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Investor Heterogeneity: Price Momentum and Trading Volume Reactions of Foreign Listed Firms

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Abstract

Investor homogeneity is an important assumption in the efficient market hypothesis. However, viewing the financial markets from the eye of a professional trader, they are never efficient. Financial markets are composed of heterogeneous investors with the aims of speculation. Due to the large gap between theory and reality, many anomalies often occur. Price momentum as one of the commonly seen anomalies attracts the most attention from both scholars and practitioners. Prior finance literature documents that momentum is caused by investors' differential beliefs or investor heterogeneity. Recognizing the importance of investor heterogeneity prompts scholars to incorporate it into asset pricing models, but they face a series of challenges. The objective of this study is to address the current challenges of quantifying and testing predictions on investor heterogeneity. By analyzing investors' compositions, I argue that foreign listed firms are natural habitats of diverse investors. Compared with pure US firms, foreign listed firms provide perfect market venues to study investor heterogeneity. Using stock data of 2,200 NYSE and NASDAQ firms from 2000 to 2017, I classified them into higher/low order foreign listed firms and pure US firms. Momentum is tested by the Winner and Loser strategy, while trading volume is modeled by a regression of absolute return on volume turnover. This study finds that the three groups of firms have long term momentum in decreasing order, and investor heterogeneity plays an important role in price momentum.

From phenomenon to essence, this study constructs a novel paradigm to quantify and forecast investor heterogeneity. It is also the first study to investigate the microstructural explanation of momentum and trading volume, and to state the relationship between liquidity and heterogeneity. The "Two Period Order Flow Model" and the "Heterogeneous Market Hypothesis(HMH)" also have important implications

and contributions in both academics and industry. The conclusions of this research can benefit professional traders and option strategists in designing their trading strategies; it can help researchers avoid using proxied variables to quantify investor heterogeneity, build heterogeneous asset pricing models and create theoretical foundations for technical analysis; the HMH is also an alternative theory in challenging the EMH; and it can also help regulators better understand the financial markets.

Key words: momentum, foreign listed firms, investor heterogeneity, market microstructure, Heterogeneous Market Hypothesis.

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1. Introduction

Although investor homogeneity is a critically important assumption in classical finance theories, there is a large gap between the investor homogeneity assumption and the market reality. This poses a serious challenge to establish theoretical frameworks such as Capital Asset Pricing Model. Many anomalies regularly occur in markets, but one of them attracts the most attention and is a source of controversy: "the Momentum Effect"[1] (Fama and French, 2007). The Momentum Effect refers to the fact that, stocks with high returns over the previous year tend to continue to have high returns in the following few months; similarly, low short-term past returns also tend to persist (Jegadeesh and Titman, 1993). The momentum trading strategies are widely used by traders. Scholars ascribe this anomaly to "differential beliefs" or "investor heterogeneity" (Chui et al., 2010; Verardo, 2009; Hong and Stein, 2007;Fama and French, 2009).

Chui et al. (2010) show that there are significant cross-country differences in momentum profits that persist across time. The cross-country differences are instigated by various characteristics of investors such as their cultural orientation. Zhang (2006) documents that US stocks with information uncertainty, measured by more dispersed analyst earnings forecasts, exhibit stronger momentum and he attributes this to the higher individualism of US investors. It is widely accepted that dispersed analyst forecasts are used as a proxy for investor heterogeneity.

[1] Fama and French (2007) point out that there are two anomalies which attract the most attention and controversy. They are the Value Effect and the Momentum Effect. The Value Effect refers to the fact that, stocks with low prices relative to fundamentals like cash flow or book value have higher average returns than predicted by the CAPM(Statman, 1980, Rosenberg, Reid, and Lanstein, 1985, Fama and French, 1992). In this study, only the Momentum Effect is related with investor heterogeneity.

Huynh and Smith (2013) find momentum exists in US, Europe Asia and Japan, and their explanation of the momentum effect is centered on investors' under-reaction to news. This conclusion is consistent with Hong and Stein's (1999) "Gradual Information Diffusion Model"[2] which provides a rationale for differential beliefs. Fama and French (2012) also point out the pervasive nature of momentum effect in North America, Europe and Asia-Pacific excluding Japan. Although Fama and French do not provide an explanation why the Japanese stocks do not exhibit momentum effect, a related study by Chui et al.(2010) provide a convincing explanation. Chui et al. (2010) attribute the insignificance of momentum effect in Japanese stocks to the collectivistic nature of the Japanese culture[3]. Using analysts' forecast dispersion as a heterogeneity proxy, Verardo (2009) shows that momentum profits are significantly larger for portfolios[4] characterized by higher heterogeneity of beliefs. On the other hand, considering the momentum effect from the market microstructure perspective, the order flows supplied by heterogeneous investors are in favor of forming and maintaining a price trend[5]. In sum, momentum which is an observable phenomenon of investor heterogeneity, has established an effective bridge for studying the heterogeneity of investors as higher level of heterogeneity results in higher momentum.

Another manifestation of investor heterogeneity is trading volume. The generated trading volume reflects traders' agreement with the current value for exchange, but at the same time, it

[2] Gradual Information Diffusion Model classifies investors into newswatchers and momentum chasers who have different views.

[3] Fama and French (2012) uses monthly returns, but Huynh and Smith (2013) use weekly returns, which could be a possible explanation for the divergence of the result.

[4] The original definition of momentum Jegadeesh and Titman(1993) refers to individual stocks, market-wide momentum is examined by forming a portfolio which consists of multiple stocks with certain characteristics. See Section II Data and Methodology for the Winner and Loser Portfolio Construction.

[5] This conclusion will be elaborated in this study. I compose a "two-period order flow model" for the order flows of the price breaking process, and support the view that investor heterogeneity supports momentum formation. It will be elaborated in section II.

also reflects their disagreement on the future value of the asset. Hence, trading volume exhibits an already-formed disagreement[6], but as Garfinkel (2009) argues trading volume does not capture the full extent of disagreement[7]. Kim and Verrecchia's (1991) seminal study shows that greater diversity of opinions caused by the differential processing of the information, leads to an increase in trading volume. Harrison and Kreps (1978) suggest that abnormal trading volume around corporate public announcements could be explained by the divergence of opinion among traders. Kandel and Pearson (1995) predict that volume will be increasing in the diversity of investor opinions around earnings events. Other empirical studies, including Bamber (1987), De Long et al. (1990), Ajinkya, Atiase and Gift (1991), and Ajinkya et al. (2004), all confirm the view that abnormal trading volume is positively associated with higher divergent opinions. Trading volume reflects differential beliefs, and it is the most direct and observable evidence of investor heterogeneity (Bamber et al., 2011; Bamber et al., 1999). The objective of this study is to employ momentum and trading volume as alternative measures to quantify investor heterogeneity, in response to the current issues in financial economics.

From the point of view of order flow[8], investors with strong heterogeneity provide sufficient buying and selling orders at different price levels on the limit order book (LOB)[9]. These non-marketable limit orders offer sufficient liquidity, which allows traders to easily find the counter parties of the transactions, and this process leads to the change of price and the generation of

[6] Many studies express trading volume as "agree to disagree".
[7] As section II suggests, Garfinkel (2009) surveys many measures of heterogeneity and summarizes that the most effective measure of heterogeneity is constructed from the comprehensive data of order flows. Using statistics from all submitted orders is the most direct and comprehensive delegate of investor heterogeneity. Trading volume only represents part of investor heterogeneity, which is the executed/transacted orders, the ones which are not executed are excluded.
[8] This strand of literature can be classified into market microstructure.
[9] Panayi et al. (2015) define LOB as the massive data structure outlining the buying and selling interest in an asset.

volume. Sufficient liquidity is manifested by continuous price levels with small spreads. On average, the smaller the spreads are, the easier the formation of transactions is. In contrast, the order flow provided by the investors with poor heterogeneity often causes price fractures on the LOB, which makes it harder for trades to match. Under the extreme circumstances of investor homogeneity, the orders are stacking merely on a single side of the LOB, resulting that new traders could not find the counter parties for their transactions, this LOB state corresponds to Milgrom and Stokey (1982)'s Pareto Optimality of the assets, also referred to as "No Trade Theorem". Poor investor heterogeneity hinders the formation of transactions, and thus hinders price changes and the generation of trading volume. This is the reason why investor heterogeneity is positively related with momentum and trading volume[10].

Classical finance theories adopt the over restrictive assumption of investor homogeneity, which sacrifices the realism for the sake of tractability (Karpoff, 1987; Bamber et al., 2011). This rigid assumption of investor homogeneity imposes a serious limitation on the applicability of classical financial theories. A case in point is the failure of returns predicted by CAPM (Statman, 1980;Rosenberg, Reid, and Lanstein, 1985;Fama and French, 1992). Under the assumption of homogeneity, it will lead to no transactions in the market (Milgrom and Stokey, 1982). In reality, each transaction reflects the disagreement of investors on the future value of the asset. The greater the trading volume is, the stronger the heterogeneity of investors is. When academia and industry widely use the theorems such as CAPM, the homogeneity assumption implied by the theorems contradicts with the heterogeneous fact implied by the real returns. Because when the real returns are used for estimation, people neglect the fact that these returns are based on the transacted volume, which is caused by heterogeneity. On the other hand,

[10] In section III, I construct a two-period order flow model to explain this idea in detail.

academics pays excessive attention on returns and ignores the trading volume, lowering down the development of volume theory, it further exacerbates the neglect of investor heterogeneity (Bamber, et al., 2011). Examining the joint behavior of return and volume can shed light on the underlying heterogeneity among investors (Karpoff, 1987;Wang, 1994;Hong and Stein, 2007). In recent years, scholars have begun to study the heterogeneity of investors for a while, mainly in behavioral finance literature, but there are still some important issues that the extant research has still not addressed.

Recognizing the importance of investor heterogeneity led scholars to develop asset models incorporating the assumption of investor heterogeneity (Miller, 1977; Harrison and Kreps, 1978; Jarrow, 1980; Mayshar, 1983; Hong and Stein, 2007; Fama and French, 2007). However, these strands of research face the following challenges:

1). It is difficult to derive testable predictions (Anderson et al., 2005; Wang and Liu, 2014).

2). Lack of tangible data to reflect heterogeneity (Anderson et al., 2005; Fama and French, 2007; Wang and Liu, 2014).

3). Existing tractable formulations of heterogeneous agent models are observationally equivalent to representative agent models. (Anderson et al., 2005; Wang and Liu, 2014).

The first two challenges mainly come from the difficulty of measuring investor heterogeneity. Investor heterogeneity, like liquidity, is hard to describe and even harder to quantify. Scholars have designed a variety of indicators to measure investor heterogeneity. Some examples are the liquidity based measures, market depth based measures, measures based on institutional

investors' fundamental data, volume based measures, and dispersion of analysts' forecasts[11] (Lerman, Livnat and Mendenhall, 2007; Alexandridis, Antoniou and Petmezas, 2007). Each measure has its own merits and drawbacks and some drawbacks are critical. The fact that there is no single widely accepted measure suggests that the current verification of heterogeneity requires tangible data. On the other hand, sources of investor heterogeneity are mixed. They could come from a variety of factors such as tax preference, risk tolerance, liquidity requirement, private information (Wang and Liu, 2014), financial constraints, and non-traded income (Wang, 1994). A relatively recent addition to the list is the culture: Chui et.al (2010) made a convincing argument that the culture is an important driver of heterogeneity. However, in the absence of a unifying theoretical framework and testable data, it is difficult to distinguish the original sources of the divergence of opinion (Wang and Liu, 2014)[12].

In order to address the third challenge, scholars begin with classifying investors into various types and try to find out their trading incentive and strategies. It is difficult to extract the trading behavior of diverse types of investors from historical transaction data. As noted by Bamber et al. (2011), academics still has very limited understanding of different classes of traders and their incentive to trade. Although these classifications are not mature, one common finding of the studies on investor types is that, large price movement and the excessive trading volume are ascribed to investors' overconfident behavior (Odean, 1998). Benos (1998) models investor behavior with rational and irrational traders, he shows that higher volume, larger depth and more volatile and informative prices are generated by the overconfident irrational traders. Hong and Stein (1999) classify traders into news-watchers and momentum followers. News-watchers

[11] Although the dispersions of analysts' forecasts are widely used, it still has critically important weaknesses. See Section II.

[12] Sources of investor heterogeneity and existing models will be discussed in Section II in detail.

trade based on their analysis of firms' fundamentals, while momentum followers only care about the price patterns, they watch the price reactions and aggressively join if they find momentum exists. Hong and Stein (1999) also conclude that large price turbulence is induced by the overconfidence of momentum traders. Odean (1998) argues that overconfidence is prevailing in the market, price-taking traders, strategic-trading insiders and risk-averse market makers could be all overconfident. Overconfidence increases expected trading volume, increases market depth and decreases the expected utility of overconfident traders. Gervais and Odean (2001) argue that traders are "learning to be overconfident" from the beginning of their trading careers. Greater confidence leads to greater trading volume. Luo et al. (2018) argue that momentum arises because late informed investors provide too much liquidity to early informed traders. Both momentum and reversals emanate from overconfidence. Chui et al. (2010) classify investors into individualistic and collectivistic, and point out that momentum is not explained by risk models, but explained by individualistic investors' overconfidence. DHS (1998) show that momentum can be generated by investors' overconfidence and self-attribution bias, the excessive trading volume is also generated by overconfidence.

Although overconfidence is of critical importance in the literature of Finance, its measurement has rarely been documented in the literature of Psychology (Olsson, 2014)[13], as it needs an individual's original expectation which is a non-observable variable. Recently, finance scholars started to address this issue by using individualism or collectivism scores from Hofstede's

[13] In the literature of psychology, overestimation, overplacement, and the calibration of subjective probabilities are all considered as different forms of overconfidence (Olsson, 2014). There are only two studies document that more than two measures of overconfidence, see Moore and Healy (2008) and Larrick et al. (2007).

cultural dimensions[14]. It is argued that individualistic people (such as the US) think positively about themselves and focus on their own internal attributes (Markus and Kitayama, 1991). They believe that they have better ability than average and tend to overestimate their abilities (Heine et al., 1999). In contrast, people in collectivistic cultures (such as Japan) do not have this belief. People from individualistic countries are likely to analyze and invest based on their own analysis rather than consensus, and investors from individualistic countries are more likely to trade on momentum (Chui et al., 2010). Individualistic cultures promote, whereas collectivistic ones suppress skepticism (Luo, 1998). All else equal, when clienteles for equities in collectivistic cultures shift to foreign ownership by individualistic cultures, momentum should increase. Using the individualism index as a proxy for overconfidence is an effective option, as it is an observable and measurable variable. It also avoids the difficulties in classifying investors. The Individualism index has been used as an instrumental variable for classifying firms and investors in recent studies (Chui et al, 2010; Verardo, 2009; Luo et al, 2018).

This study aims to address the first two issues by constructing a new paradigm on studying investor heterogeneity. I argue that trading volume and price momentum are observable and tangible variables, and they offer direct evidence of investor heterogeneity. Both of them can be used as proper measures of investor heterogeneity. This argument alleviates the lack of tangible data problem. Garfinkel (2009) and Wang and Liu (2014) compare current prevailing measures

[14] Hofstede (2001) classifies cultures into five dimensions: individualism, masculinity, power distance, uncertainty avoidance, and long-term orientation. Among these five cultural dimensions, individualism is the most closely related to overconfidence and self-attribution bias. This index is regarded as the most comprehensive in terms of both the range of countries and the number of respondents involved (Kagitcibasi, 1997).

of investor heterogeneity, they conclude that unexplained trading volume[15] is the best measure. But these and the subsequent studies do not have any predictions regarding investor heterogeneity. Neither trading volume nor momentum has been applied. In order to address the un-testable predictions of investor heterogeneity, I adopt a completely new approach. That is, first analyzing investor compositions on different market venues, then hypothesizing that heterogeneity is higher in the markets with more diverse investors, and lower for less diverse ones, and finally use trading volume and momentum reactions to test this hypothesis. Hence, choosing the right market venues with diverse investor profiles ensures higher level of heterogeneity, and it is the key to the current study.

Foreign listings, also named as International listing and cross-listing[16], are strategic choices made by firms to list their shares on an overseas market. The globalization process including technological advances, deregulation of capital markets and declining transaction costs, led to a surge in foreign listings in the past three decades (Karolyi, 2006). According to a report from World Federation of Exchanges (WFE), as of the end of 2016, there were total 2,409 international-listed firms around the world, which was 5.22% of total 46,170 listed firms. Foreign listed firms are distributed across the major markets around the world. Although recent studies (Doidge, 2017; Ciccotello, 2014;Rosett and Smith, 2014;Grullon, Larkin, and Michaely, 2015) suggest that this process has slowed down[17], foreign-listing continues to be a viable

[15] Garfinkel (2009) documents that both bid-ask spread and unexplained volume are better proxies. Analysts' forecast dispersions have very weak explanatory power.
[16] Technically speaking, cross-listing refers to a firm which is double listed in two or more countries. Foreign listing or international listing refers to a firm listed abroad, no matter it is listed domestically or not. This study will use foreign listing, international listing and cross listing interchangablely.
[17] From 2014 to 2016, total number of international-listings firms are 2,452, 2,504, and 2409, which are 5.50%, 5.47% and 5.22% of all listed firms respectively. WFE (2016; 2015). Academics calls the delisting phenomenon "listing gap".

choice for firms influencing capital raising and price discovery processes. It is an indispensable and important force for the integration of global financial markets (Gagnon and Karolyi, 2010).

Foreign listed firms can attract investors all over the world, and they are natural habitats of heterogeneous investors. There are four reasons that the investor compositions of foreign-listed firms and purely domestic firms are different:

First, firms are motivated by a variety of factors for listing their shares abroad, with broadening shareholders' base as one primary objective. Several surveys of managers conducted by Mittoo(1992), Fanto and Karmel (1997) and Bancel and Mittoo(2001) document that broadening shareholder base is a major objective of managers of the cross-listed firms. By broadening the stockholders' base, these internationally listed firms not only can raise the funds they need abroad but also reduce their cost of capital (Verrecchia, 2001; Lambert et al., 2006; Hail and Leuz, 2006). More importantly, the foreign-listing process may improve the firms' visibility and reputation in the destination country, which enhances its influences, and hence attracts more traders to join. At the micro level, the increase in the diversity of shareholders brings the market with a higher level of heterogeneity and liquidity. Second, from the perspective of investors, Theory of Psychic Distance suggests that investors normally select stocks which have the similar background as they do, especially for the foreign listed firms which have no counter-parties listed in their home markets. Both individual and institutional investors are affected by this phenomenon (Nofsinger, 2012). Third, cross-listed firms may generate opportunities for arbitrage as revealed through large, actionable deviations from price parity between the markets trading those same shares. These arbitrageurs are also a group of traders which are not found in purely domestic firms. Fourth, foreign institutional holdings also demonstrate the

higher level of heterogeneity of foreign listed firms[18]. Ng et al. (2011) point out that Foreign Direct Investment (FDI) could lower the liquidity in the host countries[19], while Foreign Portfolio Investment (FPI) will improve the host countries' liquidity. Due to the fact that liquidity and heterogeneity are highly associated, and the prediction by Psychic Distance, FPI will also add heterogeneity to the foreign listed firms.

In sum, foreign listed firms broaden investor heterogeneity both intuitively and theoretically, but have not been used in empirical analysis of heterogeneity. Both International Business theories and Finance theories support the view that foreign listed firms can maximize the heterogeneity of investors in a relatively small market, which objectively provides an almost perfect market venue for studying heterogeneity of investors.

The main premise of this study is to empirically explore the extent of investor heterogeneity in the context of foreign listed firms by using a matching control sample of non-foreign listed firms. I use all listed firms from NYSE and NASDAQ, as the US has the highest individualism score of 90 in the world. Foreign listed firms are further categorized into higher-order and lower order firms. Higher order firms are those whose home countries' individualism scores below 50, and lower-order firms are those whose home countries' individualism scores above 50. This controlling method ensures that each group of firms has distinct investor compositions. I assume that the investor heterogeneity (IH) rank of the three groups of firms is:

$$IH_{higher-order\ foreign\ listed\ firms} > IH_{lower-order\ foreign\ listed\ firms} > IH_{pure\ US\ firms}$$

[18] See statistics in Section III.

[19] Host country firms with FDI investors, who have superior information and control positions in the firms, suffer from information asymmetry between insiders and outside uninformed investors. Further, these foreign investors bring their unique skills, international expertise, and knowledge to the firms, and domestic investors may be unfamiliar with such "foreign inputs." Thus, the presence of controlling FDI investors induces an adverse selection problem, making the stock less liquid. FDI also reduces trading activities, but FPI improves.

Based on the relationship established between momentum and trading volume earlier, this study employs both momentum and trading volume reactions to test this hypothesis.

One motivation of this research is to address the issue of measuring investor heterogeneity in academic literature which has not been addressed because of lack of tangible data problem as well as the problem of testable predictions. Starting with investors' habitats, developing hypothesis and then testing the momentum and trading volume reactions. This approach alleviates the data problem and offers a new paradigm to predict and test investor heterogeneity. It also avoids the multi-type investor problem, adding new evidence to the literature related to investor overconfidence and culture's influences on stocks trading. The findings of this study add new insights to the trading volume research in the financial economics literature. The "Two-Period Order Flow Model" demonstrates the positive relationship between investor heterogeneity and momentum. To the best of my knowledge, there is no research documenting this conclusion in the market microstructural literature. It also has important implications on the price discovery process.

Additionally, my interest in this topic is partly motivated by a puzzle confronting the professional traders and option strategists: what kinds of stocks are likely to be in trending and what kinds are likely to be in consolidation patterns, as these two phases require completely different trading strategies. Prior literature suggests that price momentum (trending) is likely to happen more often in a market with wider differential beliefs or disagreement (Chui et al., 2010; Verrardo, 2009), other studies argue that momentum characteristics differ by industrial classification (Zhou and Shin, 2013; Moskowitz and Grinblatt, 1999). In this study, I argue that

foreign-listed firms are also appropriated for trend trading, because of their higher levels of investor heterogeneity generate momentum and trading volume. These can be used as confirmations. The “Two-Period Order Flow Model” of the heterogeneous market ensures the lower frequency of price reversals. Following this logic, professional traders and option strategists can use foreign-listing as a stock screening tool for their trading strategies, which could largely increase the profitability of momentum and volatility strategies.

This research is organized as follows. Section Two reviews the literature, Section Three introduces the Two-Period Order Flow Model and the new Heterogeneous Market Hypothesis which help to explain the linkage between momentum/volume and investor heterogeneity, Section Four states the research question and hypothesis, Section Five describes the data and methodology, Section Six discusses the empirical results and Section Seven concludes the study.

2. Literature Review

2.1 Investor Homogeneity and Heterogeneity

2.1.1 Definition, Sources and Importance

The homogeneous expectation is an assumption made by Markowitz (1952) in his Modern Portfolio Theory. It argues that all investors have the same expectations and make the same choices given a particular set of circumstances. The most important milestone theories in finance----Capital Asset Pricing Model (CAPM) and Black-Sholes option valuation model, as well as many other equilibrium models, assume a certain degree of investor homogeneity (Levy and Levy, 1996). Despite these differences and despite strong and persuasive arguments put forward for including heterogeneity in finance and economics, the homogeneous representative agent paradigm is still the leading structural approach to asset pricing. Without the assumption of investor homogeneity, most financial theories collapse.

People often share common information yet disagree as to the meaning of this information, not only in the evaluation of risky assets but also in the evaluation of economic policies, political candidates, etc. The divergence of opinion is often defined as a type of investor heterogeneity in financial economics, in which, investors' valuation of a signal asset diverge from each other because they hold different prior beliefs, or have different information process models (Wang and Liu, 2014). Investor heterogeneity can come from tax preference, risk tolerance, liquidity requirement, and private information (Wang and Liu, 2014), financial constraints, and non-

traded income (Wang, 1994). Limit of attention is another source of heterogeneity (Hong and Stein, 2007). However, in the absence of a unifying theoretical framework and testable data, it is difficult to distinguish the original sources of the divergence of opinion (Wang and Liu, 2014).

Ever since Keynes (1937) and Williams (1956), economists have recognized the differences in investors' preferences and proposed the marginal-investor theory which emphasizes the importance of divergence of opinion in the functioning of capital markets. Mayshar (1983) points out that the divergence of opinion not only exists but is essential in determining asset prices. It is essential because of its association with endogenous limitations on the number of active market participants. The traditional models fail to recognize the fact that investors choose not only the size of their holdings in each asset but also in which asset to invest. However, the models do agree that when short sale constraints are present, an asset pricing model with divergent opinions may differ from a model without divergent opinions.

In practice, professional traders never consider any market to be efficient, they view their trading behavior as a speculation, rather than a value investment. One market can only exist, if it was comprised of investors with different opinions, these different opinions are represented by the buying and selling orders listed on limit order book. Because the instantaneous price of a particular asset is the last transacted price, without different opinions, there will be no transaction existing, and no deal would be made.

Investor heterogeneity is of particular importance, as it has a direct linkage with the behavior of price and trading volume in a market. Scholars will be able to construct capital asset pricing models according to heterogeneous investors. Traders will be able to adjust their trading strategies when they find investor heterogeneity changes; policies regulators will be able to

understand the market better if they know more about the differential understanding of individual investors, and enact trading rules to protect public trading.

Although determining the sources or determinants of investor heterogeneity can be of great help in asset modelling, it is particularly difficult because the individual's original expectation is not observable. This study aims to measure the level of investor heterogeneity from a novel paradigm.

2.1.2 Classification of Asset Pricing Models with Investor Heterogeneity

Recognizing the importance of investor homogeneity/heterogeneity, scholars gradually release this assumption to get more realistic models. There have been many models integrating investor heterogeneity, Wang and Liu (2014) classify them into three categories:

1). Investors simply hold different beliefs. This includes Miller (1977), Jarrow (1980) and Mayshar (1983), Harrison and Kreps (1978) and Van den Steen (2004),

2). Investors generate heterogeneous beliefs on the same public information due to their different prior beliefs; Including Kandel and Pearson (1995), Kim and Verrecchia (1991) and Grundy and McNichols (1989)

3). Investors have different opinions about the same information because they interpret the information differently. Including Harris and Raviv (1993) and Anderson, Ghysels and Juergens (2005).

Wang and Liu (2014) concluded that the predictions from asset pricing models with investor heterogeneity fit the pattern of trading volume, price changes, and return volatility better than homogeneous beliefs. This is consistent with Hong and Stein (2007) and Fama and French (2007), which emphasized the importance of the divergence of opinion in improving the traditional asset pricing models built on the assumption of investor homogeneity.

2.1.3 Current Challenges in the Studies of Investor Heterogeneity

Recognizing the importance of investor heterogeneity led scholars to develop asset models incorporating the assumption of investor heterogeneity (Miller, 1977; Harrison and Kreps, 1978; Jarrow, 1980; Mayshar, 1983; Hong and Stein, 2007; Fama and French, 2007). However, these strands of research face the following challenges:

1). It is difficult to derive testable predictions (Anderson et al., 2005; Wang and Liu, 2014).

2). Lack of tangible data to reflect heterogeneity (Anderson et al., 2005; Fama and French, 2007; Wang and Liu, 2014).

3). Existing tractable formulations of heterogeneous agent models are observationally equivalent to representative agent models. (Anderson et al., 2005; Wang and Liu, 2014).

The first two challenges mainly come from the difficulty of measuring investor heterogeneity. Investor heterogeneity, like liquidity, is hard to describe and even harder to quantify. Scholars have designed a variety of indicators to measure investor heterogeneity. Some examples are the liquidity based measures, market depth based measures, measures based on institutional

investors' fundamental data, volume-based measures, and dispersions of analysts' forecasts[20] (Lerman, Livnat and Mendenhall,2007; Alexandridis, Antoniou and Petmezas, 2007). Each measure has its own merits and drawbacks and some drawbacks are critical. The fact that there is no single widely accepted measure suggests that the current verification of heterogeneity requires tangible data. On the other hand, sources of investor heterogeneity are mixed, further adding measuring difficulties. In the absence of a unifying theoretical framework and testable data, it is difficult to distinguish the original sources of the divergence of opinion (Wang and Liu, 2014).

2.1.4 Measures of Investor Heterogeneity

Although investor heterogeneity is of critical importance in the literature finance, there are no consensus on how to measure it. A direct measure of investors' beliefs is usually un-observable and the estimates are often difficult to get (Wang and Liu, 2014). Researchers in finance, accounting, and economics have to rely on certain observable proxies. Traditional measures of investor heterogeneity are all proxies. They include unexplained volume, dispersions of analysts' forecasts, and bid-ask spreads which is also a liquidity measure. Recently, new measures such as institutional investors' holding period, experience and capital percentage are used. These measures have both advantages and disadvantages. This section gives a comprehensive review of the measures of investor heterogeneity, each with merits and drawbacks.

[20] Although the dispersion of analysts' forecasts is widely used, but it still has critically important weaknesses. See Section II.

A. Analysts' Forecasts Dispersion

The dispersion among analyst earnings forecasts can be viewed as a natural experiment of the test on investor heterogeneity (Wang and Liu, 2014), it is calculated as the standard deviation of analysts' forecasted Earnings per Share (EPS). The theoretical support of analysts' forecasts being used as a proxy of investor heterogeneity is that, analysts express their unbiased opinion in their earnings reports. Investors follow analysts' unbiased forecasts, hence the dispersions of analysts' forecasts could be translated into levels of investor heterogeneity. Many studies adopt this measure (Brown, Foster, and Noreen, 1985; McNichols and O'Brien, 1997; Lin and McNichols, 1998; Dechow, Hutton, and Sloan, 2000; Lerman, Livnat and Mendenhall, 2007; Alexandridis, Antoniou and Petmezas, 2007). Empirical evidence supports using analysts' forecasts dispersion as a proxy for investor heterogeneity. Ajinkya, Atiase and Gift (1991) test the link between the dispersion in financial analysts' earnings forecasts and the abnormal trading volume as a proxy of divergence of opinion. They show that the dispersion in analysts' earnings forecasts is positively related to the abnormal trading volume following the annual earnings announcements and is a proper proxy for agents' differing beliefs about the firm's prospects, which is consistent with Varian (1985) and Karpoff (1986).

Analysts' forecasts dispersion has two advantages: easy to understand and data is accessible. Also, there are several drawbacks. First, the data which analysts use are probably biased. Second, the forecast distributions may be truncated. Abarbanell, Lanen and Verrecchia (1995) show that dispersions of analysts' forecasts are insufficient to proxy investor uncertainty, the number of forecasts and the periods could also affect the forecast dispersion. Third, favorableness of the coverage is a potential problem (Garfinkel, 2009). Forth, this measurement cannot distinguish

between the sources of investor heterogeneity, that is whether investor heterogeneity is caused by investors' prior belief or by the information processing model they use (Wang and Liu, 2014).

Bamber et al. (2011) argue that analysts' forecasts are not the same as assessing the firm's value. A change in accounting methods may affect analysts' forecasts of upcoming earnings without changing investors' expectations about the underlying value of the firm. Conversely, news that the firm has signed a lucrative long-term contract effective next period may affect investors' expectations about firm value without changing analysts' forecasts of this period's earnings. In addition, analysts are not representative of the full population of investors; analysts' forecasts likely reflect the expectations of sophisticated investors who have better information or better information processing capability than the average investor.

B. Liquidity Measures

Liquidity measures[21] the ease of trading a security. Bid-ask spread is widely accepted as the most popular liquidity measure, the smaller the spread is, the higher level of liquidity and more easy to long or short the security. In the literature of market microstructure, the rationale of liquidity that can be used as a heterogeneity measure is that it directly reflects the differential beliefs of investors. In a trading environment of higher level of heterogeneity, traders with different views are constantly submitting buying and selling orders to the limit order book,

[21] Liquidity measures include bid-ask spread, effective spread, absolute spread and Amihud (2002)'s measure. Prior literature documents that a quote-driven market system exists bid-ask spread, it is partially due to the adverse selection, inventory and labor costs of market makers. But this view is eliminated as the prevalence of order-driven system (George, Kaul, and Nimalendran, 1991).

according to the time-priority and price-priority rule, this higher level of heterogeneity will produce smaller bid-ask spread. In addition, bid-ask spread is a cost of information asymmetry (Bagehot,1971), and investor heterogeneity is caused primarily by information asymmetry[22].

Houge et al. (2001) use the opening bid-ask spread as a proxy of divergence of opinion of investors to test Miller (1977)'s hypothesis on IPOs. The authors argue that the bid-ask spread can be decomposed into three components, the order processing, adverse selection, and inventory costs. Among them, the adverse selection component reflects the dispersion between investors' opinions. The same methodology has also been adopted by Handa, Schwartz and Tiwari (2003).

The drawback of using spread liquidity measures as investor heterogeneity is that it only captures the top most layer of the ordered book, neglecting the limit orders below the first layer and the market orders. When investors submit orders into the limit order book, only limit orders are displayed, and market orders will be executed as soon as they arrived, and then disappear. The spreads created by market orders are not taken into account in spread liquidity measures. In addition, the thickness of the limit order book (other limit orders) reflects different prices levels traders want to trade, and hence their differential opinions, this is not captured in spread measures. Bid ask spread creates attenuation bias (Garfinkel, 2009; Wang and Liu, 2014).

[22] Many studies attribute investor heterogeneity to investors' prior beliefs and information processing models they used when new information arrives.

C. *Institutional Investor's Four-Dimensional Measure*

A novel measure developed by Knyazeva et al. (2015)[23], which uses a four-dimensional variable to measure investor heterogeneity: investor size, investor experience, institutional investor holding length and local experience. This measure in heterogeneity is in the precision (accuracy) of investor information rather than differences in specific beliefs about the firm's earning numbers. It captures the characteristics of institutional investors associated with the capacity to process and acquire information in general as well as the precision of investor information about a specific firm.

The main problem of this four dimensional measure is data availability and its coverage. Foreign institutional investors' hold data is not available for every firm. In addition, retail investors' characteristics are not covered.

D. *The Market Depth Measure*

Garfinkel (2009) proposes a direct measure of investor based on submitted market and limit orders. Its theoretical foundation is that buyers and sellers submit orders to the limit order book, the prices they want to buy and sell directly reflect their view on the stock. This view is consistent with Handa, Schwarz, and Tiwari (2003) and Hollifield et al. (2006).

Traders have the capability to submit either market or limit orders. These choices are based on their desire to obtain the best possible price in the transaction and how this trades off against non-execution risk. They also face adverse selection risk from trading against informed traders.

[23] Knyazeva et al. (2015). Data are from Thomson Financial Database. Knyazeva et al. (2015) has another important implication that investor heterogeneity contributes to a larger price reaction around the announcements for both positive and negative earnings.

Optimal order submission strategy and the optimal price requested is directly related to investors' reservation prices. Hollifield et al. (2006) have a similar view that using order data to represent investors' different opinion. Garfinkel (2009) calculates the market depth measure as:

$$\%Distance = \frac{OrderPrice - PriorTradePrice}{PriorTradePrice}$$

$$DIVOP = \left[\sum_{i=1}^{N} \frac{(\%Distance_i - \overline{\%Distance})^2}{N-1}\right]_{day}^{\frac{1}{2}}$$

where, OrderPrice is the price of the newly arrived market or limit order, PriorTradePrice is the price of the last transacted price, %Distance is called opinion divergence percentage, DIVOP is then the standard deviation across all orders on the day.

%Distance directly measures the differential investor's opinion difference at an instant moment, and DIVOP integrates %Distance to a whole day. There are several problems with this measure. 1). OrderPrice includes all of the prices of newly arrived order, however, not of all of these orders could contribute to the thickness (depth) of the limit order book. Investors could withdraw the newly arrived orders which haven't been executed. These withdrawn orders could be due to various reasons, which also represent the divergent opinions. 2). some of the orders are immediate or cancel (IOC) orders, these orders are considered as market orders which finds counter parties which have the same price requests, if not filled, they are automatically canceled. Especially in the era of high-frequency trading, credit traders frequently use these IOC orders as liquidity consumers to earn credit rebate[24]. 3). this measure could be affected by the extreme value bias. 4). Using average value of %Distance should be a better choice than

[24] For example, order channel is selected as BYXONLY plus IOC type. Traders earn a credit rebate of $0.0002/share. See BYX fee schedule.

standard deviation. 5). Data availability is still the biggest problem, it requires expensive high-frequency data.

E. Abnormal/Unexplained Volume Based Proxies

Using volume to interpret investor heterogeneity based on the theory that trading volume reflects differential beliefs and hence heterogeneity.

Harrison and Kreps (1978) suggest that abnormal trading volume around corporate public announcements could be explained by the divergence of opinion among traders. Kandel and Pearson (1995) predict that volume will be increasing in the diversity of investor opinions around earnings events. The seminal study, Kim and Verrecchia (1991) show that greater diversity of opinions caused by the differential processing of the information, leads to an increase in trading volume. Other empirical studies, including Bamber (1987), De Long et al. (1990), Ajinkya, Atiase and Gift (1991), and Ajinkya et al. (2004), all confirm the view that abnormal trading volume is associated with higher divergent opinion. Direct evidence is also recorded in the experimental literature, Smith, Suchanek and Williams (1988) show that even when traders observe identical probabilistic dividend distributions, then trade occurs, sometimes in large volume. They conclude that there is diversity in opinions.

One version of the benchmark is based on a trading volume market model analogous to that used in event studies on returns, as noted by Tkac (1999):

$$Trading\ Volume\ Turnover_{i,t} = \alpha_i + \beta_i Market\ Volume\ Turnover_{m,t} + \varepsilon_{i,t}$$

Where $Trading\ Volume\ Turnover_{i,t} = \frac{Vol_{i,t}}{Shrs_{i,t}}\ and\ \ Market\ Volume\ Turnover_{m,t} = \frac{Vol_{m,t}}{Shrs_{m,t}}$

$\varepsilon_{i,t}$ is the residual of the regression, called abnormal trading volume, which is trading volume generated but is not explained by the market volume. Garfinkel (2009) concludes that this unexpected volume "is the best proxy for opinion divergence. The residual component captures investor heterogeneity, it also rules out of the effect of liquidity commonality[25] and all other market factors, the information captured remain in the residual $\varepsilon_{i,t}$ represents pure investors' divergent opinion.

Garfinkel (2009) also proposes a measure called abnormal market adjusted turnover:

$$Abto_{i,t} = \frac{Vol_{i,t}}{Shrs_{i,t}} - \frac{Vol_{m,t}}{Shrs_{m,t}}$$

Where $Vol_{m,t=} \sum_1^m Vol_{i,t}$ and $Shrs_{m,t=} \sum_1^m Shrs_{i,t}$

Sufficient literature has documented that trading volume is proportional to the absolute price returns. (Bamber, 1997; Harrison and Kreps, 1978; Varian, 1985, 1989; Kandel and Pearson, 1995). The third volume-based measure which Garfinkel (2009) develops, is the Standardized

[25] Garfinkel (2009) also points out that this measure has the drawback that it cannot capture the un-transacted orders, which is an attenuated sample of investor heterogeneity.

