded funds (Panel B). Contrarily, the increase in retail holdings is always higher for common shares (Panel A) than it is for exchange-traded funds (Panel B). Thus, it appears that retail investors are more contrarian towards common shares, since common shares lost more value than exchange-traded funds, yet more retail investors bought common shares. If investors had a momentum-based ideology, they would have purchased exchange-traded funds over common shares due to their better recent performance.

Our large and unique database has allowed us to add additional insights to the findings by Dalt et al. (2019) on the contrarian behavior of retail investors. First, we use a different and more recent time period to confirm retail investor contrarian behavior. Second, using data from US markets, rather than data strictly from Finland, we confirm that retail investors display less contrarian behavior towards exchange-traded funds than towards common shares. Lastly, the study conducted by Dalt et al. (2019) only studied 1 exchange-traded fund, consisting of 25 stocks that are part of the largest index in Finland; the OMX Helsinki Index. Our results confirm the contrarian behavior of retail investors across 1787 different exchange-traded funds.

SECTION E.3: RETURN DISTRIBUTIONS ACROSS DIFFERENT MOVING AVERAGE METHODOLOGIES

The main goal of this paper is to expand the existing knowledge regarding the application of moving average trading strategies. More specifically, we try to further examine the ways in which retail investors trade on these signals and how they do so when they arise. Prior to addressing the behavior of retail investors around key moving average trading signals, we describe the return distributions across all 27 different moving average strategies. We account for the following differences in the return distributions of moving average trading strategies:

- Methodology in the calculation of the actual moving average metric (*SMA Vs. EMA*)
- Methodology in signaling buy and sell opportunities (*Single MA Vs. Double MA*)
- Lag lengths in days used to calculate the moving average (*5-day vs. 200-day*)

Knowledge on the return distributions of moving average strategies may use useful in explaining the behavior of retail investors around different signals. In **TABLE #6** we present 6 key metrics to explain the return distribution differences across all of our 27 moving average trading strategies. The findings in TABLE #6 make the distinction between common shares and exchange-traded funds. We present the mean return per trade (*RET_TRADE), the standard deviation (*RET_STD), and the skewness of trade returns (*RET_SKEW), to describe the first three moments of the return distribution. On the left axis of TABLE #6, all 27 strategies are identified based on the four respective methodologies discussed and presented in the methodology section of the paper. The mean return per trade (*RET_TRADE) decreases as we increase the lag length of the moving averages across all 4 methodologies. This finding is consistent across common shares and exchange-traded funds. We find that the mean return per trade is higher when applied to exchange-traded funds than for common shares. This finding is reversed when accounting for differences between the single moving average and the double crossover moving average methodology. Thus, the double crossover strategy becomes more profitable on stocks than on exchange-traded funds as we increase the lag lengths of applied moving averages. Lastly, we find that most strategies are more profitable when using exponential moving averages. This finding is consistent with that of Dolvin (2014), who finds that profitability is maximized when using exponential moving averages due to their ability to produce higher Sharpe ratios and alpha values. Overall, the mean return per trade in our studied sample is highest when using short-term exponential moving averages on exchange-traded funds.

The second moment of the distribution, the standard deviation, is expressed by the variable *RET_STD in TABLE #6**.** This metric represents the standard deviation of all the identified trades across all assets per respective moving average strategy. First, we find that the standard deviation increases as we increase the lag length of the moving averages. Increasing the lag lengths of the moving averages increases the range size for winning and losing trades, thus increasing the variations of the trade returns. Second, we find nearly no difference in standard deviations when comparing the simple moving average to the exponential moving average methodology. Third, standard deviations from the double moving average crossover strategy are much larger than those in the single moving average strategy. Investors applying the double moving average crossover strategy should expect to uncover much more variations in their trade returns. Lastly, we find that the standard deviations across exchange-traded funds are much lower than those observed for common shares. The logical reasoning for this finding can be explained by the lower underlying daily returns across exchange-traded funds. The standard deviation of trade returns increases when using long-term moving averages through the double crossover methodology on common share assets.

The third moment of the distribution describes the level of skewness in the distribution of the trade returns. This metric is expressed by *RET_SKEW in TABLE #6. Across all 27 moving average methodologies, the distribution of returns tends to display a positive skew. A positive skew demonstrates that there are many observations that occur below the mean of the distribution, with a few observations occurring well beyond the mean. Ebert & Hilpart (2014) study technical analysis return distributions and describe the positive skew as a situation consisting of frequent small loses and infrequent large gains. In addition, TABLE #6 demonstrates that as was we increase the lag lengths of moving average trading strategies, the level of positive skew decreases. The ratio between the right tail (positive return tail) and the left tail (negative return tail) of the distribution starts to decrease and presents more room to experience large losing trades. This finding further explains why profitability decreases as we increase moving average lag lengths. Similarly, we find that the level of positive skew is lower in the double moving average strategy compared to the single moving average strategy. The double moving average crossover strategy takes longer to respond to recent changes in asset prices and can generate large losing trades, limiting any positive skew across returns. For example, suppose a trader is using the 50-day and 200-day double moving average crossover strategy. In the event of a large and quick reduction in an asset price, investors may still have a buy signal even while the asset price is well below both moving averages. The inability of the two moving averages to respond to the large and quick price reduction result in a large negative trade return. The possibility of a large negative trade generated by the double moving average crossover strategy extend the left tail (negative tail) of the return distribution and reduces the positive skew of the distribution.

TABLE #6 presents additional information regarding the tails of the return distributions and the mean return of all moving average strategies for the entire studied period. This information is presented in **GRAPH #6**. In this graph, we distinguish the single moving average strategy (Panel A) from the double moving average crossover strategy (Panel B). In each panel, we separate the information between common shares and exchange-traded funds. In addition, the x-axis of each graph presents different lag length moving averages in an increasing fashion. At each respective lag length moving average strategy on the x-axis, we provide a vertical line to express the mean returns in the tails of each strategy. The bottom end of the vertical line represents the mean return of the worst 5% trades (BOT_RET from TABLE #6), while the top end of the vertical line represents the mean return of the best 5% trades (TOP_RET from TABLE #6). The black vertical line represents common shares, while the red vertical line represents the exchange-traded funds. In addition, we provide a small dotted horizontal line at each strategy on the x-axis to express the mean return for the studied period (RET_PER from TABLE #6). The mean return for the studied period is in black for common shares and in red for exchange-traded funds.

The simplicity of this graph conveys a few key messages that express the differences in the return distributions. First, the mean returns to both extremities of the return distribution (vertical line) increases as we increase the applied lag lengths for both Panel A and Panel B. Investor applying larger moving averages in their trading strategies can expect larger returns but can also be accompanied by larger losses. Second, the return extremities of common shares always surpass those of exchange-traded funds. This can be explained by the higher standard deviations in the trade returns of common shares. Lastly, the return extremities of the single moving average strategy (Panel A) are much smaller than those observed on the double moving average crossover strategy (Panel B). Again, this finding can be explained by the higher standard deviation in the return distribution of the double moving average crossover strategy.

GRAPH #6 presents small dotted horizontal lines to address the overall profitability of each strategy over our studied period. The findings in this graph clearly demonstrate that the profitability of strategies is highest when applied to exchange-traded funds, rather than on common shares. Ahmad M et al. (2018) argues that moving strategies are more profitable on “portfolios” due to the lack of encountered daily noise and the diversification effect. However, the double moving average crossover strategy (Panel B) becomes more profitable on common shares compared to exchange-traded funds as we increase the lag lengths in moving averages. Second, GRAPH #6 highlights that the overall profitability of each strategy decreases as we increase the lag lengths of the moving averages. This finding is consistent across the single moving average strategy (Panel A) and the double moving average crossover strategy (Panel B). Han (2012) finds similar results, arguing that profitability is highest when using lower lag length moving averages. This may be explained by the decreasing positive skew of the return distributions as the applied lag lengths in moving averages calculations increases.

The overall findings from TABLE #6 on the return distributions of all different methodologies uncovers a few key findings that will be of use in the later sections of this paper. First, winning strategies from our sample occur on exchange-traded funds instead of common shares. In addition, winning strategies from our sample consist of using single moving averages. The use of the single moving average strategies limits big swings in trade returns, especially the negative trade returns, thus improving profitability. Lastly, the use of exponential moving averages would help the chances of developing a winning strategy due to their ability to respond more quickly to asset price changes.

SECTION E.4: TRADING BEHAVIOR OF RETAIL INVESTORS

We further extend our descriptive analysis by measuring and understanding the behavior of retail investors surrounding key moving average signals. Our first analysis tries to uncover how active a retail investor would be if they were to trade moving average signals on a consistent basis. These details are provided in **TABLE #7**. The two metrics used to measure the activity level of each strategy is the frequency of signals per trade (TRD_FRQ) and the average length of each trade (TRD_LEN). The average length of winning trades ("WIN_LEN") and length of losing trades ("LEN_LOSS") are provided in TABLE #7 to uncover any possible additional information.

The findings in TABLE #7 on the trade frequency per strategy demonstrate that as we increase the lag lengths of the moving averages, we encounter fewer possibilities to trade. This can be explained by the fact that longer moving averages are not as responsive because they do not put much weight on recent asset price changes. Similarly, we find there exist more trade signals for the single moving average strategy than there are for the double moving average cross average strategy. The single moving average strategy generates more trading opportunities because it uses of the actual share price in generating trade signals. The double moving average crossover strategy only indirectly makes reference to the share price, thus limiting its response to recent price changes. Furthermore, we find that there exist less trade signals for exchange-traded funds than there are for common stocks. This result may be biased since our database contains more common share assets than exchange-traded fund assets. Lastly, in most cases, the exponential moving average methodology presents more opportunities to trade due to its quicker response to recent price changes. We compliment the frequency of trades with the average length of observable trades to explain the level of trading activity. In aggregate, we find that the average length of each trade increases as we increase the lag lengths of applied moving averages. Retail investors who use short-term moving averages as a reason to trade represent a more active behavior in the market, since their trade signals occur more frequently and are part of each trade for shorter time periods.

Results from TABLE #7 continue to express differences between common shares and exchange-traded funds, suggesting that trades for exchange-traded funds are of shorter duration across longer lag length moving average signals. However, the trade lengths are longer for exchange-traded funds among short term moving averages. The reduction of noise in exchange-traded funds as expressed by the smaller standard deviation may be of reasoning. It should be highlighted that in aggregate, the winning trades are of much longer duration than the duration losing trades. In addition, the mean length of all trades is much closer to the mean of losing trades, unveiling that there are more losing trades than positive trades. This finding confirms the positive skew in return distributions from moving average strategies. Overall findings on the trade frequency and trade length of moving average methodologies show that the selection of the moving average lag length will determine your level of activity in the market. Retail investors who seek an active behavior in the market should focus on strategies that incorporate single moving averages with short-term lag lengths. Those who seek less behavior in the markets, but want to trade on moving average signals, should use long-term moving averages on the double crossover methodology. However, findings on the return distributions of moving average strategies revealed that the former strategy would have more success than the latter strategy.

The remainder of the metrics highlighted in TABLE #7 focus on the central question of this paper: *Do retail investors trade on key technical analysis signals*? Our selected literature demonstrates that retail investors use moving average signals as a reason to trade. Fritz & Weinhardt (2015) use brokerage accounts to reveal that retail investors trade up to 11% more on moving average signal days across speculative financial products. Findings from this paper are quite limited, as they only focus on 30 large blue-chip stocks that are constitutes of the German DAX index. Etheber (2014) finds that trading volume increases between 25-55% on buy signals and increases between 15-25% on sell signals. Again, the principle of the study by Etheber (2014) only involved 983 stocks from German markets. Our unique database allows us to contribute on the current knowledge in this field in the following manner. First, we use a US market database to reveal whether retail investors trade on moving average signals in the largest financial market. Second, our paper is first to study whether or not retail investors use key moving averages signals as a reason to trade exchange-traded funds. The existing literature studies the profitability of moving average signals of exchange-traded funds, however, there exist no insights on the activity by market participants on these particular signals. Lastly, our paper is first to study the aggregate change in retail user holdings instead of changes in volume around moving average signals. The use of changes in retail user holdings uncovers whether the activity around key trading signals is an aggregate effect. Using volume around key trading signals can be biased and misleading, since it can be conducted by a few wealthy retail investors, and thus not accurately representing the aggregate image of retail investors.

We present both the change in volume and the change in retail user holdings on signal days to determine if investors trade on moving average signals. The volume activity surrounding moving average signals is presented to confirm the existing findings presented in our literature. We present in TABLE #7 the change in retail user holdings by *SELL_VOL and *BUY_VOL. The metric *SELL_VOL describes the average change in volume when a sell signal arises, while the *BUY_VOL describes the average change in volume when a buy signal occurs. We use the methodology applied by Fritz & Weindhart (2015) to calculate a volume metric to express the level activity on moving average signals. The volume metric is calculated by taking the average volume across all assets on signals days and dividing it by the average volume across all assets on non-signal days. We remove any dates where there is a moving average signal for any other respective methodology when accounting for non-signal days to remove any possible bias. The *SELL_VOL and *BUY_VOL metric is a ratio between signal days volume and non-signal days volume. A reported indicator above 1 signal that, on average, retail investors use moving average signals as a reason to trade. A value below 1, signals that retail investors do not use moving average signals as a reason to trade. The final metrics to TABLE #7 is *SELL_HOLD and *BUY_HOLD, which represent the level of activity by retail investors surrounding moving average signals. The methodology used to calculate these metrics adopts the same foundation as the volume metric, however they require more due diligence. As mentioned in section C of the paper, the Robinhood trading platform is relatively new and limits our data sample to roughly 18 months of observations. The data used in calculating a retail activity metric needs to be adapted, since the overall count of retail users on the Robinhood platform is constantly growing through the course of the studied period. In **GRAPH #7**, we provide three different data series. Panel A of GRAPH #7 presents the overall daily volume of all observed assets in our database overtime. The process of this series appears to be stationary due to the constant mean across time. In addition, the volume series continues to revert around its mean across time. We cannot say with certainty that the series is stationary, since the mean is not zero. No changes are required on the volume series when calculating the changes in volume on signal days. Panel B of GRAPH #7 shows that the overall user count constantly increases through time with a positive drift. This series cannot be used to calculate changes in retail user holdings on days where moving average signals occur, because there is a clear drift and trend. In order to end up with a stationary series, we use the log difference in retail user holdings.

As presented in Panel C of GRAPH #7, the log difference in retail user holdings appears to be stationary, as it omits any previously existing drift or trend. However, the mean of this series is very small, and above 0. If we were to use a ratio comparison metric like that used in our volume analysis, we would end up with extreme values due to the small and positive denominator. The calculation of the *SELL_HOLD metric in TABLE #7 take the average log change in retail user holdings on moving average sell signal days and *subtracts* the average log change in retail user holdings on days where no moving average signal occurs. In addition, the *BUY_HOLD metric in TABLE #7 takes the average log change in retail user holdings on moving average buy signal days and *subtracts* the average log change in retail user holdings on days where no moving average signal arises. A reported indicator above 0 would signal that retail investors in aggregate increase their holdings on moving average signal days. An indicator below 0 would indicate that retail investors in aggregate decrease their holdings on days of moving average signals as much as they would on a normal market day. The use of changes in retail user holdings allows one to make conclusions on the direction of the activity by retail holdings on days where a moving average signal occurs.

All four of the metrics regarding volume activity and retail user holding activity are presented in TABLE #7. There exists a surge in volume and retail holdings on both buy signals days and sell signals days as we increase the lag length of the simple moving averages for common share assets. We do not see a significant change in volume and retail holdings on signals derived from short-term moving averages. Retail investors use the longer length moving averages as a reason to trade common share assets. This can be explained by the fact that these trade signals are less occurring and present some form of rarity. Observations from TABLE #7 reveal that in most cases, market participants and retail investors do not use moving average strategies on exchange-traded funds. The changes in retail user holdings on exchange-traded fund signals are usually below 0, indicating that the average change in retail user holdings on signal days are below the mean activity from non-signal days. As for volume, the ratio between the volume for signal and volume for non-signal days on exchange-traded funds is below 1 in most cases. In addition, the retail investors who use the single moving average strategy tend to use the simple moving averages (SMA) over exponential moving averages (EMA). This result is reversed when looking at the double moving average strategy. There is an increase in retail user holdings and volume on exponential moving average signals derived from the double moving average crossover strategy. Overall, retail investors prefer to use long-term simple and exponential moving averages as a reason to trade common shares assets. We see the largest increases in retail user holdings on signal days from the double moving average crossover methodology, using exponential moving averages. We include the 12-day exponential moving average and the 26-day exponential moving average as part of our 27 strategies since these metrics are used in the formation of the Moving Average Convergence Divergence (MACD) indicator. The MACD indicator is calculated by subtracting the 12-day EMA from the 26-day EMA. A buy signal is generated when the 12-day EMA surpasses the 26-day EMA. A sell signal is generated when the 12-day EMA moves below the 26-day EMA. From the findings in TABLE #7, both the 12-day and 26-day exponential moving averages individually see a surge in both volume activity and retail user holdings activity. The double crossover strategy using the 12-day and 26-day exponential moving averages can be used to make sense of the activity on the MACD indicator. The findings from TABLE #7 suggest the MACD indicator encounters a surge in volume activity and retail user holding activity on both sell signals days and buy signals days. This suggests that market participants and retail investors also trade technical indicator signals other than moving averages.

Along with TABLE #7, we present **GRAPH #8** to uncover additional insights regarding investor behavior on moving average signal days. The focus of this graph highlights some of the differences between buy signal activity and sell signal activity, across changes in volume and changes in retail user holdings. Panel A focuses on the changes in retail user holdings, while Panel B demonstrates the changes in volume. In both panels, the distinction is made between common shares (circles) and exchange-traded funds (squares). In addition, we acknowledge the differences between sell trade signal activity and buy trade signal activity. We use the single moving average strategy using simple moving averages (SMA) in GRAPH #8 because they are some of the most widely used strategies by retail investors. GRAPH #8 illustrates some key findings regarding the changes in retail user holdings. First, retail investors trade more on long-term moving averages since they represent rare events. For example, the changes in retail user holdings on key moving average signals can increase up to 0.2% above the average change in retail user holdings on non-signal days. The contrary takes place when we look at exchange-traded funds, where retail investors appear to put more weight on the short-term moving averages. In aggregate, retail investors do not use moving averages as a reason to trade exchange-traded funds, since most indicators appear to be well below 0.

Our results illustrate a clear difference between the activity on sell signals and buy signals. Retail investors in aggregate increase their retail holdings more on sell signals than they do on buy signals. We observe this behavior for both common shares and exchange-traded funds. This can be explained by contrarian behavior of retail investors. When a sell signal is generated, it is in most cases caused by the negative performance of the asset in the past recent pays. Recall from the previous sections of this paper, we find that retail investors display contrarian tendencies for periods up to 6 months. They are more likely to purchase an asset that is not performing well, which explains why we see a surge in activity by retail investors on sell signals. This finding is a new contribution to the literature regarding retail activity on moving average signals. Previous literature found that, in general, investors increase volume more on buy signals than they do on sell signals (Etheber, 2014). We find that in aggregate, retail user holdings actually increase more on sell signal days than they do on buy signal days. Separating retail activity by buy signals and sell signals demonstrates that the contrarian behavior of retail investors causes a larger surge in retail user holdings on sell signals. We are the first paper to demonstrate this finding. In Panel B, we re-test the existing findings in the literature by measuring the changes in volume on moving average trade signals. It should be noted that the volume represents the overall market volume and not the retail activity volume. The findings are similar to those presented by Fritz & Weinhardt (2015), whereby we see an increase in volume on days with a moving average signal. Results are similar to Etheber (2014), where we see more volume activity on buy signals than we see on sell signals. We contribute to these findings by running the same analysis on exchange-traded fund assets. The results demonstrate that market participants do not use the longer-term moving averages as reason to trade. In fact, changes in volume on signal days decrease as we increase the lag lengths of the moving average. In addition, market participants tend to trade more on sell signals than they do for buy signals when trading exchange-traded funds. This is contrary to the findings across common share assets where we find market participants are more active on buy signal days then sell signal days.

Overall, it seems that retail investors do use moving average signals as a reason to change the common share asset holdings in their portfolio. We find a higher level of activity towards sell signals by retail investors due to their disposed contrarian behavior. Lastly, retail investors do not use moving average signals as a reason to trade exchange-traded fund assets.

SECTION E.5: COMPARISON BETWEEN STRATEGY PROFITABILITY AND RETAIL BEHAVIOR

Our previous analysis in section B.3 made a case to categorize the moving average methodologies in a manner that are most favorable to achieve highest profitability. We demonstrated that the strategies based on short-term moving averages provide the highest return over our studied period. GRAPH #6 shows that the profitability of moving average over the studied period decreases as the lag lengths of the applied moving average decrease. Our results in section B.4 demonstrate that retail investors actually increase their retail user holdings more on moving average signals that hold higher lag length periods. Thus, there exists a clear mismatch between the signals that retail investors tend to trade on and the signals that could bring them a higher chance to achieve winning strategy. A logical explanation could be that retail investors simply do not have the time to engage in short-term trading activity. Section B.4 found that trading short-term moving averages requires more attentive behavior, since trade signals occur more frequently, and each trade is on average of shorter duration. However, the rise in technology and low fees from the Robinhood trading platform should not hold back retail investors from actively engaging in the market. Investors have the ability to set limit orders and stop limit orders with specific maturity dates in advance so that they can continue their everyday activities, even when they have no time to access their portfolios. In addition, there exists a mismatch between the types of assets that bring profitability and the types of assets retail investors prefer to trade. We find that in most cases, profitability is highest on exchange-traded funds instead of common shares. The findings in GRAPH #8 clearly demonstrated that retail investors do not use exchange-traded funds to engage in moving average strategies, but rather, use common shares to trade moving average strategies. As our study has shown, retail investors should increase their trading activity towards exchange-traded funds if they want to increase their chances to forming a winning strategy. The surge in activity on common shares over exchange-traded funds may be explained by their higher disposed standard deviation. A higher standard deviation in trade returns increases the possible trade return. Results in TABLE #6 clearly demonstrate that over the course of the studied period, the strategies on exchange-traded funds using lower standard deviations bring higher profitability. Findings from the descriptive statistics analysis also uncover some findings on what retail investors do well. For example, retail investors tend to trade just as much, if not more (in some cases), on exponential moving average based strategies than they do on simple moving average trading strategies. Retail investors do this well, as the profitability of the exponential moving average strategy over the course of the studied period usually exceeds the returns of the simple moving average strategy.

In the forthcoming sections of this paper, we continue to add insights on the profitability of moving average strategies in relation to the behavior of retail investors. First, we compare the profitability and behavior of retail investors in relation to moving average strategies when accounting for differences across the fundamental metrics. This proposed analysis comes from our literature review, which finds that technical analysis strategies are proven to be more profitable when arranged on assets with certain specifications. We contribute to this knowledge by measuring if retail investors act on the assets' characteristics which could bring the highest chances of profitability. Second, we use the changes in retail user holdings activity to uncover if the actions by retail investors are profitable. We construct a long-short portfolio over our studied period to address retail investor profitability, while accounting for differences between common shares and exchange-traded funds.

EMPIRICAL FINDINGS & INSIGHTS ON RETAIL INVESTOR BEHAVIOR

Our preliminary analysis on the behavior of retail investors confirms that US investors use moving average signals as reason to trade. Although these findings already exist in the literature, we confirm the results while using unique retail investor data. Knowing that retail investors trade on moving average signals, we extend our analysis to gather further contributing insights on retail investor behavior surrounding key moving average signals. First, we use an event window study analysis to understand when retail investors act on moving average signals. We know with certainty that they trade on the day of the signal. It is possible that retail investors try to time the market by buying early on the signal, or are late to the signal and increase their holdings after the event day. Second, we are curious to know the characteristics of the assets in which retail investors use to trade moving average signals. In the earlier stages of the paper, we uncovered that retail investors tend to hold large, liquid, and volatile assets in their portfolios. Our analysis tries to determine whether these fundamental characteristics come into play when retail investors trade moving average signals. In addition, our analysis will study the profitability of moving average strategies when grouped by fundamental metric quantiles. The goal of this study is to confirm some of the findings on technical analysis profitability as discussed in our literature. Third, we use the activity occurring in the after-hours market to determine if retail investors use these non-normal market hours to trade. Our paper is the first to study whether or not retail investors use the after-hours market to trade key technical analysis signals. Lastly, we complete our analysis on the behavior of retail investors by answering one central question: *Are retail investors profitable*? To answer this question, we use an equal weighted long-short portfolio on the changes in retail user holdings.

SECTION F: EVENT STUDY WINDOW ANALYSIS AROUND KEY MOVING AVERAGE SIGNALS

Our earlier findings using both a volume analysis and retail user holdings analysis find that investors use the signals produced from moving average strategies as a reason to trade. On the day of the signal, the average daily activity level surpasses the average daily activity of non-signal days. We are curious to understand what happens on the days leading to the signal as well as the days following the produced signals. Etheber (2014) was first to address this question using a 21-day window event-study analysis on the volume surrounding key moving average signals in the German stock market. His analysis uses a volume-based metric to uncover additional insights on how market participants trade moving average signals. He finds that volume peaks on the day of the signal. In addition, Etheber (2014) finds that there is some level of persistence in the volume activity in the days following the signal. Lastly, methodologies using more than one moving average (double moving average crossover strategy) see early accumulation, more persistence in activity, and higher magnitude of activity (Etheber, 2014).

Our study tries to confirm the results found by Etheber (2014), while accounting for differences in the market location and our abbreviated volume metric. Our volume metric was derived from the paper by Frtiz & Weinhardt (2015) due to its general simplicity. The metric used by Etheber (2014) is similar to ours as it also uses daily volume in the numerator, but rather uses outstanding share count as the base denominator. Our volume metric base denominator uses the average volume for days in which no signal is produced. The findings in the descriptive statistics component of the paper frequently discovered differences in activity among retail investors from remaining market participants. We expect to uncover differences in the activity by retail investors from other market participants in the days leading to and following a moving average signal. In addition, our analysis includes an event-study window analysis on the volume activity and retail investors activity on moving average signals produced by exchange-traded fund assets.

SECTION F.1: VOLUME

Using our developed volume metric, we conduct a 21-day event window analysis to confirm the findings produced by Etheber (2014). In the methodology component of the paper, we identified 27 unique moving average strategies to generate both buy and sell signals. We select 8 of the 27 strategies for our event-study window analysis to efficiently and concisely examine the activity leading to and following a signal. The selection of our 8 strategies accounted for two factors. First, we select the strategies that present high retail investor activity to uncover additional insights. Second, we select strategies that touch across all spectrums of the methodologies. The spectrums include: **(a)** the use of simple moving average vs. the exponential moving average, **(b)** the use of the single moving average strategy vs. the double moving average strategy, and **(c)** the use of short-term moving averages and long-term moving averages. The 21-day event window study analysis findings are provided in **GRAPH #9.** This graph presents a 4-panel analysis containing a series of line graphs demonstrating how market participants and retail investors trade on moving average signals. The top two panels (Panel A and Panel B) present the volume activity surrounding sell moving average signals and buy moving average signals. The initial findings in GRAPH #9 suggest that volume activity peaks on the day of the signal. Furthermore, we find there is a higher magnitude of activity on buy signals compared to sell signals. In the days leading up to the signal, volume activity starts to increase. As the volume activity starts to increase in the days leading up to the event day, it still remains below the average of days with no moving average signals. Following a moving average signal, the volume activity remains persistently higher than in the days leading up to that signal. Market participants continue to trade on moving average signals in the days following the signal, with activity peaking on the day of the signal. These highlighted findings on volume activity from GRAPH #9 confirm the earlier findings by Etheber (2014), even while using a different volume metric. The volume activity across the different moving average methodologies presents different findings to those by Etheber (2014). He finds that the double moving average crossover strategy receives higher level of activity on the day of the signal compared to the single moving average strategy (Etheber, 2014). Based on our earlier findings on the descriptive statistics in TABLE #6, this finding is to be expected, since the double moving average crossover signals do not occur as frequently. Our findings in GRAPH #9 suggest that volume activity is higher for the single moving average strategy than it is for the double crossover moving average strategy. The differences between our findings and those by Etheber (2014) may be explained by the differences in the selected lag lengths of the applied moving average strategies.

SECTION F.2: RETAIL USER HOLDINGS

Our retail user holdings data from the Robintrack website allow us to contribute on earlier findings by Etheber (2014). Using our abbreviated metric for changes in retail user holdings, we conduct a 21-day event study window analysis on the days leading up to and following moving average signal days. As previously mentioned in GRAPH #7**,** the Robinhood platform is relatively new, and therefore, the count in participants on the platform has a positive drift through time. We use the log differences in retail user holdings across each day in time to eliminate the positive drift in retail user holdings. Our computed metric for retail user holdings compares the average log change in retail user holdings on signal days, to the average log change in retail user holdings on non-signal days. The findings on the activity of retail investors leading up to and following a moving average signal is presented in GRAPH #9, through Panel C and Panel D. Panel C highlights the activity on sell signals while Panel D highlights activity surrounding buy signals. Initial findings suggest that retail investor activity for sell signals is higher than that of buy signals. In the first day following a moving average signal, the change in retail user holdings metric is positive for both sell and buy signals. Therefore, the count in retail user holdings is higher on the day after the signal (x-axis label "+1"), than it is on the actual day of the signal (x-axis label "*EVENT*"). In the following days (x-axis label "+2"), the growth in retail user holdings metric returns to below or near 0. Retail investors activity surrounding moving average signals actually peaks on the day following the signal, suggesting that retail investors are late to trade moving average signals.

SECTION F.3: SMA vs. EMA ACTIVITY

Findings presented in GRAPH #9 only account for simple moving average (SMA) signal activity, while **GRAPH #10** presents the activity regarding exponential moving average (EMA) signal activity. Panels A and Panel B from GRAPH #10 present the volume activity, while Panels C & Panel D present the retail user holdings activity. Initial glance at the volume activity (Panel A and Panel B) does not uncover any noticeable differences to the volume activity on simple moving average signals (see GRAPH #9). The same cannot be said when comparing the activity in retail user holdings (Panel C and Panel D) across simple moving averages and exponential moving averages. GRAPH #10 on retail user holdings (Panel C and Panel D) suggest that retail investors trading exponential moving average signals try to time the market. Thus, there exist positive growth in retail user holdings on the days prior to the moving average signal. This is especially true for signals generated by the double moving average crossover strategy. For example, retail investors who trade on the crossover strategy using the 50-day and 200-day exponential moving averages will start to increase their holdings 10 days prior to the day of the signal. Lastly, we find no noticeable difference in retail user holding activity between the single moving average strategy and the double moving average cross over strategy. The previous findings in GRAPH #9 on simple moving averages suggest that retail investors prefer to trade the single moving average strategy over the double moving average crossover strategy. These findings are no longer sufficient when analyzing the activity among exponential moving averages.

SECTION F.4: EXCHANGE-TRADED FUNDS

We expand the 21-day event window analysis on exchange traded funds. The descriptive statistics component of our showed that the activity by retail investors on days of moving averages is actually below average. The 21-day event study window analysis allows us to determine if retail investors increase their holdings in the days leading up to and following the signals produced by exchange-traded funds on a relative basis. These insights are presented in both **TABLE #8** and **TABLE #9.** The information in TABLE #8 presents the activity in volume, while TABLE #9 presents the activity in retail user holdings. We find a noticeable difference in the volume activity in TABLE #8 between sell signals and buy signals across exchange-traded funds. The activity on sell signals appears to peak on the day of the signal, while the activity on buy signal days is not noticeably different from the days leading up to and following the signal. In addition, we find that the activity on the day of the signal decreases as the lag lengths of the moving averages decreases. Market participants are more likely to trade short-term sell moving average signals. These findings were first highlighted in the earlier findings of the descriptive statistics component of our paper. Our findings from GRAPH #9 event window analysis do not provide any additional insights to conclude that retail investor trade on moving average signals.

Using our unique database alongside the study conducted by Etheber (2014) allowed us to contribute new findings regarding the behavior surrounding moving average signals. First, we use our abbreviated volume metric in the US markets to confirm the previous findings by Etheber (2014). Second, we show that retail investors continue to increase their retail holdings in the day following a moving average signal, suggesting that they are late to these produced signals. Lastly, retail investors try to time the market when trading on signals derived from exponential moving average signals. This finding is especially true for signals produced by the double moving average crossover methodology on long-term moving averages.

SECTION G: FUNDAMENTAL METRIC QUANTILE ANALYSIS

Our study on aggregate retail user holdings suggests that retail investors are attracted to assets that are large in size, liquid, and are volatile. Thus, it appears that retail investors prefer to hold good quality assets that can still bring them high returns. Using these previous conclusions, we are interested to see if retail investors consider fundamental asset characteristics when trading moving average signals. We expect to see a peak in trading activity towards assets that are large, liquid, and volatile. Furthermore, the activity between sell signals and buy signals is separated due to the constant difference in behavior among both signals. This argument gives reason to suspect that there exists a difference in the types of assets traded between sell signals and buy signals. In addition, our analysis aggregates the profitability of moving average trades per firm fundamental metric. Literature on this topic suggests that applying technical analysis strategies on small, liquid, volatile firms presents higher chances to achieve profitability. Marshall et al. (2009) finds that the profitability of moving average increases when applied to small and illiquid assets. In addition, Han et al. (2013) finds that portfolios sorted by volatility are able to beat the buy and hold strategy as the level of volatility increases. We use our short-duration database to confirm these existing findings. In addition, we aggregate retail user activity by firm characteristics to determine if technical analysis users trade on assets that have the best chance to bringing them a profit.

SECTION G.1: MOVING AVERAGE PROFITABILITY BY FUNDAMENTAL METRIC QUANTILE

We gather the size, liquidity, and volatility fundamental metrics to form 10 equally weighted portfolios (per metric) on moving average trade returns. In addition, we separate the findings across common shares and exchange-traded funds to uncover any possible differences. Our primary interest lies in confirming the existing findings in the literature on technical analysis profitability when accounting for firm fundamental metrics. The findings in **GRAPH #11** demonstrate how the average profitability per trade fluctuates when accounting for differences in firm fundamentals. It should be noted that the central focus of this paper is to gain insights on how retail investors trade around key moving average signals. We do not put much emphasis on the overall profitability of moving average strategies, since this is widely studied. For reasons of simplicity, we use an equally weighted average return per trade across all assets of each portfolio to measure profitability.

Panel A of GRAPH #11 suggest that, in aggregate, the profitability of moving average strategies increases as the size of firms increase. These findings are not consistent to those found in the literature. The lower returns from moving average strategies on small firms may be explained by the higher standard deviation of the underlying asset returns. We show in the descriptive statistics component of the paper that a higher standard deviation is detrimental to the profitability of moving average strategies. The returns of moving average strategies on exchange-traded funds when accounting for differences in firm size are presented in Panel A of GRAPH #11. On average, the profitability of moving average strategies on exchange-traded funds increase as firm size increases. Our studied time frame concludes that retail investors who use moving average strategies should put more emphasis on assets that are large in size. When comparing the performance across asset types, profitability is higher for exchange-traded funds than for common shares when firm size is small. However, profitability is higher for common shares than exchange-traded funds when firm size is large. There is no clear winner between both asset types when considering technical analysis profitability by firm size.

The results in Panel B of GRAPH #11 highlight the profitability of technical analysis when accounting for differences in asset liquidity. Initial findings suggest that profitability increases as the level of firm liquidity increases. These results are contrarian to those presented in the literature review. It should be noted that the profitability of extremely liquid assets (quantile 9 & 10) decrease back towards low liquidity portfolio levels. Investors trading moving average signals should stay away from assets that suffer from extreme liquidity. Exchange-traded funds experience similar conclusion, with technical analysis profitability increasing as firm liquidity increase. When accounting for liquidity, the performance of technical analysis strategies is higher on exchange-traded fund assets.

Panel C of GRAPH #11 addresses the profitability of moving average strategies when accounting for differences in firm volatility. We find that the profitability of moving average trading strategies on common shares decreases as the level of firm volatility increases. This finding is led by the performance of quantile portfolios 9 and 10, which see huge decreases in performance when volatility is high. Our results are contrary to the existing literature, which finds that the profitability of moving average strategies increases as firm volatility increases. In addition, Panel C of GRAPH #11 presents the performance of exchange-traded funds while accounting for differences in firm volatility. The profitability of exchange traded funds decreases as firm volatility increases. We do not find any noticeable difference in the performance of exchange-traded funds and common shares when accounting for volatility. However, in the extremely high volatility portfolios (quantile 9 and quantile 10), the common share portfolios highly underperforms relative to exchange-traded fund portfolios. This finding may be sufficient to claim that the performance of exchange-traded funds is better than that of common shares when accounting for volatility.

Overall, our findings in GRAPH #11 do not confirm any previous findings on technical analysis profitability when aggregated by firm fundamental metrics. The profitability of moving average strategies throughout our short-duration sample increases when applied to large, liquid, and low volatility firms. We believe there exists two factors to explain the differences in our findings to those in the existing literature. First, our study involves a short time frame of 18 months. Our conclusions may be insufficient to make claims about the long-term performance of moving averages. Second, our studied time frame takes place during a bull market. During a bull market, the market index performs well, which means that good quality firms that make up the index perform well. The bull market occurring during our studied sample may be one reason to explain why our findings suggest that technical analysis performs better on large quality firms. Lastly, the results from GRAPH #11 confirm with previous literature that the profitability of moving average strategies is highest when applied to portfolios, such as exchange-traded funds, rather than on individual assets.

SECTION G.2: MOVING AVERAGE ACTIVITY BY FUNDAMENTAL METRIC QUANTILE ~ STOCK

The profitability of moving average strategies from our database appears to be centralized in stocks that are large, liquid, and low in volatility. This does not mean that investors direct their attention toward these types of asset characteristics when trading moving average signals. Using market participants and retail investors activity, we test if investors try to trade on the moving average signals that hold the highest chance of making a profit. In addition, we are curious to know if the holdings of retail investors who trade moving average signals are different to the holdings of investors in aggregate. Since retail investors prefer to hold large, liquid, and volatile assets in their portfolios, we expect retail investors to trade moving averages on these types of assets. To address these specific insights on retail investor behavior, we aggregate all trade activity per firm fundamental metric into 10 equally weighted portfolios. In addition, we separate buy signal activity from sell signal activity. The findings in **GRAPH #12** illustrate market participants activity surrounding key moving average signals when accounting for fundamental characteristics. Panel A and Panel B presents the volume activity surrounding sell signals and buy signals. Panel C and Panel D presents the retail user holdings activity surrounding sell signals and buy signals. In GRAPH #12, there exist no noticeable difference between the volume activity (Panel A and Panel C) to the retail user holding activity (Panel C and Panel D). For the purposes of our study, we focus on retail user holdings activity in Panel C and Panel D since our paper is centered on understanding retail investor behavior. Further, the retail user holdings metric allows us to make interpretations on the sense of direction in the activity by retail investors. Panel C of GRAPH #12 presents the changes in retail holdings on moving average sell signals when accounting for differences in firm fundamental metrics. All three firm fundamental metrics are illustrated in the panel. In the event of a sell signal, retail investors will direct their attention toward assets that are large, liquid, and volatile. Retail investors use sell signals as a reason to increase their holdings on large quality firms that can still bring them high returns (as highlighted by the high volatility).

As mentioned in the earlier sections of this paper, the Robinhood platform does not allow investors to short assets. Thus, our moving average profitability metrics only consider long trades. We cannot make claims as to whether it is strategic for retail investors to purchase on the sell signals of large, liquid, and volatile firms. The ongoing difference in activity among retail investors between buy signals and sell signals is highlighted between Panel C and Panel D. The retail user holding activity on buy signals (Panel D) is completely different than that seen on sell signals (Panel C) when accounting for differences in firm fundamental metrics. Retail investors who trade buy signals centralize their attention on stocks that are small, illiquid, and volatile. This is not strategic because, as we have previously demonstrated, profitability is lowest when applying technical analysis to firms that are small, illiquid, and volatile. Retail investors increase their holdings on buy signals from small, illiquid, and volatile assets since they dispose the possibility of making a large gain on the trade.

We conclude that retail investors do not trade on the asset characteristics that, on average, have the best chance of bringing them profitability. In addition, there exists a difference in the type of assets of interest among retail traders and retail investors. Recall from the descriptive statistics component of the paper, we show that retail investors like to hold assets with high volatility. However, our findings from GRAPH #4 show that retail investors do not maximize their holdings towards extremely volatile assets. These findings are different to the trading activity displayed in GRAPH #12, where moving average investors prefer to trade buy signals on assets with extremely volatility. There exists a difference in the asset selection among moving average investors and aggregate investors.

SECTION G.3: MOVING AVERAGE ACTIVITY BY FUNDAMENTAL METRIC QUANTILE ~ ETF

We extend our contributions towards existing knowledge on retail investor behavior by aggregating moving average activity on exchange-traded fund by firm fundamental metrics. **TABLE #10** provides activity for both market participants and retail investors, with consideration to firm fundamental metrics. Prior findings in the descriptive statistics component (Section E.4) did not provide sufficient information to claim that market participants trade on the exchange-traded fund moving average signals. TABLE #10 provides evidence to believe that market participants actually do trade on the signals derived from exchange-traded funds. The column “SELL VOL” from TABLE #10 represents the ratio of the average volume on sell signal days to the average volume on non-signal days, while the “BUY VOL” column represents the ratio of the average volume on buy signal days to the average volume on non-signal days. Market participants demonstrate a similar behavior when trading the sell and buy signals on exchange-traded funds to the findings in GRAPH #12 on common share activity. When trading sell signals, market participants display abnormal trading behavior towards large, liquid, and volatile exchange-traded funds. In addition, market participants use buy signals to trade excessively on exchange-traded funds that are small, illiquid, and volatile. Insights from TABLE #10 also present the changes in retail user holdings on sell signals and buy signals through the columns “SELL HOLD” and “BUY HOLD”. The findings on the changes in retail user holdings are similar to those seen in the volume activity. Market participants are extremely selective when acting on buy and sell signals exposed from exchange-traded fund assets. We are first to show that market participants also use exchange-traded fund moving average signals as a reason to trade.

The aggregation of investor activity surrounding key moving average signals by firm fundamental metrics reveals several additional behavioral insights. First, there exists a large discrepancy in the activity by market participants (including retail investors) across asset characteristics between buy signals and sell signals. Technical analysis traders tend to purchase on moving average buy signals for firms that are small, illiquid, and volatile. Market participants trade on these signals because they present an opportunity for making a large profitable trade, even if proven to be less profitable on average. These results are sufficient to claim that retail investors who apply moving average trading strategies do not purchase the assets that have the highest chance to make them a profit. Those who trade on sell signals will increase their holdings on assets that are large, liquid, and volatile. We do not have sufficient evidence to claim whether or not this action is strategic, since the profitability of our study does not account for profits derived from short trades. Second, we show that market participants (including retail investors), do use exchange-traded funds to trade moving average signals. Exchange-traded fund moving average traders are extremely selective in the assets they trade. The difference in activity between sell signals and buy signals of exchange-traded fund assets is similar to that seen across common share assets.

SECTION H: AFTER-HOURS MARKET ACTIVTY

The unique features of the Robinhood platform allows for gathering extensive insights on the behavior of retail investors surrounding key moving average signals. As mentioned in the Data (section C) & Methodology (section D) components of the paper, the Robinhood platform allows investors to trade in both the pre-market and the after-market hours. The data formulated by Robintrack, which is derived from the Robinhood platform, gathers the count of retail user holdings at each hour of the day, including in the pre-market and after-market hours. Using this privileged information, this section of our paper uses the after-market hours' activity to determine if retail investors use non-normal market hours to trade moving average signals. The after-hours market is open between 4 p.m. ET and 6 p.m. ET. The first observation for each asset at each date in time after 6 p.m. ET represents the close holdings of the after-hour market. The daily close holdings of the normal market hours are represented by the first observation for each asset at each date in time that occurs after 4 p.m. ET. We measure the activity in the after-hours market by the log difference in the close holdings of the after-hours market and the close holdings of the normal trading hours. Although the Robinhood platform allows for pre-market trading, the Robintrack platform does not have sufficient information during these market hours to make any insights. We only have information in the pre-market hours for a few months, rather than the entire studied period. Our analysis on the after-hours market only includes the changes in retail user holdings, and not the changes in volume activity, since this information is not provided by CRSP.

SECTION H.1: AFTER-HOURS MARKET ACTIVITY ON MA SIGNALS

We use the log differences between the after-hours market close and the normal hours market close in retail user holdings to see if retail investors use the after-hours market to trade moving average signals. Using the aforementioned approach Fritz & Weinhardt (2015), we separate the trade days activity from the non-trade days activity to form an after-hours retail investors activity metric. We measure the after-hours moving average activity by the differences between average log change in retail user holdings in after-hours market on signal days, to the average log change in retail user holdings in after-hours market on non-signal days. The activity in retail user holdings during the after-hours market on signal days were computed for the 27 moving average strategies studied throughout our paper. For reasons of simplicity, **GRAPH #13** presents the single moving average methodology, using the simple moving averages (SMA). These 6 strategies are used for two reasons. First, these strategies were selected in GRAPH #8 to express the activity by retail investors around moving average signals in the normal market hours, thus allowing for consistency throughout our paper. Second, these selected methodologies receive a lot of activity from retail investors. The activity in the after-hours market on moving average signal days displayed in GRAPH #13 is consistent to that seen in the regular market hours. First, retail investors use the after-hours market to trade moving average signals on common share assets (Panel A). However, the same cannot be said for exchange-traded fund assets (Panel B). Second, retail investors continue to display contrarian behavior in the after-hours market when trading sell signals. Retail investors will increase their holdings more on sell signals than they do on buy signals, even in the after-hours market. Lastly, retail investors are more likely to trade the signals derived from long-term moving averages. This finding is true across both buy signals and sell signals.

Although the behavior displayed by retail investors is consistent across normal and after-hours markets, the level of activity is larger in the regular market hours than it is in the after-hours market. We have contributed to the existing literature, finding that retail investors do use non-normal market hours to trade moving average signals. Knowing that retail investors trade on moving average signals in the after-hours market, we extend our study on the after-hours market activity using the methods previously seen in the paper. First, we perform an event-study window analysis on the activity in the after-hours market to uncover additional insights on the timing of activity by retail investors. Second, we aggregate the activity by retail investors in the after-hours market by firm fundamental quantiles to examine which types of assets are mostly traded.

SECTION H.2: AFTER-HOURS MARKET EVENT STUDY WINDOW ANALYSIS

Initial findings on the timing activity of retail investors towards moving average signals suggest they are late to the event; changes in retail user holdings are positive and peak in the day following the signal. Using the activity in the after-hours market, we are curious to see if the activity displayed by retail investors in the after-hours market peaks on the day of the signal, or if they continue to demonstrate late market timing behavior. In order to efficiently and concisely present our findings, we only illustrate the findings for 8 of the 27 applied strategies used in our paper. Two filters are applied in the selections of the 8 strategies. First, the strategies are of high interest by the market participants. Second, the strategies properly reference the different applied moving average methodologies discussed throughout our paper. Thus, they account for differences between: **(a)** the simple moving average & the exponential moving average, **(b)** the single moving average methodology & the double moving average crossover methodology, and **(c)** short term moving averages & long-term moving averages. The results from the event study window analysis on changes in retail user holdings in the after-hours market activity is presented in **GRAPH #14**. Panel A and Panel B of GRAPH #14 categorize the differences in sell signal activity across exponential moving average (EMA) signals and simple moving average (SMA) signals. Panel C and Panel D illustrate the difference in buy signal activity across exponential moving average (EMA) signals and simple moving average (SMA) signals.

Few insights can be gathered from the findings in GRAPH #14. First, we find that the activity on sell signals in the after-hours market is higher than that seen for buy signals. Second, retail investors do not use the after-hours market to trade in the days following a moving average signal. The level of activity in retail user holdings during after-hours market for all the days following the event day are below the average of non-signal days, with the peak in activity occurring on the day of the signal. We confirm that the final activity surrounding moving average signals occurs during normal market hours on the first day following a moving average signal (see GRAPH #9). Lastly, there is reason to believe that retail investors try to time the market by purchasing prior to moving average signals in the after-hours market. In Panel C and Panel D of GRAPH #14, retail investors use the after-hours market to purchase on the day prior of the buy signal derived from the 50-day & 200-day double moving average crossover methodology. It should be noted that there exist no substantial differences between the activity using simple moving averages (Panel A and Panel B), and activity using exponential moving averages (Panel C and Panel D).

SECTION H.3: AFTER-HOURS MARKET ACTIVITY BY FUNDAMENTAL METRIC QUANTILE

Using our fundamental quantile analysis, we are interested to see if there exists a difference in the asset characteristics that retail investors chose to trade between the after-hours market and the normal market hours. We aggregate all trade information in the after-hours market into 10 equally weighted portfolios per fundamental metric based on firm size, liquidity, and volatility. Findings in **GRAPH #15** aggregate trade activity based on firm fundamental metric. Activity in Panel A represents the activity for sell signals and Panel B presents the activity for buy signals. The activity by retail investors in the after-hours market, when accounting for differences in firm fundamental metrics, is similar to that previously seen in the normal market hours. First, on sell signals, retail investors will increase their holdings on assets that are large and that can bring them a high return. Retail investors increase their holdings towards large, liquid, and volatile firms. Second, the activity on buy signals is completely contrarian to that seen on sell signals. In the event of a buy signal, retail investors use the after-hours market to increase their holdings on small and volatile stocks. The information regarding firm liquidity for buy signals is hard to interpret, and therefore cannot make any meaningful conclusion.

Insights from the after-hours market contribute to the existing literature on the behavior of retail investors relative to moving average signals. We are the first to demonstrate that retail investors use the after-hours market to trade moving average signals of common share assets. In addition, we show that retail investors will use the after-hours market to trade particular moving average strategies prior to the signal confirmation. This is especially true for the buy signals exposed on strategies using the double crossover methodology with long-term moving averages. More notably, difference in activity between buy signals and sell signals continues to be exposed in the after-hour markets.