Unexplained Stock Trading Volume (SUV) model. He argues that it measures unexpected trading volume and isolates from the effect of both liquidity and information[26].

Standardized Unexplained Stock Trading Volume (SUV)

$$Trading\ Volume\ Turnover_i = \alpha_i + \beta_i |return_i| + \varepsilon_i$$

$$SUV_i = \frac{\varepsilon_i}{sd(\varepsilon_i)}$$

The residual of the regression $\varepsilon_{i,t}$ represents all of the factors which are not explained by absolute price returns.

Overall, these measures are prevailing in the studies of investor heterogeneity, each has merits and drawbacks. The measure I choose is based on SUV with modifications. These modifications come from both theoretical and empirical evidence, which will be elaborated in Section III.

2.1.5 Investor Types and Overconfidence

In order to address the third challenge of heterogeneous asset pricing models, scholars begin with classifying investors into various types and try to find out their trading incentive and strategies. It is difficult to extract the trading behavior of diverse types of investors from historical transaction data. As noted by Bamber et al. (2011), academics still has very limited understanding on different classes of traders and their incentive to trade. Although these classifications are not mature, one common finding of the studies on investor types is that, large

[26] See Section III methodology for a discussion.

price movement and excessive trading volume are ascribed to investors' overconfident behavior (Odean, 1998).

Benos (1998) models investor behavior with rationally and irrationally informed traders, he shows that higher volume, larger depth and more volatile and informative price are generated by the overconfident irrational traders. Benos argues that some informed traders, who are overconfident about their estimates of unknown variables, think that they are smarter than average and compete with rational informed traders. Although these overconfident informed traders are considered irrational, they can make higher individual profits than their rational colleagues and survive in the markets. The reason behind this finding is that irrational traders act aggressively, they enjoy a "first-mover advantage".

Hong and Stein (1999) classify traders into news-watchers and momentum followers. News-watchers trade based on their analysis on firms' fundamentals, while momentum followers only care about the price patterns, they watch the price reactions and aggressively join if they found momentum exists. Hong and Stein also conclude that large price turbulence is induced by the overconfidence of momentum traders. Odean (1998) argues that overconfidence is prevailing in the market, price-taking traders, strategic-trading insiders and risk-averse market makers could be all overconfident. Overconfidence increases expected trading volume, increases market depth and decreases the expected utility of overconfident traders.

Sources	Investor Types	Conclusions
Benos (1998)	rational and irrational traders	Higher volume, larger depth and more volatile and informative price are generated by the overconfident irrational traders.
Hong and Stein (1999)	newswatchers and momentum followers	Large price turbulence is induced by the overconfidence of momentum traders.
Odean (1998)	price-taking traders, strategic-trading insiders and risk-averse market makers	Traders are all overconfident. Overconfidence increases expected trading volume, increases market depth and decreases their expected utility.
Gervais and Odean (2001)		Traders are "learning to be overconfident" from the beginning of their trading careers. Greater confidence leads to greater trading volume.
Luo et al. (2018)	informed and un-informed traders	Momentum arises because late informed investor provide too much liquidity to early informed traders. Both momentum and reversals emanate from overconfidence.
Chui et al. (2010)	individualistic and collectivistic	Momentum is not explained by risk models, but explained by individualistic investors' overconfidence.
DHS (1998)		Momentum can be generated by investors' overconfidence and self-attribution bias, excessive trading volume is also generated by overconfidence.

Figure 1: Different Investor Types

Luo et al. (2018) argue that momentum arises because late informed investor provide too much liquidity to early informed traders. Both momentum and reversals emanate from overconfidence. Chui et al. (2010) classify investors into individualistic and collectivistic, and point out that momentum is not explained by risk models, but explained by individualistic investors' overconfidence. DHS (1998) show that momentum can be generated by investors' overconfidence and self-attribution bias, excessive trading volume is also generated by overconfidence.

Gervais and Odean (2001) argue that traders are "learning to be overconfident" from the beginning of their trading careers, and greater confidence leads to greater trading volume. Traders take too much credit from their prior successes, and less for their failures. This leads to overconfidence. When a trader is successful, he ascribes too much of his success to this own ability and revises his beliefs about this ability upward too much. With more experience, people develop better self-assessments.

Although overconfidence is of critical importance in the literature of Finance, its measurement has rarely been documented in the literature of Psychology (Olsson, 2014)[27], as it needs an individual's original expectation which is a non-observable variable. Recently, finance scholars started to address this issue by using individualism or collectivism from one dimension of culture[28], which starts a new research direction in classifying investors.

2.1.6 Finance Meets Culture

What is natural culture? Hofstede defines it as "A collective programming of the human mind that distinguishes the members of one group or category of people from another" (Hofstede, 1980). In his pioneer work, Hofstede defines three levels of human mental programming: 1). Universal, which is the least unique, it is the one shared by all humans, biological and inherited genetically. 2). Collective, which is common to people belonging to a certain group or category, different from people belonging to other groups or categories. It is learned, not inherited. 3). Individual, which is the truly unique part, a level of individual personality providing for a range of alternative behavior within the same collective, and likely both learned and inherited. Research in business management have been using this classification widely in relative areas, and this framework has had an enormous impact on research in various business disciplines, like

[27] In the literature of psychology, overestimation, overplacement, and the calibration of subjective probabilities are all considered as different forms of overconfidence (Olsson, 2014). There are only two studies document that more than two measures of overconfidence, see Moore and Healy (2008) and Larrick et al. (2007).

[28] Hofstede (2001) classifies cultures into five dimensions: individualism, masculinity, power distance, uncertainty avoidance, and long-term orientation. Among these five cultural dimensions, individualism is the most closely related to overconfidence and self-attribution bias. This index is regarded as the most comprehensive in terms of both the range of countries and the number of respondents involved (Kagitcibasi, 1997).

organizational behavior, strategy, and human resources management (Karolyi, 2016). Only recently, researchers have been putting attention on cultural impacts on finance.

The earliest, as well as the most impactful study used culture to analyze financial behavior is Grinblatt and Keloharju (2001). They document that investors are more likely to hold, buy, and sell the stocks of Finnish firms that are geographically proximate to the investors, that communicate in the investor's native tongue, and that have chief executive officers (CEOs) of the same cultural background. One of the intriguing findings in the study is that the influence of distance, language and culture is less prominent among the more sophisticated financial institutions with available data in the Finnish Central Securities Depository than among less-sophisticated households and government/non-profit firms.

Gelfand, Nishii, and Raver (2006) argue that individual behavior tends to be more homogenous and exhibit a lower degree of variation in culturally tight countries. This convergence in investor behavior will cause positive correlations in investors' stock selections and buy/sell decisions, and higher return co-movement in culturally tight countries are expected. Similarly, Literature from behavioral finance shows that behavioral biases can affect stock commonality [29](Hirshleifer, 2001; Shiller, 2003; Barberis, Shleifer, and Wurgler, 2005). Cultural dimensions introduce systematic biases into investor behavior and hence affect stock price movement.

In Hostede's culture measure, individualism and collectivism are the most closely related with finance. Individualism reflects the degree to which people focus on their own internal attributes to differentiate themselves from others. People are more likely to believe that they are above

[29] Stock commonality, synchronicity and comovement are used interchangeably in this study, all refer to the phenomenon that stock prices move together.

average in individualistic countries than that is in collectivistic countries (Markus and Kitayama, 1991; Heine et al., 1999). Individualistic people (such as US) think positively about themselves and focus on their own internal attributes (Markus and Kitayama, 1991), they believe that they have better ability than average and tend to overestimate their abilities(Heine et al., 1999). Individualistic investors are more likely to use their own methods to collect, process or analyze, and use their own information for trading, this behavior incorporates more firm-specific factors into stock prices, and trades made by individualistic investors have low trading correlations. As investors from individualistic countries tend to be more over-confident (Hofstede, 2001), this over-confidence results in more trading volume generated (Nofsinger, 2012) and price momentum (Chui et al, 2010). Also, individualistic investors are less concerned about their trading behavior based on opinions that differ from the norm (Eun et al., 2015), hence, less herding effect or liquidity commonality are expected in individualistic countries compared with that in collectivistic countries(Beckmann, Menkhoff and Suto, 2008).

In contrast, people in collectivistic cultures (such as Japan) do not have the belief that they are better than average, they view themselves "not as separate from the social context but as more connected and less differentiated from others" (Markus and Kitayama (1991). Collectivistic people are willing to see that they are accepted by others. When investing, collectivistic people tend to rely on consensus rather than their own analyzing ability or their own channel to get information.

Individualistic investors are inclined to view and analyze stocks from their own points of view, detach objects from the system and focus on the object's individual attributes. On the other

hand, investors from collectivistic cultures have holistic thinking styles, leading them to view stocks jointly (Eun et al., 2015). Individualistic cultures promote, whereas collectivistic ones suppress skepticism (Luo, 1998). All else equal, when clienteles for equities in collectivistic cultures shift to foreign ownership by individualistic cultures, momentum should increase.

Chui et al. (2010) argue that greater individualism is positively associated with higher trading volume, stock index return ability and the magnitude of momentum strategy return. One important conclusion from Chui et al. (2010) is that, they found investors from individual culture tend to be more overconfident than from collective culture, and these investors tend to overestimate the precision of their information, and hence more trading is made. Large trading volume is associated with large price movement. This conclusion is consistent with Odeon (1998) that overtrading leads to excess volatility. Eun et al. (2015) take their cue from the Chui et al. study on Hofstede's individualism measure, but for a different market-wide outcome measure, namely, stock price synchronicity. The commonality, or average correlatedness, among individual stock returns is negatively related to individualism. They found that stock prices move more (less) in culturally tight (loose) and collectivistic (individualistic) countries. They also suggested that culture is an important omitted variable in the literature that investigates cross-country differences in stock price co-movements. In their study, two cultural dimensions are considered, namely tightness/looseness, which is considered external constraints on individual behavior and individualism/collectivism, which focus on internal attributes that guide an individual to differentiate his or her decision from others. The literature suggests that individualistic investors are likely to be more confident in their ability to acquire and analyze information and less concerned about having different opinions from others (Markus and Kitayama, 1991; Heine, Lehman, Markus, and Kitayama, 1999; Chui, Titman, and Wei, 2010).

Therefore, one would expect to observe less herding behavior and more firm-specific information being incorporated in stock prices, which would be likely to lead to lower stock price co-movements in individualistic countries. The influence of culture on stock price co-movement is economically significant and robust.

Using the individualism index as a proxy for overconfidence is an effective option, as it is an observable and measurable variable, it also avoids the difficulties in classifying investors. The Individualism index has been used as an instrumental variable for classifying firms and investors in recent studies (Chui et al, 2010; Verardo, 2009; Luo et al, 2018).

2.1.7 Two Direct Manifestations: Price Momentum and Trading Volume

Although investor homogeneity is a critically important assumption in classical finance theories, there is a large gap between the investor homogeneity assumption and the market reality. This poses a serious challenge to establish theoretical frameworks such as Capital Asset Pricing Model. Many anomalies regularly occur in markets, but one of them attracts the most attention and is a source of controversy: “the Momentum Effect” (Fama and French, 2007). The Momentum Effect refers to the fact that, stocks with high returns over the last year tend to continue to have high returns in the following few months; similarly, low short-term past returns also tend to persist (Jegadeesh and Titman, 1993). The momentum trading strategies are widely used by traders. Scholars ascribe this anomaly to “differential beliefs” or “investor heterogeneity” (Chui et al., 2010; Verardo, 2009; Hong and Stein, 2007; Fama and French, 2009).

Chui et al. (2010) show that there are significant cross-country differences in momentum profits that persist across time. The cross-country differences are instigated by various characteristics of investors such as their cultural orientation. Zhang (2006) documents that US stocks with information uncertainty, measured by more dispersed analyst earnings forecasts, exhibit stronger momentum and he attributes this to higher individualism of US investors. It is widely accepted that dispersed analyst forecasts are used as a proxy for investor heterogeneity. Huynh and Smith (2013) find momentum exists in US, Europe Asia and Japan, and their explanation of the momentum effect is centered on under-reaction to news. This conclusion is consistent with Hong and Stein's (1999) "Gradual Information Diffusion Model" which provides a rationale for differential beliefs. Fama and French (2012) also point out the pervasive nature of the momentum effect in North America, Europe and Asia-Pacific excluding Japan. Although Fama and French do not provide an explanation why the Japanese stocks do not exhibit momentum effect, a related study by Chui et al. (2010) provide a convincing explanation. Chui et al. (2010) attribute the insignificance of momentum effect in Japanese stocks to the collectivistic nature of the Japanese culture. Using analysts' forecast dispersion as a heterogeneity proxy, Verardo (2009) shows that momentum profits are significantly larger for portfolios characterized by higher heterogeneity of beliefs. On the other hand, considering the momentum effect from the market microstructure perspective, the order flows supplied by heterogeneous investors are in favor of forming and maintaining a price trend. In sum, momentum which is an observable phenomenon of investor heterogeneity, has established an effective bridge for studying the heterogeneity of investors as higher level of heterogeneity results in higher momentum.

Another manifestation of investor heterogeneity is trading volume. The generated trading volume reflects traders' agreement with the current value for exchange, but at the same time, it

also reflects their disagreement on the future value of the asset. Hence, trading volume exhibits an already-formed disagreement, but as Garfinkel(2009) argues trading volume does not capture the full extent of disagreement. The seminal study, Kim and Verrecchia (1991) show that greater diversity of opinions caused by the differential processing of the information, leads to an increase in trading volume. Harrison and Kreps (1978) suggest that abnormal trading volume around corporate public announcements could be explained by the divergence of opinion among traders. Kandel and Pearson (1995) predict that volume will be increasing in the diversity of investor opinions around earnings events. Other empirical studies, including Bamber (1987), De Long et al. (1990), Ajinkya, Atiase and Gift (1991), and Ajinkya et al. (2004), all confirm the view that abnormal trading volume is positively associated with higher divergent opinion. Trading volume reflects differential beliefs, and it is the most direct and observable evidence of investor heterogeneity (Bamber et al., 2011; Bamber et al., 1999).

From the point of view of order flow, investors with strong heterogeneity provide sufficient buying and selling orders at different price levels on the limit order book (LOB). These non-marketable limit orders offer sufficient liquidity, which allows traders to easily find the counter parties of the transactions, this process leads to the change of prices and the generation of volume. Sufficient liquidity is manifested by continuous price levels with small spreads. On average, the smaller the spreads are, the easier the formation of transactions. In contrast, the order flow provided by the investors with poor heterogeneity often causes price fractures on the LOB, which makes it harder for trades to match. Under the extreme circumstances of investor homogeneity, the orders are stacking merely on a single side of the LOB, resulting in that new traders could not find the counter parties for their transactions, this LOB state corresponds to Milgrom and Stokey (1982)'s Pareto Optimal of the asset, which is the famous

"No Trade Theorem". Poor investor heterogeneity hinders the formation of transactions, and thus hinders price changes and the generation of trading volume. This is the reason why investor heterogeneity is positively related with momentum and trading volume.

2.1.8 Summary

This section reviews the literature of investor heterogeneity. This assumption violates the homogeneity assumption of classical finance theories, it is of critical importance for building new asset pricing models. Due to its complexity, academics has not reached an agreement on its measurement, this section provides a comprehensive review of current measures. In finding out different types of investors, this section also reviews current investor classifications, one interesting finding is that no matter what classification method scholars use, they attribute momentum and trading volume to the overconfident behavior of investors. Traders appear a process of "learning to be overconfident" through their lives. This section also surveys the literature on culture's influence on finance, mainly on individualism and collectivism. Investors from individualistic cultures tend to be more confident than who from collectivistic cultures. Finding out the determinants of investor heterogeneity is not the objective of this study, but through culture dispositions, investor heterogeneity can be further differentiated by investor composition, this differentiation is manifested by momentum and volume.

2.2 Momentum

2.2.1 Definition and Evidence

Many anomalies in finance regularly occur in markets, but one of them attracts the most attention and is a source of controversy: "the Momentum Effect"[30] (Fama and French, 2007). The Momentum Effect refers to the fact that, stocks with high returns over the last year tend to continue to have high returns in the following few months; Low short-term past returns also tend to persist (Jegadeesh and Titman (JT), 1993). The momentum effect refers to the relation between an asset's return and its recent relative performance history (Asness et al., 2013). Momentum exists not only in equity markets, it was found consistently and ubiquitously across all the markets, i.e., the bond, commodities and currency markets. Momentum exists everywhere (Asness et al., 2013).

Large volume of studies documents the existence of price momentum. JT (1993) use daily return data of the US market from 1965 to 1989, through the winner and loser portfolio methodology, they find momentum exists and point out the research direction for the following studies. Grinblatt, Timan and Wermers (1995) analyze the data from 155 mutual fund companies from 1975 to 1984, without considering the transaction costs, they find that more than 75% of these companies used momentum strategies, and their quarterly investment profit was significant. Their research demonstrates that momentum strategies could produce significant profit. Rouwenhorst (1998) examines 12 countries in Europe, he finds that momentum exists in all

[30] Fama and French (2007) point out that there are two anomalies which attract the most attention and controversy, they are the Value Effect and the Momentum Effect. The Value Effect refers to the fact that, stocks with low prices relative to fundamentals like cash flow or book value have higher average returns than predicted by the CAPM (Statman, 1980, Rosenberg, Reid, and Lanstein, 1985, Fama and French, 1992). In this study, only the Momentum Effect is related with investor heterogeneity.

developed countries, but the zero-cost portfolio[31] has very limit profitability. The profitability of momentum strategies is found in equity markets throughout the world (Rouwenhorst, 1998; Griffin, Ji, and Martin, 2003), however, Asian countries are exceptions (Chui, Titman, and Wei, 2003).

Lee and Swaminathan (2000) propose a "Momentum Life Cycle" (MLC) model. Under their framework, trading volume provides information useful in locating a given stock in its momentum/expectation life cycle. Generally, when a stock falls into disfavor, and its trading volume declines. Conversely, when a stock is popular, and its trading volume increases. The MLC would characterize high volume winners and low volume losers as late stage momentum stocks, in the sense that their price momentum is more likely to reverse in the near future. Conversely, low volume winners and high volume losers are early stage momentum stocks, in the sense that their momentum is more likely to persist in the near future.

2.2.2 Causes of Momentum

A.The Traditional Explanations

After JT (1993)'s seminal study, the momentum profit has been accepted widely, but its causes remain debated. Early explanations ascribe the momentum effect to risk models, i.e. Wang

[31] Zero-cost portfolio refers to a portfolio does not need any initial investment. i.e., buying and selling a stock at the same time.

(2000), and some scholars attribute it to data mining. Conrad and Kaul (1998) and Lo and MacKinlay (1990) are representatives. They argue that the profitability of momentum strategies could be entirely due to cross-sectional variations in mean returns rather than to any predictable time-series variations in stock returns. Conrad and Kaul argue that there are no discernable time-series variation in returns and that momentum returns arise because of cross-sectional variation in returns. This argument implies that the post-holding period returns of the momentum portfolio should be significantly positive. Momentum profits arise because of cross-sectional differences in expected returns rather than time-series predictability.

B. Investor Heterogeneity and Momentum

Recently, more scholars find momentum can be explained by investors' "differential beliefs" or "investor heterogeneity" (Chui et al., 2010; Verardo, 2009; Hong and Stein, 2007; Fama and French, 2009), related literature links investor heterogeneity with the information environment market (Allen, Morris and Shin, 2006; Banerjee, Kaniel, and Kremer, 2009; Makarov and Rytchkov, 2009), and argues that information is the main reason leads to investor heterogeneity.

Chui et al. (2010) show that there are significant cross-country differences in momentum profits that persist across time. The cross-country differences are instigated by various characteristics of investors such as their cultural orientation. Zhang (2006) documents that US stocks with information uncertainty, measured by more dispersed analyst earnings forecasts, exhibit stronger momentum and he attributes this to the higher individualism of US investors. It is widely accepted that dispersed analyst forecasts are used as a proxy for investor heterogeneity.

Huynh and Smith (2013) find momentum exists in US, Europe Asia and Japan, and their explanation of the momentum effect is centered on under-reaction to news. This conclusion is consistent with Hong and Stein's (1999) "Gradual Information Diffusion Model" which provides a rationale for differential beliefs. Fama and French (2012) also point out the pervasive nature of momentum effect in North America, Europe and Asia-Pacific excluding Japan. Although Fama and French do not provide an explanation why the Japanese stocks do not exhibit momentum effect, a related study by Chui et al. (2010) provide a convincing explanation. Chui et al. (2010) attribute the insignificance of momentum effect in Japanese stocks to the collectivistic nature of the Japanese culture. Using analysts' forecast dispersion as a heterogeneity proxy, Verardo (2009) shows that momentum profits are significantly larger for portfolios characterized by higher heterogeneity of beliefs. On the other hand, considering the momentum effect from the market microstructure perspective, the order flows supplied by heterogeneous investors are in favor of forming and maintaining a price trend. In sum, momentum which is an observable phenomenon of investor heterogeneity, has established an effective bridge for studying the heterogeneity of investors as higher level of heterogeneity results in higher momentum.

Verardo (2009) provides the empirical link between investor heterogeneity and momentum strategy profits and shows that momentum characterized portfolios have significantly larger returns for heterogeneity beliefs. This conclusion is consistent with Allen, Morris, and Shin (2006), which document that higher-order beliefs lead to price drift (Momentum). In addition, Banerjee, Kaniel, and Kremer (2009) show theoretically that differences of opinion, together with uncertainty about other agents' opinions, generate price drift in a dynamic setting. Makarov and Rytchkov (2009) present a rational model of heterogeneously informed agents, and show that this model could generate momentum.

Some of the momentum studies are showing contradicted conclusions. Hong et al. (2000) show that stocks with lower analyst coverage tend to exhibit more momentum, lower analyst coverage could represent lower investor heterogeneity. However, in their earlier and later studies, Hong and Stein (1999) imply that investor heterogeneity is positively related to momentum, and Hong and Stein (2007) characterize an economy where investors receive different information signals and erroneously believe that their signals are sufficient to forecast the asset liquidation value. The authors show that higher heterogeneity among investors implies stronger momentum. Although these studies got mixed or even contradictory results, viewing momentum from the microstructural logic, they are consistent. I will explain why most studies document the positive relation between investor heterogeneity and some of them document negative detail in Section III.

C. The Microstructural Explanation

From the point of view of order flow, investors with strong heterogeneity provide sufficient buying and selling orders at different price levels on the limit order book (LOB). These non-marketable limit orders offer sufficient liquidity, which allows traders to easily find the counter parties of the transactions, this process leads to the change of price and the generation of volume. Sufficient liquidity is manifested by continuous price levels with small spreads. On average, the smaller the spreads are, the easier the formation of transactions. In contrast, the order flow provided by the investors with poor heterogeneity often causes price fractures on the LOB, which makes it harder for trades to match. Under the extreme circumstance of investor

homogeneity, the orders are stacking merely on a single side of the LOB, resulting that new traders could not find the counter parties for their transactions, this LOB state corresponds to Milgrom and Stokey (1982)'s Pareto Optimal of the asset, which is the famous "No Trade Theorem". Poor investor heterogeneity hinders the formation of transactions, and thus hinders price changes and the generation of trading volume. This is the reason why investor heterogeneity is positively related to momentum and trading volume.

In section III, I proposed a two-period order flow model, which explains how orders are flowing as information arrives at the market. It explains how information induced trading generates momentum and trading volume.

2.2.3 Momentum Measurement

Starting from JT (1993), momentum is measured by the Winner and Loser Portfolio Method, this method has the most important and enduring influence.

According to the definition of price momentum, stocks' past returns predict future returns, stocks with positive (negative) returns tend to have positive (negative) returns in the following time period (Jegadeesh and Titman, 1993). Barberis and Shleifer (2003) define a style momentum strategy as the one that "buys into styles with good recent performance and avoids styles that have done poorly". Hence, a typical *f-h* Winner and Loser Portfolio is constructed as: first, stocks with certain characteristics[32] [33] are classified into different groups. For each group, watch the stocks for *f* months (the formation period), then the f months' returns are calculated

[32] eg. B/M ratios, sizes, industry classifications. In this study, I use individualism scores.
[33] Some studies call it double sorting methods. Blitz and Bliet (2007), Hou et al. (2009) etc.

and ranked in descending order. Stocks which ranked the top one-third (or 10% or quintiles)[34] are assigned to the Winner portfolio (Portfolio W), the strategy is to buy portfolio W. At the same time, those whose returns are ranked in the bottom one-third (or 10% or quintiles)[35] are assigned to the Loser portfolio (Portfolio L), the strategy is to sell Portfolio L. These portfolios are equally weighted and are not rebalanced over the following h months (the holding period). The third portfolio W-L is constructed by buying portfolio W and selling portfolio L. At the end of the holding period, the returns of Portfolio W, Portfolio L and Portfolio W-L are examined in order to find the momentum characteristics of this stock category. Stock return is simply the cumulative return during the formation and holding periods. If return data was missing, a typical method is using stock's beta multiplied by the market return as a replacement (Chui et al., 2010).

2.2.4 The Applicability of Momentum: Mean Reverting and Volatility Trading Strategies

Short-term traders, especially swing and trend followers, are always looking for stocks which could generate large price movement. They are looking for some overbought or oversold stocks, in other words, stocks are "mean reverting". The momentum and mean reverting strategies are widely used by practitioners from short run to intermediate time horizon, most technical indicators are designed based on momentum or mean reverting strategy. Current prevailing stock screening tools provide powerful cross-sectional characteristics to filter stocks, from fundamental to technical indicators, most of them are also based on this well-known strategy.

[34] The number of stocks in the Winner or Loser portfolio depends on data availability, usually at least 30 stocks needed within each portfolio.

[35] Using top one third or 10% cutoff depend on the size of each group of firms. Chui et al. (2010) use top or bottom one third, Jegadeesh and Titman (1993) and other studies use 10%.

Momentum traders are in favor of finding securities which are likely to be in trending, and they have to judge the direction of the price movement. In turn, volatility traders do not consider the directions of price movement, instead, they only care about how much price changes. Volatility trading is a group of strategies that enable the strategeurs to profit from the magnitude of price swings of the instruments rather than the direction of such swings (J.P.Singh, 2017). According to Carr and Mandan (2002), there are three main strategies for volatility trading. 1). Long a position in straddle. 2). Delta-hedging an option position. The prime determinant of the profitability of this strategy is the difference between the anticipated and realized volatility. 3) Buying or selling a volatility contract at an over-the-counter market, eg. A vol swap. Using straddles and strangles before earnings announcements are the most common and widely used strategies that individual and institutional investors apply.

Zhou and Shon (2013) did a comprehensive study by using more than 100,000 calls and puts to test these option strategies from 2003 to 2009 around earnings announcements. They found that in general, neither buying nor shorting straddles around earnings announcements was profitable, with the hitting ratio (success rate) of shorting much higher than buying[36]. But using the Global Industry Classification Standard (GICS)[37] to cross-sectionally analyze the test results, they find that IT industry is the most volatile and best suited for both buying and selling straddles or strangles, the average hit ratio increases significantly compared with the all-industry average; while utility industry is the most suitable for selling because these stocks seldom move very fast. Further filtering stocks by company size (market cap), implied volatility,

[36] More investors are joining the EA strategy, and elevating the implied volatility of calls and puts, which makes straddles much more expensive (inflated) than it should be.
[37] Developed by MSCI and S&P in 1999.

longing straddles had an average of 1.28% return[38], and shorting straddles had an average return of 6.28% for IT industry[39].

One important impedance for longing straddles is time decay, the underlying stock must move far enough from the strike price to make the option combination profitable before options expire. With more investors are jointing this volatility trading strategy, selecting stocks which have large price movements around earnings announcements is the key to the strategy. Greater investor heterogeneity implies that more disperse understandings and belief corrections will be generated when new information is released, so do the price momentum and the trading volume of the stock. One drawback of Zhou and Shon (2013) is that they provided very little evidence on how to filter stocks within a certain industry, only P/E, P/B and P/S ratios and the data up to 2009 was not suited for today rapidly changing market. It is reasonable to assume that, compared with non-foreign-listed firms, foreign-listed firms have more price movement and trading volume generated, this larger price movement and trading volume generated are quite a good tool for institutional investors' and hedge managers' trading strategies. This study will be a make-up for Zhou and Shon (2013) and other volatility trading literature, to provide further evidence on foreign-listing or non-foreign-listing as a new classification method. It will provide new evidence both theoretically and empirically on the literature of volatility trading. The empirical results will also benefit for retail investors in their practical use. Test results will be discussed in Section V.

[38] This return is measured by a 3-day window around each earnings announcement.
[39] This return rate is for a three-day window around earnings announcements. With the day of the earnings, the day before and the day after.

2.2.5 Summary

In this section, I review the literature of momentum. The main point of this section is that investor heterogeneity is the major source of momentum, and momentum is the direct manifestation of heterogeneity. Momentum is documented its existence across markets and instruments all over the world, momentum strategies are widely used by practitioners. Volatility trading, which is also based on momentum largely depends on the stock selection techniques. Choosing the right stocks which are likely to be in trending can increase the profitability.

In a trading environment, the price of a security is the last transacted price. Investors exchange their views of future expectations on an asset, this exchange also reflects investors' different opinions, and hence investor heterogeneity. In financial economics, trading volume is an important variable which describes the quantity of this "heterogeneity", it represents the sentiment of a market.

2.3 Trading Volume, Theories and Bridge to the Research

2.3.1 Trading Volume Theories and Investors' Disagreements

A. Early Theories of Trading Volume

The theories of trading volume have an old history. Louise Bachelier (1900) is being credited as the first scholar who investigated the fluctuations on security prices by linking the price changes

to investor disagreement and trading. In his paper, Bachelier indicated that "the influences which determine fluctuations on the exchanges are innumerable: past, present, and even discounted future events are reflected in the market price, but often show no apparent relation to price changes……Contradictory opinions concerning these changes diverge so much that at the same instant, buyers believe in a price increase and sellers in a price decrease".

Although Bachelier's work was the first to point out disagreement, his work was largely restricted by contemporary economic analysis method (Bamber, et al. 2011). After almost 70 years, researchers began to utilize advanced data analysis tools on security price formation, and Beaver (1968) is considered to be another pioneer work in the field who identified the potential for trading volume to yield unique and valuable new insights. He argues that trading volume reactions reflect a lack of consensus regarding the appropriate price of the firm's shares, and trading volume captures individual expectations while price reactions capture only the expectations in the market as a whole. Previous literature overlooks the fundamental characteristics of securities that investor disagreement leads to trades. Beaver (1968) also concludes that volume reactions may be more sensitive tests of the usefulness of public disclosures than price reactions.

Another seminal work, Stephen Ross (1989) also pointed out that, it was embarrassing that economists analyze price reactions and complete being silent on the quantity. After Ross's discussion, theorists had made significant advances in trading volume as well as price to public disclosures[40].

[40] See Verrecchia (2001) for a review.

B. Review of Price Theories

Although theorists in financial economics had realized that trading volume could reflect disagreement and this disagreement had important implications on trading, theories of trading volume developed very slowly. The reason behind this is the fact that theorists paid too much attention on price theories while these price theories left little room for trading volume theories to develop (Bamber et al., 2011). Fama (1970) proposes the most accepted theorem which states that all information including public or private is revealed in the current market price. Under this assumption, there are no trades available in the market. This No-Trade Theorem argues that all investors have rational expectations, identical views on an asset, and new information cannot induce trades if the initial allocation of shares is Pareto Optimal. All investors having rational expectations, and hence homogeneous expectations, means that all investors know that all other investors have ration expectations, all investors know that all investor know that all others have rational expectations, and so on (Milgrom and Stokey, 1982).

To allow the possibility of trades, early price models first abandoned the assumption of rational expectation, and assumed that investors learned nothing from market price and adjust their investment behavior adaptively to information releases (Epps 1975, 1976; Jennings, Starks, and Fellingham, 1981; Karpoff, 1986; Jang and Ro, 1989). These early models identify two important determinants of trading volume around earnings announcements 1). Heterogeneous prior expectations before information releases. 2). Heterogeneous reactions to the announcement. These two determinants directly lead to Beaver (1968)'s intuition that trading volume perverse difference in individual beliefs that are averaged out in price reactions.

Grossman and Stiglitz (1980) argue that investors are unable to get a return if market price fully reveals all information. Gathering information is so costly and investors are not willing to do that, and hence no trade will incur. On the other hand, Grossman and Stiglitz demonstrate that investors can earn a return with costly information under the assumption that market price partially reveals all information. Investors add noise supply to the traded assets, and this supply noise prevents prices from being fully revealing because investors can no longer fully distinguish between: 1) market fluctuations arising from new private information and 2) market fluctuations arising from supply shocks that are unrelated to information. This noise supply view is also supported by Kim and Verrecchia (1991a), which argues that the supply and demand of a security are random liquidity needs. Supply noise represents liquidity and/or asset supply shocks (Verrecchia 2001), it is general enough to capture any kind of market noise that keeps the market price from being fully revealing.

After Grossman and Stiglitz 1980, a new stream of rational expectations models assumed investors learn from price, but price reveals private information with noise (e.g., Kyle 1985; Grundy and McNichols 1989;Tkac 1999; Chae 2005). These theoretical models are frequently labeled as partially revealing or noisy rational expectations models, and they can be considered as a large step from pure price models to the combination of price and volume, further relaxing the strict assumptions made in classical finance theories.

C. Recent Theories Development

Only recently, researchers in financial economics have renewed the call for asset pricing models to give trading volume a prominent role in their models. Hong and Stein (2007) state that "we find it hard to imagine a fully satisfying asset pricing model----in either the rational or behavioral genres that does not give a front-and-center role to volume. Trading volume is extremely large across virtually all developed stock markets, and many of the most interesting patterns in prices and returns are tightly linked to movements in volume." Cready and Hurtt (2002) also provide simulation-based evidence suggesting that volume reactions are more powerful indicators of market response than price reactions. Garfinkel (2009) concludes that unexpected volume "is the best proxy for opinion divergence".

According to Bamber et al. (2011), there are three reasons why trading volume other than prices is warranted. 1). Trading is an important economic activity. Both daily trading volume and abnormal trading volume around financial disclosures increased more than tenfold over the past 20 years. 2). Trading in response to financial disclosures provides the most direct evidence that financial disclosures have affected investor's expectations and decisions. Trading volume reactions to financial disclosures are more readily detected than price reactions (Cready and Hurtt, 2002). 3). It has an important implication on information asymmetry around financial disclosures.

D. Trading Volume and Investor Heterogeneity

Beyond price momentum, trading volume is another manifestation of investor heterogeneity. The generated trading volume reflects traders' agreement with the current value for exchange, but at the same time, it also reflects their disagreement on the future value of the asset. Hence,

trading volume exhibits an already-formed disagreement. The seminal study, Kim and Verrecchia (1991) show that greater diversity of opinions caused by the differential processing of the information, leads to an increase in trading volume. Harrison and Kreps (1978) suggest that abnormal trading volume around corporate public announcements could be explained by the divergence of opinion among traders. Kandel and Pearson (1995) predict that volume will be increasing in the diversity of investor opinions around earnings events. Other empirical studies, including Bamber (1987), De Long et al. (1990), Ajinkya, Atiase and Gift (1991), and Ajinkya et al. (2004), all confirm the view that abnormal trading volume is positively associated with higher divergent opinion. Trading volume reflects differential beliefs, and it is the most direct and observable evidence of investor heterogeneity (Bamber et al., 2011; Bamber et al., 1999).

2.3.2 Empirical Measures of Volume

Measures of trading volume are debated in early studies. They have the choice of measuring trading volume using the number of shares or number of transactions. The number of transactions captures the number of times investors are motivated to act, but it is sometimes misleading. Cready and Ramanan (1995) point out that orders coming into the LOB can be divided or batched, which produces noise. The number of shares encompasses the magnitude of the action as well as the decision to act (Cready and Ramanan 1995).

Researchers use trading volume turnover as a trading volume measure. Lo and Wang (2000) argue that this turnover is a natural measure of trading volume and it automatically controls for firm size and the fact that the number of shares outstanding and the number of shares traded have grown steadily over time (Bamber et al., 2011). Empirical studies find that share turnover

still trends upward, possibly due to elimination of fixed commissions (Campbell et al. 1993), technological innovations such as online trading and Internet speed increase (Ahmed et al. 2003), and the increase in institutional investors' trading, especially hedge funds (Fung and Hsieh 2006).

Compared with the number of shares and the number of transactions, trading volume turnover is the most widely accepted measure, however, it needs adjustment. Bamber et al. (2011) point out that using log form of shares turnover is a viable option. The distributions of daily trading volume are highly skewed to the right (Ajinkya and Jain, 1989), due to a few days having extremely high trading. In the studies of the determinants of trading volume, the dependent variable(shares turnover) is so skewed that the regression residuals significantly depart from normality, evidencing severe skewness and heteroskedasticity, in this case, using a natural log of the trading volume is recommended (Bamber et al, 2011). Theoretically, Kim and Verrecchia's (1991a) model predicts that trading around an announcement is a multiplicative function of the absolute magnitude of the contemporaneous price change and differential precision of private pre-disclosure information. The natural logs of trading volume as the independent variable and price change as one dependent variable plus differential precision as another, is just suitable for their prediction[41], this prediction and its model are confirmed by Atiase and Bamber (1994).

2.3.3 Trading Volume, Information, and Earnings Announcements.

Information is the key determinant of trading in financial markets, it can affect investors' trading decision and overall strategies. Trading volume is associated positively with the absolute

[41] Recall that the properties of logarithms: log (y/x)=log (y)-log(x).

magnitude of returns (Karpoff, 1987), and empirical research supports this view (Atiase and Bamber 1994; Bamber and Cheon 1995; Bhattacharya 2001; Bailey et al. 2003; Hope et al. 2009).

However, there are some exceptions. Bamber and Cheon (1995) showed that this positive relation was not strong. They argued that about one fourth of earnings announcements generated either 1) very large trading volume without large price change or 2) large price change without large trading volume. Kandel and Pearson (1995) showed that large price reactions around earnings announcements were caused by more divergent analysts' forecasts[42], not by abnormal trading volume.

2.3.4 Earnings Announcements and Information Releases

Prior research concludes that financial disclosures, such as earnings announcements, are important enough to cause investors to take action by trading (Beaver 1968; Kiger 1972; Morse 1981; Bamber 1986, 1987). Earnings announcements release the most important and recurring information to investors, and this information releasing spurs differential belief revisions, and hence investor heterogeneity.