SECTION I: PROFITABILITY OF RETAIL INVESTORS & FAMA-FRENCH FACTOR ANALYSIS

Our paper focuses on retail investors actions and profitability surrounding moving average trading strategies. We further extend our paper to address the overall profitability of retail investors through the following question; *Can retail investors action be used to develop a profitable trading strategy*? We address the question at hand by developing a long-short portfolio formed on the actions of retail investors. The long and short portfolios are formed and rebalanced at the beginning of each month using the previous month's log differences in retail user holding count for each asset. For example, the long portfolio contains the 90^{th} percentile of stocks that had the largest increase in retail user holdings. The short portfolio consists of the bottom 10^{th} percentile of stocks that saw the largest decrease in retail user holdings. Returns from the portfolio are calculated using an equally weighted approach. At the start of each month, we hold an equal amount of each security in the portfolio. These holdings are held for the rest of the month. We do not rebalance the portfolio at the end of each day because in a real-life situation, this would require too much effort. The long-short portfolio strategy follows a momentum methodology, where we invest in stocks that saw large increases in retail user holdings and short the assets having a large decrease in retail user holdings. Positive returns on the long-short portfolio would conclude that retail investor activity can be used to form a positive trading strategy.

SECTION I.1: LONG-SHORT PORTFOLIO PERFORMANCE

Our paper is not the first to test the profitability of retail investors using the long-short portfolio methodology. Boehmer (2019) uses price improvements seen in a wholesaler brokerage firm database to identify retail investor transaction order balances to develop a long-short portfolio analysis. Although the basis of his study is similar to our analysis, it presents its own differences. First, our study is different in terms of the studied time frame. The analysis by Boehmer (2019) takes place between 2010 and 2015, while our study takes place between 2018 and the end of 2019. Second, the methodology used in the formation of our portfolios differs from that applied by Boehmer (2019). Our analysis uses the top 90th percentile and bottom 10th percentile to form the long and short portfolios, while Boehmer (2019) uses the top 80th and bottom 20th percentile to form his long and short portfolios. In addition, we use different time frames to create our portfolios. Our long and short portfolios use the previous month changes in retail user holdings, which are then held for a month. Boehmer (2019) uses the previous 5 days of retail investor activity to form his portfolios, which are then held for periods up to 12 weeks. Lastly, there exist a difference in the metrics used to formulate our portfolios. Boehmer (2019) uses order balances, while our proposed long-short portfolios use the log differences in retail user holdings. Our metric is advantageous as it gives each retail investor equal weighting in the analysis and is not affected by single large volume retail investors. We extend on Boehmer. (2019) study by conducting a sperate long-short portfolio analysis using the changes in retail user holdings of exchange-traded fund assets. This allows us to uncover any possible differences in the activity between common share and exchange-traded fund assets.

The performance of the long-short portfolios on common share assets and exchange-traded funds are separately presented in **GRAPH #16**. The performance of the long-short portfolio on common shares is presented in red, while the performance of the long-short portfolio on exchange-traded funds is presented in blue. The cumulative performance of the S&P 500 index is presented as a reference to the overall market. Both of our long-short portfolios underperform relative to the S&P 500 market index. Moreover, the performance of both long-short portfolios is well below 0 at the end of our studied time frame. From GRAPH#16, we see that there exists no noticeable difference between the performance of the common share long-short portfolio and the exchange-traded fund long-short portfolio. Both portfolios return an overall performance of just below -5% over the studied time frame. We affirm that the activity of retail investors from the Robinhood platform cannot be used to develop a profitable trading strategy.

The results from our sub-sample time period hold a different conclusion to the existing literature. Boehmer (2019) creates value-weighted portfolios based on the previous week's order balances and accounts for different holding periods. Portfolios with holding periods of 1 week saw an annualized positive return of 4.78% (Boehmer, 2019). Furthermore, Boehmer (2019) adjusts the holdings period in order to uncover any additional insights. As the holding period of the long-short portfolios increases, the cumulative period holdings decrease (Boehmer, 2019). The construction of our portfolios is based on a longer holding period and may be a contributing factor to explain the cumulative underperformance. An investor could create a profitable trading strategy using our portfolio construction methodology by betting against retail investors. For example, short the top 90th percentile portfolio and go long on the bottom 10th percentile portfolio formed on the changes of retail user holdings. In our studied time frame, this would result in a cumulative return of just over 5% for both common shares and exchange-traded fund portfolios. Both portfolios would still greatly underperform relative to the market index.

SECTION I.2: FAMA-FRENCH FACTOR ANALYSIS

We use our existing asset database to develop the three Fama-French factors to explain our long-short portfolio returns. The three principle Fama-French factors include the market performance, the performance of small firms minus big firms (SMB), and the performance of high book to market ratio firms minus low book to market ratio firms (HML). The daily returns of the S&P 500 index are used as the market performance indicator. As for the small minus big (SMB) factor, we use our Robinhood studied stock database to create the factor. All 2241 studied stocks are ranked based on our calculated firm size metric ~ market capitalization. The last observable firm size metric to each asset at the end of our sample period was used to form the small minus big (SMB) factor. The long portfolio consists of the top 90th percentile of firms by size, while the short portfolio contains the bottom 10th percentile of firms by size. Our portfolios are created at the beginning of the studied period using end on sample firm sizes and are held for the entire studied period. A similar approach was used to build the common share high minus low (HML) factor. However, the ranking of retail user holdings is based on market to book ratio rather than firm size. Our analysis involves the market to book ratio while Fama and French (1992) use the book to market ratio. We present the same metric but have inverted the numerator and denominator. Thus, the bottom 10th percentile of market to book ratio firms actually represents the top 90th percentile book to market ratios. The equally weighted long and short portfolios are formed at the beginning of the studied period and are held until the end of the studied period. We apply the same methodology across the 1787 exchange-traded funds. The high minus low (HML) factor cannot be calculated for exchange-traded fund, since they do not have a market to book ratio.

We add a calculated momentum factor based on our asset subsample to our Fama-French factor analysis for the following reasons. First, the momentum factor is widely studied in the literature and proves to be successful. Second, insights throughout our paper touch on the momentum and contrarian behavior of market participants. We demonstrate in the descriptive statistics component (section E.2) that retail investors display contrarian behavior in their portfolio asset selections. We expect the returns from our calculated momentum factor to be in opposite direction to the performance of our retail holding long-short portfolios. The methodology used to form the momentum (MOM) portfolios is similar to that used to form the retail user holdings long-short portfolio. At the start to each month of our studied time frame, we rank all assets based on the previous month's performance. The long portfolio consists of the top 90th percentile of previous month returns, while the short portfolio consists of the bottom 10th percentile. The daily returns to the long and short portfolios are calculated using an equally weighted approach. The equal weighting of the portfolios is only done at the beginning of the month. We do not adjust the portfolio after each day. The same methodology is applied to the 1787 exchange-traded fund assets to calculate the return of the momentum (MOM) factor.

The performance of each long-short portfolio formed on changes retail user holdings as well as the performance of calculated Fama-French factor is presented in **GRAPH #17**. Panel A contains the information concerning common shares and Panel B represents the information regarding exchange-traded funds. The directional performance of each Fama-French factor is consistent across both common shares and exchange-traded fund. Across both asset types, the small minus big (SMB) and the high minus low (HML) factors greatly underperforms. These findings are contrary to the original Fama-French theory. Fama and French (1992) find that daily returns between 1963 and 1990 increase as the firm size decreases and the firm book to market ratio increases. GRAPH #17 suggest that returns increase when firms are larger and hold a low book to market ratio. However, our study only uses an 18-month time period of daily returns and is not sufficient to overcome the results by Fama and French (1992). Lastly, portfolios sorted by momentum (MOM) for both common shares and exchange-traded funds are positive, and greatly exceed the returns of the market index. These results confirm the findings by Jegadeesh and Titman (1993) on the ability of momentum-based strategies to deliver positive returns.

In the aforementioned factor analysis, we calculated the Fama-French factors, including the momentum factor, from our constrained Robinhood database. We extend our Fama-French factor analysis using the actual factor returns from the Kenneth R. French data library. The factors from the Kenneth R. French data library apply the same methodology used in the Fama-French (1992) paper to calculate the factor returns. In addition, these factor returns use all of the stocks from the US market. Our calculated factors from our previous analysis only use the stocks from final Robinhood database, where several assets were removed during the cleaning of the database. The retail user holding long-short portfolio daily returns and the Kenneth R. French data library Fama-French factor daily returns are illustrated in **GRAPH #18**. The directional performance of the Kenneth R. French factors is consistent to the directional performance of the calculated factors from the Robinhood data sample. However, there exists a difference in the magnitude of each factor. The factors calculated from the Robinhood data sample hold much more extreme returns, while the returns from the Kenneth R. French data library are more conservative.

The factor performance analysis from GRAPH #17 and GRAPH #18 suggest that the calculated factors using the Robinhood data sample are representative to those seen in the Kenneth R. French data library. We extend our analysis by regressing the daily returns of our retail user holdings long-short portfolio on the daily returns of the Robinhood-based factors and the Kenneth R. French based factors. The regression allows to uncover differences across individual daily returns, rather than cumulative return over the studied period. The results from the ordinary least square regression are presented in **TABLE #11**. Panel A presents the regression output using the Robinhood based factors as independent variables, while Panel B presents the results using the Kenneth R. French factors. Our primary area of interest in the regression results rests in the alpha value. A significant alpha value implies that there are additional factors that can be used to explain the returns from the retail user holding long-short portfolio. In Panel A, common share alpha value is significant at the 90th percent level of confidence. Although not strongly significant, this finding suggests there are other factors to explain the performance in the retail user holding long-short portfolios. The coefficients output and respective p-values in the Robinhood factor regression (Panel A) show that most of the factors are significant to explain the portfolio returns. The regression coefficient outputs using the Kenneth R. French factors are presented in Panel B of TABLE #11. The alpha output values for both common shares and exchange-traded funds are not significant, suggesting that the Fama-French factors, as well as the momentum factor, are sufficient to explain the daily portfolio returns.

Although the illustrations from GRAPH #17 and GRAPH #18 demonstrate a similar directional performance across factors, our regression coefficient output begs to differ. There exists a difference in some of the signs across the factors between both methodologies. To be consistent with the existing literature, the Kenneth R. French factors are used to describe the daily returns from the long-short portfolio. For both common shares and exchange-traded funds, the market index coefficient is negative and highly significant at the 99% level. This finding suggests that the performance of the long-short portfolio is contrary to the performance of the market. When the market performed well in our studied period, most retail investors experienced poor returns. There exists a divergence in findings between common share assets and exchange-traded fund assets for the momentum (MOM) factor. The momentum factor coefficient is negative and highly significant at the 99% confidence level for common share assets but is positive and highly significant at the 99% level of confidence for exchange-traded funds. Thus, retail investors display contrarian behavior when purchasing and selling common shares, while displaying momentum tendencies when selecting exchange-traded funds. However, the assets used to form the exchange-traded fund momentum factor is not consistent to those used to form the long-short portfolio. The momentum factor from the Kenneth R. French data library is based on common share assets, while the returns of the long-short portfolio are derived from exchange-traded funds.

SECTION I.3: 10 QUANTILE PORTFOLIO ANALYSIS

We test the robustness of our findings by ranking per month asset changes of retail user holdings into 10 portfolios. At the beginning of each month, we take the change in retail user holdings of the previous month and rank them from smallest to largest. The rankings are placed into 10 portfolios, from the smallest to largest. The portfolios are equally weighted at the beginning of each month and rebalanced at the beginning of each month. We do not balance the portfolios at the end of each day throughout the month. The same methodology is conducted for exchange-traded fund assets. The cumulative performance of each portfolio is presented in **GRAPH #19**. Panel A illustrates the performance for the 10 portfolios of common share assets, while Panel B illustrates the performance for the 10 portfolios of exchange traded assets. The findings in GRAPH #19 express a clear relationship between the performance and the trading activity of investors. In both Panel A and Panel B, quantile portfolio #1 and quantile portfolio #10 show to have some of the lowest performances relative to the remaining portfolios. This finding is consistent to the empirical literature, which suggest that excessive trading by investors is detrimental to investor wealth (Barber & Odean, 2000). The quantile portfolio #1 consists of the assets that saw the largest decrease in the change of retail user holdings, while quantile portfolio #10 consists of the assets that saw the largest increase in retail user holdings. Both portfolios contained the largest trading activity, while both portfolios had some of the lowest performances, affirming that trading is hazardous to wealth (Barber & Odean, 2000).

Quantile portfolio returns from GRAPH #19 demonstrate that the performance of all 10 portfolios follows an extremely similar pattern. To confirm the robustness of the results, we run an ordinary least square regression on the daily returns of each of the 10 portfolios on the Fama-French factors daily returns derived from the Kenneth R. French data library. The coefficient outputs and p-values of the regressions are presented in **TABLE #12**. Panel A represent the regression results for the 10 common share portfolios, while Panel B address the regression results for the 10 exchange-traded fund portfolios. There exists relative consistency in coefficient results between exchange-traded funds and common shares across all 10 portfolios. First, there exist no large noticeable differences across the alpha values of the 10 portfolios for both common shares and exchange-traded funds. Using two different quantile portfolios to construct the long-short portfolio would result in similar findings to those previously seen in GRAPH #17. Second, there are more significant alpha values in the common share asset portfolios than there are for the exchange-traded fund asset portfolios. There is reason to suspect that there may be additional factors to explain the portfolio returns formed on changes in retail user holdings of common share assets. The coefficients for the market factor, small minus big (SMB) factor, and high minus low (HML) factor are relatively constant across all portfolios with no significant insights. However, the momentum (MOM) factor presents an interesting pattern. The momentum factor across common shares starts off positive in the lower quantile portfolios before becoming negative in the higher quantile portfolios. This pattern in the coefficient outputs suggests that retail investors sell good performing assets and purchase poor performing assets. The contrarian behavior of retail investors when trading common share assets continues to be highlighted in our findings. As for exchange-traded fund assets (Panel B of TABLE #12), the momentum factor starts off negative in the low quantile portfolios before becoming positive in the high quantile portfolios. Retail investors display a form of momentum behavior when deciding to purchase and sell exchange-traded funds. These results could be misleading, since we are regressing portfolio returns of exchange-traded funds on the momentum performance of stocks. We cannot confirm that retail investors display momentum behavior when purchasing exchange-traded funds. These findings give sufficient reasoning to support the idea that retail investors are less contrarian when trading exchange-traded funds than they are with common share assets (Dalt et al., 2018).

SECTION J: CONCLUSION

We use moving average strategies to aggregate the behavior of retail investors surrounding technical analysis signals. The preliminary interest of our paper focused on confirming that retail investors do trade on technical analysis signals. We find that when using the changes in retail user holdings, an equally weighted metric, retail investors do increase their holdings on the moving average signals exposed on common share assets. The confirmation that retail investors do trade on these signals led to further examining exactly *how* do moving retail investors trade on these signals. First, we find that the contrarian behavior of retail investors impacted the activity between sell signals and buy signals. Retail investors increase their holdings more on sell signals then they do on buy signals. They use sell signals exposed on recent poor performing assets as a reason to increase their portfolio holdings. Second, we are first to highlight that retail investors are late to trade moving average signals. The changes in retail user holdings is positive and peaks on the day following the signal day. In addition, retail investors start to increase their holdings prior to the day of the signal. This is especially true for signals derived from the double moving average cross over methodology. Third, we find a discrepancy in the choice of fundamental characteristics used by retail investors to trade across buy signals and sell signals. Retail investors will use buy signals to increase their holdings on small, illiquid, and volatile assets. However, the signals on assets with these fundamental characteristics show to be the least profitable on average, suggesting that retail investors do not trade on the assets that can bring them the most profits. Retail investors prefer to trade the assets that have an extremely small possibility of delivering an unlikely large return. As for sell signals, retail investors will increase their holdings on assets that are large, liquid, and volatile. Retail investors use downturns in the market to purchase high quality stocks that can still deliver them large returns. Fourth, we find that retail investors use the after-hours market to trade moving average signals. The contrarian tendencies of retail investors continues to be displayed in the after-hours market. Lastly, we present some evidence that investors do use exchange-traded fund assets to trade moving averages signals. These highlighted findings are all contributions to the existing knowledge on retail behavior surrounding technical analysis signals.

The presentation of these new findings was made possible due to the new Robintrack database derived from the Robinhood trading platform. The only limit from our study is that we only have 18 months of available data. In addition, the findings from this timeframe occur during a bull market. For future studies, it would be interesting to retest our contributed findings using a longer time period. Our findings may change when accounting for a market comprised of both bull runs and bear runs. In addition, one could use the hourly data from the Robintrack database to determine the hours at which retail investors prefer to trade. Lastly, the pre-market hours activity can be used to uncover if retail investors use these non-normal hours to trade moving average signals.

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SECTION L: KEY TABLES & GRAPHS

TABLE #4: Table represents the regression output to explain retail investor holdings. Panel A accounts for the 2241 common share assets and Panel B accounts for the 1787 exchange-traded fund assets. The dependent variable to this regression is the count of retail investors of each asset. The count of retail investors to each asset is gathered on December 31st, 2020 at the end of our sample. The independent variables to this regression include the full list of metrics presented in TABLE #3. The calculated value to each metric is based on the last available information from the CRSP and COMPUSTAT database. For each metric, we present the coefficient output and the regression p-value. Any significant p-value is assigned a * notation as reference.

TABLE #4: Regression Ouptut Describing The Fundamental Characteristics That Interest The Average Retail Investor

METRIC	Panel A: *Common Shares*			Panel B: *Exchnage-Traded Funds*		
	Sign	*Coefficient*	*P-Value*	*Sign*	*Coefficient*	*P-Value*
Log Size	(+)	5222	**0.000*** **	(+)	144	**0.012** **
Log Volatility	(+)	3902	**0.000*** **	-	509	**0.000*** **
Log Market to Book Ratio	(-)	753	0.145	-	-	-
Log Volume	(+)	2836	**0.001** **	(+)	120.36	**0.001*** **
Log 1/Close	(+)	6144	**0.000*** **	(+)	470	**0.000*** **
Log Liquidity	(-)	-1771	**0.087* **	(+)	114	0.457
Log R&D Expenses	(+)	1640	**0.000*** **	-	-	-
Leverage	(-)	-183	0.685	-	-	-
Price	(+)	15.77	**0.000*** **	(+)	56	**0.000*** **
Profitability	(+)	5514	0.278	-	-	-
OBSERVATIONS	2241			1787		
R_SQUARE	0.141			0.127		

*** Signifies that the Coefficient output is significant at the 99% confidence level **(P-Value < 0.01)**

** Signifies that the Coefficient output is significant at the 95% confidence level **(P-Value < 0.05)**

* Signifies that the Coefficient output is significant at the 90% confidence level **(P-Value < 0.1)**

TABLE #5: The table presents the regression results of the daily changes in retail user holdings on different lag period asset returns. The dependent variable to this regression is the changes in retail user holdings to each asset for each studied day in our data sample. This dependent variable is regressed on several previous period returns accounting for different time frames. There is no overlap in returns across each time period return. We use a firm fixed effect as well as a date fixed effect to account for any autocorrelation and heteroscedasticity in the panel data. We adjust the standard errors using the Newey-West adjustment. Panel A accounts for information regarding the 2241 common share assets, while Panel B accounts for the 1787 exchange traded fund assets. In each panel, we present the coefficient output and the p-value to each independent metric. Significant p-values are noted with * notation, with the legend presented in the table.

TABLE #5: Regression Ouptut To Demonstrate The Contrarian Behvaiour Of Retail Investors

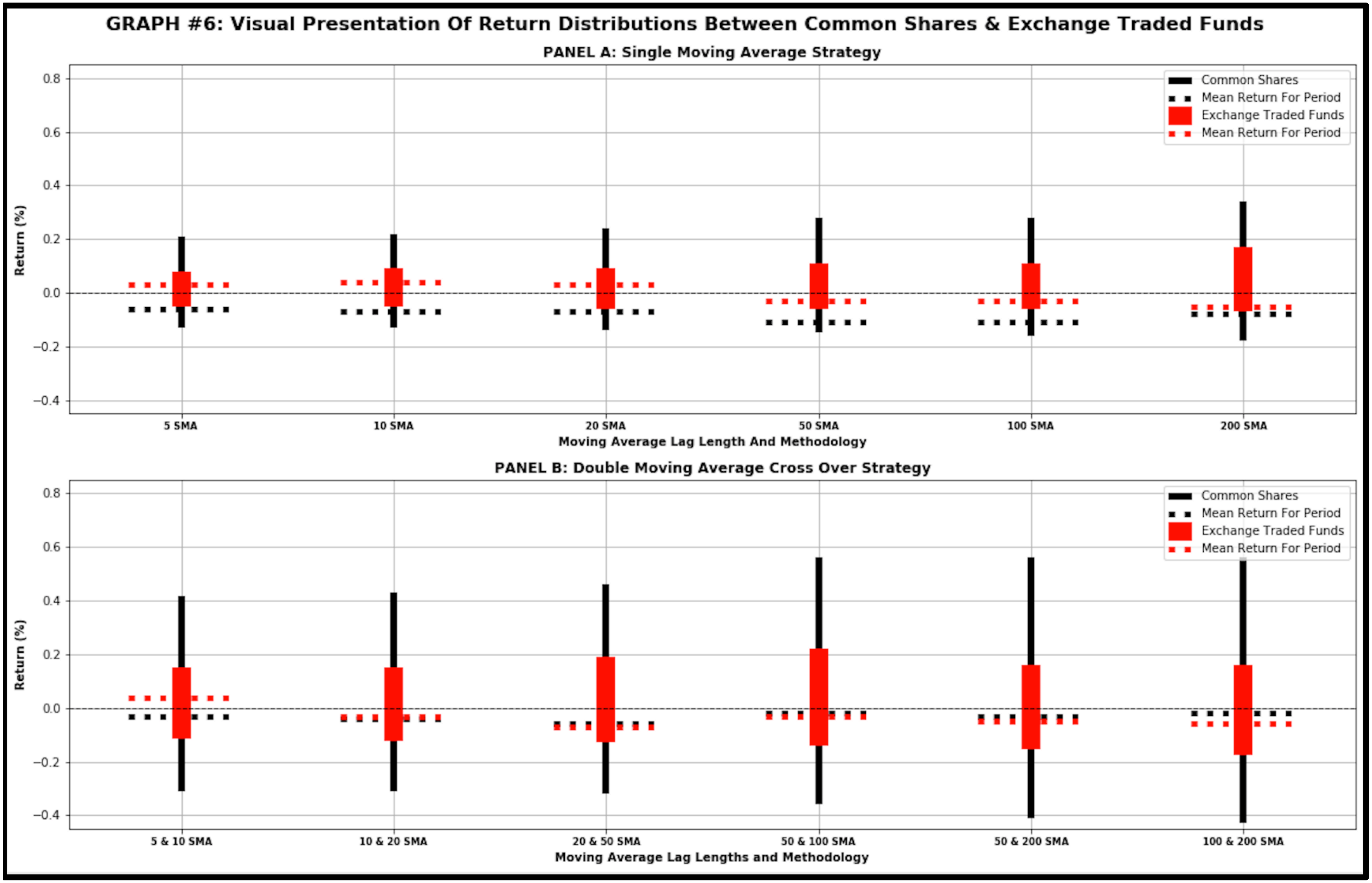
METRIC	Panel A: *Common Shares*			Panel B: *Exchange-Traded Funds*		
	Sign	*Coefficient*	*P-Value*	*Sign*	*Coefficient*	*P-Value*
1 DAY RETURN (LAG)	(-)	-0.0224	**0.0114** **	(+)	-0.0053	**0.0001*** **
1 WEEK RETURN	(-)	-0.0007	0.7589	-	-0.0012	**0.0168** **
1 MONTH RETURN	(+)	0.0009	**0.0756* **	-	-0.00002	0.9177*
3 MONTH RETURN	(-)	-0.0003	0.3635	(+)	-0.0008	**0.0000*** **
6 MONTH RETURN	(-)	-0.0005	**0.0144** **	(+)	-0.0005	**0.0000*** **
OBSERVATIONS	583 104			387 332		
R_SQUARE	0.0006			0.0003		