The Differential belief revisions have many sources. One possible source belief revision differentials are the quality of the pre-disclosure information investors possess. As predicted by Kim and Verrecchia (1991a)'s theoretical model, pre-disclosure information asymmetry spurs differential belief revisions, because investors with imprecise pre-disclosure information find the announcement more informative than those privy to more precise pre-disclosure information.

[42] According to the theories of investor heterogeneity, abnormal high trading volume and divergent analysts' forecasts are not contradicted, but the same consequences of investor heterogeneity.

Different investors have different capabilities to gather data, regardless if the information is private or public, and they also have different capabilities to analytically process the data. When earnings are released, investors receive more information than other periods, and differential beliefs exhibit more significantly than other times. Accordingly, these differential beliefs spur trades and generate trading volume; therefore, earnings announcements are considered to be good windows to capture the changes in trading activities, and hence good windows to capture investor heterogeneity which causes these trading activities.

Zhou and Shon (2013) document that recurring, predictable and impactful events are important and necessary attributes of events which trigger price movement, for individual firms, the most regular and striking economic activities are the earnings announcements.

Early empirical evidence supports the view that financial disclosures stimulate trading. Beaver (1968), the seminal study aimed to investigate whether earnings announcements are informative to investors, and he found that in earnings weeks, squared price fluctuations were 67% higher and mean trading was 33% larger than in a non-earning week. He concluded that earnings announcements have information content that spurs investors to trade. Kiger (1972) and Morse (1981) extended beaver's study. Kiger (1972) found that the mean trading volume over a three-day and five-day windows were 50% higher than that during a control period. Morse (198) reported a significant increase in trading the day before quarterly and annual earnings announcements, and this phenomenon extends to three days after the disclosure (Post Earnings Announcements Drifts).

Bamber et al. (2011) pointed out that early research on trading around financial disclosures was subjected to selection criteria, this selection method increased the likelihood of finding the reaction of earnings announcements (Bamber, Christensen, and Gaver, 1994 and 2000; Bamber, et al. 2011). Beaver (1968) used 143 firms from NYSE which had non 12/31 fiscal year-ends, and had less than 20 news items from the Wall Street Journal. Kiger (1972) used 87 firms from NYSE, and Morse (1981)'s research targets were 20 firms from NYSE, 5 from AMEX, and 25 firms over the counter. As Bamber et al. (2011) pointed out that these statistical data were subjected to some problems, and mean values were largely affected by extreme values. Beaver (1968) recommended that research should relax the selection criteria to get the generalizability of his findings.

Recent evidence suggests that the price and trading volume around financial disclosures are increasing over time. There are several explanations. First, the increased price reaction over time was attributed to the increased concurrent earnings announcements releases (Francis, Schipper, and Vincent, 2002), this view is also confirmed by Barron, Byard and Yu(2010), which showed that abnormal trading which was not explained by price changes was due to the increasing number of disclosures. Landsman and Maydew (2002) argued that because large firms' disclosures usually contained more information, the overlaid information led to the increase price reactions[43]. Second, preannouncement information asymmetry was the main reason lead to this earnings announcements reaction (Barron, Schneible, and Stevens, 2009). Third, the advent of online trading spurred more trading from less sophisticated traders also increased the price and trading volume reactions around financial disclosures (Ahmed et al.,

[43] Landsman and Maydew (2002) also supported the view that the overtime increase of price reactions to earnings announcements was due to large firms.

2003). Finally, Bailey et al. (2003) find that trading volume reactions to earnings announcements increase after Regulation Fair Disclosure (Reg FD)[44] prohibited selective disclosure. They conclude that this elevated trading reflects differential interpretations of earnings announcements, and further support this interpretation with evidence that analyst disagreement, including Kandel and Pearson's 1995 measure of differential interpretations, likewise increases after Reg FD.

Ball and Shivakumar (2008) concluded that the trading volume response to earnings announcements is statistically significant, albeit modest in magnitude, and that trading reactions to earnings announcements increased over the period 1972 to 2006.

2.3.5 Summary

This section provides the review of literature of trading volume. Theories of trading volume develop much more slowly than price theories, largely because of the assumptions of classical finance theories left little room for investor disagreement (Bamber et al., 2011). Trading volume fully reflects this disagreement, and hence investor heterogeneity. Share turnover is the best measure for trading volume, it controls for firm size, when utilize it, natural log adjustment is needed to avoid the non-normal distribution and the heteroscedasticity problem. Earnings announcements spur trades by information releasing to the market. With the arrival of new information, investors understand it differently from their prior beliefs or information process

[44] Regulation FD addresses the selective disclosure of information by publicly traded companies and other issuers. Regulation FD provides that when an issuer discloses material nonpublic information to certain individuals or entities—generally, securities market professionals, such as stock analysts, or holders of the issuer's securities who may well trade on the basis of the information—the issuer must make public disclosure of that information. In this way, Regulation FD aims to promote the full and fair disclosure.

models, further enlarges the level of heterogeneity. Numerous studies have documented the fact that large price change is accompanied by large trading volume generated, during and out of the earnings periods. In order to compare different levels of investor heterogeneity, appropriate market venues are needed.

2.4 Foreign-Listings: Status Quo and Investor Compositions

2.4.1 Background

Foreign listing, also named as International listing and cross-listing[45], is a strategic choice made by a firm to list its shares on an oversea market. The globalization process including technological advances, deregulation of capital markets and declining transaction costs, led to a surge in foreign listings in the past three decades (Karolyi, 2006). According to a report from World Federation of Exchanges (WFE), as of the end of 2016, there were total 2,409 international-listed firms around the world, which was 5.22% of total 46,170 listed firms. Foreign listed firms are distributed across the major markets around the world. Although recent studies (Doidge, 2017; Ciccotello, 2014; Rosett and Smith, 2014; Grullon, Larkin, and Michaely, 2015) suggest that this process has slowed down[46], foreign-listing continues to be a viable choice for firms influencing capital raising and price discovery processes. It is an indispensable and important force for the integration of global financial markets (Gagnon and Karolyi, 2010).

[45] Technically speaking, cross-listing refers to a firm which is double listed in two or more countries. Foreign listing or international listing refers to a firm listed abroad, no matter it is listed domestically or not. This study will use foreign listing, international listing and cross listed interchangablely.

[46] From 2014 to 2016, total number of international-listings firms are 2,452, 2,504, and 2409, which are 5.50%, 5.47% and 5.22% of all listed firms respectively. WFE (2016; 2015). Academics calls the delisting phenomenon “listing gap”.

2.4.2 Investor Composition of Foreign Listed Firms

Foreign listed firms can attract investors all over the world, they are natural habitats of heterogeneous investors. There are four reasons that the investor compositions of foreign-listed firms and purely domestic firms are different:

First, firms are motivated by a variety of factors for listing their shares abroad, with broadening shareholders' base as one primary objective. Several surveys of managers conducted by Mittoo(1992), Fanto and Karmel (1997) and Bancel and Mittoo(2001) document that broadening shareholder base is a major objective of managers of the foreign-listed firms. By broadening the stockholders' base, these internationally listed firms can not only raise the funds they need abroad but also reduce their cost of capital (Verrecchia, 2001; Lambert et al., 2006; Hail and Leuz, 2006). More importantly, the foreign-listing process may improve the firms' visibility and reputation in the destination country, which enhances its influences, and hence attracts more traders to join. At the micro level, the increase in the diversity of shareholders brings the market with a higher level of heterogeneity and liquidity. Second, from the perspective of investors, Theory of Psychic Distance suggests that investors normally select stocks which have similar background as they do, especially for the foreign listed firms which have no counter-parties listed in their home markets. Both individual and institutional investors are affected by this theory (Nofsinger, 2012). Third, foreign-listed firms may generate opportunities for arbitrage as revealed through large, actionable deviations from price parity between the markets trading those same shares. These arbitrageurs are also a component of traders which are not found in purely domestic firms. Fourthly, foreign institutional holding will also demonstrate higher level of heterogeneity of foreign listed firms[47]. Ng et al. (2011) point out that Foreign Direct

[47] See statistics in Section III.

Investment (FDI) could lower the liquidity in the host countries[48], while Foreign Portfolio Investment (FPI) will improve the host countries' liquidity. Due to the fact that liquidity and heterogeneity are highly associated, and the prediction by Psychic Distance, FPI will also add heterogeneity to the foreign listed firms.

In sum, foreign listed firms broaden investor heterogeneity both intuitively and theoretically, but have not been tested empirically. Both International Business theories and Finance theories support the view that foreign listed firms can maximize the heterogeneity of investors in a relatively small market, which objectively provides an almost perfect market venue for studying the heterogeneity of investors.

2.4.3 Summary

In sum, as academic interests of foreign-listed firms are changing from motivations of foreign-listed firms to its economic consequences. New academic interests concentrate on multimarket trading, arbitrage, price discovery process and liquidity. Especially in market microstructure literature, a study of the essence of a multi-market trading environment and liquidity change is necessary. Although high-frequency data collection and econometric method are the major challenges, there are still fruitful research results. The new hosting market such as Hong Kong is suggested for future research, not only because of the recent shift of hosting markets, but also the unique microstructure of the market.

[48] Host country firms with FDI investors, who have superior information and control positions in the firms, suffer from information asymmetry between insiders and outside uninformed investors. Further, these foreign investors bring their unique skills, international expertise, and knowledge to the firms, and domestic investors may be unfamiliar with such "foreign inputs." Thus, the presence of controlling FDI investors induces an adverse selection problem, making the stock less liquid. Also FDI reduces trading activities, but FPI improves.

Foreign-listed firms provide a naturally perfect habitat for the study of investor heterogeneity. Earnings announcement as a triggering event, generates more significant information than normal periods, this information is captured and interpreted by diverse investors, who have different prior beliefs and precisions, different information processing methods and different culture, these will all affect the investment decision they made, and hence impact the price discovery process. Whether foreign-listings and non-foreign-listings are different in this process, is still untouched in prior literature.

3. The Microstructural Explanation of Momentum: the Two-Period Order Flow Model and the Heterogeneous Market Hypothesis

In this section, I propose an order flow model, which simulates the process of order flowing when information is released to an order driven market. This model is under the condition of a single exchange and the best price execution mechanism[49].

Hong and Stein (1999) are the first to theoretically model the price momentum phenomenon using information diffusion. In their model, traders are classified into news-watchers and momentum chasers. News-watchers receive information about future fundamentals and trade stocks merely based on such kind of information, whereas momentum chasers receive no fundamental information and they make their investment decisions solely based on price forecast from past price history. As information slowly diffusing into the market (Hong and Stein, 1999), price experiences under-reaction first because news-watchers slowly adjust with the new information. Then price experiences overreaction as momentum traders attempt to profit from the under-reaction caused by news-watchers (Hong and Stein, 1999). The model delivers an important empirical implication: stocks with slower information diffusion should exhibit more pronounced momentum[50]. In a follow-up study, Hong, Lim and Stein (2000) classify stocks into slow/fast diffusion groups according to size and analysts' coverage. They find that momentum

[49] A single exchange means that there is only one trading venue for a security. Best Price execution refers to the rule of National Best Bid Offer (NBBO).

[50] After 20 years, Internet trading makes the market quite different from 20 years ago. News can diffuse much faster and momentum can be caused by short-term overreaction. How this herding effect affects the efficiency of the market is still unexplored (Chui et al, 2010).

profit earned by investing in firms with small size and/or low analyst coverage are indeed higher[51]. Chen and Lu (2017) use option implied volatility to test Hong and Stein's Gradual Information Diffusion model and support their view.

Information is crucial when explaining momentum (Chen and Lu, 2017). Previous studies on momentum document various causes of momentum, the most important one is investor's heterogeneous beliefs. However, the cause from market microstrucutre is not yet available. This research is related to Hong and Stein (1999; 2000) and Chen and Lu (2017), but it explains momentum from the perspective of information influence on the two types of traders. It also includes the trading behavior of the traders, it setups a linkage between investor heterogeneity and momentum. Trading volume can also be used as an auxiliary tool for momentum, which helps to explain the trading behavior. One thing worthy to mention is that this model is set up under the condition of short term.

3.1 Types of Traders and Their Strategies

In this model, I assume that there are two types of traders in the market: range traders and momentum (break out) traders[52]. This classification method is from price patterns or technical analysis. Although technical analysis is regarded by academics with a mixture of suspicion and contempt, it has a long history and many studies have documented its profitability, i.e. Blume et al. (1994). Range traders and momentum traders are analogue with the news-watchers and momentum chasers in Hong and Stein's (1999)'s model, respectively.

[51] This conclusion neglects the effect of price reversals.
[52] In general, there are only two strategies when trading securities: one is buying low and selling high or reverse. The other is buying the winners and selling the losers.

In Hong and Stein's model, news-watchers extract no information from prices, they analyze firms' fundamentals from the accounting facts or macroeconomic conditions, and they believe that with the information slowly diffusing to the market, other traders will eventually find the same fundamental value and push the price up or down. Hence, when there is no important information flowing into the market, they observed previous price highs and lows, and they sell at prices which are close to prior highs (resistance zone) or buy at prices which are close to prior lows (support zone), and expecting that the following movement of the price will merely "touch" or "trigger" their desired price levels, and then moves in their favorable directions. Since range traders are not sure when the new information will arrive, and believe that the arrival of the new information can cause the price to fluctuate violently, in order to prevent price fluctuation caused by the arrival of new information, they will place stop loss orders[53] to cover their positions once the price moves in the opposite direction of their positions. For sellers, they will place stop buy orders above but not far away from prior highs. In the same way, buyers will place their stop sell orders below but not far away from the previous lows. When the price increases or decreases sharply, they are able to close out their positions with minimum losses.

From the point view of LOB, a trader will see that the order depths of the support (resistance) zones are thicker than other ranges. Because of these limit buying (selling) orders are stacking around the support (resistance) zones, without the power produced by the new information, these price levels will not be broken. Thus, the price will be consolidating within the support and resistance zones. This price pattern further attracts more range traders to join.

[53] Stop loss orders are stop-market orders.

Another type of trader is the momentum trader as described by Hong and Stein (1999). Such traders chase larger price changes to gain profits. Momentum traders do not join the consolidation phase of price movement, they believe the arrival of new information will induce new round of price movements. When they observe that stock prices are moving rapidly in one direction, they believe that new information has arrived in the market, and they enter the market aggressively to pursue greater subsequent profits. Momentum traders pursue larger profits and hence tolerate higher risks.

3.2 The Relationship between Investor Heterogeneity and Liquidity

The definition of liquidity

The classification of liquidity

In a perfectly heterogeneous market for a certain period, each investor has completely different views on an asset with other traders. Under this hypothesis, once one investor submits an order to the LOB, other traders cannot submit orders with the same price and direction, in other words, the limit orders are mutually exclusive, hence the limit orders are continuously distributed on the price axis of the LOB, with bid-ask spread equaling to the smallest

incremental unit of price, i.e., \$0.01, \$1/8 or \$1/64[54]. In contrast, in a perfectly homogeneous market for a certain period, all investors have the same view of an asset. They submit identical orders of price and direction to the LOB. All orders are stacking on a single side on the LOB. Of course, the two cases are too extreme, the reality lies somewhere between them. Figure 2 and 3 show the order status of the two cases.

The relationship between investor heterogeneity and liquidity is seldom examined or even not touched. Avramov et al. (2006) studied the three-dimensional relationship among return, turnover and illiquidity. They consider turnover and illiquidity[55] as separate variables. In this study, I argue that trading volume turnover and liquidity are highly correlated. Trading volume turnover reflects investors trading interests within a certain time, while one dimension of liquidity is measured by how many transactions are formed. To some degree, trading volume and liquidity are on the same axis, and trading volume reflects the past liquidity condition within a certain range (return), while liquidity reflects the interest of possible future transactions.

[54] The minimal incremental price level is called tick size. Now, the option market still has the smallest incremental price of \$1/64, and the equity market is \$0.01.
[55] The inverse of liquidity.

Figure 2. The order status of a perfectly heterogeneous market. Orders are distributed uniformly along the price axis.

Channel	BID Price	Volume
ARCA	3.41	V
BATS	3.40	V
BYX	3.39	V
DARK	3.38	V
⋮		
EDGX	2.01	V
⋮		
IEXG	0.01	V

Channel	ASK Price	Volume
NSDQ	100.00	V
⋮		
BYX	4.00	V
⋮		
ARCA	3.44	V
BATS	3.43	V
BYX	3.42	V

Figure 3. Order status of a perfect homogeneous market. All orders are on the buy side(left), and sell side (right).

Channel	BID Price	Volume
ARCA	3.41	V
BATS	3.41	V
BYX	3.41	V
DARK	3.41	V
⋮		
EDGX	3.41	V

Channel	ASK Price	Volume

Channel	BID Price	Volume

Channel	ASK Price	Volume
ARCA	3.42	V
BATS	3.42	V
BYX	3.42	V
DARK	3.42	V
⋮		
EDGX	3.42	V

Academics believes that liquidity represents the extent of ease for trading a security (Amihud, 2009). When it is easy for an investor to buy or sell a security at a desired price for any quantity[56], it indicates that this security has high level of liquidity at the moment, conversely, low level. There are many indicators to measure this extent of ease, such as bid ask spread, the

[56] It is often assumed that quantity has no impact on price changes in academics, but in reality, each transaction, even the trading volume is as low as one share, has an impact on price changes, by consuming the liquidity on the LOB.

average waiting time in a price position, and the average trading volume. This extent of ease reflected on the limit order book is whether there are sufficient counter parties to achieve the trading processes. **The essence of higher liquidity is that, the buyers (sellers) can easily find the sellers (buyers) who are offering (biding) the same or lower (higher) prices and who are providing sufficient volume for their needs within a short period of time.** Buyers and sellers must exist at the same time to form a transaction.

Figure 4. Order status on the LOB in real situations.

Channel	BID Price	Volume
ARCA	3.41	6V
BATS	3.20	4V
BYX	3.10	12V
DARK	2.38	14V
	⋮	
EDGX	1.01	1V
	⋮	
IEXG	0.01	2V

Channel	ASK Price	Volume
NSDQ	100.00	1V
	⋮	
BYX	20.01	101V
ARCA	10.35	3V
ARCA	4.46	21V
BATS	3.98	311V
BYX	3.42	1V

Kyle (1985) defines three dimensions of liquidity, tightness, resilience, and depth, this definition has been widely accepted in the microstructural literature. Tightness refers to “the cost of turning around a position over a short period of time”, or in other words, bid-ask spread; Resiliency refers to “the speed with which prices recover from a random, uninformative shock”; and depth refers to “the size of an order flow innovation required to change prices a given amount”. High liquidity refers to smaller tightness, shorter resilience and larger depth.

Among the dimensions of liquidity, both tightness and resiliency are positively related with investor heterogeneity, while depth relates with heterogeneity negatively. Investors with strong heterogeneity provide sufficient buying and selling orders at different price levels on the limit

order book. These non-marketable limit orders[57] offer sufficient liquidity, which allows traders to easily find the counter parties of the transactions, this process leads to the change of price and the generation of volume. Sufficient liquidity is manifested by continuous price levels with small spreads. On average, the smaller the spreads are, the easier the formation of transactions. Tightness can be understood as the density of the limit orders, so higher investor heterogeneity ensures small spreads on the LOB. Bid-ask spread or its related variations[58] are used to measure liquidity tightness, it is the most widely accepted liquidity measure. Smaller spreads indicate higher liquidity. On the LOB, smaller spreads are manifested by higher density of the limit orders in a certain period. Hence, tightness is positively related with investor heterogeneity. However, when studying this tightness, time dimension should be controlled, as levels of investor heterogeneity can vary from time to time.

Securities are traded continuously in time, so resiliency which is defined as the average time or speed required for the limit orders to restore its normal level when a random shock happens, is also an important determinant of liquidity. Resiliency is positively related with investor heterogeneity. Higher investor heterogeneity implies higher participation rate. When the limit orders are removed from the LOB, either because of traders' order-withdraws or already-formed transactions, new limit orders with the same prices and direction will quickly fill up the vacuum on the LOB. During the eras of high-frequency trading (HFT), highly liquid stock recovers its liquidity almost instantaneously, resiliency can be as small as a nano-second. For less liquid stocks, it takes a longer time to recover, investors' psychology could change during this process. In this model, I assume that a stock with higher investor heterogeneity/liquidity, its resilience is

[57] Non-marketable limit orders on the LOB are the actual liquidity, and they are also called liquidity suppliers. Market orders and marketable limit orders are liquidity consumers.
[58] Such as effective bid-ask spread.

high and its liquidity will recover immediately after price shocks. On the other hand, for a low heterogeneity stock, it takes longer time for its liquidity will recover to its normal level.

Order depth is the only dimension that distinguishes liquidity and investor heterogeneity. Order depth refers to how much volume stacked in a certain price level, the more volume waiting to be transacted, the more liquid a stock is. However, more volume on the same price level means more investors have the desire to buy/sell a stock at the same price, which reflects the same price or directional expectations of traders, it has the inverse relationship with investor heterogeneity.

Overall, I argue that investor heterogeneity and liquidity are positively related in general, though both concepts are elusive (Kyle, 1985; Pastor and Stambough, 2003). In other words, when the heterogeneity of a financial market is very strong, different value and risk perceptions are prevailing on the market, the orders submitted to the LOB are both broad and deep. Investors are providing sufficient liquidity at any price levels, each price level has large volume waiting to be executed. Order Breadth refers to how many price levels are listed, and Order Depth refers to the total amount of transactions that can be provided at a certain price level on the LOB. At this point, traders on the other side can easily find the price they want to trade and the quantity is sufficient at that price. Conversely, when investor heterogeneity is low or the liquidity is low, there will be a very shallow order depth for each price level, there may even exist many price fractures on the limit order book, which makes the bid-ask spread very large.

For a certain stock, highly heterogeneous investors provide sufficient liquidity, and this kind of order arrangement on the LOB objectively creates the condition for fast price moving, hence objectively creates the foundation for momentum to generate. In contrast, highly homogeneous investors provide either scares price levels or stacking orders on the same price levels on the LOB, which hinders price movement and hinders momentum to generate. Investor heterogeneity is a necessary but not sufficient condition for price momentum[59] [60].

3.3 The Two-Period Order Flow Model

In this section, I propose a "two-period" order flow model which contains three stages and two periods, it describes how investor heterogeneity affects momentum when effective information flowing into the market.

Stage Zero: Before the arrival of information

When the market is absent of new and effective information, the price exhibits a consolidation pattern. Range traders dominate in the market, they sell at prior highs and buy at prior lows, and the price will continue this pattern until the arrival of new information. See section 3.1 for range traders' behavior.

Stage One: Information arrives at the market

[59] For some illiquid stocks, it is possible that these stocks can generate higher momentum than liquid stocks, due to their order arrangement statuses.
[60] Higher investor heterogeneity plus effective news are the sufficient and necessary condition for momentum.

If new information arrives at the market, insider traders who get the information and who have the capability to control large funds will aggressively put funds into the market in the direction implied by the information. Taking positive information as an example, insiders submit limit buy orders with execution price higher than the market price[61], which shows immediate higher buying pressure than selling pressure on the LOB. The selling orders on the right side of the LOB (selling liquidity) are being consumed very quickly, which pushes the price up.

One point worth to mention is that, there are two forces which enact the strong buying power. The first is the buying power triggered by the release of the newly arrival information, which attracts the momentum chasers who aggressively submit buying orders to the market. The second force is the prior stop-loss buying orders placed by the range traders. These stop-loss buying orders are sent directly to the market immediately once the price level triggers their stop-loss points[62]. The resultant buying orders release immerse power. Once this happens, a sufficient amount of buying orders provided by the two forces will quickly erode the selling orders on the LOB, and the transaction price rises quickly in a short period of time, accompanied by increased volume. The upper right side of the LOB will temperately exhibit a fracture of the lowest price levels[63], this is the reason why much literature documents that large price returns are accompanied with large trading volume. As more and more momentum traders joined in,

[61] Usually, experienced traders do not submit market orders to avoid the execution price too far away from desired.

[62] The stock market is usually different from the foreign exchange market for the server stop or stop-limit orders. A server stop order can be assigned a stop price, which is the triggering price. Once this price is reached, a market order will be sent, so that it will be executed immediately, it is also called stop-market orders. However, the executed price could be large from desired. A stop limit order can be assigned both stop price and limit price, once the market price triggers the stop price, the limit order will be sent to the market, but the execution is not guaranteed. The FX market has this mechanism partially due to its high liquidity compared with the stock markets.

[63] Recall that on the right or the sellers' side of the limit order book, prices are ranked in ascending order.

the overreaction phenomenon emerges, which is consistent with Hong and Stein (1999)'s momentum trading behavior.

Stage Two: After price breaks out

At this time point, we consider two scenarios:

1. For a market with strong investor heterogeneity and high level of liquidity. High liquidity implies high resilience, hence it requires less time for liquidity to recover. When the price fractures on the upper right of the LOB appear, strong heterogeneity enables investors to quickly adapt this price turbulence, and refill the price fractures. Range traders quickly quit their trades through stop orders, and momentum traders continue to trade by aggressively submitting buying orders to the market, hoping the price will go up further. For an extremely liquid market, recovering the liquidity is almost instantaneous right after liquidity disappears. The new round of negotiation starts based on the new price level, there are sufficient buying and selling orders on the LOB to maintain the new price levels. Above the broken out price levels, buyers and sellers restart their price discovery processes and momentum continues. Trading volume increases significantly during this process[64].

2. On the contrary, for a market with low investor heterogeneity and liquidity. When the price breaks through the consolidation range and forms price fractures on the upper right of the LOB, the overall market is incapable of recovering liquidity on a short period because of low liquidity resilience. At this moment, the prior range traders have already been repelled out and momentum traders are prevailing, but these momentum traders see that there lacks

[64] Large volume comes from prior sell orders around the resistance zones and the stop-loss orders. Recall that in the consolidation range, order depths around the resistance/support zones are thick.

new buying power added to the market, fear makes them begin to realize their profits by selling to liquidate their positions, hence create large selling pressure. Momentum fails to continue by price reversals. The change of trading volume in this process is not as high as that in Scenario One.

It can be seen that investor heterogeneity plays a crucial role in the formation of momentum. Strong heterogeneity facilitates momentum whereas price reversals often occur in a weak heterogeneity environment. It is worthy to note that this two-period model is setup up in a short horizon, in the current trading system[65], this process takes place within a few seconds. In the long run, if price reversals occur often, intermediate or long-term momentum cannot form, price consolidates will be in a relatively larger range. Figure 5 to figure 11 illustrate the order flow process.

Table 1: Investor Heterogeneity and its relations with liquidity, momentum, price reversal and trading volume.

High Investor Heterogeneity	Low Investor Heterogeneity
High liquidity	Low liquidity
High momentum	Low momentum
Fewer price reversals	More price reversals
Large trading volume	Small trading volume

The Two-Period Order Flow model is consistent with Wang (1999)'s conclusion that price continuations are accompanied by high trading volume when investors trading based on their

[65] POSIT etc.

private information, and Cooper (1999)'s results that reversal profitability declines with trading activity.

Channel	BID Price	Volume		Channel	ASK Price	Volume
				NSDQ	100.00	V
					⋮	
				ARCA	3.50	V
				BATS	3.49	V
				BYX	3.48	V
				DARK	3.47	V
				BATS	3.46	V
				BYX	3.45	V
				ARCA	3.44	V
				BATS	3.43	V
			3.41	BYX	3.42	V
ARCA	3.41	V				
BATS	3.40	V				
BYX	3.39	V				
DARK	3.38	V				
	⋮					
EDGX	2.01	V				
	⋮					
IEXG	0.01	V				

Figure 5:Initial Order Status

Channel	BID Price	Volume		Channel	ASK Price	Volume
				NSDQ	100.00	V
					⋮	
				ARCA	3.50	V
				BATS	3.49	V
				BYX	3.48	V
				DARK	3.47	V
				BATS	3.46	V
				BYX	3.45	V
				ARCA	3.44	V
				BATS	3.43	V
GEILI	3.45	4V	3.41	BYX	3.42	V
ARCA	3.41	V				
BATS	3.40	V				
BYX	3.39	V				
DARK	3.38	V				
	⋮					
EDGX	2.01	V				
	⋮					
IEXG	0.01	V				

Figure 6:New buying orders arrive as positive news released to the market. As noted that time priority is more important for momentum traders.

Channel	BID Price	Volume		Channel	ASK Price	Volume
				NSDQ	100.00	V
					⋮	
				ARCA	3.50	V
				BATS	3.49	V
				BYX	3.48	V
				DARK	3.47	V
				BATS	3.46	V
				BYX	3.45	V
				ARCA	3.44	V
				BATS	3.43	V
GEILI	3.45	3V	3.42			
ARCA	3.41	V				
BATS	3.40	V				
BYX	3.39	V				
DARK	3.38	V				
	⋮					
EDGX	2.01	V				
	⋮					
IEXG	0.01	V				

Figure 7:Liquidity on the sell side is consumed and the transaction price goes up.

Channel	BID Price	Volume		Channel	ASK Price	Volume
				NSDQ	100.00	V
					⋮	
				ARCA	3.50	V
				BATS	3.49	V
				BYX	3.48	V
				DARK	3.47	V
				BATS	3.46	V
				BYX	3.45	V
			3.44			
GEILI	3.45	V				
ARCA	3.41	V				
BATS	3.40	V				
BYX	3.39	V				
DARK	3.38	V				
	⋮					
EDGX	2.01	V				
	⋮					
IEXG	0.01	V				

Figure 8: Price continues to go up, right side price fractures are generated.

Channel	BID Price	Volume		Channel	ASK Price	Volume
				NSDQ	100.00	V
					⋮	
				ARCA	3.50	V
				BATS	3.49	V
				BYX	3.48	V
				DARK	3.47	V
				BATS	3.46	V
			3.45			
ARCA	3.41	V				
BATS	3.40	V				
BYX	3.39	V				
DARK	3.38	V				
	⋮					
EDGX	2.01	V				
	⋮					
IEXG	0.01	V				

Figure 9: Temporary price shock, price fractures and large bid-ask spread.

Channel	BID Price	Volume		Channel	ASK Price	Volume
				NSDQ	100.00	V
					⋮	
				ARCA	3.50	V
				BATS	3.49	V
				BYX	3.48	V
				DARK	3.47	V
				BATS	3.46	V
ARCA	3.45	V	3.45			
BATS	3.44	V				
BYX	3.43	V				
DARK	3.42	V				
ARCA	3.41	V				
BATS	3.40	V				
BYX	3.39	V				
DARK	3.38	V				
	⋮					
EDGX	2.01	V				
	⋮					
IEXG	0.01	V				

Figure 10: High investor heterogeneity enables liquidity recover immediately on the left side. New buyers quickly adapt the price changes. Price continues to go up.

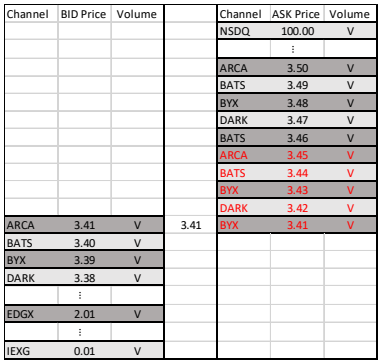


Figure 11: Low investor heterogeneity makes the anxious buyers start selling stocks to prevent stock price from dropping, which generates price reversal.

3.4 The Heterogeneous Market Hypothesis

3.4.1 The Old Heterogeneous Market Hypothesis by Muller et al. (1993)

Muller et al. (1993) use GARCH to model volatility on the FX market, based on their empirical findings, they propose the Heterogeneous Market Hypothesis, which is characterized by:

1). Different actors in the heterogeneous market have different time horizons and dealing frequencies. The high dealing frequencies are FX dealers and market makers, and the low dealing frequencies are the central banks, commercial organizations, pension fund investors with currency hedging. These different frequency dealers react differently with the same news, and the market is heterogeneous with a fractal structure of participants' time horizons.

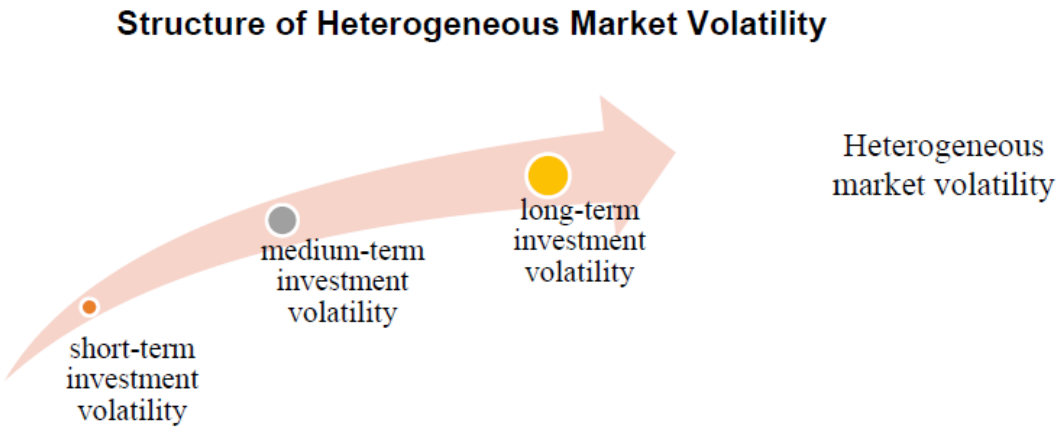
2). In a homogeneous market, the more agents are present, the faster the price should converge to the "real market value", on which all agents with a "rational expectation" agree. Thus, the volatility should be negatively correlated with market presence and activity. In a heterogeneous

market, different actors are likely to settle for different prices and decide to execute their transactions in different market situations. In other words, they create volatility.

3). The market participants of the heterogeneous market hypothesis also differ in other aspects beyond the time horizons and the geographic locations: they can have different degrees of risk aversion, institutional constraints, and transaction costs.

This HMH proposed by Muller et al. (1993) is not widely accepted, searching on Google search engine shows very few results.[66]

Figure 12: Structure of Heterogeneous Market Volatility by Muller et al. (1993). Market volatility is created by different types of investors.



3.4.2 The New Heterogeneous Market Hypothesis.

Over decades, researchers, theorists and investors are constantly looking for new findings to improve the Efficient Market Hypothesis (EMH), in order to understand the information effect on prices and to shrink the gap between the theory and the reality. i.e., Muller et al. (1993)'s HMH, this view was also supported by Dacorogna et.al. (1998), Lux and Marchesi (1999) and Peters (1994). But this HMH has not been widely accepted, largely because it merely points out

[66] Because HMH is contradicted with EMH, and EMH is regarded as the axiom in the academics. In industry, maintaining constantly abnormal positive returns is the most difficult job for traders and hedge funds, which further enhances the recognition of the EMH.

an abroad outline, but its applicability and tractability are very limited. How can traders and strategists, regulators understand the price behavior is not covered in this study. In addition, Lo (2005) proposes a new framework called the Adaptive markets hypothesis (AMH) that reconciles market efficiency with behavioral alternatives by applying the principles of evolution such as competition, adaptation and natural selection to financial interactions. “Prices reflect as much information as dictated by the combination of environmental conditions and the number and nature of ‘species’ in the economy”. This hypothesis emphasizes on the counter examples to economics rationality such as loss aversion, overconfidence, overreaction, mental accounting and other behavioral biases, it can be used to generalize the behavior of investors, which the EMH cannot. This theory is still in the early stage of development (Chin, 2015).

The analysis in this study leads me to propose a new version of HMH, based on the level of investor heterogeneity. The new Heterogeneous Market Hypothesis states that:

The price movement of any asset[67] can only be divided into two phases: the consolidation patterns and the trending patterns; Investor heterogeneity is the essence behind the two; effective news is the most important marginal factor that spurs the level of investor heterogeneity.

When the market is in the consolidation phase, due to the lack of effective information penetrated into the market, investors lack new understanding of asset prices, and the level of investor heterogeneity is at a relatively low level. Range traders dominate in the market, and they provide deep and thick buying and selling orders (liquidity) in the support and resistance

[67] This statement requires a single market venue and National Best Bid Offer (NBBO) mechanism.

zones, respectively. These order depths are so strong that when the market lacks of newly effective information, the price will remain in this state. Rational investors should continue to buy at support levels and sell at resistance levels until prices effectively break through the established support and resistance zones.

When effective information penetrates into the market, investors' cognitive differences make the level of heterogeneity boosted. The order arrangement on the limit order book objectively creates the condition for rapid price changes, and the involvements of large funds lead trending to start. Rational traders should continue to enter long or short positions at the first time of the price breakouts, or re-enter in the pullback positions after the momentum is generated, until the price momentum disappears.

Similarly to the EMH, I argue that there are three forms of HMH: the strong, the semi-strong and the weak forms. The strong-form of HMH is the state that, when effective information flows into the market, price breaks out of the consolidation phase, and the price continues to move without the happening of price reversals, this process is accompanied by the highest volume. Semi-strong form of HMH is the state that price reversals happen after the price break-outs, prices forms an up-parallelogram, medium volume is generated. The weak form of HMH is the consolidation phase. There is one point worthy to note, the perfectly homogeneous market corresponds to the efficient market (Hull, 2012), which new information is fully reflected immediately, at this moment, there is no trades happen, the market reaches to a Pareto Optimal as discussed in Section II.

The level of investor heterogeneity is a relative concept. For the same stock, it is different from time to time; for different stocks at the same time, they could also be at various levels. Figure 7 shows AAPL from Jan 2018 to June 2018, and it illustrates how I segment the market into different phases according to the new HMH, and Figure 6 in the appendix shows an investor heterogeneity spectrum summarizing all related market characteristics.