*** Signifies that the Coefficient output is significant at the 99% confidence level **(P-Value < 0.01)**

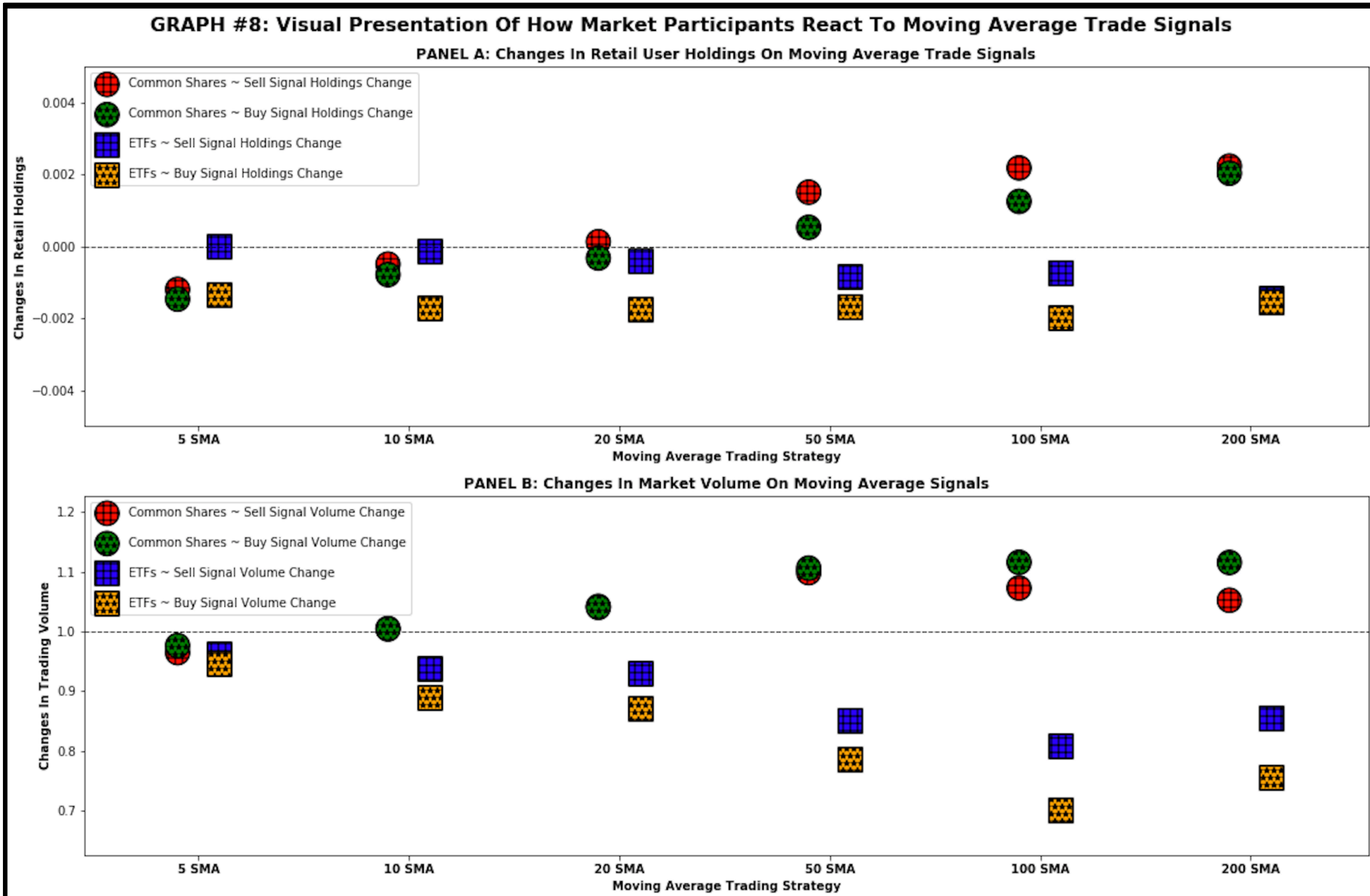
** Signifies that the Coefficient output is significant at the 95% confidence level **(P-Value < 0.05)**

* Signifies that the Coefficient output is significant at the 90% confidence level **(P-Value < 0.1)**

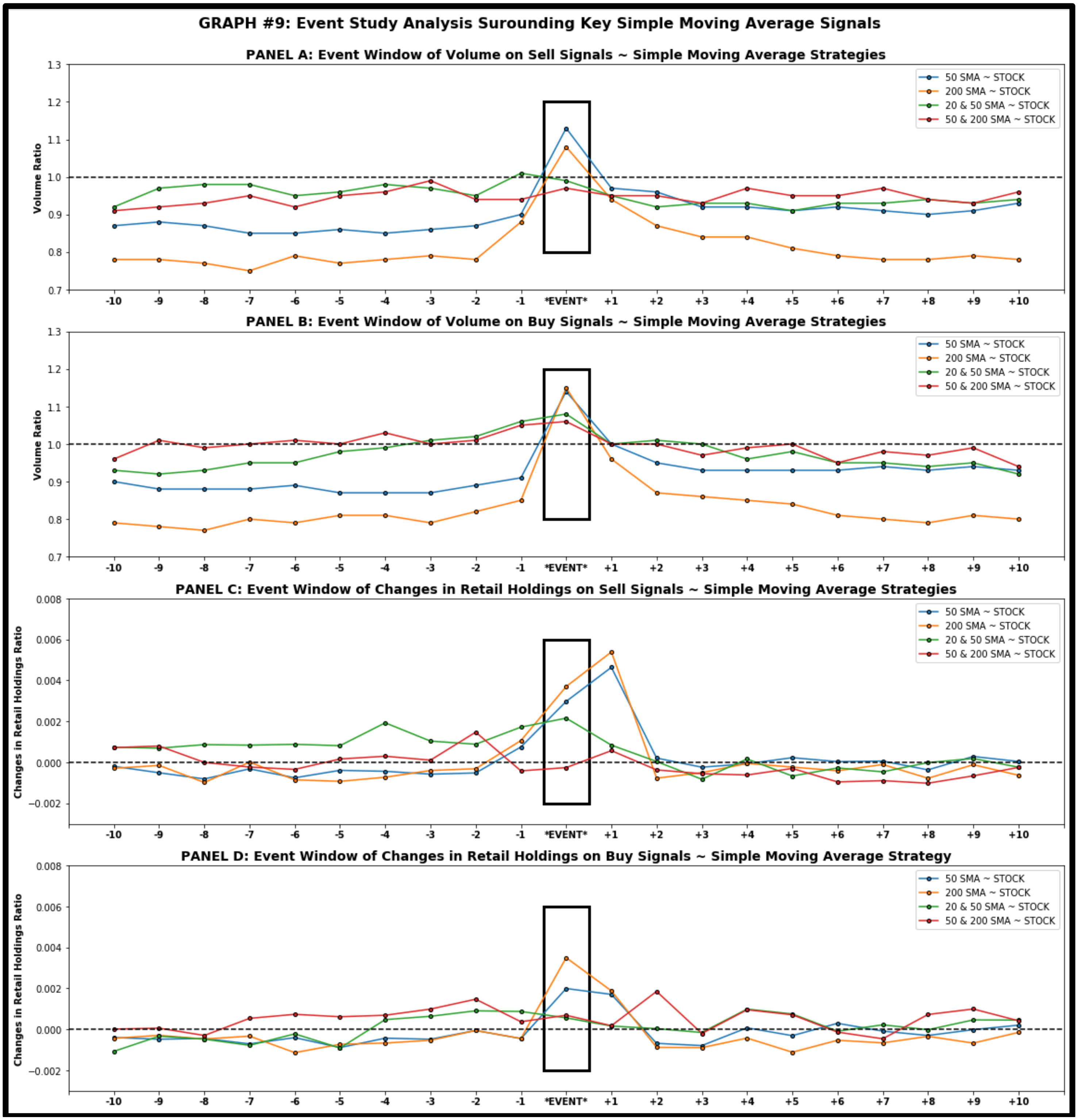
GRAPH #6: The graph illustrates the differences in return distributions and profitability of moving average strategies when considering for differences in asset type and moving average methodology. Panel A presents findings the for the single moving average methodology using simple moving averages (SMA). Panel B presents findings for the double moving average cross over methodology using simple moving averages (SMA). The vertical solid black line (to each graph) uses the TOP_RET and BOT_RET metrics from TABLE #6 ~ Panel A to show the tail of the return distributions of common shares. The vertical solid red line uses the TOP_RET and BOT_RET from TABLE#6 ~ Panel B to show the tail of the return distributions of exchange-traded funds. The horizontal dotted black line is the PER_RET metric value from TABLE #6 ~ Panel A, expressing the average period return of the respective strategy for common shares in the studied time period. The horizontal dotted red line is the PER_RET metric value from TABLE #6 ~ Panel B, expressing the average period return of the respective strategy for exchange-traded funds in the studied time period.



GRAPH #8: The graph shows the activity of market participants on the days in which different moving average signals are generated. We select the trading strategies that use single moving average methodology and simple moving averages (SMA) since they get the most activity. Panel A represents the activity by retail investors on signal days, using the difference in average log change in retail user holdings on signal days to the average log difference in retail user holdings on non-signal days. Panel B represent the activity by all market participants, using the ratio of average volume on signal days to the average volume on non-signal days. In each panel, we make the distinction between the activity on sell signals and buy signals. In addition, we make the distinction between common share activity (circle) to exchange-traded fund activity (square). The respective trading strategy is presented on the x-axis.



GRAPH #9: The graph illustrates an event study window analysis for volume and retail user holding activity leading to and following a simple moving average (SMA) signal. Panel A shows the event study window analysis in volume activity across all common shares sell signals. Panel B shows the event study window analysis in volume activity across all common shares buy signals. The volume activity metric used in Panel A & Panel B is the ratio of average volume on signal days to the average volume on non-signal days. Panel C presents the event study window analysis in retail investor activity across all common share sell signals. Panel D presents the event study window analysis in retail investor activity across all common share buy signals. The retail investor activity metric used in Panel C & Panel D is the difference in the average log change in retail user holdings on signal days to the average log change in retail user holdings on non-signal days. The x-axis presents the number of days prior (-) and the number of days following (+) the signal day (*EVENT*). Each panel present the event window analysis for 4 strategies, accounting for the differences in the methodologies studied throughout the paper.



GRAPH #12: The graph illustrates the relationship between the activity surrounding moving average signals and the rankings of firm fundamental metrics. The x-axis to each panel line graph represents the quantile grouping of firms by fundamental metric. Quantile group #1 (x-axis value of 1) represents the bottom 10% of firms and quantile group #10 (x-axis value of 10) represents the top 10% of firms. Panel A & Panel B uses the volume metric to measure activity and Panel C & D uses the retail user holdings metric to measure activity. The volume metric consists of the ratio between the average volume on signal days to the average volume on non-signal days. The retail user holdings metric is the difference between the average log change in retail user holdings on signal days to the average log change in retail user holdings on non-signal days. In addition, Panel A & Panel C identify activity on sell signal days while Panel B & D identify activity on buy signal days. In each panel, we represent the activity by firm size quantiles (red), firm liquidity quantiles (blue) and firm volatility quantiles (green). The metrics used to assign each fundamental characteristic are consistent to Graph #11. The graph only focuses on the activity of common shares.

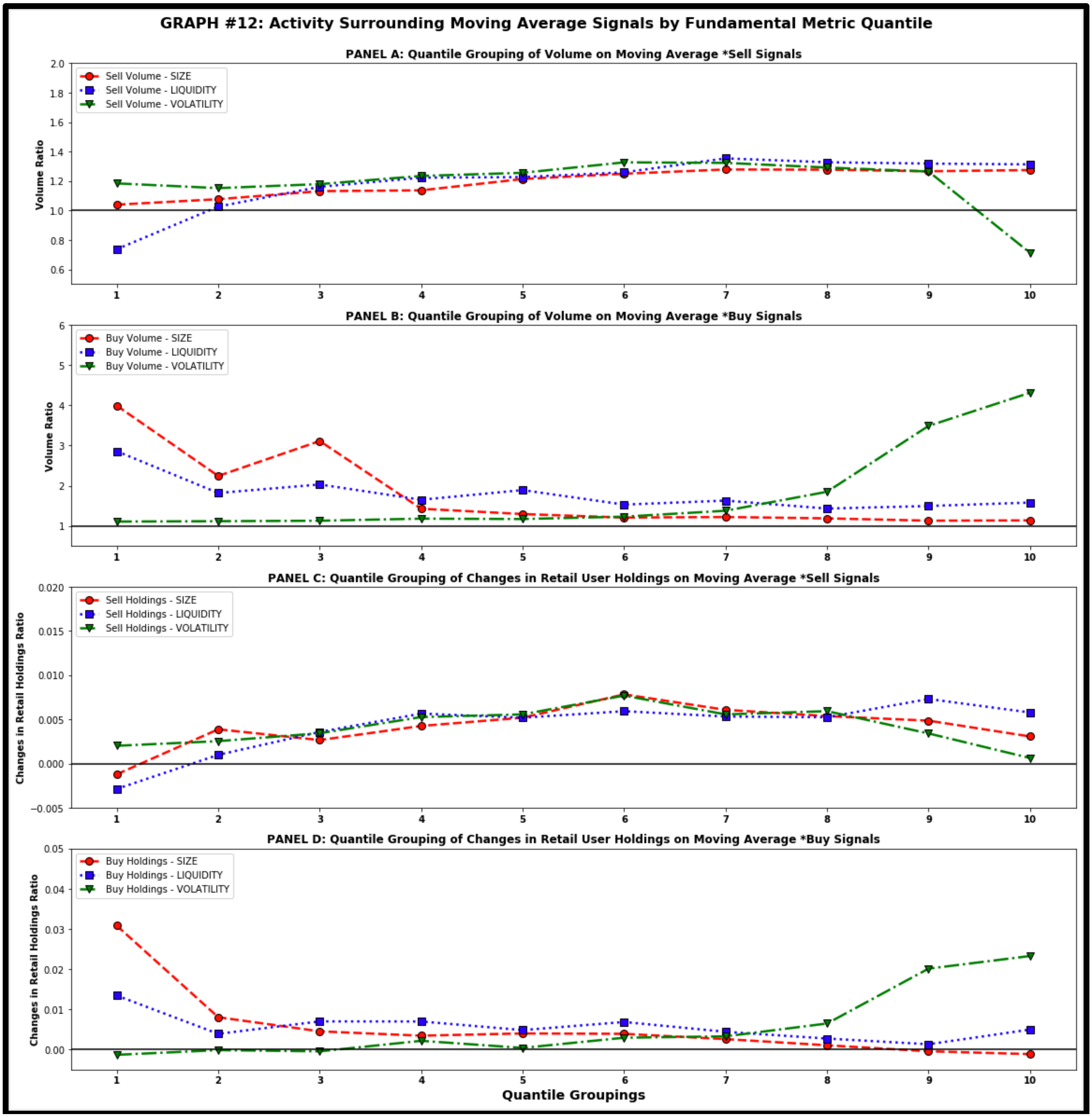


TABLE #10: The table compliments Graph #12 and presents findings on the relationship between the activity surrounding moving average indicators and the ranking of firm fundamental metrics. The table adds new information on the activity regarding exchange-traded funds (Panel B). Only 8 of the 27 moving average strategies presented in these findings (further detail in paper). ***MA Return*** measures the average return per trade and ***B&H Return*** presents the average return across all assets for the entire studied period. ***SELL VOL*** is volume activity around sell signal days, ***BUY VOL*** is the volume activity around buy signals, ***SELL HOLD*** is the retail investor activity around sell signals, and ***BUY HOLD*** is the retail activity around buy signals. The volume activity metric and the retail investors activity metric are consistent to those presented in previous tables and graphs. The column *METRIC separates the findings by either firm size (TABLE #3 ~ Log Size), firm liquidity (TABLE #3 ~ Log Volume), and firm volatility (TABLE #3 ~ Log Volatility). The column QUANTILES separate the metric by ranking. For example, Quantile #1 represents the 0 – 10th percentile of a respective metric whereas Quantile #10 represents the 91st – 100th percentile of a respective metric.

TABLE #10: Profitability & Activity of Moving Average Strategies Across Fundamental Metric Quantiles

*METRIC	QUANTILES	Panel A: Common Shares						Panel B: Exchange-Traded Funds					
		MA Return	*B&H Return*	*SELL VOL*	*BUY VOL*	*SELL HOLD*	*BUY HOLD*	*MA Return*	*B&H Return*	*SELL VOL*	*BUY VOL*	*SELL HOLD*	*BUY HOLD*
FIRM SIZE	*Quantile #1*	-0.110	-0.50	1.04	3.99	-0.001	0.031	-0.013	-0.04	0.36	1.44	-0.001	0.036
	Quantile #2	-0.045	-0.30	1.08	2.24	0.004	0.008	-0.008	0.01	0.46	1.27	0.005	0.009
	Quantile #3	-0.021	-0.11	1.13	3.11	0.003	0.005	-0.001	0.04	0.75	0.91	0.003	0.005
	Quantile #4	-0.011	-0.05	1.14	1.43	0.004	0.003	-0.006	-0.01	0.78	1.23	0.004	0.003
	Quantile #5	-0.005	0.00	1.21	1.30	0.005	0.004	-0.003	0.03	0.97	1.15	0.006	0.004
	Quantile #6	0.008	0.10	1.25	1.21	0.008	0.004	0.000	0.04	0.97	1.04	0.008	0.004
	Quantile #7	0.005	0.21	1.28	1.22	0.006	0.003	0.000	0.06	1.15	1.00	0.006	0.002
	Quantile #8	0.022	0.22	1.28	1.19	0.005	0.001	-0.001	0.06	1.11	1.00	0.005	0.001
	Quantile #9	0.018	0.25	1.27	1.13	0.005	0.000	0.001	0.08	1.11	1.00	0.005	0.000
	Quantile #10	0.019	0.27	1.27	1.14	0.003	-0.001	0.004	0.09	1.20	0.98	0.003	-0.001
FIRM LIQUIDITY	*Quantile #1*	-0.029	0.00	0.74	2.86	-0.003	0.013	-0.005	0.052	0.20	1.91	-0.004	-0.002
	Quantile #2	-0.015	-0.04	1.03	1.82	0.001	0.004	-0.006	0.027	0.58	1.02	-0.003	-0.002
	Quantile #3	-0.019	-0.06	1.16	2.03	0.004	0.007	-0.008	0.025	0.69	0.95	-0.001	0.000
	Quantile #4	-0.007	-0.01	1.22	1.65	0.006	0.007	-0.003	0.046	0.89	1.03	0.000	0.002
	Quantile #5	-0.005	0.05	1.23	1.89	0.005	0.005	0.000	0.062	1.01	1.12	0.003	-0.001
	Quantile #6	-0.002	0.06	1.26	1.53	0.006	0.007	0.002	0.034	1.05	1.00	0.001	-0.004
	Quantile #7	-0.002	-0.04	1.35	1.63	0.005	0.004	-0.002	0.048	1.11	1.00	0.003	-0.001
	Quantile #8	0.003	0.06	1.33	1.43	0.005	0.003	-0.001	0.020	1.03	0.99	0.000	-0.002
	Quantile #9	-0.009	0.11	1.32	1.50	0.007	0.001	0.000	0.046	1.14	1.01	0.000	0.000
	Quantile #10	-0.028	-0.04	1.31	1.58	0.006	0.005	-0.002	0.020	1.17	1.04	0.001	0.001
FIRM VOLATILITY	*Quantile #1*	0.010	0.20	1.18	1.11	0.002	-0.001	0.000	0.031	0.98	0.96	0.002	-0.002
	Quantile #2	0.004	0.14	1.15	1.12	0.003	0.000	0.000	0.039	1.07	0.97	0.001	-0.003
	Quantile #3	0.005	0.17	1.18	1.13	0.003	0.000	-0.001	0.065	1.05	0.95	-0.001	0.003
	Quantile #4	0.004	0.09	1.23	1.18	0.005	0.002	0.003	0.096	1.10	1.03	0.001	-0.003
	Quantile #5	0.008	0.10	1.26	1.17	0.006	0.000	0.000	0.083	1.07	1.04	-0.001	-0.001
	Quantile #6	0.014	0.08	1.33	1.23	0.008	0.003	0.002	0.044	1.10	0.97	0.000	-0.001
	Quantile #7	-0.003	-0.02	1.32	1.38	0.006	0.003	-0.007	0.013	1.12	1.01	-0.001	-0.001
	Quantile #8	-0.005	-0.13	1.29	1.85	0.006	0.006	-0.009	-0.052	0.99	1.31	0.001	0.000
	Quantile #9	-0.063	-0.63	1.26	3.49	0.003	0.020	-0.011	0.011	0.27	0.97	0.000	0.000
	Quantile #10	-0.097	0.10	0.71	4.31	0.001	0.023	-0.004	0.044	0.09	1.84	-0.003	-0.001

GRAPH #13: The graph illustrates the activity by retail investors in the after-hours market on key moving average signal days. As seen on the x-axis, the graph only includes 6 of the 27 strategies. The selected strategies involve the single moving average methodology using simple moving averages. Each of the 6 strategies are labeled on the x-axis to the graph. Panel A presents the retail activity for common shares (circles) in the after-hours market. Panel B represents the retail activity for exchange-traded funds (square) in the after-hours market. Each panel makes the distinction between the activity on sell signals (red) and buy signals (green). The metric in these graphs measure the difference between the average log change in retail user holdings activity in the after-hours market on signal days to the average log change in retail user holdings in the after-hours market on non-signal days.

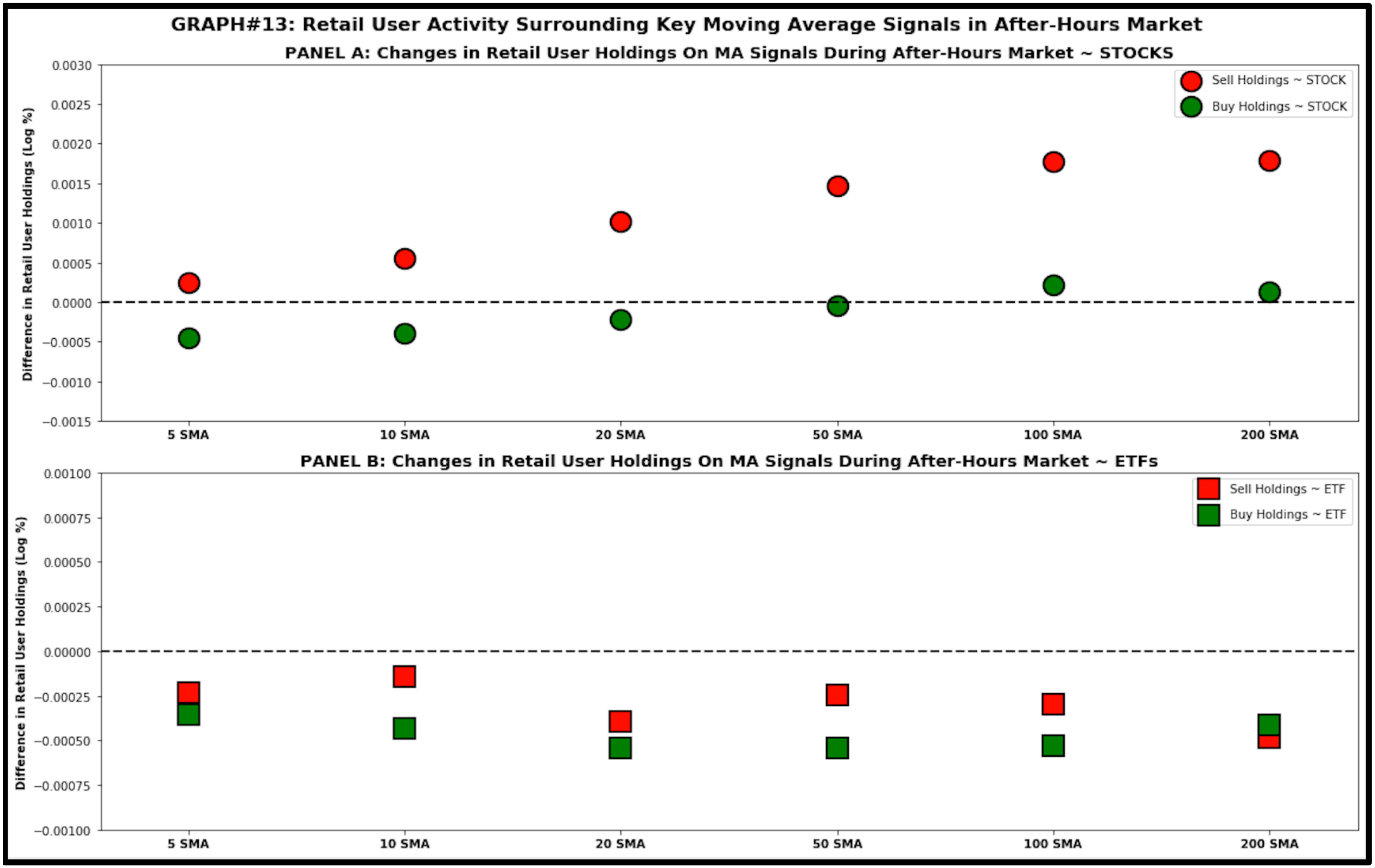


TABLE #11: The table presents the regression results of the daily returns from the long-short portfolio on the Fama-French factors. The dependent variable in this regression is the daily returns of the long-short portfolio formed on changes in retail user holdings. Panel A uses the Robinhood calculated Fama-French factor daily returns as the independent values. Panel B uses the Fama-French factor daily returns from the Kenneth R. French data library as the independent values. Each Panel presents the factor sign, the coefficient output, and the respective p-value. Any significant independent variable will be identified with a * notation in the p-value column. In addition, each panel makes the distinction between common share data and exchange-traded fund data.

TABLE #11: Regression Ouptut of Daily Retail Investors Portfolio Performance on Fama & French Factors

PANEL A: Development of The Fama & French Factors Using RobinHood Database

METRIC	COMMON SHARES			EXCHANGE TRADED FUNDS		
	Sign	*Coefficient*	*P-Value*	*Sign*	*Coefficient*	*P-Value*
ALPHA	(+)	0.0026	0.906*	(-)	-0.0111	0.48
Market Factor	(+)	0.0495	0.064*	(-)	-0.1982	0***
SMB Factor	(+)	0.1187	0***	(-)	-0.1844	0.004***
HML Factor	(-)	-0.1145	0***	-	-	-
MOM Factor	(-)	-0.0007	0.751	(-)	-0.0461	0***

PANEL B: Development of The Fama & French Factors Using R. Kenneth Database

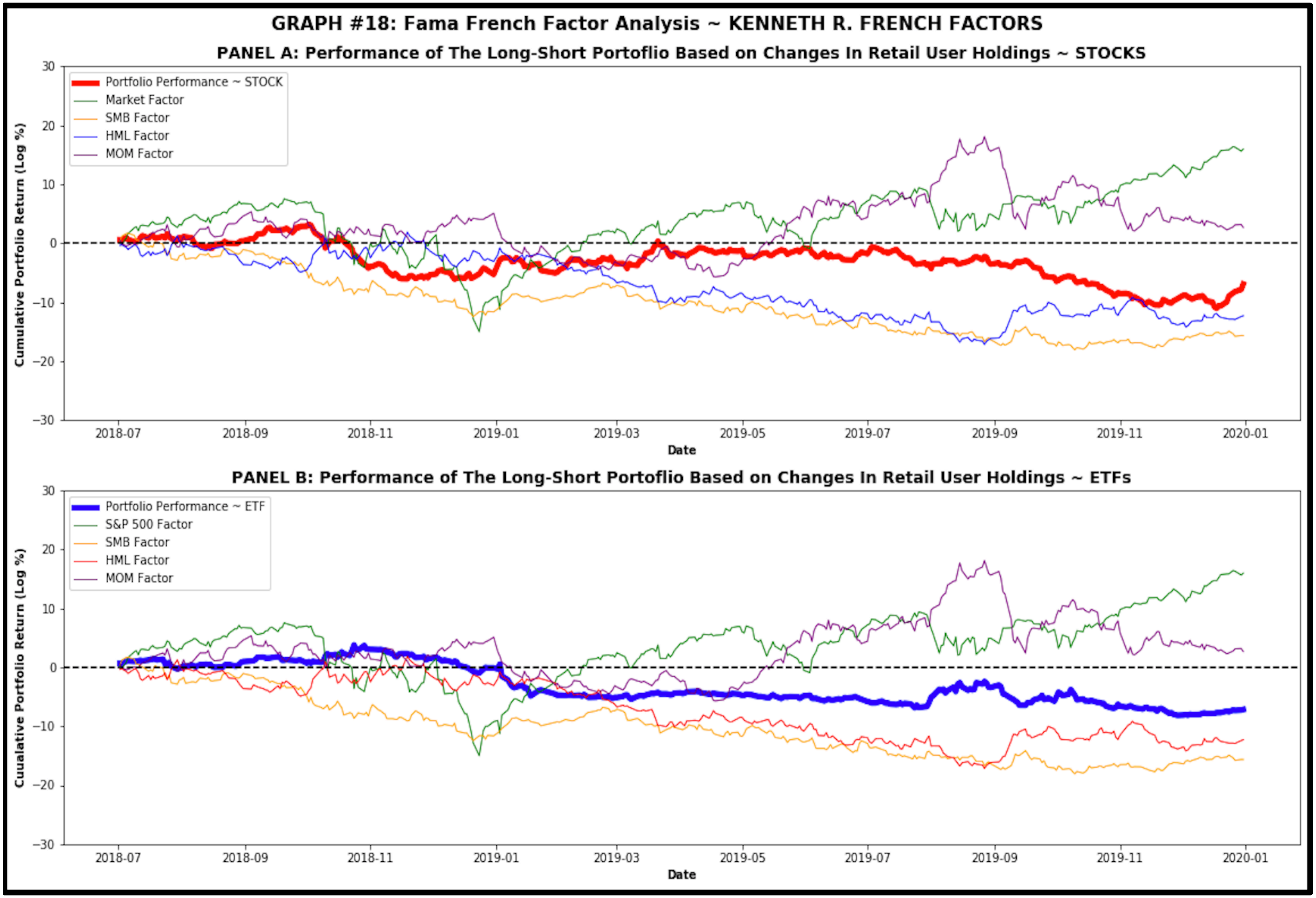
METRIC	COMMON SHARES			EXCHANGE TRADED FUNDS		
	Sign	*Coefficient*	*P-Value*	*Sign*	*Coefficient*	*P-Value*
ALPHA	(-)	-0.0002	0.249	(-)	-0.0001	0.437
Market Factor	(-)	-0.0016	0.95**	(-)	-0.1554	0***
SMB Factor	(-)	-0.0278	0.559	(+)	0.0474	0.173
HML Factor	(-)	-0.2199	0***	(-)	-0.0126	0.738
MOM Factor	(-)	-0.1204	0.004***	(+)	0.0969	0.002***

*** Signifies that the Coefficient output is significant at the 99% confidence level **(P-Value < 0.01)**

** Signifies that the Coefficient output is significant at the 95% confidence level **(P-Value < 0.05)**

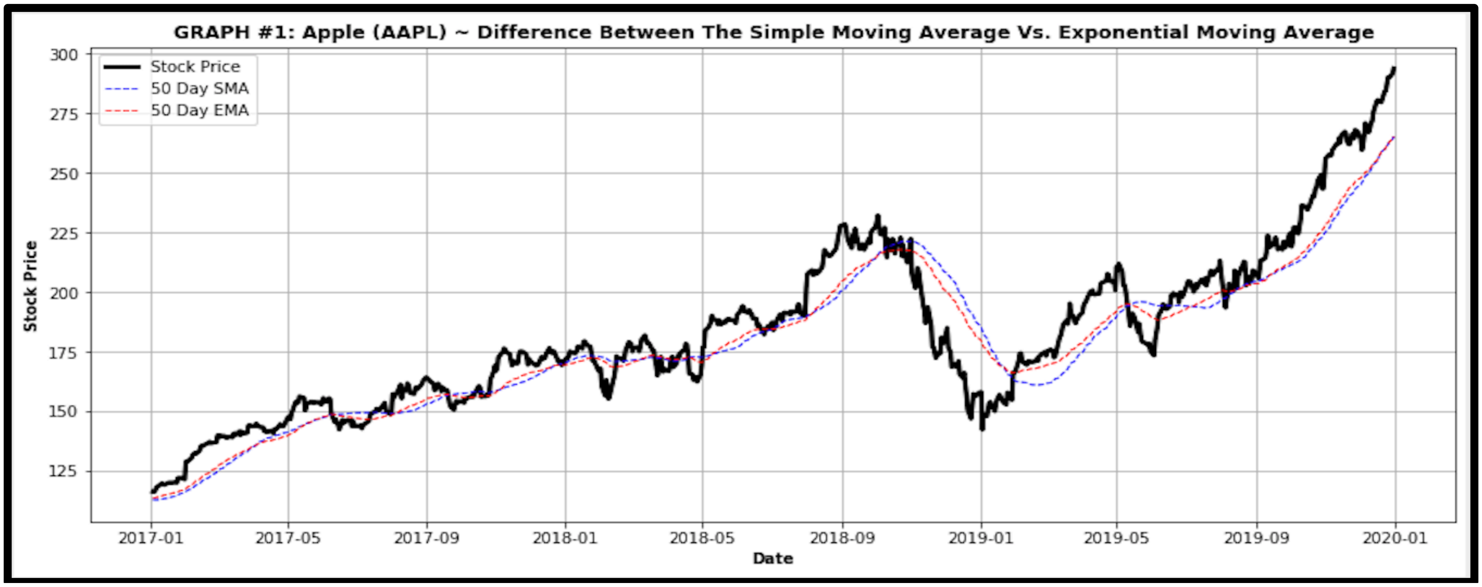
* Signifies that the Coefficient output is significant at the 90% confidence level **(P-Value < 0.1)**

GRAPH #18: The graph presents the performance of the long-short portfolios relative to the Kenneth R. French factors. Panel A presents the performance of the common share long-short portfolio and Fama-French factors. Panel B presents the performance of the exchange-traded fund long-short portfolio and Fama-French factors. Each panel presents the Fama-French factor retrieved from the Kenneth R. French data library. The Market Factor is presented in green, the Small Minus Big factor (SMB) is presented in orange, the High Minus Low factor (HML) is presented in blue, the Momentum factor (MOM) is presented in purple. All factors in the graph are expressed in terms of cumulative return over the studied period.



SECTION M: APPENDIX

GRAPH #1: The graph presents the Apple Inc stock price across time in relation to moving average indicators. The graph is presented to express the differences between the simple moving average (SMA) and the exponential moving average (EMA). The simple moving average is presented in the blue dotted line and the exponential moving average highlighted in red.



GRAPH #2: The graph illustrates a few trade scenarios between the single moving average trading strategy and the double moving average cross over strategy. Panel A presents the trade ideas on the Apple Inc stock when using the single moving average strategy. Panel B provides a few trade ideas on the Apple Inc stock when using the double moving average cross over strategy. Across both panels, the "BUY" indicators (in green) indicate a moment in which the strategy recommends purchasing Apple Inc stock. The "SELL" indicators (in red) present a moment in time where the strategy recommends selling Apple Inc stock.

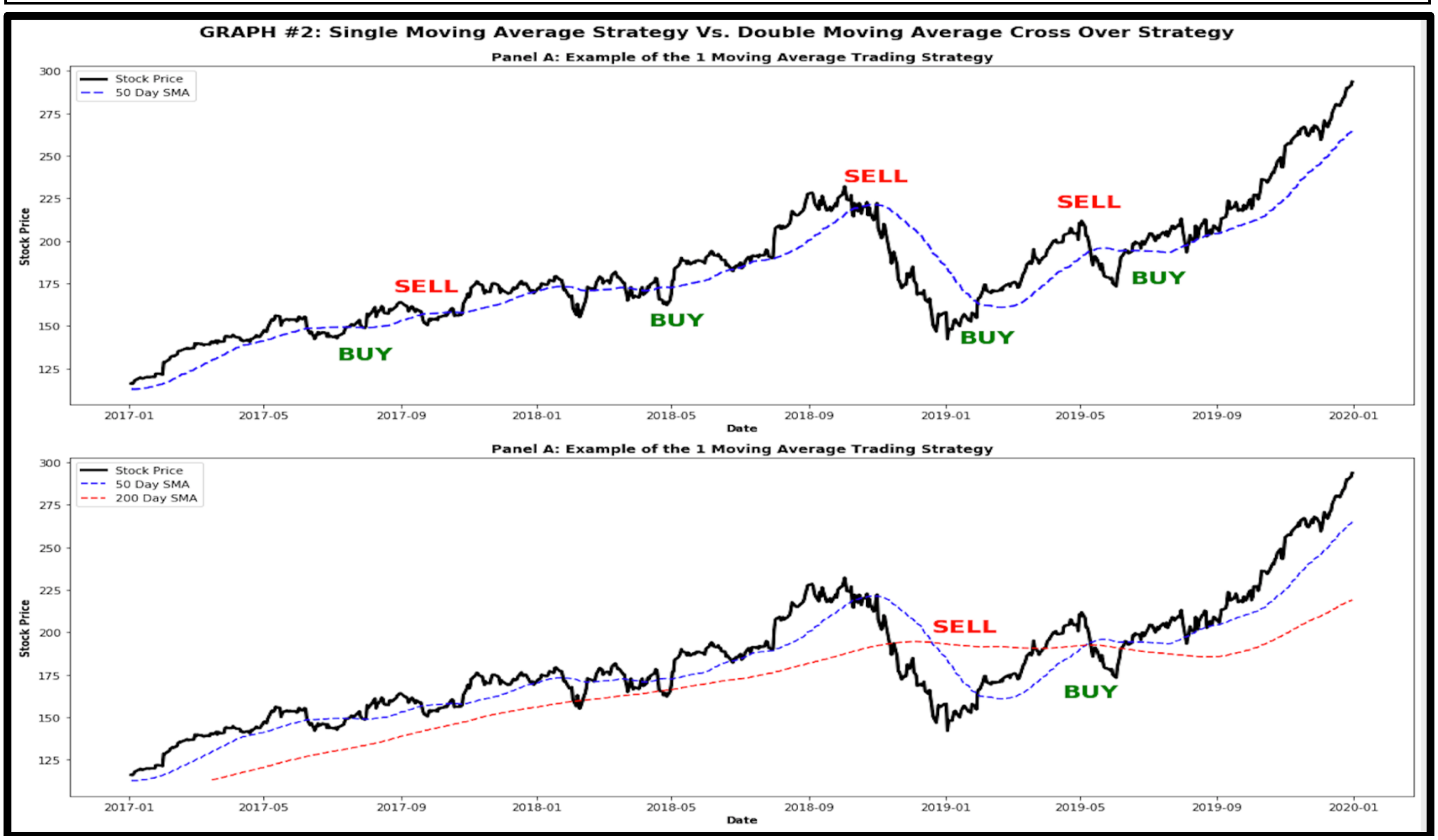


TABLE #2: The table identifies the 27 different moving average strategies studied throughout the course of our paper. We separate all strategies by the different methodologies discussed throughout the paper. Panel B presents the strategies using the single moving average methodology. Panel B presents the strategies using double moving average cross over methodology. Each of the methodologies are separated among the strategies involving the simple moving average (SMA) vs. the strategies involving the exponential moving average (EMA). The strategies involving the exponential moving averages (EMA) contain the 12-day and 26-day indicators to reference the Moving Average Convergence Divergence (MACD) indicator.

TABLE #2 : List of The Different Moving Average Trading Strategies Based On Methodology And Lag Lengths			
PANEL A: ***SINGLE MOVING AVERAGE TRADING STRATEGY***		**PANEL B:** ***DOUBLE MOVING AVERAGE CROSS OVER TRADING STRATEGY***	
SIMPLE MOVING AVERAGE	***EXPONENTIAL MOVING AVERAGE***	***SIMPLE MOVING AVERAGE***	***EXPONENTIAL MOVING AVERAGE***
5 SMA	5 EMA	-	-
10 SMA	10 EMA	5 & 10 SMA	5 & 10 EMA
-	12 EMA	10 & 20 SMA	10 & 20 EMA
20 SMA	20 EMA	-	12 & 26 EMA
-	26 EMA	20 & 50 SMA	20 & 50 EMA
50 SMA	50 EMA	50 & 100 SMA	50 & 100 EMA
100 SMA	100 EMA	50 & 200 SMA	50 & 200 EMA
200 SMA	200 EMA	100 & 200 SMA	100 & 200 EMA

GRAPH #3: The table presents the distribution of firms by size. The size of firms is measured using market capitalization. Panel A presents the distribution of firms when firm size values unadjusted. Panel B presents the distribution of firms when adjusted using the natural log value. The distribution of the firms in each panel are separated into 25 buckets. The value to each of the buckets is the count of firms within that range, and not the percent representation across all firms.

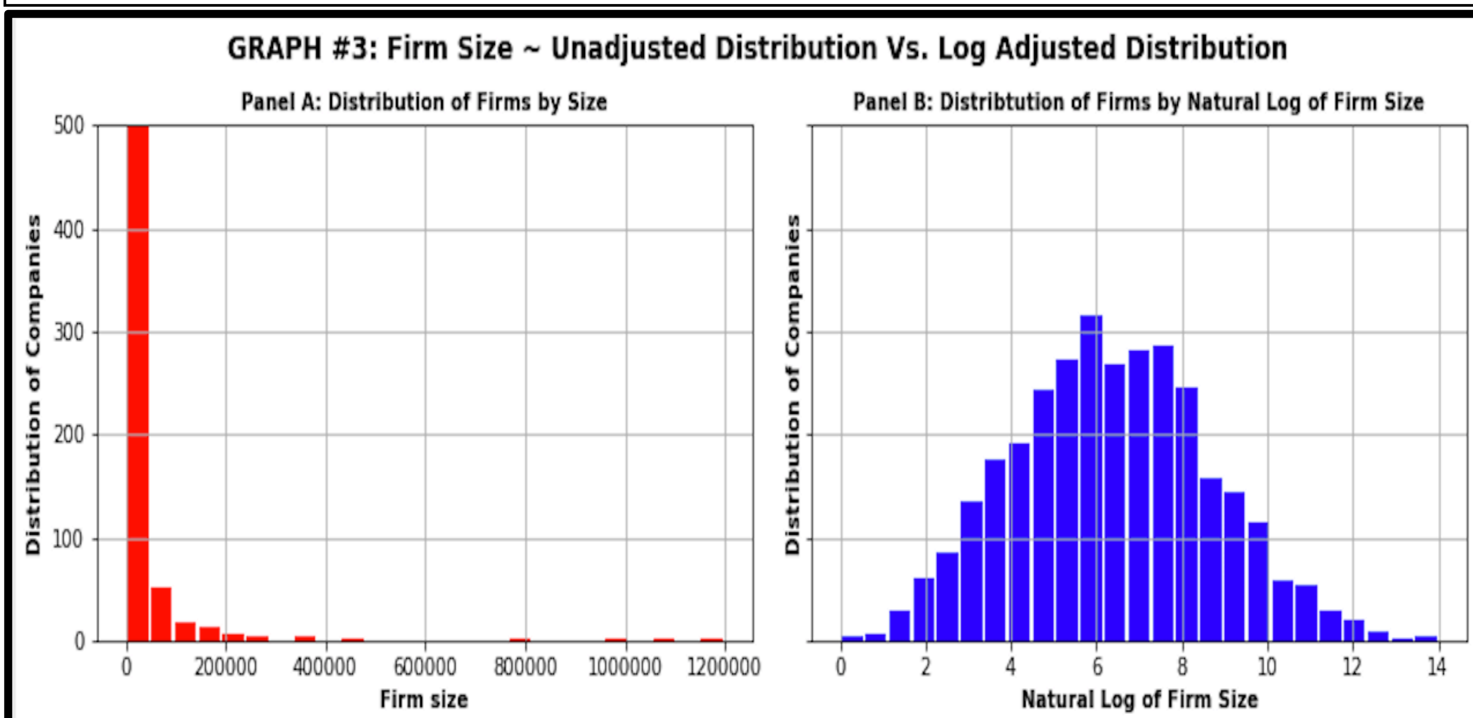
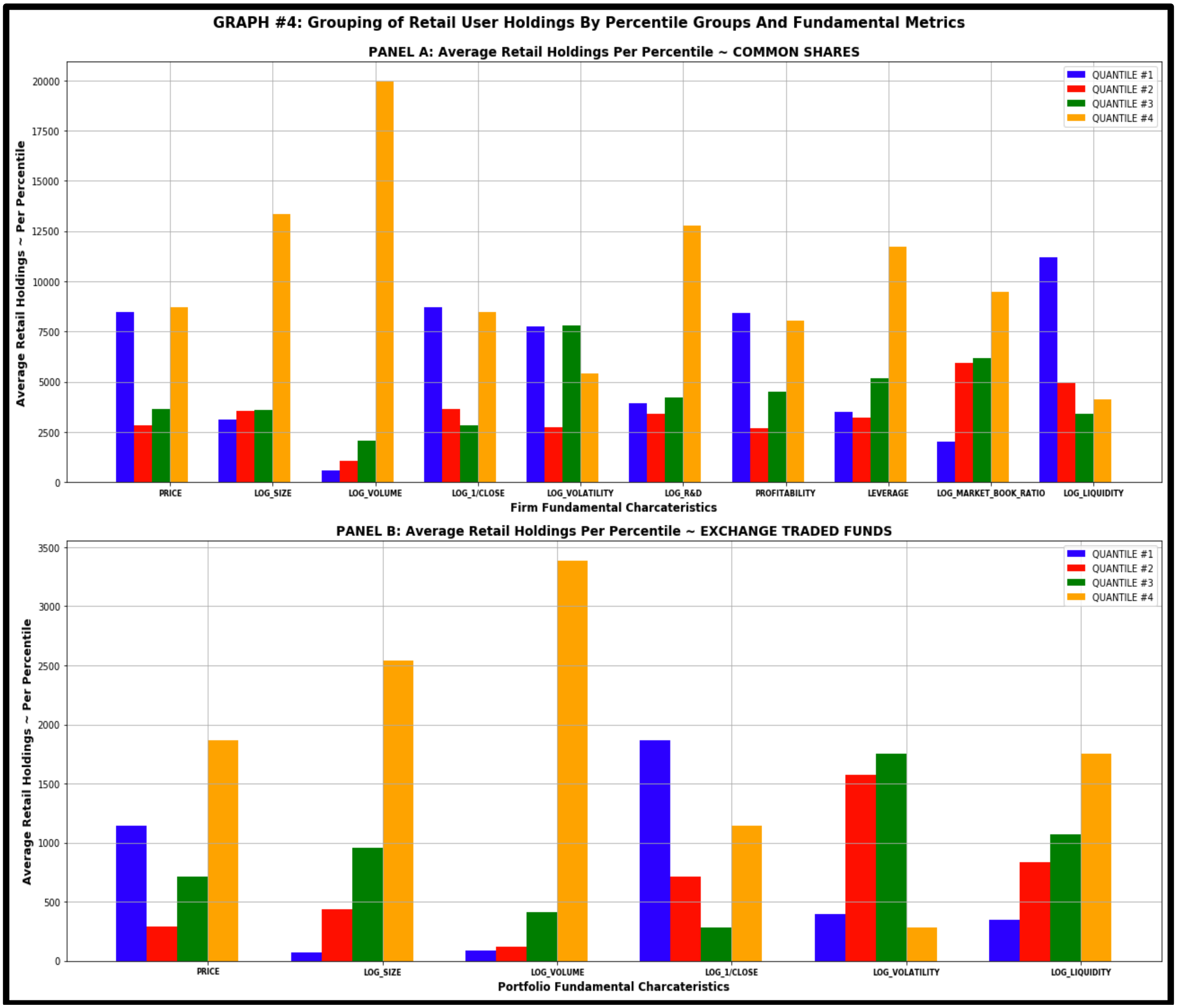


TABLE #3: The table presents a list of all the fundamental metrics discussed throughout our paper to describe retail investor holdings. The column ***"METRIC"*** presents the short metric name of each metric used in paper tables and graphs. The column ***"FULL NAME OF METRIC"*** provides a full name of each metric to give better idea as to what it represents. In addition, each metric is assigned a full description as to how the actual metric was calculated. Metrics involving any data from COMPUSTAT are accompanied with the information code, presented in bold and in bracket. Metrics involving data from CRSP are indicated in the metric description column.

TABLE #3: DESCRIPTION OF ALL FUNDAMENTAL METRICS USED IN DESCRIBING RETAIL INVESTOR HOLDINGS

METRIC	FULL NAME OF METRIC	DESCRIPTION ON HOW THE METRIC WAS CALCULATED USING COMPUSTAT AND CRPS INFORMATION
Log Size	Log of the Asset Market Capitalization	Calculation of the "Market Capitalization" is the product of *COMMON SHARES OUTSTANDING* **(CSHOQ)** times *PRICE CLOSE - QUARTER* **(PRCCQ).** We take the Log of Market Capitlaization and get the value for **Log Size**
Log Volatility	Log of the Asset Volatility Measured Using Standard Deviation	The Volatility of the asset is obtained by taking the log of the standard deviation for the last 250 observations per asset. This gives us an approxiamtion of the standard devation for the last year, and get **Log Volatility**
Log Market to Book Ratio	Log of the Firms Market to Book Ratio	We calculate the Market value by taking the calculated Market Capitalization (***See Log Size**) and substract asset leverage (***See Leverage**), subract *PREFFERED/PREFERENCE STOCK (CAPITAL) - TOTA* L **(PSTKQ)**, subtract *DEFERRED TAXES AND INVESTMENT TAX CREDIT* **(TXDITCQ)**. We take this product and divide by *ASSETS - TOTAL* **(ATQ).** The log of this value is taken to obtain **Log Market to Book Ratio**
Log Volume	Log of the Asset Volume	We obtain the value of **Log Volume** by taking the log of the daily volume for our last observation observation
Log 1/Close	Log of 1 over the Previous Day Closing Price	Divide 1 over the last observable stock price for each asset, and take the log of this value to get **Log 1/Close**
Log Liquidity	Log of the *Firms Liquidity Stautus	Obtain the sum of Volume (from CRSP) of the last month and divide by *COMMON SHARES OUTSTANDING* **(CSHOQ)**. The log of this value gives **Log Liquidity**
Log R&D Expenses	Log of the Firms Research and Development expenses	Simply take the log of *RESEARCH AND DEVELOPMENT EXPENSES* **(XRDQ)** to get **Log R&D Expenses**
Leverage	Log of the Firms leverage	Take the sum of *LONG-TERM DEBT - TOTAL* **(DLTTQ)** and *DEBT IN CURRENT LIABILITIES* **(DLCQ)** to obtain **Leverage**
Price	The Assets Previous Day Closing Price	Take the last observed Price for each asset from CRSP database to obtain **Price**
Profitability	Log of the Firms Profitability	Take the *OPERATING INCOME BEFORE DEPRECIATION - QUARTERLY* **(OIBDPQ)** and divide by *ASSETS - TOTAL* **(ATQ)** to obtain the level of **Profitability**

GRAPH #4: The graph presents the count of retail user holdings to each fundamental metric in 4 quantile groups. Panel A represents the retail investor counts by quantile group for common shares. Panel B represents the retail investor counts by quantile group for exchange-traded funds. Each “quantile” holds the average count of investors based on the percentile ranking to the attributed metric. *For example*: QUANTILE #1 for PRICE represents the average count of retail investors across all assets for which the PRICE is in the 0 – 24TH percentile. All quantiles are equally weighted into 4 groups based on the percentile ranking. *For example*: QUANTILE #2 hold the average count of retail investors for a specific metric that are part of the 25TH – 50TH percentile.



GRAPH #5: The graph expresses the relationship between the average asset return vs. the average change in retail user holdings across a desired period of time. The goal of this graph is to show the higher contrarian behavior across common share assets to that of exchange-traded funds. Panel A represents the 2241 common share assets and Panel B represents the 1787 exchange-traded fund assets. The variables on the x-axis present the previous returns for the respective holding period across all assets from our sample. The **Asset Return** metric presents the average change in asset return across all assets, while **Retail Holdings Return** presents the average change in retail user holdings across all assets. We use the log difference to measure the returns for both metrics.