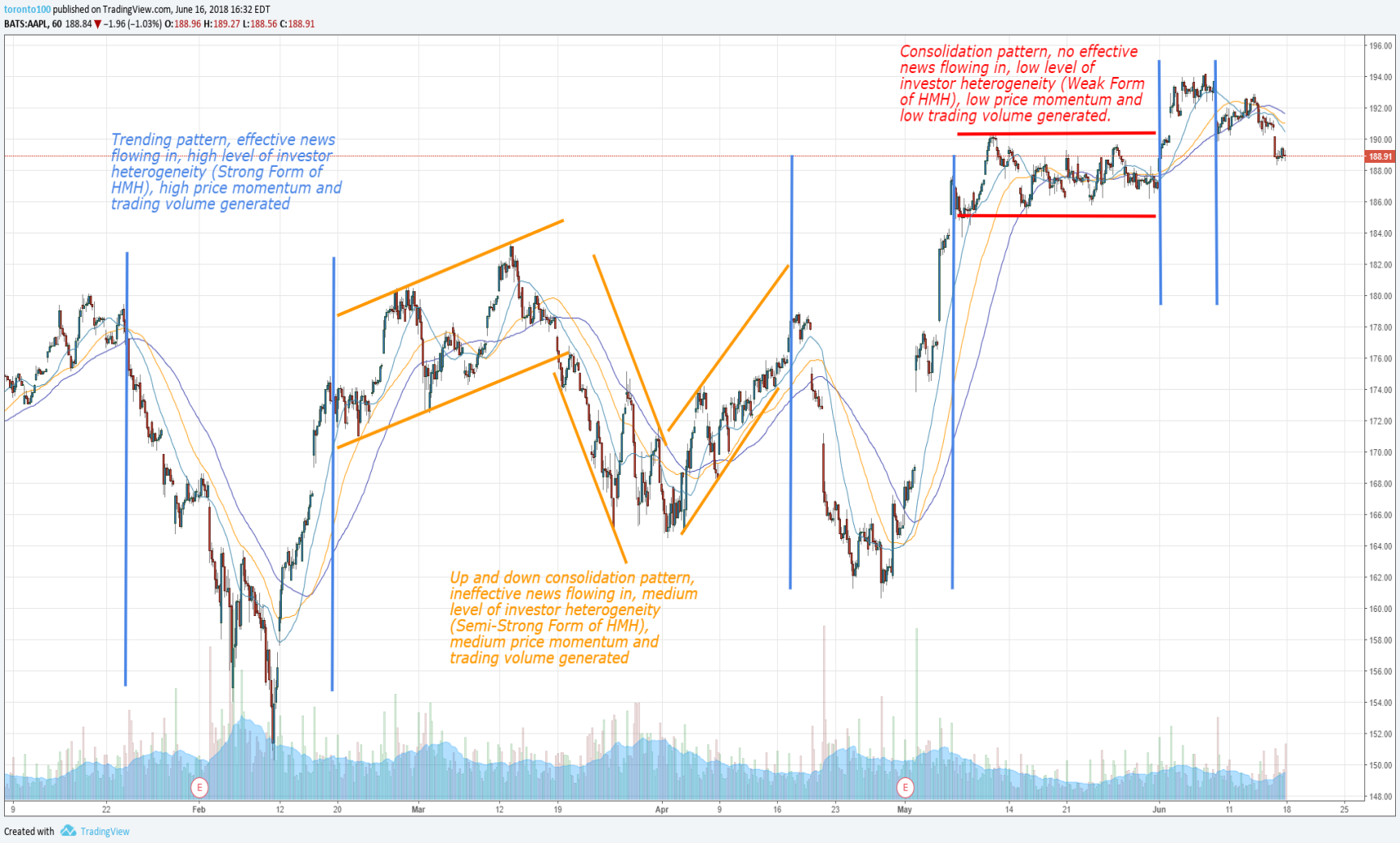


Figure 14: Illustration of different phases of HMH. AAPL as an example. Time: January to June, 2018.

4. Problem Statement, Hypothesis Development, Motivation and Contribution

This study aims to address the first two issues by constructing a new paradigm on studying investor heterogeneity. I argue that trading volume and price momentum are observable and tangible variables, and they offer direct evidence of investor heterogeneity, both of them can be used as proper measures of investor heterogeneity. This argument alleviates the problem of the lack of tangible data. Garfinkel (2009) and Wang and Liu (2014) compare current prevailing measures of investor heterogeneity, they conclude that unexplained trading volume[68] is the best measure. But these studies and the subsequent studies did not have any predictions regarding investor heterogeneity, neither trading volume nor momentum has been applied. In order to address the un-testable predictions on investor heterogeneity, I adopt a completely new approach. That is, first analyzing investor compositions on different market venues, then hypothesizing that heterogeneity is higher on the markets with more diverse investors, and lower for less diverse ones, and finally use trading volume and momentum reactions to test this hypothesis. Hence, choosing the right market venues with diverse investor profiles ensures higher level of heterogeneity, it is the key to the research.

Foreign listed firms broaden investor heterogeneity both intuitively and theoretically, but have not been tested empirically. Both International Business theories and Finance theories support the view that foreign listed firms can maximize the heterogeneity of investors in a relatively

[68] Garfinkel (2009) documents that both bid-ask spread and unexplained volume are better proxies. Analysts' forecast dispersions has very weak explanatory power.

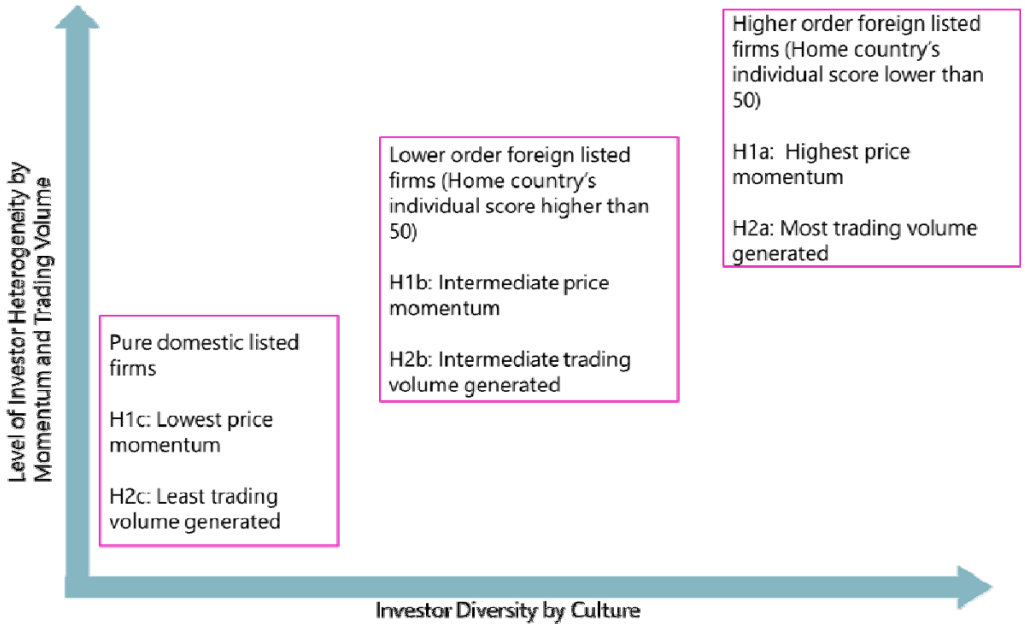
small market, which objectively provides an almost perfect market venue for studying heterogeneity of investors.

The main premise of this study is to empirically explore the extent of investor heterogeneity in the context of foreign listed firms by using a matching control sample of non-foreign listed firms. I use all listed firms from NYSE and NASDAQ, as the US has the highest individualism score of 90 in the world. Foreign listed firms are further categorized into higher-order and lower order firms. Higher order firms are those whose home countries' individualism scores below 40, and lower-order firms are those whose home countries' individualism scores above 40. This controlling method ensures each group of firms has distinct investor compositions. I assume that the investor heterogeneity (IH) rank of the three groups of firms is:

$$IH_{higher-order\ foreign\ listed\ firms} > IH_{lower-order\ foreign\ listed\ firms} > IH_{pure\ US\ firms}$$

According to the analysis of the relation between momentum and trading volume, this study is going to use both momentum and trading volume reactions to verify this hypothesis.

Figure 15: Research hypothesis. The more diverse a stock group is, it may imply higher investor heterogeneity manifested by price momentum and trading volume.



One motivation of this research is to address the issue of measuring investor heterogeneity in academics: the lack of tangible data problem as well as the problem of testable predictions, as prior studies documented. Starting from investors' habitats, making hypothesis and then proving by momentum and trading volume reactions, this approach alleviates the data problem and provides a new paradigm to predict and test investor heterogeneity. It avoids the multi-type investor problem, it also adds new evidence to the literature of investor's overconfidence and culture's influences on stocks. The conclusion of this study will also add new insights into the trading volume research in the literature of financial economics. The "Two-Period Order Flow Model" demonstrates that the positive relationship between investor heterogeneity and momentum, to the best of my knowledge, there is no research documents this conclusion in the market microstructural literature. It also has important implications on the price discovery process.

In addition, my interest in this topic is in part due to the fact that hedge fund managers, professional traders and option strategists are suffering the puzzle that what kinds of stocks are likely to be in trending and what kinds are likely to be consolidation patterns, as these two phases have completely different trading strategies. Prior literature suggests price momentum (trending) is likely to happen more often in a market with wider differential beliefs or disagreement (Chui et al., 2010; Verrardo, 2009), other studies argue that momentum characteristics differ by industrial classification (Zhou and Shin, 2013; Moskowitz and Grinblatt, 1999). In this study, I argue that foreign-listed firms are also appropriated for trend trading, because of its higher level of investor heterogeneity facilitates to generate momentum and trading volume can be used as confirmations. The "Two-Period Order Flow Model" of heterogeneous market ensures the less frequency of price reversals. Following this logic, professional traders and option strategists can use foreign-listing as a stock screening tool for their trading strategies, which could largely increase the profitability of momentum and volatility strategies.

This study will add new evidence on behavioral finance literature that it explains the question why in some Asian countries, momentum strategy profits are lower than that in US and Europe. Chui et al. (2010) found this conclusion and leave this question open, and implies that "some countries, but not all, are subject to the psychological biases that cause momentum".

Finally, it will have implications on asset pricing models researchers. Heterogeneous expectations violate Efficient Market Hypothesis and MM's propositions (and other finance foundational theories) in that they all assume investors are all rationale with homogeneous

expectations. Research of heterogeneous beliefs have a long history and most of them have been used to modify the asset price models. The research results of this study will provide new evidence of asset pricing models of foreign-listed firms and non-foreign-listed firms, from the aspect of investor heterogeneity.

5. Data and Methodology

5.1 Data

I collected about 2200 stocks from NYSE and NASDAQ with the highest trading activities, measured by daily volume turnover. Of these stocks, 1820 are pure US stocks, and 400 stocks are foreign-listed stocks. Foreign listed stocks are grouped further by their countries' individualism scores. Higher-order foreign listed firms are those whose home countries' individualism score below 40, and lower-order foreign listed firms are with individualism scores of home country above 40.

Stock data are from 2001 to 2017, daily close prices[69], trading volume, transaction time, quarterly earnings announcements data including earnings dates, actual EPS, and estimated EPS are collected from Bloomberg. Individualism scores are from Hofstede (2001).

There are totally 2,169 firms. In order to rule out the effect of illiquidity, I deleted the most inactive ones. The cutoff level is set by 2017 trading volume turnover, stocks with daily trading volume turnover less than 0.0001% are deleted. The average trading volume turnover of all stocks is 1.0976%. Table 1 shows the descriptive statistics of the firms.

[69] Using daily close prices create the flexibility to analyze stock returns in a relative short, intermediate or long horizons.

Group	Home Country	Individualism Score	Number of Firms	Average Volume Turnover(Daily, 2017)
Pure US	US	91	1807	1.1251%
Low Order Foreign Listed	AU	91	5	0.0207%
	GB	89	27	0.9128%
	NL	80	10	0.7970%
	DE	80	2	0.1889%
	CA	80	87	0.7593%
	IT	76	3	0.0158%
	BE	75	2	0.1910%
	DK	74	1	0.0749%
	SE	71	2	0.3925%
	FR	71	4	0.1709%
	IE	70	10	0.5305%
	NO	69	4	0.6135%
	CH	68	7	0.6957%
	FI	63	1	0.2592%
	LU	60	4	0.6606%
	ZA	58	6	0.5058%
	IL	54	35	0.6351%
	ES	51	3	0.0517%
	Total Firms	213	Average Volume Turnover	0.4153%
High Order Foreign Listed	IN	48	8	0.3098%
	JP	46	10	0.0170%
	AR	46	10	0.3652%
	RU	39	2	0.3342%
	BR	38	20	0.1717%
	GR	35	7	0.7698%
	PH	32	1	0.0418%
	MX	30	7	0.0272%
	HK	25	8	0.5411%
	CL	23	6	0.0599%
	TH	20	1	1.6504%
	SG	20	2	0.4939%
	CN	20	51	1.7575%
	KR	18	4	0.2301%
	TW	17	10	1.0061%
	CO	13	2	0.0202%
	Total	149	Average Volume Turnover	0.4872%

Table 2: Firms Statistics by individualism scores. For the total 4500 stocks from NYSE and NASDAQ, I deleted the most inactive ones (by average trading volume turnover over the entire horizon), 2,200 stocks are selected.

5.2 Empirical Methodology: Momentum

5.2.1 Momentum ----Winner and Loser Portfolio Method

I adopt Jegadeesh and Titman (1993)'s Winner and Loser Portfolio Momentum Examination method to test momentum. This method is the most widely accepted one, it is straightforward and has the most enduring influence on momentum studies (Chao et al., 2012)[70].

According to the definition of price momentum, stocks' past returns predict future returns, stocks with positive (negative) returns tend to have positive (negative) returns in the following time period (Jegadeesh and Titman, 1993). Barberis and Shleifer (2003) define a style momentum strategy as the one that "buys into styles with good recent performance and avoids styles that have done poorly". Hence, a typical *f-h* Winner and Loser Portfolio is constructed as: first, stocks with certain characteristics[71] [72] are classified into different groups. For each group, watch the stocks for *f* months (the formation period), then the f months' returns are calculated and ranked in descending order. Stocks which ranked the top one-third (or 10% or quintiles)[73] are assigned to the Winner portfolio (Portfolio W), the strategy is to buy portfolio W. At the same time, those whose returns are ranked in the bottom one-third (or 10% or quintiles)[74] are assigned to the Loser portfolio (Portfolio L), the strategy is to sell Portfolio L. These portfolios are equally weighted and are not rebalanced over the following h months (the holding period). The third portfolio W-L is constructed by buying portfolio W and selling portfolio L. At the end of

[70] Studies employ this method include Jegadeesh and Titman (1993); Asness, (1994); Fama and French, (1996); Grinblatt and Moskowitz (2004); Gutierrez and Kelley (2008); Verardo (2009); Chui et al (2010); Boussaidi (2017) and others.
[71] eg. B/M ratio, firm size, industry classification. In this study, I use individualism score and trading volume turnover.
[72] Some studies call it double sorting methods. Blitz and Bliet (2007), Hou et al. (2009) etc.
[73] The number of stocks in the Winner or Loser portfolio depends on data availability, usually at least 30 stocks needed within each portfolio.
[74] Using top one third or 10% cutoff depend on the size of each group of firms. Chui et al. (2010) use top or bottom one third, Jegadeesh and Titman (1993) and other studies use 10%.

the holding period, the returns of Portfolio W, Portfolio L and Portfolio W-L are examined in order to find the momentum characteristics of this stock category. Stock return is simply the cumulative return during the formation and holding periods. If return data was missing, a typical method is using stock's beta multiplied by the market return as a replacement (Chui et al., 2010). For higher-order foreign listed firms, lower-order foreign listed firms and pure US listed firms, the expected testing results are that their returns of Portfolio W and W-L in the holding periods are monotonically decreasing, and their returns of Portfolio L are monotonically increasing.

As suggested by Jegadeesh and Titman (1993) and the subsequent studies, overlapping momentum portfolios or time rolling is used. For example, for a typical 6-6 Winner and Loser Portfolio starting from the beginning of January is formed as follows: the formation period is the previous 6 months, from last July to December, and the holding period is from January to June. Then, for the portfolio starts from February, the formation period is from last August to this January and the holding period is from this February to July. The compositions of winner and loser portfolios in January or February could be different, depend on the return performances at the end of each formation period.

5.2.2 Potential Issues of the Momentum Model

Although this Winner and Loser Portfolio Momentum Method is widely accepted, according to Chao et al. (2012), there are three potential issues. The first one is whether equal weighting or value weighting should be used when forming portfolios. Equal-weighting puts more weights on small stocks, from Jagadeesh and Timan (1993) to Chui et al. (2010) all important momentum studies use equal weighting (Chao et al., 2012). Value weighting confers three potential benefits.

First, it is consistent with most theoretical asset pricing models that rely on the value-weighted market portfolio to generate appropriate risk measures. Second, and more importantly for portfolio managers, value-weighting is the dominant weighting scheme for benchmark indexes, and, these indexes are likely to serve as the basis for the portfolio strategies and exchange traded funds that asset allocators are apt to employ. Finally, value-weighting does not impose the overall capacity constraints that equal-weighting imposes on trading strategies. Lewellen (2002) uses B/M ratio as a control variable for the value weighting. In this study, the main objective is to find investor heterogeneity through momentum instead of portfolio construction for practical use, so equal-weighting facilitates a direct comparison of style momentum and stock momentum profitability (Chao et al., 2012). In addition, I will control the stocks through volume turnover at first, some illiquid stocks are ruled out, therefore, the equal weighting scheme will be adopted as prior studies did.

The second issue is the choices of combinations of forming period and holding period. After the initial work of Jegadeesh and Titman (1993), the dominant portfolio strategy in the stock momentum literature involves a six-month formation period followed by a six-month holding period. While a variety of other combinations ranging from one to twelve months formation and holding periods are contemplated in the literature, the consensus view appears to be that the results of the 6 – 6 combination are reasonably representative of the other strategies. For example, Chui et al. (2010), Griffin et al. (2010), and Jegadeesh and Titman (2001) all follow the Jegadeesh and Titman (1993)'s protocol and report the results from a single momentum strategy involving a six month formation period and a six month holding period. Whether this single momentum strategy is truly representative of style momentum around the world is an

empirical matter (Chao et al., 2012). In my work, I will consider portfolio strategies with f and h ranging from 1 to 12, a total of 144 forming and holding for each portfolio. These combinations of the choices further contribute to the momentum literature in finding the time variations and lasting capability of momentum, this choice of f and h has not been used by prior studies.

The third issue is whether to skip a month between the forming and holding period. Chao et al. (2012) argue that winner stocks tend to close the month at the ask price and loser stocks tend to close at the bid. When these stocks bounce to the other side of the market on the open, reported returns to momentum strategies are lower than what would obtain if a suitable period of time were placed between the two measurement periods. However, prior studies have different views on this issue. Chen and De Bondt (2004) show that skipping a month has little impact on reported style momentum returns. Lewellen (2002) employs a model that does not skip a month in his study of U.S. style momentum. Barberis and Shleifer (2003) suggest that skipping a month should not hurt style momentum returns. Jegadeesh and Timan (1993), Chui et al. (2010) and Griffin et al. (2010) use the skipping technique. This bid-ask bounce is actually a microstructural issue (Chao et al., 2012), it happens due to lack of liquidity. If liquidity is controlled in the analysis, the bid-ask bounce is not as large as thought. In this study, I use daily close prices to calculate the monthly returns, so there is no need to skip a month between the formation and holding period.

There is another issue of using the Winner and Loser Portfolio Method, whether to use weekly or monthly returns. Prior literature suggests that using weekly return data may suffer from the problem of price reversal (Lehmann, 1990; Lo and Makinlay, 1990), which can largely affect the

momentum strategies. Causes of reversals can be various, Kaul and Nimalendran (1990) and Conrad, Kaul, and Nimalendran (1991) show that part of the return reversal is due to bid-ask bounce. Lo and MacKinlay (1990) and Boudoukh, Richardson, and Whitelaw (1994) note that nonsynchronous trading contributes to contrarian profits. Jegadeesh and Titman (1995b) observe that market makers set prices in part to control their inventories, which induces a return reversal. Gutierrez and Kelly (2008) argue that the momentum profitability at the weekly frequency is more puzzling and represents stronger under-reaction to news than at the monthly frequency. Avramov, Chordia, and Goyal (2006) show that weekly reversals are strongest for stocks in which liquidity is low and turnover is high[75]. Using weekly returns to assess potential explanations of momentum affords researchers greater confidence in identifying the news that underlies the return, the 6- or 12-month returns commonly used to examine momentum theories preclude such identification (Gutierrez and Kelley, 2008). In order to alleviate the problem of reversal, I will use monthly data in this study, weekly return will also be examined in order to explain momentum in short horizons as well as test the information environment of the sample[76].

In sum, for the concerns of Winner-Loser Portfolio Momentum method, I will utilize equal weighting schemes, multiple choices of formation and holding periods, daily data to avoid the skipping problem and monthly returns as suggested by prior literature.

[75] This conclusion is critically important, it is linked with the microstructural issue of the market. In this study, I argue that high investor heterogeneity can make investors quickly accept the newly broken out prices, which reduces the chances of price reversals. Higher turnover ratio also helps to build this belief.
[76] For the information environment and information asymmetry, see section II for a review.

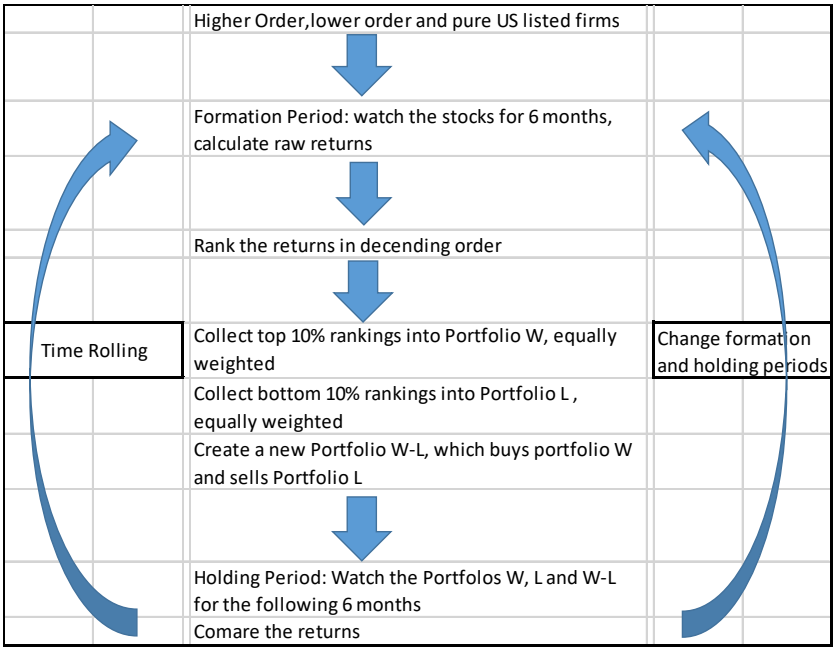


Figure 16: The flow of W/L Portfolio Momentum Strategy. Also called double sorting momentum strategy. First sort the stocks by some certain fundamental characteristics, such as market capitalization, sectors. Then, sort the stocks by their formation period returns. Finally, compare the holding period returns to see the momentum results.

5.3 Trading Volume

5.3.1 The Measure of Volume: Volume Turnover

As aforementioned in Section I and II, trading volume is the direct manifestation of investor heterogeneity, its reactions have the potential to yield insight into the effects of financial disclosures on unobservable disagreement across investors. In order to capture investors' heterogeneous characteristics, I use trading volume turnover as the volume measure. Trading volume turnover is defined as the percentage of shares traded relative to the number of shares outstanding, it is a natural measure of trading activity (Lo and Wang 2000), it also automatically controls for firm size (Garfinkel, 2009).

5.3.2 Model Development

As discussed in Section II, Garfinkel (2009) compares the prevailing measures of investor heterogeneity with high-frequency tick data and concludes that unexplained volume measures are the best suited for investor heterogeneity, this view is also supported by Wang and Liu (2014). In this study, in order to find the best volume measure of investor heterogeneity incorporating the microstructural explanations from Section II, my measure is based on Garfinkel's measure, but different by some modifications.

Garfinkel (2009) documents that the standard unexplained volume is calculated using the equation:

$$Trading\ Volume\ Turnover_i = \alpha_i + \beta_i |return_i| + \varepsilon_i \quad \text{..... (1)}$$

$$SUV_i = \frac{\varepsilon_i}{sd(\varepsilon_i)}$$

Where SUV is Standard Unexplained Volume and ε_i is the residual. In Garfinkel (2009)'s model, heterogeneity is represented by the residual of Equation (1) divided by its standard deviation, he argues that for each individual stock, there is inherently generated volume when price changes, this could be caused by market wide trading activities or liquidity commonality, it is captured by the return[77]. By using the residual of the regression, SUV captures the volume which is not explained by this market wide liquidity. Liquidity commonality is primarily caused by program trading (Choe and Yang, 2010). Garfinkel (2009) implies that these electronic traders do not have fundamental views on the assets, they are just looking for counter parties to trade, which is known as "chase for liquidity" (O'Hara, 2015). Hence, Garfinkel (2009)[78] concludes that the excessive trading volume which is not explained by this market wide trading activities, reflects

[77] In a standard market model of CAPM, firm return is regressed with market return. Wang (1994) uses a similar modelling method, which regresses volume with market-wide volume.
[78] Garfinkel (2009) refers this idea as the liquidity effect.

investor heterogeneity of individual stocks. However, Garfinkel neglects the fact that even orders which are generated and sent by computer programs, are not randomly produced, they are based on some trading logics designed by humans, which also reflect the designers' views, and hence reflect investor heterogeneity. Most of the trading logics are designed based on charts, only a few are designed based on firms' fundamentals. Therefore, I argue that in Equation One, the coefficient of the absolute return:

$$\beta_i = \frac{\Delta Trading\ Volume\ Turnover_i}{\Delta|Return_i|} \quad \text{.....(2)}$$

is the right measure of investor heterogeneity. From the definition equation, β_i represents the trading volume generated per unit change of absolute price return. Given a certain return, larger trading volume generated indicates that more liquidity on the limit order book (LOB) were consumed, and hence more agreements on "disagreements" are reached[79]. Knyazeva et al. (2014) find that firms with more investor heterogeneity exhibited higher trading volume overall and higher trading volume reaction per unit price reaction. Higher consumed liquidity represents higher investor heterogeneity in the current period. In contrast, given the same amount of return, lower volume indicates that there is very few liquidity consumed on the LOB, and hence less agreements reached during this price change process. This could be due to the fact that the investors were less interested in participating or have less incentives to trade, hence the market shows lower investor heterogeneity at the moment.

From the point view of liquidity measurement, Goyenko et al. (2009) do a comprehensive study on the current prevailing liquidity measures, they conclude that Amihud (2002)'s illiquidity measure is the best to capture the price impact effect of liquidity among all liquidity indicators.

[79] See section II for a discussion on trading volume.

Amihud (2002)'s measure captures the daily price response associated with one dollar of trading volume[80]:

$$Illiquidity = Average\left(\frac{|Return_i|}{Dollar\ Trading\ Volume_i}\right) \quad \text{.....(3)}$$

The reciprocal of this measure is the liquidity measure. As demonstrated in Section II, the positive relationship between liquidity and investor heterogeneity, I believe that the coefficient β_i is the right measure for investor heterogeneity[81]. This conclusion is in line with Ahmed et al. (2003), Ahmed and Schneible (2007), Hope et al. (2009) and Bamber et al. (2011)'s conclusion that "the slope coefficient from a regression of trading volume on the magnitude of price changes is a good proxy for differential precision of preannouncement information", and I argue that it is also a good proxy for earnings periods.

5.3.3 The Earnings Period and Non-Earnings Periods

Bamber et al. (2011) point out that further researching the validity of this measure has important implications for information asymmetry, which is one main source of investor heterogeneity. Due to the fact that earnings announcements could spur trades, investor heterogeneity is maximized when the release of the earnings announcements. I am going to examine investor heterogeneity in both earning periods and non-earnings periods. Similar to Zhou and Shin (2013), I will use Equation 1 and 2, plus a nine-day window to capture the earnings period. Starting from five days before the earnings date until three days after the earnings date, there are totally nine days for the earnings period. Each firm has four reported

[80] Amihud uses dollar trading volume as the denominator, another study argues that this measure is the same as using trading volume.

[81] This measure could be subjected to the influence of price reversal in long horizons. In this study, I use daily returns to capture investor heterogeneity to minimize the effect of price reversal.

10Q file each year, so there are four earnings windows, and the remaining days are the non-earnings windows.

The expected testing results are: the coefficient β_i is positive across all firm groups and all periods; Higher-order foreign listed firms have the highest level of trading volume, lower-order foreign list firms follow, and pure US listed firms have the lowest level of volume, for both earnings and non-earnings periods. Earnings periods have higher trading volume generated than that of non-earnings periods, because the arrival of new information stimulates heterogeneity to reach a higher level.

6. Results

6.1 The Momentum Reactions

This section reports the test results of the Winner and Lower Momentum Strategy. For each stock category (high order foreign listed, low order foreign listed and pure US, and hence high, low and US), for a certain month, the returns of the whole group in the past f months (formation period) are ranked in descending order, and the top and bottom 10%[82] of the stocks (rounded to the nearest whole number) will be collected to Portfolio W and Portfolio L, respectively. These two portfolios will be watched for the following h months (holding period). The stocks are equally weighted for simplicity and academic scrutiny[83]. Ideally, the returns of Portfolios W and L in the holding period are supposed to be positive and negative, respectively, as predicted by

[82] Chui et al. (2010) use 10%, and Asness et al. (2013) use one third. This proportion is depended on the number of stocks in each category.
[83] In reality, weighted portfolio will be used depending on the capital pool and manager's interest.

the definition of momentum. The zero cost strategy[84] Portfolio W-L, is also tested in order to compare the strength of the positive and negative momentum. To increase the power of the tests, overlapping portfolios are constructed, and the overlapping interval is set to one month. Portfolios are not rebalanced during the holding period, as previous studies did.

<Insert Table 1 here>

<Insert Table 2 here>

<Insert Table 3 here>

<Insert Table 4 here>

6.1.1 The Winner Portfolios: How Investors React with Past Positive Returns

From the test results of average returns of portfolio Ws, the average monthly returns of the holding period of high order, low order and pure US firms over the entire time horizon are 0.0477, 0.0231 and 0.0172, respectively, and all of them are very strongly significant. The returns are in descending order, this result is consistent with my prediction that investor heterogeneity is descending among the three groups. It shows that investor heterogeneity is the highest for the high group, and the lowest for the pure US group. The ANOVA tests show that the average p-values[85] of Portfolio Ws of high, low and US is 0.2360, and this number is unacceptable to reach the conclusion that the high, low and US are significantly different. However, after reviewing the detailed data for the individual holding period, I find that for each portfolio, if the holding period is greater than 6 months, the ANOVA tests results are quite

[84] A zero cost strategy is a portfolio buying and selling securities at the same time to offset initial investment capitals.
[85] The P-value of ANOVA test is based on the F-statistic and F distribution.

significant. After controlling the holding periods to 6 to 12 months, the average p-values of the ANOVA tests are 0.0084[86], and they are acceptable at the 1% level and highly significant, which suggests that the positive momentum for the groups are significantly different over intermediate to long terms, in orders words, investors react to positive returns differently in the medium to long terms[87], not in the short terms. This conclusion is consistent with Hong and Stein's (1999) model that information is diffusing into the market gradually, the diffusing process starts from 6 months and up to 12 months. The positive momentum returns are the most in the 6 months holding period, after 6 months, they start to decrease, and still significant until the 12 month. Investor Heterogeneity is manifested from 6 to 12 month periods, in the short-term it is not reflected.

After controlling the sampling periods to pre, during and post-financial crisis, this conclusion still holds. In the pre-financial crisis period (2000 to 2007), the average returns are 0.0971, 0.0387 and 0.0249, respectively, which is also in descending order. It shows the decreasing level of investor heterogeneity, and it also exhibits similar patterns as the whole sample. In the financial crisis (October 2007 to March 2009), all returns are negative and highly significant. This indicates that investors react to positive returns negatively in the financial crisis, with the loss of confidence, investors were escaping from the stock market to avoid further potential loss. We could see the immense power of this confidence loss, and hence the loss of liquidity. This trend is not found during the post-financial crisis period. One amazing finding in this period is that some of the US firms have very large returns during the financial crisis. This can be understandable, I consider the pure US firm as the ones having the lowest level of investor

[86] Exclude the one month formation period.
[87] Six to twelve months.

heterogeneity, according to the Two-Period Order Flow Model, stocks with the lower level of heterogeneity tend to reverse after breakouts. This conclusion is consistent with Zhou and Shin (2013) that large MNEs, especially IT firms have higher momentum/volatility. Further studies should focus on which stocks produce so large abnormal returns under the circumstances of the overall loss of market confidence, what fundamental characteristics these firms have. Hedge fund managers could be interested in these stocks.

However, in the recent years of the post-financial crisis (2009 to 2017), the explanatory power of investor heterogeneity decreases, although the mean returns of the three groups are 0.0188, 0.0185 and 0.0131 respectively, still in a decreasing manner. The ANOVA tests have a low average p-value of 0.1340, compared with 0.0084 for the whole sample, and the 0.0454 for the pre-financial crisis period. The following t-tests between groups show that only the 12 months holding periods have the significant difference between High and low order. For the 12 month formation periods, high and low order groups have significant difference starting from 3 months holding to 12 months holding. A possible reason is with the advent of Internet trading, investors are able to trade different stock categories. The restrictions of cultural background are weakened. This phenomenon exists among all firm groups. The Internet is possibly producing a homogenizing process of investors and momentum is diminishing[88].

The t-tests between groups show that the mean monthly returns of portfolio Ws are higher for high order foreign listed firms than that of low order foreign listed firms, and low orders are

[88] This is another topic worthy to study further. How does Internet change investor's behavior, does it homogenize or heterogenize investors? Another school of thought says that Internet is enlarging investor heterogeneity, because it makes investor trade easier.

higher than that of pure US firms. This is consistent with my first hypothesis that Investor Heterogeneity of the three groups is in descending order. But in the financial crisis period, the differences are not apparent. In the post-financial crisis period, it is not significant. I also attribute this phenomenon to the reason of Internet trading.

Overall, investors positively response with past positive returns, high order foreign listed firms have higher returns than low order foreign listed firms, which has higher returns than that of the pure US firms. The ANOVA tests show the differences between the three groups of Portfolio W. Most of the significant tests are found in the 6-12 holding period of 6-12 formation period, indicating that the momentum effect differences between the three group are in the intermediate or the long term, in other words, investor heterogeneity are best explained in the intermediate to the long term. But the group differences of Portfolio W are decreasing, which shows that investor heterogeneity reflected by Portfolio W is decreasing over time. A possible explanation of this phenomena is that as investors get more familiar with the US market, they are not limited to invest stocks which are closely related with them, they are investing other stock categories, which reduces investor heterogeneity in a certain group. The effect of Psychic Distance is diminishing. With the development of the Internet, language barriers are reducing, and analysts in different languages emerge which also facilitates foreign investors to join the trading process of local stocks.

The t-tests between groups show that from intermediate to long term, high order stocks and low order stocks have significant differences, and its mean difference is positive, indicating high momentum effect for high order firms and hence higher level of investor heterogeneity. According to Chui et al. (2010), their test results reveal that momentum profits monotonically increase with the score of the individualism index. This study also supports this conclusion. The

high, low and pure US groups have monotonically decreasing profits, which also indicates that individualism is playing an important role in investors' behavior.

<Insert Table 5 here>

6.1.2 Portfolio L: How Investors React with Past Negative Returns

For Portfolio Ls, the test results are quite interesting. The average monthly returns of the holding period of high order, low order and pure US firms are 0.0297, 0.0328 and 0.4764, respectively, for the entire horizon, all of them are very strongly significant. For all subsamples, all of the holding returns of Portfolio Ls are positive, except for some returns in the financial crisis. From the definition of momentum, past negative returns could predict future negative returns. However, in my test results, all groups have positive returns for portfolio L. This phenomenon can be explained as the happening of price reversals after severe price drops. The average psychology of investors is on the long side, and hence investors are willing to buy back these stocks, other than further shorting them. This conclusion is consistent with Avramo et al. (2006) that price reversals are mainly confronted with loser stocks.

In previous studies, Chui et al. (2010) and Asness et al. (2013) documented the results of positive returns of portfolio Ls, however, they did not provide reasons for this price reversals. According to the Heterogeneous Market Hypothesis and the Two-Period Order Flow model, markets with poor investor heterogeneity tend to produce price reversals. High orders firms have the highest level of investor heterogeneity, and hence have the lowest chances of price reversal. This conclusion is consistent with JT (1993) that lack of liquidity is a potential reason for price reversals, in my sample, the pure US group has the lowest level of investor heterogeneity and hence the lowest level of liquidity.

Secondly, for all subsample periods and the whole sample period, the returns of the three groups are in a monotonically increasing order, except for the financial crisis period with slight difference between the high and low group. The price reversals are higher for the first of the holding period, than that of the second and the third month. For the high and low groups, the price reversal effect is diminishing, however, price reversals start to continue after 6 months for the pure US group. The following t-tests between groups show that the difference between the high and the low group is insignificant, but highly significant between the low and the US group. As the assumption is that the US group has the lowest level of investor heterogeneity, plus low level of heterogeneity tends to create price reversals, these test results are consistent with my original assumption.

For all groups around all subsample periods, the pure US firm group has the highest returns, which is much higher and much more significant than the other two groups. Some of the returns are very high and can be up to 102% per month for the whole and can up to 640% monthly return in the financial crisis period[89]. As the level of investor heterogeneity the pure US firms is the lowest within the three group, it could have the large rebound on average, this conclusion is not consistent with the hypothesis that momentum should be monotonically decreasing, however, it can be explained by the Two-Period Order Flow model. After breakouts, stocks with high level of heterogeneity tend to have the same direction as the breakout, while stocks with low level of heterogeneity tend to have the opposite direction (price reversals). The same as the Portfolio Ws, the ANOVA tests show that the returns of the three groups are significantly

[89] Could be affected by the financial crisis returns. In the financial crisis period, returns are extremely large compared with normal periods.

different after 6 months of holding, which indicates that investor heterogeneity identified by individualism scores have long-term differences.

The returns of portfolio Ls are exhibiting decreasing order. That is, the first month right after the formation period has the highest return, and the returns of the following months are getting lower and lower. On the other hand, examining the time variations returns of Portfolio Ls shows that the momentum is decreasing for all groups. This phenomenon also exists in the Portfolio Ws. I also attribute this phenomenon to the advent of Internet trading.

6.1.3 Portfolio W-L: The Differences between Positive and Negative Momentum

Portfolio W-Ls measures the differences between positive and negative momentum. In general, the returns of Portfolio W-L are negative and very significant, which demonstrates that investors react with negative returns more aggressively than positive returns. Only in the period of pre-financial crisis, the positive momentum is higher than the negative ones. The only significant group is the pure US, as this group has quite a high price reversal return. Other two groups show very weak differences. Again, for the portfolios with holding periods more than 6 months, the W-L portfolios also passed the ANOVA tests, which indicates the medium to long-term heterogeneity differences between the three groups.

The subsequent t-tests between groups show that in general, in the winner portfolio, high order firms have higher returns than low order firms, which is consistent with my prediction because of its higher level of investor heterogeneity. But this positive difference is not significant. Low order firms have higher returns than that of pure US firms in general, the significance is much higher in the medium to the long run.