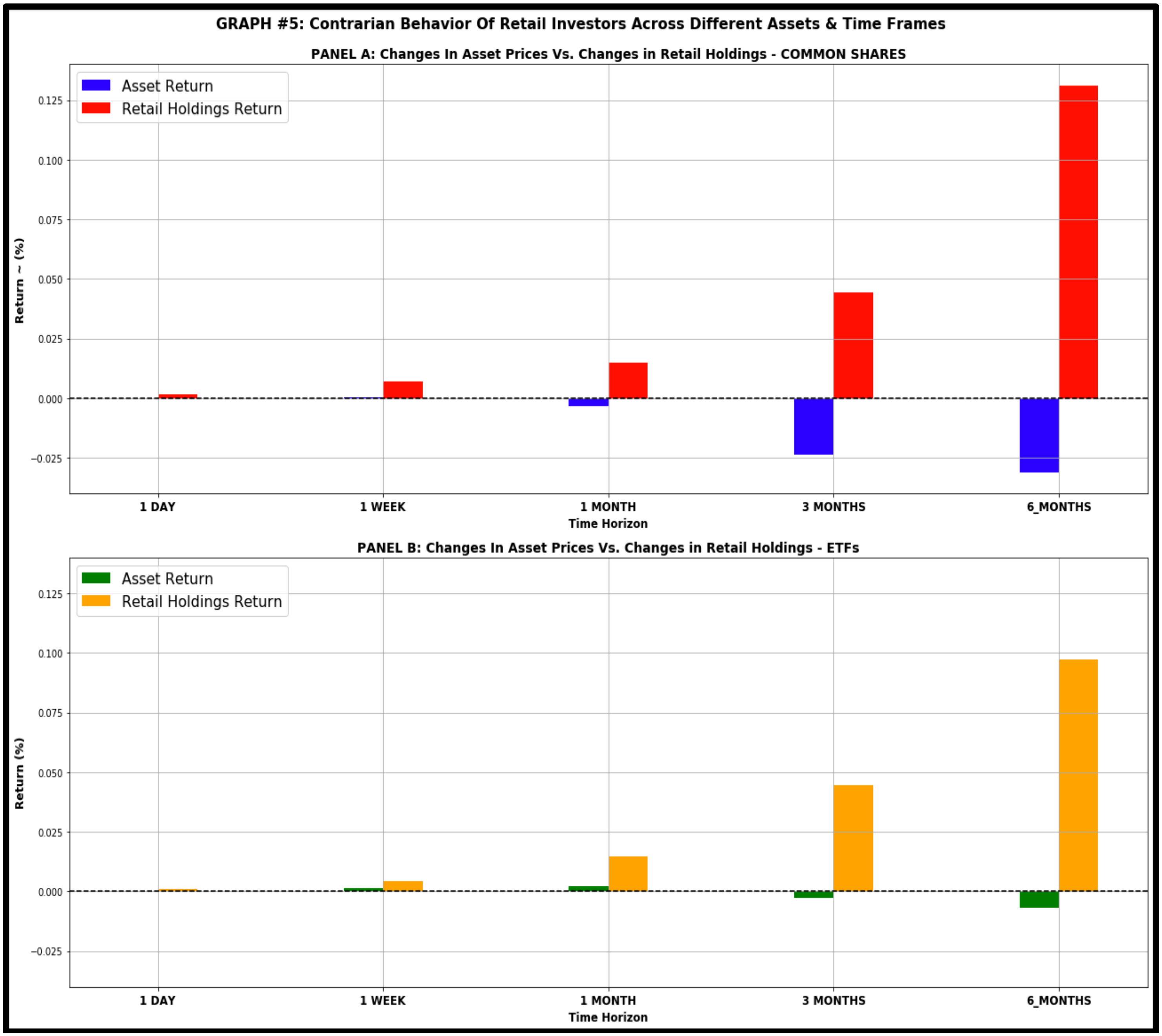


TABLE #6: The table presents several metrics to describe the different moments to each of the 27 trading strategies studied throughout the paper. Panel A presents findings on the return distribution moments for common share assets. Panel B presents findings on the return distribution moments for exchange-traded-fund assets. Each panel addresses 6 metrics. ***RET_TRADE*** expresses the average trade return (first moment), ***BOT_RET*** is the average return of 5% worst trades, ***TOP_RET*** is the average return of 5% best trades, ***PER_RET*** is the overall return for the strategy across the entire studied period, ***RET_STD*** is the standard deviation in trade returns (second moment), and ***RET_SKEW*** is the skewness of return distribution. For each studied metric, we present the findings across each of the trading strategies. The trading strategy can be identified through the ***"APPLIED METHODOLOGY"*** section of the graph.

TABLE #6: DESCRIPTIVE STATISTICS ON THE RETURN DISTRIBUTIONS OF TRADING STRATEGIES

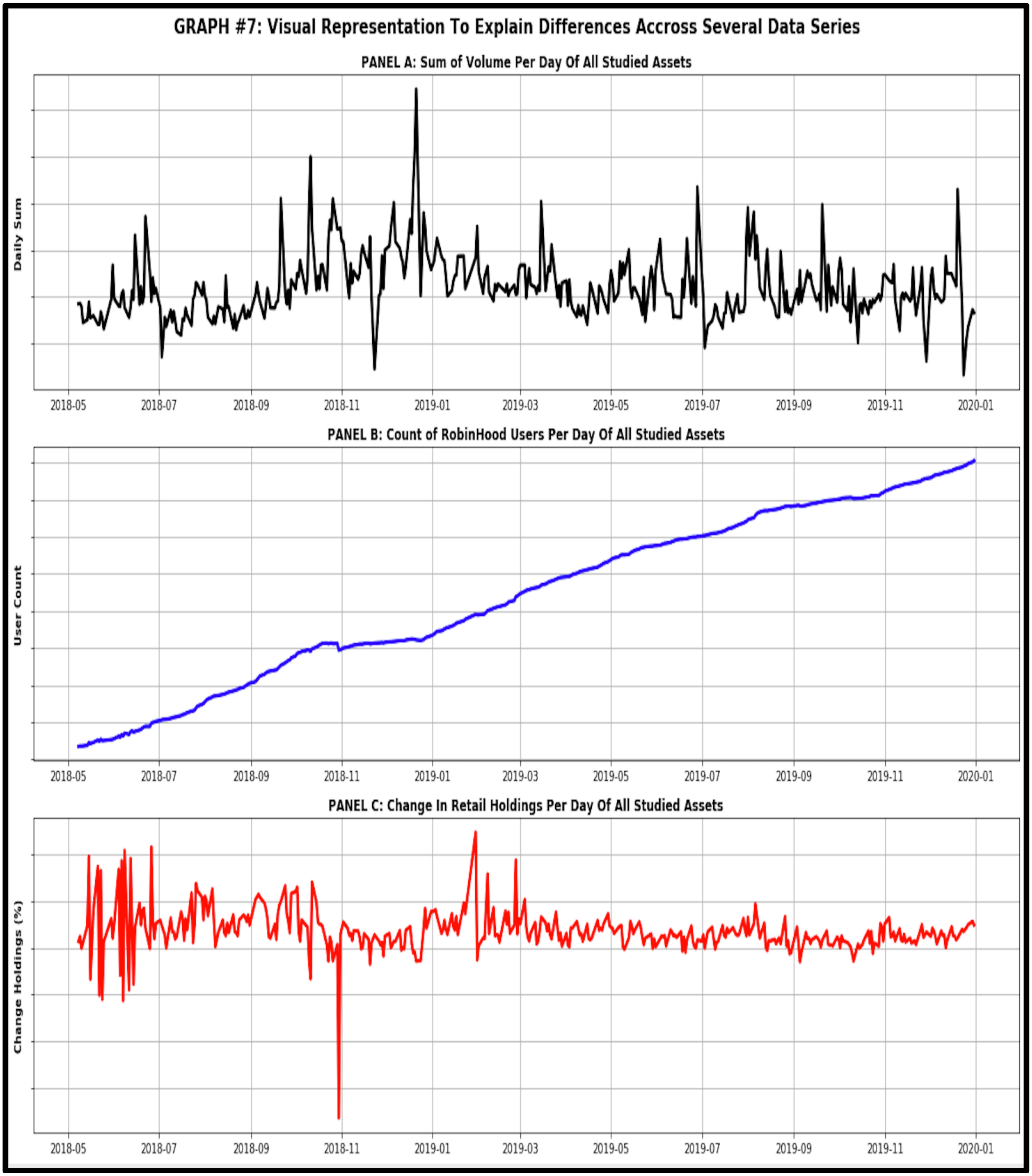
APPLIED METHODOLOGY			Panel A: *Common Shares*						Panel B: *Exchange-Traded Funds*					
MA STRATEGY	MA TYPE	LAG LENGTH	*RET_TRADE	BOT_RET	TOP_RET	PER_RET	*RET_STD	*RET_SKEW	*RET_TRADE	BOT_RET	TOP_RET	PER_RET	*RET_STD	*RET_SKEW
SINGLE MOVING AVERAGE STRATEGY	SMA	5 SMA	-0.0011	-0.13	0.21	-0.06	0.07	10.43	0.0006	-0.05	0.08	0.03	0.03	2.33
		10 SMA	-0.002	-0.13	0.22	-0.07	0.08	8.58	0.0015	-0.05	0.09	0.04	0.04	9.01
		20 SMA	-0.0031	-0.14	0.24	-0.07	0.1	7.84	0.0015	-0.06	0.09	0.03	0.04	8.59
		50 SMA	-0.0077	-0.15	0.28	-0.11	0.11	5.97	-0.0024	-0.06	0.11	-0.03	0.06	13.94
		100 SMA	-0.0089	-0.16	0.34	-0.08	0.14	5.09	-0.0059	-0.07	0.11	-0.05	0.06	1.06
		200 SMA	-0.0096	-0.18	0.41	-0.06	0.16	3.25	-0.0082	-0.06	0.17	-0.05	0.06	-1.95
	EMA	5 EMA	-0.0013	-0.13	0.21	-0.06	0.07	10.77	0.0009	-0.05	0.08	0.04	0.03	3.86
		10 EMA	-0.0021	-0.13	0.23	-0.07	0.08	9.02	0.0012	-0.06	0.09	0.03	0.04	7.64
		12 EMA	-0.0024	-0.13	0.23	-0.08	0.08	8.78	0.0013	-0.06	0.09	0.03	0.04	14.85
		20 EMA	-0.0036	-0.14	0.24	-0.09	0.09	7.57	0.0013	-0.06	0.1	0.03	0.05	13.27
		26 EMA	-0.0044	-0.14	0.25	-0.1	0.1	7.66	0.0009	-0.06	0.1	0.01	0.05	13.03
		50 EMA	-0.0070	-0.15	0.28	-0.11	0.11	6.43	-0.0013	-0.06	0.11	-0.02	0.06	8.7
		100 EMA	-0.0082	-0.15	0.33	-0.09	0.13	5.29	-0.0051	-0.07	0.11	-0.05	0.05	0.72
		200 EMA	-0.0066	-0.17	0.42	-0.05	0.16	4.34	-0.0059	-0.07	0.19	-0.04	0.07	1.37
DOUBLE MOVING AVERAGE CROSS OVER STRATEGY	SMA	5 & 10 SMA	-0.0013	-0.31	0.42	-0.03	0.11	6.88	0.0011	-0.11	0.15	0.04	0.05	8.03
		10 & 20 SMA	-0.0042	-0.31	0.43	-0.04	0.15	5.22	-0.0017	-0.12	0.15	-0.03	0.06	1.81
		20 & 50 SMA	-0.0137	-0.32	0.46	-0.06	0.21	2.55	-0.0088	-0.13	0.19	-0.07	0.1	2.21
		50 & 100 SMA	-0.0081	-0.36	0.56	-0.02	0.3	1.44	-0.0064	-0.14	0.22	-0.03	0.12	1.28
		50 & 200 SMA	-0.0176	-0.41	0.56	-0.03	0.38	0.44	-0.0181	-0.16	0.16	-0.05	0.14	-3.54
		100 & 200 SMA	-0.0139	-0.43	0.56	-0.02	0.38	0.19	-0.022	-0.18	0.16	-0.06	0.15	-3.81
	EMA	5 & 10 EMA	-0.0031	-0.33	0.42	-0.05	0.12	6.45	0.0016	-0.13	0.15	0.04	0.06	8.25
		10 & 20 EMA	-0.0094	-0.32	0.45	-0.08	0.16	4.12	-0.0024	-0.13	0.17	-0.03	0.07	5.87
		12 & 26 EMA	-0.0115	-0.32	0.46	-0.07	0.17	3.57	-0.0037	-0.13	0.17	-0.04	0.08	5.72
		20 & 50 EMA	-0.0135	-0.33	0.51	-0.05	0.23	2.94	-0.013	-0.14	0.19	-0.08	0.09	0.39
		50 & 100 EMA	-0.0042	-0.38	0.61	-0.01	0.35	1.15	-0.017	-0.14	0.23	-0.05	0.14	-0.27
		50 & 200 EMA	0.0016	-0.39	0.59	0.00	0.39	0.71	-0.0141	-0.14	0.22	-0.03	0.16	-0.44
		100 & 200 EMA	0.0075	-0.41	0.57	0.01	0.42	0.33	-0.0235	-0.16	0.21	-0.04	0.17	-1.29
EQUAL WEIGHTED AVERAGE			**-0.0059**	**-0.25**	**0.39**	**-0.06**	**0.18**	**5.07**	**-0.0055**	**-0.10**	**0.14**	**-0.02**	**0.08**	**4.47**

TABLE #7: The table presents descriptive statistics on the trading behavior of retail investors surrounding key technical moving average signals across all 27 trading strategies. Panel A presents findings for common share assets and Panel B presents findings for exchange-traded fund assets. Within each panel, we present 8 different metrics to highlight investor behavior. ***TRD_FRQ*** is the number of trades, ***TRD_LEN*** is the average length (in days) to each trade, ***LOSS_LEN*** is the average length (in days) of all losing trades, while ***WIN_LEN*** is the average length (in days) of all winning trades. These metrics describe how often retail investors can expect to trade moving average strategies. ****SELL_HOLD*** expresses the difference in the average change in retail user holdings on BUY signal days to the average change in retail user holdings for non-signal days. ****BUY_HOLD*** expresses the difference in the average change in retail user holdings on SELL signal days to the average change in retail user holdings for non-signal days. ****SELL_VOL*** expresses the ratio in the average volume on SELL signal days to the average volume on non-signal days. ****BUY_VOL*** expresses the ratio in the average volume on BUY signal days to the average volume on non-signal days. The change in any metric is done by using the log difference. Each of these metrics are categorized by respective trading strategy, identified in the APLLIED METHODOLOGY column.

TABLE #7: DESCRIPTIVE STATISTICS ON THE TRADING BEHAVIOR OF MOVING AVERAGE STRATEGIES

APPLIED METHODOLOGY			Panel A: Common Shares								Panel B: Exchange-Traded Funds							
MA STRATEGY	MA TYPE	LAG LENGTH	TRD_FRQ	TRD_LEN	LOSS_LEN	WIN_LEN	*SELL_HOLD	*BUY_HOLD	*SELL_VOL	*BUY_VOL	TRD_FRQ	TRD_LEN	LOSS_LEN	WIN_LEN	*SELL_HOLD	*BUY_HOLD	*SELL_VOL	*BUY_VOL
SINGLE MOVING AVERAGE STRATEGY	SMA	5 SMA	118076	5.56	3.29	10.27	-0.00119	-0.00147	0.96	0.98	84091	6.07	3.55	10.85	0.00000	-0.00135	0.96	0.94
		10 SMA	79377	8.23	4.39	18.25	-0.00049	-0.00078	1.00	1.00	56973	9	4.81	19.48	-0.00013	-0.00171	0.94	0.89
		20 SMA	54034	12.07	5.8	32.65	0.00013	-0.00032	1.04	1.04	41332	12.57	6.24	34.74	-0.00041	-0.00175	0.93	0.87
		50 SMA	33962	18.47	8.39	68.34	0.00151	0.00054	1.10	1.11	28952	17.17	9.11	72.28	-0.00084	-0.00171	0.85	0.79
		100 SMA	24292	25.21	10.54	121.38	0.00219	0.00126	1.07	1.12	23711	20.13	10.57	109.74	-0.00075	-0.00198	0.81	0.70
		200 SMA	17683	35.75	12.96	220.07	0.00224	0.00204	1.05	1.12	18298	23.64	13.71	196.65	-0.00146	-0.00157	0.85	0.75
	EMA	5 EMA	115095	5.75	3.21	11.56	-0.00100	-0.00138	0.98	0.98	79737	6.64	3.8	12.6	-0.00013	-0.00134	0.99	0.95
		10 EMA	83017	7.92	4.02	18.62	-0.00064	-0.00098	1.00	1.01	58410	9.05	4.81	20.43	-0.00044	-0.00171	0.99	0.93
		12 EMA	75957	8.65	4.28	21.21	-0.00057	-0.00078	1.01	1.01	53964	9.81	5.15	23.12	-0.00043	-0.00176	0.98	0.91
		20 EMA	59028	11.06	5.16	30.88	-0.00015	-0.00045	1.04	1.04	43532	12.23	6.13	32.83	-0.00044	-0.00172	0.93	0.87
		26 EMA	52283	12.39	5.63	37.18	0.00025	-0.00015	1.06	1.05	38883	13.53	6.73	39.4	-0.00049	-0.00179	0.92	0.85
		50 EMA	38295	16.45	7.02	59.93	0.00111	0.00083	1.08	1.10	31203	16.35	8.09	62.93	-0.00055	-0.00144	0.91	0.83
		100 EMA	28348	22.12	8.88	102.78	0.00160	0.00174	1.12	1.16	25870	18.92	10.08	95.08	-0.00043	-0.00132	0.83	0.72
		200 EMA	21519	31.38	10.93	189.64	0.00184	0.00270	1.08	1.14	21978	22.36	11.79	172.24	-0.00046	-0.00119	0.80	0.72
DOUBLE MOVING AVERAGE CROSS OVER STRATEGY	SMA	5 & 10 SMA	48856	13.04	8.34	20.83	0.00133	0.00107	1.05	1.03	73191	12.19	8.07	20.42	-0.00071	-0.00046	0.94	0.87
		10 & 20 SMA	24510	26.05	16.75	41.44	0.00194	0.00121	1.01	1.04	39022	22.25	15.44	37.29	-0.00036	-0.00097	0.88	0.81
		20 & 50 SMA	10224	60.68	36.97	108.4	0.00185	0.00026	0.98	1.06	16953	48.98	33.09	90.43	-0.00023	-0.00108	0.86	0.74
		50 & 100 SMA	5052	128.11	75.74	221.9	-0.00056	0.00039	0.96	1.05	9288	93.52	65.7	160.61	0.00018	0.00015	0.71	0.69
		50 & 200 SMA	2959	217.93	118.06	408.91	0.00142	0.00159	0.99	1.03	5015	165.29	100.28	340.72	-0.00106	-0.00011	0.91	0.67
		100 & 200 SMA	2706	249.05	152.72	396.57	0.00028	0.00121	1.01	0.94	4395	193.11	131.63	307.1	-0.00110	-0.00028	0.83	0.76
	EMA	5 & 10 EMA	38947	16.62	8.75	37.05	0.00236	0.00172	1.11	1.11	62437	14.12	7.74	34.96	-0.00003	-0.00067	0.89	0.81
		10 & 20 EMA	20174	31.24	16.55	73.36	0.00539	0.00276	1.12	1.17	35648	24.12	14.16	71.41	-0.00006	-0.00078	0.88	0.74
		12 & 26 EMA	16364	38.2	20.19	93.76	0.00549	0.00300	1.10	1.15	30123	28.66	16.81	92.87	-0.00002	-0.00049	0.82	0.70
		20 & 50 EMA	9567	64.85	31.87	171.92	0.00478	0.00314	1.07	1.13	19702	42.9	24.88	157.62	-0.00020	-0.00076	0.83	0.63
		50 & 100 EMA	4711	147.91	66.04	398.81	0.00380	0.00227	1.00	1.11	9726	92.12	52.11	395.59	0.00002	0.00050	0.72	0.56
		50 & 200 EMA	3525	208.73	86.51	562.02	0.00369	0.00486	0.95	1.03	7395	131.22	67.95	545.86	0.00064	0.00037	0.79	0.54
		100 & 200 EMA	2608	285.23	121.71	661.52	0.00256	0.00219	1.00	1.02	5152	188.38	99.9	636.84	0.00064	0.00402	0.92	0.62
EQUAL WEIGHTED AVERAGE			**36710**	**63.28**	**31.66**	**153.31**	**0.00152**	**0.00105**	**1.03**	**1.06**	**34259**	**46.46**	**27.49**	**140.52**	**-0.00034**	**-0.00085**	**0.88**	**0.77**

GRAPH #7: The graph illustrates the different data series used to calculate the changes in volume and changes in retail user holdings on key moving average signals. Panel A shows the total volume across all studied assets throughout our studied time period. Panel B presents the cumulative count of users on the Robinhood trading platform across time. Panel C presents the daily log difference in the count of retail users on Robinhood platform. The log changes in retail user holdings are used instead of the cumulative count of users to measure retail activity due to its stationary appearance.



GRAPH #10: The graph illustrates an event study window analysis for volume and retail user holding activity leading to and following an exponential moving average (EMA) signal. Panel A shows the event study window analysis in volume activity across all common shares sell signals. Panel B shows the event study window analysis in volume activity across all common shares buy signals. The volume activity metric used in Panel A & Panel B is the ratio of average volume on signal days to the average volume on non-signal days. Panel C presents the event study window analysis in retail investor activity across all common share sell signals. Panel D presents the event study window analysis in retail investor activity across all common share buy signals. The retail investor activity metric used in Panel C & Panel D is the difference in the average log change in retail user holdings on signal days to the average log change in retail user holdings on non-signal days. The x-axis presents the number of days prior (-) and the number of days following (+) the signal day (*EVENT*). Each panel present the event window analysis for 4 strategies, accounting for the differences in the methodologies studied throughout the paper.

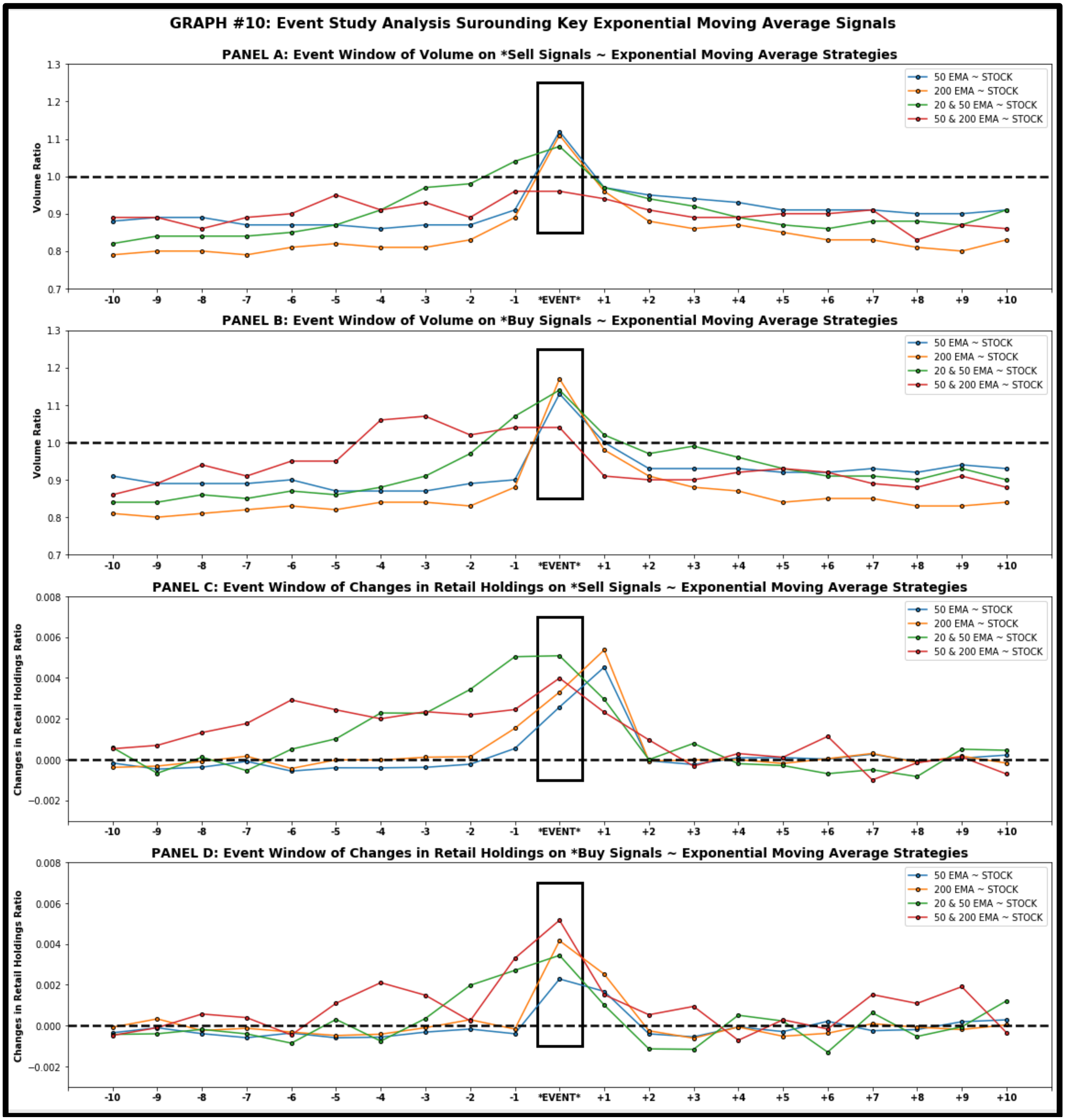


TABLE #8: The table is presented in conjunction to GRAPH #9 and GRAPH #10 to present findings on the *volume* event study window analysis across all exchange-traded fund moving average signals. The volume activity in this table represents the ratio between the average volume on signal days to the average volume on non-signal days. Findings from this table only account for 8 of the 27 moving average strategies, of which are labeled in separate columns of the table. The strategies were selected to account for all differences in methodologies studied throughout the paper. Panel A presents the volume activity across common shares and Panel B presents volume activity across exchange-traded funds. The days prior to the signal (-) and the days following the signal (+), as well as the event day itself (*EVENT*) can be identified in the ***"EVENT WINDOW"*** column. Column ***"STRATEGY"*** makes a distinction in the activity between simple moving averages (SMA) and exponential moving averages (EMA).