In sum, using the individualism index as a culture measure shows momentum differences in the 6 to 12 months holding periods. High order foreign listed firms generate higher returns than that of low order foreign listed firms, and the pure US group has the lowest return. From this point, we could see investor heterogeneity identified by individualism index is effective. Practitioners can use this index as a stock screening tool in the long run. For momentum traders, they would better choose stocks with low individualism index as they have larger chances to produce momentum, while it is better for range traders to choose pure US firms as it has smaller chances of momentum because of lower investor heterogeneity.

6.1.4 Alternative Tests: Using Trading Volume Turnover as an Investor Heterogeneity Filter

As section II argues, trading volume also reflects another dimension of investor heterogeneity, I also test the momentum effect by using trading volume turnover as an alternative indicator. The reasoning is that, trading volume turnover reflects how active a stock is, higher turnover suggests higher investor participation rate, and hence higher investor heterogeneity[90]. I group all of the firms by their average trading volume turnover over the most recent period from 2009 to 2017. With Group One having the highest trading volume turnover, and Group Five having the lowest. Each group has about 430 stocks. According to the relationship between investor heterogeneity and liquidity, Group One also has the highest liquidity, and Group Five has the lowest liquidity. I would like to test whether trading volume turnover an effective indicator of investor heterogeneity. If it was, momentum must be reflected through this classification method. Price momentum is positively related with investor heterogeneity, hence the

[90] Recall in section III that investor heterogeneity is positively related with liquidity.

momentum reactions of the five groups should be: momentum is monotonically decreasing from Group One to Group Five. Group One should has the lowest chance of price reversals, and group five has the largest chances.

The Winner and Loser testing strategy is the same as prior tests. From Table 7, we could see that the average returns for portfolio Ws are 0.0201, 0.0186, 0.0173, 0.0155, and 0.0120 respectively, all of them are significant. This monotonically decreasing order is consistent with my prediction that investor heterogeneity has a positive effect on price momentum. The following months in the holding periods exhibit a slightly decreasing manner, which shows that the momentum effect is decreasing. The average returns of portfolio Ws in the holding periods is about from 1% to 2%, the ANOVA tests show that there are no significant differences between the groups in all holding months in general, and the subsequent t-tests between groups confirm this results. Again, from the test results of Portfolio Ws, we also see that in general, investors react with positive returns positively, this reaction reflects investor's psychology that they believe that the positive news is still dominating the market, and the stock price is experiencing an under-reaction process.

For portfolio Ls, the test results show that all returns are positive and most of them are significant, this result is consistent with the prior tests grouped by individualism scores. Investors negatively react with negative returns: when investors observed large negative stock returns, they are inclined to buy it back and with a flunking mind of "bottom fishers", this pushes up the stock prices. The testing results are worthy to elaborate.

The following ANOVA tests show that in general, the five groups have no significant differences, but for 6 to 9 holding months, the test results are quite significant. The following t-tests also confirm this relationship. Combined with the momentum tests grouping by individualism scores, 6 to 12 months are good windows to capture investor heterogeneity. From this aspect, the two conclusions are consistent. This further illustrates that investor heterogeneity is playing a key role in the medium to the long term. In the short term, investor heterogeneity is not manifested, but in the longer terms(over 12 months), momentum starts to diminish and thus is not a determinant variable to control investor heterogeneity, further studies should check longer holding periods, ie. (18 to 36 months)[91], and also extend the holding period to see the momentum effect, but this test could be subjected to another problem, that is, the change of investor psychology over time caused by firms' fundamental changes. The highest returns are generated in the month right after the formation periods, all of the samples are higher than 2%.

In general, the returns of Portfolio Ls for Group one to Group five exhibit a U-Shaped pattern. Group one has a generally larger return around 40% per month, the returns are very significant. The highest returns are generated in the month right after the formation periods, all of the samples are higher than 40%. The following months in the holding periods exhibit a decreasing manner, which shows that the price reversal effect[92] is decreasing. This is the same as the corresponding returns in Portfolio Ws. As Group One has the highest level of investor heterogeneity measure by TV turnover, this could be explained as that, when investors observed large price drops, a market full of aggressive and active investors are tending to buy the stocks back, hoping to grasp the price bottom, and as more investors saw the formation of price

[91] Over 18 months holding months is considered problematic, it is considered as another Portfolio W.
[92] Negative formation period returns, and positive holding period returns.

bottom, more investor begin to join in. The following months (2-12) are all positive returns, which indicates that investors begin to accept this price reversal, sellers have been ruled out of the market. One striking phenomenon is that the returns of month 2 to 9 in the holding period are decreasing, but they are still very ideal (around 20%), especially, the returns of month 12 increase to about 40% again, which reflect investors' psychology.

For Group Two, the returns are quite stable in all months, about 2% to 3%. Group three has an interesting pattern, returns in later months, the holding periods greater than the formation months, are increasing. As Group Three has the medium level of heterogeneity, reasons have to be further analyzed. Group Four has a very stable and quite large return around 15% per month, do not change with holding periods, the returns decrease slightly right after the holding periods exceed the formation period.

The most striking is Group Five, with the lowest level of heterogeneity by TV turnover. After 6 months of the holding period, the average monthly return is more than 300%, but this high return does not exclude the outliners in around the financial crisis. During the financial crisis, the average trading volume turnover is sharply lower than the normal periods, this low investor heterogeneity and hence low liquidity could lead too much air for the returns. In order to exclude this effect, I conduct the 2009 to 2017 test which is reported in Table 8.

<Insert Table 7 here>

<Insert Table 8 here>

Table 8 reports the momentum strategy profits using trading volume turnover as grouping method, time spans from 2009 to 2017. This time span does not cover the period of financial crisis, hence it has fewer extreme returns. For Portfolio Ws, all returns are positive and highly significant, but all returns regardless of the formation and holding periods, are around 1%. The ANOVA tests show that in general, investor heterogeneity does not affect positive momentum, Group One, Three and Five have no significant differences. Investors react with positive momentum calmly, different groups have no differences according to the results of the ANOVA tests. The following t-tests between groups show that there is very little difference between the means, and these differences are insignificant.

For portfolio Ls, it also shows that from Group One to Group Five, the returns exhibit a U-shaped pattern. Group One and Group Five have the highest and second highest returns, with Group Three the lowest. In this classification method, Group One has the highest level of heterogeneity, and Group Five has the lowest, this U-shaped pattern can be explained as investor heterogeneity is helping to build positive momentum, with less price reversals. However, for Group Five, because it has the lowest level of investor heterogeneity, price reversals frequently happen, but low liquidity could produce extremely large returns which offsets the price reversals. Consistent with previous tests, negative momentum has all positive returns in the following holding periods, which shows that investors are willing to accept the already-dropped stocks, and start to buy them back. Theories behind this phenomenon are worthy to study further. Group One exhibits a return decreasing manner, that is from one month holding to 12 months holding, its returns are monotonically decreasing, with the first month holding returns

0.83, and the third month 0.55 to the twelve month 0.18, however, their significance level is increasing. It can be explained as high investor heterogeneity starts to function in the momentum strategies, this phenomenon repeats for both 9 and 12 formation periods, also, the average returns for the same holding month are almost the same regardless of the formation periods for Group One and Group Three, except Group Five. I can also explain this phenomenon by the level of investor heterogeneity of Group Five. As it has the lowest level, its momentum effect is relatively unstable compared with the groups with high heterogeneity.

Portfolio W-L generally shows negative returns, which further confirms Portfolio Ls have larger returns than Portfolio Ws.

6.1.5 Summary

In summary, investor heterogeneity is playing an important role in the Winner and Loser Momentum Strategy. Both individualism scores and trading volume turnover can be used as investor heterogeneity identifiers. Combined with the Two-Period Order Flow Model, I argue that investor heterogeneity can be measured by price momentum in the medium to the long-term (from 6 to 12 months), further studies should build on this conclusion to find other insights about investor heterogeneity and momentum.

Practitioners can use foreign listing as a stock screener. For trend traders, they can choose high-order foreign listed firms as their trading targets for trend following strategies. While, for range traders, pure US firms with low average trading volume and small market capitalization are good choices, because their low level of investor heterogeneity reduces the chances of trending.

From section 6.1.4, we could see the power of trading volume turnover as an alternative measure of investor heterogeneity. Section 6.2 reports the test results combined with both return and trading volume.

6.2 The Trading Volume Reactions

6.2.1 Trading Volume Reactions around Normal Periods

<Insert Table 9 here>

Table 9 reports the regression statistics of trading volume for all timeframes. Trading volume is defined as the total monthly volume divided by the outstanding shares. The coefficient beta can be explained as the trading volume generated per unit change of absolute return. According to my analysis in Section II and III, more trading volume generated per absolute return represents higher level of investor heterogeneity. According to Table 2, beta is positive and significant over the whole period and the sub-periods, indicating that absolute returns have high explanatory power in trading volume.

For the whole period (2000 to 2017), the betas of the high, low and US groups are 0.7834, 0.2672 and 0.4052 respectively. The means of the betas are not the same as my prediction. Ideally, investor heterogeneity of the three groups are in decreasing order, and hence their betas, but the low group has the smallest beta. The high order group has the highest beta as predicted. For all periods, the high group has larger betas than the low group, and the US group has larger betas than the low group, which indicates that investor heterogeneity is higher for the high group and lower for the US group, it is the lowest for the low order group. The final two columns show the mean differences and their related p-values for the t-tests. I find that the beta differences are significant all over the periods, except the high-low group in the financial crisis period. This indicates that in general, high order foreign listed firms have higher investor heterogeneity than that of low order foreign listed firms, but this difference is only significant at the 0.1 level.

We could see that the R-squared values for the regressions are relatively stable over the periods. The highest level of R-square is 16.53% for all groups over all periods, which suggests that absolute return is not the only variable could explain trading volume, there are other factors behind it, this conclusion is consistent with Garfinkel (2009). High order firms have the highest average R-squares, which indicates that absolute return has the highest explanatory power in this firm group. The R-squares reach to the highest level in the financial crisis period for all three groups, this is consistent with my prediction, in that, in the financial crisis period, the explanatory power of absolute return increased. Panic of financial loss leads investors to trade in the crisis period.

The difference between low and US group is highly significant. For all periods, the US group has higher beta than that of the low order foreign listed group, the difference is significant at the 0.01 level, which suggests that investor heterogeneity is higher for the US group. However, this conclusion should include the chances that there are large MNEs in the US group, these large MNEs have enough influence so that their investor heterogeneity is still quite higher. In Section 6.1.4, I use trading volume turnover to group the same data set, in group one, which has the highest trading volume and hence highest investor heterogeneity, I find that the firms in Group one are mainly the firms from the Pure US group. This indicates that 1). these two classifications are not uniform, 2).there is indeed, that some pure US firms have higher investor heterogeneity than high order and low order firms, such as Apple, Google, Amazon, etc. In order to eliminate this large-MNEs effect, I use market capitalization as a filtering option, subtracting the top 5% of all market capitalization(of the whole sample) from the US group as well as the high and low order group, and retest the betas of Equation One.

<Insert Table 10 here>

Table 10 reports the betas for the regression tests omitting the stocks which have the top 5% market capitalizations of each group. The mean differences between groups increased compared with previous tests, and the p-values show that they are more significant. Removing larger stocks (by market capitalization) does have a significant effect on investor heterogeneity.

6.2.2 Trading Volume Reactions around Earnings Announcements

<Insert Table 11 here>

Table 11 reports the regression statistics around the earnings announcements period. For each firm, I collect the earnings announcements dates from Bloomberg. According to my analysis in Section III, earnings announcements spur trades (Bamber et al., 2011), and enlarges investor heterogeneity. I set the window to a (-5, 5) window, which is, five days before the earnings date, plus five days after the earnings dates.

Many studies i.e., Zhou and Shin (2013) find that Post Earnings Announcements Drifts (PEAD) exists, and other literature documents the existence of trading volume surge around the earning dates. In this test, I am assuming that earnings announcements spur investor heterogeneity to a higher level than the non-earnings periods. In addition, the high order foreign listed group should have trading volume generated than that of the low and US firm, because of its higher level of heterogeneity. From the last two rows of Table 11. One amazing finding of the earnings period regressions are that all means of coefficients are negative, and these means are all

insignificant, indicating that earnings announcements have less explanatory power in investor heterogeneity.

7. Conclusion

7.1 Summary

The empirical analysis shows that investor heterogeneity of high order foreign listed, low order foreign listed, and pure US firms are in monotonically descending order. This result is consistent with my original research hypothesis. It can be inferred that investor heterogeneity is manifested by price momentum from the medium to the long timeframe (6 to 12 months), however, in the short run (less than 6 months), the test result shows less explanatory power. According to a report from MFS Investment Management Canada, the average holding period of NYSE stocks was 2.5 years in 1929, it reached to a historical high of 30 years in 1940, and recently dropped to 1.67 years in 2012 (Roberge et al., 2014). If the average holding period is expected to be a long-term variable, short-term variations of momentum are considered as noise, which cannot represent generality. For the holding periods longer than 12 months, it involves the overlap of a new round of momentum, hence it was not covered in this study. I split the entire period into three sub-periods, pre-financial crisis period (2000-2007), the financial crisis (2007-2009), and post-financial crisis (2009-2017) [93] . Except for the financial crisis sub-period, the other two also shows this heterogeneity-descending relationship.

Another interesting finding of this study is that, investors positively react with past positive returns and negatively react with past negative returns. In other words, investors are inclined to

[93] For the post-financial crisis period, the average momentum does not show a descending order of heterogeneity of the three groups, but for the significant periods, this conclusion still holds. See section 6 test results.

buy past winners and buy past losers, which shows a “chase rising effect” and a “bottom fishing effect”. Buying past winners (positive momentum) did not show significant returns, however, buying past losers of low-liquidity (low heterogeneity) stocks generates significantly higher returns. Stocks with the lowest level of investor heterogeneity generates the highest returns after prices collapse. This conclusion is counter-intuitive with momentum but can be explained jointly by the theory of mean-reverting and the Two-Period Order Flow Model. In the Two-Period Order Follow Model, I argued that stocks with low level of heterogeneity tend to reverse after price breakouts, this conclusion is in line with Avramvo et al. (2006) that there are substantially more reversals in less liquid stocks than in highly liquid stocks.

In addition, I used trading volume turnover as an alternative investor heterogeneity splitter, and reallocated the stocks into five groups. Because trading volume itself represents investor heterogeneity, this classification method also ranks stocks from the highest level of heterogeneity to the lowest. The testing results show a monotonically decreasing order of positive momentum among the groups, which shows that the stocks with higher level of investor heterogeneity generate higher momentum constantly over long time, and lower levels tend to generate price reversals. The negative momentum tests show a “U-shaped” pattern, this could be explained as that high investor heterogeneity supports momentum to accumulate, and low investor heterogeneity supports price reversals to happen. Using trading volume as an index of investor heterogeneity is an effective option, it has important implications for practitioners for their strategy design.

In summary, the momentum tests show that investors are chasing for price continuation. They react with positive returns positively and react with negative returns negatively. When stocks have positive past returns, fundamental analysts explain them as good economic conditions. According to Hong and Stein (1999)'s model, information is diffusing into the market slowly. As good news gradually spreads across the markets, investors start to react with the news. The behavior of optimistic investors overcomes the pessimists', which leads to the significantly positive returns in the following months. When stocks have past negative returns, investors' "bottom fishing" psychology starts to function, aggressive investors start buying the stocks back and the confidence of optimists is rebuilt. In general, after 12 months the momentum effect disappears. Investor heterogeneity identified by Hofstede's individualism score or trading volume turnover is playing an important role in momentum, its level determines the medium to the long-term momentum profits.

For the tests of trading volume reactions, the results are not as significant as the momentum tests, but they still show that higher order foreign listed firms have the highest level of investor heterogeneity among the three groups. The Pure US group had higher trading volume generated per unit return than the lower order group, and this conclusion was contradicted with my original hypothesis. This phenomenon happens partially because some of the large US MNEs have the highest market capitalizations which can also attract more investors[94], and hence it alleviates the heterogeneity of the pure US group.

[94] This conclusion is in line with Zhou and Shin (2013) that stocks with largest market capitalization have higher momentum.

This study creates a new paradigm on quantifying investor heterogeneity. That is, starting from investors' composition first, then hypothesizing that investor heterogeneity is higher for the more diverse groups and lower for the less ones, finally using price momentum and trading volume to test this hypothesis. It successfully create an example to address the original two issues: 1) lacking tangible data to represent investor heterogeneity and 2) the untestable predictions. This method is novel and can be considered as a starting point for further studies on quantifying and testing the forecasts of investor heterogeneity.

This study also contributes to the current literature on stock selection methods: Using individualism scores and trading volume turnover as stock screening tools. Professional traders and option strategists could benefit from using the individualism scores or trading volume turnover to classify firms. Trend traders should choose foreign listed stocks with low individualism scores or high trading volume turnover stocks, as these stocks have higher level of investor heterogeneity, and hence larger chances for trending or momentum. On the other hand, range traders should choose stocks with higher individualism scores, pure US stocks and stocks with lower trading volume turnover, as these ones have larger chances to be in a consolidation pattern because of their lower heterogeneity. However, large pure US MNEs, such as Apple, Google, Intel, which have the largest market capitalizations, also tend to be in a trending because of its higher level of investor participation rate and hence heterogeneity, this conclusion is consistent with Zhou and Shin (2013) and other studies that IT industry is the most volatile among all sectors. Option strategists should choose stocks with low individualism scores as volatility buyers, and stocks with high individualism scores as volatility sellers to make joint strategies.

The analysis of this study leads me to posit the new Heterogeneous Market Hypothesis (HMH). This new theory gives all investors and regulators a new framework to understand the price actions of any asset, and it also points out the theoretical foundation for heterogeneous asset pricing models. The price movement of any asset can be classified into two phases: either trending or consolidation. The essence behind the two phases is the level of investor heterogeneity. The news is the most important factor affecting investor heterogeneity. Depending on the level of heterogeneity, a market can be further classified into strong, semi-strong and weak forms of heterogeneity. Again, this hypothesis is contradicted with the Efficient Market Hypothesis which assumes that all investors have the same expectation. But it also has a linkage with EMH, which is, under the extreme case of homogeneous expectation, information arrives at the market and spreads instantaneously, all investors understand the new information in the same way and reflect their expectations on the limit order book by the same way, which is Milgrom and Stokey (1982)'s Pareto optimization condition. At this moment, no trades happen, and the market is fully efficient[95]. This new version of HMH has no material differences with Muller et al. (1993)'s version, which argues that market volatility is caused by different types of investors. However, it has wider applicability. The Two-Period Order Flow Model also demonstrates the relationship between investor heterogeneity, price momentum and price reversals, it can be used to explain the breakout patterns and price reversals in any asset market.

For decades, technical analysis is considered contemptuous in academics, because it lacks mathematical proof and merely reflects traders' subjective visual feeling. In addition, as the

[95] See the Heterogeneous investor spectrum in section 3.4.

EMH dominates in financial economics, it left little room for the foundational theories of technical analysis to develop. The wide applications of technical analysis by practitioners illustrate its effectiveness. In this study, I argue that investor heterogeneity is the main cause of price volatility, compared with investors' homogeneous assumption in the EMH, the investors' heterogeneous assumption in the HMH can be used as the theoretical foundation for technical analysis. Of course, defining heterogeneity is much more difficult than defining homogeneity, this study is merely a starting point. Theories on heterogeneity have to rely on future research.

7.2 Limitations and Recommendations for Future Research

There are several limitations to this study. Firstly, the overall test results are not ideal when using trading volume as an investor heterogeneity measure. The average R-squared is 18%, which indicates that the overall explanatory power is low. A significant portion of variations of absolute returns on trading volume is not explained. For the future research, a better fitted trading volume model should be employed.

Secondly, the sample data has a potential problem in that, both higher order and lower order foreign listed firms have too few firms. They are 149 and 213 respectively, while the pure US group has 1816 firms. It could affect the explanatory power of the individualism score. For the future research, Chui et al. (2010) suggest that using Hong Kong as a target country because Hong Kong has the easiest listing requirements, and its geographic location ensures that it is a concurrent of culture. WFE (2017) shows that Hong Kong has 131 foreign listed firms out of 1987 total, Euronext has 162 foreign listed firms out of 1093 total, Singapore has 267 foreign

listed firms of 483 total and Taiwan[96] has 119 foreign listed firms of 1549 total. Future studies can use these exchanges as target venues. However, these exchanges have different trading mechanisms, i.e., short selling constraints, or the availability of the option and other derivatives' markets[97], these factors will also affect the level of investor heterogeneity. In selecting the samples, researchers have to consider the problem that firms with the largest market capitalizations are natural collectors of diverse investors. Many studies document that higher momentum is generated by these large firms, i.e. Zhou and Shin (2013), future studies should control firm size in order to reduce the selection bias.

Third, the relationship between EMH and HMH is worthy to explore further. Muller et al. (1993) argue that the more homogeneous the investors are, the more closely the price converges to its "real value". This "real price" discovery process is also the process to the market efficiency. Market vitality is composed of liquidity, while liquidity is provided by heterogeneous investors. It is because of these heterogeneous investors, who could get information from different channels and immediately reflect the value of new information on prices, can make the market free of arbitrage and more "efficient". In my opinion, there is no "real value" of an asset, investors buy and sell only for profits, and the markets are completely speculative. The argument that Investors are constantly finding the "real values" of the assets, implies some degrees of homogeneity. These investors believe that they could find the "real value" earlier than other investors using the same information set. As we discussed in Section III, it is not homogeneity, but heterogeneity generates trades.

[96] There are two stock exchanges in Taiwan: the Taipei Exchange and the Taiwan Stock Exchange.
[97] Derivative markets provide a perfect hedging tool and hence can attract more diverse investors. According to my understanding, the US stock market has the most competitive and fairest trading rules, as it provides multiple ECN channels connected to the exchange. These ECN channels have different charging/rebating mechanisms, which allowed investors can get access to liquidity with different needs.

Muller et al. (1993) use the FX market as the research target, I believe it is the most heterogeneous market in the world. According to BIS (2016), the currency market has the largest daily market capitalization of 5.1 trillion dollars, and this value is quite stable over time. EURUSD is considered as the most liquid underlying security in the world. Future studies can also focus on other underlying markets other than the equity and currency markets. Up until now, there is no evidence document that momentum exists in the option markets, there are several possible reasons. First, the mechanism of options are much more complex than that of stocks, hence fewer participants and lower levels of heterogeneity. The other reason is that the value of an option is depended on its underlying security, option value could dramatically change instantly after security changes. Long-term momentum cannot be formed under this mechanism. However, the value of an option is largely depended on its extrinsic value, which is a function of time. Whether the extrinsic value has a momentum effect has not been explored yet.

Many studies believe that asset prices should follow a martingale process[98] over short time horizons (Avramov et al., 2006), and argue that this stochastic process is due to the arrival of unpredictable information. Under the environment of efficient market, the systematic short-run changes in fundamental values can be negligible. However, GARCH is widely used to model volatility and McMillan (2012) argues that stock volatility is a relatively stable variable, both of

[98] In general, it is widely accepted that stock price follows a Generalized Wiener Process. A Generalized Wiener Process is a stochastic process which the incremental value depends on its current value plus a time related noise. $dS = \mu S dt + \sigma S dz$, where S is the current value of the security, μ is the expected value at time t, it is also called the drift rate, σ^2 is the variance or historical volatility of the security, and dz is a typical Markov Process. A martingale is a zero drift process. (Hull, 2018). The Wiener Process is consistent with the weak form of market efficiency (Hull, 2018).

these demonstrate that stock value is bounded by some already-known factors. From the aspect of investor heterogeneity, investors trading for a certain stock are relatively stable, hence the value of a stock should be somewhat depended on its previous values, this is in line with the martingale process. There is much to explore in this direction.

Figure 13 shows the investor heterogeneity spectrum. It shows how stock prices react with investor heterogeneity from pure homogeneity, low heterogeneity to high heterogeneity. On the right most side, there is a missing level of pure heterogeneity. How momentum and volume reactions are under the condition of pure heterogeneity is beyond the scope of this study. Ideally, investors must have some degree of homogeneity in a large timeframe, but to the extreme case, it can be assumed that within a certain short timeframe, no two investors have the identical views on an asset. In other words, there are no more than one buying/selling orders at the same price level within a certain short timeframe. How does the stock price react under this special assumption? It has to be tested in with a laboratory simulation.

Previous studies suggested that price returns and trading volume should be studied jointly (Bamber et al., 2011). Kim and Verrecchia (1997) show that the cross-sectional differences in the precision of preannouncement information and differential interpretations manifest themselves as differences in the relation between price changes and trading volume. Dontoh and Ronen (1993) demonstrate that neither price nor trading volume alone provides a complete characterization of information. This study actively attempted to integrate the two factors, i.e., using trading volume turnover as a grouping variable to find the medium to long-term

momentum, and the results are very ideal. Future studies should use Volume Weighted Average Price (VWAP) as an alternative measure of price.

$$VWAP = \frac{\sum P_k V_k}{\sum V_k}$$

where P_k is the actual close price of a day, and V_k is the volume generated during a day. VWAP considers all the intra-day prices at which transactions have occurred. It is documented that the daily returns computed with VWAP have a smaller realized variance than that with the closing price (Ting, 2006). VWAP is a relatively less research area in academics (Sahadev, 2018), but referenced frequently by professional traders to find the average costs. Ting (2006) provides an example which evidences that, relative to the volatility of VWAP returns, the volatility of closing price returns tends to understate the beta risk estimation result. By consequence, the research suggests that by using VWAP along with the closing price, estimation of financial risk and asset pricing can be performed with considerably less noise (Ting, 2006).

Further, using Amihud (2002)'s liquidity measure can also be an alternative measure of investor heterogeneity. In this study, I elaborated the relationship between investor heterogeneity and liquidity. In general, investor heterogeneity has a positive relationship with all dimensions of liquidity[99], i.e., bid-ask spread, resilience, depth and width. Amihud (2002)'s illiquidity measure:

$$Illiquidity = Average\left(\frac{|Return_i|}{Dollar\ Trading\ Volume_i}\right)$$

captures the effects of both price and volume, hence it is a good attempt to control the level of investor heterogeneity.

[99] Except the trading volume dimension (order depth) at the same side and at the same price level on the LOB.

Finally, the Two-Period Order Flow model is based on short-term order reactions after price breakouts. For longer timeframes, I assume that a stock's long-term volatility is comprised of the accumulations of short-term volatility, and this short-term order reaction can be generalized into long terms. However, the momentum test results are based on long time frames, i.e., from 6 to 12 months, this study did not reach a consistency at this point. To test the short-term volatility, high-frequency data (less than one minute) is needed. Whether this model and its conclusions can be generalized into longer terms is also an important issue for the future research.

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Appendix I: Tables

Table 1 reports the testing results of the Winner/Loser Portfolio strategy from 2000 to 2017. For each portfolio, I include 10% of total stocks of each group in portfolio W and L. Time rolling interval is one month[100]. Column 3 to 11 show the monthly portfolio returns of each group, with the corresponding t-statistics underneath. Column 1 shows the formation month and column 2 shows the holding months. Rolling starts at January 3, 2000 and ends at December 29, 2017. Column 12 to 15 show the ANOVA p-values among the groups(high, low and US) and the remaining columns show the t tests of difference of the means between the groups. For portfolio Ws, the average monthly returns of the holding period of high order, low order and pure US firms over the entire time horizon are 0.0477, 0.0231 and 0.0172, respectively, and all of them are very strongly significant. The returns are in descending order, this result is consistent with my prediction that investor heterogeneity is descending among the three groups. It shows that investor heterogeneity is the highest for the high group, and the lowest for the pure US group. As discussed in Section III, high investor heterogeneity implies less chances of price reversals and higher momentum. After controlling the holding periods to 6 to 12 months, the average p-values of the ANOVA tests are 0.0084 and they are acceptable at the 1% level and highly significant, which suggests that the positive momentum for the groups are significantly different over intermediate to long terms, in orders words, investors react to positive returns differently in the medium to long terms, but not in the short terms. Investor heterogeneity is statistically significant among the groups, the higher order, lower order and pure US groups of stocks have heterogeneity in decreasing order. The t-tests between groups show that the mean monthly returns of portfolio W are higher for high order foreign listed firms than that of low order foreign listed firms, and low orders are higher than that of pure US firms. This is consistent with my first hypothesis that Investor Heterogeneity of the three groups are in descending order. But in the financial crisis period, the differences are not apparent. In the post-financial crisis period, it is not significant. I also attribute this phenomenon to the reason of Internet trading. In general, if the formation period is larger than 6 months and the holding period is larger than 6 months, all groups shows significant differences in momentum. For Portfolio Ls, almost all returns are positive, which shows that the average psychology of investors is on the long side, and hence investors are willing to buy back these stocks other than further shorting them. The average monthly returns of the holding period of high order, low order and pure US firms are 0.0297, 0.0328 and 0.4764 respectively, they are monotonically increasing. The high order group has the lowest positive returns, and the pure US group has the highest positive returns, this can be explained in

[100] On average, each month has 21 trade days.

that price reversals happen mostly in the group of stocks with the least investor heterogeneity, is it consistent with the hypothesis and the Two-Period Order Flow Model.

Starting Dat	1/3/2000	End Date	12/29/2017		No.of Firn	10%		Rolling Pe	21 days												
Formation Period (month)	Holding Period (month)	Holding Period Monthly Return (Mean, t-statistic)									ANOVA (High Order, Low Order, Pure US) (p-Value)			t-Test for Two Groups(mean differences, p-value)					
		Portfolio W			Portfolio L			Portfolio W-L						Portfolio W		Portfolio L		Portfolio W-L	
		High	Low	US	High	Low	US	High	Low	US	Portfolio W	Portfolio L	Portfolio W-L	High/Low	Low/US	High/Low	Low/US	High/Low	Low/US
1	1	0.0616	0.0203	0.0167	0.0315	0.0346	0.1181	0.0301	-0.0143	-0.1014	0.3867	0.2546	0.1479	0.0413	0.0036	-0.0031	-0.0836	0.0444	0.0872
		(1.4220)	(2.7361)	(2.9635)	(3.5418)	(3.6412)	(1.6505)	(0.7091)	(-1.5953)	(-1.4167)				0.1741	0.3503	0.4059	0.1241	0.1537	0.1142
	2	0.0264	0.0193	0.0205	0.0242	0.0334	0.0969	0.0022	-0.0141	-0.0765	0.8163	0.1423	0.1277	0.0071	-0.0011	-0.0092	-0.0635	0.0163	0.0624
		(2.4708)	(3.6396)	(2.4043)	(3.4032)	(4.1037)	(2.0262)	(0.2052)	(-1.8519)	(-1.5840)				0.2762	0.4550	0.1970	0.0960	0.1094	0.1016
	3	0.0195	0.0209	0.0185	0.0245	0.0268	0.0821	-0.0051	-0.0058	-0.0635	0.9552	0.0936	0.0828	-0.0015	0.0024	-0.0022	-0.0553	0.0008	0.0577
		(3.4189)	(4.1680)	(2.9639)	(4.2081)	(4.5046)	(2.3020)	(-0.9423)	(-1.0812)	(-1.7682)				0.4235	0.3818	0.3947	0.0637	0.4603	0.0569
	6	0.0372	0.0202	0.0261	0.0253	0.0258	0.0892	0.0120	-0.0057	-0.0631	0.3853	0.0478	0.0466	0.0171	-0.0059	-0.0006	-0.0634	0.0176	0.0574
		(2.8600)	(5.0986)	(3.6685)	(4.8188)	(5.0980)	(2.4997)	(0.9189)	(-1.2917)	(-1.7422)				0.1055	0.2334	0.4685	0.0401	0.1004	0.0585
	9	0.0288	0.0207	0.0225	0.0251	0.0255	0.1475	0.0037	-0.0048	-0.1250	0.4106	0.1436	0.1341	0.0081	-0.0018	-0.0004	-0.1220	0.0085	0.1202
		(5.0456)	(6.0930)	(5.5007)	(5.0874)	(5.6786)	(1.6889)	(0.6870)	(-1.3492)	(-1.4272)				0.1120	0.3690	0.4745	0.0823	0.0949	0.0859
	12	0.0317	0.0242	0.0201	0.0235	0.0240	0.1820	0.0082	0.0002	-0.1619	0.1629	0.1195	0.0970	0.0075	0.0041	-0.0005	-0.1580	0.0080	0.1621
		(5.1899)	(7.2706)	(6.8349)	(5.1962)	(5.9640)	(1.6821)	(1.5217)	(0.0486)	(-1.4932)				0.1421	0.1758	0.4644	0.0731	0.1084	0.0684
3	1	0.0643	0.0262	0.0157	0.0376	0.0390	0.1254	0.0267	-0.0128	-0.1097	0.3794	0.2483	0.1280	0.0381	0.0104	-0.0013	-0.0864	0.0395	0.0968
		(1.4723)	(2.7574)	(3.3733)	(3.7501)	(4.0388)	(1.7324)	(0.6301)	(-1.1419)	(-1.5146)				0.1972	0.1627	0.4617	0.1190	0.1840	0.0938
	2	0.0282	0.0243	0.0233	0.0269	0.0309	0.1147	0.0013	-0.0066	-0.0913	0.9162	0.0624	0.0566	0.0038	0.0010	-0.0040	-0.0837	0.0079	0.0847
		(2.5804)	(4.1592)	(2.7680)	(3.6999)	(4.1465)	(2.2782)	(0.1183)	(-0.8310)	(-1.8037)				0.3782	0.4612	0.3500	0.0506	0.2771	0.0499
	3	0.0235	0.0260	0.0232	0.0280	0.0271	0.1015	-0.0046	-0.0011	-0.0783	0.9353	0.0302	0.0272	-0.0025	0.0028	0.0009	-0.0744	-0.0035	0.0772
		(3.7459)	(5.0668)	(3.6900)	(3.9877)	(4.7179)	(2.6465)	(-0.6562)	(-0.1926)	(-2.0300)				0.3787	0.3660	0.4585	0.0282	0.3534	0.0246
	6	0.0468	0.0228	0.0220	0.0302	0.0272	0.1113	0.0166	-0.0043	-0.0893	0.0759	0.0106	0.0037	0.0240	0.0008	0.0030	-0.0842	0.0210	0.0850
		(3.3066)	(5.8712)	(5.7227)	(4.7740)	(5.5341)	(2.9459)	(1.1194)	(-0.9471)	(-2.3650)				0.0518	0.4391	0.3525	0.0141	0.0893	0.0133
	9	0.0371	0.0231	0.0196	0.0263	0.0269	0.3636	0.0108	-0.0038	-0.3440	0.0213	0.0168	0.0133	0.0139	0.0035	-0.0006	-0.3367	0.0146	0.3402
		(5.4252)	(6.8415)	(6.8571)	(4.7626)	(6.3650)	(2.1894)	(1.5861)	(-1.0242)	(-2.0661)				0.0341	0.2118	0.4649	0.0220	0.0303	0.0212
	12	0.0404	0.0258	0.0182	0.0256	0.0261	0.3157	0.0148	-0.0003	-0.2975	0.0089	0.0162	0.0108	0.0145	0.0076	-0.0006	-0.2896	0.0151	0.2972
		(5.0586)	(7.8581)	(7.9089)	(5.0964)	(6.5954)	(2.2209)	(2.0193)	(-0.0871)	(-2.0875)				0.0467	0.0293	0.4649	0.0215	0.0321	0.0192
6	1	0.0697	0.0255	0.0167	0.0469	0.0459	0.1544	0.0228	-0.0205	-0.1377	0.3028	0.1638	0.0806	0.0442	0.0087	0.0010	-0.1085	0.0433	0.1172
		(1.5732)	(3.9696)	(3.9215)	(3.1830)	(4.5792)	(1.9753)	(0.5111)	(-2.1154)	(-1.7635)				0.1620	0.1285	0.4784	0.0851	0.1722	0.0689
	2	0.0668	0.0228	0.0163	0.0381	0.0359	0.1429	0.0286	-0.0131	-0.1266	0.2119	0.0263	0.0120	0.0440	0.0065	0.0022	-0.1070	0.0418	0.1135
		(1.7719)	(4.7510)	(4.7748)	(3.4208)	(5.0522)	(2.6586)	(0.7518)	(-1.9229)	(-2.3726)				0.1243	0.1334	0.4345	0.0249	0.1409	0.0180
	3	0.0585	0.0239	0.0162	0.0399	0.0336	0.1257	0.0185	-0.0097	-0.1095	0.1261	0.0134	0.0042	0.0345	0.0077	0.0063	-0.0921	0.0282	0.0998
		(2.2053)	(5.3818)	(5.5115)	(4.0905)	(5.5091)	(3.0538)	(0.6725)	(-1.7168)	(-2.6801)				0.1002	0.0737	0.2924	0.0140	0.1583	0.0082
	6	0.0564	0.0223	0.0163	0.0307	0.0336	0.5578	0.0257	-0.0113	-0.5415	0.0117	0.0125	0.0086	0.0341	0.0060	-0.0029	-0.5242	0.0370	0.5302
		(3.2904)	(6.0364)	(6.7462)	(4.2796)	(6.3565)	(2.2312)	(1.4337)	(-2.5543)	(-2.1615)				0.0265	0.0878	0.3723	0.0186	0.0231	0.0178
	9	0.0394	0.0258	0.0158	0.0273	0.0302	0.6554	0.0120	-0.0043	-0.6396	0.0012	0.0009	0.0006	0.0135	0.0101	-0.0028	-0.6253	0.0163	0.6353
		(5.8279)	(7.5931)	(7.1897)	(4.9054)	(6.7626)	(2.7856)	(1.6930)	(-1.1929)	(-2.7112)				0.0376	0.0068	0.3469	0.0043	0.0206	0.0038
	12	0.0378	0.0249	0.0154	0.0293	0.0333	0.4177	0.0085	-0.0084	-0.4023	0.0034	0.0015	0.0009	0.0129	0.0095	-0.0040	-0.3844	0.0169	0.3939
		(5.2024)	(8.0537)	(7.8474)	(5.3508)	(6.7968)	(2.7684)	(1.1647)	(-2.0110)	(-2.6585)				0.0516	0.0048	0.2956	0.0058	0.0226	0.0050
9	1	0.0781	0.0165	0.0170	0.0389	0.0438	0.9281	0.0392	-0.0272	-0.9112	0.1619	0.2673	0.2440	0.0616	-0.0004	-0.0049	-0.8844	0.0664	0.8840
		(1.7458)	(2.5873)	(3.8716)	(3.3474)	(4.1788)	(1.2036)	(0.8847)	(-2.6871)	(-1.1810)				0.0872	0.4781	0.3783	0.1264	0.0727	0.1267
	2	0.0819	0.0183	0.0153	0.0284	0.0379	0.9216	0.0535	-0.0196	-0.9063	0.1279	0.0728	0.0599	0.0636	0.0030	-0.0094	-0.8837	0.0731	0.8867
		(1.8201)	(3.7877)	(4.7324)	(3.5948)	(4.9286)	(1.6831)	(1.1892)	(-2.6127)	(-1.6526)				0.0807	0.3028	0.1962	0.0541	0.0553	0.0537
	3	0.0431	0.0226	0.0153	0.0268	0.0348	0.9866	0.0163	-0.0122	-0.9713	0.0469	0.0252	0.0224	0.0205	0.0072	-0.0080	-0.9519	0.0285	0.9591
		(3.2753)	(4.9227)	(5.4514)	(3.9493)	(5.4252)	(1.9863)	(1.2269)	(-1.9643)	(-1.9515)				0.0711	0.0901	0.1957	0.0284	0.0266	0.0277
	6	0.0557	0.0253	0.0145	0.0229	0.0333	0.9861	0.0328	-0.0080	-0.9716	0.0124	0.0007	0.0005	0.0305	0.0108	-0.0104	-0.9528	0.0409	0.9635
		(3.2746)	(6.4801)	(6.3307)	(4.7934)	(6.1456)	(2.7883)	(1.9174)	(-1.7071)	(-2.7405)				0.0412	0.0089	0.0754	0.0038	0.0111	0.0036
	9	0.0361	0.0240	0.0139	0.0255	0.0336	0.7927	0.0106	-0.0096	-0.7788	0.0020	0.0001	0.0001	0.0121	0.0101	-0.0081	-0.7590	0.0202	0.7692
		(5.4447)	(7.2291)	(7.0738)	(5.1574)	(6.8133)	(3.2108)	(1.7180)	(-2.3928)	(-3.1450)				0.0526	0.0046	0.1233	0.0012	0.0032	0.0011
	12	0.0337	0.0221	0.0134	0.0309	0.0356	0.4850	0.0028	-0.0135	-0.4715	0.0046	0.0004	0.0002	0.0115	0.0087	-0.0047	-0.4493	0.0163	0.4580
		(4.9635)	(7.8216)	(7.6906)	(5.7548)	(7.0499)	(3.0516)	(0.4654)	(-3.2678)	(-2.9580)				0.0587	0.0045	0.2608	0.0026	0.0127	0.0023
12	1	0.0840	0.0250	0.0178	0.0308	0.0372	0.9456	0.0531	-0.0122	-0.9278	0.2678	0.2627	0.2362	0.0589	0.0073	-0.0064	-0.9084	0.0654	0.9156
		(1.5497)	(3.8982)	(4.0159)	(2.9539)	(3.5960)	(1.2008)	(0.9929)	(-1.1699)	(-1.1775)				0.1406	0.1761	0.3311	0.1250	0.1160	0.1233
	2	0.0810	0.0255	0.0147	0.0281	0.0317	0.9418	0.0529	-0.0062	-0.9270	0.1756	0.0709	0.0576	0.0555	0.0108	-0.0036	-0.9101	0.0591	0.9208
		(1.7503)	(5.2513)	(4.5664)	(3.5675)	(4.1826)	(1.6843)	(1.1493)	(-0.8081)	(-1.6552)				0.1172	0.0326	0.3711	0.0526	0.1034	0.0509
	3	0.0684	0.0265	0.0139	0.0275	0.0315	1.0218	0.0408	-0.0051	-1.0079	0.1076	0.0223	0.0177	0.0419	0.0126	-0.0040	-0.9902	0.0459	1.0028
		(2.0961)	(6.1812)	(4.9498)	(4.2584)	(4.8547)	(2.0144)	(1.2415)	(-0.8329)	(-1.9829)				0.1022	0.0072	0.3318	0.0262	0.0857	0.0249
	6	0.0387	0.0249	0.0133	0.0266	0.0360	1.0379	0.0122	-0.0111	-1.0247	0.0145	0.0005	0.0004	0.0138	0.0116	-0.0094	-1.0020	0.0232	1.0136
		(3.9721)	(6.5210)	(6.1111)	(4.9895)	(6.2026)	(2.8635)	(1.2185)	(-2.2588)	(-2.8197)				0.0936	0.0043	0.1167	0.0031	0.0187	0.0029
	9	0.0282	0.0226	0.0125	0.0286	0.0339	0.8311	-0.0004	-0.0113	-0.8186	0.0182	0.0001	0.0000	0.0056	0.0101	-0.0053	-0.7972	0.0109	0.8073
		(4.8793)	(7.0430)	(6.7753)	(5.7880)	(6.7003)	(3.2775)	(-0.0875)	(-2.7929)	(-3.2183)				0.2002	0.0033	0.2266	0.0010	0.0462	0.0009
	12	0.0293	0.0216	0.0128	0.0357	0.0334	0.5127	-0.0064	-0.0118	-0.5000	0.0297	0.0002	0.0001	0.0077	0.0088	0.0024	-0.4793	0.0054	0.4882
		(4.2304)	(7.9264)	(7.6393)	(6.5318)	(6.7787)	(3.1531)	(-0.9655)	(-2.9028)	(-3.0649)				0.1499	0.0030	0.3745	0.0018	0.2445	0.0016
Average		0.0477	0.0231	0.0172	0.0297	0.0328	0.4764	0.0180	-0.0096	-0.4592	0.2360	0.0709	0.0541	0.0246	0.0059	-0.0030	-0.4437	0.0276	0.4496
t-statisitc		(13.4569)	(49.9648)	(26.9614)	(28.6615)	(34.4420)	(7.0994)	(5.7010)	(-8.6497)	(-6.8002)	(4.3351)	(4.3897)	(4.3024)	(6.8797)	(6.9276)	(-4.0028)	(-6.6437)	(7.4077)	(6.6868)

Table 2:Momentum strategy returns from 2000 to 2007

Starting Dat	1/3/2000	End Date	10/11/2007		No.of Firms in each g		10%	Rolling Period		21 days										
Formation Period (month)	Holding Period (month)	Holding Period Monthly Return (Mean, t-statistic)									ANOVA (High Order, Low Order, Pure US) (p-Value)			t-Test for Two Groups(mean differences, p-value)					
		Portfolio W			Portfolio L			Portfolio W-L						Portfolio W		Portfolio L		Portfolio W-L	
		High	Low	US	High	Low	US	High	Low	US	Portfolio W	Portfolio L	Portfolio W-L	High/Low	Low/US	High/Low	Low/US	High/Low	Low/US
1	1	0.1280	0.0338	0.0235	0.0349	0.0507	0.0674	0.0931	-0.0168	-0.0439	0.3689	0.4633	0.2140	0.0942	0.0103	-0.0157	-0.0167	0.1099	0.0270
		(1.3001)	(2.6678)	(2.5342)	(2.4469)	(3.2152)	(2.8176)	(0.9604)	(-1.0370)	(-1.9132)				0.1726	0.2561	0.2302	0.2801	0.1330	0.1686
	2	0.0437	0.0286	0.0171	0.0333	0.0545	0.1079	0.0104	-0.0258	-0.0908	0.4143	0.4415	0.2553	0.0151	0.0115	-0.0212	-0.0535	0.0362	0.0650
		(1.9632)	(3.3126)	(2.9726)	(2.6051)	(3.5914)	(1.5231)	(0.4460)	(-1.7154)	(-1.2869)				0.2645	0.1346	0.1436	0.2311	0.0971	0.1849
	3	0.0254	0.0316	0.0179	0.0281	0.0409	0.0463	-0.0027	-0.0093	-0.0283	0.4717	0.4474	0.2006	-0.0062	0.0136	-0.0128	-0.0054	0.0066	0.0190
		(2.7498)	(3.6581)	(3.5500)	(3.1069)	(4.0368)	(3.9136)	(-0.2763)	(-0.8924)	(-2.5779)				0.3119	0.0877	0.1735	0.3653	0.3235	0.1060
	6	0.0682	0.0283	0.0238	0.0341	0.0398	0.1193	0.0341	-0.0115	-0.0955	0.1496	0.3087	0.1414	0.0399	0.0045	-0.0056	-0.0796	0.0455	0.0840
		(2.3050)	(4.6042)	(5.1657)	(4.0061)	(4.8928)	(1.5903)	(1.1370)	(-1.5046)	(-1.2739)				0.0950	0.2815	0.3169	0.1473	0.0720	0.1339
	9	0.0511	0.0328	0.0269	0.0387	0.0364	0.0924	0.0124	-0.0037	-0.0655	0.0837	0.2292	0.0902	0.0183	0.0059	0.0022	-0.0560	0.0160	0.0619
		(4.3406)	(5.9610)	(5.8308)	(4.2624)	(5.1205)	(2.1199)	(1.0347)	(-0.6229)	(-1.4984)				0.0809	0.2075	0.4231	0.1042	0.1156	0.0822
	12	0.0570	0.0398	0.0310	0.0368	0.0364	0.2090	0.0202	0.0033	-0.1780	0.1251	0.3536	0.2837	0.0172	0.0088	0.0004	-0.1726	0.0169	0.1813
		(4.2168)	(6.7007)	(5.4480)	(4.3489)	(5.5549)	(1.2414)	(1.6344)	(0.4850)	(-1.0562)				0.1227	0.1443	0.4856	0.1544	0.1177	0.1428
3	1	0.1318	0.0460	0.0203	0.0398	0.0528	0.0798	0.0919	-0.0068	-0.0595	0.3794	0.3556	0.1878	0.0857	0.0258	-0.0130	-0.0270	0.0987	0.0527
		(1.3124)	(2.3895)	(2.7505)	(2.3459)	(3.5089)	(3.0435)	(0.9461)	(-0.3069)	(-2.4143)				0.2019	0.1072	0.2840	0.1867	0.1622	0.0563
	2	0.0492	0.0395	0.0204	0.0308	0.0458	0.1474	0.0184	-0.0063	-0.1270	0.3905	0.1660	0.0773	0.0096	0.0192	-0.0151	-0.1015	0.0247	0.1207
		(2.1355)	(3.5861)	(3.6446)	(2.4693)	(3.5340)	(1.8497)	(0.8208)	(-0.3897)	(-1.6051)				0.3534	0.0617	0.2017	0.1058	0.1864	0.0692
	3	0.0386	0.0424	0.0253	0.0335	0.0382	0.0922	0.0051	0.0041	-0.0669	0.3567	0.1049	0.0275	-0.0037	0.0170	-0.0047	-0.0540	0.0010	0.0710
		(3.4729)	(4.6357)	(5.0026)	(2.5899)	(4.0448)	(2.7239)	(0.3836)	(0.3417)	(-2.0348)				0.3976	0.0524	0.3843	0.0639	0.4781	0.0225
	6	0.0933	0.0377	0.0272	0.0429	0.0405	0.1554	0.0504	-0.0029	-0.1282	0.0367	0.1455	0.0395	0.0557	0.0105	0.0024	-0.1149	0.0533	0.1253
		(2.8534)	(5.7468)	(6.1528)	(3.5354)	(5.0137)	(1.9360)	(1.4513)	(-0.3199)	(-1.5996)				0.0492	0.0940	0.4351	0.0790	0.0704	0.0619
	9	0.0697	0.0409	0.0299	0.0395	0.0392	0.1181	0.0302	0.0017	-0.0882	0.0116	0.0783	0.0124	0.0288	0.0110	0.0003	-0.0789	0.0285	0.0899
		(4.7052)	(7.0477)	(5.8347)	(3.6412)	(6.1315)	(2.4886)	(1.9536)	(0.2526)	(-1.8474)				0.0365	0.0782	0.4915	0.0516	0.0462	0.0328
	12	0.0775	0.0452	0.0286	0.0390	0.0419	0.2448	0.0385	0.0033	-0.2163	0.0095	0.2592	0.1606	0.0323	0.0166	-0.0029	-0.2030	0.0352	0.2196
		(4.2263)	(7.3555)	(6.8703)	(3.9482)	(6.7766)	(1.3986)	(2.2515)	(0.4999)	(-1.2344)				0.0489	0.0134	0.4031	0.1250	0.0290	0.1070
6	1	0.1475	0.0340	0.0241	0.0643	0.0647	0.1416	0.0832	-0.0307	-0.1175	0.2773	0.3768	0.1513	0.1135	0.0099	-0.0004	-0.0768	0.1139	0.0868
		(1.4195)	(3.2850)	(4.0123)	(2.1033)	(3.9177)	(2.0323)	(0.7951)	(-1.7737)	(-1.7085)				0.1401	0.2042	0.4952	0.1429	0.1428	0.1120
	2	0.1382	0.0335	0.0249	0.0583	0.0523	0.1902	0.0798	-0.0188	-0.1653	0.2286	0.1270	0.0624	0.1047	0.0086	0.0060	-0.1379	0.0987	0.1464
		(1.5497)	(4.3229)	(4.7385)	(2.4835)	(4.4412)	(2.1175)	(0.8845)	(-1.4842)	(-1.8525)				0.1227	0.1810	0.4099	0.0658	0.1410	0.0538
	3	0.1199	0.0377	0.0259	0.0663	0.0470	0.1293	0.0536	-0.0093	-0.1034	0.1427	0.1258	0.0567	0.0822	0.0118	0.0193	-0.0823	0.0629	0.0941
		(1.9115)	(5.1898)	(5.6712)	(3.2754)	(4.7690)	(2.7864)	(0.8197)	(-0.8803)	(-2.2741)				0.0982	0.0860	0.1965	0.0430	0.1724	0.0233
	6	0.1161	0.0394	0.0268	0.0529	0.0488	0.1852	0.0633	-0.0094	-0.1583	0.0181	0.0949	0.0168	0.0767	0.0125	0.0041	-0.1364	0.0727	0.1489
		(2.8469)	(6.4521)	(6.4962)	(3.6775)	(6.1239)	(2.1630)	(1.4717)	(-1.2868)	(-1.8513)				0.0331	0.0454	0.4018	0.0582	0.0496	0.0432
	9	0.0726	0.0465	0.0270	0.0465	0.0449	0.1508	0.0261	0.0016	-0.1238	0.0037	0.0219	0.0018	0.0261	0.0195	0.0016	-0.1060	0.0245	0.1255
		(4.8777)	(7.8013)	(6.6361)	(4.3400)	(6.5634)	(2.9110)	(1.6372)	(0.2750)	(-2.3772)				0.0534	0.0038	0.4493	0.0229	0.0766	0.0095
	12	0.0766	0.0447	0.0270	0.0498	0.0546	0.3010	0.0268	-0.0099	-0.2741	0.0040	0.1628	0.0955	0.0318	0.0178	-0.0048	-0.2464	0.0367	0.2642
		(4.5129)	(7.6613)	(7.3037)	(4.6653)	(6.4372)	(1.6408)	(1.5728)	(-1.2881)	(-1.4928)				0.0396	0.0056	0.3620	0.0918	0.0261	0.0773
9	1	0.1600	0.0256	0.0249	0.0569	0.0519	0.1543	0.1031	-0.0263	-0.1295	0.2114	0.1918	0.0886	0.1344	0.0007	0.0050	-0.1025	0.1294	0.1032
		(1.4943)	(2.3654)	(4.0884)	(2.6211)	(2.9632)	(2.1308)	(0.9740)	(-1.4601)	(-1.8089)				0.1076	0.4762	0.4283	0.0861	0.1157	0.0826
	2	0.1714	0.0325	0.0241	0.0462	0.0536	0.2011	0.1252	-0.0210	-0.1769	0.1821	0.0858	0.0388	0.1388	0.0084	-0.0073	-0.1475	0.1462	0.1559
		(1.5733)	(3.8492)	(5.0541)	(3.2341)	(4.0813)	(2.1368)	(1.1488)	(-1.5087)	(-1.8937)				0.1037	0.1941	0.3531	0.0621	0.0934	0.0512
	3	0.0781	0.0400	0.0255	0.0431	0.0492	0.1349	0.0350	-0.0092	-0.1094	0.1182	0.0513	0.0086	0.0381	0.0145	-0.0061	-0.0857	0.0442	0.1002
		(2.5455)	(4.8508)	(5.8423)	(3.7243)	(4.7939)	(2.7600)	(1.1373)	(-0.7926)	(-2.2769)				0.1167	0.0614	0.3476	0.0448	0.0910	0.0228
	6	0.1129	0.0465	0.0250	0.0411	0.0498	0.2198	0.0718	-0.0033	-0.1948	0.0303	0.0291	0.0043	0.0664	0.0216	-0.0087	-0.1700	0.0751	0.1915
		(2.7283)	(6.6978)	(6.5196)	(5.3866)	(6.1720)	(2.4045)	(1.7080)	(-0.4239)	(-2.1306)				0.0588	0.0038	0.2175	0.0338	0.0413	0.0200
	9	0.0695	0.0456	0.0251	0.0419	0.0515	0.2070	0.0277	-0.0060	-0.1819	0.0054	0.0012	0.0001	0.0240	0.0205	-0.0097	-0.1554	0.0337	0.1759
		(4.6103)	(7.3391)	(7.2601)	(4.9908)	(6.3654)	(3.4653)	(1.9837)	(-0.8947)	(-3.0261)				0.0725	0.0023	0.2037	0.0059	0.0159	0.0024
	12	0.0722	0.0414	0.0246	0.0506	0.0596	0.3394	0.0216	-0.0181	-0.3148	0.0033	0.1206	0.0716	0.0307	0.0168	-0.0090	-0.2799	0.0397	0.2967
		(4.4775)	(7.7595)	(7.9533)	(5.1374)	(6.7168)	(1.7479)	(1.5759)	(-2.5311)	(-1.6202)				0.0369	0.0037	0.2502	0.0771	0.0058	0.0657
12	1	0.1909	0.0425	0.0289	0.0381	0.0488	0.1552	0.1528	-0.0063	-0.1264	0.2597	0.1347	0.0805	0.1484	0.0136	-0.0107	-0.1065	0.1590	0.1201
		(1.4343)	(3.8818)	(4.9315)	(2.0457)	(2.7915)	(2.0793)	(1.1636)	(-0.3289)	(-1.7028)				0.1349	0.1373	0.3384	0.0842	0.1170	0.0602
	2	0.1813	0.0420	0.0252	0.0429	0.0479	0.2085	0.1384	-0.0059	-0.1833	0.1907	0.0709	0.0338	0.1393	0.0168	-0.0050	-0.1606	0.1443	0.1774
		(1.5835)	(5.0378)	(5.6950)	(3.0058)	(3.6556)	(2.1308)	(1.2144)	(-0.4084)	(-1.8839)				0.1143	0.0391	0.3981	0.0538	0.1063	0.0375
	3	0.1539	0.0415	0.0246	0.0441	0.0473	0.1735	0.1099	-0.0058	-0.1489	0.1081	0.0068	0.0062	0.1125	0.0169	-0.0032	-0.1263	0.1156	0.1432
		(1.9039)	(5.9459)	(6.0074)	(4.0861)	(4.3850)	(3.1804)	(1.3458)	(-0.5344)	(-2.7564)				0.0848	0.0195	0.4179	0.0128	0.0820	0.0055
	6	0.0867	0.0431	0.0242	0.0415	0.0569	0.2898	0.0452	-0.0138	-0.2656	0.0066	0.0027	0.0004	0.0435	0.0189	-0.0154	-0.2329	0.0590	0.2519
		(3.7230)	(6.2670)	(7.1793)	(5.4185)	(6.0203)	(2.9890)	(1.8868)	(-1.6944)	(-2.7346)				0.0381	0.0075	0.1034	0.0096	0.0110	0.0058
	9	0.0621	0.0401	0.0234	0.0453	0.0522	0.2296	0.0168	-0.0121	-0.2062	0.0064	0.0002	0.0000	0.0220	0.0166	-0.0069	-0.1774	0.0289	0.1940
		(4.7109)	(6.7103)	(7.7147)	(6.0827)	(6.1739)	(3.8543)	(1.5373)	(-2.0497)	(-3.4391)				0.0654	0.0073	0.2713	0.0021	0.0109	0.0009
	12	0.0709	0.0382	0.0243	0.0585	0.0559	0.3745	0.0124	-0.0177	-0.3501	0.0054	0.0902	0.0560	0.0327	0.0139	0.0027	-0.3186	0.0300	0.3325
		(4.1851)	(7.4491)	(8.7478)	(6.2833)	(6.7865)	(1.8445)	(0.7646)	(-2.8422)	(-1.7238)				0.0341	0.0096	0.4149	0.0607	0.0434	0.0531
Average		0.0971	0.0387	0.0249	0.0440	0.0485	0.1755	0.0532	-0.0097	-0.1506	0.1533	0.1683	0.0821	0.0584	0.0138	-0.0045	-0.1271	0.0629	0.1409
t-statisitc		(11.6671)	(36.7350)	(44.5031)	(25.0037)	(37.7695)	(12.2321)	(6.8733)	(-5.8851)	(-10.6014)	(5.5943)	(6.4271)	(5.5319)	(6.9329)	(13.8307)	(-2.9566)	(-9.1949)	(7.5987)	(10.0060)

Table 3:Momentum strategy returns from 2007 to 2009

Starting Dat	10/12/2007	End Date	3/9/2009		No.of Firms in each gro		10%	Rolling Period		21 days										
Formation Period (month)	Holding Period (month)	Holding Period Monthly Return (Mean, t-statistic)									ANOVA (High Order, Low Order, Pure US) (p-Value)			t-Test for Two Groups(mean differences, p-value)					
		Portfolio W			Portfolio L			Portfolio W-L						Portfolio W		Portfolio L		Portfolio W-L	
		High	Low	US	High	Low	US	High	Low	US	Portfolio W	Portfolio L	Portfolio W-L	High/Low	Low/US	High/Low	Low/US	High/Low	Low/US
1	1	-0.0429	-0.0645	-0.0324	0.0018	-0.0407	-0.0226	-0.0448	-0.0238	-0.0098	0.7007	0.6736	0.4520	0.0216	-0.0321	0.0425	-0.0180	-0.0209	-0.0141
		(-1.2122)	(-2.7035)	(-1.5964)	(0.0429)	(-1.2893)	(-0.9082)	(-1.7070)	(-1.4095)	(-0.7393)				0.3088	0.1573	0.2145	0.3287	0.2543	0.2592
	2	-0.0056	-0.0535	-0.0271	0.0113	-0.0368	-0.0300	-0.0169	-0.0168	0.0029	0.2824	0.4568	0.7333	0.0479	-0.0265	0.0480	-0.0068	-0.0001	-0.0197
		(-0.1877)	(-3.5436)	(-1.9227)	(0.2687)	(-1.7668)	(-1.5964)	(-0.5442)	(-1.2154)	(0.2990)				0.0842	0.1055	0.1582	0.4055	0.4988	0.1274
	3	-0.0132	-0.0446	-0.0240	0.0211	-0.0406	-0.0235	-0.0343	-0.0040	-0.0005	0.4535	0.1807	0.2171	0.0314	-0.0206	0.0617	-0.0171	-0.0303	-0.0036
		(-0.5194)	(-3.4311)	(-2.1364)	(0.5903)	(-2.4736)	(-1.8758)	(-1.4977)	(-0.4763)	(-0.0625)				0.1432	0.1207	0.0668	0.2083	0.1161	0.3782
	6	-0.0146	-0.0332	-0.0239	-0.0039	-0.0355	-0.0185	-0.0108	0.0022	-0.0054	0.5977	0.1976	0.7194	0.0186	-0.0093	0.0316	-0.0169	-0.0129	0.0076
		(-0.8070)	(-3.1663)	(-3.1578)	(-0.2274)	(-3.5980)	(-2.5669)	(-0.6130)	(0.3040)	(-1.1675)				0.1937	0.2404	0.0636	0.0911	0.2533	0.1933
	9	-0.0210	-0.0295	-0.0189	-0.0023	-0.0299	-0.0193	-0.0187	0.0005	0.0004	0.6727	0.2468	0.2028	0.0085	-0.0105	0.0276	-0.0106	-0.0192	0.0001
		(-1.7973)	(-3.8316)	(-3.1892)	(-0.1265)	(-5.0721)	(-3.7051)	(-1.4616)	(0.0867)	(0.0812)				0.2784	0.1489	0.0913	0.1004	0.0990	0.4958
	12	-0.0273	-0.0276	-0.0199	-0.0151	-0.0359	-0.0238	-0.0122	0.0083	0.0039	0.7709	0.3066	0.1421	0.0003	-0.0077	0.0208	-0.0121	-0.0206	0.0044
		(-2.5057)	(-3.3180)	(-3.8010)	(-1.1124)	(-6.1246)	(-4.1593)	(-1.1000)	(1.6064)	(2.8663)				0.4921	0.2298	0.1066	0.0894	0.0740	0.2261
3	1	-0.0414	-0.0500	-0.0222	0.0069	-0.0452	-0.0331	-0.0483	-0.0049	0.0108	0.8083	0.6451	0.4141	0.0086	-0.0278	0.0521	-0.0121	-0.0434	-0.0157
		(-0.9438)	(-2.4540)	(-0.9934)	(0.1312)	(-1.3024)	(-1.0196)	(-0.9860)	(-0.2323)	(0.6507)				0.4304	0.1833	0.2087	0.4005	0.2132	0.2818
	2	-0.0510	-0.0484	-0.0245	-0.0231	-0.0480	-0.0360	-0.0279	-0.0004	0.0115	0.4952	0.8115	0.3253	-0.0026	-0.0239	0.0249	-0.0120	-0.0275	-0.0119
		(-2.4555)	(-3.3104)	(-1.5464)	(-0.6737)	(-2.1756)	(-1.5492)	(-1.0979)	(-0.0273)	(0.7726)				0.4591	0.1390	0.2746	0.3562	0.1767	0.2817
	3	-0.0344	-0.0465	-0.0253	-0.0255	-0.0416	-0.0253	-0.0089	-0.0049	0.0000	0.7419	0.7964	0.9073	0.0121	-0.0212	0.0161	-0.0163	-0.0040	-0.0049
		(-1.2899)	(-3.1309)	(-1.8180)	(-1.0376)	(-2.3214)	(-1.7192)	(-0.4292)	(-0.5899)	(0.0000)				0.3477	0.1549	0.3012	0.2454	0.4306	0.3592
	6	-0.0311	-0.0344	-0.0209	-0.0207	-0.0399	-0.0203	-0.0103	0.0055	-0.0006	0.8159	0.3314	0.5502	0.0034	-0.0135	0.0192	-0.0195	-0.0158	0.0060
		(-1.4771)	(-2.5509)	(-2.1329)	(-1.7488)	(-3.9393)	(-2.2605)	(-0.6476)	(0.8928)	(-0.1332)				0.4474	0.2159	0.1184	0.0844	0.1883	0.2169
	9	-0.0364	-0.0308	-0.0193	-0.0297	-0.0385	6.7702	-0.0066	0.0077	-6.7895	0.3636	0.1208	0.1220	-0.0055	-0.0116	0.0087	-6.8087	-0.0143	6.7971
		(-3.3232)	(-4.6072)	(-2.8298)	(-4.2636)	(-5.1327)	(1.5546)	(-0.8297)	(1.5588)	(-1.5582)				0.3386	0.1268	0.2068	0.0894	0.0825	0.0898
	12	-0.0445	-0.0386	-0.0262	-0.0360	-0.0445	-0.0320	-0.0085	0.0060	0.0058	0.2402	0.2951	0.1619	-0.0059	-0.0124	0.0084	-0.0125	-0.0144	0.0001
		(-5.7740)	(-5.9630)	(-4.0283)	(-6.1771)	(-14.5387)	(-5.2450)	(-1.0286)	(1.6633)	(4.3266)				0.2949	0.1238	0.1449	0.0835	0.1075	0.4874
6	1	-0.0557	-0.0580	-0.0424	-0.0496	-0.0471	-0.0322	-0.0060	-0.0109	-0.0102	0.9462	0.9549	0.9920	0.0023	-0.0156	-0.0025	-0.0149	0.0048	-0.0007
		(-1.1601)	(-2.1447)	(-1.5038)	(-1.0140)	(-1.0767)	(-0.8460)	(-0.1618)	(-0.3921)	(-0.5063)				0.4835	0.3471	0.4848	0.4000	0.4591	0.4921
	2	-0.0517	-0.0465	-0.0369	-0.0486	-0.0498	-0.0257	-0.0031	0.0034	-0.0112	0.9375	0.8184	0.8419	-0.0053	-0.0096	0.0012	-0.0241	-0.0065	0.0146
		(-1.2910)	(-2.1395)	(-1.5815)	(-1.4117)	(-1.7504)	(-0.9439)	(-0.1401)	(0.2200)	(-0.8006)				0.4549	0.3838	0.4892	0.2742	0.4063	0.2465
	3	-0.0453	-0.0478	-0.0312	-0.0495	-0.0492	-0.0226	0.0041	0.0014	-0.0086	0.8946	0.6041	0.8005	0.0025	-0.0166	-0.0003	-0.0266	0.0027	0.0099
		(-1.3023)	(-2.1407)	(-1.4707)	(-1.9681)	(-2.3486)	(-1.2702)	(0.2133)	(0.1245)	(-0.8475)				0.4767	0.2983	0.4965	0.1742	0.4517	0.2575
	6	-0.0481	-0.0377	-0.0216	-0.0348	-0.0441	10.1698	-0.0133	0.0064	-10.1914	0.5428	0.1204	0.1215	-0.0104	-0.0161	0.0093	-10.2139	-0.0197	10.1978
		(-2.6944)	(-2.2012)	(-1.4324)	(-2.2119)	(-2.8523)	(1.5579)	(-2.1910)	(0.6976)	(-1.5607)				0.3419	0.2483	0.3410	0.0892	0.0538	0.0896
	9	-0.0619	-0.0387	-0.0291	-0.0439	-0.0499	21.3422	-0.0180	0.0111	-21.3714	0.0813	0.0000	0.0000	-0.0231	-0.0097	0.0060	-21.3921	-0.0291	21.3824
		(-7.1227)	(-3.5966)	(-5.7283)	(-3.7062)	(-4.3043)	(12.0517)	(-3.6223)	(1.4624)	(-12.0458)				0.0865	0.2396	0.3685	0.0034	0.0201	0.0034
	12	-0.0627	-0.0394	-0.0425	-0.0533	-0.0468	17.3873	-0.0093	0.0074	-17.4297	n/a	n/a	n/a	-0.0233	0.0031	-0.0065	-17.4341	-0.0167	17.4371
		n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a				n/a	n/a	n/a	n/a	n/a	n/a
9	1	-0.0386	-0.0764	-0.0341	-0.0715	-0.0649	-0.0478	0.0329	-0.0115	0.0138	0.7893	0.9407	0.6521	0.0378	-0.0423	-0.0067	-0.0171	0.0444	-0.0253
		(-0.6014)	(-2.0213)	(-0.9763)	(-1.2363)	(-1.4582)	(-1.0741)	(0.6668)	(-0.4833)	(0.6807)				0.3109	0.2123	0.4644	0.3952	0.2182	0.2162
	2	-0.0517	-0.0793	-0.0431	-0.0669	-0.0765	11.3229	0.0152	-0.0029	-11.3659	0.8417	0.3868	0.3881	0.0276	-0.0362	0.0096	-11.3993	0.0181	11.3631
		(-0.8205)	(-2.2629)	(-1.3751)	(-1.2284)	(-2.7947)	(0.9946)	(0.4841)	(-0.2059)	(-0.9985)				0.3551	0.2279	0.4394	0.1777	0.3064	0.1784
	3	-0.0736	-0.0709	-0.0440	-0.0638	-0.0762	20.3376	-0.0098	0.0053	-20.3816	0.8116	0.1208	0.1218	-0.0027	-0.0269	0.0124	-20.4137	-0.0151	20.3869
		(-1.5391)	(-2.5899)	(-1.6076)	(-1.3913)	(-3.2473)	(1.5573)	(-0.5678)	(0.3927)	(-1.5592)				0.4814	0.2517	0.4084	0.0894	0.2536	0.0898
	6	-0.0880	-0.0660	-0.0442	-0.0496	-0.0630	32.0092	-0.0384	-0.0030	-32.0534	0.3743	0.0000	0.0000	-0.0221	-0.0218	0.0134	-32.0722	-0.0354	32.0504
		(-4.6928)	(-3.4637)	(-1.9295)	(-1.5742)	(-6.1093)	(12.0553)	(-3.0067)	(-0.2879)	(-11.9747)				0.2278	0.2534	0.3596	0.0034	0.0500	0.0035
	9	-0.0758	-0.0522	-0.0368	-0.0543	-0.0635	23.1769	-0.0215	0.0112	-23.2137	n/a	n/a	n/a	-0.0236	-0.0154	0.0092	-23.2404	-0.0327	23.2249
		n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a				n/a	n/a	n/a	n/a	n/a	n/a
	12	-0.0581	-0.0391	-0.0389	-0.0534	-0.0440	3.8184	-0.0046	0.0049	-3.8573	n/a	n/a	n/a	-0.0190	-0.0002	-0.0094	-3.8624	-0.0095	3.8622
		n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a				n/a	n/a	n/a	n/a	n/a	n/a
12	1	-0.1539	-0.1056	-0.0956	-0.1369	-0.1122	31.7459	-0.0170	0.0066	-31.8416	0.3754	0.3962	0.3968	-0.0483	-0.0100	-0.0247	-31.8582	-0.0236	31.8482
		(-5.4559)	(-3.3457)	(-3.1133)	(-3.2076)	(-2.3279)	(0.9966)	(-0.3724)	(0.2112)	(-0.9998)				0.1437	0.4134	0.3557	0.1869	0.3412	0.1869
	2	-0.1618	-0.1084	-0.0967	-0.1233	-0.1038	45.9125	-0.0384	-0.0046	-46.0091	0.1515	0.1062	0.1066	-0.0534	-0.0117	-0.0195	-46.0163	-0.0339	46.0045
		(-24.5818)	(-4.3961)	(-3.2424)	(-2.9920)	(-2.4687)	(1.7008)	(-1.0650)	(-0.2521)	(-1.7040)				0.0581	0.3864	0.3757	0.0934	0.2224	0.0935
	3	-0.1571	-0.1051	-0.1014	-0.1242	-0.1011	64.0325	-0.0329	-0.0040	-64.1339	0.1398	0.0000	0.0000	-0.0520	-0.0037	-0.0231	-64.1336	-0.0289	64.1299
		(-14.7703)	(-4.8261)	(-4.7365)	(-3.0848)	(-4.0226)	(12.0366)	(-0.8915)	(-0.5572)	(-12.0111)				0.0622	0.4547	0.3283	0.0034	0.2585	0.0034
	6	-0.1190	-0.0808	-0.0848	-0.0970	-0.0951	34.7630	-0.0220	0.0143	-34.8478	n/a	n/a	n/a	-0.0382	0.0040	-0.0019	-34.8581	-0.0363	34.8621
		n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a				n/a	n/a	n/a	n/a	n/a	n/a
	9	-0.0804	-0.0634	-0.0678	-0.0724	-0.0593	5.0852	-0.0080	-0.0040	-5.1530	n/a	n/a	n/a	-0.0170	0.0044	-0.0131	-5.1445	-0.0040	5.1490
		n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a				n/a	n/a	n/a	n/a	n/a	n/a
	12	-0.0447	-0.0258	-0.0354	-0.0165	-0.0109	6.9676	-0.0282	-0.0149	-7.0030	n/a	n/a	n/a	-0.0189	0.0096	-0.0056	-6.9785	-0.0133	6.9881
		n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a				n/a	n/a	n/a	n/a	n/a	n/a
Average		-0.0597	-0.0548	-0.0404	-0.0442	-0.0545	11.1476	-0.0155	-0.0003	-11.1880	0.5762	0.3963	0.3904	-0.0050	-0.0144	0.0103	-11.2021	-0.0153	11.1877
t-statisitc		(-8.0617)	(-12.9190)	(-9.1676)	(-6.0970)	(-12.6983)	(3.7240)	(-4.9882)	(-0.1748)	(-3.7329)	(10.3650)	(6.2507)	(6.0968)	(-1.0736)	(-6.4339)	(2.6108)	(-3.7379)	(-4.6888)	(3.7324)