TABLE #8: Event Study Window Analysis On Volume Surrounding Moving Average Signals

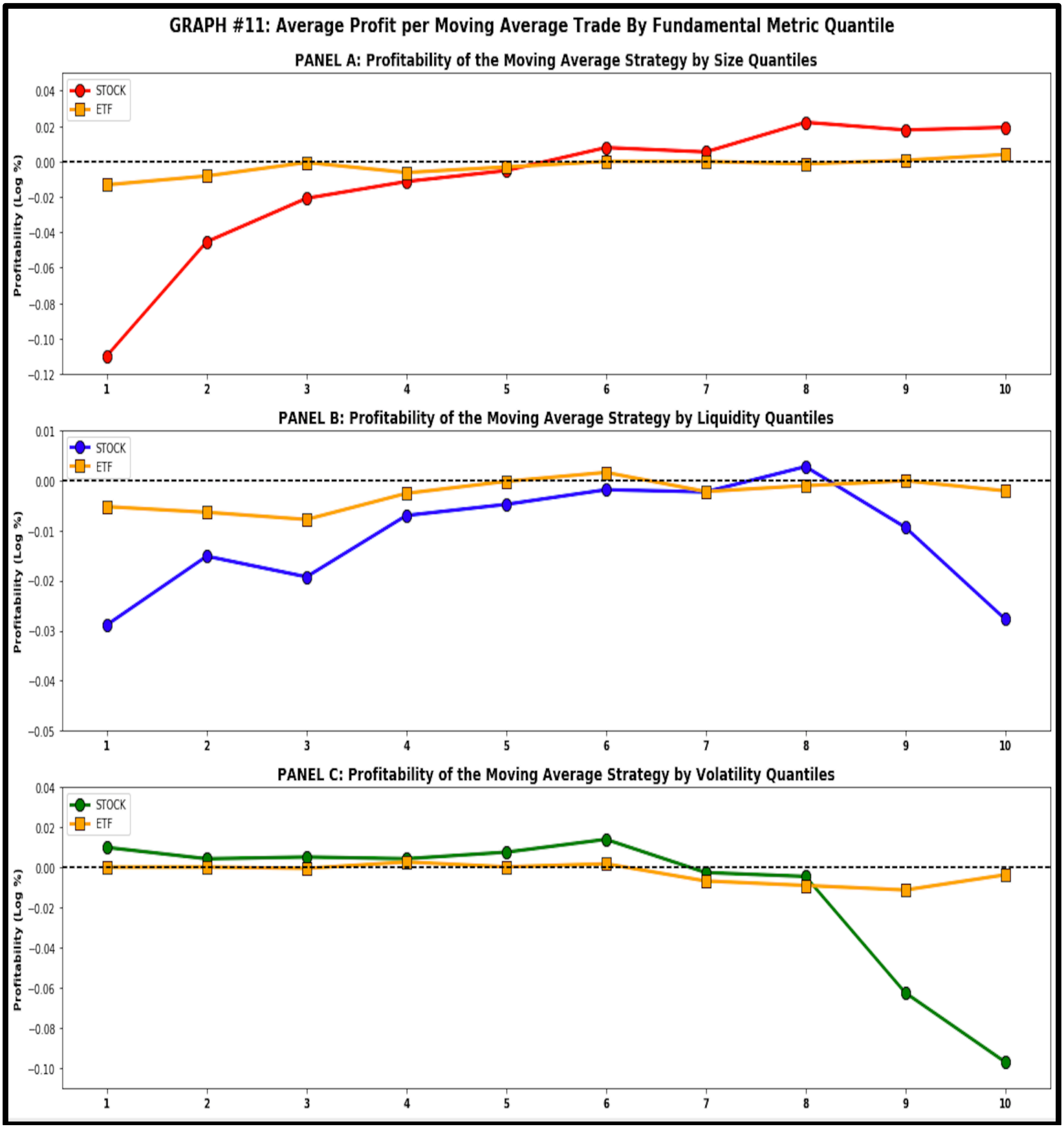
STRATEGY	EVENT WINDOW	Panel A: *Common Shares*								Panel B: *Exchange-Traded Funds*							
		SELL SIGNAL				*BUY SIGNAL*				*SELL SIGNAL*				*BUY SIGNAL*			
		50 MA	*200 MA*	*20 & 50 MA*	*50 & 200 MA*	*50 MA*	*200 MA*	*20 & 50 MA*	*50 & 200 MA*	*50 MA*	*200 MA*	*20 & 50 MA*	*50 & 200 MA*	*50 MA*	*200 MA*	*20 & 50 MA*	*50 & 200 MA*
SIMPLE MOVING AVERAGE (SMA)	-10	0.87	0.78	0.92	0.91	0.90	0.79	0.93	0.96	0.72	0.72	0.8	0.78	0.78	0.73	0.74	0.7
	-9	0.88	0.78	0.97	0.92	0.88	0.78	0.92	1.01	0.72	0.7	0.79	0.75	0.77	0.7	0.78	0.74
	-8	0.87	0.77	0.98	0.93	0.88	0.77	0.93	0.99	0.74	0.67	0.82	0.75	0.8	0.73	0.78	0.72
	-7	0.85	0.75	0.98	0.95	0.88	0.80	0.95	1.00	0.72	0.68	0.8	0.73	0.78	0.73	0.78	0.74
	-6	0.85	0.79	0.95	0.92	0.89	0.79	0.95	1.01	0.72	0.71	0.82	0.71	0.79	0.72	0.8	0.75
	-5	0.86	0.77	0.96	0.95	0.87	0.81	0.98	1.00	0.75	0.73	0.85	0.74	0.75	0.73	0.79	0.68
	-4	0.85	0.78	0.98	0.96	0.87	0.81	0.99	1.03	0.77	0.73	0.87	0.71	0.77	0.73	0.78	0.73
	-3	0.86	0.79	0.97	0.99	0.87	0.79	1.01	1.00	0.74	0.7	0.89	0.74	0.79	0.76	0.77	0.75
	-2	0.87	0.78	0.95	0.94	0.89	0.82	1.02	1.01	0.75	0.71	0.88	0.74	0.77	0.76	0.77	0.72
	-1	0.90	0.88	1.01	0.94	0.91	0.85	1.06	1.05	0.73	0.71	0.88	0.76	0.81	0.81	0.76	0.68
	EVENT	***1.13***	***1.08***	***0.99***	***0.97***	***1.14***	***1.15***	***1.08***	***1.06***	***0.84***	***0.84***	***0.89***	***0.73***	***0.77***	***0.74***	***0.76***	***0.71***
	1	0.97	0.94	0.95	0.95	1.00	0.96	1.00	1.00	0.84	0.84	0.85	0.75	0.74	0.71	0.74	0.72
	2	0.96	0.87	0.92	0.95	0.95	0.87	1.01	1.00	0.82	0.78	0.82	0.74	0.74	0.71	0.71	0.77
	3	0.92	0.84	0.93	0.93	0.93	0.86	1.00	0.97	0.83	0.79	0.82	0.7	0.76	0.73	0.73	0.73
	4	0.92	0.84	0.93	0.97	0.93	0.85	0.96	0.99	0.81	0.77	0.83	0.73	0.77	0.73	0.8	0.75
	5	0.91	0.81	0.91	0.95	0.93	0.84	0.98	1.00	0.79	0.73	0.83	0.7	0.74	0.75	0.78	0.75
	6	0.92	0.79	0.93	0.95	0.93	0.81	0.95	0.95	0.75	0.75	0.9	0.66	0.76	0.71	0.78	0.77
	7	0.91	0.78	0.93	0.97	0.94	0.80	0.95	0.98	0.76	0.72	0.84	0.7	0.74	0.71	0.78	0.75
	8	0.90	0.78	0.94	0.94	0.93	0.79	0.94	0.97	0.79	0.73	0.83	0.68	0.75	0.73	0.76	0.77
	9	0.91	0.79	0.93	0.93	0.94	0.81	0.95	0.99	0.78	0.72	0.85	0.74	0.74	0.76	0.78	0.77
	10	0.93	0.78	0.94	0.96	0.93	0.80	0.92	0.94	0.78	0.72	0.82	0.71	0.73	0.72	0.75	0.78
EXPONENTIAL MOVING AVERAGE (EMA)	-10	0.88	0.79	0.82	0.89	0.91	0.81	0.84	0.86	0.84	0.68	0.69	0.7	0.9	0.71	0.76	0.62
	-9	0.89	0.80	0.84	0.89	0.89	0.80	0.84	0.89	0.81	0.67	0.69	0.76	0.87	0.68	0.75	0.65
	-8	0.89	0.80	0.84	0.86	0.89	0.81	0.86	0.94	0.82	0.67	0.67	0.7	0.89	0.71	0.75	0.64
	-7	0.87	0.79	0.84	0.89	0.89	0.82	0.85	0.91	0.81	0.68	0.67	0.72	0.87	0.71	0.73	0.65
	-6	0.87	0.81	0.85	0.90	0.90	0.83	0.87	0.95	0.78	0.68	0.68	0.71	0.87	0.71	0.72	0.61
	-5	0.87	0.82	0.87	0.95	0.87	0.82	0.86	0.95	0.82	0.7	0.71	0.7	0.83	0.71	0.7	0.64
	-4	0.86	0.81	0.91	0.91	0.87	0.84	0.88	1.06	0.82	0.69	0.71	0.72	0.84	0.7	0.65	0.59
	-3	0.87	0.81	0.97	0.93	0.87	0.84	0.91	1.07	0.78	0.69	0.68	0.7	0.84	0.72	0.71	0.59
	-2	0.87	0.83	0.98	0.89	0.89	0.83	0.97	1.02	0.79	0.69	0.75	0.7	0.81	0.74	0.73	0.63
	-1	0.91	0.89	1.04	0.96	0.90	0.88	1.07	1.04	0.76	0.68	0.8	0.82	0.86	0.8	0.7	0.7
	EVENT	***1.12***	***1.11***	***1.08***	***0.96***	***1.13***	***1.17***	***1.14***	***1.04***	***0.9***	***0.79***	***0.86***	***0.82***	***0.82***	***0.71***	***0.65***	***0.56***
	1	0.97	0.96	0.97	0.94	1.00	0.98	1.02	0.91	0.89	0.82	0.86	0.79	0.8	0.66	0.64	0.61
	2	0.95	0.88	0.94	0.91	0.93	0.91	0.97	0.90	0.87	0.78	0.77	0.7	0.79	0.69	0.67	0.63
	3	0.94	0.86	0.92	0.89	0.93	0.88	0.99	0.90	0.87	0.73	0.73	0.68	0.8	0.69	0.67	0.63
	4	0.93	0.87	0.89	0.89	0.93	0.87	0.96	0.92	0.87	0.76	0.72	0.74	0.84	0.7	0.65	0.57
	5	0.91	0.85	0.87	0.90	0.92	0.84	0.93	0.93	0.85	0.73	0.7	0.77	0.81	0.71	0.66	0.59
	6	0.91	0.83	0.86	0.90	0.92	0.85	0.91	0.92	0.81	0.72	0.71	0.73	0.84	0.69	0.67	0.58
	7	0.91	0.83	0.88	0.91	0.93	0.85	0.91	0.89	0.84	0.71	0.74	0.72	0.81	0.7	0.7	0.59
	8	0.90	0.81	0.88	0.83	0.92	0.83	0.90	0.88	0.84	0.71	0.73	0.76	0.81	0.7	0.66	0.64
	9	0.90	0.80	0.87	0.87	0.94	0.83	0.93	0.91	0.83	0.75	0.67	0.77	0.83	0.71	0.68	0.64
	10	0.91	0.83	0.91	0.86	0.93	0.84	0.90	0.88	0.86	0.72	0.68	0.72	0.8	0.71	0.69	0.65

TABLE #9: The table is presented in conjunction to GRAPH #9 and GRAPH #10 to present findings on the *retail investor activity* event study window analysis across all exchange-traded fund moving average signals. The retail investor activity in this table represents the difference between the average log change in retail user holdings on signal days to the average log change in retail user holdings on non-signal days. Findings from this table only account for 8 of the 27 moving average strategies, of which are labeled in separate columns of the table. The strategies were selected to account for all differences in methodologies studied throughout the paper. Panel A presents the volume activity across common shares and Panel B presents volume activity across exchange-traded funds. The days prior to the signal (-) and the days following the signal (+), as well as the event day itself (*EVENT*) can be identified in the ***"EVENT WINDOW"*** column. Column ***"STRATEGY"*** makes a distinction in the activity between simple moving averages (SMA) and exponential moving averages (EMA).

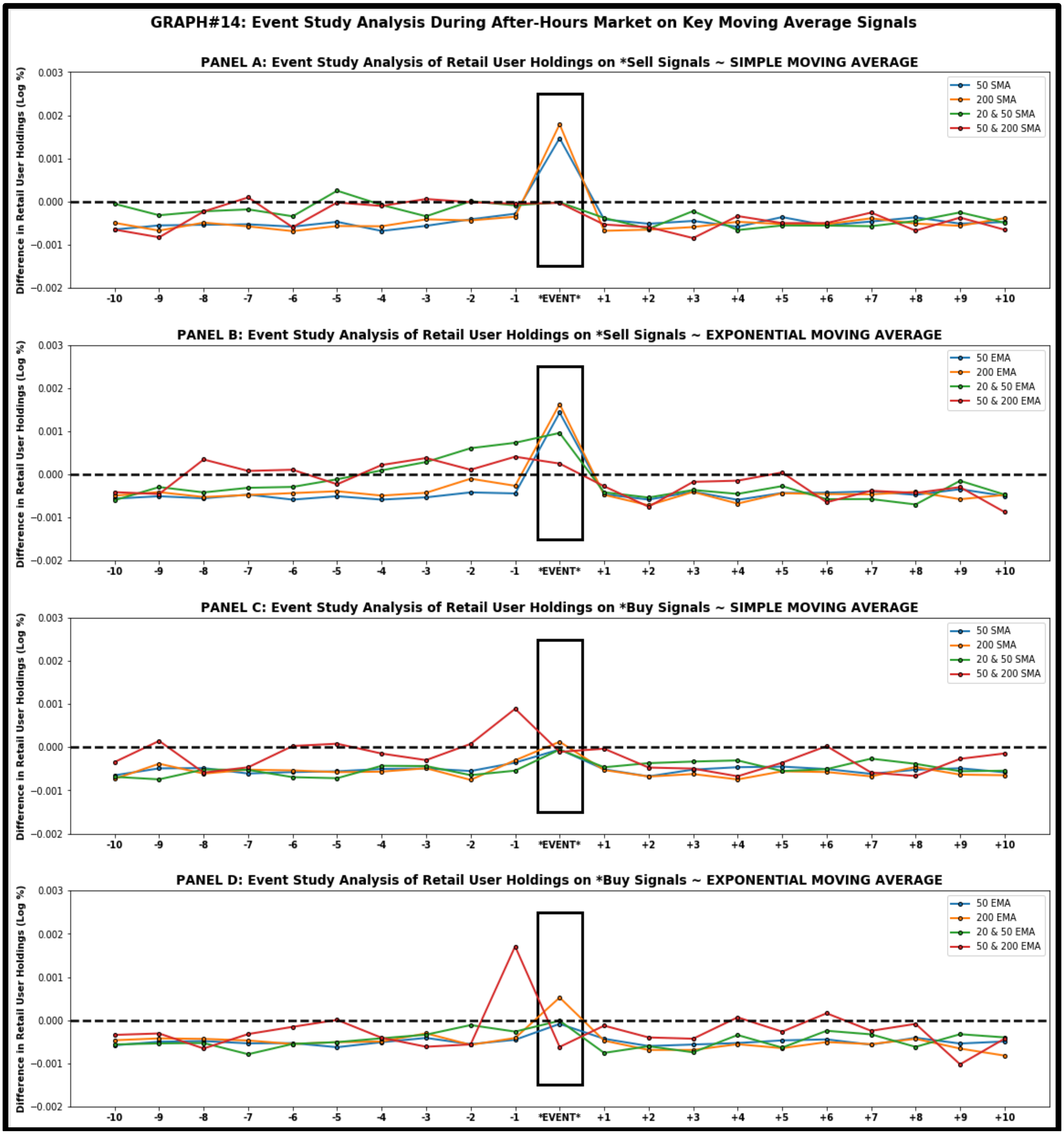
TABLE #9: Event Study Window Analysis On Retail User Holdings Surrounding Moving Average Signals

STRATEGY	EVENT WINDOW	Panel A: *Common Shares*								Panel B: *Exchange-Traded Funds*							
		SELL SIGNAL				*BUY SIGNAL*				*SELL SIGNAL*				*BUY SIGNAL*			
		50 MA	*200 MA*	*20 & 50 MA*	*50 & 200 MA*	*50 MA*	*200 MA*	*20 & 50 MA*	*50 & 200 MA*	*50 MA*	*200 MA*	*20 & 50 MA*	*50 & 200 MA*	*50 MA*	*200 MA*	*20 & 50 MA*	*50 & 200 MA*
SIMPLE MOVING AVERAGE (SMA)	**-10**	-0.0002	-0.0003	0.0007	0.0007	-0.0004	-0.0004	-0.0011	0.0000	-0.0003	-0.0007	0.0009	-0.0012	-0.0003	-0.0007	-0.0005	0.0011
	-9	-0.0005	-0.0002	0.0007	0.0008	-0.0005	-0.0003	-0.0003	0.0001	0.0001	-0.0005	0.0008	-0.0005	-0.0002	-0.0005	-0.0004	0.0007
	-8	-0.0008	-0.0010	0.0009	0.0000	-0.0004	-0.0005	-0.0005	-0.0003	-0.0002	-0.0005	-0.0005	0.0001	-0.0002	-0.0009	-0.0004	-0.0003
	-7	-0.0003	0.0000	0.0008	-0.0002	-0.0007	-0.0003	-0.0008	0.0005	0.0000	-0.0005	0.0004	-0.0008	-0.0002	-0.0008	-0.0010	0.0001
	-6	-0.0008	-0.0009	0.0009	-0.0003	-0.0004	-0.0011	-0.0002	0.0007	-0.0002	-0.0009	0.0004	-0.0003	-0.0001	-0.0004	-0.0009	-0.0003
	-5	-0.0004	-0.0009	0.0008	0.0002	-0.0009	-0.0007	-0.0009	0.0006	-0.0002	-0.0003	0.0000	-0.0017	0.0001	-0.0002	0.0000	-0.0013
	-4	-0.0004	-0.0007	0.0019	0.0003	-0.0004	-0.0007	0.0005	0.0007	0.0001	-0.0002	0.0002	-0.0004	-0.0005	-0.0013	-0.0008	0.0000
	-3	-0.0006	-0.0004	0.0010	0.0001	-0.0005	-0.0005	0.0006	0.0010	-0.0002	-0.0010	-0.0001	-0.0005	-0.0003	-0.0007	0.0007	-0.0006
	-2	-0.0005	-0.0003	0.0009	0.0015	-0.0001	-0.0001	0.0009	0.0015	-0.0002	-0.0005	-0.0004	-0.0002	-0.0002	-0.0007	-0.0005	-0.0013
	-1	0.0007	0.0011	0.0017	-0.0004	-0.0005	-0.0004	0.0009	0.0004	-0.0003	-0.0006	-0.0003	-0.0013	-0.0007	-0.0011	0.0003	-0.0002
	EVENT	***0.0030***	***0.0037***	***0.0022***	***-0.0003***	***0.0020***	***0.0035***	***0.0006***	***0.0007***	***-0.0001***	***-0.0007***	***0.0002***	***0.0006***	***-0.0010***	***-0.0008***	***-0.0007***	***0.0006***
	1	0.0046	0.0054	0.0008	0.0006	0.0017	0.0019	0.0002	0.0002	-0.0001	-0.0008	-0.0007	-0.0013	-0.0001	0.0000	0.0007	0.0007
	2	0.0002	-0.0008	0.0000	-0.0004	-0.0007	-0.0009	0.0000	0.0019	-0.0001	-0.0005	-0.0011	-0.0011	-0.0002	-0.0006	0.0011	0.0000
	3	-0.0002	-0.0005	-0.0008	-0.0006	-0.0008	-0.0009	-0.0002	-0.0002	0.0001	-0.0005	0.0003	-0.0002	-0.0003	-0.0010	0.0011	-0.0003
	4	-0.0001	-0.0001	0.0002	-0.0006	0.0001	-0.0004	0.0010	0.0010	-0.0001	-0.0010	-0.0002	-0.0015	-0.0005	-0.0007	-0.0002	-0.0003
	5	0.0002	-0.0002	-0.0007	-0.0003	-0.0003	-0.0011	0.0008	0.0007	-0.0002	-0.0007	-0.0001	-0.0009	-0.0005	-0.0010	0.0009	0.0004
	6	0.0000	-0.0004	-0.0003	-0.0010	0.0003	-0.0005	-0.0001	-0.0001	-0.0011	-0.0010	-0.0004	-0.0021	0.0001	-0.0005	0.0000	-0.0001
	7	0.0001	-0.0001	-0.0005	-0.0009	-0.0001	-0.0007	0.0002	-0.0005	-0.0001	-0.0004	-0.0002	-0.0002	-0.0002	-0.0006	-0.0004	0.0002
	8	-0.0004	-0.0008	0.0000	-0.0010	-0.0003	-0.0003	0.0000	0.0007	-0.0005	-0.0010	-0.0008	-0.0017	-0.0003	-0.0006	-0.0001	-0.0001
	9	0.0003	-0.0001	0.0002	-0.0007	0.0000	-0.0007	0.0005	0.0010	-0.0002	-0.0009	0.0002	-0.0012	-0.0001	-0.0002	0.0000	-0.0003
	10	0.0000	-0.0006	-0.0002	-0.0003	0.0002	-0.0001	0.0005	0.0004	-0.0002	0.0001	-0.0014	-0.0013	-0.0007	-0.0011	0.0008	-0.0001
EXPONENTIAL MOVING AVERAGE (EMA)	**-10**	-0.0002	-0.0004	0.0006	0.0005	-0.0004	-0.0001	-0.0004	-0.0005	0.0001	0.0003	0.0018	0.0020	0.0004	0.0001	0.0003	0.0006
	-9	-0.0005	-0.0003	-0.0007	0.0007	-0.0001	0.0003	-0.0004	-0.0001	0.0002	0.0003	0.0008	0.0014	0.0000	-0.0001	-0.0002	0.0002
	-8	-0.0004	-0.0001	0.0001	0.0013	-0.0004	-0.0002	-0.0002	0.0006	-0.0002	-0.0001	0.0011	0.0008	0.0000	0.0000	-0.0006	0.0010
	-7	-0.0001	0.0002	-0.0005	0.0018	-0.0006	-0.0001	-0.0004	0.0004	0.0002	0.0002	0.0006	0.0012	0.0000	0.0003	0.0001	0.0015
	-6	-0.0006	-0.0004	0.0005	0.0029	-0.0004	-0.0003	-0.0009	-0.0005	0.0001	0.0002	0.0005	0.0009	0.0001	0.0002	-0.0003	0.0010
	-5	-0.0004	0.0000	0.0010	0.0024	-0.0006	-0.0005	0.0003	0.0011	0.0001	0.0003	0.0003	0.0012	0.0003	0.0003	0.0002	0.0004
	-4	-0.0004	0.0000	0.0023	0.0020	-0.0006	-0.0004	-0.0008	0.0021	0.0004	0.0006	0.0014	0.0021	-0.0004	-0.0004	0.0001	0.0018
	-3	-0.0004	0.0001	0.0023	0.0023	-0.0003	-0.0001	0.0004	0.0015	0.0002	0.0002	0.0002	0.0011	0.0001	0.0001	-0.0009	0.0013
	-2	-0.0002	0.0001	0.0034	0.0022	-0.0002	0.0003	0.0020	0.0002	0.0002	0.0001	0.0008	0.0000	0.0001	0.0003	0.0000	0.0010
	-1	0.0005	0.0015	0.0050	0.0024	-0.0004	-0.0002	0.0027	0.0033	-0.0001	0.0003	-0.0006	0.0009	-0.0008	-0.0006	0.0008	0.0011
	EVENT	***0.0026***	***0.0033***	***0.0051***	***0.0040***	***0.0023***	***0.0042***	***0.0034***	***0.0052***	***0.0002***	***0.0003***	***0.0002***	***0.0011***	***-0.0007***	***-0.0005***	***-0.0003***	***0.0008***
	1	0.0045	0.0054	0.0029	0.0023	0.0017	0.0025	0.0010	0.0015	-0.0002	-0.0005	-0.0009	-0.0018	0.0001	0.0010	0.0007	0.0018
	2	-0.0001	-0.0001	0.0000	0.0010	-0.0004	-0.0003	-0.0011	0.0005	0.0000	0.0004	0.0012	0.0014	0.0000	0.0000	0.0000	0.0025
	3	-0.0002	0.0000	0.0008	-0.0003	-0.0006	-0.0006	-0.0012	0.0009	0.0000	0.0004	0.0005	0.0017	-0.0001	0.0001	-0.0004	0.0009
	4	0.0001	0.0000	-0.0002	0.0003	-0.0001	-0.0001	0.0005	-0.0007	-0.0002	0.0000	-0.0004	0.0002	-0.0004	0.0000	-0.0002	0.0005
	5	0.0001	-0.0002	-0.0003	0.0001	-0.0003	-0.0005	0.0002	0.0003	0.0001	0.0000	0.0005	0.0010	-0.0004	-0.0003	0.0006	0.0002
	6	0.0000	0.0000	-0.0007	0.0011	0.0002	-0.0004	-0.0013	-0.0002	-0.0001	0.0001	0.0008	0.0009	-0.0002	0.0002	0.0008	0.0014
	7	0.0003	0.0003	-0.0005	-0.0010	-0.0002	0.0001	0.0006	0.0015	0.0001	0.0003	0.0008	0.0010	0.0000	0.0002	0.0000	0.0021
	8	-0.0001	-0.0001	-0.0008	-0.0002	-0.0002	-0.0001	-0.0005	0.0011	-0.0002	-0.0003	-0.0004	0.0005	0.0001	0.0003	0.0006	0.0004
	9	0.0001	0.0002	0.0005	0.0001	0.0002	-0.0002	-0.0001	0.0019	0.0000	0.0000	-0.0003	-0.0001	0.0000	0.0000	0.0003	0.0020
	10	0.0002	-0.0002	0.0005	-0.0007	0.0003	0.0000	0.0012	-0.0003	-0.0001	-0.0001	-0.0001	0.0004	-0.0004	-0.0005	0.0006	0.0007

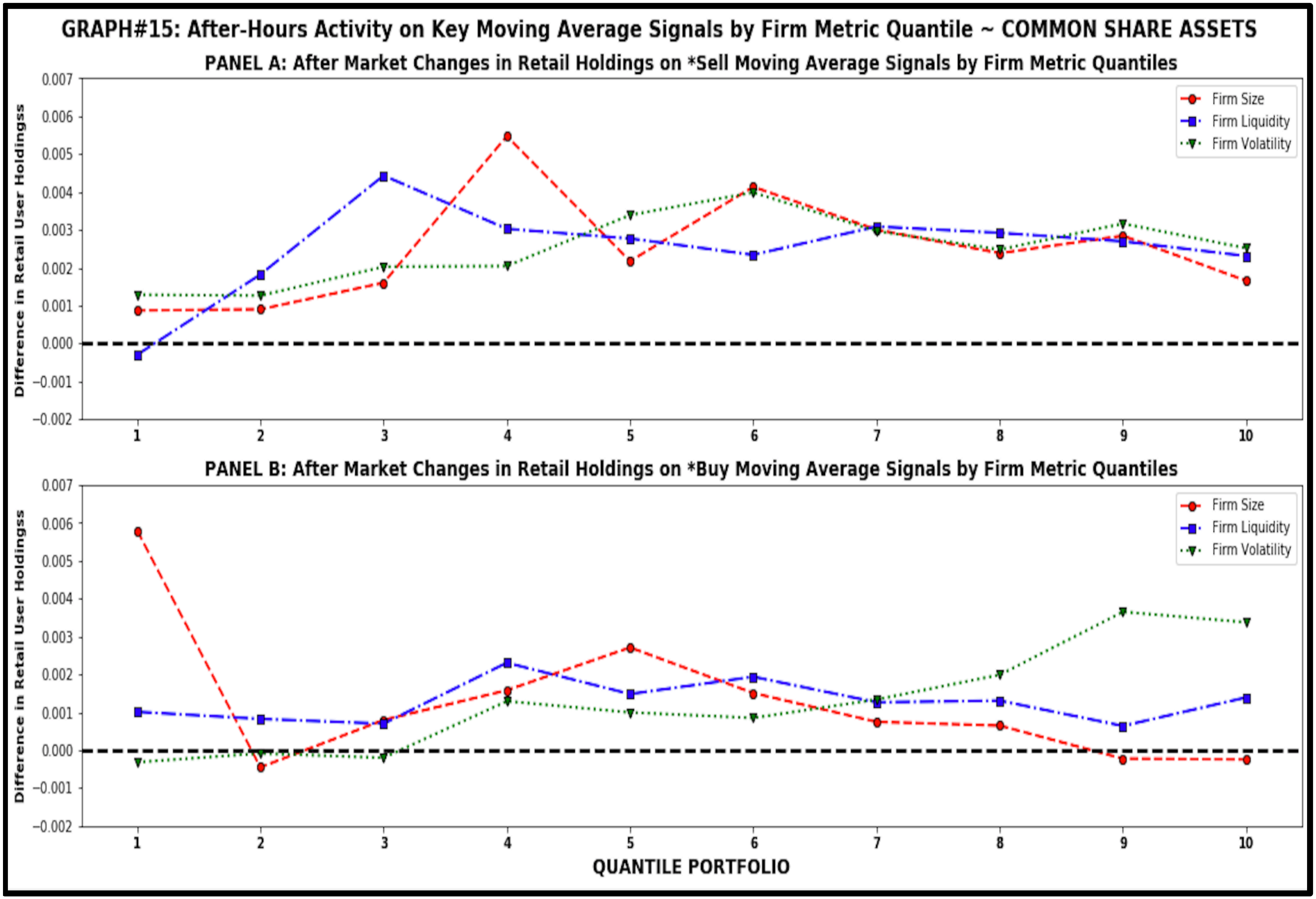
GRAPH #11: The graph illustrates the relationship between the profitability of moving average strategies and the rankings of firm fundamental metrics. The x-axis to each panel line graph represents the quantile grouping of firms by fundamental metric. Quantile group #1 (x-axis value of 1) represents the bottom 10% of firms and quantile group #10 (x-axis value of 10) represents the top 10% of firms. Panel A expresses the relationship between firm size and profitability. The assignment of firms by size is based on the ***"Log Size"*** metric from TABLE #3. Panel B expresses the relationship between firm liquidity and profitability. The assignment of firm liquidity is based on the ***"Log Volume"*** metric from Table #3. Panel C expresses the relationship between firm volatility and profitability. The assignment of firm volatility is based on the ***"Log Volatility"*** metric from Table #3. Each panel presents findings for both common shares and exchange-traded funds.



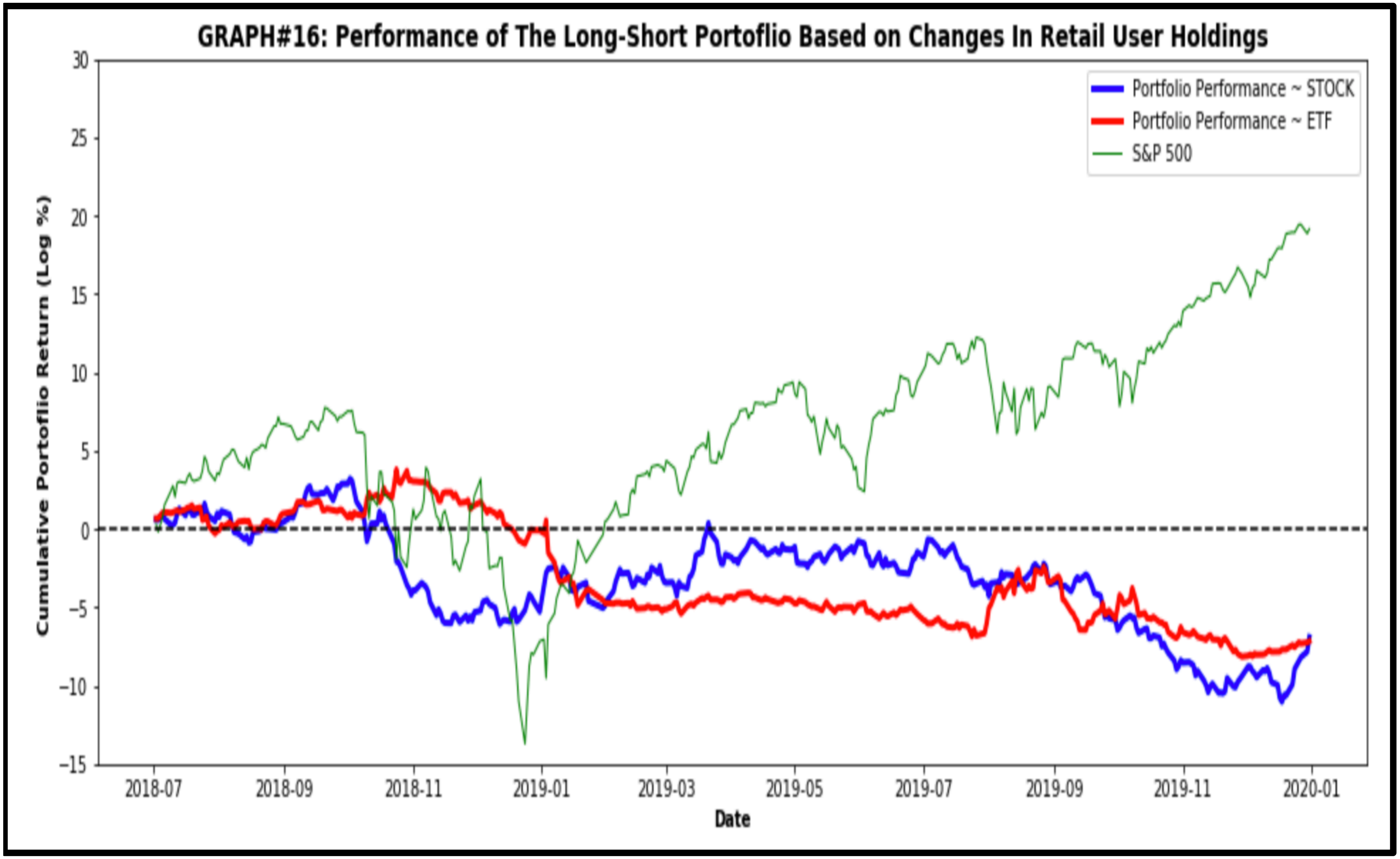
GRAPH #14: The graph shows how retail investor activity in the after-hours market changes in the days leading up to and following a moving average signal day. The metric used in all panels is the difference between the average log change in retail user holdings in the after-hours market on signal days to the average log change in retail user holdings in the after-hours market on non-signal days. Panel A & Panel B account for activity on sell signal days and Panel C & Panel D account for activity on buy signal days. In addition, Panel A & Panel C use simple moving averages (SMA) while Panel B & Panel D use exponential moving averages (EMA). The x-axis indicates the number of days prior to the signal (-), the number of days after the signal (+), and the actual day of the signal (*EVENT*). Each panel presents the event window study analysis of 4 different strategies to account for differences across methodologies.



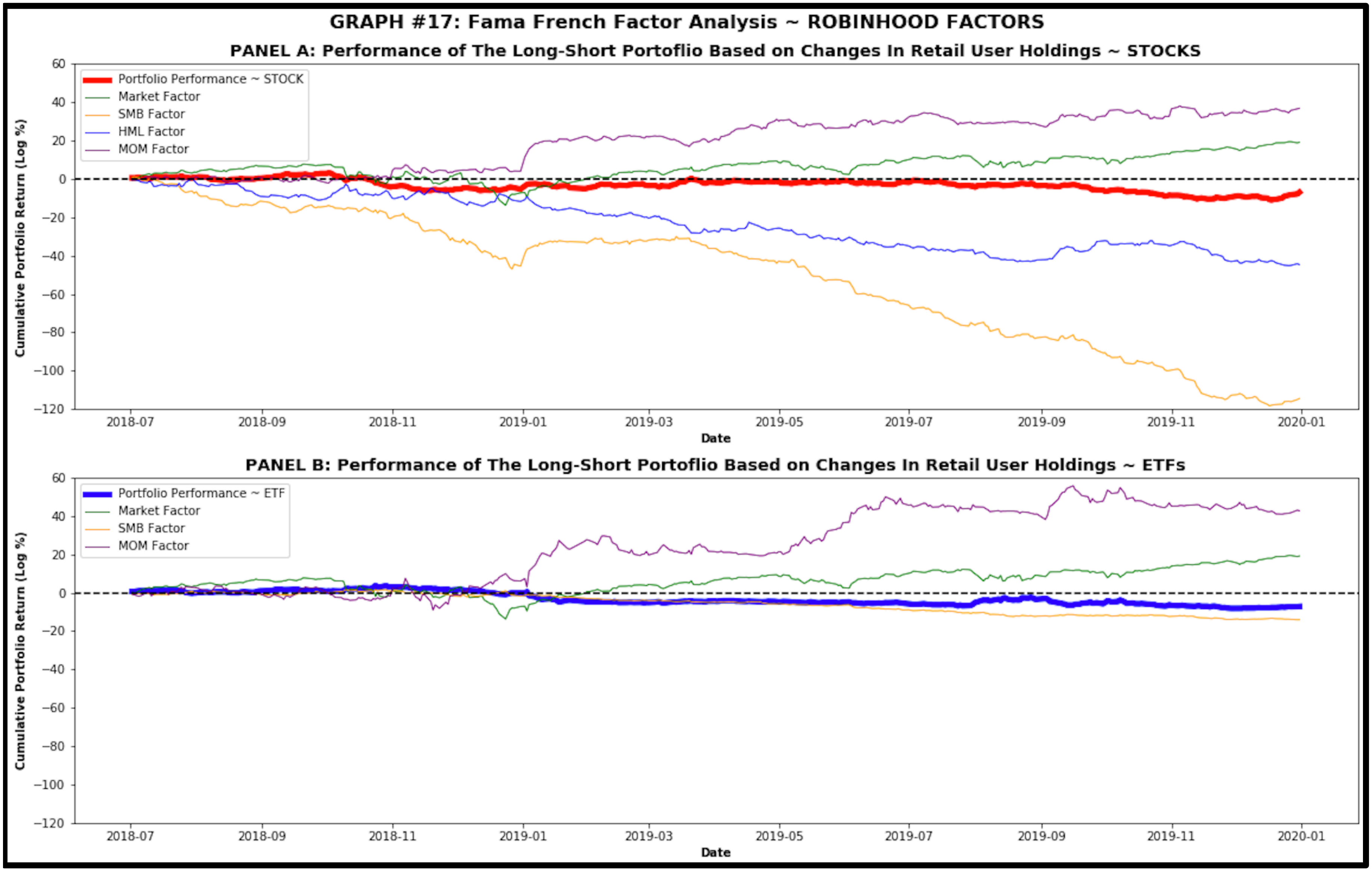
GRAPH #15: The graph expresses the relationship between retail investor activity in the after-hours market and the ranking of firm fundamental metrics. Investors activity is measured by the difference between the average log change of retail user holdings in the after-hours market on signal days to the average log change of retail user holdings in the after-hours market on non-signal days. Panel A addresses activity surrounding sell signal days and Panel B addresses activity surrounding buy signal days. Each panel presents investor activity when accounting for firm size (red), firm liquidity (blue), and firm volatility (green). The x-axis presents the different quantile group numbers. For example, quantile #1 (represented by value of 1 on x-axis) holds the bottom 10% of firms by the respective fundamental metric.



GRAPH #16: The graph presents the performance of the long-short portfolios formed on the changes in retail user holdings relative to the market performance. The performance of the common share long-short portfolio is expressed in blue, whereas the exchange-traded fund long-short portfolio is expressed in red. The “long” portfolio holds the top 10% of stocks which had the largest incremental increase in retail user holdings in the previous month. The “short” portfolio holds the bottom 10% of stocks which had the largest incremental increase in retail user holdings in the previous month. The portfolios are equally weighted at the beginning of the month and held for the entire month. We use the S&P 500 market index to represent the market performance (green).



GRAPH #17: The graph presents the performance of the long-short portfolios relative to our calculated Fama-French factors, using our final Robinhood database. Panel A presents the performance of the common share long-short portfolio and Fama-French factors. Panel B presents the performance of the exchange-traded fund long-short portfolio and Fama-French factors. Each panel holds the calculated Fama-French factors using the final database of selected assets. The Market Factor presented in green is the cumulative return of the S&P 500 index. The Small Sinus Big factor (SMB) presented in orange adopts a long-short portfolio using the end of sample firm size to each asset. The High Minus Low factor (HML) presented in blue adopts a long-short portfolio using the end of sample firm market to book ratio to each asset. Panel B does not have the HML factor. The Momentum factor (MOM) presented in purple adopts a long-short portfolio methodology based on the previous month asset returns. The long portfolio invests in the top 10% of assets that saw the largest increase in price, whereas the short portfolio shorts the bottom 10% of assets with the largest decrease in price. The MOM factor is adjusted monthly. All factors in the graph are expressed in terms of cumulative return over the studied period.



GRAPH #19: The graph illustrates the performance of quantile portfolios formed on the level of retail investor activity. Panel A accounts for the 2241 common shares and Panel B accounts for the 1787 exchange-traded funds. Each panel holds 10 different quantile portfolios. The quantile portfolios are formed on the previous month's changes in retail user holdings per asset and is held with equal weighting across all selected assets over the course of the following month. For example, **Quantile 1** portfolio will adjust its portfolio at the start of each month based on the previous months bottom 10% of stocks in terms of changes in retail user holdings. The cumulative performance of Quantile 1 and Quantile 10 portfolios over the studied period are presented in bold to highlight key findings.

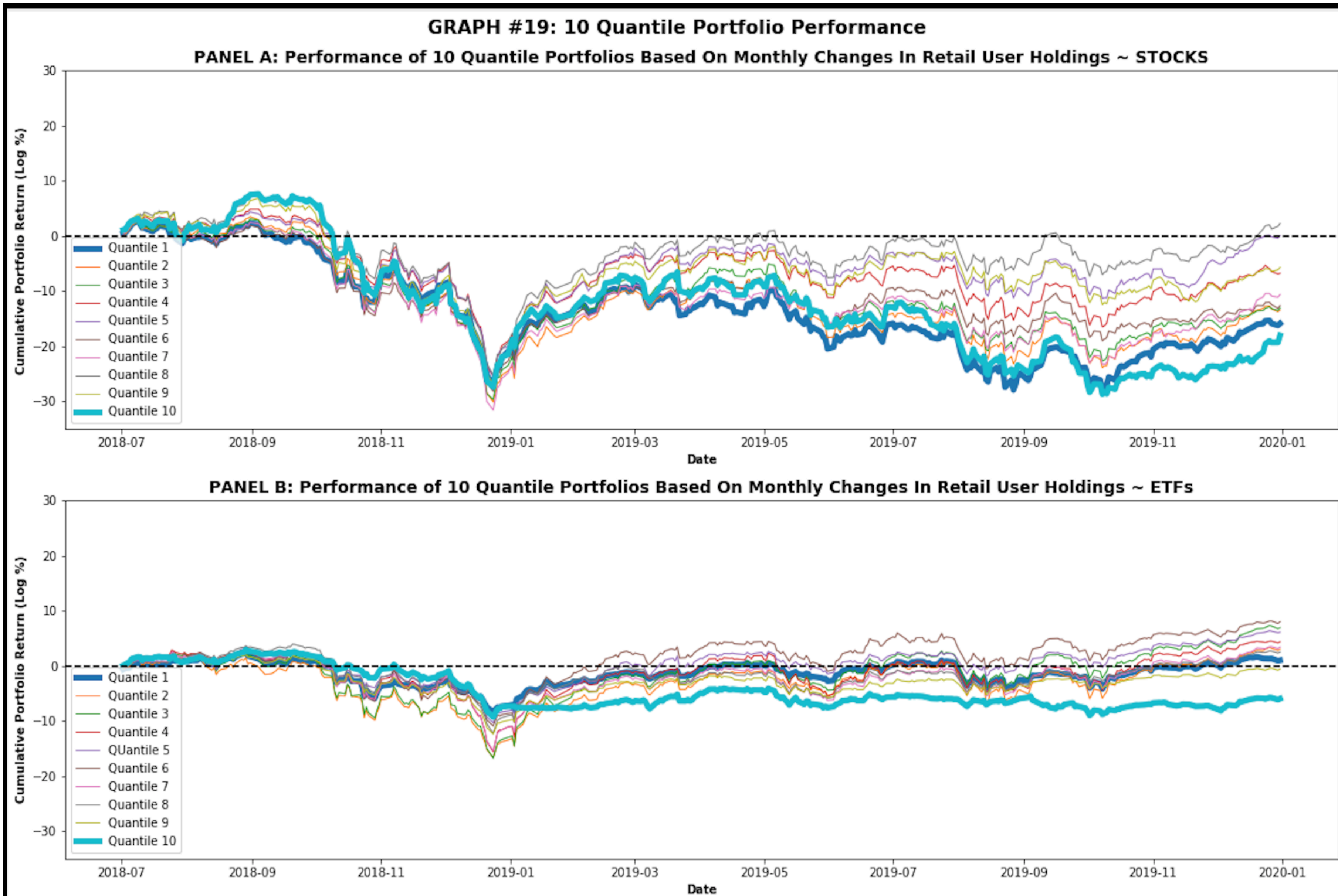


TABLE #12: The table presents the regression output of the daily returns for each quantile portfolio on the Fama-French factors. The daily returns of the 10 quantile portfolios formed on retail user holding changes represents the dependent variables. The independent variables include the Fama-French factor daily returns from the Kenneth R. French data library. Panel A presents the regression results for common shares, using the daily returns of the 10 quantile portfolios derived from common shares as the dependent variable. Panel B presents the regression results for exchange-traded funds, using the daily returns of 10 quantile portfolios derived from exchange-traded funds as the dependent variable. Each panel presents the coefficient outputs, followed by the p-value output each independent variable as well as the constant. We present the R output value to each quantile portfolio.

TABLE #12: Regression Output of Quantile Portfolios Formed Based the Changes In Retail User Holdings

PANEL A: 10 Quantile Portfolio Regression on Fama & French Factors ~ COMMON SHARES

FACTOR	1	2	3	4	5	6	7	8	9	10
ALPHA	-0.0376	-0.0373	-0.0403	-0.0265	-0.0077	-0.041	-0.041	-0.0008	-0.0221	-0.0498
Market Factor	0.86	0.92	0.91	0.86	0.86	0.85	0.91	0.00	0.90	0.86
SMB Factor	0.80	0.76	0.72	0.66	0.61	0.64	0.64	0.71	0.74	0.78
HML Factor	0.19	0.12	0.01	-0.03	-0.01	0.00	-0.09	-0.03	-0.03	-0.03
MOM Factor	0.06	0.00	-0.03	-0.07	-0.10	-0.03	-0.06	0.00	0.02	-0.06
P (Alpha)	0.01	0.01	0.01	0.08	0.62	0.00	0.01	0.96	0.22	0.02
P (Market)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
P (SMB)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
P (HML)	0.00	0.00	0.70	0.46	0.85	0.96	0.02	0.36	0.46	0.53
P (Momentum)	0.05	0.87	0.33	0.01	0.00	0.18	0.07	0.98	0.66	0.14
R	0.92	0.94	0.93	0.92	0.91	0.93	0.92	0.92	0.90	0.87

PANEL B: 10 Quantile Portfolio Regression on Fama & French Factors ~ EXCHANGE TRADED FUNDS

FACTOR	1	2	3	4	5	6	7	8	9	10
ALPHA	-0.0129	-0.0174	-0.0105	-0.0179	0.0004	-0.0034	-0.0163	-0.0135	-0.0174	-0.0252
Market Factor	0.45	0.72	0.75	0.74	0.49	0.64	0.66	0.57	0.45	0.30
SMB Factor	0.04	0.09	0.09	0.06	0.08	0.08	0.07	0.10	0.10	0.08
HML Factor	0.07	0.04	-0.04	-0.02	0.02	-0.04	-0.01	0.05	0.01	0.06
MOM Factor	-0.02	-0.06	-0.08	-0.09	-0.06	-0.08	-0.06	0.03	0.03	0.07
P (Alpha)	0.24	0.14	0.33	0.14	0.97	0.77	0.06	0.15	0.05	0.04
P (Market)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
P (SMB)	0.10	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00
P (HML)	0.01	0.13	0.16	-0.50	0.48	0.14	0.78	0.05	0.64	0.06
P (Momentum)	0.41	0.01	0.00	0.00	0.01	0.00	0.00	0.10	0.04	0.00
R	0.80	0.91	0.93	0.91	0.94	0.90	0.94	0.90	0.87	0.59