Table 4: Momentum strategy returns from 2009 to 2017

Starting Dat	3/10/2009	End Date	12/31/2017	No.of Firms in each g	10%	Rolling Period	21 days											
Formation Period (month)	Holding Period (month)	Holding Period Monthly Return (Mean, t-statistic)									ANOVA (High Order, Low Order, Pure US) (p-Value)			t-Test for Two Groups(mean differences, p-value)					
		Portfolio W			Portfolio L			Portfolio W-L						Portfolio W		Portfolio L		Portfolio W-L	
		High	Low	US	High	Low	US	High	Low	US	Portfolio W	Portfolio L	Portfolio W-L	High/Low	Low/US	High/Low	Low/US	High/Low	Low/US
1	1	0.0114	0.0292	0.0176	0.0279	0.0364	0.2162	-0.0165	-0.0072	-0.1986	0.4304	0.3708	0.3623	-0.0178	0.0116	-0.0085	-0.1798	-0.0093	0.1914
		(1.3955)	(2.1101)	(3.1719)	(2.6964)	(3.2325)	(1.1748)	(-1.8262)	(-0.4667)	(-1.0774)				0.1350	0.2196	0.2896	0.1658	0.3020	0.1516
	2	0.0147	0.0306	0.0338	0.0189	0.0299	0.1099	-0.0042	0.0006	-0.0761	0.5731	0.3499	0.4778	-0.0159	-0.0032	-0.0111	-0.0800	-0.0048	0.0767
		(2.0771)	(2.3078)	(1.8425)	(2.5087)	(3.6551)	(1.3229)	(-0.6361)	(0.0452)	(-0.8939)				0.1462	0.4431	0.1604	0.1701	0.3776	0.1879
	3	0.0138	0.0289	0.0278	0.0211	0.0302	0.1337	-0.0073	-0.0013	-0.1059	0.4273	0.1337	0.1768	-0.0151	0.0012	-0.0091	-0.1034	-0.0060	0.1046
		(2.2820)	(3.2051)	(2.4201)	(2.9288)	(4.3730)	(1.7720)	(-1.3526)	(-0.1535)	(-1.3857)				0.0826	0.4685	0.1807	0.0875	0.2745	0.0883
	6	0.0159	0.0274	0.0371	0.0218	0.0293	0.0801	-0.0059	-0.0019	-0.0429	0.2496	0.0678	0.2981	-0.0115	-0.0097	-0.0075	-0.0507	-0.0039	0.0410
		(2.8092)	(3.9824)	(2.9074)	(3.5060)	(4.2777)	(2.5013)	(-1.2212)	(-0.2677)	(-1.2457)				0.0998	0.2515	0.2082	0.0620	0.3258	0.1234
	9	0.0140	0.0235	0.0298	0.0176	0.0295	0.0639	-0.0036	-0.0061	-0.0341	0.1352	0.0330	0.1974	-0.0095	-0.0063	-0.0119	-0.0344	0.0025	0.0281
		(3.3219)	(4.5506)	(4.2389)	(2.7822)	(4.7646)	(3.1023)	(-0.8110)	(-0.9722)	(-1.5718)				0.0785	0.2356	0.0895	0.0563	0.3730	0.1081
	12	0.0114	0.0213	0.0252	0.0140	0.0267	0.0511	-0.0026	-0.0054	-0.0259	0.0651	0.0242	0.1849	-0.0098	-0.0039	-0.0126	-0.0245	0.0028	0.0205
		(3.5129)	(5.4643)	(4.6813)	(2.7339)	(4.7199)	(3.4092)	(-0.7625)	(-1.0810)	(-1.6381)				0.0269	0.2779	0.0499	0.0647	0.3233	0.1089
3	1	0.0196	0.0181	0.0155	0.0283	0.0303	0.2203	-0.0087	-0.0121	-0.2049	0.9449	0.3580	0.3461	0.0015	0.0027	-0.0020	-0.1901	0.0034	0.1928
		(1.6480)	(2.1871)	(3.1264)	(2.8527)	(2.9248)	(1.1743)	(-0.8106)	(-1.2380)	(-1.0902)				0.4596	0.3907	0.4457	0.1571	0.4066	0.1541
	2	0.0176	0.0211	0.0359	0.0290	0.0319	0.1147	-0.0114	-0.0109	-0.0788	0.5279	0.3785	0.5482	-0.0035	-0.0148	-0.0029	-0.0828	-0.0006	0.0680
		(2.2651)	(3.4688)	(1.9324)	(3.7216)	(3.9172)	(1.3556)	(-1.4006)	(-1.6076)	(-0.9105)				0.3619	0.2250	0.3977	0.1662	0.4789	0.2178
	3	0.0146	0.0231	0.0289	0.0298	0.0324	0.1368	-0.0152	-0.0093	-0.1079	0.4854	0.1580	0.2260	-0.0084	-0.0058	-0.0025	-0.1044	-0.0059	0.0986
		(2.2978)	(3.9113)	(2.4748)	(4.1225)	(4.5675)	(1.7781)	(-2.2009)	(-1.7098)	(-1.3854)				0.1665	0.3295	0.4009	0.0897	0.2517	0.1047
	6	0.0146	0.0206	0.0246	0.0207	0.0291	0.0933	-0.0061	-0.0086	-0.0687	0.3709	0.0247	0.0504	-0.0060	-0.0040	-0.0085	-0.0642	0.0025	0.0602
		(3.1963)	(4.6038)	(4.1095)	(3.3362)	(4.7888)	(2.7067)	(-1.3391)	(-1.8149)	(-1.9780)				0.1740	0.2962	0.1649	0.0348	0.3537	0.0446
	9	0.0139	0.0176	0.0207	0.0147	0.0259	0.0728	-0.0009	-0.0082	-0.0521	0.4337	0.0049	0.0111	-0.0038	-0.0031	-0.0111	-0.0469	0.0073	0.0439
		(3.8316)	(4.7558)	(5.3061)	(2.5927)	(5.2345)	(3.3555)	(-0.2155)	(-2.1711)	(-2.3961)				0.2331	0.2853	0.0705	0.0186	0.0934	0.0247
	12	0.0112	0.0180	0.0185	0.0112	0.0223	0.0585	0.0000	-0.0043	-0.0400	0.1742	0.0023	0.0062	-0.0069	-0.0005	-0.0111	-0.0362	0.0043	0.0357
		(3.7095)	(5.4885)	(6.1923)	(2.3482)	(4.8702)	(3.6769)	(-0.0024)	(-1.1603)	(-2.5163)				0.0626	0.4571	0.0465	0.0154	0.2049	0.0154
6	1	0.0149	0.0258	0.0154	0.0267	0.0229	0.2254	-0.0118	0.0029	-0.2100	0.5886	0.3430	0.3245	-0.0109	0.0104	0.0039	-0.2025	-0.0147	0.2129
		(1.3045)	(3.2407)	(3.5056)	(2.5573)	(2.2673)	(1.1675)	(-1.0411)	(0.2936)	(-1.0871)				0.2187	0.1263	0.3952	0.1487	0.1646	0.1368
	2	0.0137	0.0204	0.0156	0.0195	0.0236	0.1332	-0.0057	-0.0032	-0.1177	0.6854	0.2104	0.2003	-0.0066	0.0048	-0.0041	-0.1097	-0.0026	0.1145
		(2.0145)	(3.4948)	(4.3600)	(2.6008)	(3.1080)	(1.5027)	(-0.7357)	(-0.4459)	(-1.3304)				0.2300	0.2419	0.3514	0.1103	0.4038	0.0999
	3	0.0141	0.0190	0.0153	0.0149	0.0242	0.1498	-0.0009	-0.0052	-0.1345	0.7250	0.0726	0.0690	-0.0050	0.0037	-0.0092	-0.1256	0.0043	0.1293
		(2.7110)	(3.7817)	(4.9268)	(2.2688)	(3.5945)	(1.8802)	(-0.1386)	(-0.8877)	(-1.6892)				0.2469	0.2658	0.1639	0.0596	0.3082	0.0542
	6	0.0139	0.0149	0.0147	0.0074	0.0206	0.0988	0.0065	-0.0057	-0.0841	0.9755	0.0039	0.0037	-0.0010	0.0002	-0.0132	-0.0781	0.0122	0.0784
		(3.8110)	(3.8122)	(6.2986)	(1.7545)	(4.7053)	(2.7873)	(1.9756)	(-1.4329)	(-2.3877)				0.4248	0.4786	0.0153	0.0155	0.0096	0.0146
	9	0.0122	0.0143	0.0141	0.0025	0.0185	0.0746	0.0097	-0.0042	-0.0606	0.8397	0.0003	0.0004	-0.0021	0.0002	-0.0159	-0.0562	0.0139	0.0564
		(4.0576)	(4.4190)	(7.3712)	(0.6955)	(5.2527)	(3.3564)	(3.3122)	(-1.2178)	(-2.7405)				0.3172	0.4793	0.0009	0.0071	0.0012	0.0066
	12	0.0087	0.0141	0.0131	0.0018	0.0164	0.0615	0.0069	-0.0023	-0.0484	0.2344	0.0000	0.0001	-0.0053	0.0010	-0.0146	-0.0451	0.0093	0.0461
		(3.4397)	(5.1150)	(8.3073)	(0.6128)	(5.1837)	(3.7870)	(2.5422)	(-0.6966)	(-2.9892)				0.0787	0.3812	0.0005	0.0038	0.0169	0.0032
9	1	0.0183	0.0148	0.0156	0.0126	0.0328	0.2310	0.0057	-0.0180	-0.2153	0.9280	0.3357	0.3325	0.0035	-0.0009	-0.0201	-0.1982	0.0237	0.1973
		(2.3775)	(2.0059)	(3.2561)	(1.2988)	(2.1888)	(1.1615)	(0.6127)	(-1.2099)	(-1.0814)				0.3700	0.4604	0.1307	0.1614	0.0893	0.1627
	2	0.0138	0.0142	0.0136	0.0100	0.0315	0.1353	0.0038	-0.0173	-0.1218	0.9955	0.2099	0.2052	-0.0004	0.0007	-0.0215	-0.1038	0.0210	0.1045
		(2.5024)	(2.6228)	(3.7719)	(1.3191)	(2.2373)	(1.4830)	(0.5665)	(-1.2404)	(-1.3387)				0.4779	0.4602	0.0907	0.1317	0.0875	0.1295
	3	0.0130	0.0147	0.0131	0.0091	0.0268	0.1513	0.0039	-0.0122	-0.1382	0.9503	0.0748	0.0723	-0.0016	0.0016	-0.0178	-0.1245	0.0161	0.1260
		(2.9958)	(3.0732)	(4.4502)	(1.3247)	(2.6901)	(1.8431)	(0.6943)	(-1.2545)	(-1.6848)				0.4007	0.3895	0.0722	0.0677	0.0769	0.0652
	6	0.0105	0.0131	0.0128	0.0023	0.0225	0.0986	0.0082	-0.0094	-0.0858	0.8078	0.0046	0.0052	-0.0027	0.0003	-0.0203	-0.0761	0.0176	0.0764
		(3.2899)	(3.4285)	(5.7054)	(0.5109)	(3.1855)	(2.6900)	(2.6426)	(-1.3304)	(-2.3463)				0.2968	0.4731	0.0082	0.0221	0.0121	0.0214
	9	0.0077	0.0122	0.0117	-0.0004	0.0202	0.0778	0.0081	-0.0080	-0.0660	0.3695	0.0002	0.0004	-0.0046	0.0005	-0.0206	-0.0575	0.0161	0.0580
		(3.0246)	(4.0067)	(6.5888)	(-0.1197)	(4.2251)	(3.3802)	(3.6977)	(-1.5951)	(-2.8751)				0.1250	0.4433	0.0003	0.0080	0.0020	0.0076
	12	0.0045	0.0123	0.0110	0.0010	0.0164	0.0681	0.0034	-0.0042	-0.0571	0.0191	0.0000	0.0000	-0.0078	0.0013	-0.0154	-0.0517	0.0076	0.0530
		(2.1473)	(4.7370)	(7.6052)	(0.3397)	(4.7610)	(4.0091)	(1.7681)	(-1.0939)	(-3.3522)				0.0099	0.3369	0.0005	0.0018	0.0388	0.0015
12	1	0.0110	0.0167	0.0146	0.0112	0.0170	0.2340	-0.0001	-0.0003	-0.2194	0.8421	0.3208	0.3248	-0.0056	0.0021	-0.0058	-0.2171	0.0002	0.2191
		(1.4269)	(2.2231)	(2.9002)	(1.1128)	(1.6145)	(1.1392)	(-0.0133)	(-0.0291)	(-1.0660)				0.3010	0.4099	0.3447	0.1470	0.4945	0.1452
	2	0.0086	0.0178	0.0132	0.0085	0.0147	0.1382	0.0001	0.0030	-0.1250	0.4624	0.1703	0.1701	-0.0092	0.0045	-0.0062	-0.1235	-0.0030	0.1280
		(1.5258)	(2.9672)	(3.5700)	(1.1238)	(1.9648)	(1.4653)	(0.0091)	(0.4021)	(-1.3264)				0.1333	0.2613	0.2812	0.0975	0.3856	0.0895
	3	0.0072	0.0178	0.0124	0.0068	0.0157	0.1543	0.0003	0.0021	-0.1419	0.2354	0.0618	0.0623	-0.0106	0.0054	-0.0089	-0.1386	-0.0018	0.1440
		(1.5724)	(3.3533)	(4.0143)	(1.0316)	(2.4330)	(1.8170)	(0.0551)	(0.3181)	(-1.6692)				0.0649	0.1902	0.1691	0.0535	0.4206	0.0473
	6	0.0043	0.0154	0.0117	0.0013	0.0152	0.1048	0.0031	0.0003	-0.0931	0.0486	0.0019	0.0026	-0.0111	0.0038	-0.0139	-0.0896	0.0028	0.0934
		(1.4107)	(3.7770)	(5.1498)	(0.3140)	(3.4924)	(2.7610)	(0.9708)	(0.0605)	(-2.4497)				0.0156	0.2104	0.0103	0.0105	0.3096	0.0083
	9	0.0025	0.0146	0.0112	-0.0002	0.0157	0.0889	0.0027	-0.0011	-0.0777	0.0035	0.0000	0.0000	-0.0121	0.0034	-0.0159	-0.0732	0.0038	0.0766
		(1.0839)	(4.2587)	(6.4908)	(-0.0671)	(4.6079)	(3.6978)	(1.2048)	(-0.2867)	(-3.2266)				0.0020	0.1862	0.0004	0.0016	0.1920	0.0011
	12	0.0014	0.0136	0.0108	0.0020	0.0121	0.0731	-0.0006	0.0015	-0.0624	0.0004	0.0000	0.0000	-0.0122	0.0028	-0.0100	-0.0610	-0.0021	0.0639
		(0.6410)	(4.8586)	(7.6026)	(0.6704)	(4.2682)	(4.1838)	(-0.3017)	(0.4858)	(-3.5593)				0.0004	0.1861	0.0084	0.0004	0.2841	0.0003
Average		0.0118	0.0188	0.0185	0.0131	0.0240	0.1217	-0.0013	-0.0052	-0.1032	0.4843	0.1239	0.1553	-0.0071	0.0003	-0.0110	-0.0976	0.0039	0.0980
t-statisitc		(14.3613)	(19.3418)	(12.7607)	(7.3982)	(19.5975)	(11.9284)	(-1.0284)	(-5.1515)	(-9.7906)	(8.1302)	(4.7725)	(5.2889)	(-7.4970)	(0.3377)	(-9.7893)	(-9.8566)	(2.3215)	(9.3822)

Table 5: W/L Portfolio Returns by Different Periods. It shows that in all periods, the entire period, pre and during the financial crisis, the three groups have monotonically decreasing momentum for Portfolio Ws. It further confirms that investor heterogeneity among the three groups is decreasing. The ANOVA p-values show very low explain power, which indicates that momentum differences have to be found in the longer holding periods. In general, the momentum effect is decreasing from 2000 to 2017, this effect can be explained by the advert of Internet makes information asymmetry less significant, and the under-reaction over the short run and overreaction in the long run of prices have diminishing. Portfolio Ls show monotonically increasing returns except the post-financial crisis.

Sampling Period		Holding Period Monthly Return (Mean)									ANOVA (High Order, Low Order, Pure US) (p-Value)			t-Test for Two Groups(mean)					
		Portfolio W			Portfolio L			Portfolio W-L						Portfolio W		Portfolio L		Portfolio W-L	
		High	Low	US	High	Low	US	High	Low	US	Portfolio W	Portfolio L	Portfolio W-L	High/Low	Low/US	High/Low	Low/US	High/Low	Low/US
Entire Horizon	2000-2017	0.0477	0.0231	0.0172	0.0297	0.0328	0.4764	0.0180	-0.0096	-0.4592	0.2360	0.0709	0.0541	0.0246	0.0059	-0.0030	-0.4437	0.0276	0.4496
Pre-Financial Crisis	2000-2007	0.0971	0.0387	0.0249	0.0440	0.0485	0.1755	0.0532	-0.0097	-0.1506	0.1533	0.1683	0.0821	0.0584	0.0138	-0.0045	-0.1271	0.0629	0.1409
Financial Crisis	2007-2009	-0.0597	-0.0548	-0.0404	-0.0442	-0.0545	11.1476	-0.0155	-0.0003	-11.1880	0.5762	0.3963	0.3904	-0.0050	-0.0144	0.0103	-11.2021	-0.0153	11.1877
Post-Financial Crisis	2009-2017	0.0118	0.0188	0.0185	0.0131	0.0240	0.1217	-0.0013	-0.0052	-0.1032	0.4843	0.1239	0.1553	-0.0071	0.0003	-0.0110	-0.0976	0.0039	0.0980

Table 7: Momentum Test Results using trading volume turnover as a grouping measure. This table reports the momentum test results using trading volume turnover as an alternative investor heterogeneity filter, instead of individualism scores. Group One has the highest trading volume, and group five has the lowest. Higher trading volume turnover indicates higher participation rates and hence higher investor heterogeneity.

Starting Dat	1/3/2000	End Date	12/29/2017					No.of Firms in each g		10%			Rolling Period		21 days																				
Formation Period (month)	Holding Period (month)	Holding Period Monthly Return (Mean, t-statistic)																ANOVA (Group1,Group2,Group3)			ANOVA (Group3,Group4,Group5)			t-Test for Two Groups(mean differences, p-value)						t-Test for Two Groups(mean differences, p-value)					
		Portfolio W					Portfolio L					Portfolio W-L												Portfolio W			Portfolio L			Portfolio W-L			Portfolio W			Portfolio L			Portfolio W-L		
		Group1	Group2	Group3	Group4	Group5	Group1	Group2	Group3	Group4	Group5	Group1	Group2	Group3	Group4	Group5		Portfolio W	Portfolio L	Portfolio W-L	Portfolio W	Portfolio L	Portfolio W-L	Group1/ Group2	Group2/ Group3		Group1/ Group2	Group2/ Group3		Group1/ Group2	Group2/ Group3		Group3/ Group4	Group4/ Group5		Group3/ Group4	Group4/ Group5		Group3/ Group4	Group4/ Group5	
6	1	0.0234	0.0201	0.0259	0.0150	0.0115	0.4009	0.0357	0.0333	0.1650	0.0468	-0.3774	-0.0156	-0.0074	-0.1500	-0.0353	0.8645	0.2382	0.2398	0.3375	0.2903	0.2615	0.0033	-0.0058	0.3651	0.0024	-0.3618	-0.0082	0.0108	0.0036	-0.1320	0.1182	0.1428	-0.1146
		(3.7858)	(4.3585)	(2.4242)	(2.9577)	(2.9235)	(1.3131)	(3.8207)	(4.2789)	(1.4688)	(4.2592)	(-1.2349)	(-2.0216)	(-0.6543)	(-1.3364)	(-3.4149)								0.3340	0.3097	0.1166	0.4215	0.1190	0.2747	0.1801	0.2901	0.1212	0.1481	0.1034	0.1551
	2	0.0217	0.0201	0.0245	0.0134	0.0128	0.3735	0.0300	0.0305	0.1558	0.0381	-0.3518	-0.0099	-0.0060	-0.1424	-0.0253	0.8749	0.0771	0.0763	0.2970	0.1140	0.0907	0.0016	-0.0044	0.3435	-0.0005	-0.3419	-0.0039	0.0109	0.0006	-0.1257	0.1177	0.1366	-0.1171
		(5.1699)	(5.4360)	(2.7373)	(3.7194)	(3.7583)	(1.7479)	(4.0207)	(4.0676)	(1.9029)	(4.9567)	(-1.6469)	(-1.6962)	(-0.5848)	(-1.7465)	(-3.6420)								0.3874	0.3249	0.0548	0.4812	0.0556	0.3707	0.1274	0.4555	0.0639	0.0770	0.0489	0.0769
	3	0.0229	0.0213	0.0222	0.0140	0.0129	0.2900	0.0266	0.0305	0.1662	0.0333	-0.2672	-0.0053	-0.0083	-0.1522	-0.0204	0.9712	0.0513	0.0528	0.2727	0.0447	0.0365	0.0016	-0.0009	0.2634	-0.0039	-0.2618	0.0030	0.0082	0.0011	-0.1358	0.1329	0.1439	-0.1318
		(6.1241)	(6.6317)	(3.4220)	(4.4456)	(4.7456)	(1.9193)	(4.4034)	(4.6019)	(2.2029)	(5.1360)	(-1.7669)	(-1.1917)	(-1.0141)	(-2.0262)	(-3.5201)								0.3725	0.4495	0.0415	0.3329	0.0425	0.3752	0.1288	0.3939	0.0372	0.0404	0.0291	0.0409
	6	0.0223	0.0213	0.0194	0.0153	0.0135	0.3328	0.0271	0.0252	0.1411	1.6728	-0.3105	-0.0058	-0.0057	-0.1258	-1.6593	0.8335	0.0271	0.0284	0.3759	0.0604	0.0597	0.0010	0.0019	0.3057	0.0020	-0.3047	-0.0001	0.0041	0.0018	-0.1161	-1.5317	0.1201	1.5335
		(7.7926)	(7.7718)	(4.8774)	(5.6923)	(6.2154)	(2.0692)	(4.7792)	(5.4644)	(2.5632)	(1.7623)	(-1.9299)	(-1.3389)	(-1.2150)	(-2.2951)	(-1.7473)								0.4108	0.3498	0.0294	0.3944	0.0299	0.4941	0.1989	0.3004	0.0184	0.0543	0.0150	0.0542
	9	0.0227	0.0204	0.0146	0.0168	0.0132	0.2332	0.0264	0.0280	0.1148	2.1442	-0.2105	-0.0060	-0.0134	-0.0980	-2.1310	0.0881	0.0057	0.0074	0.5109	0.0043	0.0043	0.0023	0.0057	0.2069	-0.0017	-0.2045	0.0074	-0.0024	0.0037	-0.0871	-2.0293	0.0847	2.0330
		(7.0695)	(8.4670)	(6.3951)	(6.2416)	(7.4785)	(2.5960)	(5.1491)	(4.0832)	(2.8987)	(2.4199)	(-2.3389)	(-1.5380)	(-2.0651)	(-2.4778)	(-2.4035)								0.2795	0.4020	0.0112	0.4222	0.0121	0.1642	0.2522	0.1274	0.0157	0.0116	0.0178	0.0115
	12	0.0226	0.0201	0.0133	0.0157	0.0125	0.4319	0.0278	0.0490	0.1205	1.0856	-0.4093	-0.0076	-0.0357	-0.1047	-1.0731	0.0268	0.1976	0.2069	0.4889	0.0205	0.0203	0.0024	0.0068	0.4041	-0.0213	-0.4017	0.0281	-0.0024	0.0032	-0.0714	-0.9652	0.0690	0.9684
		(7.0814)	(9.1677)	(6.5776)	(6.8123)	(8.1448)	(1.3999)	(5.8574)	(3.0364)	(3.6388)	(2.1469)	(-1.3264)	(-1.9951)	(-2.2170)	(-3.1825)	(-2.1201)								0.2646	0.0112	0.0959	0.1038	0.0972	0.0456	0.2132	0.1239	0.0266	0.0291	0.0303	0.0288
9	1	0.0217	0.0189	0.0274	0.0159	0.0122	0.4103	0.0336	0.0440	0.1656	3.0522	-0.3885	-0.0147	-0.0166	-0.1497	-3.0399	0.7394	0.2384	0.2369	0.3120	0.3807	0.3783	0.0029	-0.0085	0.3767	-0.0104	-0.3738	0.0019	0.0114	0.0037	-0.1223	-2.8866	0.1337	2.8903
		(3.4756)	(3.9231)	(2.4702)	(3.2955)	(3.1348)	(1.3252)	(3.7382)	(3.4502)	(1.4550)	(1.0160)	(-1.2537)	(-1.9226)	(-1.0630)	(-1.3163)	(-1.0118)								0.3579	0.2414	0.1126	0.2530	0.1146	0.4566	0.1711	0.2776	0.1432	0.1690	0.1226	0.1688
	2	0.0190	0.0187	0.0249	0.0155	0.0115	0.3838	0.0276	0.0313	0.1598	3.0450	-0.3647	-0.0089	-0.0064	-0.1443	-3.0335	0.7314	0.0704	0.0673	0.2662	0.1449	0.1434	0.0003	-0.0062	0.3561	-0.0036	-0.3558	-0.0026	0.0093	0.0040	-0.1288	-2.8852	0.1381	2.8892
		(4.4945)	(5.2911)	(2.6852)	(4.3307)	(4.0585)	(1.7699)	(3.8434)	(4.2299)	(1.9082)	(1.4372)	(-1.6838)	(-1.5316)	(-0.6041)	(-1.7303)	(-1.4313)								0.4756	0.2664	0.0511	0.3620	0.0510	0.4159	0.1739	0.1885	0.0635	0.0875	0.0509	0.0873
	3	0.0205	0.0198	0.0177	0.0152	0.0121	0.2936	0.0257	0.0263	0.1692	3.3625	-0.2731	-0.0059	-0.0086	-0.1540	-3.3504	0.8547	0.0485	0.0505	0.4783	0.0565	0.0562	0.0006	0.0021	0.2679	-0.0006	-0.2673	0.0027	0.0025	0.0031	-0.1431	-3.1933	0.1455	3.1964
		(5.5030)	(6.2899)	(4.4996)	(4.8418)	(4.8985)	(1.9163)	(4.3220)	(4.8420)	(2.2129)	(1.7458)	(-1.7810)	(-1.2715)	(-1.6555)	(-2.0202)	(-1.7388)								0.4476	0.3388	0.0410	0.4695	0.0415	0.3483	0.3132	0.2199	0.0317	0.0496	0.0291	0.0495
	6	0.0198	0.0192	0.0156	0.0152	0.0127	0.3385	0.0276	0.0460	0.1646	3.2689	-0.3187	-0.0083	-0.0304	-0.1495	-3.2562	0.5152	0.0344	0.0361	0.6626	0.0045	0.0045	0.0005	0.0036	0.3109	-0.0184	-0.3104	0.0220	0.0004	0.0025	-0.1187	-3.1042	0.1191	3.1067
		(6.2724)	(7.4505)	(6.0331)	(5.7073)	(6.2838)	(2.0739)	(4.8992)	(2.7321)	(2.7982)	(2.4132)	(-1.9530)	(-1.8572)	(-1.7950)	(-2.5460)	(-2.4024)								0.4479	0.1600	0.0292	0.1505	0.0293	0.1047	0.4535	0.2301	0.0268	0.0115	0.0262	0.0115
	9	0.0199	0.0189	0.0133	0.0151	0.0118	0.2361	0.0303	0.0700	0.1567	2.5982	-0.2162	-0.0114	-0.0567	-0.1416	-2.5865	0.1244	0.0181	0.0204	0.5249	0.0010	0.0010	0.0010	0.0056	0.2058	-0.0397	-0.2048	0.0453	-0.0018	0.0033	-0.0867	-2.4415	0.0849	2.4448
		(6.7231)	(8.3328)	(6.4756)	(6.3141)	(7.1913)	(2.5943)	(5.6048)	(3.0040)	(3.4237)	(2.7613)	(-2.3742)	(-2.5977)	(-2.4146)	(-3.0935)	(-2.7468)								0.3931	0.0342	0.0125	0.0493	0.0129	0.0297	0.2892	0.1282	0.0462	0.0051	0.0499	0.0051
	12	0.0195	0.0181	0.0125	0.0150	0.0107	0.4409	0.0321	0.0667	0.1530	1.2602	-0.4214	-0.0140	-0.0542	-0.1380	-1.2495	0.0816	0.2096	0.2160	0.2895	0.0093	0.0092	0.0014	0.0056	0.4088	-0.0346	-0.4074	0.0402	-0.0025	0.0042	-0.0863	-1.1072	0.0838	1.1115
		(8.8495)	(8.5051)	(6.3032)	(6.6835)	(7.4968)	(1.4087)	(6.3628)	(3.0814)	(4.1272)	(2.3816)	(-1.3465)	(-3.3633)	(-2.4895)	(-3.7363)	(-2.3590)								0.3480	0.0264	0.0965	0.0603	0.0972	0.0354	0.2011	0.0558	0.0225	0.0190	0.0257	0.0188
	18	0.0166	0.0167	0.0126	0.0170	0.0103	0.1995	0.0324	0.0811	0.1179	0.1575	-0.1829	-0.0156	-0.0684	-0.1009	-0.1472	0.1838	0.1256	0.1279	0.0177	0.6178	0.5984	-0.0002	0.0041	0.1671	-0.0487	-0.1673	0.0528	-0.0044	0.0067	-0.0372	-0.0396	0.0328	0.0463
		(8.1652)	(9.4230)	(8.3614)	(7.5658)	(9.2503)	(1.9814)	(8.7512)	(3.6413)	(4.7661)	(1.7466)	(-1.8175)	(-4.9164)	(-3.0870)	(-4.4825)	(-1.6291)								0.4742	0.0393	0.0493	0.0160	0.0491	0.0097	0.0510	0.0041	0.1315	0.3360	0.1615	0.3107
	24	0.0158	0.0169	0.0128	0.0171	0.0108	0.1634	0.0367	0.1179	0.0931	0.0637	-0.1477	-0.0198	-0.1051	-0.0760	-0.0530	0.1602	0.2244	0.2141	0.0309	0.1892	0.2093	-0.0011	0.0041	0.1267	-0.0812	-0.1279	0.0853	-0.0044	0.0063	0.0242	0.0294	-0.0286	-0.0230
		(8.9127)	(10.4256)	(9.9206)	(6.7324)	(10.8403)	(1.9067)	(9.2763)	(3.9453)	(5.3664)	(6.0921)	(-1.7227)	(-5.4752)	(-3.5564)	(-4.3675)	(-4.9706)								0.3209	0.0236	0.0706	0.0038	0.0688	0.0023	0.0616	0.0105	0.2414	0.0740	0.2016	0.1300
12	1	0.0254	0.0203	0.0292	0.0187	0.0153	0.4113	0.0337	0.0337	0.1738	3.1104	-0.3859	-0.0135	-0.0045	-0.1551	-3.0951	0.7229	0.2370	0.2391	0.3841	0.3821	0.3800	0.0051	-0.0090	0.3776	0.0000	-0.3724	-0.0090	0.0105	0.0034	-0.1401	-2.9366	0.1505	2.9400
		(4.0276)	(4.2883)	(2.6187)	(3.9076)	(3.7704)	(1.3096)	(3.6677)	(4.3478)	(1.5008)	(1.0154)	(-1.2273)	(-1.7556)	(-0.3808)	(-1.3370)	(-1.0103)								0.2584	0.2302	0.1155	0.4997	0.1189	0.2639	0.1947	0.2931	0.1145	0.1696	0.0990	0.1694
	2	0.0203	0.0183	0.0181	0.0162	0.0140	0.3868	0.0290	0.0478	0.1708	3.1448	-0.3665	-0.0108	-0.0297	-0.1547	-3.1307	0.9048	0.0839	0.0864	0.7221	0.1470	0.1466	0.0020	0.0002	0.3577	-0.0187	-0.3557	0.0190	0.0019	0.0021	-0.1231	-2.9739	0.1250	2.9761
		(4.8123)	(5.2221)	(4.4720)	(4.6016)	(4.7394)	(1.7585)	(3.8669)	(2.2596)	(1.9998)	(1.4371)	(-1.6661)	(-1.7132)	(-1.4224)	(-1.8138)	(-1.4302)								0.3564	0.4817	0.0528	0.2023	0.0538	0.1927	0.3619	0.3211	0.0817	0.0880	0.0780	0.0879
	3	0.0196	0.0183	0.0152	0.0150	0.0123	0.2996	0.0268	0.0692	0.2140	3.4496	-0.2800	-0.0084	-0.0540	-0.1990	-3.4373	0.6129	0.0784	0.0829	0.7342	0.0608	0.0607	0.0013	0.0031	0.2729	-0.0424	-0.2716	0.0455	0.0002	0.0026	-0.1452	-3.2356	0.1454	3.2382
		(5.4834)	(5.8984)	(5.0879)	(4.7477)	(5.0482)	(1.9272)	(4.3871)	(2.0938)	(2.5007)	(1.7493)	(-1.7977)	(-1.6704)	(-1.6292)	(-2.3305)	(-1.7423)								0.3929	0.2352	0.0405	0.1041	0.0414	0.0877	0.4785	0.2539	0.0572	0.0514	0.0567	0.0513
	6	0.0180	0.0180	0.0137	0.0144	0.0121	0.3465	0.0301	0.1019	0.2274	3.3837	-0.3286	-0.0122	-0.0882	-0.2130	-3.3716	0.4143	0.0566	0.0582	0.7767	0.0053	0.0053	0.0000	0.0042	0.3164	-0.0718	-0.3164	0.0760	-0.0006	0.0023	-0.1255	-3.1563	0.1249	3.1586
		(6.1686)	(7.3506)	(5.7324)	(5.5492)	(6.1930)	(2.0939)	(5.2355)	(2.9432)	(3.3908)	(2.4194)	(-1.9848)	(-2.6167)	(-2.5271)	(-3.1887)	(-2.4093)								0.4984	0.1095	0.0287	0.0210	0.0287	0.0160	0.4292	0.2425	0.0487	0.0126	0.0493	0.0126
	9	0.0183	0.0169	0.0118	0.0138	0.0106	0.2391	0.0320	0.1047	0.2001	2.6983	-0.2208	-0.0152	-0.0929	-0.1863	-2.6877	0.1212	0.0322	0.0350	0.5139	0.0011	0.0011	0.0014	0.0050	0.2071	-0.0727	-0.2057	0.0778	-0.0020	0.0032	-0.0953	-2.4983	0.0934	2.5014
		(6.5961)	(7.6610)	(6.0831)	(5.9917)	(6.7754)	(2.5908)	(5.8714)	(3.2491)	(3.9687)	(2.7887)	(-2.3914)	(-3.4673)	(-2.8671)	(-3.7034)	(-2.7755)								0.3452	0.0434	0.0131	0.0136	0.0136	0.0092	0.2574	0.1277	0.0560	0.0053	0.0598	0.0053
	12	0.0180	0.0165	0.0120	0.0149	0.0099	0.4578	0.0324	0.1105	0.1820	1.3161	-0.4398	-0.0159	-0.0985	-0.1671	-1.3062	0.1113	0.2222	0.2274	0.1648	0.0116	0.0114	0.0016	0.0045	0.4254	-0.0781	-0.4238	0.0826	-0.0029	0.0050	-0.0715	-1.1341	0.0686	1.1391
		(7.4298)	(8.2801)	(6.3965)	(6.5587)	(7.4714)	(1.4414)	(6.6335)	(3.2977)	(4.5825)	(2.3914)	(-1.3847)	(-3.9990)	(-2.9263)	(-4.2201)	(-2.3711)								0.3076	0.0516	0.0910	0.0110	0.0918	0.0078	0.1643	0.0291	0.0848	0.0206	0.0937	0.0202
	18	0.0169	0.0151	0.0120	0.0163	0.0099	0.2019	0.0364	0.1299	0.1362	0.1658	-0.1851	-0.0213	-0.1178	-0.1198	-0.1559	0.1164	0.1650	0.1694	0.0167	0.8998	0.8771	0.0017	0.0031	0.1655	-0.0934	-0.1638	0.0965	-0.0043	0.0064	-0.0063	-0.0297	0.0020	0.0361
		(8.5964)	(9.6129)	(8.4252)	(7.5972)	(9.2656)	(1.9772)	(8.7035)	(4.1470)	(5.1873)	(1.7660)	(-1.8125)	(-5.8515)	(-3.7761)	(-4.5693)	(-1.6575)								0.2453	0.0723	0.0535	0.0017	0.0553	0.0012	0.0483	0.0039	0.4387	0.3806	0.4804	0.3560
	24	0.0167	0.0149	0.0122	0.0162	0.0104	0.1664	0.0385	0.2009	0.1107	0.0695	-0.1497	-0.0236	-0.1887	-0.0946	-0.0591	0.1013	0.1134	0.1083	0.0330	0.0104	0.0103	0.0017	0.0028	0.1278	-0.1623	-0.1261	0.1651	-0.0041	0.0058	0.0891	0.0413	-0.0932	-0.0355
		(9.0990)	(10.5466)	(10.1749)	(6.9429)	(11.0071)	(1.9131)	(8.6284)	(4.0485)	(6.0003)	(6.3764)	(-1.7213)	(-5.8670)	(-3.8226)	(-5.1093)	(-5.3282)								0.2278	0.0664	0.0718	0.0007	0.0745	0.0005	0.0601	0.0112	0.0460	0.0275	0.0385	0.0505
Average		0.0201	0.0186	0.0173	0.0155	0.0120	0.3199	0.0308	0.0672	0.1572	1.7803	-0.2998	-0.0123	-0.0499	-0.1417	-1.7684	0.4616	0.1161	0.1176	0.3732	0.1571	0.1530	0.0015	0.0013	0.2891	-0.0363	-0.2876	0.0376	0.0017	0.0036	-0.0902	-1.6231	0.0920	1.6267
t-statisitc		(36.8761)	(47.9441)	(14.1384)	(59.6385)	(40.1661)	(16.1422)	(38.1390)	(7.0487)	(22.1974)	(6.0692)	(-15.3524)	(-11.1078)	(-4.8163)	(-19.6359)	(-6.0311)	(6.1880)	(6.5082)	(6.5823)	(7.4665)	(3.1788)	(3.1716)	(5.3427)	(1.2221)	(14.4290)	(-4.0407)	########	(3.9553)	(1.4224)	(10.1087)	(-7.0540)	(-5.6162)	(6.7532)	(5.6309)

Table 8. Momentum test results by TV turnover 2009-2017.

Starting Da	3/10/2009	End Date	12/29/2017		No.of Firms in each g		10%	Rolling Period		21 days											
Formation Period (month)	Holding Period (month)	Holding Period Monthly Return (Mean, t-statistic)									ANOVA (Group1,Group3,Group5)			t-Test for Two Groups(mean differences, p-value)					
		Portfolio W			Portfolio L			Portfolio W-L						Portfolio W		Portfolio L		Portfolio W-L	
		Group1	Group3	Group5	Group1	Group3	Group5	Group1	Group3	Group5	Portfolio W	Portfolio L	Portfolio W-L	group1/group3	group3/Group5	group1/group3	group3/Group5	group1/group3	group3/Group5
6	1	0.0157	0.0162	0.0139	0.8365	0.0300	0.0507	-0.8208	-0.0138	-0.0368	0.9507	0.3813	0.3823	-0.0005	0.0023	0.8065	-0.0206	-0.8070	0.0229
		(2.5675)	(3.1476)	(3.0931)	(1.0333)	(3.8346)	(2.9447)	(-1.0133)	(-2.3615)	(-2.1965)				0.4732	0.3698	0.1608	0.1384	0.1608	0.0992
	3	0.0175	0.0142	0.0131	0.5368	0.0248	0.0433	-0.5193	-0.0106	-0.0302	0.6610	0.1047	0.1088	0.0033	0.0011	0.5120	-0.0185	-0.5087	0.0197
		(4.1896)	(4.0792)	(4.3370)	(1.6103)	(4.5250)	(4.1686)	(-1.5560)	(-2.7264)	(-3.1117)				0.2712	0.4034	0.0639	0.0583	0.0653	0.0312
	6	0.0161	0.0126	0.0147	0.3321	0.0184	0.0388	-0.3160	-0.0057	-0.0241	0.6417	0.0158	0.0169	0.0035	-0.0021	0.3137	-0.0205	-0.3102	0.0184
		(5.2603)	(5.0303)	(6.4602)	(2.2444)	(5.0100)	(5.1934)	(-2.1342)	(-2.5592)	(-3.5264)				0.1893	0.2703	0.0183	0.0076	0.0194	0.0060
	9	0.0153	0.0116	0.0153	0.2404	0.0151	0.0291	-0.2251	-0.0035	-0.0138	0.3871	0.0043	0.0047	0.0037	-0.0037	0.2253	-0.0140	-0.2216	0.0103
		(5.9352)	(6.0451)	(7.7444)	(2.5977)	(5.0435)	(6.1083)	(-2.4294)	(-1.7689)	(-3.0949)				0.1269	0.0914	0.0084	0.0069	0.0093	0.0178
	12	0.0143	0.0107	0.0144	0.1792	0.0130	0.0382	-0.1649	-0.0023	-0.0238	0.2459	0.0062	0.0073	0.0036	-0.0037	0.1662	-0.0252	-0.1626	0.0216
		(6.6955)	(7.5205)	(8.8008)	(2.6579)	(5.6044)	(3.8261)	(-2.4386)	(-1.4306)	(-2.3508)				0.0835	0.0465	0.0077	0.0077	0.0090	0.0190
9	1	0.0170	0.0154	0.0135	0.8571	0.0307	0.0479	-0.8401	-0.0153	-0.0344	0.9083	0.3839	0.3866	0.0015	0.0020	0.8264	-0.0171	-0.8248	0.0191
		(2.3410)	(3.1596)	(3.0203)	(1.0272)	(3.3355)	(2.6394)	(-1.0063)	(-1.8619)	(-1.9188)				0.4311	0.3822	0.1622	0.2003	0.1628	0.1670
	3	0.0149	0.0106	0.0142	0.5474	0.0239	0.0377	-0.5325	-0.0132	-0.0235	0.6446	0.1062	0.1087	0.0043	-0.0036	0.5235	-0.0138	-0.5192	0.0103
		(3.6319)	(3.4158)	(4.6422)	(1.5935)	(3.7778)	(3.6051)	(-1.5494)	(-2.3950)	(-2.2793)				0.2037	0.2070	0.0654	0.1294	0.0671	0.1907
	6	0.0139	0.0114	0.0145	0.3378	0.0171	0.0308	-0.3239	-0.0057	-0.0164	0.6752	0.0155	0.0159	0.0025	-0.0030	0.3207	-0.0137	-0.3182	0.0107
		(4.9338)	(4.8438)	(5.7588)	(2.2143)	(4.1896)	(4.3526)	(-2.1229)	(-1.6697)	(-2.4489)				0.2513	0.1903	0.0191	0.0479	0.0199	0.0782
	9	0.0126	0.0105	0.0137	0.2446	0.0139	0.0403	-0.2320	-0.0035	-0.0267	0.5248	0.0062	0.0065	0.0021	-0.0032	0.2307	-0.0264	-0.2286	0.0232
		(5.5770)	(6.1317)	(6.5366)	(2.5664)	(4.5844)	(3.1982)	(-2.4346)	(-1.4316)	(-2.0663)				0.2245	0.1181	0.0087	0.0221	0.0092	0.0400
	12	0.0114	0.0094	0.0132	0.1832	0.0124	0.0643	-0.1718	-0.0030	-0.0511	0.2448	0.0132	0.0141	0.0020	-0.0038	0.1707	-0.0519	-0.1688	0.0481
		(6.4053)	(7.4791)	(7.8118)	(2.6379)	(5.7145)	(3.2057)	(-2.4746)	(-1.6626)	(-2.4990)				0.1817	0.0370	0.0079	0.0058	0.0085	0.0106
12	1	0.0173	0.0135	0.0158	0.8780	0.0203	0.0400	-0.8608	-0.0068	-0.0242	0.9022	0.3807	0.3836	0.0038	-0.0023	0.8577	-0.0197	-0.8539	0.0174
		(2.3544)	(2.6146)	(3.1711)	(1.0195)	(2.7761)	(2.1627)	(-0.9987)	(-1.1023)	(-1.3149)				0.3374	0.3729	0.1610	0.1622	0.1622	0.1866
	3	0.0149	0.0127	0.0155	0.5628	0.0182	0.0303	-0.5479	-0.0055	-0.0148	0.8443	0.1016	0.1030	0.0022	-0.0028	0.5446	-0.0121	-0.5424	0.0093
		(3.6167)	(3.8045)	(4.8616)	(1.5870)	(3.6295)	(3.2283)	(-1.5428)	(-1.5263)	(-1.6575)				0.3389	0.2735	0.0640	0.1288	0.0651	0.1684
	6	0.0120	0.0116	0.0139	0.3477	0.0138	0.0479	-0.3358	-0.0022	-0.0340	0.7976	0.0187	0.0186	0.0003	-0.0023	0.3339	-0.0341	-0.3336	0.0318
		(4.0882)	(4.9645)	(5.6118)	(2.2108)	(4.2131)	(2.5614)	(-2.1327)	(-0.9809)	(-1.8002)				0.4630	0.2512	0.0182	0.0377	0.0184	0.0488
	9	0.0110	0.0096	0.0138	0.2522	0.0120	0.0784	-0.2412	-0.0023	-0.0646	0.3266	0.0125	0.0126	0.0014	-0.0042	0.2403	-0.0664	-0.2389	0.0623
		(4.9455)	(5.7223)	(6.6473)	(2.5683)	(4.5822)	(2.9010)	(-2.4578)	(-1.2651)	(-2.3777)				0.3135	0.0602	0.0082	0.0081	0.0084	0.0122
	12	0.0117	0.0095	0.0132	0.1900	0.0117	0.0800	-0.1783	-0.0022	-0.0668	0.2717	0.0141	0.0152	0.0022	-0.0037	0.1783	-0.0683	-0.1761	0.0646
		(5.8139)	(7.0632)	(8.8882)	(2.6584)	(5.7494)	(3.5824)	(-2.4955)	(-1.4589)	(-2.9994)				0.1779	0.0321	0.0072	0.0015	0.0078	0.0024
Average		0.0135	0.0112	0.0133	0.4079	0.0172	0.0436	-0.3944	-0.0060	-0.0303	0.5641	0.0978	0.0991	0.0022	-0.0021	0.3907	-0.0264	-0.3884	0.0243
t-statisitc		(23.7567)	(20.5801)	(60.1308)	(6.2338)	(10.4729)	(10.5546)	(-6.0656)	(-5.0150)	(-7.0971)	(8.5881)	(2.5518)	(2.5733)	(6.4357)	(-3.6799)	(6.1042)	(-5.4315)	(-6.0638)	(5.2074)

Table 9: Regression statistics for trading volume turnover. The regression equation is $Volume\ Turnover_i = \alpha_i + \beta_i|return_i| + \varepsilon_i$ *. For each firm group, the coefficient is beta, and its next columns are beta's t-statistic and p-value respectively. R-square is the Goodness of fit of the regressions. Average TV turnover is the average monthly trading volume turnover over the corresponding periods. As mentioned in Section III, trading volume turnover self represents investor heterogeneity from another dimension. The last two columns show the differences in means and the p-values of the tests between groups.*

Period	High Order Foreign Listed Firms					Low Order Foreign Listed Firms					Pure US Foreign Listed Firms					t-Tests Between	
	Coefficient	t-statistic	p-value	R Square	Average TV Turnover	Coefficient	t-statistic	p-value	R Square	Average TV Turnover	Coefficient	t-statistic	p-value	R Square	Average TV Turnover	High-Low	Low-US
2000-2017	0.7834	3.1730	0.1443	0.0898	0.1851	0.2672	3.0092	0.1713	0.0730	0.0976	0.4052	4.0067	0.0900	0.1034	0.1599	0.5163	-0.1381
	(2.0771)	(14.8997)	(6.6333)	(10.0137)	(3.9150)	(7.4187)	(16.2671)	(8.7197)	(12.9281)	(13.1004)	(26.3021)	(56.8462)	(18.8635)	(40.3921)	(42.0193)	0.0890	0.0003
2000-2007	0.2859	1.4848	0.3246	0.1140	0.1595	0.1300	1.3807	0.3145	0.0773	0.0787	0.2079	2.0317	0.2435	0.0964	0.1288	0.1559	-0.0778
	(3.2213)	(4.3801)	(10.9230)	(5.6557)	(3.6021)	(4.0711)	(9.4082)	(12.9660)	(8.0802)	(8.7217)	(17.7954)	(35.3290)	(31.2839)	(27.3773)	(38.6094)	0.0503	0.0115
2007-2009	0.1318	1.3990	0.3046	0.1653	0.1701	0.1215	1.4593	0.3055	0.1571	0.0901	0.2765	1.4757	0.3054	0.1627	0.1905	0.0104	-0.1550
	(2.6226)	(9.5401)	(10.8929)	(10.7124)	(4.6872)	(7.3286)	(12.9073)	(13.6040)	(13.2719)	(9.9429)	(25.6230)	(34.4100)	(38.8625)	(36.8932)	(42.8272)	0.4226	0.0000
2009-2017	0.3029	1.5499	0.3024	0.1494	0.1819	0.2500	1.5610	0.3029	0.1433	0.1683	0.4449	3.4403	0.1042	0.1269	0.1699	0.0529	-0.1949
	(8.2431)	(33.5165)	(38.3409)	(35.3944)	(30.1602)	(20.3273)	(33.9169)	(38.3942)	(34.9578)	(39.5757)	(27.1854)	(56.6353)	(20.5060)	(42.4058)	(40.0212)	0.0863	0.0000

Table 10.Regression Analysis with 5% omitted each stock category.

Period (-5%)	High Order Foreign Listed Firms					Low Order Foreign Listed Firms					Pure US Foreign Listed Firms					t-Tests Between	
	Coefficient	t-statistic	p-value	R Square	Average TV	Coefficient	t-statistic	p-value	R Square	Average TV	Coefficient	t-statistic	p-value	R Square	Average TV Turnover	High-Low	Low-US
2000-2017	0.7982	3.1989	0.1459	0.0923	0.1868	0.2870	2.9992	0.1773	0.0749	0.1051	0.4011	3.9704	0.0907	0.1026	0.1591	0.7112	-0.1141
	(1.9193)	(14.1159)	(6.2651)	(9.4134)	(3.6536)	(7.2053)	(14.8541)	(8.3277)	(12.0948)	(12.9787)	(25.5019)	(55.6865)	(18.6522)	(39.5224)	(41.0299)	0.0082	0.0000
2000-2007	0.2481	1.6778	0.2996	0.1260	0.1291	0.1423	1.4673	0.2936	0.0839	0.0852	0.2070	2.0339	0.2450	0.0974	0.1272	0.1958	-0.0647
	(3.5537)	(4.4609)	(9.9852)	(5.5969)	(6.2845)	(3.9945)	(9.1928)	(11.6686)	(7.9430)	(8.5902)	(17.2312)	(34.4448)	(30.7523)	(26.7431)	(37.8763)	0.0503	0.0020
2007-2009	0.1119	1.3527	0.3130	0.1649	0.1432	0.1226	1.4699	0.2994	0.1598	0.0937	0.2643	1.4313	0.3126	0.1584	0.1876	-0.0107	-0.1417
	(2.1246)	(8.4999)	(10.4684)	(9.9440)	(7.1852)	(6.8853)	(12.2348)	(12.9444)	(12.7882)	(9.5721)	(24.3725)	(32.9152)	(38.8233)	(35.6074)	(41.6421)	0.0042	0.0000
2009-2017	0.3030	1.5335	0.3048	0.1497	0.1827	0.2518	1.5412	0.3064	0.1441	0.1700	0.4397	3.4187	0.1050	0.1259	0.1697	0.3511	-0.1879
	(8.1667)	(33.1089)	(38.4346)	(35.1586)	(30.0949)	(20.2004)	(33.2564)	(38.4787)	(34.7118)	(39.6489)	(26.3943)	(55.1985)	(20.3409)	(41.3357)	(39.1768)	0.0186	0.0000

Table 11. Regression analysis around earnings announcements

Period	High Order Foreign Listed Firms					Low Order Foreign Listed Firms					Pure US Foreign Listed Firms					t-Tests Between	
	Coefficient	t-statistic	p-value	R Square	Average TV	Coefficient	t-statistic	p-value	R Square	Average TV	Coefficient	t-statistic	p-value	R Square	Average TV Turnover	High-Low	Low-US
2000-2017 EA	-0.0135	0.0367	0.4963	0.1029	0.0091	-0.0035	0.0550	0.5011	0.1021	0.0063	-0.0023	0.0350	0.4961	0.1028	0.0081	-0.0101	-0.0011
	(-1.5436)	(2.6470)	(148.6035)	(67.9868)	(14.1761)	(-0.6153)	(3.6223)	(185.6746)	(82.3403)	(24.0881)	(-1.0073)	(5.9196)	(531.2334)	(242.7924)	(123.0417)	0.1669	0.4266
2000-2007 EA	0.0028	0.0558	0.4905	0.1067	0.0073	0.0056	0.0755	0.5104	0.1013	0.0052	0.0006	0.0464	0.4956	0.1029	0.0067	-0.0028	0.0050
	0.513107041	2.070288	76.09373	35.60092	11.21015	1.360573899	3.332377	104.8806195	43.79399	17.59368	0.361046	2.890854	289.998256	132.54042	84.71918272	0.3411	0.1313
2007-2009 EA	0.0100	0.1188	0.4996	0.1016	0.0103	-0.0007	0.0386	0.5224	0.0981	0.0055	-0.0019	-0.0007	0.4923	0.1041	0.0097	0.0107	0.0012
	1.232080156	2.584708	45.246214	19.6078	9.150302	-0.18737185	1.04927	56.71143885	23.40321	21.56283	-0.6753275	-0.05351	150.442726	69.865484	72.99669391	0.1151	0.4098
2009-2017 EA	-0.0237	0.0170	0.4979	0.1016	0.0097	-0.0086	0.0471	0.4928	0.1032	0.0071	-0.0038	0.0341	0.4969	0.1025	0.0086	-0.0151	-0.0048
	-1.762448103	0.980408	119.17354	54.52285	10.15457	-0.94037848	2.161564	142.34666	65.93031	17.22361	(-1.0555)	(6.4037)	(418.7853)	(190.9783)	(87.6960)	0.1769	0.3140

Table 12: Tightness and Individualism Scores. Equal weighted R2 is the R2 calculated from the regression from Eun et al. (2015), which represents the stock comovement or synchronicity. Tightness scores are from Gelfand et al.(2010). Individualism scores are from Hofstede (2001).

Country	Period for R2 Estimation	Equal-weighted R2	Tightness	Individualism
United States	1990-2010	0.17	5.1	91
Australia	1990-2010	0.17	5.1	91
United Kingdom	1990-2010	0.261	6.9	89
Canada	1990-2010	0.249		80
Germany	1990-2010	0.249		80
Netherlands	1990-2010	0.316	3.3	80
Hungary	1994-2010	0.334	2.9	80
Italy	1990-2010	0.381	6.8	76
Belgium	1990-2010	0.275	23	75
Denmark	1990-2010	0.255		74
France	1990-2010	0.264	6.3	71
Sweden	1990-2010	0.32		71
Ireland	1990-2002	0.255		70
Norway	1990-2010	0.305	9.5	69
Switzerland	1990-2010	0.3		68
Finland	1991-2010	0.315		63
Luxembourg	1992-2009	0.254		60
Poland	1995-2010	0.35	6	60
Czech Republic	1994-2007	0.256		58

South Africa	1994-2007	0.256		58
New Zealand	1994-2007	0.256		58
Austria	1990-2010	0.297	6.8	55
Israel	1990-2010	0.315	3.1	54
Spain	1990-2010	0.366	5.4	51
India	1990-2010	0.3	11	48
Japan	1990-2010	0.361	8.6	46
Argentina	1993-2010	0.38		46
Russian Federation	1997-2010	0.263		39
Brazil	1992-2010	0.255	3.5	38
Turkey	1990-2010	0.452	9.2	37
Greece	1990-2010	0.387	3.9	35
Philippines	1990-2010	0.288		32
Mexico	1990-2010	0.314	7.2	30
Portugal	1990-2010	0.288	7.8	27
Malaysia	1990-2010	0.391	11.8	26
Hong Kong	1990-2010	0.319	6.3	25
Chile	1990-2010	0.275		23
Thailand	1990-2010	0.333		20
Singapore	1990-2010	0.37	10.4	20
China	1993-2010	0.549	7.9	20
South Korea	1990-2010	0.365	10	18
Taiwan	1990-2010	0.45		17
Peru	1991-2010	0.262		16
Pakistan	1993-2010	0.296	12.3	14
Indonesia	1990-2010	0.297		14
Columbia	1992-2010	0.311		13
Venezuela	1994-2009	0.324		12

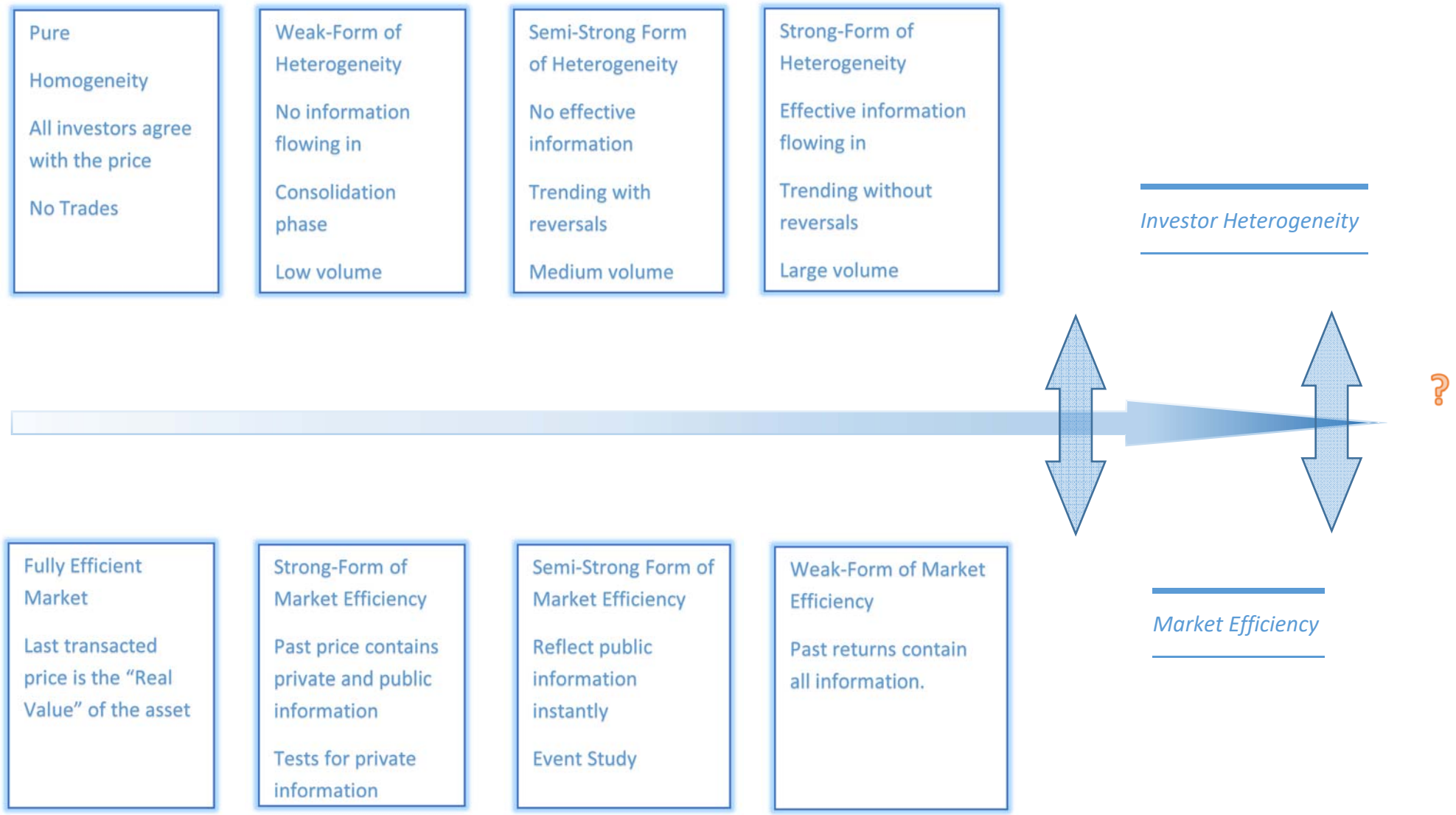

Figure 13: Investor Heterogeneity Spectrum. Momentum and trading volume increase as investor heterogeneity increases.

Appendix II: Eviews Code for the Winner and Lower Portfolio Strategy

```
include Momentum
include addtable5


        scalar for_length=21*12
        scalar hol_length=21*12
        scalar percentagetocollect=0.1
        scalar timerollingperiod=21*1

        call addtable_title


    '================================================================================
==========================1955, 1956 to 2308, 2309 to 4528


        !for_startday=2309
        !n=3
        !hol_endday=1

        while  !hol_endday <= 4528

        !for_endday=!for_startday+{for_length}-1
        !hol_startday=!for_endday+1
        !hol_endday=!hol_startday+{hol_length}-1

        if !hol_endday>=4528 then !hol_endday=4528
        endif


        string firmgroup="p_ho"
        call Momentum
        call addtable_dates
        call addtable_Highorder


        string firmgroup="p_lo"
        call Momentum
        call addtable_Loworder

        string firmgroup="p_us"
        call Momentum
        call addtable_pureus

        call addtable_monthborder

        !for_startday=!for_startday+{timerollingperiod}

        !n=!n+1

        wend




subroutine Momentum
```

```
'================================================================================
=======================
scalar numberofstocks=@columns({firmgroup})
scalar numberofdays=@rows({firmgroup})
matrix({numberofstocks},2) For_{firmgroup}

!i = 1 'iteration counter
!numberofiterate={numberofstocks}   '!numberofiterate is a temp variable equals to number of stocks.
while !i <= !numberofiterate           ' note that this place can not use {numberofstocks} directly

    For_{firmgroup}(!i, 1)=!i
    For_{firmgroup}(!i, 2)=({firmgroup}(!for_endday,!i)-{firmgroup}(!for_startday,!i))/{firmgroup}(!for_startday,!i)

     !i=!i+1

wend

'================================================================================
'Read the returns in the formation period, and rank stock number and return in decending order.

vector rank_identifier = @ranks(@columnextract(For_{firmgroup}, 2),"d","i")

matrix for_{firmgroup}_R = @capplyranks(For_{firmgroup}, rank_identifier)

'================================================================================

scalar N_V_R_{firmgroup}=@obs(@columnextract(for_{firmgroup}_R, 2))

scalar N_c_{firmgroup}=@round(percentagetocollect*N_V_R_{firmgroup})

Matrix ({N_c_{firmgroup}}, 3 ) Pf_W_{firmgroup}
Matrix ({N_c_{firmgroup}}, 3 ) Pf_L_{firmgroup}


!num1={N_c_{firmgroup}}
!num2={N_V_R_{firmgroup}}



for !counter1=1 to !num1

                Pf_W_{firmgroup}(!counter1, 1)=for_{firmgroup}_R(!counter1, 1)
                Pf_W_{firmgroup}(!counter1, 2)=for_{firmgroup}_R(!counter1, 2)
                Pf_W_{firmgroup}(!counter1, 3)={firmgroup}(!hol_endday,for_{firmgroup}_R(!counter1))/
{firmgroup}(!hol_startday,for_{firmgroup}_R(!counter1))-1

                Pf_l_{firmgroup}(!counter1, 1)=for_{firmgroup}_R(!num2-!counter1+1, 1)
                Pf_l_{firmgroup}(!counter1, 2)=for_{firmgroup}_R(!num2-!counter1+1, 2)
                Pf_l_{firmgroup}(!counter1, 3)={firmgroup}(!hol_endday,for_{firmgroup}_R(!num2-!counter1+1))/
{firmgroup}(!hol_startday,for_{firmgroup}_R(!num2-!counter1+1))-1

next
scalar ave_for_PF_w_{firmgroup}=@mean(@columnextract(Pf_W_{firmgroup}, 2))
scalar ave_hol_PF_w_{firmgroup}=@mean(@columnextract(Pf_W_{firmgroup}, 3))
scalar ave_for_PF_l_{firmgroup}=@mean(@columnextract(Pf_l_{firmgroup}, 2))
scalar ave_hol_PF_l_{firmgroup}=@mean(@columnextract(Pf_l_{firmgroup}, 3))

endsub


subroutine addtable_title
```

```
table R_{for_length}_{hol_length}
setcell (R_{for_length}_{hol_length},1,1,"Formation","l")
setcell (R_{for_length}_{hol_length},4,1,"Holding","l")
setcell (R_{for_length}_{hol_length},1,2,"Start Date","l")
setcell (R_{for_length}_{hol_length},2,2,"End Date","l")
setcell (R_{for_length}_{hol_length},3,2,"Duration","l")
setcell (R_{for_length}_{hol_length},4,2,"Start Date","l")
setcell (R_{for_length}_{hol_length},5,2,"End Date","l")
setcell (R_{for_length}_{hol_length},6,2,"Duration","l")
setcell (R_{for_length}_{hol_length},1,3,timecorres(!for_startday,1),0)
setcell (R_{for_length}_{hol_length},2,3,timecorres(!for_endday,1),0)
setcell (R_{for_length}_{hol_length},3,3,for_length, 0)
setcell (R_{for_length}_{hol_length},4,3,timecorres(!hol_startday,1),0)
setcell (R_{for_length}_{hol_length},5,3,timecorres(!hol_endday,1),0)
setcell (R_{for_length}_{hol_length},6,3,hol_length,0)

R_{for_length}_{hol_length}.setlines(a1:c3) +a -h -v
R_{for_length}_{hol_length}.setlines(a4:c6) +a -h -v
endsub


subroutine addtable_Highorder
%group="High Order"
setcell (R_{for_length}_{hol_length},1,4,"Group Name","l")
setcell (R_{for_length}_{hol_length},2,4,"No.of Stocks","l")
setcell (R_{for_length}_{hol_length},3,4,"Average Returns","l")
setcell (R_{for_length}_{hol_length},3,5,"Formation","l")
setcell (R_{for_length}_{hol_length},5,5,"Holding","l")
setcell (R_{for_length}_{hol_length},3,6,"Portfolio W","l")
setcell (R_{for_length}_{hol_length},4,6,"Portfolio L","l")
setcell (R_{for_length}_{hol_length},5,6,"Portfolio W","l")
setcell (R_{for_length}_{hol_length},6,6,"Portfolio L","l")

setcell (R_{for_length}_{hol_length},1,5,%group)
setcell (R_{for_length}_{hol_length},2,5,numberofstocks, 0)
setcell (R_{for_length}_{hol_length},3,7,ave_for_PF_w_{firmgroup}, 4)
setcell (R_{for_length}_{hol_length},4,7,ave_for_PF_l_{firmgroup}, 4)
setcell (R_{for_length}_{hol_length},5,7,ave_hol_PF_w_{firmgroup}, 4)
setcell (R_{for_length}_{hol_length},6,7,ave_hol_PF_l_{firmgroup}, 4)
R_{for_length}_{hol_length}.setlines(d1:g6) +a -h -v
endsub

subroutine addtable_loworder
%group="Low Order"
setcell (R_{for_length}_{hol_length},1,8,"Group Name","l")
setcell (R_{for_length}_{hol_length},2,8,"No.of Stocks","l")
setcell (R_{for_length}_{hol_length},3,8,"Average Returns","l")
setcell (R_{for_length}_{hol_length},3,9,"Formation","l")
setcell (R_{for_length}_{hol_length},5,9,"Holding","l")
setcell (R_{for_length}_{hol_length},3,10,"Portfolio W","l")
setcell (R_{for_length}_{hol_length},4,10,"Portfolio L","l")
setcell (R_{for_length}_{hol_length},5,10,"Portfolio W","l")
setcell (R_{for_length}_{hol_length},6,10,"Portfolio L","l")

setcell (R_{for_length}_{hol_length},1,9,%group)
setcell (R_{for_length}_{hol_length},2,9,numberofstocks, 0)
setcell (R_{for_length}_{hol_length},3,11,ave_for_PF_w_{firmgroup}, 4)
setcell (R_{for_length}_{hol_length},4,11,ave_for_PF_l_{firmgroup}, 4)
setcell (R_{for_length}_{hol_length},5,11,ave_hol_PF_w_{firmgroup}, 4)
setcell (R_{for_length}_{hol_length},6,11,ave_hol_PF_l_{firmgroup}, 4)
R_{for_length}_{hol_length}.setlines(h1:k6) +a -h -v
```

```
endsub

subroutine addtable_pureus
%group="Pure US"
setcell (R_{for_length}_{hol_length},1,12,"Group Name","l")
setcell (R_{for_length}_{hol_length},2,12,"No.of Stocks","l")
setcell (R_{for_length}_{hol_length},3,12,"Average Returns","l")
setcell (R_{for_length}_{hol_length},3,13,"Formation","l")
setcell (R_{for_length}_{hol_length},5,13,"Holding","l")
setcell (R_{for_length}_{hol_length},3,14,"Portfolio W","l")
setcell (R_{for_length}_{hol_length},4,14,"Portfolio L","l")
setcell (R_{for_length}_{hol_length},5,14,"Portfolio W","l")
setcell (R_{for_length}_{hol_length},6,14,"Portfolio L","l")

setcell (R_{for_length}_{hol_length},1,13,%group)
setcell (R_{for_length}_{hol_length},2,13,numberofstocks, 0)
setcell (R_{for_length}_{hol_length},3,15,ave_for_PF_w_{firmgroup}, 4)
setcell (R_{for_length}_{hol_length},4,15,ave_for_PF_l_{firmgroup}, 4)
setcell (R_{for_length}_{hol_length},5,15,ave_hol_PF_w_{firmgroup}, 4)
setcell (R_{for_length}_{hol_length},6,15,ave_hol_PF_l_{firmgroup}, 4)
R_{for_length}_{hol_length}.setlines(l1:o6) +a -h -v
endsub
```

Appendix III: Eviews Code for the Trading Volume Reactions and the Regressions for the Earnings Announcements

```
'all firms regression

'%sample="2000m02 2017m11"
'%sample="2000m02 2007m09"
'%sample="2007m09 2009m04"
%sample="2009m04 2017m11"

smpl %sample

'%firmgroup="ho"
'%firmgroup="lo"
%firmgroup="us"



'================================================================================
==
'above are the user inputs

!numberoffirms=1

if %firmgroup="ho" then
        !numberoffirms=150
endif
if %firmgroup="lo" then
        !numberoffirms=213
endif
if %firmgroup="us" then
        !numberoffirms=1816
endif
'scalar display=!numberoffirms
'string displaystring=%firmgroup

Table Areg_stat



setcell (Areg_stat,1,1,"Regression Statistics","l")
setcell (Areg_stat,1,3,"Group Name","l")
setcell (Areg_stat,1,4,%firmgroup,"l")
'setcell (Areg_stat,1,4,"Dependent V.","l")
'setcell (Areg_stat,1,5,"Independent V.","l")



setcell (Areg_stat,2,1,"Sample Period","l")
setcell (Areg_stat,2,3,%sample,"l")


setcell (Areg_stat,3,1,"Firm Number","l")
setcell (Areg_stat,3,2,"Coefficient","l")
setcell (Areg_stat,3,3,"t-statistic","l")
setcell (Areg_stat,3,4,"p-value","l")
setcell (Areg_stat,3,5,"R Square","l")
setcell (Areg_stat,3,6,"Average Trading Volume Turnover","l")
```

```
for !f=1 to !numberoffirms

        equation EQ_temp.ls tv_{%firmgroup}_!f c abs(r_{%firmgroup}_!f)
'       equation EQ1_temp.ls abs(r_{%firmgroup}_!f)  c tv_{%firmgroup}_!f
        setcell (Areg_stat,!f+3,1,!f,0,"c")
        setcell (Areg_stat,!f+3,2,EQ_temp.@coefs(2),"l")
        setcell (Areg_stat,!f+3,3,EQ_temp.@tstats(2),"l")
        setcell (Areg_stat,!f+3,4,EQ_temp.@pvals(2),"l")
        setcell (Areg_stat,!f+3,5,EQ_temp.@r2,"l")
        setcell (Areg_stat,!f+3,6,@mean(tv_{%firmgroup}_!f),"c")

next


'all firms regression


'%firmgroup="ho"
'%firmgroup="lo"
%firmgroup="us"


!windowpre=5
!windowpost=5


'================================================================================
==
'above are the user inputs

!numberoffirms=1

if %firmgroup="ho" then
        !numberoffirms=150
endif
if %firmgroup="lo" then
        !numberoffirms=213
endif
if %firmgroup="us" then
        !numberoffirms=1816
endif
'scalar display=!numberoffirms
'string displaystring=%firmgroup

Table EAreg_{%firmgroup}


setcell (EAreg_{%firmgroup},1,1,"Earnings Announcement Regression Statistics","l")
setcell (EAreg_{%firmgroup},1,4,"Firm Group","l")
setcell (EAreg_{%firmgroup},1,5,%firmgroup,"l")
setcell (EAreg_{%firmgroup},1,6,"Window Width","l")
setcell (EAreg_{%firmgroup},1,7,!windowpre+!windowpost,0, "l")

setcell (EAreg_{%firmgroup},2,1,"Firm Number","l")
setcell (EAreg_{%firmgroup},2,2,"EA Number","l")
setcell (EAreg_{%firmgroup},2,3,"EA Date","l")
setcell (EAreg_{%firmgroup},2,4,"Start Date","l")
setcell (EAreg_{%firmgroup},2,5,"End Number","l")
setcell (EAreg_{%firmgroup},2,6,"Coefficient","l")
setcell (EAreg_{%firmgroup},2,7,"t-statistic","l")
setcell (EAreg_{%firmgroup},2,8,"p-value","l")
setcell (EAreg_{%firmgroup},2,9,"R Square","l")
```

```
setcell (EAreg_{%firmgroup},2,10,"Average TV_Turnover","l")


'the starting date of 2007-2009 financial crisis is Oct 11, 2007 (1953)  and the ending date is Mar 9, 2009
(2306).
'pre financial crisis: 1 to 1953,
'financial crisis: 1954 to 2306
'post-financial crisis 2307 to 4258

scalar lc=3


for !i=1 to !numberoffirms

        !k=@ilast(@columnextract(ea_{%firmgroup},!i))   '!k is the number of EAs for each firm
        'scalar numberofeas=!k

        setcell (EAreg_{%firmgroup},lc,1,!i,0,"l")

        for !j=1 to !k
            !eadate=@columnextract(ea_{%firmgroup},!i)(!j)
            !startdate=!eadate-!windowpre
            !enddate=!eadate+!windowpost

            smpl !startdate !enddate
            equation EQ_temp.ls tv_{%firmgroup}_!i c abs(r_{%firmgroup}_!i)

            setcell (EAreg_{%firmgroup},{lc},2,{!j},0,"c")
            setcell (EAreg_{%firmgroup},{lc},3,datecorresponding(!eadate,1),"l")
            setcell (EAreg_{%firmgroup},{lc},4,datecorresponding(!startdate,1),"l")
            setcell (EAreg_{%firmgroup},{lc},5,datecorresponding(!enddate,1),"l")

            setcell (EAreg_{%firmgroup},{lc},6,EQ_temp.@coefs(2),"l")
            setcell (EAreg_{%firmgroup},{lc},7,EQ_temp.@tstats(2),"l")
            setcell (EAreg_{%firmgroup},{lc},8,EQ_temp.@pvals(2),"l")
            setcell (EAreg_{%firmgroup},{lc},9,EQ_temp.@r2,"l")
            setcell (EAreg_{%firmgroup},{lc},10,@mean(tv_{%firmgroup}_!i),"c")

            lc={lc}+1
        next

next



'all firms regression


%firmgroup="ho"
%firmgroup="lo"
%firmgroup="us"


!windowpre=5
!windowpost=5
```

```
'================================================================================
=Following is the time-divided program for EA.

!numberoffirms=1

if %firmgroup="ho" then
        !numberoffirms=150
endif
if %firmgroup="lo" then
        !numberoffirms=213
endif
if %firmgroup="us" then
        !numberoffirms=1816
endif
'scalar display=!numberoffirms
'string displaystring=%firmgroup

Table EAreg_{%firmgroup}


setcell (EAreg_{%firmgroup},1,1,"Earnings Announcement Regression Statistics","l")
setcell (EAreg_{%firmgroup},1,4,"Firm Group","l")
setcell (EAreg_{%firmgroup},1,5,%firmgroup,"l")
setcell (EAreg_{%firmgroup},1,6,"Window Width","l")
setcell (EAreg_{%firmgroup},1,7,!windowpre+!windowpost,0, "l")

setcell (EAreg_{%firmgroup},2,1,"Firm Number","l")
setcell (EAreg_{%firmgroup},2,2,"EA Number","l")
setcell (EAreg_{%firmgroup},2,3,"EA Date","l")
setcell (EAreg_{%firmgroup},2,4,"Start Date","l")
setcell (EAreg_{%firmgroup},2,5,"End Number","l")
setcell (EAreg_{%firmgroup},2,6,"Coefficient","l")
setcell (EAreg_{%firmgroup},2,7,"t-statistic","l")
setcell (EAreg_{%firmgroup},2,8,"p-value","l")
setcell (EAreg_{%firmgroup},2,9,"R Square","l")
setcell (EAreg_{%firmgroup},2,10,"Average TV_Turnover","l")



'the starting date of 2007-2009 financial crisis is Oct 11, 2007 (1953)  and the ending date is Mar 9, 2009
(2306).
'pre financial crisis: 1 to 1953,
'financial crisis: 1954 to 2306
'post-financial crisis 2307 to 4258

scalar lc=3


for !i=1 to !numberoffirms

        !k=@ilast(@columnextract(ea_{%firmgroup},!i))   '!k is the number of EAs for each firm
        'scalar numberofeas=!k

        setcell (EAreg_{%firmgroup},lc,1,!i,0,"l")

        for !j=1 to !k
            !eadate=@columnextract(ea_{%firmgroup},!i)(!j)

            if  (!eadate>2307)  then

            !startdate=!eadate-!windowpre
            !enddate=!eadate+!windowpost
```

```
        smpl !startdate !enddate
        equation EQ_temp.ls tv_{%firmgroup}_!i c abs(r_{%firmgroup}_!i)

        setcell (EAreg_{%firmgroup},{lc},2,{!j},0,"c")
        setcell (EAreg_{%firmgroup},{lc},3,datecorresponding(!eadate,1),"l")
        setcell (EAreg_{%firmgroup},{lc},4,datecorresponding(!startdate,1),"l")
        setcell (EAreg_{%firmgroup},{lc},5,datecorresponding(!enddate,1),"l")

        setcell (EAreg_{%firmgroup},{lc},6,EQ_temp.@coefs(2),"l")
        setcell (EAreg_{%firmgroup},{lc},7,EQ_temp.@tstats(2),"l")
        setcell (EAreg_{%firmgroup},{lc},8,EQ_temp.@pvals(2),"l")
        setcell (EAreg_{%firmgroup},{lc},9,EQ_temp.@r2,"l")
        setcell (EAreg_{%firmgroup},{lc},10,@mean(tv_{%firmgroup}_!i),"c")

        lc={lc}+1

      endif
    next


next
```

Appendix IV. Internet Appendix

Additional test results of momentum and trading volume including the original data from Bloomberg can be found at:

https://drive.google.com/drive/folders/1ZMXBu1NZ4gMPC6f_ehWXBngOVR1KQXXP?usp=sharing